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DETECTING FINANCIAL BUBBLES: DYNAMICAL AND FUNDAMENTAL APPROACHES

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Abstract

Financial bubbles are notable for disruptive events and severe financial consequences that adversely affect economic and financial activities. Consequently, much research and experimentation attempt to understand, identify, and forecast potential bubbles, and to mitigate related financial and economic risks. However, despite decades of inquiry and analysis, researchers still do not understand well the formation and termination of financial bubbles. In fact, they cannot even agree on a common definition, or even whether they are just patterns retrospectively classified with huge hindsight biases, such as being recognized only after they burst.

This research focuses on how to detect price-related and fundamental-related financial bubbles in real time, and in particular before they end. Chapter one provides theoretical backgrounds and a social bubble framework, and describes the log-periodic power-law singularity (LPPLS) model. Chapter two focuses on macro-level bubbles, while Chapters three and four concentrate on financial bubbles from price and fundamental perspectives, using the LPPLS model and machine learning approaches. Conclusions are outlined in Chapter five.

Chapter one of this thesis first presents a general introduction to market efficiencies and inefficiencies such as the Efficient Market Hypothesis and its critics, and introduces some alternative hypotheses. It then proposes a general Social Bubble framework, that incorporates financial bubbles. Based on economic scale, we further separate financial bubbles into two groups: macro-level bubbles (economic booms and busts), and micro-level bubbles, which contain three subclasses: price, valuation, and fundamental.

Chapter two is based on a working paper, analyzing 20 financial bubbles in global history in support of the proposed ‘Bubble Triangle Theory’. It is posited that all 20 bubbles share three essential elements: (1) Disruptive Novelty (new product, new market, change of economic policy, or catastrophic event), (2) Abundant Liquidity and Credit (domestic credit expansion and international capital flows); and (3) the ‘Social Bubble’ spirit.

Chapter three uses the LPPLS methodology to diagnose price bubbles. This chapter consists in two papers. The first paper, released in English and German, focuses on the market index level of price bubbles. It uses the ‘Corona Crash’ case study to illustrate how to use the LPPLS method to predict a market crash. Our analysis suggests that the S&P 500 index crash in February 2020 was endogenous in nature in the sense that the market had matured into a critical regime over the previous few years, characterized by a large susceptibility to external shows and the likelihood of a burst. In this regime, the burst did occur and was triggered by the exogenous Corona crisis shock. There are various bubbles similar to the Corona Crash, and they can be predicted in advance using the LPPLS model. The second paper applies the Event Study methodology to statistically investigate whether the ‘LPPLS Confidence Indicator’ can help predict the presence of price bubbles and crashes *ex-ante* and causally. The research utilizes both American and Chinese industry-level data. The empirical results suggest that the LPPLS method can identify regime shifts of both positive and negative price bubbles. Specifically, positive price bubbles contain two subclass regime shifts: (i) larger positive LPPLS Confidence Indicators can detect faster-than-exponential (super-exponential) price growth, followed by a drawdown or crash, and (ii) smaller positive LPPLS Confidence Indicators can detect faster-than-exponential (super-exponential) price growth followed by a plateau, suggesting convergence to a relatively stable price

level. The first regime change occurs as a result of the existence of a price bubble. In addition, the stronger negative bubbles detected by the LPPLS Confidence Indicator values are associated with higher price volatility, which breaks the symmetry with the price pattern documented for positive bubbles. This research can assist professional investors, financial institutions, and momentum-strategy funds to detect portfolio tail risks in advance and potentially avoid the losses associated with a market crash.

Chapter four explores how to use machine-learning methods to diagnose financial statement fraud (which cause fundamental bubbles). Specifically, we manually collect fraudulent cases selected by sophisticated short sellers along with standard (non-fraud) company cases in the U.S. market. We then use this dataset to train nine machine-learning algorithms to classify the fraud and non-fraud firms, based on well-known financial factors, financial variables, and accounting red flags. The results suggest that machine-learning algorithms can identify the patterns of fraudulent cases quite well with only a handful of financial statement features, indicating a potential fully automated financial analysis. Based on the results and short-selling reports, we propose the 'Polytope Fraud Theory', which identifies ten accounting issues that can be used as a checklist to detect financial statement fraud. We then use the famous Enron case to exemplify the Polytope Fraud Theory. In addition, we propose the 'Unified Investor Protection framework' (UIPF), which categorizes investor protection-related theories from macro-, middle-, and micro-levels. This framework can act as a financial education material for investors to understand the general fundamental risks at different timescales.

Chapter five summarizes the 'Bubble Triangle' and explains price-related and fundamental-related bubble detection methods. It offers our conclusions based on the empirical results of Chapters three and four. It also discusses the limitations of our research and suggests possible future research directions.

Kurzfassung

Finanzblasen zeichnen sich durch disruptive Ereignisse und schwerwiegende finanzielle Folgen aus, die sich nachteilig auf wirtschaftliche und finanzielle Aktivitäten auswirken. Folglich versuchen viele Forschungen und Experimente, potenzielle Blasen zu verstehen, zu identifizieren und vorherzusagen und die damit verbundenen finanziellen und wirtschaftlichen Risiken zu mindern. Trotz jahrzehntelanger Untersuchungen und Analysen verstehen Forscher die Entstehung und Beendigung von Finanzblasen jedoch immer noch nicht vollständig. Tatsächlich können sie sich nicht einmal auf eine gemeinsame Definition einigen.

Diese Forschung konzentriert sich darauf, wie preisbezogene und fundamentalbezogene Finanzblasen erkannt werden. Kapitel Eins bietet theoretische Hintergründe und einen Rahmen für soziale Blasen und beschreibtdas Modell der log-periodischen Power-Law-Singularität (LPPLS). Kapitel Zwei konzentriert sich auf Blasen auf Makroebene, während sich Kapitel Drei und Vier auf die Finanzblasen aus Preis- und Fundamentalperspektiven konzentrieren, wobei das Modell der log-periodischen Power-Law-Singularität (LPPLS) und Ansätze des maschinellen Lernens verwendet werden. Schlussfolgerungen werden in Kapitel Fünf gegliedert.

Kapitel Eins dieser Arbeit präsentiert zunächst eine allgemeine Einführung in Markteffizienzen und -ineffizienzen wie die Markteffizienzhypothese und ihre Kritik und führt einige alternative Hypothesen ein. Dann schlägt diese Arbeit einen allgemeinen Rahmen für soziale Blasen vor, einschließlich Finanzblasen. Basierend auf ihrem wirtschaftlichen Ausmaß unterteile ich Finanzblasen weiter in zwei Gruppen: Blasen auf Makroebene (Wirtschaftsbooms und -krisen) und Blasen auf Mikroebene, die drei Unterklassen enthalten: Preis, Bewertung und Fundamentaldaten.

Kapitel Zwei basiert auf einem unvollendeten Papier, das 20 Finanzblasen in der globalen Geschichte analysiert, unterstützt durch die vorgeschlagene „Blasendreieckstheorie“. Es wird davon ausgegangen, dass alle 20 Blasen drei wesentliche Elemente haben: (1) disruptive Neuheit (neues Produkt, neuer Markt, Änderung der Wirtschaftspolitik oder katastrophales Ereignis), (2) reichliche Liquidität und Kredit (inländische Kreditexpansion und internationale Kapitalströme) ; und (3) der „Geist der sozialen Blase“.

Kapitel Drei verwendet die LPPLS-Methodik, um Preisblasen zu diagnostizieren. Dieses Kapitel erwägt zwei Papiere. Das erste Papier, das in englischer und deutscher Sprache veröffentlicht wurde, konzentriert sich auf das Marktindexniveau von Preisblasen. Das erste Papier verwendet die Fallstudie „Corona-Crash“, um zu veranschaulichen, wie die LPPLS-Methode verwendet wird, um einen Marktcrash vorherzusagen, d. h. der S&P-500-Index-Crash im Februar 2020 war instinktiv endogen und platzte aufgrund des exogenen Corona-Krisenschocks. Es gibt verschiedene Blasen, die dem Corona-Crash ähneln und die mit dem LPPLS-Modell im Voraus vorhergesagt werden können. Das zweite Papier wendet die Event-Study-Methodik an, um statistisch zu untersuchen, ob der „LPPLS-Vertrauensindikator“ dazu beitragen kann, das Vorhandensein von Preisblasen und -crashs **ex ante** und ursächlich vorherzusagen. Die Forschung nutzt sowohl amerikanische als auch chinesische Daten auf Industrieebene. Die empirischen Ergebnisse deuten darauf hin, dass die LPPLS-Methode Regimewechsel sowohl positiver als auch negativer Preisblasen identifizieren kann.

Insbesondere positive Preisblasen enthalten zwei Subklassen- Regimewechsel: (i) größere positive LPPLS-Vertrauensindikatoren können ein schnelleres als exponentielles (superexponentielles) Preiswachstum erkennen, gefolgt von einem Rückgang oder Absturz, und (ii) kleinere positive LPPLS-Vertrauensindikatoren können ein schneller als exponentielles (superexponentielles) Preiswachstum erkennen, gefolgt von einem Plateau, was auf eine Konvergenz zu einem relativ stabilen Preisniveau hindeutet. Der erste Regimewechsel ist als Preisblase bekannt. Darüber hinaus sind die stärkeren negativen Blasen, die von den Werten des LPPLS-Konfidenzindikators erkannt werden, mit einer höheren Preisvolatilität verbunden, was die Symmetrie mit dem für positive Blasen dokumentierten Preismuster bricht. Diese Forschung kann professionellen Anlegern, Finanzinstituten und Momentum-Strategie-Fonds dabei helfen, Portfolio-Tail-Risiken im Voraus zu erkennen und möglicherweise einen Marktcrash zu vermeiden.

Kapitel Vier untersucht, wie Methoden des maschinellen Lernens verwendet werden, um Betrug bei Bilanzen, (der grundlegende Blasen verursacht,) zu diagnostizieren. Insbesondere sammeln wir manuell betrügerische Fälle, die von erfahrenen Leerverkäufern ausgewählt wurden, zusammen mit standardmäßigen (nicht betrügerischen) Unternehmensfällen auf dem US-Markt. Anschließend verwenden wir diesen Datensatz, um neun Algorithmen für maschinelles Lernen zu trainieren, um die betrügerischen und standardmäßigen Firmen auf der Grundlage bekannter Finanzfaktoren, Finanzvariablen und Buchhaltungswarnzeichen zu klassifizieren. Die Ergebnisse deuten darauf hin, dass maschinelle Lernalgorithmen die Muster von Betrugsfällen mit nur einer Handvoll Finanzberichtsmerkmalen recht gut identifizieren können, was auf eine potenzielle vollautomatische Finanzanalyse hinweist. Basierend auf den Ergebnissen und Leerverkaufsberichten schlagen wir die „Polytope Betrugstheorie“ vor, die zehn Rechnungslegungsprobleme identifiziert, die als Checkliste zur Aufdeckung von Bilanzbetrug verwendet werden können. Wir verwenden dann den berühmten Enron-Fall, um die Polytope Betrugstheorie zu veranschaulichen. Darüber hinaus schlagen wir das Unified Investor Protection Framework (UIPF) vor, das anlegerschutzbezogene Theorien auf Makro-, Mittel- und Mikroebene kategorisiert. Dieser Rahmen kann Anlegern als finanzielles Lehrmaterial dienen, um die allgemeinen fundamentalen Risiken in unterschiedlichen Zeitskalen zu verstehen.

Kapitel Fünf fasst das „Blasendreieck“ zusammen und erläutert preis- und fundamentalbezogene Blasenerkennungsmethoden. Es bietet unsere Schlussfolgerungen auf der Grundlage der empirischen Ergebnisse der Kapitel Drei und Vier. Es diskutiert auch die Grenzen unserer Forschung und schlägt mögliche zukünftige Forschungsrichtungen vor.

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Chapter 1

Introduction

Hunting financial bubbles is an ambitious goal. Numerous investors, entrepreneurs, and scientists have either become rich or lost their wealth during bubbles. Although it is very difficult to “surf” a bubble from the bottom and exit before the crash, bubbles still attract many followers, as successfully hunting bubbles can be an exciting and rewarding journey. The financial market is a non-linear and dynamic system which continuously self-evolves. Millions of retail investors, professional institutions, risk-taking speculators, risk-avoiding arbitragers, and complex computer-based algorithms make decisions separately and interact with others’ behavior adaptively, which makes financial markets particularly complex systems. Countless factors such as rumours, insider information, beyond/below expectation data, shocking events, unexpected policies, misleading news, and so on affect the financial markets every day, impacting people’s decisions, informing investors’ sentiment, and amplifying psychological biases.

To identify a bubble, investors must deal with ambiguous fundamental and moody price changes. Theoretically, a market price is a result of all current information and future expectation. However, even different people in the same investment groups can react to the same information differently. Investors may have totally contradictory opinions and actions due to their different backgrounds, knowledge-sets, risk preferences, target returns, capital sizes, investment horizons, tax-bases, and so on, and their views may vary from time to time.

Hopeful bubble hunters need to understand that some people may believe a particular asset is highly overvalued and will aggressively short the asset with leverage, while others may think it is fairly valued and that the trend will be sustained, so they will hold their positions. Yet others might decide it is unbelievably undervalued and will build their position and possibly also advise their friends to do the same. All the above can happen at the same time, and it is the aggregative outcome of this gaming that forms the asset price. Thus, hunting bubbles is also considered one of the most challenging topics in finance.

Fama claims that the market is efficient, there is no way to systematically identify bubbles in advance, and bubbles can only be interpreted after the fact. However, in this thesis, I will present two ways to identify financial bubbles in real time: (i) how to use the LPPLS model to systematically detect market index and industry-level stock price bubbles, and (ii) how to use machine-learning methods to systematically diagnose accounting fraud bubbles in financial statements. In addition, I also propose a Bubble Triangle Theory that might explain what characteristics the macro-level financial bubbles of boom-and-bust share.

1.1 The Debate of Market Efficiency

The Nobel Prize in Economic Sciences for 2013 was shared by three Americans: Eugene Fama, Robert Shiller, and Lars Peter Hansen. This is ironic, since anyone who is familiar with the Efficient Market Hypothesis (EMH) debate over the years will know that Fama hypothesized that market prices accurately reflect all available information, while Shiller argued that market prices can deviate far from rationality. In other words, Fama and Shiller were honoured with the same prize in the same year for their fundamentally different opinions on "market efficiency". At the time, the Royal Swedish Academy of Sciences committee (the awarding body) commented that their findings showed that markets are driven by "a mix of rational calculus and human behaviour[1]".

1.1.1 Efficient Market Hypothesis (EMH) and its Critics

The Efficient market hypothesis (EMH) is the cornerstone of modern finance. Fama (1965) showed the randomness of stock returns and proposed the "efficient market" concept, indicating that the stock prices "fully reflect" all market information. Samuelson (1965) also independently found that the stock price fluctuates randomly, and thus stock price changes must be unforecastable. Roberts (1967), based on Fama's concept, proposed the Efficient Market Hypothesis (EMH), and divided the market into 'strong' and 'weak' forms. Fama (1970) added the 'semi-strong' form of market efficiency, reflecting different levels of accuracy and rapidity of price adjustments to new information, conditional on different information sets. Samuelson (1973) argued that even the best investors cannot beat the stock market index, or randomly selected

[1] For more information, see: https://www.nobelprize.org/prizes/economic-sciences/2013/summary/.

stock portfolios. All the above research concludes that the stock market is efficient, and market prices fully incorporate all the available information, which can be expressed as equation (1),

$$P_t = V_t \equiv \sum_{i=1}^{\infty} \frac{E_t(D_{t+i})}{(1+r)^i} \tag{1.1}$$

where $E_t(D_{t+i})$ denotes the expected dividend payment, and r is the required rate of return.

Equation (1.1) indicates that the real price of a stock is defined as the present discounted value of future dividends. Normally, the market efficiency-related empirical tests focus on the return predictability. However, if market prices reflect all the publicly available information, then future returns would be impossible to predict.

Sharpe (1964), Lintner (1965), and Black (1972) developed the Capital Asset Pricing Model (CAPM), which claimed that the expected returns of securities have a positive linear relationship with the systematic risk (market beta) they bear in the markets. In addition, they argued that market beta is the sole factor that determines the cross-section of expected returns.

Grossman (1976) pointed out that the more people believe that the market is efficient, the less the market will be efficient, since there is no incentive for investors to actively acquire and process information. Grossman and Stiglitz (1980) also indicated that since information is costly, prices cannot perfectly reflect the information that is available, and thus, mispricing opportunities must exist to compensate informed traders. Moreover, if the market were perfectly efficient, the market would surely collapse since there would be no trading. Shiller (1981) found in his excess volatility puzzle[2] that equity return volatility cannot be justified by the variation in subsequent dividends, which opposes the EMH.

De Bondt and Thaler (1985) proposed in their Overreaction Hypothesis that investors are influenced by waves of optimism and pessimism that cause prices to deviate systematically from their fundamental values. In the long term, however, the price presents mean-reversion patterns. De Bond and Thaler also found there exists a

[2] Lev (1989) and Easton and Harris (1991) later showed that earnings explain around 10% of the variation in annual cross-sectional returns. Chen and Zhang (2007) indicated that a broader set of explanatory variables such as changes in profitability, growth opportunities, and discount rates increase the explanatory power up to about 20%. Liu and Thomas (2000) suggested that the revisions of analyst expectation can bring up the explanatory power to around 30%.

“January effect” that refutes the EMH. Black (1986) introduced the ‘noise trader’ concept: that individuals trade on what they consider “information”, but which is, in fact, noise. Bernard and Thomas (1989) indicated that there is a tendency for cumulative abnormal returns to drift for several weeks or months after an unexpected earnings announcement, which is known as post-earnings-announcement drift (PEAD). Lehmann (1990) and Jegadeesh (1990) rejected the EMH by finding the short-term reversal.

Around the same time, Fama (1991) proposed the joint hypothesis problem, pointing out that since the test for market efficiency is very difficult, any attempts to test market efficiency should involve asset pricing models, which can be used to compare the expected returns of models against real returns. Later, Fama and French (1993) proposed the three-factor model, which includes market excess return, the outperformance of small size premium, and outperformance of value risk premium to justify the excess abnormal returns of cross-section expected stock returns. They claimed that most of the recognised anomalies can be captured by the three-factor model.

Jegadeesh and Titman (1993) showed that the ‘momentum effect’ exists in the market, whereby buying past winners and shorting past losers will generate excess risk-adjusted returns, which also contradicts the EMH. Odean (1999), Barber and Odean (2000) proposed the excess trading puzzle that retail investors tend to trade too much, and that the traders who trade the most perform the worst. Lo and MacKinlay (1999) rejected the Random Walk Hypothesis by finding that the short-term return correlation is not zero. They pointed out that the Random Walk Hypothesis is not equal to EMH, which very nearly became a “religious devotion” of economists. Rubinstein (2001) proposed a new version of EMH with his ‘competitive efficient market’, which claims that any possible predictability of future returns that investors observe should not be hastily exploited after consideration of transaction costs.

Fama and French (2004) rejected the CAPM model by showing that on average the relationship between market “beta” and portfolio returns is flat rather than upward sloping, as CAPM predicts. They argued that size factor might be a better proxy for risk and suggested that their finding does not mean that the market is inefficient. Malevergne and Sornette (2005) indicated that stock returns distribution has a heavy tail, which is the consequence of long-range time dependence. They further proposed a two-factor model which shows superior performance to the three-factor model of Fama and French. The model is based on two ingredients: (i) the market portfolio is constituted of assets whose returns it is supposed to explain, and (ii) the distribution of the firms' capitalizations is heavy-tailed according to Zipf's law. They then show that there is a diversification premium in addition to the systematic risk captured by the CAPM model, indicating that the original CAPM model is incomplete in the presence of a broad distribution of firm sizes (Malevergne & Sornette, 2007; Malevergne, Santa-Clara & Sornette, 2009).

Fama and French (2015) expanded the three-factor model to a five-factor model, adding the profitability factor and investment factor, which further improved the explaining power of the three-factor model. However, the five-factor model still fails the Gibbons-Ross-Shaken (GRS) test (1989), that the estimated alpha should be zero under the efficient market assumption.

Meanwhile, around this time behavioural finance gradually emerged, which is based on two pillars: (i) limits of arbitrage; and (ii) boundary rationality. Limits to arbitrage claims that since risks, costs, and constraints exist in the market, market anomalies are likely to appear (Shleifer & Vishny, 1997). For instance, Lee (2014) indicated that the central problem of the EMH is the naïve and unrealistic assumption that the information costs associated with arbitrage are trivial or unimportant. Besides, boundary rationality suggests that investors are not fully rational, and that they show behavioural biases in the decision-making process, which can lead to undesirable outcomes. Some behavioural bias examples are loss aversion (Kahneman & Tversky, 1979), psychological accounting (Tversky & Kahneman, 1981), overreaction (DeBondt & Thaler, 1985), and regret (Bell, 1982).

Recent literature (Hirshleifer & Teoh, 2009; Lee, 2014; Shiller, 2014; Sohn & Sornette, 2020) also reveals that the existence of economic incentives, behavioral biases, noise traders, market frictions, investor expectations and opinions, and various risk factors significantly influence the price discovery process and market efficiency. It also reveals many market puzzles that EMH cannot explain, such as equity premium puzzles, excessive trading volume puzzles, excess volatility puzzles, various evidence of return predictability, active managed fund puzzles, idiosyncratic volatility puzzles, and so on. Hence, the focus on market efficiency has gradually shifted from the yes/no debate of fully efficient markets to locating factors that could affect the timely incorporation of information.

1.1.2 Noise Trader Model (NTM)

Shiller's (1984) Noise Trader Model (NTM) is an important alternative hypothesis to the EMH for understanding the dynamic price evolution of the market.

$$P_t = \sum_{k=0}^{\infty} \frac{E_t D_{t+k} + \varphi E_t Y_{t+k}}{(1+\rho+\varphi)^{k+1}} \tag{1.2}$$

Equation (1.2) indicates that the present value of the stock is equal to the sum of the expected future dividend payments ($E_t D_{t+k}$) and φ times the expected future demand by noise traders ($\varphi E_t Y_{t+k}$), discounted to present value at a discount rate ($1 + \rho + \varphi$). ρ denotes the expected real return assuming that there is no information trader, while φ represents the expected compensation rate that would induce the information trader to hold all the shares[3]. If φ goes to zero, the equation (1.2) is equal to the equation (1.1). In other words, the price at time *t* is determined by the fundamental value of a firm, and the future noise trader demand of its stock price.

Although Shiller himself acknowledges that the model is restrictive, the conceptual kernel of the hypothesis includes behavior finance, and the three most essential elements cover (i) firm fundamentals, (ii) investor sentiment, and (iii) arbitrage costs[4]. Furthermore, the model also indicates that noise trader activities impose risks on all market participants and such risks will impact the valuation anchor of the market by disturbing the cost-of-capital. Thus, market prices and the intrinsic value of the company will likely be unequal from time to time.

According to Shiller's NTM model, there are three conclusions: (1) the collective and interactive behavior of noise traders can drive prices far from the fundamentals and mispricing appears from time to time; (2) noise trading is a key risk of the market, which should be managed; and (3) the cost of arbitrage will influence the magnitude and duration of the mispricing.

1.1.3 Adaptive Market Hypothesis (AMH)

Lo (2004) indicated that the EMH is an incomplete hypothesis because financial markets are not always rational and are sometimes driven by the fear and greed of participants. Based on "evolutionary psychology" and "bounded rationality", Lo (2004) proposed the Adaptive Market Hypothesis (AMH), which reconciles EMH with

[3] See Shiller (1984) for more details.

[4] Shleifer and Vishny (1997) indicated that arbitrage cost has three subclasses: (i) trading costs, (ii) holding costs, (iii) information costs.

behavioral economics. Lo claimed that the financial market, like ecological evolution, involves competition, reproduction, and natural selection, and is a dynamic and changing environment. In other words, the financial market can sometimes reflect the "wisdom of crowds", sometimes the "madness of mobs", and sometimes the transitional phases between the two.

The main ideas of AMH include: (1) market participants act in their own self-interest; (2) participants, without doubt, make mistakes; (3) participants, with many behavioral biases such as overconfidence, overreaction, and so on, can adapt to a changing environment via simple heuristics; (4) the primary objective for market participants is survival through innovation; and (5) evolution determines market dynamics (Lo, 2004; 2005).

There are also three implications due to the nature of the AMH: (1) the risk-reward relationship exists but is unstable over time; (2) unlike in the EMH, arbitrage opportunities appear from time to time; and (3) investment strategies perform well in certain environments but poorly in others.

1.1.4 Emerging Intelligence Market Hypothesis (EIMH)

Sornette (2014) proposed the Emerging Market Intelligence Hypothesis (EIMH). He reckons that the financial market can be considered as the sum of all engines that transform information into price and there are lots of highly intelligent, motivated, and capable investors in the market. It is their continuous actions that are aggregated in the prices.

Unlike the EMH that assumes all the information is fully reflected in price and therefore investors cannot "beat the market", EIMH recognises that the market is a complex system, similar to the sandpile model of self-organized criticality (Bak 1996), which consistently functions at the edge of chaos. The repetitive non-linear dynamical interactions among heterogeneous agents produce a 'market intelligence' which is more powerful than that most of its agents. Thus, the noise traders naturally emerge because of the emergent collective intelligence of the market which makes most investment strategies look like noise.

The whole is more than the sum of the part (Sornette, 2014). The "collective intelligent" dwarfs the individual investors, making them look like noise and transforming most of the trading strategies into losing strategies that only provide liquidity and transaction volume. Sornette indicates that the agents who optimize their strategies perform in general worse than non-optimizing strategies. In other words, low entropy (more informative) strategies underperform the high entropy (less informative) strategies because the complex financial market system is unpredictable most of the time (Sornette 2003; Satinover and Sornette, 2007a; 2007b; 2009).

1.1.5 Inelastic Markets Hypothesis (IMH)

Supported by the empirical results of fluctuations in the aggregate stock market, Gabaix and Koijen (2021) concluded that macro elasticity is small, which contradicts neoclassicals' frictionless theories. In addition, they asserted that the main driver of price change is the order flow, rather than fundamental information. Based on this order driven view, Gabaix and Koijen (2021) proposed the Inelastic Markets Hypothesis (IMH) that due to demand inelasticity, net order inflow will push up the aggregate stock market price, and $1 order inflow can result in an M[5] dollar increase of market value.

They reasoned that demand is inelastic in the aggregate stock market because: (1) financial institutions are fairly constrained by their asset allocation mandates, so they have a stable equity share; (2) hedge funds are too small, accounting for less than 5% of the market, and they face capital outflow and binding risk constraints when the equity market is not good; (3) risk transfer across sectors is small; and (4) the macro elasticity is lower than the micro elasticity, indicating that the stock market is "micro efficient".

The IMH implies that persistent flows can result in persistent deviations in prices, and the aggregate stock market is not good at absorbing very persistent shocks, which might lead to drifts in prices.

To conclude, the idea that market prices are assumed to equal fundamental value oversimplifies the human-decision process and undervalues the continuous flow of new information such as news, rumors and innuendo disguised as information. It also fails to capture the richness of market dynamics and the complicities of the price discovery process that not only requires time and effort, but also involves substantial costs and risks.

An interesting analogy to understand the problem of the efficient market hypothesis in real markets is this: One cannot claim that the ocean is flat simply because one observes that the force of gravity flattens the water in a cup. No one questions the

[5] M denotes the GK's multiplier M, which is around 5 (Gabaix & Koijen, 2021).

power of gravity, nor the natural phenomenon of water flowing downhill, but based on these observations alone one cannot infer that the Pacific Ocean should look like a mirror all the time. If oceans were flat, then how does one explain the existence of small waves and huge tsunamis? More to the point, if financial markets were efficient, how do we explain the bubbles and crashes in financial markets as tsunamis pour forth from the ocean?

Bubbles, an obvious, consistent, and dangerous market phenomenon with different timescales and mispricing magnitudes, are one of the most exciting topics evaluating the market efficiency. During a bubble, asset prices can significantly deviate from their intrinsic value, and the market can also remain irrational longer than most investors can remain solvent[6]. It might be information, or psychological biases, or costs and risks related to the market, or irrational expectation, or rational behaviour, or the combination of all that distorts asset prices.

DeRosa (2021) claimed in his book that it is important to evaluate whether the price development during a bubble is rational from a Bayesian point of view. In other words, people may recognise that bubble after it bursts but not before. He claimed that during the ascent of the bubble, there is no way to diagnose the bubble and the price growth can be explained by "rational" explanations, and the after-the-crash reclassification of such price trajectories as a bubble is not useful from an operational point of view. However, from theoretical and conceptual point of view, his claim is hollow, and he also made many logical errors in causality attribution[7] in his book. In addition, many practitioners, researchers, and central bankers show that bubbles can be detected and recognised before they burst and there are plenty of evidence that the LPPLS model developed by Sornette's group can detect the burst of bubbles in real-time and *ex-ante*.

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[6] John Maynard Keynes's original words are, "Markets can stay irrational longer than most investors can stay solvent." (Keynes, 1936, p. 123)

[7] For instance, DeRosa reckoned that the GAMESTOP is a short squeeze and thus not a bubble. However, a bubble can also be characterised by short squeeze by construction. Moreover, many rational hedge funds first recognised that the GAMESTOP was a bubble and would burst finally so they built short positions. It is the abundant liquidity and unfavored volatilities that "squeeze" their short positions and thus pushed the bubble to become even bigger. Thus, DeRosa made a logical error in causality attribution. Besides, DoRose also denied the existence of the dot-com bubble. However, many practitioners such as Julian Robertson from Tiger Management, Stanley Druckenmiller from Quantum Fund and many investors had identified the dot-com bubble and shorted it. Even the Chairman of the Federal Reserve Bank pointed out that the dot-com bubble was a "irrational exuberance" in 1996. They all correctly identified the dot-com bubble before it burst, although they were not sure or not correct when the exact right time was for the dot-com bubble to end. Therefore, that a bubble cannot be identified before it burst is a wrong and misleading claim.

1.2 Rethinking Bubbles

Bubbles are generally considered to have negative effects since they are often destructive and economically inefficient and can generate financial waste. For example, the Dot.com bubble in 2000 evaporated around 6 trillion dollars of U.S. market capitalization. The 2008 Global Financial Crisis led to $250 billion losses in U.S. subprime loans and securities, $4,700 billion cumulative loss in world output, a $26,400 billion decrease in the value of the global stock market, and 6 million people losing their jobs (Sornette & Woodard, 2009).

However, we can learn from history that many disruptive technologies such as electricity, steam and railways, large scale utilization of steel, and chemical, industrial, and electrical products are legacies of 'social bubbles', since these new technologies and their underlying infrastructural networks emerged from the wreckage of speculative bubbles. We also know that bubbles can appear across the spectrum of assets, such as tulip bulbs, railways, commodities, stocks, bonds, derivatives, algorithms[8], cryptocurrencies, electrical vehicles, and so on.

So, the question is simple: what is a bubble?

1.2.1 Financial Bubbles and Social Bubbles

The bubbles we most often discuss with others and read about in the financial media belong to a specific bubble category: the financial bubbles, which exist in financial markets where people trade different financial assets. A financial bubble can be generally defined as a situation where the market price is largely deviating from the intrinsic value of the underlying assets. However, there is no unified definition of financial bubbles upon which all financial economists agree.

Shiller (1981) indicated that, if market value cannot be justified based on future dividend flows, a bubble might present in share prices. McGrattan and Prescott (2001a, 2001b) identified bubbles using '*q* theory', which assumes that, if a set of assets is worth more than the sum of the individual assets' values, then there is a bubble. Based on the same theory, DeLong and Shleifer (1991) compared the value of closed-end funds with their underlying stock holdings and concluded there was a bubble in 1929. Later, Shiller (2001) used cyclically adjusted price to earnings (CAPE) ratios to

[8] AlphaGo's win against Lee Sedol ignited the ongoing Artificial Intelligence bubble in 2016.

determine if the stock market is overvalued (or not) and concluded that the U.S. stock market in 2000 was in a bubble based on extreme stock overvaluations.

However, where intrinsic value is ambiguous to define or difficult to measure, such as in commodities, antiques, or growth stocks that have substantial uncertainties and potentials, then other matrices must be relied upon. Kindleberger (1978, p.16) defined a bubble as "an upward price movement over an extended range that then implodes". Santoni and Dwyer (1990) defined a bubble as a period when stock market returns do not follow a random walk. Sornette (2003) defined a bubble as a "super-exponential price increase followed by a crash", and he successfully diagnosed the U.S. property market bubble in real time in June 2005 and predicted its peak to occur in mid-2006 (Zhou & Sornette, 2006).

This thesis classifies financial bubbles into two groups based on scale: macro-level bubbles, which reflect the booms and busts of the economy, and micro-level bubbles, which reflect the performance of specific financial assets and the interactive behaviors between heterogenous agents in the financial markets. Inspired by Yinglu Qiao's framework[9], I further slice the micro-level financial bubbles into three layers: (i) price layer, (ii) valuation layer, and (iii) fundamental layer. This thesis mainly focuses on detecting financial bubbles in the price layer and the fundamental layer.

For financial bubbles, the core feature is unsustainability, either in price pattern, or in high valuation, or in fundamental situation. For price bubbles, I follow Sornette's definition that the unsustainable *super-exponential*[10] price growth followed by crashes is a bubble, which are caused by a self-reinforcing positive feedback mechanism due to imitation processes and the herding effect. Chapter 3[11] presents the high suitability of the LPPLS model to diagnose price bubbles in the U.S. and Chinese stock markets.

The fundamental-related financial bubbles are more difficult to define, as judging a business is very complicated. It takes years for a top business school student to learn the basic idea of what a good business is, but environment and technology evolve continuously. Even the savviest investors, such as Warren Buffett and Charles Munger, make mistakes. However, there is one situation where no one can deny that a company is in a fundamental bubble: where the company produces a fraudulent

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[9] For more information, see: https://barrons.blog.caixin.com/archives/59183.
[10] "Super-exponential" is defined as the growth rate of the price grows itself (Sornette, 2003).
[11] Section 3.2 summarizes and categorizes the bubble theories in the literature in detail. Section 3.3 summarizes the LPPLS-related literature.

financial statement. Thus, I define fundamental-related financial bubbles as the financial statement fraud that no reasonable fundamental reality can justify. Chapter 4 discusses how to utilize the judgement of sophisticated activist short sellers to train machine algorithms to tell whether a company is in a fundamental bubble or not.

There is a more general bubble category: i.e., the social bubble, which is a broader concept that doesn't occur solely in the financial market. It is not necessarily negative and can appear in scenarios where strong social interactions between enthusiastic supporters of an idea, concept, or project trigger a self-reinforcing feedback loop, leading to widespread endorsement and extraordinary commitment (Sornette, 2008; Gisler et al., 2011; Gisler et al., 2013; Gisler & Sornette, 2021).

Gisler and Sornette (2021) indicated that social bubbles can lead to explorations of previously unknown territories and niches in science and technology. In other words, social bubbles can act as a catalyst for the development of disruptive technology because they can break the traditional cost/benefit analysis rules of finance. Otherwise, based on traditional cost/benefit analysis rules, rational investors would never invest in disruptive innovations, because such technologies, in the early stages, are immature and highly uncertain. In a social bubble, complex networks of interaction between enthusiastic supporters can cultivate a collective risk-taking attitude, break the stereotype of risk avoidance, and activate large-scale scientific or technology innovations.

Social bubbles can trigger economic revolutions such as the four great industrial revolutions (Gisler & Sornette, 2021), innovation booms such as the Apollo program (Gisler & Sornette, 2009), major scientific explorations such as the Human Genome project (Gisler & Sornette, 2011), massive government projects such as the construction of the Pyramids in Ancient Egypt, political activities such as the Nazi regime in Germany, and so on.

Take, for example, the story of Thomas Edison. We've all heard that there were 1,000 attempts before Edison finally found the right combination of elements to invent the light bulb. In addition to admiring Edison's perseverance, we must consider where he got the funds for the first 1,000 attempts[12]. And what if Edison failed 1,001 times

[12] Edison received funding for his research from John Pierpont Morgan and the Vanderbilt family. Electric light was one of the most remarkable technological breakthroughs of the second industrial revolution. Due to many successful investments during the second industrial revolution the Morgan family (the founding family of financial powerhouses J.P. Morgan and Morgan Stanley) became one of the most powerful families in U.S. history.

and still could not find the right materials? Would he have been bankrupted? Clearly, there must be some factor that can break the traditional cost/benefit analysis and convince investors to be bold enough to invest in something that has never previously existed in the world.

Figure 1, below, illustrates the Social Bubble Framework.

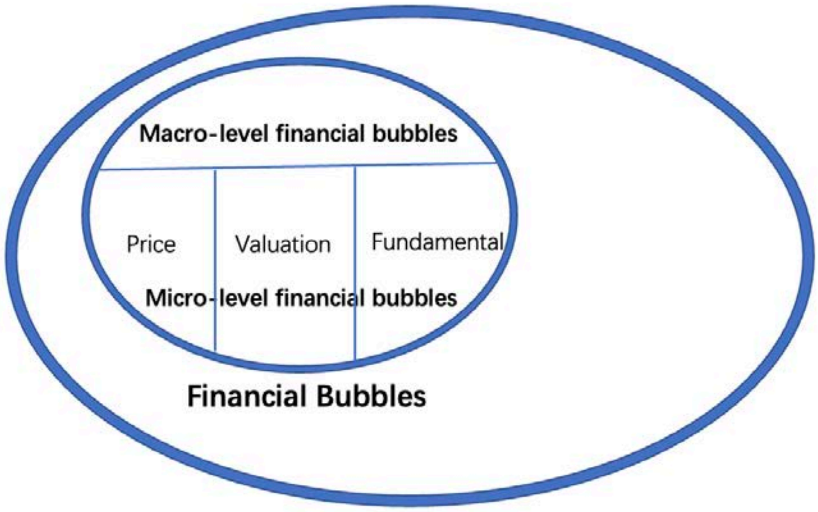

Figure 1. *Social Bubble Framework.*

1.2.2 Productive Bubbles and Destructive Bubbles

Based on their outcomes, bubbles can also be classified into two groups: productive bubbles and destructive bubbles.

Productive bubbles finance technological developments at a cost to unlucky investors, while destructive bubbles can devastate financial systems and lead to severe economic turmoil. William Janeway (2018) argued that bubbles are not necessarily wasteful, as scientists need "inefficient" trial-and-error experimentation to finally be rewarded with success (if they are also lucky). Carlota Perez (2002) identified that for the five distinct technology revolutions in human history, from British railway mania to the Dot.com bubble, financial capital created productive bubbles, which provided funding for large-scale technological projects. Although the busts that followed the bubbles could destroy personal wealth for some investors, the long-term benefits of productive bubbles far outweigh the short-term costs. In addition, a bubble (with astonishingly high prices as a strong market signal), can attract many talents to its field to serve and solidify the foundation of assets, which can potentially transform the "bubble" into "gold" [13]. Hence, productive bubbles are significant contributors to many of the technological breakthroughs we have seen throughout history.

Destructive Bubbles are bubbles that are highly speculative and evolve with large financial leverage and credit booms. Such bubbles are extremely dangerous and toxic, since they can totally ruin the financial or banking systems, which, in turn, destroy the underlying infrastructures of economic and business activities, resulting in deep financial depressions and substantial losses in economic outputs (Sornette, 2003; Sornette & Woodard, 2010). Normally, the destructive bubbles are zero-sum games in which speculators trade assets such as financial derivatives, real estate, or stocks with borrowed money from banks. The gains and losses associated with the bubble do not relate to productivity improvements — traders are just playing the pure financial gambling game and hoping to part fools from their money. In contrast, the productive bubbles are positive-sum games because such bubbles nurture the improvement of the productivity. The Collateralized Debt Obligations (CDO), Credit Default Swap (CDS), and other structured investment finance products that led to the Global Financial Crisis were typical destructive bubbles. Those financial innovations caused "irrational exuberance" in the property and derivatives markets that eventually ruined the banking systems in the U.S., the U.K., and many other countries.

1.3 Bubblenomics

When Alfred Marshall borrowed the concept of "equilibrium" from mechanics (physics) to explain the relationship between supply and demand in his book *Principles of Economics* (1890), he would never have believed that the concept of equilibrium has limited the minds of modern economists right up to the present. Johan Maynard Keynes (1936) famously said, "Practical men, who believe themselves to be quite exempt from any intellectual influences, are usually the slaves of some defunct economist.". Given the field's inability to explain the increasingly complex world, many people reckon that

13 Elon Musk, a master bubble hunter, is a typical example of using bubbles to fulfill his ambitions. He took advantage of the Dot.com bubble and became a millionaire by selling a digital mapping software, Zip2, in the 1990s. Thanks to the Fintech bubble, he later co-created PayPal and sold it to Ebay, making him a billionaire in 2002. After that, he focused on EV and solar systems, becoming a pioneer of the green energy bubble (Giorgis, Huber & Sornette, 2022). Both his EV business, Tesla, and solar business, Solar City, went public and gained him substantial rewards – Musk was the richest man in the word in 2021. Elon Musk is currently exploiting the space explorations and cryptocurrencies, which are also bubbles.

economists should bring something new to liberate the current economic thinking[14]. Modern economics could certainly benefit from borrowing the concept of "out-of-equilibrium" from physics and applying it to economic analysis.

This thesis proposes the idea of "Bubblenomics". The word "bubble" indicates the out-of-equilibrium economic phenomenon, while "economics" means understanding the mechanism behind the phenomenon. We believe that Bubblenomics — the merging of the two terms and the two concepts — can attract crucial attention to the "out-of-equilibrium" macro and micro phenomenon, both in the public realm, and in those 'hallowed halls' still walked by "defunct economists".

1.3.1 Macro-level Bubble

There are several financial theories that may explain the macro-level bubbles that show boom-and-bust patterns.

Hyman Minsky (1975) proposed the 'Financial Instability Theory'. He asserted that supplies of credit were pro-cyclical, and that financial systems contained internal instabilities. Banks increase the supply of credit during the economic expansion period and reduce credit supply when the growth rate slows, leading to fragility in financial arrangements and increasing the likelihood of a banking crisis (Corsi & Sornette, 2014). Minsky believed that it is internal financial instability that creates the self-fulfilling and the self-defeating phases of boom-and-bust economic cycles.

Minsky (1975) classified three taxonomies of finance: hedge finance, speculative finance, and Ponzi finance. Hedge finance means that the anticipated operating income is more than sufficient to pay the interest and the scheduled reduction of debts. Speculative finance refers to the situation where a firm's anticipated operating income is just sufficient to fulfill its interest and debt obligations. Ponzi finance, an unsustainable pattern of finance, is where the anticipated cash flow of a firm would not honor its matured loans, and the firm must borrow new loans to maintain future payments of interest and maturing loans. If the economy slows and corporate profits decline, a hedge finance company could slide backwards into speculative finance. Even worse, a speculative finance firm could fall into Ponzi finance.

[14] H. Eugene Stanley coined the word "Econophysics" in year 1995, advocating to bring statistical mechanics models to economic analysis. Notable present-day econophysicists include Jean-Philippe Bouchaud, Doyne Farmer, János Kertész, Hideki Takayasu and Didier Sornette.

Richard Koo, Chief Economist at Nomura Research, introduced the idea of a "Balance Sheet Recession" (2009). Koo proposed that an economic recession might be triggered by high levels of private sector debt that restricts individual and corporate investment and consumption, rather than standard fluctuations in the business cycle. To be specific, high private sector debt repayments exhaust the cash flow of individuals and corporates, who need to focus on saving and debt repayment rather than spending and investing. The drop in spending and investing results in a further economic slowdown and asset value shrinkage (Koo, 2011). In other words, if credit is overheated, the banking system may face analogous risks caused by the inability to service the interest on the debts.

Hélène Rey (2013) noticed a high degree of co-movement in risky asset prices, capital flows, leverage, and financial aggregates around the world, and proposed the 'Global Financial Cycle' theory. Global Financial Cycles, which are associated with rises and falls in gross capital flows and boom-bust cycles in domestic asset prices, can lead to excessive credit growth in boom times, and excessive retrenchment in bad times. Unlike Mundell-Fleming Models[15], Rey (2013) argued that global capital is freely mobile, and the Global Financial Cycle dominates national monetary policies regardless of the exchange rate regime. In addition, Rey (2015) suggested that the real rate of interest in the developed economies dominates both the foreign investment in emerging countries, and the international capital flows between countries; she also found that the VIX index can be considered as a market proxy, measuring risk aversion and uncertainty[16].

1.3.2 Micro-level Bubble

The Micro-level financial bubble can generally be considered a significant price deviation from the fundamental value. However, given the ambiguity of the fundamental value, and the difficulty of accurately predicting the future income cash flow ex-ante, this method can only be narrowly applied in practice, especially when the

[15] Based on the Mundell-Fleming model, Paul Krugman hypothesized the "Impossible Trinity" in his essay *O Canada – a neglected nation gets its Nobel*. He concluded that a stable foreign exchange rate, free capital movement, and an independent monetary policy cannot be achieved together, and that central banks must forgo one of the objectives. For more information, see: https://slate.com/business/1999/10/o-canada.html.

[16] Rey (2015) indicated that carry trade tends to have a reserve relationship with the VIX, in that carry trade flows collapse when the VIX spikes and increase when the VIX is low.

intrinsic value is difficult to define and measure. Thus, more flexible methods are urgently needed to diagnose micro-level bubbles.

I will start with classical demand-supply equilibrium. Traditional supply and demand curves are highly theorical and under very strict pre-assumptions. EMH assumes that when any of the curves is changing, a new equilibrium will soon be achieved. However, in the real world, especially in the financial market that involves emotions, unstable expectations, and other market dynamics, the demand and supply curves are not always static straight lines, and the price changing process is not always done suddenly and properly due to the internal positive feedback loops embedded in the price transmission mechanism.

Why is the positive feedback loop so critically important? I use a metaphor to explain: The major difference between a nuclear power plant and an atomic bomb is whether the reaction triggers a positive feedback loop or not. If the reaction of a nuclear power plant goes beyond a certain level (critical mass), triggering a positive feedback loop, a domino effect (i.e., a chain reaction) will follow and the nuclear power plant could become an atomic bomb (Sornette et al., 2018; Oka et al., 2013).

Positive feedback loops are very common phenomenon in the financial world. For instance, if a government finances its budget deficit by printing more currency, it can easily trigger public fear and sometimes panics. Positive feedback loop in inflation expectation can easily lead the country into hyperinflation. Two famous examples: the Germany's hyperinflation in the 1920s, and the Venezuela's hyperinflation since 2016.

Momentum strategies is another classic case that has the positive feedback loop. Momentum funds buy stocks with the highest past performance and short stocks with worst past returns, which further push up the winners and hammer the loser. Moreover, even passive index investment can create a positive feedback loop. A market index or ETF index is a collection of capitalization-weighted stocks. When investors buy the index, a significant proportion of capital is allocated to purchasing individual stocks in the collection with big capitalizations. The stocks accounting for a larger percentage of the index will naturally be allocated more capital, while stocks with smaller caps will attract a smaller proportion of capital. As time passes and people's passive investment accumulates, the larger stocks become ever larger, while smaller companies cannot catch up.

Below are two examples of positive feedbacks mechanisms[17]:

- From the supply side: the traditional microeconomic view assumes that a higher price per unit will attract greater supply from producers. However, in many cases, the higher the price, the more likely producers are to rationally restrict supply, since people may have an anticipation that the future price increases can be sufficiently large to compensate for delaying the current "impatient" selling, which is similar to a backward-sloping supply curve[18].
- From the demand side: the traditional view holds that a higher price will lead to a lower demand. However, in many cases we see that a higher price leads to greater willingness of buyers to purchase now, for various reasons: fear of missing out (FOMO)[19], the financial inventive from joining the speculative trend, or other reasons, leading to a herding effect and creating more demand.

Due to positive feedback loops within the real demand and supply curves, we often see the price of goods or financial products get quickly out of control, and there is very little that can be done about this. The equilibrium theory generated from static and straight demand and supply lines alone cannot explain the bubble phenomenon originating from nonlinear dynamic properties of complex systems.

The highly counterintuitive contradictions between the classic microeconomic theory and causal reality have existed for centuries but have largely been ignored by mainstream economists. Economists, on the one hand, arbitrarily claim that the market is efficient, and on the other hand, claim that bubbles are caused by market failure. Even after government intervention, the bubbles still exist in the black market[20], which ought to be a market self-correction mechanism caused by the out-of-equilibrium triggers.

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[17] There are many positive feedback mechanisms that exist in the financial market, such as the portfolio insurance, momentum trading algorithms, option hedging strategies, stop-loss order, margin-call and forced liquidation, and so on. For more information, see *Why Stock Markets Crash?* (Sornette, 2003).

[18] The backward-sloping supply curve was first discovered by labor economists in 1960s. Finegan (1962) and Krueger (1962) found that, when real wages increase beyond a certain level, people tend to substitute leisure for paid work, and so higher wages will result in a decrease in labor supply.

[19] Fear of missing out (FOMO) is a typical result of social imitation, i.e., when information is limited, the best strategy is to imitate others (Sornette, 2003).

[20] After a government intervention, the price in the market may be limited in its ascent, but ordinary people still find it hard to transact the goods or buy the products. However, the black market – which reflects the real demand and supply caused by out-of-equilibrium triggers and amplified by the positive feedback mechanism – will often prevail in this environment.

1.4 The Origin of Price-related Financial Bubbles and Crashes

Bubbles can not only arise from irrational behavioural bias (Shiller, 2000) but also from rational expectations derived from diverse but correlated beliefs (Sohn & Sornette, 2020). Bubbles can decay slowly[21] instead of leading to severe crashes, and crashes can happen without a preceding bubble.

Mathematically, it has been proposed that large stock market crashes belong to the class of critical phase transition phenomena, which can also be observed in examples from statistical physics such as earthquakes, magnetism, melting, and the phase transformation process between solids, liquids, and gas (Sornette, 2003).

The existence of imitating processes, crowd behaviour, and self-fulfilling enthusiasm among investors, traders, and speculators always leads to a positive feedback mechanism in the financial market. The interaction among those heterogeneous agents often translates into accelerating growth of the market price[22] over months and years, which ignites self-reinforcing over-optimistic anticipation. The progressive build-up of cooperativity among these agents also results in the development of endogenous systemic instabilities. When the market enters the unstable phase, any trivial disturbance or external shock may trigger endogenous instability and lead to a crash.

Thus, the true origin of the stock price bubble is the positive feedback mechanism that leads to transient unsustainable price increases, and the crash after the bubble is fundamentally caused by endogenous instability but triggered by some exogenous (minor) factor of the moment.

1.4.1 Log-Periodic Power Law Singularity Model (LPPLS)

The Johansen-Ledoit-Sornette (JLS) model is a rational expectation bubble model that built on the mechanism of positive feedbacks at the origin of super-exponential price accelerations (Johansen et al., 1999, 2000) and of 'log-periodic power law singularity' (LPPLS) structures. The JLS model assumes that the asset price is determined by repeated non-linear interactions among heterogenous agents[23]. In its

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[21] The gap between price and its fundamental value can gradually narrow.
[22] Price acceleration is one of the typical features of a market bubble.
[23] The asset price is determined by rational agents reacting to non-rational noise traders, whose behavior leads to a change of regimes.

simplest version, the expected asset price $p(t)$ at time t follows a martingale process; that is, $E_t[p(t')] = p(t), \forall t' > t$, where $E_t[\cdot]$ denotes the expectation conditional on the information available up to time t (Schatz & Sornette, 2020). The asset price dynamics is described as

$$\mathrm{d}p = \mu(t)p(t)\mathrm{d}t - kp(t)\mathrm{d}j + \sigma(t)\mathrm{p(t)dW} \tag{1.3}$$

where dW is the infinitesimal increment of the standard Wiener process with zero mean and variance equal to $\mathrm{d}t$, $\mu(t)$ denotes the time-dependent return, $\sigma(t)$ represents the volatility, $\mathrm{d}j$ is the discontinuous jump with $j = 0$ before the regime change, and $j = 1$ after the regime change occurred; $k \in (0,1)$ is the percentage price drop during a change of regime and $h(t)\mathrm{d}t$ is the probability that the regime change occurs between t and $t + \mathrm{d}t$, conditional that it has not yet happened. The no-arbitrage and rational expectations imply

$$E[\mathrm{dp}] = \mu(t)p(t)\mathrm{d}t - kp(t)[0 + 1.\,h(t)\mathrm{d}t] = \mu(t)p(t)\mathrm{d}t - kp(t)h(t)\mathrm{d}t \tag{1.4}$$

yielding

$$\mu(t) = kp(t) \tag{1.5}$$

Then the expected asset price dynamics, conditioned on the fact that no regime change occurs, can be described by the equation, $E[\mathrm{d}\ \ln p(t)] = kh(t)\mathrm{d}t$ (neglecting the Ito term $\frac{\sigma^2}{2}$) with the following solution

$$E_t\left[ln\left[\frac{p(t)}{P(t_0)}\right]\right] = k\int_{t_0}^{t} h(t')\,dt' \tag{1.6}$$

Johansen et al., (1999, 2000) assumed that the crash hazard rate develops a finite-time singularity at some critical time t_c. This assumption has been elaborated by showing that it is supported by various micro-founded models of agents' behaviors in (Sornette and Johansen, 1997; 1998; Seyrich and Sornette, 2016).

This critical time is a random variable whose value is unknown to investors, but it is characterized by a probability density function q(t). The corresponding cumulative distribution function Q(t) and hazard rate $h(t) = \frac{q(t)}{[1-Q(t)]}$ indicate the probability of a regime change[24] in the next time period, given the fact that the critical time has not been reached. Sornette and Johansen (1997) proposed a Hierarchical

[24] Regime change denotes a change from super-exponential growth to lower growth, or even a fierce reverse movement.

Diamond Lattice (HDL) to model the network of interactions between noise traders whose herding behaviour leads to the change of regime. They were able to derive analytically that imitation on the HDL creates an oscillatory finite-time singularity for the probability χ that a group of agents will have the same state or reach an agreement to buy or sell, conditioned by some small random external influence on the network, in the form

$$\chi \approx A'_0(t_c - t)^{-\gamma} + A'_1(t_c - t)^{-\gamma}\cos[\omega \ ln(t_c - t) + \psi] + \cdots \qquad (1.7)$$

where A'_0, A'_1, ω and ψ are real numbers, and γ is a positive critical exponent. The oscillations are periodic in the variable $ln(t_c - t)$ (hence called 'log-periodic'), and decorate the pure power-law singularity, reflecting the approximate discrete scale invariance (Sornette, 1998) of the financial price dynamics. When the local period shrinks to 0, the oscillations reach the critical time, and the system changes to another regime as the dynamics beyond t_c change in nature. Under this mechanism, the crash hazard rate can be written as

$$h(t) \approx \mathrm{B}_0(t_c - t)^{m-1} + \mathrm{B}_1(t_c - t)^{m-1}\cos[\omega \ ln(t_c - t) + \psi' \qquad (1.8)$$

where $\mathrm{B}_0, \mathrm{B}_1, m, \omega, \psi'$ are parameters. Equation (1.6) indicates that before the occurrence of regime change, the hazard rate increases dramatically as the interactions among noise traders rise. Substituting equation (1.6) into the solution of equation (1.4), we obtain the LPPLS formula:

$$\mathrm{E}[\ln p(t)] \approx \mathrm{A} + \mathrm{B}(t_c - t)^m\{1 + \mathrm{C}\cos[\omega \ ln(t_c - t) + \theta\,]\} \qquad (1.9)$$

where $\mathrm{A} = \ln p(t_c)$ >0 and B<0 quantifies the amplitude of the price acceleration, C is the magnitude of the oscillations around the power-law singular growth, ω denotes the angular log-frequency of the oscillations before the critical time t_c, θ is the phase parameter between (0, 2π), and the exponent m is between (0, 1) and controls the shape of the price acceleration. Equation (1.7) is the fundamental equation of the LPPLS model, which describes the evolution of the expected price trajectory before the critical point.

1.4.2 LPPLS Calibration

Filimonov and Sornette (2013) rewrote equation (1.7) to simplify the calibration by expanding the term $\mathrm{C}\cos[\cdot]$ to reduce the number of nonlinear parameters from 4 (m, ω, t_c, θ) to 3 (m, ω, t_c) while increasing the number of linear parameters to 4 $(\mathrm{A}, \mathrm{B}, \mathrm{C}_1, \mathrm{C}_2)$, where $\mathrm{C}_1 = \mathrm{C}\cos\theta$ and $\mathrm{C}_2 = \mathrm{C}\sin\theta$. So, we get the modified expression of the LPPLS model:

$$\mathrm{LPPLS}(\mathrm{t}) \equiv E_t[\ln p(t)] \approx \mathrm{A} + \mathrm{B}(t_c - t)^m + \mathrm{C}_1(t_c - t)^m \cos[\omega\ ln(t_c - t)] + \mathrm{C}_2(t_c - t)^m \sin[\omega\ ln(t_c - t)] \quad (1.10)$$

where phase θ is included in C_1 and C_2. Mathematically, using the L^2 norm, the sum of the squares of residuals is

$$\mathrm{F}(t_c, \mathrm{m}, \omega, \mathrm{A}, \mathrm{B}, C_1, C_2) = \sum_{i=1}^{N} \{\ln p(\tau_i) - \mathrm{A} + \mathrm{B}(t_c - \tau_i)^m - \mathrm{C}_1(t_c - \tau_i)^m \cos[\omega\, ln(t_c - \tau_i)] - \mathrm{C}_2(t_c - \tau_i)^m \sin[\omega\, ln(t_c - \tau_i)]\}^2 \quad (1.11)$$

where $\tau_1 = t_1$, $\tau_2 = t_2$. The calibration of the LPPLS model consists in finding the parameters $(\mathrm{A}, \mathrm{B}, \mathrm{C}_1, \mathrm{C}_2, m, \omega, t_c)$ that make F minimum.

The solution to this nonlinear optimization problem proceeds in two steps. First, subordinating the linear parameters $\{\mathrm{A}, \mathrm{B}, C_1, C_2\}$ to the non-linear parameters $\{t_c, \mathrm{m}, \omega\}$, we obtain the following matrix equations:

$$\begin{bmatrix} N & \sum f_i & \sum g_i & \sum h_i \\ \sum f_i & \sum f_i^2 & \sum f_i\, g_i & \sum f_i g_i \\ \sum g_i & \sum f_i g_i & \sum g_i^2 & \sum g_i\, h_i \\ \sum h_i & \sum f_i h_i & \sum g_i\, h_i & \sum h_i^2 \end{bmatrix} \begin{bmatrix} \hat{A} \\ \hat{B} \\ \hat{C} \\ \hat{D} \end{bmatrix} = \begin{bmatrix} \sum y_i \\ \sum y_i f_i \\ \sum y_i g_i \\ \sum y_i h_i \end{bmatrix} \quad (1.12)$$

where $f_i = (t_c - \tau_i)^m$, $g_i = (t_c - \tau_i)^m$ and $h_i = (t_c - \tau_i)^m \sin(\omega \ln(t_c - \tau_i))$. The solution of the linear system (10) yields $\{\mathrm{A}, \mathrm{B}, C_1, C_2\}$ as a function of $\{t_c, \mathrm{m}, \omega\}$. Inserting expression (9), we obtain the new cost function $F_1(t_c, \mathrm{m}, \omega) = \min_{\mathrm{A}, \mathrm{B}, C_1, C_2} F_1(t_c, \mathrm{m}, \omega, \mathrm{A}, \mathrm{B}, C_1, C_2)$. Then the three nonlinear parameters are estimated as $\{\hat{t_c}, \hat{\mathrm{m}}, \hat{\omega}\} = \arg\min F_1(t_c, \mathrm{m}, \omega)$. This nonlinear minimization is accomplished by using the differential evolution method.

1.5 Detailed Overview of Thesis

This is a cumulative thesis based on a series of four published, submitted, and working papers. Chapter 2 is based on an first-authored working paper with Didier Sornette. Chapter 3 is based on two papers: the first is a published paper co-authored with Didier Sornette and first-authored by Jan-Christian Gerlach, the second submitted paper is a first-authored paper co-authored with Didier Sornette. Chapter 4 is based on a submitted first-authored paper co-authored with Zhongli Wang, Florian Schweizer-Gamborino, and Didier Sornette. Chapter 5 concludes and summarizes the work, objectives, and major results. My contributions to the Chapter 2 paper include the analysis of each of the discussed historical bubble case studies, co-formulating the theory, and writing the manuscript. My contributions to the first paper of Chapter 3 include formulation of the research questions, co-implementation of the research, and co-analyzing the research results. In the second paper of Chapter 3, I formulated the research questions, designed the research methodology, conducted the research, and drafted the manuscript. For the paper in Chapter 4, I proposed the research questions, designed the research methodology, co-conducted the research, analysed the research results, and proposed the two theories, in addition to drafting the manuscript. Below is a summary of each of the five thesis chapters.

Chapter 2: Global Financial Bubble History and the Bubble Triangle

This chapter is a working paper. We have analyzed 20 financial bubbles in global history and collected six fundamental summaries based on a detailed study of the individual cases. In addition, we propose the 'Bubble Triangle Theory', which indicates that all macro financial bubbles share three basic elements: (1) Disruptive Novelty (new product, new market, change of economic policy, and catastrophe events); (2) Abundant Liquidity and Credit; and (3) Social Bubble Spirit.

Chapter 3.1: Forecasting Financial Crashes: A Dynamic Risk Management Approach

Since 2009, stock markets have stayed in a long bull market regime. Passive investment strategies have succeeded during this low-volatility growth period. From 2018 onwards, however, there was a transition into a more volatile market environment interspersed by corrections increasing in amplitude and frequency. This calls for more adaptive dynamic risk management strategies, as opposed to static buy-and-hold strategies. To hedge against market drawdowns, the greatest source of risk that should accurately be estimated is crash risk. This article applies the Log-Periodic Power Law Singularity (LPPLS) model of endogenous asset price bubbles to monitor crash risk. The model is calibrated to 15 years of market history for five relevant equity country indices. Emphasis is placed on the U.S. S&P 500 Composite Index and the recent market history of the "Corona" year 2020. The results show that relevant historical bubble events, including the Corona Crash, could be detected with the model and derived indicators. Many of these events were predicted in advance in monthly reports by the Financial Crisis Observatory (FCO) at ETH Zurich maintained in the Chair of Entrepreneurial Risks led by Prof. D. Sornette. The Corona Crash, as the most recent event of interest, is discussed in further detail. Our conclusion is that unsustainable price dynamics leading to an unstable bubble, fueled by quantitative easing and other policies, already existed well before the pandemic started. Thus, the bubble that burst in February 2020 was of endogenous nature. The burst, which was triggered by the exogenous Corona crisis, was predictable to some degree based on the endogenous price dynamics preceding it. A fast recovery of the price to pre-crisis levels ensued in the months following the crash. This leads us to conclude that, while the underlying origins and the macroeconomic environment that created this bubble do not change, bubbles will continue to grow and potentially spread to other sectors. This may cause even more hectic market behavior, overreaction, and volatile corrections in the future.

Chapter 3.2: Bubbles for Fama from Sornette

Galvanized by the claims of Greenwood et al. (2017, p. 20) in Bubbles for Fama that "a sharp price increase of an industry portfolio does not, on average, predict unusually low returns going forward", and Fama's quote in June 2016 that "Statistically, people have not come up with ways of identifying bubbles[25]", we present significant evidence to the contrary of both statements. Using a methodology called Log-Periodic Power Law Singularity (LPPLS), which has been developed by the Sornette group over more than two decades, we show that a LPPLS-based "bubble confidence indicator" allows one to diagnose ex-ante the presence of a bubble. Using superposed epoch

[25] For more information, see: https://www.chicagobooth.edu/review/are-markets-efficient.

analysis we find an excellent performance in timing price regime shifts, even more so in the case of larger bubble confidence indicators. Moreover, we identify two classes of regime shifts following an accelerated price growth qualified by LPPLS: (i) bubbles followed by a large drawdown or crash, and (ii) price catch-up followed by a plateau, associated with the convergence to a stable price level. Indiscriminately mixing these two types of accelerated transient price increases may explain, in part, previous failures to diagnose bubbles and their aftermath. The existence of the first class of transient accelerated price increases followed by crashes is a long-standing puzzle. Additionally, the existence of the second class of transient accelerated price increases followed by a plateau poses a challenge to the efficient market hypothesis. Thus, a new puzzle emerges: the convergence to a stable price level, while accelerating, is slow, with investors and the market taking weeks to months to digest available information and to progressively converge to the final higher valuation consensus.

Chapter 4: Polytope Fraud Theory

Polytope Fraud Theory (PFT) extends the existing triangle and diamond theories of accounting fraud with ten abnormal financial practice alarms that a fraudulent firm might trigger. These warning signals are identified through evaluation of the shorting behavior of sophisticated activist short sellers, which are used to train several supervised machine-learning methods in detecting financial statement fraud using published accounting data. Our contributions include a systematic manual collection and labeling of companies that are shorted by professional activist short sellers. We also combine well-known asset pricing factors with accounting red flags in financial features selections. Using 80 percent of the data for training and the remaining 20 percent for out-of-sample test and performance assessment, we find that the best method is XGBoost, with a Recall of 79 percent and F1-score of 85 percent. Other methods have only slightly lower performance, demonstrating the robustness of our results. This shows that the sophisticated activist short sellers, from whom the algorithms are learning, have excellent accounting insights, tremendous forensic analytical knowledge, and sharp business acumen. Our feature importance analysis indicates that potential short-selling targets share many similar financial characteristics, such as bankruptcy or financial distress risk, clustering in some industries, inconsistency of profitability, high accrual, and unreasonable business operations. Our results imply the possible automation of advanced financial statement analysis, which can both improve auditing processes and effectively enhance investment performance. Finally, we propose the Unified Investor Protection Framework, summarizing and categorizing investor-protection related theories from the macro-level to the micro-level.

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Chapter 2

Global Financial Bubble History and the Bubble Triangle

Abstract

This chapter is based on a working paper. We have analyzed 20 financial bubbles in the global history. Then we collected six fundamental summaries based on a detailed study of the individual cases. In addition, we proposed the Bubble Triangle Theory, which indicates that all macro financial bubbles share three basic elements: Disruptive Novelty (New Product, New Market, Change of Economic policies, and Catastrophe events); Abundant Liquidity and Credit; and Social Bubble Spirit.

2.1 Global Financial Bubbles in Human History

This section summarizes 20 global financial bubbles in human history.

2.1.1 Tulip Mania

Tulip Mania, or Dutch Tulpenwindhandel, might be the first well-documented economic speculative bubble in human history. The tulip bulb was first introduced to the Netherlands as a gift from 16^{th} century Turkish Sultan Suleiman I, known as Suleiman the Magnificent. Due to their intense saturated petal colors, certain variants of cultivated tulips became a highly favored status symbol of the wealthy Dutch upper class. The flower rapidly gained popularity in the west European countries, and by 1636 the tulip had become the fourth most important export product for the Netherlands. Against the background of a highly prosperous Dutch economy, the surging price of tulip bulbs led to investor over-confidence in the value of the flower, and speculators began to participate in a trading game with the bulbs (Sornette, 2003).

Due to the established financial market in Amsterdam, buyers could sign a contract before a notary to buy tulips in advance (effectively a future contract), making trade more accessible across all levels of Dutch society. The Tulip price peaked in February 1637 at around 5,500 guilders for a rare bulb but plummeted back to the original price in later years when the bubble burst and the Tulip market crashed (Garber, 1989). Within just a few months, some of the best-selling Tulip bulbs lost more than 95 percent of their peak value (Thompson, 2007).

2.1.2 The Mississippi Bubble and the South Sea Bubble

Childless despite two marriages and lacking an heir to his crown, King Carlos II of Spain chose his grand-nephew, Philip, Duke of Anjou, and second-eldest grandson of Louis XIV of France, to become the new king of Spain in 1700. Fearful that the new king might unify the French and Spanish empires, Britain, the Dutch Republic, and the Roman Empire declared war on Spain in 1701, bringing about the War of the Spanish Succession (1701-1714) and later, the War of the Quadruple Alliance (1718-1720) (Quinn & Turner, 2020). These wars were very costly, and the highly indebted French, British, and Dutch governments urgently needed to reduce their public debt levels to avoid social risks (revolutions) and costs of government financing in the future.

The French Government chose to adopt the financial innovations of John Law[26], a Scottish finance theorist, to raise equity and refinance the government debt at a cheaper rate[27] (Frehen et al., 2013). In 1716 Law created a fiat currency via a new, state-owned central bank (Banque Générale Privée, or "General Private Bank") to massively expand credit, and in 1717 he purchased and floated the Mississippi Company, which was granted complete colonial privileges to trade French tobacco and African slaves in the French colony of Louisiana in the United States. Because trade with the East Indies had previously brought wealth to Europe, public opinion was that the trade with the U.S. would do the same. An effective marketing scheme greatly exaggerated the wealth of Louisiana, and the French government made promises of extraordinary gains from the exploitation of the new colony. In addition, several newspapers promoted the Mississippi Company's stock under the instruction of the French government. This led to wild speculation on the company's shares, and within two years, a share in the Mississippi Company originally costing around 150 livres was worth over 15,000 livres (Quinn & Turner, 2020). Law eventually came to realize he could not sustain the stock price indefinitely, nor prevent investors converting their shares into gold and silver coin. Soon after, the French government recognized that Law's bold experiment had fatal flaws and, after the collapse of the Mississippi Company in 1721, Law was summarily dismissed and then exiled from France.

The British government followed the French government's financial innovations and ambitious reforms using British joint stock company, the South Sea Company, thereby creating the 'South Sea Bubble', which burst in late 1720[28]. Whilst the Dutch Government did not follow the debt conversion innovation, it similarly promoted its own asset bubble, i.e., the "Windhandel bubble". The Mississippi Bubble, the South Sea Bubble, and the Windhandel Bubble are widely considered the first global financial bubbles (Frehen et al., 2013), and the Mississippi Bubble and South Sea Bubble resulted in economic crises in the U.K. and in France (Kindleberger & Aliber, 2011).

[26] As an influential economist, John Law originated ideas such as the scarcity theory of value and real bill doctrine.

[27] Investors had to use government debt to pay for Mississippi Company stocks.

[28] Sir Isaac Newton lost a significant amount of his wealth in the South Sea Bubble, since he bought the stock at its peak. He later famously quoted, "I can calculate the motion of heavenly bodies, but not the madness of people." This is a direct quote and therefore should have a source.

2.1.3 Railway Mania and Bicycle Mania

The 'Railway Mania' (1840s) and the 'Bicycle Mania' (1880s-1890s) financial bubbles shared many similarities: Both bubbles were accompanied by revolutionary technological advances in transportation (i.e., steam-powered railways and the bicycle); both bubbles contributed to the proliferation of modern transportation in the United Kingdom (and people today still enjoy the legacy); and both bubbles attracted a large number of investments in the stock market through exaggerated expectations of profits, which preceded colossal evaporation of stock prices. During the Railway Mania, actual investments in railway construction accounted for as much as 8 percent of British GDP (Quinn & Turner, 2020). However, many railway companies provided fraudulent financial statements. Many of today's biggest accounting firms can trace their roots to the Railway Mania, as they were hired to audit the railway companies' mysterious balance sheets (Brown 1905; Bryer 1991).

The safety bicycle, the one we use today, was invented in 1876, and the motorcycle was invented in 1885; both were technological innovations developed during the Bicycle Mania. During this bubble the financial index of the bicycle industry increased by more than 350 percent. In 1896 the Initial Public Offering (IPO) of new bicycle and tire companies rose by more than 17 million British pounds, accounting for one-eighth of the total IPO increase for that year, and 15 percent of total new patents in the U.K. were related to bicycles in some way. The bicycle industry was the only industry that remained prosperous during the economic recessions of the time, and the 'Bike Boom' lasted almost a decade.

2.1.4 Australian Land Boom

In 1788 Britain established a penal colony in Australia, and over the next 80 years more than 160,000 convicts were transported to Australia from Britain in lieu of being sentenced to the death penalty. Several goldfields were later discovered in Victoria (in the 1850s), and a huge influx of people from around the world came to Melbourne to make their fortunes in the gold rush that followed, swelling the population of Melbourne by more than 70 percent in the ten years from 1881 to 1891[29]. This

[29] In 1891, Melbourne had the second largest population of the Commonwealth Countries, behind London. It had a reputation as the richest city in the world.

population boom led to a high rate of economic growth, which attracted a large amount of foreign capital from Britain[30].

Land prices, benefiting from the population boom as well as recent improvements in transportation, increased significantly. For example, a piece of land in Surrey Hills reportedly increased from 15 shillings in 1884 to 15 pounds in 1887 — a twentyfold increase in less than four years. The number of newly incorporated property companies and banks also skyrocketed due to the land boom. Over the first few months of 1888, the value of land in central Melbourne increased by 50 percent, and prices of some nearby rural areas trebled, due to the new convenience of public tram transportation. A rate hike on 22 October, 1888, marked the end of the land boom. By December 1888 land prices had plummeted by around 35 percent, and by 1889 prices had dropped to 50 percent of the peak. In the following years, many property companies became insolvent and some of Australia's biggest banks went bankrupt[31].

2.1.5 The Roaring Twenties and The Great Depression

Many countries in Europe suffered huge economic and population losses during World War I (1914-1918) and were facing enormous debts and economic recessions[32] by the time the War was finally over. By comparison, America, who had exported weapons and petrol during the war, and sold manufacturing products after the war[33], accumulated great wealth during this period. In addition, the U.S. had made many industrial breakthroughs. Families prospered and automobiles[34], telephones, radio and other modern technologies proliferated. The U.S. experienced unprecedented economic growth during the 1920s. Real estate and stock market prices both saw significant increases. The economist, Irving Fisher, famously proclaimed, "Stock prices have reached what looks like a permanently high plateau"[35].

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[30] Foreign investment from Britain accounted for more than 10% of Australian GDP in 1888 (Quinn & Turner, 2020).

[31] The gold rush in Western Australia also absorbed capital from Melbourne.

[32] For example, Germany suffered from hyperinflation due to war reparations, and France had lost most of its industrial areas to bombing and had incurred massive debt.

[33] European countries not only suffered from World War I, but also from the Spanish Flu, which delayed their recovery. After European factories were rebuilt and economies recovered several years after WWI, the demand for U.S. products in Europe declined, resulting in over-production of U.S. goods in the late 1920s.

[34] Henry Ford innovatively introduced the assembly line to the U.S. car industry in December 1913.

[35] Irving Fisher was quoted in the New York Times on 16 October, 1929, p.8.

During the financial boom commercial banks continued to grant loans to investors and speculators, and many financial leaders[36] advocated for their clients to buy stocks. Moreover, the Federal Reserve Bank's refusal to raise the discount lending rate several times also fueled speculation. In August 1929, the Federal Reserve finally raised the discount rate to 6 percent (Meltzer, 2003). The U.S. stock market crashed 12.82 percent on 28 October, 1929, however, and another 11.72 percent the following day, marking the end of the continued uptick in U.S. prosperity.

Investors and speculators started to panic. The stock market not only failed to rally as expected, but it also actually dropped even further. Lots of margin calls were triggered, and the impact soon spread to other industries. A coalition of bankers attempted to restore confidence by purchasing stocks at high prices, but these efforts failed. What's worse, banks later refused to grant new credits to commercial and manufacturing companies, since their collateral had dropped in value, which triggered another downward spiral. What had become known as 'The Crash' frightened investors, and consumers reduced their spending on big ticket items such as automobiles, which, in turn, led to increased unemployment (Romer, 2003). Many banks failed because of the bank run in 1930, which is considered the start of the Great Depression. By the end of 1933, the number of operating banks was just above half the number that existed in 1929[37] (Bernanke, 1983). Consequently, the unemployment rate surged from 3.2 percent in 1929 to 24.9 percent in 1933 (Lebergott, 1957).

Due to the international gold standard, the Federal Reserve's tightening policies showed spill-over effects, leading to a contraction of international commerce, and a slowing of the international economy (Eichengreen, 1992; Friedman & Schwartz, 1963; Temin, 1993). When the bear market finally hit bottom in 1932, the Dow Jones Industrial Index had plummeted roughly 90 percent. In 1933, the U.S. Congress passed the Glass-Steagall Act, separating commercial banks and investment banks, since they determined that commercial banks were overinvolved in highly risky stock market investment.

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[36] Including Charles E. Mitchell, the president of the National City Bank (now CitiBank) and director of the Federal Reserve Bank of New York.

[37] Ben Bernanke (1983), the former Chairman of the Federal Reserve Bank, reckoned that the massive meltdown of the U.S. banking system led to the Great Depression spinning on for more than 10 years, as normal economic recessions typically last for 1 to 2 years.

2.1.6 Oil Crises

On 14 September, 1960, in Baghdad, five countries (Iran, Iraq, Kuwait, Saudi Arabia, and Venezuela) founded the Organization of the Petroleum Exporting Countries (OPEC) to coordinate and unify the petroleum policies of member countries[38]. In 1973, after the Fourth Middle East War (Yom Kippur War), a group of Arab countries led by Saudi Arabia declared an oil embargo against the U.S., the U.K., Canada, Japan, the Netherlands, etc. By the end of the embargo in March 1974, the oil price had surged by around 300 percent — from 3 dollars per barrel to around 11.65 dollars per barrel globally (Merrill, 2007). The oil price surge triggered the global 'first oil crisis', and the energy supply shock led to a 4.5 percent drop in America's GDP, a 2.5 percent drop in Europe's GDP, and a 7 percent drop in GDP for Japan (Salameh, 2015).

In 1979, an Iranian revolution resulted in a massive oil production decline in Iran, kicking off the 'second oil crisis' (Romer & Romer, 2013). Due to religious conflict, competing economic interests in the Persian Gulf, and fear of 'exporting' the Iran revolution, Iraq invaded Iran, and the Iran-Iraq War began. Oil production in both countries decreased drastically[39], and the oil price increased from around 15 dollars per barrel to 39.5 dollars per barrel within 12 months, leading to a worldwide economic recession (Romer & Romer, 2013).

Meanwhile, other oil-exporting countries accumulated huge current account surpluses of U.S. dollars, later named "Petrodollar", and helped to mature the Eurodollar system. The petrodollar was later invested in multiple Latin American countries during the late 1970s. Former Federal Reserve Bank Chairman, Paul Volcker, had to spike the interest rate to 20 percent in April 1980 from 11.5 percent in the mid-1970s to fight against inflation[40] (Bernanke, 2004; Volcker & Gyohten, 1992). Industrial nations had to switch from OPEC oil to new oil supply sources and start looking to coal, natural gas, or nuclear power as alternative energy sources. In 1985, Saudi Arabia increased oil production and the oil price fell to around 7 dollars per barrel.

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38 The OPEC later extended to 13 countries, and today OPEC members together control an estimated 44% of global oil production and 81.5% of the world's "proven" oil reserves. OPEC members' decisions have significant impacts on the global oil market and geopolitical relations. Source needed.

39 Iraq and Iran attacked each other's oil facilities, petrochemical plants, and oil refineries during the war to cause economic disruption.

40 U.S. monetary policy had a big international "spill over" effect, in that the high interest rate in the U.S. since the early 1980s absorbed the petrodollar back to the U.S., causing debt crises in Latin America countries.

Due to a series of conflicts, OPEC's global market share fell from 50 percent in 1979 to 29 percent in 1986[41].

On 2 August, 1990, Iraq invaded Kuwait, starting the "third oil crisis", as Iraq argued that Kuwait's overproduction led to financial stress for Iraq[42]. The oil price increased from 28 dollars per barrel to 46 dollars per barrel. To mitigate oil supply risks the U.S. conducted rapid military intervention, which led to the retreat of Iraqi forces and ended the nine-months war.

The oil price kept increasing in the late 2000s. The global oil supply remained stable, however global economic prosperity – especially China's economic development, as well as commodity speculation – significantly increased demand for oil (Sornette et al., 2009). Moreover, the drop in value of the U.S. dollar accelerated the oil and gold bubbles (Tokic, 2010). The oil price was less than 60 dollars per barrel in January 2007, by March 2008, the oil price had reached around 100 dollars per barrel, and by mid-July, the oil price was beyond 147 dollars per barrel[43]. The oil price surge happened alongside the collapse of the U.S. housing bubble and economic slowdown, which deteriorated the world economy and amplified the U.S. recession.

In 2009, the Global Financial Crisis (GFC) hammered global oil demand, crashing the oil price to around 40 dollars per barrel. In 2011, the Arab Spring and Libyan civil war disrupted oil production and the oil price rose above 100 dollars per barrel, however new shale oil technology, as well as global oil oversupply in 2014/15 meant the oil price fluctuated between 30 and 80 dollars per barrel. The COVID-19 pandemic plummeted the oil price to negative 37.63 dollars per barrel on 20 April, 2020. Since then, the oil price has gradually increased due to the global reopening and economic recovery. However, the Russia-Ukraine War that began in February 2022 has pushed another oil price surge and significant volatility.

2.1.7 Latin American Debt Bubble

The first oil crisis in 1973 created a current account deficit for many Latin American countries due to the cost of oil and of imported goods, while oil-exporting

[41] Many industrial countries had to reduce their reliance on Middle Eastern oil production and turn to non-OPEC oilfields such as Siberia, North Sea, Alaska, the Gulf of Mexico, Brazil, etc. Consequently, the Soviet Union became the world's largest oil producer.

[42] Due to the Iran-Iraq War, Iraq accumulated a huge amount of debt to Arab countries. The overproduction of OPEC in the middle of the 1980s lowered the oil price and weakened Iraq's ability to pay its debt.

[43] The price of oil increased by more than 140% in the 18 months between January 2007 and July 2008.

countries accumulated large surpluses. With the encouragement of the U.S. government, large multinational ‘money-center’ banks[44] began to link the two groups as financial intermediaries—absorbing the petrodollar from oil-exporting nations and lending it to Latin American countries through dollar-denominated bank deposits (FDIC, 1997). The Third World lending services also contributed to the emergence of the Eurodollar market, a new international financial system. The interest rate of the Eurodollar lending market was based on the London Interbank Offering Rate (LIBOR)[45]. The debt of Latin American countries kept increasing dramatically during the 1970s[46], as they needed capital to invest in basic infrastructure, natural resources exploration, and economic modernization. U.S. banks were very active in lending to less-developed countries[47] (Kindleberger & Aliber, 2011).

In 1979, the second oil crisis drove the oil price higher, and in 1980 the Federal Reserve Bank had to increase interest rates to 20 percent to curb oil-based inflation. The persistently high oil price, the relatively high interest rate in the U.S., overvalued exchange rates, and highly indebted economies soon led to capital flight from Latin American countries, intensifying Latin America’s debt-service problem (Ferguson, 1999). However, Latin American nations continued their borrowing in the Eurodollar market[48]. On 12 August, 1982, Mexico’s Minister of Finance informed the Federal Reserve, the U.S. treasury department, and the International Monetary Fund (IMF) that Mexico was not able to service its 80-billion-dollar international debt. In 1983, 23 less-developed countries (LDCs), including 16 Latin American countries accounting for 74 percent of total LDC debt, applied to reschedule their debt. Consequently, many money-center banks stopped their international lending services and recycling petrodollar from LDCs to try to control their risk exposure[49].

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[44] Money-center banks provide borrowing and lending services to governments, large multinational corporations, and regular banks.

[45] The LIBOR has been replaced by the Secured Overnight Financing Rate (SOFR).

[46] By the end of 1970, the total outstanding debt of Latin America was only $29 billion, while by the end of 1978, the debt had surged to $159 billion, 80% of which was sovereign funded. Mexico and Brazil together accounted for around $89 billion (Federal Deposit Insurance Corporation, 1997).

[47] In the 1970s, Walter Wriston, former Citibank CEO, famously said: “Countries do not go bankrupt” (Sachs, 1989).

[48] Between 1979 and 1982, the total outstanding debt of Latin America doubled, rising from $159 billion to $327 billion. Seidman (2000), the president’s Economic Advisor to the Ford Administration, reckoned that most of the increasing debts were used to pay the interest of previous debt, rather than for productive investments.

[49] Almost all money-center banks had financial overexposure in third world lending, and many of them had debt exposure in Mexico violating the ‘10% to a single borrower’ rule.

The abrupt cut-off of this financing channel directly resulted in deep economic recession for many Latin American nations. To avoid deterioration of the situation, the Federal Reserve Bank of U.S. took a leading role in organizing an "international lender of last resort", with cooperation from money-center banks[50], central banks, the World Bank, and the IMF. In return, LDCs had to undertake structural reforms to eliminate their budget deficits (Sachs, 1988). Instead of cancelling state-owned enterprises' subsidies, many LDCs reduced their public spending in infrastructure, health, and education, and laid-off state employees, leading to high unemployment, declines in average income, and persistent economic stagnation (Devlin & Ffrench-Davis, 1995).

After years of negotiation, the creditor banks finally understood that the in-debt nations could not repay most of the loans, so they began to prepare loan loss provisions. In 1989, Nicholas Brady, Secretary of the Treasury to the Bush administration, proposed the 'Brady Plan', which aimed to raise substantial funds from the IMF, the World Bank, and other sources to facilitate debt reduction. The in-debt nations used the funds to retire bonds, conduct debt-equity swaps, buybacks, and other solutions to optimise debt structures. Although the Brady Plan had many limitations, it was considered a practical solution to the LDCs debt problem.

2.1.8 Tequila Crisis

Since the Great Depression, the Mexican government has followed an Import Substitution Industrialization (ISI) policy. Under the ISI, Mexico set high import tariffs and installed non-tariff barriers on foreign goods importation. The Mexican government also heavily subsidized state-owned enterprises, which enjoyed a captive domestic market with little or no competition. However, except for a few industries, Mexico did not conduct large scale international trade, making it difficult for the government to develop enough foreign exchange reserve. Due to the balance-of-payments crisis caused by the oil-related shocks of 1982, Mexico undertook large scale economic reforms under the creditor banks' requirements, which included trade liberalizations, liberalization of capital flows, dollarization of its currency, and privatization of the banks (Kindleberger & Aliber, 2011). As part of this process

[50] U.S. banking regulators allowed banks to gradually recognize losses from LDCs lending, preventing multinational banks from becoming insolvent. According to Seidman (2000), this regulatory forbearance effectively stopped financial panic, otherwise 7 or 8 of the 10 largest banks in the U.S. might have been bankrupt.

Mexico became a member of the General Agreement on Tariffs and Trade (GATT) in 1986[51]. To attract more international investors, the Mexican government also fixed the Mexican peso to the U.S. dollar[52]. After renegotiation with international creditors in 1989, Mexico was allowed to borrow from the international market again, and the Mexican government reset the Foreign Investment Act to allow foreign investors to invest in the Mexican stock market. As a result, foreign direct investment went up from zero (due to control) in 1989 to $3.4 billion in 1990, to $18 billion in 1992 (Musacchio, 2012). Debt flows also rose significantly, as Mexican companies started to borrow foreign-currency loans for infrastructure, economic modernization, and oil exploration in the Gulf of Mexico.

In the meantime, the U.S. dropped the interest rate in the early 1990s, which made Mexican asset returns more attractive. During the 1994 Mexican presidential election, the assassination of the presidential candidate and violent uprising resulted in political instability, leading to escape of global capital flows and increased risk premium on Mexican assets. In response, the Mexican central bank intervened in the foreign exchange rate market[53] and increased the interest rate, trying to maintain the value of the peso. However, the interest rate increase hurt the economy and deteriorated the capital drain. By the end of 1994, the Mexican central bank had run out of foreign reserve and had to devalue the peso, which triggered the collapse of the currency[54] (Musacchio, 2012).

Mexico experienced 52 percent inflation in 1995 and the collapse of several banks. The crisis spread to other emerging markets in Asia and Latin America, and the impact on Chile and Brazil became known as the "Tequila Effect"[55]. In 1995, the U.S. government coordinated a 50-billion-dollar rescue package from the IMF, the Bank of International Settlement (BIS) and other developed nations to save the Mexican

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[51] Mexico later joined the North America Free Trade Agreement (NAFTA) in 1994 and the WTO in 1995.

[52] There were three reasons for Mexico to adopt a fixed exchange rate: (1) dollarization reduces the foreign exchange risk, which can attract more global investors and stable import and export trade, (2) a fixed exchange rate can be considered as preparation for the opening of free trade with the U.S. (which happened in 1995), and (3) pegging to the U.S. dollar can force the central bank of Mexico to adopt more neutral monetary policies based on the balance of payments, instead of political whims.

[53] The Mexican central bank issued new short-term public debt in U.S. dollars and used the borrowed U.S. dollar capital to buy back the peso and maintain it at a higher level. However, speculators soon found out that the peso was artificially overvalued and increased their bet against the Mexican central bank.

[54] The value of the Mexican peso dropped by around 50%.

[55] Tequila Effect indicates that capital flight might trigger economic crisis due to loss of confidence of foreign investors.

economy. However, Mexico still experienced a severe recession, and its economy did not recover until the late 1990s.

2.1.9 Japan's Economic Miracle

After World War II, the Japanese economy experienced a deep economic recession caused by the war and the military procurement paid to America. By 1952, Japanese gross national product (GNP) was little more than one third of either France or the U.K. America reformed Japanese society through political, economic, and civic changes during the occupation period, and Japan itself also undertook ambitious economic reform (Income Doubling Plan) in the 1960s (Vogel, 1979).

The system of over-loaning, combined with a relaxation of anti-monopoly laws, revived conglomerate groups called *Keiretsu*[56], who could tolerate short-runs and low profits to focus on long-term strategic goals. In addition, the Japanese government expanded its investment in core infrastructure such as highways, high-speed railways, subways, airports, port facilities, and dams. Such economic reforms boosted technological innovations and improved the global economic competitiveness of Japanese goods. Japanese products soon lead the way in many global industries such as automobiles[57], shipping manufacturing[58], household appliances (TV, refrigerators, etc.), small electric manufacturing (printing machines, Walkmans, etc.), and optical equipment[59].

By the late 1970s, Japan's GNP was as large as the U.K.'s and France's combined, and more than half the size of America's (Vogel, 1979). In 1985, America concluded that the strong U.S. dollar value was due to 'the Fed's' (the Federal Reserve's) tightening monetary policy designed to fight oil-based inflation, and its huge current account deficit[60] with other countries, especially Japan. To counter this it forced Japan

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[56] Keiretsu conglomerates lent generously within the group and formalized cross-shareholdings structures, which protected against hostile takeover from outsiders. The *Keiretsu* also conducted horizontal and vertical integration, locking out foreign companies from entering Japanese industries.

[57] In 1978, Japanese Honda replaced Volkswagen in the U.S. as the third largest automobile exporter. In addition, the British motorcycle industry was virtually eliminated by the Japanese motorcycle industry and several of the most successful motorcycle companies in the U.S. were Japanese (except Harley-Davidson).

[58] Japan produced about 50% of the world's shipping tonnage in the late 1970s.

[59] Japan also replaced Germany in the camera and lens industry.

[60] There is a "Triffin Dilemma" in having the U.S. dollar as the world's reserve currency (Triffin, 1978): If the U.S. stops the current account deficit, then the international community will lose its largest source of reserve currency. However, if the U.S. continues the current account deficit too long, then the international community will lose confidence in the value of the U.S. dollar, which means they will no longer use the U.S. dollar as a reserve currency.

to sign the 'Plaza Accord', attempting to appreciate Japanese currency and therefore reduce the trade deficit with the U.S. and Western European nations[61] (Kindleberger & Aliber, 2011). However, significant economic growth, appreciation of the Japanese currency, low interest-rate and monetary expansion policies, and over-lending by Japanese banks as well as further financial liberation reform (e.g., tax law reform allowing a separate short-term investment fund known as *tokkin*) kept attracting foreign capital inflows, which further fueled speculative activities in Japan (Quinn & Turner, 2020).

The stock market and land prices saw a massive increase in Japan after 1985. By 1989, the Japanese stock market exceeded 4 trillion dollars, more than half of global equity market capitalisation. At the land rush peak, Tokyo land value alone was worth more than the entire American land price, and the total value of land in Japan was four times that of the total land value of America (Rubino, 2003).

In 1990, the Japanese central bank finally increased its interest rate, in part to allay concerns of an asset bubble. However, with the peak of labour population and an overleveraged private sector, Japan began to experience a "balance sheet recession"[62] (Koo, 2009, 2011). The collapse in stock and land prices, along with "zombie companies[63]" harmed the banking sector due to the low quality of loan books and shrinkage of collaterals, which marked Japan's "Lost Decades" (1991-now). The Japanese GDP decreased by more than a trillion dollars, real wages fell by around 5 percent, and the country experienced a price stagnation between 1993 to 2007. As of 2022, the Japanese interest rate is still close to zero.

2.1.10 Asia's Economic Miracle

Inspired by Japan's successful economic reforms, many East Asian countries introduced new export-oriented policies in the 1960s to energize their economic growth. There were many Newly Industrializing Economies (NIEs) that achieved obvious industrialization and significant economic growth between the 1960s and 1990s, the leading four of which were known as the Four Asian Tigers: South Korea, Taiwan,

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[61] The Plaza Accord only successfully reduced the trade deficit between Western European nations and Japan, not the trade deficit between U.S. and Japan (Bello, 1999).

[62] Balance Sheet Recession (BSR) indicates an economic recession triggered by high levels of debt in the private sector rather than the economic cycle. During a BSR consumers and companies spend most of their capital to pay down debt rather than spending on investment, which causes a decline in economic growth.

[63] 'Zombie companies' are companies that survive only with subsidies from the government.

Hong Kong, and Singapore. Hong Kong and Singapore became international financial centers, whereas South Korea and Taiwan built competitive advantages in manufacturing electronic components and devices. Other Asian countries also made significant economic progress by mimicking Japanese economic policy.

Even with the Plaza Accord, the U.S. could not reduce the trade deficit with Japan, but it did make Japanese products more expensive in the U.S., which forced Japan to seek out alternative low-cost production areas in East Asian countries. Consequently, around 15 billion dollars flowed into NIEs from Japan between 1985 and 1990 (Bello, 1999). To attract more international capital, many small Asian countries adopted fixed exchange rate policies and financial liberalization policies, including elimination of capital control, allowing foreign banks to directly participate in domestic banking operations, opening of financial sectors for foreign institutions, and dollarization of local currencies. Due to their relatively high interest rates, fixed exchange rates, and financial liberalization, huge international capital flowed into many NIEs[64], and consequently international institutions created new asset classes for developing-economy assets.

The international capital not only accelerated the industrial development of the NIEs countries, but also pushed up the property and equity markets. After the Japanese asset bubble burst in 1992, Japanese investments in many Asian countries gradually faded away, and Japan no longer needed the supply chains of many small Asian countries. When the U.S. dollar index strengthened and the Fed' increased the U.S. interest rate in the middle of the 1990s, many Asian countries lost their cheap-price competitiveness and relatively high yield attractiveness. In addition, the Asian countries' over-reliance on the banking sector delayed technological development and improvement of total factor productivity[65] (Krugman, 1994).

On 2 July, 1997, Thailand first began to devalue its currency against the U.S. dollar due to shrinkage of the foreign reserve; at around the same time, the U.S. began to increase the interest rate, marking the start of the Asian economic crisis. In later months, the property and stock markets in Thailand collapsed, and foreign capital began to escape from the country. Then Malaysia, the Philippines, and Indonesia all abandoned

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[64] U.S. mutual funds continued to supply net new capital to NIEs countries at roughly 4 billion dollars per year for the first half of the 1990s.

[65] Paul Krugman (1994) argued that the Asian Economic Miracle was not a result of new and original economic models, but from intensive capital investment and increasing labor force participation.

their fixed exchange rate policies and significantly devalued their own local currencies (Kindleberger & Aliber, 2011). The banking systems in many Asian countries were facing huge pressure, as their countries' capital accounts overly relied on international short-term debt. Many international speculators also took the opportunity to massively short sell some of their local currencies and equities in these countries, causing significant currency crises[66] and asset price crashes[67] (Wolf 1998, as cited in Bello, 1999).

2.1.11 1987 Black Monday

After the second oil crisis, the Federal Reserve Bank's Chairman, Paul Volcker, raised the interest rate to 20 percent (in 1980), and the U.S. experienced a two-years long economic recession. Volcker's tightening of monetary policy succeeded in depressing inflation, although these two years also saw an unemployment rate of more than 10 percent. The high interest rate in the U.S. also triggered the 'Latin America Debt Crisis', and a flooding of capital into the U.S. market (to enjoy high interest rates through 'carry trading'). However, the tightening monetary policy helped the U.S. stock market to remain stable until 1982[68], when Chairman Volcker reversed monetary policy by significantly lowering the interest rate.

Due to the expansionary monetary policy and global capital inflow, the U.S. economy began to recover, and the stock market began to rise in the latter part of 1982. Moreover, in 1985, the U.S. government forced the Japanese government to sign the Plaza Accord, significantly appreciating Japanese and west European countries' currencies to reduce the U.S. current account deficit[69]. The low interest rate, the sudden devaluation of the U.S. dollar in 1985 (Johansen & Sornette, 2010) and the drop in oil price due to Saudi Arabian overproduction in 1985 improved confidence in the U.S. economy. After 1985, the U.S. stock market index began to accelerate, and the leverage buyout business experienced a boom due to the prosperous stock market and junk bond

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[66] A year after the crisis began, the Indonesian rupiah had lost 82% of its value against the U.S. dollar, Thai baht had lost 42%, Malaysian ringgit 38%, and the Philippines peso lost 34%. South Korea also had a significant currency fall due to its large foreign debt, losing around 40%.

[67] Indonesia's stock market fell 89%, Malaysia's 73%, Thailand's 71%, and the Philippines 57%. Hong Kong, Singapore, and South Korea all saw at least 60% losses in their dollar value.

[68] Based on Shiller's S&P500 CAPE valuation model, the inflation-adjusted valuation of the U.S. stock market reached a 40-year low in 1983.

[69] The U.S. dollar appreciated 50% against the Japanese yen, Deutsche mark, French franc, and British pound between 1980 to 1985. After the Plaza Accord, the Japanese yen appreciated 20% within 3 months. The yen then kept appreciating after 1985, which led to currency speculation and Japan's economic bust in the early 1990s.

market development. Between August 1982 and August 1987, the S&P 500 index surged from around 120 to around 320[70], including a 39 percent increase between September 1986 and September 1987 (Sornette, 2003).

In February 1987, the Federal Reserve tightened the monetary policy according to the 'Louvre Accord', halting further U.S. dollar depreciation. The contractionary monetary policy directly led to a drop in U.S. money supply and liquidity shrinkage in the stock market. The U.S. stock market reached its peak on 25 August, 1987. An unexpectedly high economic trade deficit led to a 3.81 percent drop on 14 October, 1987. During the week after, the large mutual funds enabled customers to redeem their shares, and computer models showed portfolio insurers dictating large sales, which were precursors to a stock market regime change (Johansen & Sornette, 2000; Shiller, 2006. On the morning of 19 October, 1987, a large volume of sell orders soon outweighed buy orders, delaying the open of 95 large stocks on the S&P 500 index. The highly imbalanced market orders soon resulted in a market price drop, and the price drop, in turn, caused further imbalance, and so on in a downwards spiral (Sornette et al., 1996).

The "domino effect" was accelerated by the portfolio insurance protections mechanism and quantitative trading algorithms (Sornette, 2003; Sornette & Johansen, 2001). The total trading volume on that day was so large that many large funds transfers were delayed for hours. The market meltdown triggered severe margin calls, which amplified the liquidity spiral (Shiller, 2006). The Dow Jones Industrial Average index had dropped 22.6 percent by market close. The stock market crash in the U.S. spread to other developed markets: The Hong Kong market index plummeted 45.8 percent the same day, New Zealand's stock market fell 15 percent, and the U.K. stock market index dropped 23 percent over two days. It took 11 months for the U.S. stock market to recover to the original price level.

2.1.12 Dot-com Bubble

Although the internet was first developed in the 1960s by the United States Department of Defence and used by regional academic and military networks in the 1970s, the days of the large-scale civilian version of the internet we use today didn't dawn until 1989. Tim Berners-Lee, an independent contractor at the European

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[70] The Shiller S&P500 CAPE rose from around 6 in 1983 to 18 in August 1987.

Organization for Nuclear Research, first proposed a decentralized document system based on the concepts of hypertext, TCP, DNS etc., to facilitate sharing and updating of information amongst global researchers. Berners-Lee later named the system the 'World Wide Web' (WWW) and built the first web site on 20 December, 1990. In January 1991, the World Wide Web was opened to the public, and a 21-year-old part-time employee of the University of Illinois, Marc Andreessen[71], advanced browser technology to make it more functional on all operating systems (his web browser was known as 'Mosaic', which later became 'Netscape Navigator'). As a result of technological improvements, the number of people online increased from 14 million in 1993 to 281 million in 1999, and to 2.95 billion (62.5 percent of the world's total population) in January 2021 (Quinn & Turner, 2020).

The boom in technology sectors as well as financial turmoil[72] in multiple developing countries during 1994-1998 attracted high global capital flow into the U.S. financial market[73], resulting in a long-term bull market of technology company stock prices. Meanwhile, the IPO boom[74] throughout the 1990s attracted years of global capital inflows to the U.S. (Sornette & Zhou, 2004). The U.S. stock market valuations continued to surge[75], and on 5 December, 1996, the Fed' Chairman at the time, Alan Greenspan, gave his now-famous speech, warning about the "irrational exuberance" of the stock market (Shiller, 2006). Still, stock prices kept going up, and in March 2000, the S&P 500 was more than 100 percent higher than when Greenspan made his speech. Arguments about the valuation of the stock market gradually disappeared, however, since the bull market lasted for many years, and most of the bearish voices seemed to be proven wrong within that period. Many reports, articles, and books published during

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[71] Andreessen's unprofitable Netscape, which was considered the "big band" of the Dot.com era, went to IPO on 19 August 1995. Hundreds of new, unprofitable, high growth internet companies followed Netscape's route and were floated as IPOs on the Nasdaq in the late 1990s.

[72] Mexico and some of Latin America suffered currency crises in 1994, parts of Asia experienced financial crises in 1997, and Russia's Central Bank defaulted on its debt in 1998.

[73] After 1987's Black Monday and Alan Greenspan's active monetary policy response to the stock market crash, many investors believed that Greenspan would implement policies to limit the stock market's decline beyond a certain threshold. This became known as the "Greenspan Put" (Sornette, 2003).

[74] Since investors were extremely eager to invest in internet stocks, any companies' names with internet-related prefixes or a ".com" suffix would attract tremendous investment interest when they raised money from IPOs.

[75] According to Robert Shiller's cyclically adjusted price-to-earnings ratio (CAPE), the S&P 500 reached around 45 times its annual earnings in 2001, which was way above the long-term average of 16 (Shiller, 2006).

the Dot.com era commented on the "delusional optimistic opinion"[76] (Gordon, 2005). During the bull market, many retail investors gave up their jobs to become full time day traders[77], while some "value" investors managed to short the stock market, but also suffered big losses[78]. In addition, the 'Y2K' problem—predicted computer errors related to calendar format and the pending date-change from 1999 to 2000—convinced the Fed' to build abundant liquidity into the banking system in late 1999 to counter the end-of-the-millennium transition risk[79] (Kindleberger & Aliber, 2011).

The NASDAQ composite index reached 5133 on 10 March, 2000—the highest point of the Dot.com bubble, and crashed to 3300 a month later (Johansen & Sornette, 2000). The stock market crashed without any apparent positive or negative news (De Long & Magin, 2006; Sornette & Cauwels, 2015). The September 11 attacks and the Enron Scandal in 2001, and the WorldCom Scandal in 2002 further damaged investor confidence, and by the end of the stock market downturn of 2002, the Nasdaq had plummeted to around 80 percent of its peak (Sornette, 2003). Many small retail investors, professional institutions, and prominent investors suffered massive losses[80], and technology sectors in Europe and Asia were also impacted.

2.1.13 Subprime Crisis

The Dot.com bubble, the September 11 attacks, and the Enron and WorldCom Scandals led to loss of confidence in the stock market, resulting in a severe bear market. To alleviate the consequences of the liquidity spiral, the U.S. Federal Reserve lowered

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[76] (1). In 1989, 9% of analyst recommendations were "sell", while in 1999, only 1% of recommendations were "sell". (2). Jim Cramer criticized the price-to-earnings ratio as 'useless for the new economy' in 2000. (3). Kevin Hassett (who became the head of President Trump's Council of Economic Advisers in 2017) and James Glassman published a famous book called *Dow 36,000*, saying that the Dow, which at the time was around 10,000, would quickly rise to 36,000. (4). In December 1999, around the peak of the Dot.com bubble, Barron's published an article called "What's wrong, Warren?", questioning whether Warren Buffet was too conservative, and even passé. (5). Many financial news channels emerged during the 1990s: CNBC, CNN, Bloomberg, etc., and began to offer 24-hour coverage of stock market news and information on investment products (Quinn & Turner, 2020).

[77] Many small retail day traders joined Yahoo chat rooms, such as Silicon Investor and RagingBull.com, to share information and tips.

[78] For example, Julian Robertson was a legendary investor and the founder of Tiger Management, who held a short position on some 'zombie' technology companies. However, the 'delusional optimistic opinion' of investors pushed up junk stocks, and Robertson had to close his positions at the peak of the market, with huge losses, which led to the permanent closure of the Tiger Management fund (Zhao & Sornette, 2021).

[79] U.S. President, Bill Clinton, considered the Y2K problem "the first challenge of the 21st century successfully met" (Bennett, 1999). The Fed' Chairman, Alan Greenspan, also conducted precautionary policies in case the Y2K problem damaged banking and sensitive manufacturing industries.

[80] Stanley Druckenmiller, the lead portfolio manager of George Soros' Quantum Fund, lost 3 billion dollars, or 22% of its portfolio value because he bought at the top of the Dot.com bubble.

the federal funds rate from 6.5 percent in 2000 to 1 percent in 2004. However, the extraordinarily low prime rate and abundant liquidity created an uptrend of the real estate market in the U.S., and U.S. banks and mortgage companies also relaxed their lending standards, extending credit lines and mortgages to people with poor credit rating historiesknown as a subprime mortgage. The hot property market in the U.S. spread to other countries through the multinational banking system and "spillover effect" of the global financial cycle[81] (Duca & Muellbauer, 2013).

Property prices in the U.K., Iceland, Spain, Ireland, France, Australia, and other major developed countries began to take off, accompanied by house-building booms. In Spain, more than 5 million new houses were completed between 2002 and 2006[82]. Moreover, the expansion of mortgage credit was further amplified by the securitization of mortgages[83] (Zhou & Sornette, 2006, 2008). Banks can collect, slice, and package normal mortgages into mortgage-backed securities (MBS), and risky mortgages can also be financially engineered and repackaged as Collateralized Debt Obligations (CDO) (Shiller, 2006, 2012). Credit agencies then give credit ratings to these MBS and CDO products, making them investable for institutional clients.

Not only were government-sponsored Fannie Mae and Freddie Mac encouraged to buy MBS, but investment banks, insurance funds, and pension funds also flooded into the MBS and CDO market to enjoy profitable returns. In 2006, 600 billion dollars of subprime loans were originated (most were securitized), accounting for 23.5 percent of all mortgage originations (Financial Crisis Inquiry Commission, 2011). However, many mortgage borrowers of the underlying financial derivatives assets conducted fraudulent behavior to obtain mortgages, and credit agencies implemented oversimplified and problematic quantitative statistical models to rate those derivatives.

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[81] According to the Bank of International Settlement, the Global Financial Cycle, aggregating credit expansion, credit flows, and property prices, is dominated by the U.S. economy. In other words, the Global Financial Cycle is a proxy of the U.S. financial cycle. Consider a source (and reference) here.

[82] In each year, Spain built more houses than Germany and France combined, while the population in Span was less than one third of the combined populations of Germany and France. In the peak year of 2006, the number of new houses built in Spain was more than Germany, France, and the U.K combined.

[83] The securitization of mortgages had three effects on property and financial markets: first, it allowed banks to offer more mortgages, which significantly increased their leverage; second, the transfer of risk from mortgage underwriters to MBS and CDO buyers broke the link between the risk-reward relationship—the financial institutions tend to be more careless about mortgage default risks, as this risk is not borne by themselves; and third, the new financial derivatives products created new immature yet complex investment tools for investors, particularly for speculators, rather than real home buyers (Quinn & Turner, 2020).

U.S. economic growth began overheating in late 2004, and the Fed' had to increase the historically low interest rate from 1 percent in 2004 to 5.25 percent in late 2006[84]. At the same time, rapid global economic development (especially in China) along with the drop of the U.S. dollar index and commodities speculations pushed up oil prices and many other commodity prices to extreme levels. With the tightening of monetary policies and significant increases in living expenses, the mortgage delinquency rate began to rise in 2006, and accelerated in 2007. It is believed that the root of the subprime crisis was the mutual reinforcement of multiple bubbles in the preceding decades, which led to the illusion of a "perpetual money machine", and a substantial deviation between artificial stock market growth and economic growth (Sornette & Cauwels, 2014). The default of some homeowners created a chain reaction of real estate price drops, leading to massive defaults on mortgages (Sornette & Woodard, 2010). The risks within the financial system were gradually exposed, causing a bank run on the shadow banking system, including investment banks and other non-depository financial entities (Bernanke, 2013). In September 2008, Lehman Brothers, the fourth largest investment bank in the U.S. by asset size, went bankrupt, triggering a liquidity spiral and a massive credit crunch (Mishkin, 2011; Sornette & Woodard, 2010).

The meltdown of the banking system in the U.S. spread globally, leading to the Global Financial Crisis[85] (GFC) (Bernanke, 2012). The Federal Reserve Bank had to keep buying long-term securities for years through the quantitative easing (QE) program, until the job market became stable and the unemployment rate remained low (Bernanke, 2013; Yellen, 2013). After the GFC, the Federal Reserve, influenced by Modern Monetary Theory (MMT), increased the U.S. monetary base from 820 billion dollars to 4 trillion dollars (around 5 times), while the U.S. GDP only increased by 1.5 times—which might be the reason for the long bull stock market from early 2009 through to early 2020.

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[84] Ben Bernanke (2005) [2004? Or reference needed] proposed the Global Saving Glut (GSG) theory, indicating that many rich countries such as Japan and Germany (with aging and shrinking populations), use their excess savings to invest in the U.S., which, to some extent, lowered the U.S. interest rate in the early 2000s.

[85] Losses due to U.S. subprime loans and securities, estimated in October 2007, were around 250 billion dollars, while cumulative loss in world output, estimated in November 2008, was about 4,700 billion dollars (20 times the subprime loss), and the aggregate drop in global financial markets, estimated between July 2007 and November 2008, was 26,400 billion dollars (100 times the subprime loss) (Sornette & Woodard, 2010).

2.1.14 Chinese Stock Market Bubble

In 1978, after reformist Deng Xiaoping came to power, China initiated "socialism with Chinese characteristics", by introducing more market-oriented economic policies to replace the old government-oriented economic policies[86]. In the late 1970s, Chinese GDP was one thirteenth of Western Europe's. In 2011 it exceeded Japan's GDP, becoming the second largest economy in the world (Huang & Ge, 2019). There were three stages of economic reforms in China: (1) creating a large number of financial institutions such as banks and insurance companies in the 1980s; (2) developing capital markets such as Shanghai and Shenzhen stock exchanges and adopting dollarization foreign exchange policy during the 1990s; and (3) partial opening up of financial sectors to attract foreign institutions and accelerating the pace of internationalization of the renminbi (RMB) after China joined the World Trade Organization in 1995 (WTO) (Quinn & Turner, 2020). Learning from many developing-nations' experiences, China implemented "asymmetric liberalization" policies, which completely liberalized agriculture, industrial, and service products, while controlling production factors such as labour, capital, land, and energy[87] (Huang et al., 2013). Specifically, China introduced stock markets in 1990 to create direct financing channels alternative to banks. Many township and village enterprises (TVEs) and state-owned enterprises (SOEs) issued stocks in the stock markets in Shenzhen and Shanghai to access alternative capital for their developments. However, state and local governments were still the largest shareholders.

In 2001, China took the first step to release the state-ownership percentage of listed companies, however it did not get a positive response from investors, due to fears that more tradable stocks appearing in the market would reduce the value of their own holdings. The government had to abandon the first reform (Quinn & Turner, 2020). In 2005, state and local government still controlled 63.7 percent of the shares of listed companies. To increase company efficiency and competitiveness, the central

[86] One of the major characteristics of the Chinese government's reforms is to gradually privatize public ownership to individuals and private corporates, which stimulates economic activity and increases the efficiency of resources allocations.

[87] The government keeps tight controls of the banking and insurance industries, as well as the exchange rate system, making the financial system much more resistant to the Asian Financial Crisis and the Global Financial Crisis. Those repressive financial policies showed the Stiglitz Effect before 2010. Since the Chinese financial markets were underdeveloped, the repressive policy can help protect institutions when external shocks occur (Stiglitz, 1994). In addition, financial institutions were immature and vulnerable to capital flow fluctuations and financial instability (Huang et al., 2013).

government allowed for further privatization of listed companies, releasing more stocks to the market that were previously non-tradable shares. In 2005, the central government attempted to release non-tradable shares to the market again, and this time the state media helped to promote the stock market to ordinary citizens. In addition, GDP growth reached 12.7 percent in 2006, which catalysed market sentiment. Many retail investors such as shopkeepers, domestic cleaners, retired people and even farmers with little finance knowledge and limited capital entered the stock market for the first time and became day traders. By October 2007, the stock market had reached its peak, with a greater than 400 percent increase since the end of 2005. Inevitably, the market bubble crashed significantly in later months.

Additionally, the Global Financial Crisis collapsed global financial markets and economies in 2008, which also impacted Chinese economic growth. Thus, the Chinese stock market kept plummeting, recording a more than 70 percent loss from its peak (Jiang et al., 2009). In response to the GFC, China adopted aggressive monetary policies to revive the economy, resulting in a substantial increase of macro leverage, from 143.1 percent in October 2008 to 215.8 percent in April 2014[88].

In 2013, China further liberated the banking system and emphasized the decisive role of the stock market in market allocation. The new reform reduced the stamp duty for trading stocks and encouraged companies to be listed on the stock market to seek a direct financing channel. In 2014, the central government of China began to worry about the high debt level, risks associated with the shadow banking system, and the high financing costs of corporates, as well as the slowing of economic growth[89]. In addition, China had the third highest M2-to-CDP ratio in the world, indicating that Chinese economic development was overly reliant on indirect financing (the banking sector), rather direct financing (for example, the stock and bond markets) (Huang & Ge, 2019). Understanding that this could lead to negative financial repression of the general economy in the long run[90], authorities engineered another stock market bubble.

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88 The significant increase in debt level was a result of aggressive, nation-wide stimulations in property industries, and heavy investments in infrastructure to support economic growth after the GFC, while the property market experienced significant growth at the same time. The 2015 stock market crash did not impact the general economy and the property market since the banking system was relatively well regulated compared to many countries during the Asian Financial Crisis.

89 Chinese GDP growth decreased to single digits from double digits in 2011.

90 The ‘McKinnon Effect’ indicates that an underdeveloped financial market might hinder both financial efficiency and financial development, as the traditional banking system is insufficient to support technological innovation and industrial upgrading (McKinnon, 1973).

The People's Bank of China (PBoC) also announced more monetary policies, reducing the interest rate twice, and lowering the required reserve ratio for banks in November 2014. In addition, the state media kept delivering bull market signals and advocating the dividend of economic structural reforms [91] . Irrational positive investment sentiment was soon ignited, and a huge number of retail investors flooded into the stock market in response. The SSCI index reached 5178 points on 12 June, 2015, and then crashed by around 30 percent within three weeks (Sornette et al., 2015). After the crash, the Chinese government implemented multiple measures to support the stock market—but none of them worked. There are three elements posited by analysts that contributed to a crash of this magnitude: first, regulators banned out-of-control margin lending in the stock market, which triggered the crash; second, the tightening of monetary policies strengthened instability in the market; and third, the unexpected rejection of Chinese shares from the MSCI index smashed investors' hope of further capital inflow into the Chinese stock market.

2.1.15 Chinese Property Bubble

For the past three decades, China has experienced one of the largest urbanizations in human history, with the urbanization rate increasing from 35 percent in 1999 to 60 percent in 2019 (Hu et al., 2021). Urbanization is the outcome of rapid economic development, which, in turn, can upgrade the industrial structure and significantly grow "urban wealth" (Glaeser & Gottlieb, 2009). Three major factors of urbanization are population, capital, and land, and the combination of the three enhances the agglomeration effect, which paves the way for industrial development. China has implemented many economic reforms to encourage the urbanization process. In 1994, China created the tax-sharing system reform as a milestone in the transition of the Chinese fiscal system from planned economy to market economy. In 1997/98, China set up the land reserve system and privatization of the housing system.

In 2003, China introduced the "bid invitation, auction, and listing" system. In addition to these economic reforms, China gradually adopted the "land finance

[91] In April 2015, when the Shanghai Stock Exchange Composite Index (SSCI) reached 4000 points, the *People's Daily* published an editorial stating that the 4000 points was the beginning of a bull market.

model"[92] (with Chinese characteristics[93],) which drove up land value. The real estate price, reflecting the improvement of urban living quality and an increase in residential income levels, surged alongside the rapid economic development[94]. Local governments also benefitted from the increased land value[95], as transferring the use-rights of land can generate more revenue for urban infrastructure projects such as transport, medical, and education systems[96] (Hu et al., 2021). China's GDP per capita increased from 959 dollars in 2007 to 4,550 dollars in 2010, and the GDP averaged a 9.8 percent increase year-on-year (YoY) for the first three decades (1980s-2010s) (Huang & Ge, 2019). Promising economic expectation also fueled speculation in the real estate sector. Many developers took on extremely high leverage to expand their land reservation, and traditional banking also provided abundant capital for developers' risk-taking behaviours[97]. The underdevelopment of the financial system also provided limited investment opportunities for investors and financing ability for corporate entities[98]. The household sector had accumulated a high saving rate[99], which also contributed to high property prices, as households often see the property market as safe and stable in comparison to the stock market. Moreover, after the Global Financial Crisis of 2007/08, the Chinese central government undertook expansive monetary policies with aggressive fiscal stimulations, and this credit expansion created a boom in the real estate sector. An overreliance on the real estate sector resulted in a more singular economic structure,

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92 Land finance in China indicates a particular fiscal finance model that means land transaction-related revenue (an upfront land conveyance fee paid by developers for buying the use-rights of the land from the local government), serves as a major source of local public revenue for urban and infrastructure development in Chinese cities (Wu et al., 2015).

93 Local governments implement rigorous fiscal management, strict land-use control, and monopoly of land supply (Xu, 2019).

94 Increased urbanization pushes up real estate prices for three major reasons: (1) urbanization leads to growth in the urban population, which increases demand for housing and pushes up house prices; (2) the acceleration of urban industrialization results in a shortage of urban land resources, which pushes up land prices; and (3) upgrading of urban infrastructure due to the land finance model promotes secondary and tertiary industry development, which improves the average wage; higher wages, in turn, leads to higher property prices.

95 The land transfer fee was 50 billion yuan in 1999; it reached 6,510 billion yuan in 2018 (Hu et al., 2021).

96 Land sales can account for as much as 80% of financing sources of Government Managed Funds (GMF) (Wu, 2015).

97 Due to immature house pre-sale policies, many developers can use their pre-sale deposit to construct a property without sufficient regulation.

98 After 2010, the repressive financial policies began to show the McKinnon effect: That the underdeveloped financial market hinders both financial efficiency and financial development.

99 In China individuals have 69% of their financial assets in bank deposits, 20% in securities products, and 11% in pension and insurance products. This contrasts with other developed nations that have relatively low individuals saving rates, for example, European countries average 36% and America averages around 14% in bank deposits.

as middle-class mortgage payment commitments depressed consumer spending (Huang & Ge, 2019).

In 2010, the World Bank issued a cautionary report about the Chinese property market bubble. However, to maintain a strong employment rate against the European Debt Crisis, China chose to stimulate the economy through expansionary fiscal and monetary policies. The disproportional property market development soon led to overcapacities in industries such as iron, steel, cement, glass, etc. After 2010, the Chinese GDP had a regime shift from over 10 percent growth to around 7 percent, as it had lost the low-cost advantages (Huang & Ge, 2019). The property price kept increasing, whilst there were signs of financial idling, overleverage of developers, and capital escapes from the real economy and floods into the virtual economy[100]. In 2018, there were 97,000 developers in China, while in the U.S. there were around 500 developers registered across 50 states (Huang, 2020). From 2000 to 2020, the average property price in China increased by 5.4 times[101], while the government's Debt-to-GDP ratio increased from 33.6 percent in 1995 to 66.8 percent in 2020. Furthermore, since 2014 China's demographic structure has showed some worrying signs, since the working-age population has reached its peak.

In addition, the debt problem worsened after the Chinese government implemented property market stimulation in 2016. In 2017, the total Debt-to-GDP ratio of China was beyond 250 percent (Huang, 2020). To avoid the systemic risks of banks that have too much exposure to the real estate sector, in 2020 the Chinese government issued the 'three red lines[102]' policy, to reduce the leverage of developers. However, in September 2021, Evergrande, one of the top three property developers in China, showed insolvency risk regarding a 300-billion-dollar bond liability (2 percent of China's GDP), shocking global investors. In April 2022, the revenue of the top 100 developers in China had dropped 45 percent Year-on-Year, indicating the general vulnerability of the entire property sector. It is still too early to say that the drop in revenue will lead to a property

[100] The real economy needs capital, but the capital does not finance the real economy since the businesses have difficulty in transformation and upgradation. It is also the reason shadow banking and fintech industries expand significantly.

[101] The Price-to-Rent ratio in Beijing in 2021 was 55, while the Price-to-Rent ratio in Tokyo in 1990 (the peak of the Japanese property bubble) was around 18. For more information, see: https://cn.nikkei.com/china/ceconomy/46182-2021-09-27-01-38-47.html?start=0).

[102] 'Three red lines' policy: To get credit from the banks, developers must keep liability-to-asset ratio (excluding pre-sales) at less than 70%, net debt ratio less than 100%, and cash ratio higher than 1.

price crash or a large economic recession in China, however this author currently holds a pessimistic view.

2.1.16 Cryptocurrency Bubble

On 31 October, 2008, the Bitcoin white paper[103] was published by the pseudonym author, Satoshi Nakamoto, to introduce the world's first cryptocurrency, Bitcoin. Bitcoin is a peer-to-peer (P2P) payment system that negates the need for traditional banking systems as intermediaries (Nakamoto, 2019). New bitcoins are generated by a competitive and decentralized "mining" process, and at the time of writing there are 21 million Bitcoins available, and hundreds of new versions of cryptocurrencies have been created. Bitcoin transactions are verified by Asymmetric Encryption (Public-Key Cryptography) and recorded through distributed ledger technology called Blockchain[104]. Bitcoin technology has seen gradual acceptance due to the low cost of transactions, dissatisfaction with central banks' unlimited quantitative easing monetary policies, and a desire for wealth privacy.

With this gradual proliferation the Bitcoin price has slowly increased, with price accelerations and crashes from a few cents to thousands of dollars between 2008 to 2016. Bitcoin saw super-exponential price growth until 17 December, 2017, reaching around 20,000 dollars (Wheatley et al., 2018). However, the price then crashed below 11,000 dollars less than a week later, (on 22 December, 2017_) a fall of 45 percent from its peak. By late 2018, the Bitcoin price had plummeted to around 80 percent of its 2017 peak (Gerlach et al., 2018). A few years later, in April 2021, Bitcoin rebuilt its price to around 60,000 dollars, due to the market's belief that Bitcoin could hedge against huge quantitative easing from the global central banks. By July 2021, Bitcoin had crashed by around 50 percent again, after which it surged to around 65,000 dollars and then again crashed to 50 percent in January 2022. At the time of writing (April 2022), the price of Bitcoin was around 39,700 dollars.

Opposition to Bitcoin comes from a variety of groups. Nine Nobel prize winners of Economics have publicly criticized Bitcoin, claiming it is a speculative bubble. Many

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[103] Bitcoin: A Peer-to-Peer Electronic Cash System.

[104] Satoshi's Bitcoin version of blockchain solved the famous distributing computing system problem, i.e., Byzantine Generals' Problem, by introducing Proof-of-Work (PoW) common consensus algorithm. Ethereum, another cryptocurrency solved this problem by using Proof-of-Stake (PoS). Byzantine Generals' Problem is a game theory problem that describes the difficulty of decentralized parties to arrive at consensus without relying on a trusted central party.

business leaders, such as George Soros, Warren Buffet, Charles Manger, and Jack Ma, have also warned that Bitcoin is a bubble, and the CEO of J.P. Morgan Chase, Jamie Dimon, once called Bitcoin a "fraud". Many governments have also banned cryptocurrencies, since it not only finances criminal activities such as money laundering, but many wealthy people use cryptocurrencies for tax evasion. Despite this, Bitcoin and cryptocurrencies have been gaining in popularity over the years as a technology innovation (Huber & Sornette, 2020). Many retail investors and family companies have started to invest in cryptocurrency, since it can not only generate rapid returns in very short periods (due to high volatility), but can also be considered a new asset class, because of low correlations with other, traditional asset classes. Central banks also find value in the cryptocurrency technology and are plaining to issue Central Bank Digital Currency (CBDC) as a new, competing financial product innovation to handle international bank settlements. The value of Bitcoin and future usefulness of cryptocurrencies are still controversial topics 14 years after it was first created.

2.1.17 Pandemic Bubble

In December 2019, a severe, acute respiratory syndrome, Coronavirus 2 (SARS-CoV-2), was identified in an outbreak in China. Soon, the highly infectious virus had spread across the world, and on 30 January 2020, the World Health Organization (WHO) issued a 'Public Health Emergency of International Concern' to warn all nations[105] (Ram & Sornette, 2020). On 11 March, 2020, the WHO declared COVID-19 a global pandemic. To keep rates of infection to manageable levels and avoid overwhelming hospital and other medical resources and staffing, particularly of Intensive Care Units (ICUs), many countries implemented urgent actions[106] to suppress the COVID-19 spread. By April 2020, almost half the world's population (3.9 billion in more than 90 countries) was under 'lockdown' policy.

The COVID-19 pandemic shock led to the largest stock market and bond market crashes globally since the financial crisis of 2007/08[107], due to the disrupted supply-demand relationship around the world, sharp deterioration of economic activities, weak

[105] COVID-19 can transmit through air contaminated by droplets and small airborne particles that contain the virus.
[106] Stay at home orders, mandatory face mask requirements, international border closures, social distancing, travel restrictions, mandatory quarantines, etc.
[107] The U.S. S&P 500 market index crashed by around 35% between 20 February, 2020, and 24 March, 2020.

economic expectations, and general panic among the population (Gerlach et al., 2020). To prevent the potential economic crisis, calm the stock and bond markets, and stabilize global currencies, the Federal Reserve Bank took a series of actions, such as cutting the federal funds target rate, buying unlimited mortgage-backed securities (MBS), and conducting repurchase agreement (repo) operations and temporary currency swaps with nine additional central banks (Brainard et al., 2021; Clarida et al., 2021). The Reserve Bank of Australia, Bank of Japan, European Central Bank, Bank of England, and 23 other central banks took similar actions, and all of them implemented large-scale Asset Purchase Programmes (APP) (Bonifacio, 2021).

The massive buyback programs soon stabilized the global financial markets and pushed the stock and bond markets back up, however, the pandemic still caused severe global supply chain disruption, the global electronic chip shortage, high inflation, food price surges, etc. To alleviate the economic impacts, the central banks kept expanding their balance sheets. In 2020 alone, the Federal Reserve increased 3.2 trillion dollars (76 percent YoY) in its balance sheet, while the European Central Bank and the Bank of Japan expanded their balance sheets by 3.3 trillion and 1.5 trillion dollars, respectively (European Central Bank, 2020; Mosser, 2020). The large-scale liquidity injection into the market also had many unintended side effects. The U.S. stock market doubled, and U.S. property prices surged 27 percent from March 2020 to December 2021. The global stock, bond, and property markets all witnessed significant increases. During the stock market surge, many retail investors joined the market boom and became day traders. The technology sector was the biggest winner, since pandemic lockdown in many countries forced people to work from home. Technology stocks such as FAANG[108], and ZOOM had substantial increases within two years. Apple, for instance, had tripled its stock price between the pandemic low of late March 2020 and early January 2022, adding more than 2 trillion dollars to its market size. With limited knowledge, many retail investors bought MEME stocks[109], cryptocurrencies, and so on. In addition, many people also flooded into the financial markets due to the ‘fear of missing out’ (FOMO) mindset (Lyócsa et al., 2021). Lots of people also purchased bigger land, houses, and apartments. Inflation hit 7.9 percent in the U.S. (a 40-year high)

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[108] FAANG indicates Facebook, Amazon, Apple, Netflix, and Google.

[109] Retail investors purchased many MEME stocks such as GameStop, Blackberry, and AMC, leading to “short squeezes” in many professional institutions.

in February 2022, and Germany experienced a 7.3 percent increase in inflation (a 30-year high) in March 2022.

The Russia-Ukraine war that began on 20 February, 2022, also deteriorated the global economic recovery. The supply chain disruption due to the pandemic, unfavorable weather, and continued conflicts may lead to further increases in global energy and agriculture prices. Central banks have already expressed their concerns regarding inflation risk, and it is believed any future tightening of monetary policies and quantitative easing will lead to more volatile markets.

2.2 Discussion

There are several remarkable features that can be identified in the above 20 bubble and bust cases. First, the busts that followed asset bubbles were often unforeseen by most people, including economists. For example, Irving Fisher, one of the leading American economists of his time and a professor of Economics at Yale University, claimed that the stock market had reached "a permanently high plateau" nine days before the 1929 stock market crash. In 2008, when Queen Elisabeth visited the London School of Economics, she asked professors there about the Global Financial Crisis, wondering, "How come nobody could foresee it?[110]"

Second, financial collapses were never triggered when things looked terrible. Instead, they usually occurred before people had any negative expectations. Large asset price bubbles are considered the best predictors of financial crisis, but the crash only happens when the bubble cannot be sustained. In other words, a sudden change in people's extreme positive expectation usually causes the worst outcomes, and often financial chaos ensues.

Third, there exist long-range dependences between the current bubbles and crashes and previous system states (series of events). In other words, the root of the current boom and bust can almost always be traced back months or years, rather than from any current status quo. So, when we diagnose and analyze the current bubble or crash, we need to dig into the history to discover the likely mechanisms, rather than looking to economic data released 'last week'.

Fourth, there exists a "spillover effect" of the bubbles and crashes amongst different asset classes and different countries. If real estate, as the major collateral of

[110] See: https://www.theguardian.com/uk/2009/jul/26/monarchy-credit-crunch

the banks, experiences a surge in asset price, then the banks can lend more money or people can refinance more capital due to the increase in collateral. Then, the new credit released from the banking system can spill over to other assets such as the stock market or commodities. Moreover, a crash in one country might trigger the “domino effect”, resulting in crashes in different countries with similar situations. Panic is almost always “contagious”, and financial crises might spread to more countries if not handled well.

Fifth, many investors deliberately employ diversification tactics to reduce any systemic risks they might face. However, during a crisis, many asset classes can crash simultaneously, with high correlations. In addition, other economies may also be impacted due to global financial market integration. Thus, investors still face the systemic risks they are trying to avoid, even when they think they are well-diversified by holding diverse assets and assets offshore.

Finally, debt, especially short-term debt, can lead to economic instability. Many countries experience very rapid economic growth before a crisis, and over-leverage is often a major contributing factor. “Financial liberation” is just a fancy way to express the "increase of leverage". It is either the government, corporates, financial institutions, or individuals (or a combination of these) that borrow too much leverage during an economic boom. Although high growth in debt-financing can be beneficial to short-term economic growth, 'easy' debt can also fuel speculative euphoria. It may lead to debt addiction, causing a banking crisis when the economy slows.

2.3 Bubble Triangle

Based on the study of the above 20 global financial bubbles, this paper proposes a ‘Bubble Triangle’ that can generally summarize the three essential characteristics of a bubble: (1) Disruptive Novelty, (2) Abundant Liquidity and Credit, and (3) Social Bubble Spirit. The three elements always appear together, reinforcing each other in the dynamical development of the bubble. Interestingly, every bubble is a wealth re-distribution opportunity.

Figure 2. *Bubble Triangle: Disruptive Novelty, Abundant Liquidity and Credit, and Social Bubble Spirit*

Disruptive Novelty contains the emerging elements that might interrupt the existing demand-supply equilibrium and create new turbulences or chaos in the past order within the complex system of a national or the global economy. Such triggers might be:

- **New Product**: New technological innovations, financial innovations, new goods brought to market, etc. The penetration of the new market into the existing market can be calibrated as a logistic curve.
- **New Market**: A new market can create new demand, which can leverage existing or new products or services of the old market, or a population boom due to immigration, urbanization, and so on that can enlarge the existing market demand. A new market can extend the current logistic curve of the new or existing product or service.
- **Change of Economic Policy**: Banking or financial industry deregulation, tax reductions, significant fiscal stimulus, a shift in government policies, and so on.
- **Catastrophic Event**: Wars or conflicts, pandemics, earthquakes, floods, droughts, and so on.

Disruptive Novelty can be either good or bad, since it can bring substantial uncertainty on the potential scenarios to the world. For instance, no one knows how good or great a new-technology product will be in the future. With the human mind's tendency to be optimistic and driven by hope, extraordinarily good scenarios in some cases are predicted, which then feed upon themselves like a bootstrap, with positive feedback loops between the exciting stories for the future and the financial markets.

Since markets are like financial options, they are most sensitive to and reflect optimistic scenarios and tend to underestimate negative ones. Hence the bubbles emerge.

Abundant Liquidity and Credit refers to the money that can push up asset prices. This might come from domestic credit expansion such as monetary stimulus, international "hot money”[111] inflow, or both. When global capital flows into a country, it tends to amplify the domestic economic cycle or disturb the local policy effects, overheating the economy during a boom or delaying the recovery during a bust. Many developing countries use capital control and macro-prudential policies to alleviate the ‘hot money effect’.

The **Social Bubble Spirit** arises when strong social interactions between enthusiastic supporters trigger a network of self-reinforcing feedback loops, leading to widespread endorsement and extraordinary commitment (Sornette, 2003; Gisler & Sornette, 2021). This collective enthusiasm can undermine standard cost-benefit analysis and even rationalize unconventional value systems (Gisler, Sornette, & Woodward, 2011; Gisler, Sornette, & Grote, 2013). The Social Bubble Spirit is complex, yet not necessarily bad and wasteful (Janeway, 2018). In fact, it is argued to be a necessary catalyst to the generation of technology revolutions (Perez, 2002). It allows wealth generating large scale risk-taking at the society level that would not otherwise take place. It can also be the rational sentiment of diverse but correlated opinions (Sohn & Sornette, 2020). That is, when the time-dependent utility function overweights expected future returns and underweights the risks, the social bubble spirit arises as a correspondent to a transient dynamical regime where more people are "explorers" (taking risks) than "exploiters" (avoiding risks) (Sornette et al., 2019).

Attention is costly in an information-overloaded society. If anything triggers the enthusiasm of a crowd, more and more people will focus on it due to social imitation. If the topic is attractive or controversial, it will soon spread through the population like an epidemic[112], and more investors will join the herding trend. The Social Bubble Spirit can foster and catalyze new ideas, concepts, or projects (Gisler & Sornette, 2009, 2010, 2021). The key concepts that explain and illustrate it in detail are the imitation process, the herd effect, self-organized cooperation, and the positive feedback loop, which lead to the development of endogenous instabilities (Sornette, 2003).

[111] "Hot money" refers to funds controlled by investors who actively seek short-term returns.

[112] Sometimes, professional or retail investors or speculators may spread enthusiasm through rumours, media propaganda, and get-rich-quick stories, or even through the increase of the price.

A study of the most famous financial bubbles in global history may give insight into the Bubble Triangle. Table 2.1 briefly summarizes the 20 historical bubbles and their major triggers. Note: All three elements of the bubble triangle are discovered in the 20 bubble cases, but we specially emphasis the most critical elements[113] in the Table 2.1.

[113] All bubbles involve the Social Bubble Spirit element.

Table 2.1. Major Bubbles in World History

Bubble	Countries	Years	Assets	Bubble Triangle	Crisis Triggered?
Tulip Mania	Dutch	1636	Tulip Bulb	New Product (Luxury and Financial) & New Market	No
Mississippi Bubble	France	1719-20	Stocks	New (Financial) Product & Change of Economic Policy & New (Credit) Money	Yes
South Sea Bubble	UK	1719-20	Stocks	New Product (Financial) & Change of Economic Policy	Yes
Windhandel Bubble	Netherlands	1719-20	Stocks	New Product (Financial) & Change of Economic Policy	No
Railway Mania	UK	1840s	Railway Stocks	New Product (Technology)	Yes
Australian Land Boom	Australia	1883-89	Stocks and Real Estate	New Market & New (Technology) Product & New (Credit + Hot) Money	Yes
Bicycle Mania	UK	1880s-1890s	Bicycle Company Stocks	New Product (Technology)	No
Roaring Twenties	US	1920-31	Stocks	New Product (Technology) & Change of Economic Policy	Yes
Oil Crises	Middle East	1973-4;1979;1990; 2008; 2011;2022	Commodity (Oil)	Catastrophe Event (War) & Change of Economic Policy	Yes
Latin America Debt Bubble	Latin America	1980s	Debt	New Market & Change of Economic Policy & New (Hot) Money	Yes
Japan's Economic Miracle	Japan	1985-1992	Stocks and Real Estate	New (Technology) Product & Change of Economic Policy & New (Credit + Hot) Money	Yes
1987 Black Monday	23 Countries	1987	Stocks	New Economic Policies	No
Asian Financial Miracle	East Asia	1992-97	Stocks and Real Estate	New (Manufacturing) Product & Change of Economic Policy & New (Credit + Hot) Money	Yes
Tequila Crisis	Latin America	1990-94	Debt	New (Hot) Money	Yes
Dot-Com Bubble	US	1995-2001	Stocks	New (Technology) Product & Change of Economic Policy& New (Credit) Money	No
Subprime Bubble	US, UK, Spain, Ireland, Iceland, etc.	2002-2007	Real Estate and Stocks	New (Financial) Product & Change of Economic Policy & New (Credit) Money	Yes
Chinese Stock Market Bubble	China	2007; 2015	Stocks	Change of Economic Policy & New (Credit) Money	No
Chinese Property Boom	China	2010- On going	Property	Change of Economic Policy & New (Credit) Money	Unknown
Cryptocurrency Bubbles	Global	2009- On going	Cryptocurrencies	New (Technology) Product & New (Credit) Money	No
Pandemic Bubble	Global	2020- On going	All Asset Classes	Catastrophe Event (Epidemic) & New (Credit) Money	Unknown

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Chapter 3

3.1 Forecasting Financial Crashes: A Dynamic Risk Management Approach

Full Reference:
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Abstract

Since 2009 stock markets have stayed in a long bull market regime. Passive investment strategies have succeeded during this low-volatility growth period. From 2018 onwards, however, there was a transition into a more volatile market environment interspersed by corrections increasing in amplitude and frequency. This calls for more adaptive dynamic risk management strategies, as opposed to static buy-and-hold strategies. To hedge against market drawdowns, the greatest source of risk that should accurately be estimated is crash risk. This article applies the Log-Periodic Power Law Singularity (LPPLS) model of endogenous asset price bubbles to monitor crash risk. The model is calibrated to 15 years of market history for five relevant equity country indices. Emphasis is placed on the U.S. S&P 500 Composite Index and the recent market history of the "Corona" year 2020. The results show that relevant historical bubble events, including the Corona Crash, could be detected with the model and derived indicators. Many of these events were predicted in advance in monthly reports by the Financial Crisis Observatory (FCO) at ETH Zurich. The Corona Crash, as the most recent event of interest, is discussed in further detail. Our conclusion is that unsustainable price dynamics leading to an unstable bubble, fueled by quantitative easing and other policies, already existed well before the pandemic started. Thus, the bubble bursting in February 2020 as a reaction to the Corona pandemic was of endogenous nature and burst in response to the exogenous Corona crisis, which was predictable to some degree based on the endogenous price dynamics. A fast recovery of the price to pre-crisis levels ensued in the months following the crash. This leads us to conclude that while the underlying origins and the macroeconomic environment that created this bubble do not change, bubbles will continue to grow and potentially spread to other sectors. This may cause even more hectic market behavior, overreaction, and volatile corrections in the future.

3.1.1 Introduction

Financial markets embody all the hopes, fears, and uncertainties of the world: economic measures, geopolitical influences, future profit expectations, technological innovations, legendary investors and even pandemics, as well as countless other factors play into the formation of asset prices. Consequently, financial markets are non-stationary, their properties change; they are punctuated by phases of volatile sideway dynamics, bubbles, big drawdowns, bullish and bearish trends and other regimes. Since the year 1995, the S&P 500 Composite Index has first roughly tripled in value (+210%) (increase of the DAX Performance Index over the same period: +280%), then lost 75% (DAX: -70%) peak-to-bottom during the burst of the Dotcom bubble until 2003, after that appreciated by 120% (DAX: +210%) until the peak of the real estate bubble in 2007 and then again lost more than half of its value during the following two years. The years 1995-2009 were thus governed by two successive boom-bust-cycles of expanding and contracting prices, each of 6-8 years duration.

The decade following the great recession, however, marks a new regime of almost uninterrupted, exuberant growth, which is characterized by low volatility and a more than fivefold surge of the S&P 500 (DAX: 220%) (as of October 2020). At this immense increase, until 2020, a passive "buy-and-hold" (B&H) investor who bought around the dip in 2009 would have achieved an attractive Compound Annual Growth Rate (CAGR) of no less than 15% per year! Contrasted to the common reference figure of about 7% per year (since 1970) for the long-term CAGR of the S&P 500 Composite, this performance is outstanding, especially considering the low-maintenance and low-cost required for passive investment strategies such as the B&H-strategy.

Given this extraordinary performance that seems to be decoupled from fundamental economic factors but rather fueled by quantitative easing phases and accommodative central bank policies, many analysts and investors worry that the risk of an imminent market crash may have substantially grown. The bull market regime lasting since 2009, during which passive investment strategies flourished, has long surpassed the previous economic cycles in duration and amplitude. From 2018 on, there were notable warning signs for the transition into a new market regime; as a first precursor, the short, but intense market correction of about 10% of the S&P 500 during February 2018 and the concomitant spike in volatility marked the end of a previous phase of ordered and low-volatility market growth. Furthermore, 2018 was the first year since the trough in 2009 for which an overall negative yearly performance of the S&P 500 Composite of about -10% resulted. During the same year, the DAX experienced a net loss of almost -20%.

In 2020, the Corona Virus paralyzed a significant part of the world economy, triggering a major economic crisis. The corresponding crash of -32% of the S&P 500 (DAX: -35%) was equivalent to the evaporation of about 5 trillion U.S. Dollars in U.S. public equity market capitalization within a single month, from mid-February 2020 to mid-March 2020.

Following this strong drawdown, meanwhile, most major stock market indices have already recovered to about pre-crisis levels, even though the majority of smaller companies still record a YTD loss in stock prices (Rattner, 2020). By all means, and with greatest efforts, central banks and governments are restoring and preserving the status of "peace and order" in the economy and stock markets through an immense (and apparently limitless) supply of liquidity. This readiness to counteract was for instance expressed by German minister of finance, Olaf Scholz, who called the primary aid package released as a reaction to the Corona crisis the "bazooka" in the arsenal of available financial counter-weapons.

The global economy is currently experiencing the worst phase since the 1930's world economic crisis, as is the new popular saying. This is evident for instance from the contraction of various countries' Gross Domestic Product (GDP) during 2020 (Sornette et al., 2020). Yet, stock markets have been inflated to ever higher levels, repetitively marking record all-time highs throughout recent years. On top of existing monetary programs, the provision of financial aid packages, such as the Pandemic Emergency Purchase Programme (PEPP) by the European Central Bank (2020) even further strengthen this development, although they are obviously and undisputedly intended to support the economy. Whilst these measures on the one hand might provide a false sense of safety to market participants, additionally, financial markets appear increasingly disconnected from the real economy.

Although stock markets may likely continue to surge, the risk of stronger and more frequent crashes, and thus, a generally more volatile market environment, will continue to rise, as long as the current economic state does not improve. Passive investment strategies have wonderfully worked during the past bull regime of low volatility. But they fail to circumvent or hedge against market drawdowns and therefore, they might not work as well in the future anymore. Fund managers, in particular the ones that performed well in the past, often fall victim to the "prevailing bias", i.e., the tendency to stick to what has worked in the past and reject other possibilities. However, in order to stay at the edge, flexible and robust strategies of capital management are needed. To build such resilient strategies, a much more active and adaptive approach of dynamic risk management (Kovalenko and Sornette, 2013), as contrasted to “static” passive investing, will be required.

At ETH Zurich, Switzerland, as part of research on speculative bubbles and crashes, the Financial Crisis Observatory (FCO)114 was founded by Prof. Didier Sornette in 2008 (Sornette et al., 2009, 2010; Woodard et al., 2010), as a reaction to the severe impact of the financial crisis, with the intention to build a resilient warning system for dynamic risk management of crash risk (Kovalenko and Sornette, 2013). Since then, the observatory has served as a scientific, automated forecasting platform with the mission of monitoring the evolution of non-sustainable price dynamics across various financial markets and asset classes. On a daily base, thousands of indices, stocks, commodities, exchange rates and even cryptocurrency pairs are systematically scanned for potential inefficiencies and predictable patterns. At the core of this quantitative system, the Log-Periodic Power Law Singularity (LPPLS) model is employed to hunt for the distinct fingerprint of financial bubbles (Johansen et al., 2000; Sornette, 2009; Johansen and Sornette, 2010).

3.1.2 The LPPLS Model

The LPPLS model was first formulated in 1995 (Sornette et al., 1996) and further studied and extensively reviewed by Sornette and Johansen (1997); Sornette (1998); Sornette and Johansen (1998); Johansen and Sornette (1999a, b). Later, it was elaborated into a rational expectations bubble model by Johansen, Ledoit and Sornette (Johansen et al., 1999, 2000) to provide real-time diagnostics of bubbles and forecasts of crashes. It gained increased attention with the 2003 book Why Stock Markets Crash (Sornette, 2003b, 2004) 115.

[114] Currently, the FCO and the monthly released reports are used by 600+ institutions world-wide, including universities, think tanks, sovereign wealth funds, hedge funds, family offices, banks and pension funds, with numerous past successful prediction examples and traceable track records. The platform is currently sponsored by ETH Zurich and Southern University of Science and Technology (SUSTech) at Shenzhen China under the collaboration institute “Risks-X”.

[115] The model has recently been generalized into a more universal framework allowing for non-rational behaviour and market failures (Schatz and Sornette, 2020).

The theoretical backbone of the LPPLS model comprises diverse concepts such as discrete-scale invariance, self-similarity and -organization, criticality, collective behaviour and phase transitions (Sornette, 1998; Gluzman and Sornette, 2002) that are drawn from the fields of complex critical systems and statistical physics (Sornette, 2003a). The combination of these concepts with insights from financial economics and behavioural finance (Jiang et al., 2010) resulted in the LPPLS model, which describes the expected logarithm of the asset price as a power law decorated with log-periodic oscillations:

$$\mathrm{E}[\ln p(t)] \approx \mathrm{A} + \mathrm{B}(t_c - t)^m\{1 + \mathrm{C}\cos[\omega \; ln(t_c - t) + \theta\,]\} \qquad (3.1)$$

The model comprises seven model parameters θ: = {A, B, C1, C2, tc, m, ω}, with the three nonlinear parameters {tc,m,ω} being of particular importance.

Asset price patterns emerging during bubble regimes often follow characteristic, log-periodic signatures 116 (Sornette and Johansen, 2001). The recurrence of these distinctive patterns in advance to crashes suggests the temporal existence of certain “pockets of predictability” during which price trajectories follow the dynamics described by the LPPLS model. Hence, by detecting these patterns, extrapolation with the LPPLS formula allows forecasting crashes (Yan et al., 2010).

From the economic point of view, the LPPLS model defines a bubble as a period of unsustainable growth during which the price of an asset climbs to ever higher levels, accompanied by a series of accelerating phases of corrections and rebounds (Sornette and Cauwels, 2015). Thereby, the market value of the asset increasingly decouples from its intrinsic fundamental value (Kindleberger, 1978; Sornette, 2003b). On a micro-level, this faster-than-exponential, so-called super-exponential price growth is assumed to originate from the interplay between two types of agents in a complex network of market participants (Johansen et al., 2000): (i) informed traders with rational expectations117 and (ii) unsophisticated noise traders. The latter group of traders collectively forms their decisions based on (a) imitation of adjacent agents in the network and (b) the global network trend. This mechanism of local imitation induces a self-reinforcing positive feedback cycle (Johansen et al., 1999; Abreu and Brunnermeier, 2003) that causes

[116] The occurrence of log-periodicity had already long been observed in diverse physical phenomena such as alignment of atomic spins to create magnetization (Sornette, 1998; Johansen et al., 2000), rupture of composite materials and pressure tanks under mechanical stress (Anifrani et al., 1995, 1997) or earthquake propagation (Sornette and Sammis, 1995), when, in 1995, its occurrence in asset price dynamics was first recognized (Sornette et al., 1996; Feigenbaum and Freund, 1996).
[117] Following the theory of rational expectations by Blanchard and Watson (1982).

accelerating price growth, in other words, increasing price momentum (Ardila et al., 2015). Eventually, the price diverges up to the finite peak time tc, the so-called critical time at which the price undergoes a transition into a new regime, often a crash resulting from synchronized panic (euphoria in case of a negative bubble) amongst traders and a consequential sell-off (or buy frenzy in case of a negative bubble) of the asset.

Mathematically, the LPPLS formula (1) expresses the dynamics of the log-price as a power law decorated with log-periodic oscillations. The power law (with amplitude B and exponent 0 < m < 1) captures the super-exponential price dynamics caused by the positive feedback effect, while the log-periodic oscillation terms (with amplitude $C = \sqrt{C_1^2 + C_2^2}$ and angular frequency ω) symbolize the tension and competition between experts and noise traders (Yan et al., 2010). A negative (positive) value of the power law amplitude B classifies a positive (negative) price bubble. Ultimately, at the critical time tc, the bubble culminates in its final peak (with log-peak-price A), reaching a finite-time singularity, after which the crash or deflation of the bubble follows. Analogously to critical points in statistical physics (Sornette and Johansen, 1998), at the critical time tc, the system enters a new regime, after which the LPPLS formula is not defined (mathematically, due to the then negative argument of the logarithm in Eq.(1)). Obviously, the time tc of the phase transition is a major model parameter of interest, as its estimation provides a direct (ex-ante) forecast of the most probable time of the crash.

The LPPLS model has proven valuable in the detection of financial bubbles and forecasting of crashes. Multiple speculative bubbles have been identified ex-ante and ex-post to obey endogenous LPPLS dynamics. Examples comprise the Black Friday Crash of October 1929 (Zhang et al., 2016a), the Black Monday Crash of October 1987 (Johansen and Sornette, 2010; Sornette and Johansen, 2001), the Dotcom Bubble (Johansen and Sornette, 2000; Sornette and Zhou, 2002; Zhou and Sornette, 2003a,b; Zhang et al., 2016a), as well as theU.S.real estate bubble (Zhou and Sornette, 2006; Sornette and Woodard, 2010). But also "ancient" bubbles such as the Tulip Mania in the 1630's and the South Sea Bubble in 1720 (Sornette, 2003b), as well as bubbles on novel assets such as Bitcoin (Gerlach et al., 2019; Wheatley et al., 2019) and cryptocurrencies in general have been investigated in this context.

Figure 3.1 shows three example plots displaying regression fits of the LPPLS model to the S&P 500 Composite Index ˜different historical time periods; the bubble ending with the Black Friday 1929 crash, the bubble ending with the Black Monday 1987 crash, as well as the U.S. housing bubble (early 2000s until approximately mid 2007). The third panel shows an additional, fourth "negative bubble" fit (parameter B > 0) for prediction of the rebound after the U.S. market crash in 2009.

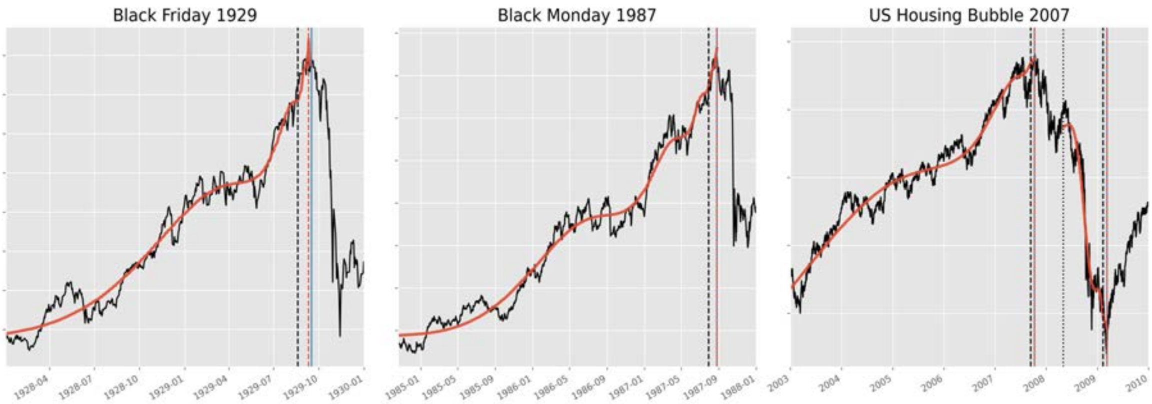

Figure 3.1. *Four examples of historical LPPLS-type bubbles on the S&P500 Composite Index. The black line depicts the index time series. The best fit of the LPPLS model in terms of Sum of Squared Errors (SSE) is drawn in red for each window. The start time of the plot and the vertical black dashed line represent the fit window [t_1,t_2] over which the model was calibrated. The blue solid line marks the price peak / trough time of the bubble, while the red dashed line points out the predicted critical time t_c. In the third panel, an additional negative bubble fit to the rebound of the U.S. market in 2009 is shown. The start time of that fit is indicated by the black vertical dotted line. Each window end time t_2 is set approximately one month before the "true" critical time, ensuring that only data until one month before the crash is used in calibration. The true value of t_c was determined as the date of the price peak (trough) of the corresponding positive (negative) bubble. All times are summarized in Table 3.2. These plots demonstrate the ex-post explanatory power of the LPPLS model. They should not be understood as an illustration of the prediction methodology since non-causal information is used with respect to the choice of t_2 for instance.*

	t1	*t2*	*t2 − t1*	*tc, true*	t_c
0	*1928-01-03*	*1929-08-19*	*594*	*1929-09-16*	*1929-09-10*
1	*1984-10-19*	*1987-07-29*	*1013*	*1987-08-25*	*1987-08-25*
2	*2003-01-01*	*2007-09-12*	*1715*	*2007-10-09*	*2007-10-09*
3	*2008-05-01*	*2011-01-01*	*975*	*2009-03-09*	*2009-03-09*

Table 3.2. *The timeframes over which the model was calibrated for the four examples in Figure 3.1, expressed in date format. The fit window size is $t_2 - t_1$. Additionally, the true and estimated values of the critical time are stated. The true critical time $t_{c,true}$ serves as a proxy for validating the predicted critical time. It is determined as the date of the next price peak (or trough) after t_2.*

For each fit, the LPPLS model is calibrated to price data over a corresponding time window [t1, t2]. The time t1 is the window start time and is marked by the start of each plot panel in Figure 3.1, while the window end time t2 is indicated by the black, vertical, dashed lines. Each window end time t2 is set to approximately one month before the "true" critical time, ensuring that only data until one month before the crash is used for calibration. The true value of tc was determined as the date of the price peak (trough) of the corresponding positive (negative) bubble. Table 3.3 lists the window timeframes and sizes, as well as the true and predicted critical times.

	A	B	C_1	C_2	$tc - t2$	m	ω
0	3.49	0.0214	0.0030	0.0006	14	0.54	3.75
1	5.84	0.0100	0.0006	0.0007	18	0.64	5.84
2	7.35	0.0005	0.0001	0.0000	24	0.99	3.31
3	6.61	0.0030	0.0001	0.0007	24	0.99	4.71

Table 3.3. *Parameter estimates corresponding to the four fits drawn in Figure 3.1. The parameter sets are provided line by line according to the appearance of the four bubbles from left to right in Figure 3.1. The value of the critical time t_c is expressed relative to the end time t_2 of each fit window, i.e., as $t_c - t_2$.*

The estimation of the seven model parameters follows a calibration scheme by Filimonov and Sornette (2013). A combination of grid search and numerical optimization for the nonlinear parameters (tc,m,ω) with an Ordinary Least Squares (OLS) regression for the linear parameters (A,B,C1,C2) is applied to minimize the sum of squared errors (SSE) as the objective function118. During optimization, the search space for the nonlinear parameters is constrained (see Table 3.3 left three columns), whereas the linear parameters are free.

Optimization Search Space			Qualified Fit Search Space		
t_c	m	ω	t_c	m	ω
[−60, 252]	[0, 1]	[1, 50]	(−60, 252)	(0, 1)	[2, 15]

[118] Other methods of calibration such as Modified Profile Likelihood (Filimonov et al., 2017) or Generalized Least Squares (GLS) (Wheatley et al., 2019), as well as different error model specifications such as AR(1)-GARCH(1,1) (Gazola et al., 2008), have been tested in the past.

Table 3.4. *Left three columns: search space boundaries for the nonlinear parameters during optimization. Right three columns: filtering conditions for qualified fit classification.*

In Table 3.4, for each fit, the corresponding model parameter estimates are stated. In all cases, the critical time is fairly accurately predicted out-of-sample one month before the crash (or rebound). Many more examples of such predictions are found in (Sornette et al., 2018).

3.1.3 Historical Performance of LPPLS Indicators

As stated above, the LPPLS model is implemented as the operational core of a dynamic risk management platform, the FCO, in order to scan asset prices for bubble signals in real-time and generate corresponding warning signals in advance to crashes. In essence, a systematic, moving-window calibration procedure is used to achieve this. For a given window end time t2, the LPPLS is fit to multiple time windows of different sizes according to the calibration scheme summarized above. This produces an ensemble of short- to long-window LPPLS fits that all have the same window end time t2, but varying start times t1. Typically, the window start times t1 are swept in steps of 1 day with the window size t2 −t1 ranging between [30,720] days, respectively [20,504] business days. So, for any "pseudo-present time" t2, this yields a number of 720−30+1 = 691 fits that are each defined in terms of their seven LPPLS model parameter estimates θˆ.

The data accumulating in course of this procedure is aggregated into various meaningful metrics that quantify "crash risk". One such metric is the DS LPPLS Confidence Indicator (CI) (Sornette et al., 2015; Zhang et al., 2016b). In short, the Confidence Indicator at time t, CI(t), is computed as the number of "qualified fits" at time t, nqual(t), divided by the total number of available fits ntot (i.e., 691) at time t:

$$\text{CI(t)} := \frac{n_{qual}(t)}{n_{tot}} \text{ where ntot} = 691 \qquad (3.2)$$

For qualified fits, the corresponding parameter estimates lie within specific filtering ranges (see Table 3.4 right three columns). The choice of the ranges is based on empirical studies of LPPLS parameter values for historical, well-known, and understood bubbles, such as the ones displayed in Figure 3.1. Based on the ranges, a fit is classified as valid, when the model parameters correspond to realistic values that lie within acceptable ranges, and rejected otherwise.

The DS LPPLS CI is a measure of bubble risk. It indicates over what fraction of scanned timescales LPPLS signatures are detected. As it is constrained between [0,1], it can be understood as an empirical probability (of encountering a true LPPLS pattern). The larger the indicator, the more frequently valid LPPLS signals that indicate the existence of a true bubble are detected. The indicator is typically computed separately for positive bubbles (PB) (i.e., grouping all fits with parameter B < 0) and negative bubbles (NB) (all fits with B > 0).

Throughout Figures 3.2-3.8, the positive (red) and negative bubble (blue) DS LPPLS Confidence Indicator time series (left scale) are provided for various equity indices between 2006 and October 2020; the S&P 500, the DAX, the MSCI World, the STOXX Europe 600 Index, as well as the MSCI China. Together, these indices capture a wide range of economies and corresponding financial markets.

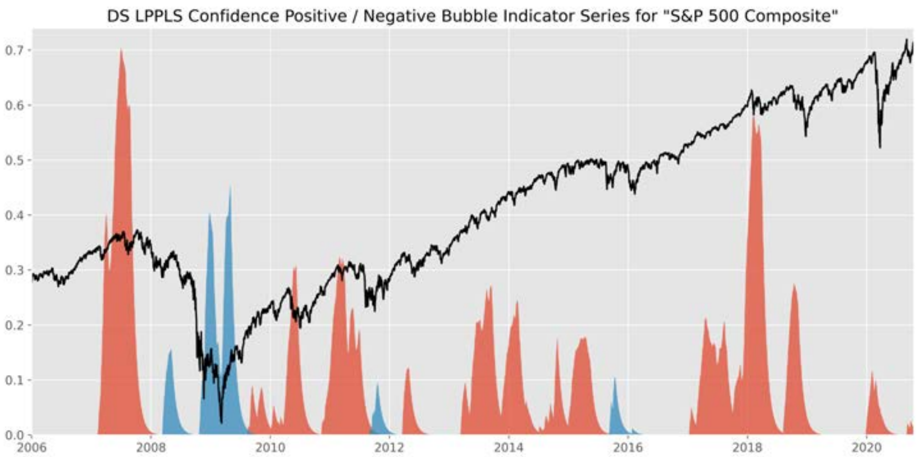

Figure 3.2. *Time series of the positive (red) and negative (blue) bubble DS LPPLS Confidence Indicator for the S&P 500 Composite Index.*

The major peaks of the Confidence Indicator time series shown in the plots identify remarkably well important market events and regime transitions of the past 15 years: (i) the peak and crash of the real estate bubble, (ii) the following trough and rebound after the real estate bubble (as indicated by the negative bubble indicator), (iii) the February 2018 correction and (iv) the end of the bull market regime in 2017/18[119]. The peak

[119] During the low-volatility period from 2009 - 2018, there are peaks that are not all directly followed by a correction or a crash. However, these are lower in amplitude, mostly reaching a maximum value of less than 0.2. Thus, they can be interpreted as minor warning signals. Furthermore, they culminate in the 2015/16 stagnation of most indices, which can also be seen as a change of regime.

indicator values preceding the Corona crash in Feb/Mar 2020 are not as strong as peaks preceding the other major events.

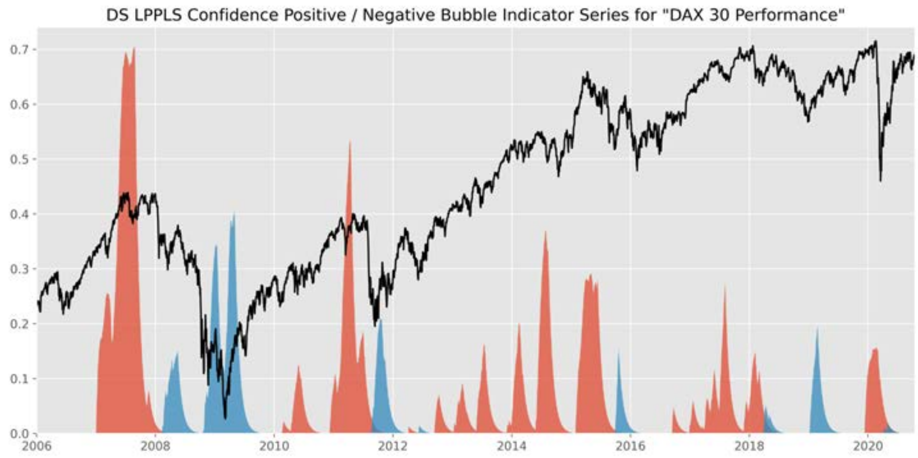

Figure 3.3. *Time series of the positive (red) and negative (blue) bubble DS LPPLS Confidence Indicator for the DAX 30 Performance Index.*

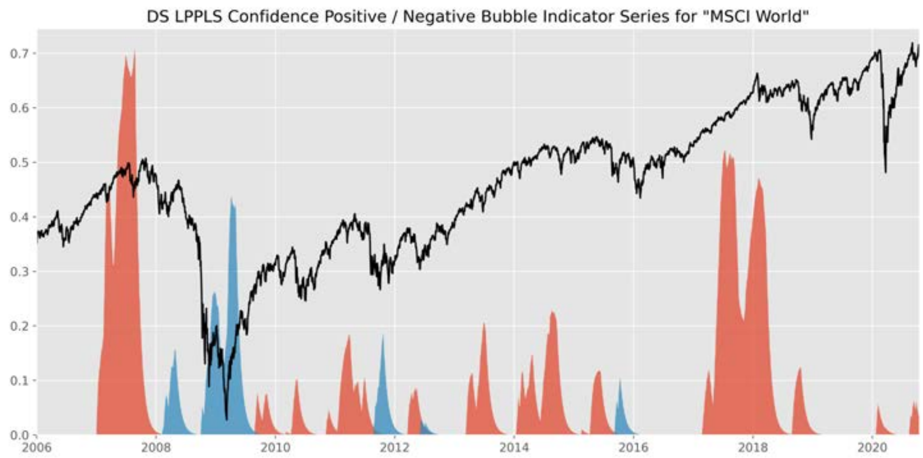

Figure 3.4. *Time series of the positive (red) and negative (blue) bubble DS LPPLS Confidence Indicator for the MSCI World Index.*

Figure 3.4 shows a refined view of the Confidence Indicator for the S&P 500 Index between 2017 and October 2020, where the indicator was split into three separate indicators. These "multi-scale" Confidence Indicators (MS CI) are computed according to the same methodology as the Confidence Indicator; however each are based on different subsets of fits with window sizes separated and split into respective short, medium and long ranges from [1 month, 3 months], [3 months, 1 year] and [1 year, 2 years][120]. The breakdown of the CI into these separate time domains represents the different psychological timescales and investment horizons on which market participants assess risk.

Often, early warnings of a forming bubble are signaled by a sole increase of the short-range MS CI, as it takes into account only the shortest fit windows, and thus is the most reactive. As the bubble grows, successively, the medium and long MS CI increase, which further strengthens the confidence in the signal. Observing the three different metrics in concurrence therefore allows monitoring the growth of a bubble over time.

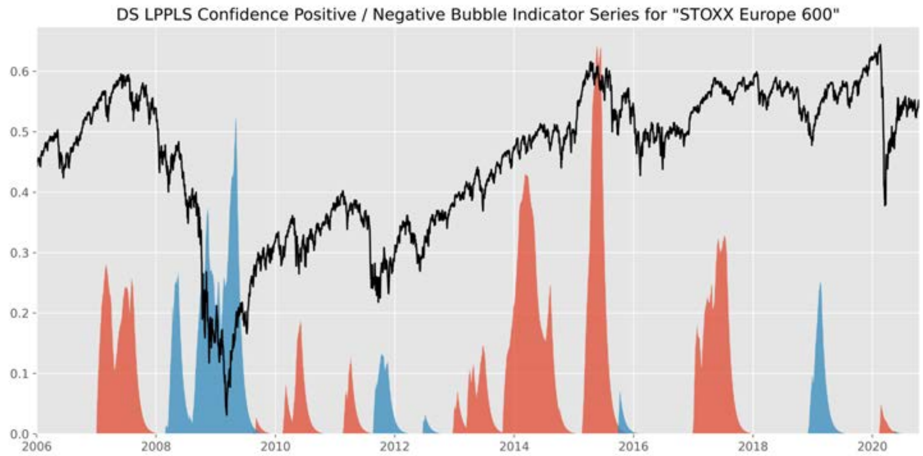

Figure 3.5. *Time series of the positive (red) and negative (blue) bubble DS LPPLS Confidence Indicator for the STOXX Europe 600 Index.*

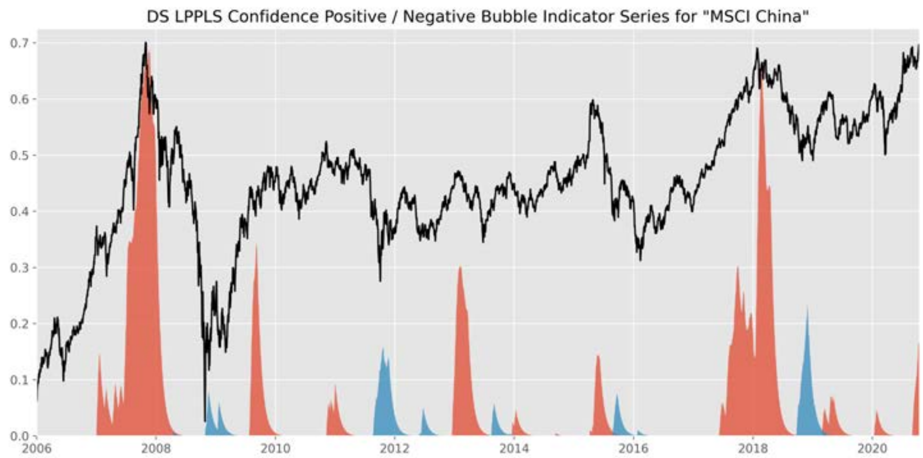

Figure 3.6. *Time series of the positive (red) and negative (blue) bubble DS LPPLS Confidence Indicator for the MSCI China Index.*

120 Again, the ranges cover all window sizes in increments of 1 day.

As Figure 3.6 shows, all multi-scale indicators peak around the February 2018 crash and then again later in 2018 before the market drawdown. In advance to the Corona crash, the short and medium indicators peak.

Thus, a strong price acceleration on short and medium timescales was detected prior to the crash in February 2020: over 2019, the U.S. market price had strongly appreciated again and the general market mood was very positive, as a year of strong corporate earnings was expected. Even when the Chinese government announced the breakout of the Corona pandemic in January 2020, the Western society did not consider it a big concern, yet. The Corona epidemic and consequential measures were highly exogenous, unprecedented market events. Nevertheless, the bubble developing up to the peak in February 2020 (and still developing further now) was a result of the already existing policies of central banks and treasuries fueling price growth, and thus, was of endogenous nature. Already before COVID-19, stock markets followed a non-sustainable trajectory, especially in the US, and the corresponding danger of a nearing crash grew. Then, the market was disrupted by the news of the economic shutdown and a panicking sell-off leading to the (temporary) drawdown ensued over the following weeks. The pandemic was an exogenous trigger causing the premature burst of a developing endogenous market bubble, which would have destabilized in subsequent months anyway.

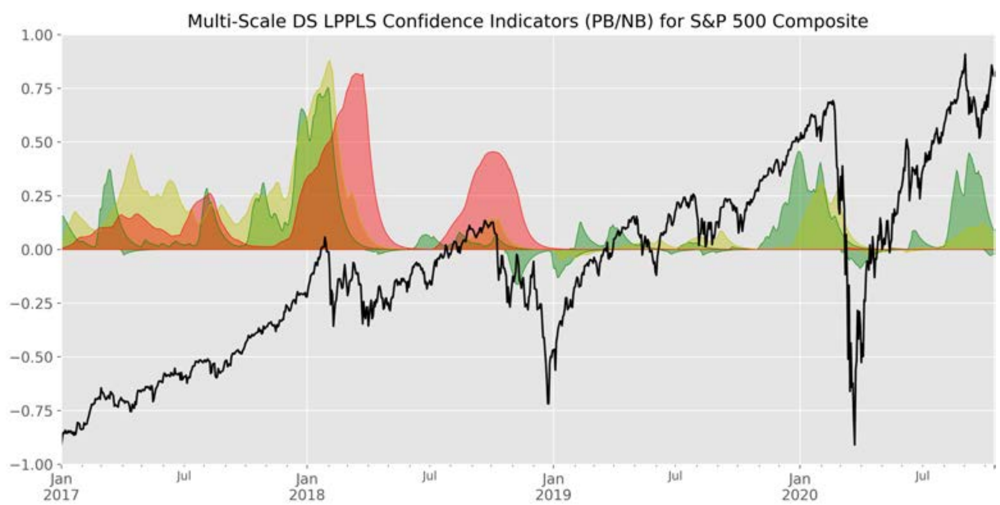

Figure 3.7. *Time series of the positive and negative bubble multi-scale DS LPPLS Confidence Indicators for the S&P 500 Composite Index from 2017 to October 2020. The short / medium / long indicator is color-coded in green / yellow / red and the type of bubble, i.e., positive or negative is indicated by a positive, respectively, negative value of the indicator.*

A more aggregate picture of bubble activity for various asset classes over the past years is provided in Figure 3.7. The fractions of positive and negative bubble signals (FPB / FNB) amongst four major asset classes are displayed: equities, fixed income, commodities and currencies. Each asset class consists of a representative selection of price indices. In total, about 500 price time series are analyzed. For each time series, the value of the Confidence Indicator is first individually computed in monthly steps from 2017 onwards. Then, the fraction of positive / negative bubbles is defined as the number of assets within an asset class for which the positive / negative Confidence Indicator is non-zero, divided by the number of assets belonging to that asset class. The depicted time series thus quantify bubble activity across the entire landscape of assets belonging to a specific asset class.

As Figure 3.7 shows, at the beginning of 2020, about 15% of all analyzed equity indices were in a positive bubble. In February, the crash followed. Since prices recovered during the months following March 2020, bubble activity rose again. However, in contrast to the situation before February 2020, throughout the summer of 2020, not only the equity class, also the commodities and fixed income class peaked in positive bubble activity, reaching levels of more than 20%. Although towards October the fractions decayed below 5% again, as a result of another correction, the current situation may still have worsened, as there are signs of a contagion of bubble activity from the equity sector to other asset classes.

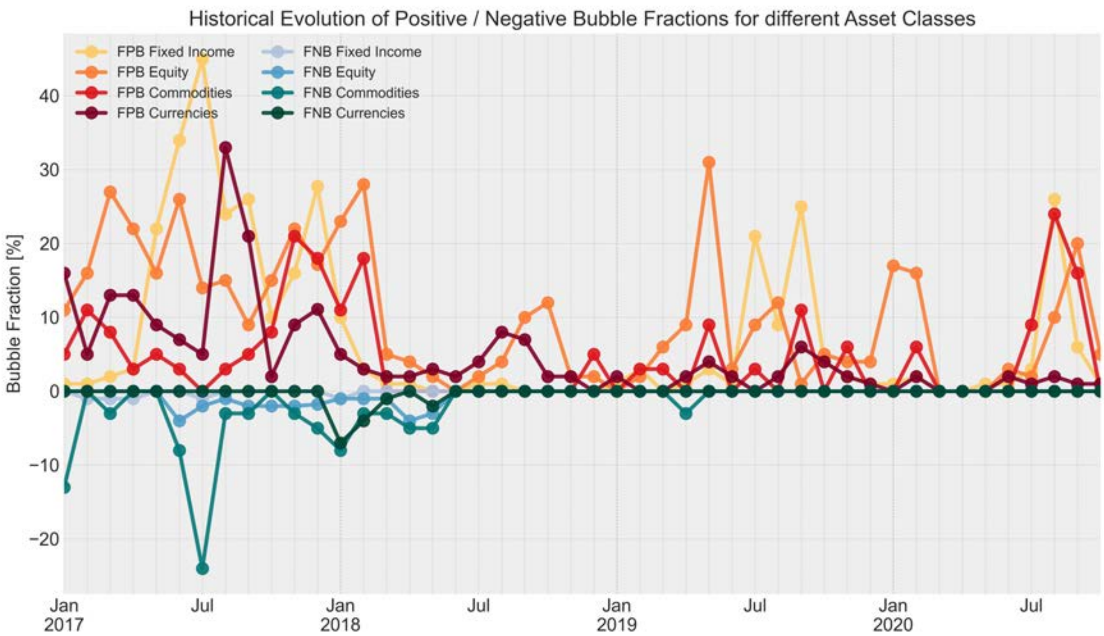

Figure 3.8. *An overview of positive and negative bubble activity from 2017 until October 2020. The fraction of positive (FPB) and fraction of negative (FNB) bubbles is defined as the number of assets at a given time for which the PB / NB indicator is non-zero, i.e., a bubble signal is found, divided by the total number of assets within the analyzed asset class. The fractions are provided for the four major asset classes; equity, fixed income, commodities and currencies. Positive (negative) values of the bubble fraction correspond to the FPB (FNB) and are provided in percent.*

3.1.4 Conclusion

Concluding, in recent years, the stock market environment has changed. The current, more volatile market regime calls for dynamic risk management, in contrast to static passive investing. Driving corresponding adaptive and resilient strategies requires primarily the estimation of the currently greatest source of risk: crashes and large drawdowns. The LPPLS model is a flexible and reliable tool for dynamic crash risk estimation and real-time bubble monitoring. A simplified and reduced part of the LPPLS research "toolbox" employed in the Financial Crisis Observatory at ETH Zurich was presented here. These tools were applied to historically well-known examples of past bubbles and to more than a decade of recent market history of five relevant equity indices. Major crisis events of the past were in fact detected with the corresponding indicators derived from the LPPLS model. These were also pointed out in many monthly reports of the FCO at ETH Zurich.

The Corona crash was an exogenous and improbable event, with an abrupt market impact in February 2020. Nevertheless, it was only the trigger of an endogenous crash that was already "looming". Although markets have recovered since the crash, the risk of a further crash remains high, if not even elevated, as the underlying economic situation has not particularly improved; the measures for crisis management undertaken by controlling institutions essentially remain the same. The majority of stock market companies record losses in current stock price and the superficial recovery of major equity market indices is mainly driven by large-cap technology companies. Moreover, a potential spread of bubble activity towards various other financial markets such as the commodities sector is detected. The stock market rally of November 9, 2020 following the announcement of a potentially working vaccine adds to the risks, given the many remaining medical uncertainties and the level of wishful thinking that can be attributed to this event.

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3.2 Bubbles for Fama from Sornette

Full Reference:

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Abstract

We present strong evidence that financial bubbles can be identified ex-ante and that a sharp price increase, when suitably qualified by a bubble indicator called LPPLS confidence, does on average predict unusually low returns going forward. For this, we use a methodology called log-periodic power law singularity (LPPLS) combined with the event study method applied to industry sectors in China over 2005–2020 and the US over 2009–2020. We identify a new class of apparent bubble regimes corresponding to the convergence to a stable price level, which can be disentangled using LPPLS-based indicators from standard bubbles followed by crashes.

3.2.1 Introduction

Eugene F. Fama is known for rejecting the existence of bubbles based on the lack of a sufficient *ex-ante* evidence and of a systematic identification methodology. In his Nobel lecture, Fama (2014) defines a bubble as an "irrational strong price increase that implies a predictable strong decline." Based on their post-mortem analysis of industry statistics, Greenwood, Shleifer, and You (2019) also claim that "a sharp price increase of an industry portfolio does not, on average, predict unusually low returns going forward." We object to this conclusion by presenting a systematic methodology for identifying bubbles at the industry level. Specifically, we use the log-periodic power law singularity (LPPLS) methodology developed by the Sornette research group over more than two decades ago. We claim that the LPPLS-based methodology in a straightforward operational implementation can allow for an *ex-ante* and causal (in real-time) identification of bubbles, especially in assets experiencing a strong *super-exponential* price increase [121] (Sornette & Johansen, 2002; Sornette, 2003). Our evidence confirms that a *super-exponential* price change—characterizing a strong, irrational price movement—is *unsustainable,* and hence it causes a break in the pre-existing price dynamics.

The models of standard neoclassical economics fail to incorporate the nonlinear dynamics and complex non-equilibrium and non-stationary properties of financial markets. These properties transcend the explanatory abilities of neoclassical financial theories. The European Central Bank's (ECB) Governor Jean-Claude Trichet points out this limitation in relation to the Great Financial Crisis, in 2010[122], in the following quote: "As a policy-maker during the crisis, I found the available models of limited help. In fact, I would go further: in the face of the crisis, we felt abandoned by conventional tools." In this context, we elaborate on the insights of Sornette and his co-workers, who have built on the existence of several positive feedback mechanisms in financial markets that make them intrinsically unstable (Minsky, 1972, 1992). Specifically, this instability

[121] We define a bubble as a "super-exponential" price increase, which is followed by a sudden collapse. "Super-exponential" indicates that the growth rate of the price (or average return) grows itself. Recall that a constant growth rate means that the price grows exponentially, which is the standard regime of financial assets owing to proportional growth and the law of compounding interests. When the growth rate grows itself, the price accelerates hyperbolically, which is unsustainable.

[122] Opening address by Jean-Claude Trichet, President of the ECB, at the ECB Central Banking Conference Frankfurt, 18 November 2010. (https://www.ecb.europa.eu/press/key/date/2010/html/sp101118.en.html).

takes the form of long-lived phases of super-exponential price acceleration (Johansen & Sornette, 2010; Ardila-Alvarez, Forro, & Sornette, 2021), followed by regime changes manifested through sharp corrections or volatile plateaus.

These alternating phases of transient price acceleration and corrections call for modifying the standard mean reversion model of market dynamics to reflect the long-lived transient, unstable regimes self-correcting in abrupt market "*ruptures*." The modified model should capture that the market reverts only in the long-term and in a strong nonlinear style. Figure 3.9 vividly illustrates such nonlinear regime shifts in the Hang Seng Index from 1970 to 1997. At that time, the Hong Kong market presented a textbook example of free capital flows driven by market forces, which contributed to a succession of stock market and property bubbles. In the figure, the straight line followed by abrupt ruptures represents large excursions away from the average annual growth. Specifically, the figure shows several periods where the log-price trajectory exhibits an upward curvature, indicating a transient super-exponential growth until the onset of a sharp drawdown. The figure outlines the eight largest transient episodes, though there were other episodes at smaller scales. The logarithmic scale in Figure 3.9 should clearly indicate that, during a bubble episode, the price shoots up by 50% to 1,000% within a span of a few months to a few years.

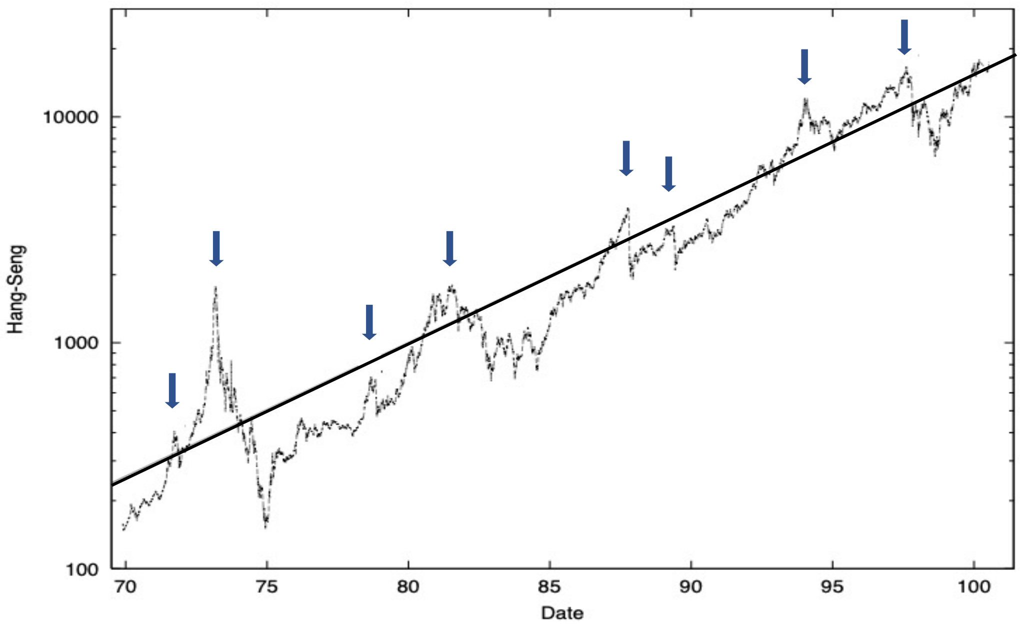

***Figure 3.9**. The Hang-Seng composite index of the Hong Kong stock market from November 1969 to September 1999. The culmination of the bubbles followed by strong*

corrections or crashes corresponding to a drawdown larger than 15% in less than three weeks is indicated by arrows at October 1971, February 1973, September 1978, October 1980, October 1987, April 1989, January 1994, and October 1997. The straight line shows an average exponential growth rate of ≈ 13.6% per year. (Adapted from Sornette and Johansen (2001).

In this context, it must be understood that fund managers and professional investors cannot avoid bubbles. Investors should not only hold large positions in the right stocks and buy them at bargain prices but also hope to cash out their positions close to the peak, and a failure to do so may spoil their efforts[123]. However, the key problem is how to determine the right time—neither too early nor too late.

Consider the Dot-com bubble to further illustrate the conundrums that investors face. At that time, the legendary investor and funder of the Tiger Fund, Julian Robertson, refused to follow the herd owing to its irrational crowd behavior and consequent market overvaluation. In 1999, the Tiger Fund was dissolved because its value stocks could not keep pace with the technology stocks. Stanley Druckenmiller, who at that time was the manager of the Quantum Fund, also detected market overvaluation. He thus exploited the market, overplayed his hand, and suffered a massive loss in 2000 when the crash occurred before he could unwind his positions. Although both Julian Robertson and Stanley Druckenmiller were disciplined and intelligent investors and they clearly predicted a bubble (as confirmed later by the crash), they both suffered losses for different reasons and hold unhappy memories of the event. While both detected the irrational behavior, the former avoided the technology stocks, while the latter made an ill-timed short bet[124,125].

The fund managers who leave the market too early earn negligible profits and are shadowed by peers who enjoy the appreciation of the bubble, while the fund managers who leave the market too late lose part of, all, or more than the capital gains accumulated during the appreciation. Managers who make the highest profit are not

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[123] Investors who fail to time the market peak before the crash might face the curse of Sisyphus. According to Greek mythology, Sisyphus tries to push a boulder to the mountaintop. However, every time he reaches the mountaintop, the stone rolls down and he starts pushing the boulder uphill again.

[124] Legendary value investor Charles de Vaulx's refusal to join the *crowd* and the performance pressure led to his suicide in 2021 (https://www.barrons.com/articles/legendary-value-manager-charles-de-vaulx-found-dead-51619564407).

[125] For example, the failure of Archegos Capital in 2021 can be attributed to its overplay in the herding trend—a combination of leverage and momentum-chasing led to the margin call. (https://www.moneycontrol.com/news/business/personal-finance/vital-lessons-for-investors-from-the-archegos-saga-6713791.html).

deceived by misrepresentations and lies, ride the trend, and step off before it is discredited (getting out of the market before the crash). We suggest that this objective can be achieved by using a suitable measure of unsustainable price dynamics as explained below.

This study has thus two objectives. First, we present an LPPLS model using advanced confidence indicators to detect bubbles (positive and negative) at the industry-group level in both China and the U.S. market. Second, we use the event study method to record price behaviors systematically, before and after the rise of LPPLS-based confidence indicators. We also categorize bubbles according to the magnitude of the LPPLS confidence indicators. To the best of our knowledge, this is the first study to identify bubbles at the industry-group level in both China and the U.S. and to use event study to examine the predictability of the LPPLS model.

We present three major findings. First, bubbles can be detected *ex-ante* and causally by using the LPPLS confidence index, unlike the claim by Fama (2014) and Greenwood et al. (2019) that bubbles cannot be identified in real time. Our finding proves that prices contain sufficient information to achieve bubble detection capabilities.[126] Second, bubbles frequently appear at the industry-group level in the Chinese and U.S. markets. Particularly, the Chinese market has more collective bubbles (signaling an impending price decline) that simultaneously develop in different industries, despite their different business cycles. In contrast, the bubbles in the U.S. market exhibit a more uniform distribution (signaling a large impending price decline) over a period, suggesting more decoupling. Third, positive bubbles and negative bubbles do not have symmetric shapes in the Chinese and U.S. markets. Specifically, a larger positive LPPLS confidence indicator suggests overreaction and a subsequent strong price decline (bubble crash or large drawdown), while a smaller positive LPPLS confidence indicator implies underreaction and a subsequent plateauing of the price. For negative bubbles[127], a negative LPPLS confidence indicator with a large amplitude quantifying an accelerated price decline signals higher future volatility. The upward price rebound that sometimes follows a price decline is more apparent in the U.S. than that in the Chinese market.

[126] We are the first to apply the LPPLS Confidence Indicator to the U.S. and Chinese industry-level datasets. The empirical evidence reported in this study in particular on Chinese markets can be considered an "out-of-sample" test of the LPPLS Confidence Indicator.

[127] A negative bubble is characterized by a fast-accelerating declining price, which is symmetric to a positive bubble via the symmetry $\ln[p(t)] \rightarrow -\ln[p(t)]$).

The study most similar to ours is titled *Bubbles for Fama* by Greenwood et al. (2019), which uses historical industry-level data for both U.S. and other countries to test whether significant stock run-ups will lead to crashes; however, their paper differs from ours in its event selection methodology, i.e., they use fixed thresholds for the industry price increases (e.g., a 100% price run-up during two consecutive years) to filter their events and to analyze what happens afterward, while we use the LPPLS Confidence Indicator to identify the event date, observing the market behavior after the event date. Based on the general criterion of a significant deviation from the standard exponential growth, this method can be considered agnostic with respect to the mispricing level qualifying a bubble, and hence more flexible to adapt to different bubble price structures. Our study also differs from Greenwood et al. (2019) in that the latter uses monthly returns data, while we use daily return data. For transient bubble episodes, monthly data may be too coarse-grained; for example, a bubble lasting 12 or 24 months will have only 12 or 24 data points. Our model daily price resolution is more adapted to capture transient abnormal super-exponential price dynamics, given that our model uses a dedicated calibration to account for large daily residuals. Based on their methodology, Greenwood et al. (2018) conclude that considerable price increases do not lead to market crashes, but when the stock price goes up a lot, the probability of a substantial crash increases. In contrast, we come to the conclusion that strong super-exponential price increases, detected by higher LPPLS Confidence Indicators, will be followed by substantial market declines (crashes). The opposing conclusions can be attributed to the fact that our methodology is better adapted to bracket the peaks of the bubbles. A fixed threshold, as in Greenwood et al. (2018), such as a 100% price run-up during two consecutive years, may lead to the selection of a time that does not capture the full course of the bubble. The time at which the 100% price run-up threshold is reached may be when the bubble is still running its course upward and not when it bursts. The averaging over many such configurations taken at random times (corresponding to the arbitrary 100% price run-up) in the lifetime of the bubbles may lead to the misleading conclusion that there is no subsequent price decline following a bubble. In other words, by averaging over cases when the bubble is still growing strongly and when the price is in its drawdown phase after the bubble has burst, it is logical that Greenwood et al. (2018) conclude that the average behaviour does not exhinit substantial market declines.

The conclusion of our study is similar to that of Hong and Stein (1999) in their classification of the post-event price performance. Our results also provide a conceptual framework to reconcile the short-term underreaction and long-term overreaction patterns in financial markets. Our paper is also similar in spirit to Kinlaw et al. (2018), as we both aim to time the market at the industry level. Kinlaw et al. (2018) used the asset centrality measure based on a Principal Component Analysis of the covariance matrix of the returns of a set of sectors and argued that large asset centrality is indicative of crowded trading, which is often associated with the formation of bubbles. In contrast, we use the LPPLS model that builds on signatures associated with positive feedbacks to identify the end of bubbles. We find that our LPPLS-based approach outperforms Kinlaw et al.'s method.

Two other papers related to our work are Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). Barroso and Santa-Clara (2015) show that a run of a momentum portfolio enjoying a remarkably good performance is occasionally followed by a large crash, which makes the strategy risky. They show that the tail risk can be managed by controlling the realized variance of daily returns. Daniel and Moskowitz (2016) use momentum premium and volatility to generate portfolios with dynamic asset weights that have a better Sharpe ratio and larger alpha than Barroso and Santa-Clara's static momentum portfolio. Daniel and Moskowitz (2016) focus on portfolio risk management, while we adopt a straightforward approach of directly predicting which kind of price increase (acceleration) is likely to lead to a crash.

The remainder of this paper is organized as follows. Section 2 presents a short review of the relevant literature. Section 3 explains the theory underpinning and methodologies implementing the LPPLS model and event study. Section 4 presents the data, and Section 5 discusses the empirical findings. Section 6 concludes the study.

3.2.2 Literature Review

The efficient market hypothesis (EMH) implies the unpredictability of future returns and the absence of bubbles that can be exploited for arbitrage opportunity. Fama (1965) reckons that although behavioral/boundedly rational traders exist in financial markets, sophisticated arbitrageurs correct any exploitable potential mispricing induced by these behavioral traders. However, a large body of research exhibit evidence that market inefficiency (limits of arbitrage such as costs, risks, and restrictions) and bounded rationality (cognitive limitations, information imperfection, and constraints) may promote the existence of transient bubbles. Several empirical findings provide evidence of financial bubbles, and hence may be in contrast with the EMH. In this regard, it must be noted that, owing to momentum trading, trend chasing, and the likes, a large number of *behavioral* agents are subjected to animal spirits, fads and fashions, and overconfidence, which might lead to positive feedback loops. In this context, psychological and behavioral elements of stock price determination may make the stock return predictable, at least in pockets of predictability associated with the end of the bubble regimes as we discuss below.

Background and Historical Attempts to Define Bubbles

Bubbles refer to the significant, sustained mispricing of financial or real assets. According to the basic asset pricing theory, the asset value should be equal to the discounted future fundamental income flow, otherwise, arbitrage opportunities will arise. However, the difficulty in accurately predicting the future fundamental income flow ex-ante poses a real-world problem. Abstracting from the economic issues, any trivial change in the assumptions of the valuation model can generate a large range of current fundamental values (Black, 1986). Thus, the use of such ambiguous characterization of the fundamental value always muddles the evidence for bubbles.

Some financial economists deny the existence of bubbles because they believe in efficient markets (the price reflects all publicly available information) (Fama 1965, 1970; Samuelson, 1965, 1973). As per their theory, rational speculators stabilize the price, and sophisticated investors do not allow for the emergence of a bubble (Fama, 1965; Friedman, 1953). In efficient markets, there are no free lunch. In contrast, Shiller (1984) suggests that the argument behind the EMH is invalid because it ignores the agents' psychology and the interactions between agents at the origin of price fluctuations. He also claims that market values cannot be justified based on future dividend flow, thus supporting the existence of bubbles (Shiller, 1986; 2015). Keynes (1936) also suggests the possible existence of speculative bubbles. Scheinkman and Xiong (2003) show that, although the aggregate beliefs of investors may be unbiased, large fluctuations in heterogeneous beliefs can lead to the formation of significant bubbles. According to behavior finance theory, the limits to arbitrage and the presence of irrational investors may also lead to the formation of bubbles.

Concerning its definition, the exact definition of bubbles varies in the financial literature (Brunnermeier, 2012). Kindleberger (1978) defines a bubble as an upward price movement over an extended range that then implodes. Santoni and Dwyer (1990) describe a bubble as a regime that appears when the market does not follow a random walk. Stiglitz (1990) defines a bubble as a situation followed by marked price declines, which occur without any apparent new information. Using the Q-theory of investment, McGrattan and Prescott (2001) define bubbles as periods when the value of a set of assets exceeds the sum of the values of individual assets. Siegel (2003) defines a bubble as any time the realized asset return over a given future period is more than two standard deviations from its expected return.

Concerning modeling the bubbles, Schatz and Sornette (2020) propose a mathematical framework accommodating discrete and continuous-time bubble models featuring market inefficiencies. This framework provides a solid theoretical background to embed feasible asset price processes during financial speculation and frenzy. Through this framework, Schatz and Sornette (2020) demonstrate that the rational expectation bubbles models suffer by design from the paradox that a rational market should not allow for mispricing, both in discrete and continuous cases. They also show that this problem is not solved within the finite time *strict local martingale* approach to bubbles (Jarrow et al., 2011; Protter, 2013).

In line with Schatz and Sornette (2020), we classify the bubble literature into two groups. The type-I group considers bubbles as the premium of a future crash risk leading to exorbitant (inefficient) stock price development. A typical representative member of this group is the rational expectation bubble model. This group is further sub-divided into the symmetric and asymmetric information bubble groups. The type-II group argues that bubbles represent a temporary departure from market efficiency. These prices return to efficient levels (e.g., through efficient crashes) after the correction of inefficiency occurring during a drawdown. Theories underpinning the bubbles of the type-II group include the heterogeneous beliefs, behavior finance and complex system theories. As per the *theory of heterogeneous beliefs*, bubbles result from prior heterogeneous beliefs in the asset fundamental value. The *behavior finance theory* holds that bubbles arise owing to limits to arbitrage or positive feedback caused by noise or not fully rational investors. *Complex system theory* argues that bubbles emerge owing to the imitation and collective herding behavior of heterogeneous agents. Specifically, the repetitive nonlinear interaction between agents may create positive feedback loops leading to speculative bubbles. The following sections elaborately explain these approaches.

3.2.2.1 Rational Expectation Bubble

3.2.2.1.1 Rational Expectation Bubble under Symmetric Information

Rational Bubble According to Blanchard and Watson

Rational bubbles emerge owing to investors' self-fulfilling expectations about future price trajectories (Blanchard, 1979). The agents fully understand the fundamental asset value but are willing to pay more than the underlying value. This can occur if agents' expectations of future price growth are high enough to compensate for the risk they are willing to take. In other words, the expected return is higher than the required rate of return, and the investors can sell the asset, on average, at a profit in the future.

In this regard, motivated by non-fundamental factors (e.g., sentiment and over-optimism, etc.), Blanchard and Watson (1982) propose a model in which the asset price can be decomposed into a fundamental and non-fundamental factor,

$$P_t = V_t + B_t \tag{3.1}$$

where P_t is the asset market price, V_t indicates the asset fundamental value, and B_t represents the bubble component at time t.

Blanchard and Watson (1982) consider that the bubble, expected to grow at a long-term growth rate of $\bar{r}$, persists with probability π and bursts with a probability of $(1-\pi)$. The bubble has a growth rate $(1+\bar{r})/\pi$ to ensure a fair risk-neutral valuation condition. Thus, during the time that the bubble persists, it has to grow faster than the historical average return.

Lux and Sornette (2002) have investigated the statistical properties of rational expectation bubbles and found that the distribution of returns belongs to the class of so-called heavy-tailed distribution so that the tails of the distribution of returns follow approximately a power law distribution with a tail exponent smaller than 1 (owing to the rational expectation conditions). This contradicts the stylized facts of financial data that the tail exponent is in the range 2 to 4. The rational exponential bubble models of this class thus fail at a very elementary level.

Intrinsic Bubble According to Froot and Obstfeld

Froot and Obstfeld (1991) proposed a specific rational bubble model under symmetric information, also known as the intrinsic bubble model. A prerequisite of this model is that the bubble component is determined by the dividends (a proxy of fundamentals) in a non-linear deterministic approach. This model suggests that the bubble emerges because of overreactions to the stochastic dividends. The price dynamics reads:

$$\hat{P}_t = \hat{V}_t + B(D_t) \tag{3. 2}$$

$$B(D_t) = cD_t^{\gamma} \tag{3. 3}$$

where $\hat{P}_t$ is the asset market price, $\hat{V}_t$ is the fundamental value, B denotes the bubble component, and D_t is the dividend at time t; c>0 and γ >1 are parameters.

The bubble component is deterministically related to the dividends, as the exponential growth of the bubble follows the growth rate of the dividends. If the fundamentals remain the same (i.e., the dividends remain constant), the bubble component will remain the same. However, if the fundamental shows an up-side shift (i.e., the dividends show an up-side shift) or investors expect the fundamental to be up-side shifting, the bubble component will cause an accelerated surge in the asset market price.

While the intrinsic bubble model is also a self-fulfilling bubble, it is driven by fundamental expectations. In contrast, it is the non-fundamental factors that drive the rational bubble of Blanchard and Watson.

3.2.2.1.2 Rational Expectation Bubble under Asymmetric Information

Under the assumption of symmetric information, a bubble is commonly known by all rational investors. However, in the case of asymmetric information, everybody is aware of the existence of a bubble, but they do not know whether other investors are aware of its existence. The asymmetric information theory assumes that investors share a common prior belief distribution, but possess different information. Under this assumption, the price has the following two roles: (i) price reflects the aggregate information, and (ii) price itself is the informative signal, as it induces others to partially reveal their aggregate information.

It must be noted that the lack of higher-order knowledge makes it possible for a finite bubble to emerge. Allen et al. (1993) proposed the *contrapositives* of the no-trade theorem, highlighting the following necessary conditions for the existence of bubbles. First, the price cannot be fully revealed, as the investors remain asymmetrically informed after exposure to prices and net trade information. Second, investors have limited short-selling ability, which makes the bubbles persist. Third, the market structure, which assumes that the initial allocation is interim Pareto efficient, is not common knowledge.

Tirole (1982) showed that, if market information is common knowledge, then there is no gain from trading. Any bid or offer to initiate a transaction will reveal the bidder's private knowledge and place them in an unfavorable situation. In other words, trading requires that investors believe that they gain something from the trade. For instance, fund managers who invest for their clients buy assets even during the bubble stage. This convinces the clients that their managers have superior information that drives their superior performance. An inability to trade will reveal their lack of superior private information that can lead to profit. Given this, bad fund managers tend to *churn bubbles* by taking on overvalued assets, despite knowing that they might be the *last in line* (Allen and Gorton, 1993).

3.2.2.2 Inefficient Market Bubble

Fama has been a staunch upholder of the hypothesis that markets are efficient. He also believes that an observed excess return is not the result of investing in an inefficient market ut that it is a risk premium associated with other unknown risk factors. However, a large body of literature seems to contradict Fama's view. These works suggest that a systematic error (i.e., mispricing) owing to *inefficient* or not fully rational agents can lead to excess returns.

3.2.2.2.1 Heterogeneous Belief Bubble

Investors may disagree about the fundamental value of the asset or may be constrained by short selling. In such a scenario, investors hold overpriced assets if they can resell them to someone less informed or, in Kindleberger's (1978) terms, to a greater fool. The prices of these assets are determined at equilibrium to reflect the heterogeneous beliefs. Beliefs differ given that investors have different prior belief distributions because of psychological biases. For example, heterogenous beliefs and short-selling restrictions force the pessimists out of the market as they fail to counterbalance the high asset prices determined by the optimists. Miller (1977) shows that the optimists inflate the new equilibrium to a higher level. Simsek (2013) proposes that the disagreements on belief constrain optimists' ability to borrow from pessimists. Intuitively, pessimists are more inclined to fund optimists when the disagreement is about the upside than the downside state.

Lintner (1969), Chen, Hong, and Stein (2002), and Kurz (1996) show that heterogeneous beliefs with short-sale constraints restrictions can lead to overpricing.

Scheinkman and Xiong (2003) show that a high trading volume and price volatility are features of heterogeneous-belief bubbles. Ofek and Richardson (2003) and Cochrane (2003) link this argument to the dot.com bubble of the late 1990s. In this context, Sohn and Sornette (2020) propose an extension of the class of rational expectations bubbles to the more general rational beliefs setting of Kurz (1994), in which a heterogenous population of agents can hold more than one *rational* expectation. This can lead to the emergence of correlated beliefs allowing for the convergence of rational but diverse beliefs. These beliefs may not cancel each other in aggregate, and this can make them an object of rational speculation. Thus, diverse but correlated beliefs can account for speculative bubbles, without the need for irrational agents or limits to arbitrage.

3.2.2.2.2 Behaviour Finance Theory

EMH reasons that bubbles do not exist because the sophisticated arbitragers (rational investors) eliminate mispricing opportunities introduced by irrational investors. However, behaviour finance theory holds that the markets are inefficient because (i) there is a limit to arbitrage, and (ii) investors do not always process information correctly. Costs and risks also deter sophisticated investors and professional arbitragers from eliminating the arbitrage opportunities.

Short Selling Restrictions

Lee et al. (1999) state that price and value form a co-integrated system and converge in the long-term owing to arbitraging. However, as a result of exogenous forces (e.g., arbitrage costs) and constraints (e.g., short-selling constraints), prices can depart from their fundamental value. For example, Almazan et al. (2004) indicate that roughly 70% of the mutual funds explicitly claim that they have short-selling restrictions. Koski and Pontiff (1999) show that 79% of the equity mutual funds do not access derivatives, suggesting that they cannot use synthetic ways to take short positions. The failure of short-sellers to correct overpricing might also be caused by sentiment-driven traders who exacerbate overpricing (De Long, Shleifer, Summers, and Waldmann, 1990a; Shleifer & Vishny, 1997).

Costs of Arbitrage

Grossman and Stiglitz (1980) show that the market cannot be perfectly informationally efficient because information acquisition is costly. If the market were efficient, then investors spending resources to obtain knowledge would receive no compensation and would stop such investments, thus removing the forces pushing the market toward its efficiency frontier. Shleifer and Vishny (1997) believe that arbitrage costs can be divided into the following three subclasses: trading, holding, and information costs. Trading costs include the brokerage fees, price slippage, bid-ask spreads, and other costs related to building or closing the positions. Holding costs comprise costs for sustaining the positions of various durations and implementing short selling. Information costs are associated with accessing, analyzing, and monitoring information.

Fundamental Risk

Fundamental risk refers to the arbitrageurs being wrong about the subsequent fundamental news of the targeted companies and thus taking wrong arbitrage positions, which leads to losses. For instance, rational investors might short a bubble, but the subsequent positive shift in fundamentals might unwind the arbitrage strategies, if the initial overpricing is justified by the new fundamentals.

Theoretically, the fundamental risk can be hedged by taking a reverse position of a closely related asset. For example, the arbitrageur has a long position on shares A and is aware of their downside risk. In theory, the best strategy would be to short shares B, which is a perfect substitute for shares A. However, there are no perfect substitute securities of shares A, and shares B themselves might be mispriced. Thus, it is challenging to eliminate fundamental risk (Barberis & Thaler, 2003)

Noise Trade Risk

Kyle (1985) and Black (1986) refer to noise traders as irrational investors. They also point out that the EMH does not account for noise trading, which could explain daily excess trading and unreasonable price movements. According to the noise trader model, market prices and the company's fundamental value deviate from each other over a relatively long term (De Long et al., 1990). In addition, noise traders' activities pose a risk to all market participants, which impacts the valuation anchor of the market by disturbing the cost of capital. Shleifer and Vishny (1997) show that arbitrageurs have short investment horizons because they often manage the money of investors with different time preferences. The unpredictable behavior of noise traders creates a risk in the assets, deterring rational arbitrageurs from aggressively betting against them. In addition, the performance of the arbitrageurs is usually judged based on their short-term returns because any temporary losses might trigger fund outflows, which might unwind their position when the mispricing is the largest.

Synchronization Risk

Abreu and Brunnermeier (2002, 2003) argue that bubbles cannot be offset unless arbitrageurs coordinate their actions, given that individual investors do not play a significant role in controlling an overpriced market. Thus, lack of coordination is another reason for persistent mispricing. Rational arbitrageurs know that market bubbles will collapse as soon as an adequate number of rational traders sell the stocks. However, the dispersion of rational arbitrageurs' opinions regarding the timing of the bubble inception delays their arbitrage orders (i.e., sell-off). This is attributed to the fact that, if arbitrageurs attack the bubble too early, they will forgo profits owing to the subsequent run-up caused by momentum traders. Given this, arbitrageurs uncertain about the beginning of the bubble might find it optimal to ride rather than attack the still growing bubble. Demos and Sornette (2017) further show that determining the start of a bubble is easier than determining the end of a bubble. Technically, the maximum likelihood estimation of the time of the bubble inception is much more rigid than the estimation of the end time of the bubble, which is more inaccurate in a technical sense. Therefore, Demos and Sornette (2017, 2019) argue that bubbles persist owing to arbitrageurs' difficulty to synchronize their belief about the end rather than about the beginning of the bubble.

Concerning this synchronization risk, based on the Securities and Exchange Commission's equity position data from 1998 to 2000, Brunnermeier and Nagel (2004) investigate the holdings of hedge funds (i.e., funds of well-known managers such as Paul Tudor and George Soros). They find that hedge fund portfolios were weighted more to the technology segments during the dot.com bubble. These sophisticated investors started reducing their holdings on a stock-by-stock basis before the collapse of some stocks. However, they switched to other technology stocks that still had a rising trend. The excess returns the hedge funds enjoyed in the technology segment support the existence of synchronization risk and disprove the claims of Friedman (1953) and Fama (1965) that rational speculators will stabilize the price and sophisticated investors will not allow the emergence of bubbles.

Positive Feedback Caused by Noise Traders

Behavior finance theory maintains that investors have inherent psychological biases, such as conservatism and overconfidence, and are subject to the disposition effect and the representativeness bias. These psychological biases can lead to an overreaction or underreaction behavior, both of which lead to positive feedback dynamics at the origin of momentum effects.

Jegadeesh and Titman (1993) develop a pioneer study on the momentum effect arising from the positive feedback of trading strategies that buy or sell assets with superior and inferior past performance. Ardila-Alvarez et al. (2021) introduce the *acceleration* effect (and factor) defined as the variation in the momentum over a suitable time frame. They show that this positive feedback strategy even overperforms the momentum factor to a large extent at the time of bubbles and crashes. Fama and French (1993, 1996) claim that most return reversals and other anomalies can be explained mainly by the three-factor model, except for the momentum effect. Fama and French (2015) extend their three-factor model to a five-factor model in order to address the parts of stocks' average return patterns unexplained by the three-factor model. However, the five-factor model still fails to explain the momentum factor (Fama and French, 2018).

According to Edwards (1968), investors tend to underweight new information when updating their information set. De Bondt and Thaler (1985) find overreaction in the stock market by showing that investors are influenced by waves of optimism and pessimism that cause prices to deviate systematically from their fundamental values; however, in the long-term, prices exhibit mean reversion. Lehmann (1990) and Jegadeesh (1990) document short-term reversal effects of one-week and one-month, respectively. Cross-sectional return predictability exists in many markets (Rouwenhorst, 1998) and appears between and within industries (Maskowitz & Grinblatt, 1999; Hameed et al., 2010).

Barberis et al. (1998) explain that the conservatism bias might lead investors to underreact to information, generating momentum profits. The conservatism bias suggests that prices slowly adjust to new information and that returns have no further predictability once the price reflects this information. Grinblatt and Han (2005) propose that the disposition effect leads to underreaction, which means that loss-averse investors anchoring on past prices tend to hold on to their past losers and sell their past winners. Delong et al. (1990) describe the delayed overreaction bias by showing that positive feedback trading strategies, where one buys past winners and sells past losers, cause prices to deviate from their fundamental value. Andreassen and Kraus (1990) empirically demonstrate that investors tend to chase price trends corresponding to positive feedback trading based on extrapolative expectations.

Based on the representative heuristic proposed by Tversky and Kahneman (1974), Barberis et al. (1998) argue that investors tend to mistakenly conclude that firms realizing consistent extraordinary earnings growth are more likely to continue to offer similar extraordinary increases in the future. This representativeness causes prices to overshoot in the short term and reverse to the fundamental value over the long terms.

Daniel et al. (1998) hypothesize that informed traders have self-attribution bias, which means that traders attribute the performance of ex-post winners to their stock selection skills while attributing a bad performance to simple bad luck. As a result of this cognitive bias, these investors overestimate the precision of their signals for asset valuation. However, their overconfidence in their signals pushes up the past winners beyond their fundamental value. The delayed overreaction in this model results in momentum profits and reversal behaviors.

Hong and Stein (1999) propose a unified underreaction and overreaction model. They consider two groups of investors—news-watching and momentum-trading investors—assuming that private information diffuses gradually across the news-watching investor population. Accordingly, the new information obtained by news-watching investors is transmitted with delays. Thus, it is progressively reflected in the price, which leads to short-term underreaction and the momentum effect. Conversely, the momentum traders, who trade based on limited price history and who arbitrage away any underreaction left behind by the news-watchers, push the past winners above their fundamental values. This behavior eventually leads to long-term price reversals.

3.2.2.2.3 Complex System Theory of Bubbles and Crashes

Social Imitation, Collective Herding, Bifurcation, and Phase Transitions

Imitation and herding might be the most visible imprint of human beings' behaviors in our social affairs. Psychologists and neuroscientists have studied imitation as one of the humans' most evolved cognitive processes; it requires sophisticated brain processing abilities and a very developed cortex. According to the social brain hypothesis of R. Dunbar (1998), imitation and other social skills co-evolved with the brains of mammals, in the form of evolutionarily advantageous traits, to strengthen group cohesion. Dunbar (1998) shows that humans have the largest cortex-to-brain ratio, the most sophisticated social and imitative aptitudes, and the largest social group sizes among mammals. Moreover, it is optimal to imitate others when we lack sufficient time, energy, and information based only on private information and limited processing ability (Roehner & Sornette, 2000). Hirshleifer (2015) emphasizes the effect of social interactions and contagion behavior in the propagation of individual cognitive biases, calling for more work beyond behavioral finance.

The main message of complex system theory is that a system (comprising several heterogeneous interacting agents with repetitive interactions) tends to self-organize its internal structure, leading to surprising emergent [128] out-of-equilibrium properties. For instance, the tendency for humans to imitate others can result in herding and crowd effects at the macroscopic level. Cooperative herding and social imitation within the group can form positive feedback, reinforcing interaction among the agents and leading to virtuous or vicious circles. A central property of a complex system is that the repetitive non-linear interactions among its constituents can lead to large-scale collective behavior with a rich structure (Goldenfeld & Kadanoff, 1999; Sornette, 1999, 2002, 2003).

A typical complex system such as the financial market has a group of competing agents subjected to a myriad of influences. With exogenous news and endogenous interactions, the market can develop self-organized and self-reinforcing extreme behaviors. Bubbles and crashes will also emerge through a self-organization process (Kaizoji et al., 2015; Westphal & Sornette, 2020). Mathematicians call this extreme behavior bifurcation or catastrophe (Thom, 1989). Statistical physicists call it phase transition (Stanley, 1987). As per the bifurcation theory, a trivial change in circumstance, interaction strength, or heterogeneity (e.g., avalanche, earthquake, or financial crash) could lead to a sudden and dramatic shift in behaviour at the macro-level.

Nonlinear Positive Feedback Bubble

Roehner and Sornette (2000) propose that the fundamental ingredient of bubbles is rooted in the repetitive actions of interactive nonlinear influences leading to large-scale correlations and eventually catastrophic events. During a bubble, the progressively increasing build-up of cooperativity and active interactions between investors in the market can form the herding behavior. The self-reinforcing positive feedback mechanism propels the market price to accelerate in a super-exponential way, which eventually reaches a critical point beyond which a crash can occur in the form of an

[128] Emergence refers to the formation of rich collective behaviors in a complex system that cannot be predicted from the rules of interactions, at the microscopic level of elementary agent or components. Emergence is the oppositive of the representative agent approach, given that macro behavior is expected to be fundamentally different from the individual agents' micro-behaviors.

abnormal drawdown. Johansen and Sornette (2002, 2010) define a crash as a drawdown outlier, i.e., an abnormally large cumulative loss over consecutive days of negative returns, which can be interspersed among small positive returns, occurring after the critical point.

According to complex system theory, the specific origin of the prices' collapse is not the most important issue—the market crashes because the market has entered into an unstable phase. Trivial disturbances or news can reveal the underlying instability of the market and trigger the crash. Over-leveraged financial institutions, complex derivatives, the expansion of credit, immature technology and innovations, and delusional mood are contributors to the positive feedback mechanisms at the origin of financial market instabilities. In this view, the market crashes because the system has matured toward instability and has reached an unsustainable critical point. Several mathematical stochastic processes have been proposed to capture the positive feedback dynamics leading to transient super-exponential price dynamics ending at critical points, also known as finite-time singularities (Ide & Sornette, 2002; Sornette & Andersen, 2002; Andersen & Sornette, 2004; Lin & Sornette, 2013; Lin et al., 2014, 2019). It must be noted that super-exponential bubbles exist in equity and real estate markets as well as commodities and cryptocurrency markets (Gerlach et al., 2019; Wheatley et al., 2019). While fundamental valuation tools can be used to recognize bubbles in the equity and real estate markets, this intrinsic value is more difficult to define in the commodities and cryptocurrency markets.

3.2.3 Methodology

The present work builds on the LPPLS (log-periodic power law singularity) framework. It is based on the combination of (i) positive feedback mechanisms caused by factors such as imitation and herding (Sornette 1999, 2017) and (ii) discrete scale invariance (Sornette, 1998) associated with an approximate hierarchical structure of human groups (Zhou et al., 2005) and/or generated dynamically via the interplay between fundamentalists and chartists (Ide & Sornette, 2002). The following section explains how to use the LPPLS framework as an advanced tool to detect a speculative bubble (i.e., a super-exponential price increase followed by a crash).

3.2.3.1 The log-periodic power law singularity (LPPLS) Model

In a nutshell, the LPPLS model describes a positive bubble regime by expressing the expected log-price (Sornette, et al., 1996; Feigenbaum & Freund, 1996) as

$$E[\ln p(t)] \approx A + B(t_c - t)^m\{1 + C\cos[\omega \; ln(t_c - t) + \theta]\} \qquad (3.4)$$

where $A = \ln[p(t_c)] > 0$ and B<0 quantifies the amplitude of the price acceleration whose shape is controlled by the exponent 0<m<1, C is the magnitude of the oscillations around the power-law singular growth, ω is the angular log-frequency of the oscillations before the critical time t_c denoting the end of the bubble embodying the hierarchical discrete scale invariance of the accelerating large-scale volatility structure. θ is a phase parameter in (0,2π) that corresponds to an encoded time unit. The term $B(t_c - t)^m$ with 0<m<1 and B<0 describes the super-exponential growth of the price up to the critical time t_c (Ardila-Alvarez et al., 2021), which we propose to be characteristic of bubbles. The last cosine term accounts for a long-term volatility structure also accelerating up to t_c. It is derived from the existence of hierarchical social structures (Zhou et al., 2005) and/or the interplay between nonlinear momentum and nonlinear value investing in the presence of inertia in the trading decision-making process (Ide and Sornette, 2002). The case B>0 corresponds to a negative bubble—a price that accelerates downward.

The LPPLS model was first formalized with the rational expectation bubble framework by Johansen, Ledoit and Sornette (1999) and Johansen, Sornette, and Ledoit (2000). In this framework, the price acceleration is treated as the remuneration for the exposure to an accelerated crash hazard rate. This is known as the Johansen-Ledoit-Sornette (JLS) model (for pedagogical reviews, see Geraskin and Fantazzini, 2013; Jhun, Palacios, and Weatherall, 2018). For the derivation of the LPPLS model, we also refer to Johansen et al. (1999), Johansen et al. (2000), Sornette and Johansen (2001), and Sornette and Cauwels (2015a). For a description of its efficient calibration, we refer to Filimonov and Sornette (2013).

The LPPLS model was first developed for studying the precursory behaviors before finite-time singularities, which pervade the solutions of (non-stochastic and stochastic) nonlinear ordinary and partial differential equations describing many systems in nature (Sornette, 1998, 2006). Examples include acoustic emissions before the rupture of engineering structures (Anifrani, et al., 1995) or seismic and chemical precursors of earthquakes (Sornette & Sammis, 1995; Johansen et al., 1996).

The original LPPLS model has been extended in the following studies. It was extended by constructing higher-order LPPLS 'Landau' versions and generalized Weierstrass-type LPPLS models (Gluzman & Sornette, 2002; Zhou & Sornette, 2003a). It has been generalized to second-order and higher harmonics (Sornette & Johansen, 1997; Sornette & Zhou, 2002). The augmented LPPLS model has been used for financial bubble modeling with macro-economic factors (Zhou & Sornette, 2006a). Studies have also derived a relationship between the LPPLS parameters from the condition that the crash hazard rate *h(t)* must remain positive by definition (Bothmer & Meister, 2003). The model has been supplemented with the fundamental value of the stock and with the idea of an *efficient crash* (Yan, et al., 2014; Kreuser & Sornette, 2019). It has also been extended to include negative bubbles (Yan, et al., 2010). Studies have introduced the LPPLS-autoregressive (AR)(1) and LPPLS-generalized autoregressive conditional heteroskedasticity (GARCH)(1) models to reflect a mean-reverting volatility process with a stochastic conditional return (Gazola, et al., 2008; Liberatore, 2010; Lin, et al., 2014). Studies have recommended the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root test to verify the Ornstein-Uhlenbeck property of the LPPLS fitting residuals (Geraskin & Fantazzini, 2013).

An improvement in the LPPLS model with quantile regression has led to the introduction of LPPLS confidence and trust indicators known to provide robust alarm signals (Sornette & Cauwels, 2015; Zhang, et al., 2016). Another study has improved LPPLS by presenting rigorous likelihood methods generating interval estimates of the parameters and, in particular, of the critical time denoting the end of the bubble (Filimonov, et al., 2017) and by adjusting for the sloppiness of parameters (Bree et al., 2010). Sevrich and Sornette (2016) have provided a plausible micro-founded model for the power law finite time singular form of the crash hazard rate in the JLS model of rational expectation bubbles. We also note extensions by using the Levenberg–Marquardt algorithm (LMA) algorithm (Liberatore, 2011), likelihood inference approach (Filimonov, et al., 2017), and an improved genetic algorithm gyration method (Dai, et al., 2018). These extensions aim at improving the calibration accuracy of the LPPLS model. As already mentioned, for explosive semi-martingales, Schatz and Sornette (2020) introduce a mathematical framework transcending the rational expectation bubble framework used in the JLS model, thus allowing for many extensions.

The LPPLS model has been used in the ex-ante diagnosis and post-mortem analysis of bubbles and crashes in the stock markets as well as in bond, commodity, real estate, and cryptocurrency markets, among others. This reflects the proposed universality of the super-exponential speculative bubble in the following markets:

- The **U.S. stock market**: Standard & Poor (S&P) 500 index (Sornette & Zhou, 2002, 2006; Zhou & Sornette, 2003a, 2003b, 2006a; Drozdz, et al., 2003; Zhang et al., 2016; Gerlach, et al., 2020; Shu & Zhu, 2021), the Dow Jones index (Vandewalle, 1998; Bolonek-Lason & Kosinski, 2011; Gustavsson, et al., 2016), and Nasdaq (Johansen & Sornette, 2000a), among others.
- The **global stock market**: global stock market indexes (Johansen & Sornette, 2001; Drozdz, et al., 2008), the Japanese stock market (Johansen & Sornette, 1999, 2000b; Lynch & Mestel, 2017), the Korean stock market (Ko et al., 2018), the German stock market (Kurz-Kim, 2012; Bartolozzi, et al., 2005; Wosnitza & Leker, 2014a), the Brazilian stock market (Cajueiro, et al., 2009), the Polish stock market (Gnacinski & Makowiec, 2004), the Romanian stock market (Pele, et al., 2013), and the Chinese stock market (Bastiaensen, et al., 2009; Jiang et al., 2010; Yan et al., 2012; Sornette et al., 2015; Chong, 2017; Shu & Zhu, 2020), among others.
- **Commodities**: Precious metals (Drozdz et al., 2008; Liberatore, 2010; Akaev, et al., 2011a, 2011b; Geraskin & Fantazzini, 2013), and the oil bubble (Sornette, et al., 2009; Cheng, et al., 2018), among others.
- **Property market**: Real estate in the United Kingdom (Fry, 2009; 2014; Bianchetti, et al., 2016), the United States (Zhou & Sornette, 2006b, 2008; Brauers, et al., 2014), the Hong Kong and Seoul property markets (Xiao, 2010), and Switzerland (Ardila-Alvarez et al., 2013; 2017; 2018), among others.
- **Bond market**: Corporate bond yield (Clark, 2004), government bond CDS spread (Wosnitza & Denz, 2013), and financial institutions' CDS spread (Wosnitza & Leker, 2014b; Wosnitza & Sornette, 2015), among others.
- **Other applications**: Election prediction (Fry & Burke, 2020), flash crash (Matsushita & Silva, 2011), and bitcoin (Gerlach, et al., 2019; Wheatley, et al., 2019), among others.

Moreover, in August 2008, Sornette and collaborators created the Financial Crisis Observatory[129] (FCO) at ETH Zurich. This scientific platform aims to test and quantify, rigorously and systematically and on a large scale, the hypothesis that financial markets exhibit a degree of inefficiency and potential for predictability, especially, during the start of the bubble regimes.

3.2.3.2 LPPLS Confidence Indicator

The LPPLS confidence indicator was introduced in the methodology of the FCO in the early 2010s and was presented to the academic community in (Sornette & Cauwels, 2015). The LPPLS confidence indicator is defined as the fraction of the fitting windows satisfying pre-defined conditions at a given time of analysis (present time). These conditions are derived from the cumulative empirical experience obtained by the previous calibration of many financial bubbles, as summarized by Zhang et al. (2016) for instance. We also perform additional qualifying tests to judge whether the calibrations are acceptable; these tests include the unit-root test of the residuals, the Lomb log-periodic tests (Sornette & Zhou, 2002), and other criteria (Sornette, 2017). A large value of the LPPLS confidence indicator suggests that the LPPLS model accurately depicts the present regime, thereby qualifying the existence of an ongoing bubble. This diagnostic is usually associated with the existence of a super-exponential price increase in the analyzed empirical time series. Conversely, a vanishing or small value of the LPPLS confidence indicator means that no time window or a few time windows can be satisfactorily fitted by the LPPLS equation, suggesting the absence of a bubble and the presence of a more normal regime.

As previously mentioned, we define the upward- and downward-accelerating price increases as positive and negative bubbles, respectively. At a given present time denoted t_2, we calibrate a given log-price time series by the LPPLS model (Filimonov

[129] https://er.ethz.ch/financial-crisis-observatory.html: The FCO has been monitoring approximately 25,000 assets worldwide, including indices, stocks, bonds, commodities, currencies, and derivatives. It has constructed daily updates of several bubble indicators based on the analyses of price time series using the LPPLS model presented above. As part of the research conducted within the FCO, motivated by the fact that back-testing is subjected to several possible biases, in November 2009, the financial bubble experiment (FBE) was initiated within the FCO. The FBE was based on an innovative framework to perform secure, verifiable ex-ante forecasts on financial crises using a creative digital fingerprint system to ensure the authenticity of forecasts released 6 months later for verification. Forecasts were revealed only after the predicted event, with the original date in which they produced these same results being publicly and digitally authenticated (Sornette et al., 2009, 2010a, 2010b; Woodard, Sornette, and Fedorovsky, 2010). Additionally, the FCO has been providing monthly reports since February 2014 of the "bubbly" state of the major financial assets worldwide.

& Sornette, 2013) over a set of N time windows $[t_1, t_2\ ]$ obtained by varying t_1 over a certain range. We calculate the LPPLS confidence indicators over the set of time windows such that t_2-t_1 spans from 30 to 250 trading days in steps of 1 trading day, corresponding to N=221 time windows. We add the condition that fits are acceptable only if $t_c - t_2$ lies between 0 and $t_2 - t_1$, that is, the critical time is not too far into the future. If the LPPLS confidence indicator is non-zero with B<0, it will represent a positive bubble signal and we will report a positive value for the confidence indicator. If it is non-zero with B>0, it will represent a negative bubble signal and we will report a negative value for the confidence indicator (See **Chapter 3 Appendix A** for more information on the LPPLS confidence indicator.)

3.2.3.3 Market Model for Event Study

The statistical market model we use for the event study measures the return of any given security relative to the return of the market portfolio (Ball & Brown, 1968; McWilliam & Siegel, 1997). The linear specification of the model is complemented by the assumption of joint normality for the asset returns. The market model for security *i* is

$$R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it},\ \mathrm{E}(\varepsilon_{it}) = 0 \text{ and var } (\varepsilon_{it}) = \sigma^2_{\varepsilon_i} \qquad (3.5)$$

where R_{it} and R_{mt} are, respectively, the return of security *i* and of the market portfolio at period *t*, and ε_{it} is the zero-mean residual term. α_i,β_i, and $\sigma^2_{\varepsilon_i}$ are the period-*t* parameters of the market model for the given security *i*.

From expression (3.5), the abnormal sample return $\hat{AR}_{it}$ is defined by

$$\hat{AR}_{it} = \hat{R}_{it} - \hat{\alpha}_i - \hat{\beta}_i * R_{mt} \qquad (3.6)$$

The cross-sectional average abnormal return $(A\acute{A}R)$ over the N stocks at time t is:

$$A\acute{A}R_t = \frac{1}{N}\sum_{i=1}^{N} \hat{AR}_{it} \qquad (3.7)$$

The cumulative average abnormal return $(C\acute{A}AR)$ is the mean cumulative return over the entire time window of all events:

$$C\acute{A}AR_{(t1,t2)} = \sum_{t=t_1}^{t_2} A\acute{A}R_{it} \qquad (3.8)$$

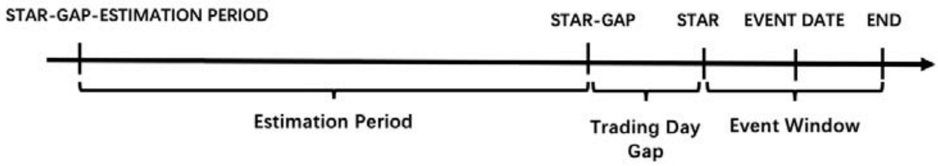


Figure 3.10. *Timeline for an event study*

We adopt the event study method (MacKinlay, 1997). Figure 3.10 presents the timeline of the event study. We set the estimation period to 200 days and the event window to 61 days (30 days before and 30 days after the event date). We have set the trading day gap to 30 days to reduce the influence of the estimation period on the event window.

We define the event date as the date when the LPPLS confidence indicator exceeds a certain threshold. By definition, the LPPLS confidence indicator takes values between -1 to 1; the thresholds that we test for a positive LPPLS confidence indicator are 0, 0.1, 0.2…0.8, 0.9, 1. The thresholds that we test for a negative LPPLS confidence indicator are 0, -0.1, -0.2…-0.8, -0.9, -1.

To obtain more information on how the stock performs after a given event date, we also decompose both positive and negative LPPLS confidence indicators into different interval groups of (0, 0.1), (0.1, 0.2) ... (0.8, 0.9), (0.9, 1) and (0, -0.1), (-0.1, -0.2) … (-0.8, -0.9), (-0.9, 1), respectively. All LPPLS confidence indicators failing to meet a chosen threshold or thresholds outside of a chosen interval were set to zero. When the LPPLS confidence indicator meets or goes beyond a chosen threshold or enters into a chosen interval, a bubble alarm signal (LPPLS confidence indicator) appears. Hence, we qualify those days as event dates. Moreover, we define a regime change as a clear price trend break.

Our null hypothesis (H0) and alternative hypothesis (H1) are:

H0: *A regime change in the price does not occur after the event date.*

H1: *A regime change in the price occurs after the event date.*

3.2.4 Data

For data on the Chinese market, we use the daily closing price of the China Securities Index Southwest Securities (CSI SWS) for 28 different industries, for the period February 27, 2004 to July 23, 2020 (122,100 observations). The CSI SWS industry index contains the security prices of public companies in 28 industries listed in the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). This index presents the capital-weighted aggregated price performance of different industries. We use the Wind database to obtain all the 28 industry sector indexes. The U.S. dataset comprises the daily closing price of the U.S. Morgan Stanley Capital International (MSCI) industry indexes. It represents the 24 industry groups in the U.S. market; we use Thomson Reuters to obtain all the 24 industry indexes. Owing to data limitations, we could access the corresponding industry sector indexes from January 20, 2009, to July 23, 2020 (72,000 Observations).

We study the industry-level data for four reasons. First, in line with Greenwood et al. (2019), we implement our methodology for detecting bubbles using similar industry-level data. We agree with Greenwood et al. (2019) that most of the well-known historical bubbles have strong industry features. Second, industry-level data can provide more discriminatory statistical power to identify financial bubbles at a disaggregated level than at the market index level. In other words, we need more data to get a more generalized result. Third, we can compare one industry with others in the same period to obtain more detailed information about bubbles and to establish interconnections between industries in different markets. Fourth, industry-group level data are less influenced by an individual company's idiosyncratic risk, which makes the results less noisy.

To calculate the daily average abnormal returns for the U.S. and Chinese events, we use the SSE composite index and S&P500 daily closing prices, with a corresponding time range as the market benchmarks. For the event study in China, we collect 1,131 positive and 383 negative LPPLS alarm signal events for the 28 industry groups in the Chinese market. For the event study in the U.S. market, we collect 546 positive and 173 negative LPPLS alarm signal events for the 24 U.S. industry groups. The details are presented in the **Chapter 3 Appendix**.

3.2.5 Empirical Findings

In the following three subsections, we use both Chinese CSC SWS and MSCI U.S. Industry groups' indexes to calculate the LPPLS confidence indicator. The duration t_2-t_1 of the time window is scanned from 250 trading days to 30 trading days in steps of 1 trading day. We calculate the LPPLS confidence indicators for both positive (upward-accelerating price increases) and negative (downward-accelerating price decreases) bubbles. Subsequently, we present the cumulative average abnormal return (CAAR) for different LPPLS confidence signal thresholds and the LPPLS confidence signal intervals for the U.S. and Chinese industry groups.

3.2.5.1 LPPLS Confidence Indicator for the U.S. and Chinese Industry Groups

Figure 3.11 shows two time periods (in the middle of 2007 and 2015) during which the majority of the Chinese industry groups collectively showed strong positive LPPLS confidence indicators. It also shows two periods when several industry groups showed non-zero but smaller positive LPPLS confidence indicators (in late 2009 and early 2019). It shows three periods (late 2008, late 2012, and late 2018) when some of the Chinese industry groups concurrently had negative LPPLS confidence indicators.

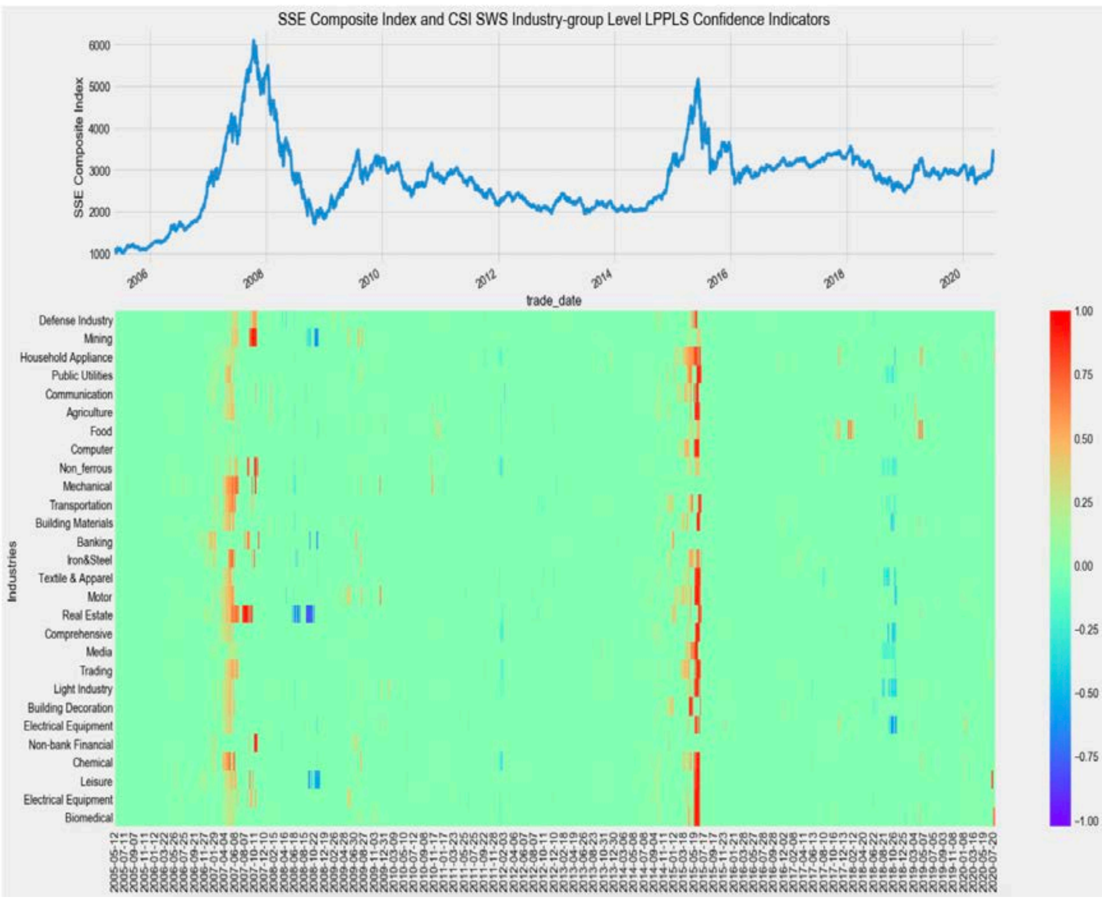


Figure 3.11. *SSE Composite Index and LPPLS Confidence Indicator for the CSI SWS Industry Groups in thermal color scale given on the right. Hot (cold) colors correspond to positive (negative) bubbles. Sample period from 12/5/2005 to 23/7/2020.*

By comparing the LPPLS Confidence Indicator patterns with the SSE composite index, it can be qualitatively seen that all of the industry-level bubble signals are followed by index-level regime changes—crashes or volatile sideway plateaus. This qualitative observation is quantified below by the event study.

Figure 3.12 shows that the LPPLS bubble signals for the U.S. Industry groups do not exhibit the same patterns of collective clustering as those observed for the Chinese Industry groups. It shows that the U.S. index rises much more consistently than that of the Chinese index. There are three time periods (early 2011, early 2013, late 2017) where many industries show moderate positive bubble alarm signals simultaneously. It also shows two time periods (late 2018 and early 2020) where some of the industries show negative bubble alarm signals. The first two periods of positive bubble clusters (early 2011 and early 2013) are not followed by significant crashes. However, a large crash occurs after 15 industries together exhibit positive bubble alarm signals in early 2018.

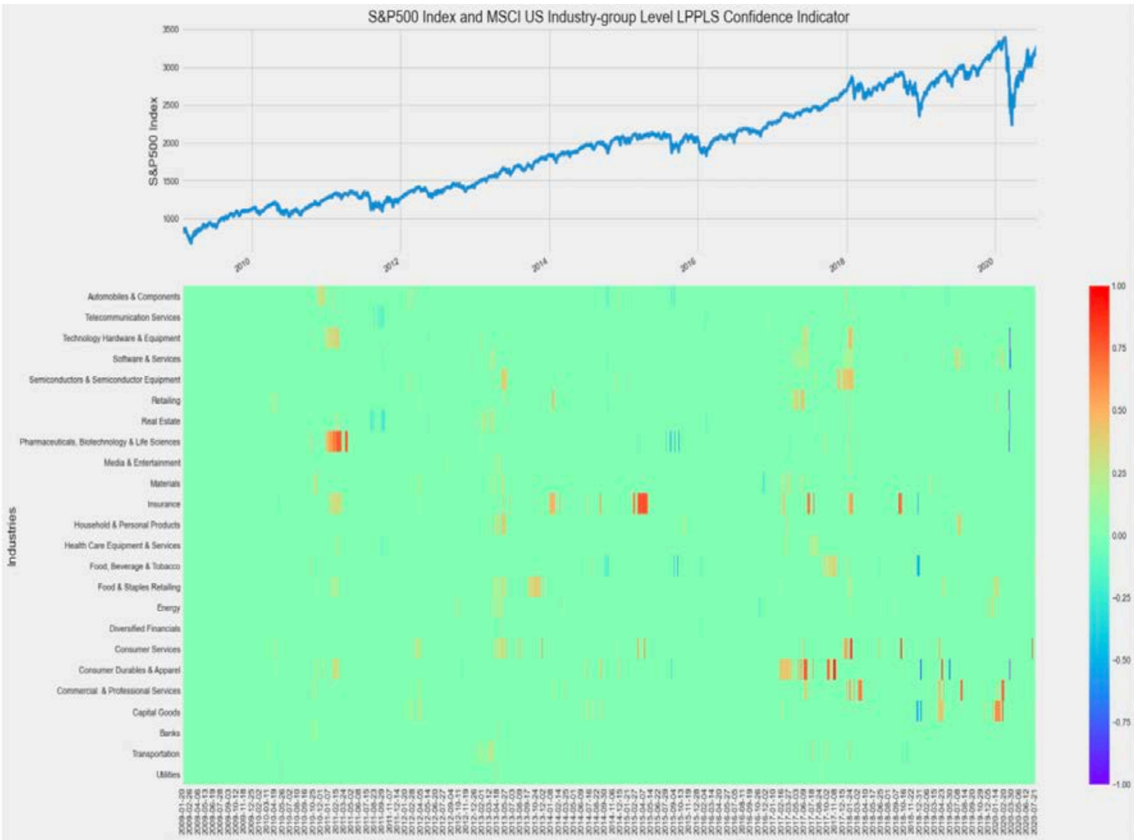


***Figure 3.12**. S&P 500 Index and LPPLS (Positive and Negative) Alarm Signals for MSCI U.S. Industry Groups in thermal color scale given on the right. Hot (cold) colors correspond to positive (negative) bubbles. Sample period from 12/5/2005 to 23/7/2020.*

The LPPLS bubble alarm signals for the U.S. and Chinese industry groups exhibit two different patterns. For the Chinese industry groups, the bubble signals are more concentrated and clustered in time. The prices of different Chinese industry groups also have quite similar bubble patterns, even though those industries have different business cycles. Conversely, for the different MSCI U.S. industry groups, the bubble signals are more evenly distributed in time, though sometimes some of the industries collectively show milder bubble alarm signals.

3.2.5.2 Event Study for the LPPLS Confidence Indicators in the Chinese Market

To quantify the value presented by the LPPLS confidence indicator to an investor, we apply the event study method. This helps us to analyze the market behavior before and after the events tagged by the LPPLS confidence indicator. The LPPLS confidence indicator is used to define a positive (negative) bubble event, called an *alarm* when (i) the LPPLS confidence indicator meets or crosses a pre-defined threshold or (ii) the LPPLS confidence indicator enters into the predefined interval groups. Case (i) corresponds to Figures 3.13, 3.14, and 3.16, while case (ii) corresponds to Figures 3.15 and 3.17. The numbers of events for the different thresholds and the two cases are given in Table B.1 of the **Chapter 3 Appendix B**.

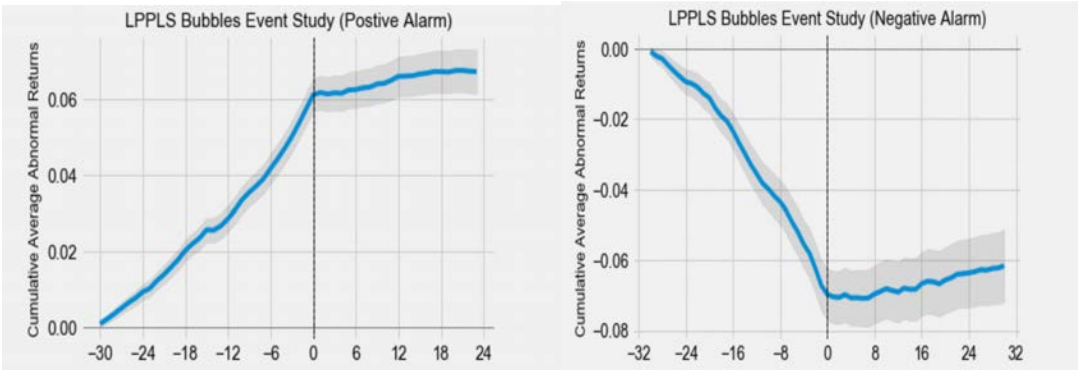


***Figure 3.13**. Plot of the Cumulative Average Abnormal Return (CAAR) for aggregated positive (left) and negative (right) LPPLS events from 30 days before to 30 days after each event for the Chinese CSI SWS Industry Groups from 2005 to 2020 described in section 3.2.4. The averages are performed over 1131 positive and 383 negative bubble alarm events, respectively, corresponding to the minimum threshold (condition to just be positive for positive bubbles and to be negative for negative bubbles). The Abnormal Return (AR) (3) is calculated by using the Market Model (2). The shadow area is the 95% confidence interval[130] for the CAAR.*

For 1,131 positive and 383 negative bubble alarm events identified in the Chinese CSI SWS industry groups from 2005 to 2020, Figure 3.13 shows the CAAR from 30 days before to 30 days after the event date. Both panels of Figure 3.13 demonstrate that, when an alarm is declared based on the LPPLS confidence indicator (for both positive and negative trends or bubbles), there is a clear change of regime from a strong increasing (decreasing) price acceleration to an approximate price plateau or rebound (for negative bubbles). In detail, the shadow area is the 95% confidence interval[9] for the CAAR. The cumulative aggregated 30-day price abnormal return before the positive LPPLS confidence indicator event date grows by an average of 6% (a gain of 72% linearly annualized or 102% compounded), relative to the post-event cumulative aggregated average return of around 0.5% over the next 30 trading days. Similarly, for negative events identified by a negative LPPLS confidence indicator, the cumulative average abnormal return drops by 7% over the 30 trading days preceding the event date (a loss of 84% linearly annualized or 58% compounded), and the aggregated abnormal rebounds by around 1% over the 30 days following the event date. The general

[130] Confidence Interval = $\hat{r}_{i,t+e} \pm t_{CV}$ * se($\hat{r}_{i,t+e}$), where $\hat{r}_{i,t+e}$ is the average after-event return, t_{CV} is the critical value (1.96 represents a .95 level of confidence), se($\hat{r}_{i,t+e}$) is the standard error of the regression and subscript (t+e) refers to the day of the event.

price behaviors of the outcomes of 1,131 positive alarm events and 383 negative alarm events in the Chinese market are consistent with the existing findings that the LPPLS model can detect regime shifts. The aggregated price dynamics around these events indicate that both positive and negative alarms can statistically predict the occurrence of changes of regime in the form of significant adjustments of price trends in Chinese industry-level data, which none of previous LPPLS-related research has covered.

Figure 3.14 records the (-30 days,30 days) event window of price performance on the condition that the LPPLS confidence indicator meets different positive thresholds (defined in section 3.2.3). The graph indicates that, the higher the alarm thresholds, the larger is the increase in the average stock price within 30 days before the event date. Interestingly, after the event date, the outcomes exhibit two kinds of price trajectories. The green lines of the lower thresholds show that the price average will reach plateaus, while the red lines of the higher thresholds show that, the higher the signals, the more will be the number of precipitous crashes. Thus, we can conclude that the stronger the positive LPPLS confidence indicator (filtered by the thresholds), the larger is the confidence of a stronger unsustainable upward price acceleration (positive bubble), and the higher is the likelihood of a steep price decline thereafter (bubble crash). We reconcile Figures 3.13 and 3.14 by noting that the average presented in the left graph of Figure 3.13 is dominated by the lower thresholds shown in Figure 3.14, which are much more numerous and correspond to a transition to a plateau. For thresholds larger than 0.5, we observe a clear drawdown following the peak, which include 194 out of 1,131 events.

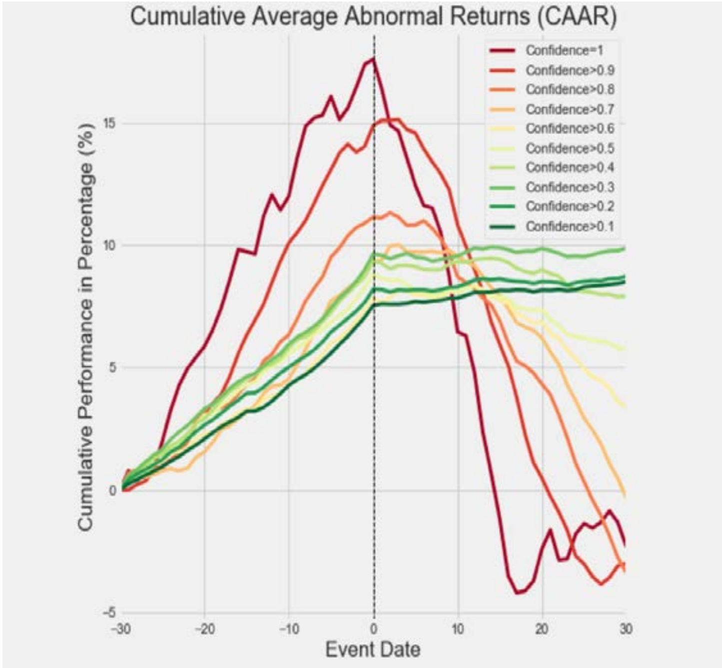
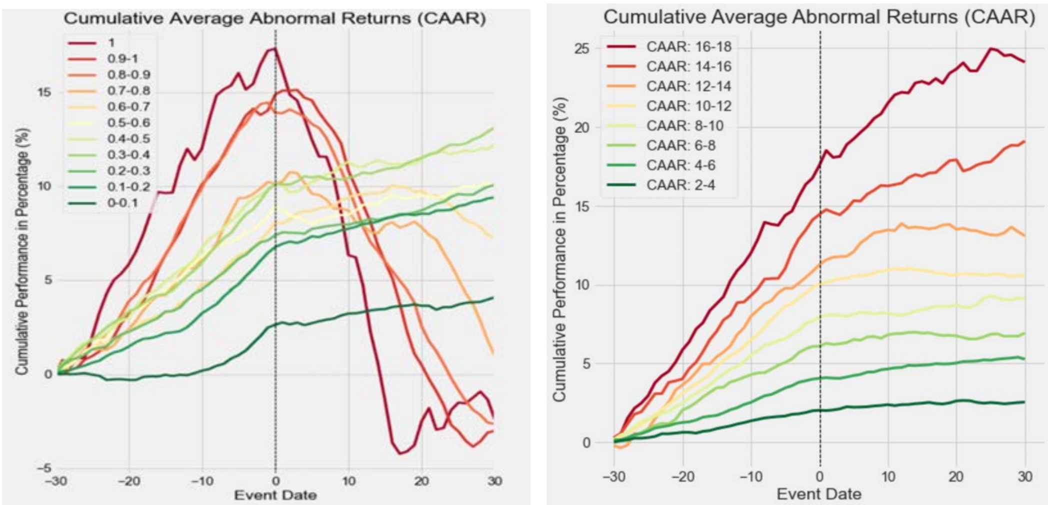


Figure 3.14. *Plot of the Cumulative Average Abnormal Return (CAAR) for positive LPPLS events according to different LPPLS Positive Alarm Thresholds defined in section 3.2.3. The event window covers 30 days before to 30 days after each event for the Chinese CSI SWS Industry Groups from 2005 to 2020 described in section 3.2.4. The averages are performed over the corresponding subsets of a total of 1,131 positive bubble alarm events corresponding to the different LPPLS Positive Alarm Thresholds (condition to just be positive bubbles). The number of events in each threshold class is given in Appendix 3B Table B.1. The Abnormal Return (AR) (3) is calculated by using the Market Model (2).*

Plot (a) of Figure 3.14 classifies the price performance for LPPLS confidence indicators that fall into different alarm intervals. This figure confirms the relationship between the level of the LPPLS confidence indicator and the extent of post-event price performances—the larger is the association between the positive LPPLS confidence and fiercer increases, the more aggressive are the price declines. Conversely, the smaller positive LPPLS confidence indicator does not necessarily predict crashes; instead, the average price performance might still have an upward trend, but the speed of the price increase clearly drops after the event date. In particular, the strongest positive LPPLS confidence indicator average shows a more than 17% relative return drop in around 15 trading days (leading to a 283% annual linear loss) in the Chinese market.

Plot (b) of Figure 3.14 presents a sanity check that our results are not just rediscovering the standard short term reversal effect (Jegadeesh, 1990). It shows the Cumulative Average Abnormal Return (CAAR) obtained from 1600 randomly selected events. Specifically, we form eight groups of 200 events, each group defined by a given return interval in the first 30-day period. These return intervals are 2-4%, 4-6%, 6-8%, …, 16-18%. In other words, for a group defined by a given return interval, say 8-10%, we pick 200 random times such that the CAAR of the Chinese stock market CSI SWS Industry Groups over the interval from 30 days preceding each random time to this random time is found between 8 and 10%. The curves in Plot (b) of Figure 3.14 show the CAAR averaged over the 200 random events in each group. The times from -30 days to 0 are before the random event times. The positive times from 0 to 30 days correspond to the post (random) event times. Comparing with Plot (a), the CAAR of the randomly selected events in Plot (b) show a clear momentum effect, instead of the impressive change of regimes in the form of transitions from strongly increasing prices to large drawdowns detected for the larger LPPLS Confidence Indicators in Plot (a).



(a) (b)

***Figure 3.15**. Plot (a) presents the Cumulative Average Abnormal Return (CAAR) for 1,131 positive bubble alarm events corresponding to the different LPPLS Positive Alarm Intervals defined in section 3.2.3. The number of events in each interval class is given in Appendix 3B Table B.1. As a comparison, plot (b) presents for 1,600 randomly selected events the corresponding 30-day Cumulative Average Abnormal Return (CAAR). The data is the Chinese CSI SWS Industry Groups from 2005 to 2020 described in section 3.2.4. The Abnormal Return (AR) (3) is calculated by using the Market Model (2).*

We also tested the negative LPPLS confidence indicator with different thresholds. The result shows that the price behaviour is noisier than that for the positive LPPLS confidence indicator. Figure 3.15 shows that the most negative LPPLS confidence indicator values are followed by more volatile cumulative returns after the event date. Conversely, the mildly negative LPPLS confidence indicator values are followed by more stable price plateaus.

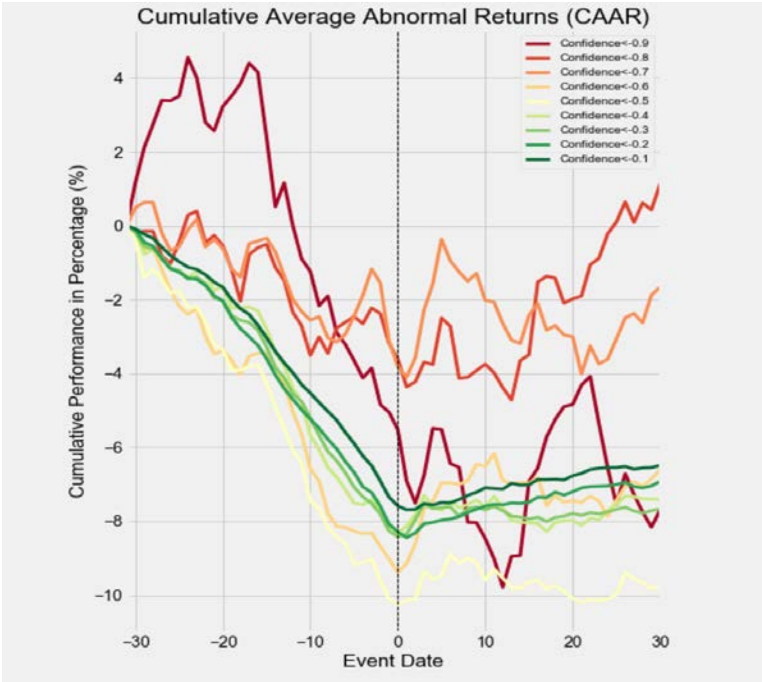
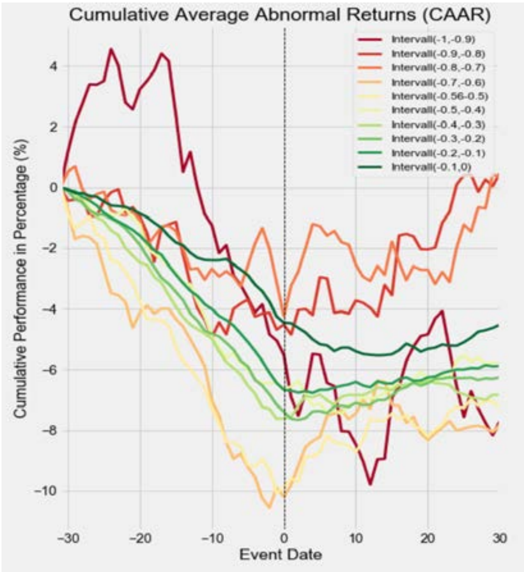
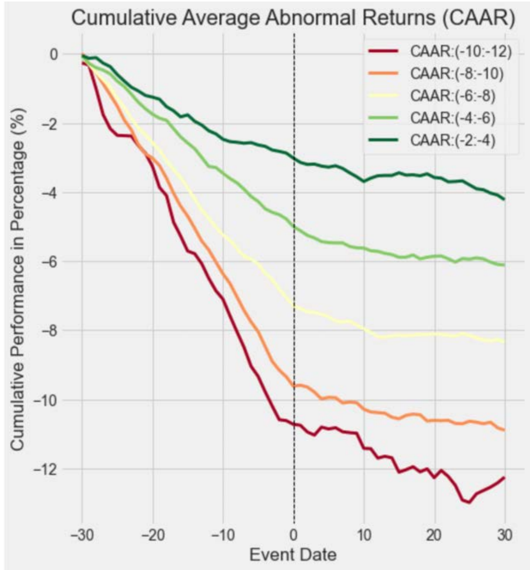


***Figure 3.16**. Plot of the Cumulative Average Abnormal Return (CAAR) for negative LPPLS events according to different LPPLS Negative Alarm Thresholds defined in section 3.2.3. The event window covers 30 days before to 30 days after each event for the Chinese CSI SWS Industry Groups from 2005 to 2020 described in section 3.2.4. The averages are performed over the corresponding subsets of a total of 383 negative bubble alarm events corresponding to the different LPPLS Negative Alarm Thresholds (condition on being negative bubbles). The number of events in each threshold class is given in Appendix 3B Table B.1. The Abnormal Return (AR) (3) is calculated by using the Market Model (2).*

We also classify the negative LPPLS confidence indicator into different intervals. Relative to Figure 3.16, Figure 3.17 presents clearly that the stronger the negative alarm signals before the peak, the more volatile is the price after the peak. It must be noted that the patterns observed for the negative alarm signal results do not mirror those obtained for the positive alarm signal results mentioned earlier (the higher positive LPPLS confidence indicators are followed by large crashes). The larger negative LPPLS confidence indicator values do not lead to strong rebounds; instead, they lead to a higher level of volatilities. Notwithstanding this difference, there is clear evidence that the LPPLS negative alarm signals clearly detect well-defined regime changes.



(a)



(b)

Figure 3.17*. Plot (a) presents the Cumulative Average Abnormal Return (CAAR) for 383 positive bubble alarm events corresponding to the different LPPLS Positive Alarm Intervals defined in section 3.2.3. The number of events in each interval class is given in Appendix 3B Table B.1. As a comparison, plot (b) presents for 1,000 randomly selected events the corresponding 30-day Cumulative Average Abnormal Return (CAAR). The data is the Chinese CSI SWS Industry Groups from 2005 to 2020 described in section 3.2.4. The Abnormal Return (AR) (3) is calculated by using the Market Model (2).*

Plot (b) of Figure 3.17 is the analogy of Plot (b) of Figure 3.15 for large negative CAAR over the pre-event time interval. It shows the Cumulative Average Abnormal Return (CAAR) obtained from 1000 randomly selected events. Specifically, we form five groups of 200 events, each group defined by a given return interval in the first 30-day period. These return intervals are -2 to -4%, -4 to -6%, -6 to -8%, -8 to -10%, -10 to -12%. In other words, for a group defined by a given return interval, say -8 to -10%, we pick 200 random times such that the CAAR of the Chinese stock market CSI SWS Industry Groups over the interval from 30 days preceding each random time to this random time is found between -8 and -10%. The curves in Plot (b) of Figure 3.17 show the CAAR averaged over the 200 random events in each group. The times from -30 days to 0 are before the random event times. The positive times from 0 to 30 days correspond to the post (random) event times. Comparing with Plot (a) of Figure 3.17, the CAAR of the randomly selected events in Plot (b) exhibit a momentum effect, rather than the rebound and increased volatilities detected for the larger LPPLS Confidence Indicators in Plot (a).

3.2.5.3 Event Study for the LPPLS Confidence Indicators in the U.S. Market.

Since the evidence presented in the previous section strongly rejects the null hypothesis and thus supports the hypothesis that the LPPLS confidence indicator can detect regime changes in China (a typical emerging market), we investigate whether the LPPLS confidence indicator can detect regime changes occurring in the S.market—a developed market. We apply the same method, as in section 3.2.3, by setting positive and negative LPPLS confidence thresholds and interval groups and event dates, as defined in section 3.2.3. Our method is as follows: (i) the LPPLS Confidence indicator meets or crosses the LPPLS event alarm thresholds defined in section 3.2.3, and (ii) the LPPLS confidence indicators enter into different LPPLS event alarm intervals defined in section 3.2.3. Figures 3.18, 3.19, and 3.20 belong to (i), and Figures 3.21 and 3.22 belong to (ii). The number of events in these different classes is given in Table B.2 of **Chapter 3 Appendix B**.

For the 24 MSCI U.S. industry groups from 2009 to 2020, all 546 positive LPPLS alarm signal event studies give a CAAR before the LPPLS alarm event of 2.5% over 30 trading days. After the event data, the price level reached a plateau, with a potential downward trend, as shown in Figure 3.18. Conversely, for the 173 negative bubble events, the pre-event 30-day showed a 5% price downward CAAR. After the event date, the price bounced back a little and had an upward potential trend, as shown in Figure 3.18. Hence, for the U.S. market, the LPPLS confidence indicator can also be used to predict regime changes. Notably, the aggregated positive bubbles in the U.S. market are smaller than those in the Chinese market.

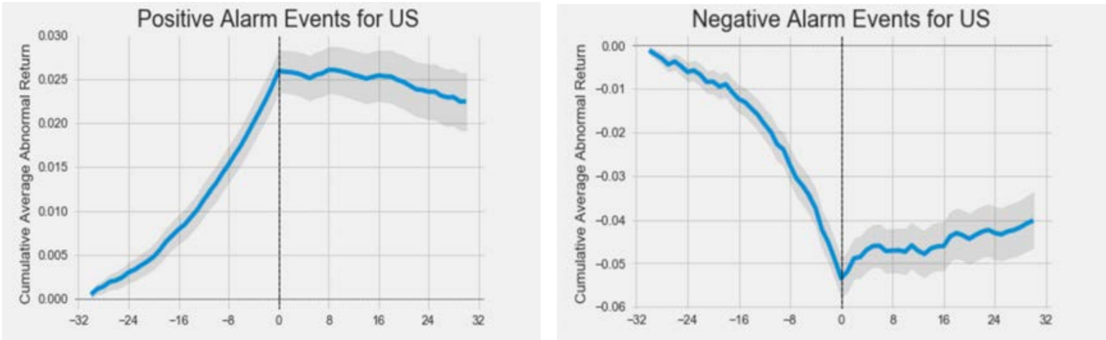


Figure 3.18*. Plot of the Cumulative Average Abnormal Return (CAAR) for aggregated positive (left) and negative (right) LPPLS events from 30 days before to 30 days after each event for the MSCI U.S. Industry Groups from 2009 to 2020 described in section 3.2.4. The averages are performed over 546 positive and 173 negative bubble alarm events, respectively, corresponding to the minimum threshold (condition to just be positive for positive bubbles and to be negative for negative bubbles). The Abnormal Return (AR) (3) is calculated by using the Market Model (2). The shadow area is the 95% confidence interval for the CAAR.*

Following the same methodology as for the Chinese market with classes of events defined by different threshold values of the confidence indicator, Figure 3.19 shows that the larger the LPPLS thresholds, the larger is the subsequent drop of the price trajectory. However, the U.S. market's CAAR and the relative crashes after the event date are not as large and severe, respectively, as those of the Chinese market.

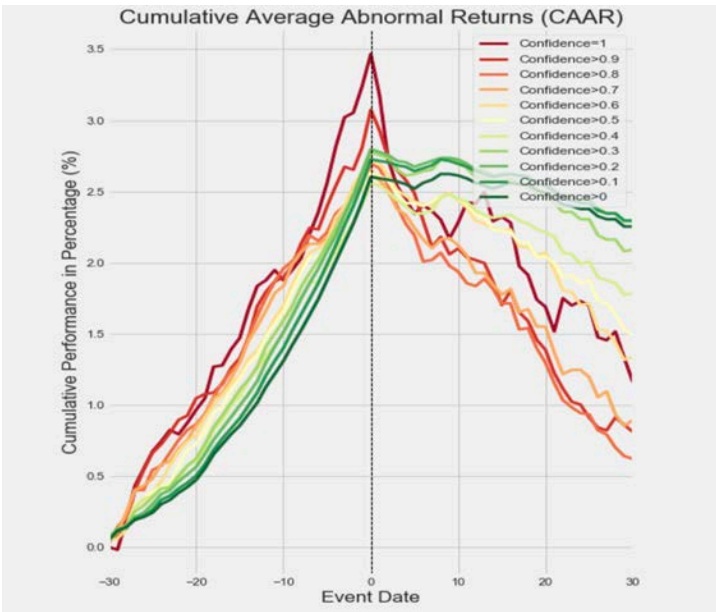
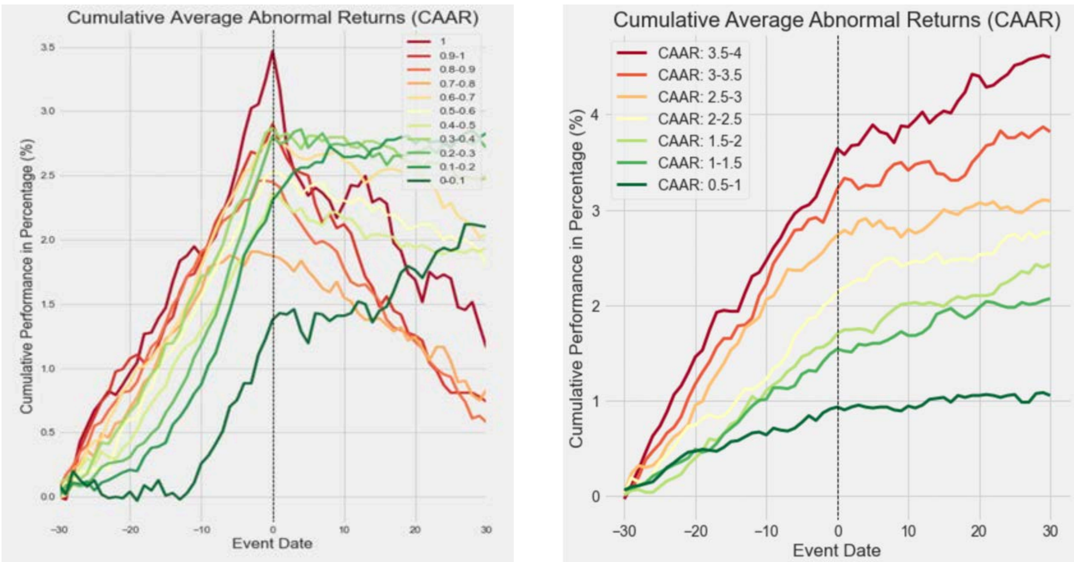


__Figure 3.19__. Plot of the Cumulative Average Abnormal Return (CAAR) for positive LPPLS events according to different LPPLS Positive Alarm Thresholds defined in section 3.2.3. The number of events in each interval class is given in Appendix 3B Table B.2. The event window covers 30 days before to 30 days after each event for the MSCI U.S. Industry Groups from 2009 to 2020 described in section 3.2.4. The averages are performed over the corresponding subsets of a total of 546 positive bubble alarm events corresponding to the different LPPLS Positive Alarm Thresholds (condition to just be positive bubbles). The Abnormal Return (AR) (3) is calculated by using the Market Model (2).

We also divide the alarm signals into different intervals. Plot (a) of Figure 3.20 shows results similar to those in Plot (a) of Figure 3.15, for the Chinese market. On average, the larger positive LPPLS confidence indicator values correspond to sharp increases and steep crashes, while smaller LPPLS confidence indicator values correspond to a transition from an increased price to a plateau.



(a) (b)

__Figure 3.20__. Plot (a) presents the Cumulative Average Abnormal Return (CAAR) for 546 positive bubble alarm events corresponding to the different LPPLS Positive Alarm Intervals defined in section 3.2.3. The number of events in each interval class is given in Appendix 3B Table B.2. As a comparison, plot (b) presents for 700 randomly selected events the corresponding 30-day Cumulative Average Abnormal Return (CAAR). The data is the MSCI U.S. Industry Groups from 2009 to 2020 described in section 3.2.4. The Abnormal Return (AR) (3) is calculated by using the Market Model (2).

Plot (b) of Figure 3.20 is the same as Plot (b) of Figure 3.15, but with different return intervals that match the different return amplitudes of the US stock market. It shows the Cumulative Average Abnormal Return (CAAR) obtained from 700 randomly selected events. Specifically, we form seven groups of 100 events, each group defined by a given return interval in the first 30-day period. These return intervals are 0.5-1.0%, 1.0-1.5%, …, 3.5-4.0%. For a group defined by a given return interval, say 3.0 to 3.5%, we pick 100 random times such that the CAAR of the US stock market Industry Groups over the interval from 30 days preceding each random time to this random time is found between 3 and 3.5%. The curves in Plot (b) of Figure 3.20 show the CAAR averaged over the 100 random events in each group. The times from -30 days to 0 are before the random event times. The positive times from 0 to 30 days correspond to the post (random) event times. Comparing with Plot (a) of Figure 3.20, the CAAR of the randomly selected events in Plot (b) show a momentum effect, which is clearly distinct from the large drawdowns following the bubble regimes detected by larger LPPLS Confidence Indicators in Plot (a).

Testing the negative LPPLS thresholds in the United States, we find that the negative LPPLS confidence indicator is particularly suited for detecting the regime changes in this country. Figure 3.21 shows that, after the event date, the index prices bounce up immediately. Similar to the Chinese market, the higher the amplitude of the negative LPPLS Confidence Indicator, the more volatile will be the post-event price performance.

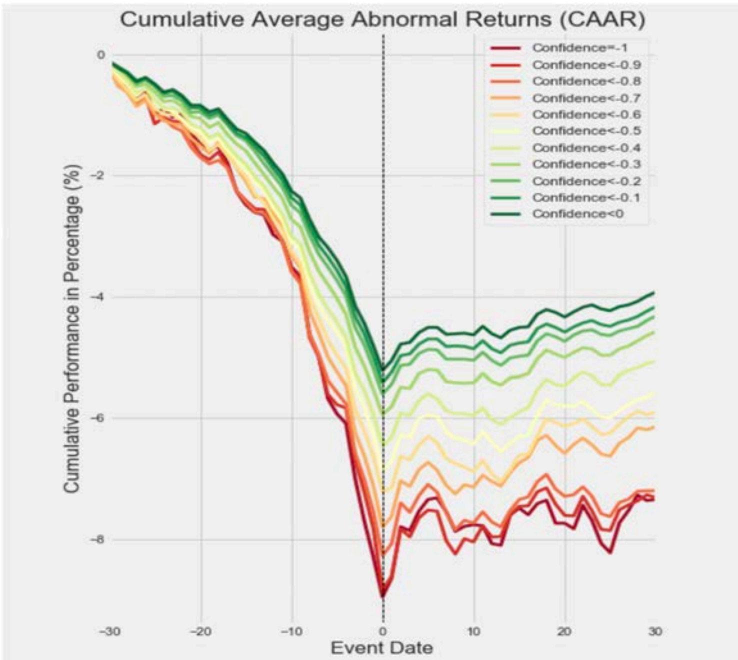
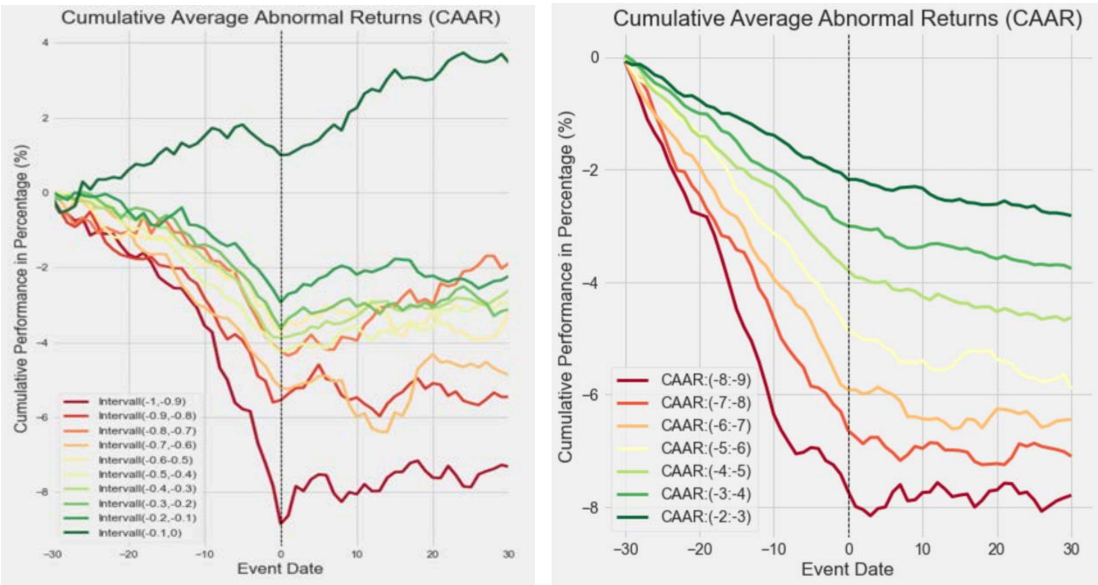


Figure 3.21. *Plot of the Cumulative Average Abnormal Return (CAAR) for negative LPPLS events according to different LPPLS Negative Alarm Thresholds defined in section 3.2.3. The number of events in each interval class is given in Appendix 3B Table*

B.2. The event window covers 30 days before to 30 days after each event for the MSCI U.S. Industry Groups from 2009 to 2020 described in section 3.2.4. The averages are performed over the corresponding subsets of a total of 173 negative bubble alarm events corresponding to the different LPPLS Negative Alarm Thresholds (condition on being negative bubbles). The Abnormal Return (AR) (3) is calculated by using the Market Model (2).

Plot (a) of Figure 3.22 shows that the stronger the negative LPPLS confidence indicator values, the faster are the price declines before the event date and the more sudden are the rebounds. Moreover, the larger negative bubble signals are associated with a higher level of the volatility after the event date.



(a) (b)

***Figure 3.22**. Plot (a) presents the Cumulative Average Abnormal Return (CAAR) for 173 positive bubble alarm events corresponding to the different LPPLS Positive Alarm Intervals defined in section 3.3. The number of events in each interval class is given in n Appendix 3B Table B.2. As a comparison, plot (b) presents for 600 randomly selected events the corresponding 30-day Cumulative Average Abnormal Return (CAAR). The data is the MSCI U.S. Industry Groups from 2009 to 2020 described in section 3.2.4. The Abnormal Return (AR) (3) is calculated by using the Market Model (2).*

Plot (b) of Figure 3.22 is the analog of Plot (b) of Figure 3.17 for large negative CAAR over the pre-event time interval. It shows the Cumulative Average Abnormal Return (CAAR) obtained from 700 randomly selected events. Specifically, we form seven groups of 100 events, each group defined by a given return interval in the first 30-day period. These return intervals are -2 to -3%, -3 to -4%, …, -8 to -9%. For a group defined by a given return interval, say -6 to -7%, we pick 100 random times such that the CAAR of the US stock market Industry Groups over the interval from 30 days preceding each random time to this random time is found between -6 and -7%. The curves in panel (b) of Figure 3.22 show the CAAR averaged over the 100 random events in each group. The times from -30 days to 0 are before the random event times. The positive times from 0 to 30 days correspond to the post (random) event times. Comparing with Plot (a) of Figure 3.22, the CAAR of the randomly selected events in Plot (b) exhibit a momentum effect, in clear contrast with the rebound and increased volatility effect detected by larger LPPLS Confidence Indicators in Plot (a).

3.2.5.4 Comparison Between the U.S. and Chinese Markets

The evidence presented in previous sections for both the U.S. and Chinese markets strongly rejects the null hypothesis that no regime change can be detected and supports the alternative hypothesis that the LPPLS confidence indicator can predict the regime changes around event dates corresponding to market peaks. The model detects clear breaks in the price acceleration before the event date, followed by a correction or plateau after the event date, depending on the amplitude of the LPPLS confidence Indicators. The pre-event price accelerations of positive bubbles in the U.S. market are smaller than those in the Chinese market. The industry groups in the Chinese market tend to have synchronized LPPLS confidence indicator values, even though each industry has a different cycle. This phenomenon suggests that the different trends observed in the Chinese market are the result of the collective behavior of several industries. This finding implies stronger herding behaviors in the whole market developing in synchrony.

We have used the thresholds and intervals to decompose and categorize the LPPLS confidence indicator in different event classes. The analysis shows that, for positive LPPLS confidence indicators in both the U.S. and Chinese markets, larger thresholds and interval values are associated with severe price drops within a very short period (a crash) after the event date. However, the price after the event date for lower quantile groups tends to reach a plateau. We conclude that the *crashes* that economists would like to characterize are associated with the interval groups with the larger positive LPPLS Confidence indicators.

For negative bubbles in both the U.S. and Chinese markets, the magnitudes of the bounce-backs following the event date are mild, which breaks the symmetry with the price patterns documented for positive bubbles. Moreover, we observe that price volatilities increase in both the U.S. and Chinese markets after the event date.

3.2.5.5 Interpretation of the Two Classes of Post-event Dynamics: Overreaction and Underreaction

Figure 3.23 summarizes our main findings on how an accelerating price trajectory ends. Specifically, we identify two classes of regime shifts—(i) super-exponential price growth followed by a crash (genuine bubble) and (ii) super-exponential price growth followed by a plateau, suggesting a convergence to a relatively stable price level (apparent bubble).

Figure 3.23. *Simplified representation of the two regime shifts identified in the study of accelerated price trajectories in the Chinese and U.S. markets. Left: a genuine bubble followed by a crash or large drawdown. Right: apparent bubble with strong price growth culminating in a plateau, suggesting a new consensus for the underlying fundamental value.*

In the genuine bubble case (left panel of figure 3.23), the price overshoots and subsequently corrects with a drawdown. Specifically, after the price accumulates a large deviation from its implicit fundamental value (i.e., the stable price level), selling orders may suddenly synchronize, while there is an exhaustion of available cash for buying orders. Together, the large, synchronized sell-out orders and the absence of buyers lead to a cascading decline in prices. This synchronization behavior can be detected by the LPPLS model as shown above (Sornette & Cauwels, 2015a).

In the apparent bubble case (right panel of Figure 3.23), the accelerating price should be interpreted as, in fact, a *slow* convergence (even if accelerating) to a stable price level. Investors may misinterpret this price acceleration as a genuine bubble and short it. However, this would be unsuccessful, owing to the progressively growing consensus on the underlying value of the assets. The plateau, following the break in the acceleration phase, embodies the new equilibrium associated with all available information that has finally been *digested* by the investors.

In an efficient market, a stock price ought to perfectly adjust to a new level (almost) immediately after new information comes to the market (Fama, 1970). However, in line with a large body of literature presenting evidence against the EMH theory, the speed and magnitude of a price adjustment are not always efficient, and the market is, to some extent, predictable owing to structural and behavioral reasons. In addition, arbitrage opportunities can exist for a long-time in the presence of frictional costs and risks. Our empirical result strongly rejects the EMH that the current price reflects all of the information. Our finding suggests that it is possible to predict the market price patterns based on the past price trajectory, at least in pockets of predictability associated with large amplitudes of the LPPLS confidence indicator.

Our finding of the two types of regime changes is somewhat related to the overreaction hypothesis and underreaction hypothesis. Overreaction indicates that investors tend to be excessively optimistic about new information, and hence stock prices tend to go beyond their true value and are followed by subsequent corrections. This is exemplified by the genuine bubble regime shown in the left panel of Figure 3.23. Underreaction, which always leads to price momentum or post-earnings announcement price drift, implies that stock prices change less than their true value justified by the news (De Bondt & Thaler, 1985). This leads to delays in the price adjustment processes, as illustrated in the right panel of Figure 3.23.

We have found that larger LPPLS confidence indicator values (implying longer super-exponential price trajectories) statistically lead to faster and larger price corrections, which suggests an overreaction. In contrast, smaller LPPLS confidence indicator values (indicating shorter super-exponential price trajectories) are associated with a price plateau after the event date. This shows that the LPPLS confidence indicator can detect regime changes both in the presence of overreaction and underreaction, according to the strength of the indicator. Thus, we can conclude that the LPPLS confidence indicator can *unify* the overreaction and underreaction hypotheses, converging to a similar conclusion as that of Hong and Stein (1999), while using different models.

Few academic studies have provided behavioral explanations of overreaction and underreaction. They suggest that overreaction comes from herding, representativeness, and overconfidence. They attribute underreaction to anchoring, conservatism, the disposition effect, and the slow diffusion of information (Antonacci, 2016).

In the case of overreaction, investors tend to herd when information is scarce or not easily available (Bikhchandani & Sharma, 2000). It is boundedly rational to imitate in the absence of sufficient information (Roehner & Sornette, 2000). Young male investors with lower portfolio values and less educated investors exhibit more overconfidence, and thus display more irrational behavior (Tekce & Yilmaz, 2015). Representativeness, as defined by Tversky and Kahneman (1974), refers to the fact that investors believe that the history of a remarkable performance of a given firm is *representative* of the firm performance and that this will continue by extrapolation. Hence, overreaction can be a part of the explanation for the occurrence of bubbles. The literature discusses several other mechanisms (e.g., Kaizoji & Sornette, 2010; Brunnermeier & Oehmke, 2013; Xiong, 2013; Sornette & Cauwels, 2015b).

Concerning underreaction, investors are influenced by the initial price as the reference point, which leads to adjustments of their usually insufficient estimation. This is known as the anchoring effect (Hong & Stein, 1999). This underreaction is also attributed to conservatism, which means that people tend to cling to their prior views at the expense of acknowledging new information (Kahneman & Tversky, 1979). The disposition effect, proposed by Shefrin and Statman (1985), holds that investors are likely to sell the profit-making stocks while holding the loss-making stocks. The theory on the slow diffusion of information holds that the slow diffusion of information and interaction between investors can explain price underreaction and overreaction in the short- and mid-runs, respectively (Hong & Stein, 1999). While possibly part of the explanation of the dynamical development of apparent bubbles, these effects may not fully elucidate why the price plateaus at the end of the accelerated price phase. In an apparent bubble, the market participants progressively convince themselves that the new correct price is higher. However, this self-convincing takes a long time (weeks, months, or years) and likely involves imitation, herding, and various feedback loops[131], together with some form of fundamental information that anchors the price to its final plateau.

[131] It is similar to the positive feedback investment strategies proposed by DeLong et al. (1990).

3.2.5.6 Leverage effect for the negative LPPLS Confidence Indicators

Following a large price appreciation, based on a strong reading of the positive LPPLS confidence indicator, the price corrects in a crash or large drawdown. Following a large price depreciation, based on a strong reading of the negative LPPLS confidence indicator, the price does not rebound as it would if there were symmetry between upward price acceleration for positive bubbles and downward price acceleration for negative bubbles. Conversely, a large price depreciation, based on a strong reading of the negative LPPLS confidence indicator, is followed by an increase in its volatility, and not so much by a rebound (which would be the symmetric shape to a crash).

Two explanations can be advanced for this increased volatility following a strong price decline associated with a negative bubble. The leverage effect, first proposed by Black (1976), might be part of the explanation. When asset prices decline, companies become more leveraged as the ratio of their debt value over equity rises. This increases the leverage of the firms' capital structures. The increased leverage deteriorates the financial state of public companies and, consequently, increases the systematic risk of common stocks. Consequently, the cost of capital becomes larger to reflect the higher risk of financial insolvency, generating a volatility feedback effect (Campbell & Hentschel, 1992). Thus, declines in stock prices are expected to be accompanied by increases in volatility (Nelson, 1991; Engle & Ng, 1993). However, this explanation may be insufficient to explain the observed increases in volatility after a price decline. Other mechanisms, including behavioral ones, may play a significant role (Figlewski & Wang, 2000; Bouchaud, et al., 2001).

A second explanation may be captured by the statement that "misfortunes never come singly." Ding, et al. (2009) note the existence of a cross-sectional self-exciting behavior of volatility in the sense that the default or the large negative shock to one company, cross-sectionally, tends to increase the likelihood of default or large downward movements of other companies (see also Sieczka, et al., 2011; Smug et al., 2022). Overall, such cross-sectional propagation leads to a self-exciting pattern in the market and, therefore, volatility spillovers from one company to others. Thus, investors are likely to observe that one episode of market turmoil increases the chance of another subsequent turmoil (Azizpour, et al., 2018; Smug et al., 2022). Accordingly, when bad news is initially released to the public, the price might drop. In such a scenario, while some investors might sell the stock owing to stop-loss orders, margin calls, portfolio insurance, or regulatory constraints, others may buy the cheaper stock. Overall, there is an increase in transaction volume, translating into an increase in volatility (Gabaix, et al., 2003). In the presence of the self-exciting behavior mentioned above, the initial negative shock, like the *tip of the iceberg*, might lead to more bad news and further increase the volatility of the stock price[132].

3.2.6 Conclusion

We applied the event study method to study systematically the LPPLS (Log-Periodic Power Law Singularity) confidence indicators. The daily closing prices of the Chinese CSI SWS industry groups and MSCI U.S. industry groups were used to identify positive and negative bubbles. The event study method allowed us to statistically characterize the pre- and post-event price behaviors of positive and negative bubbles.

Our main result strongly supports the hypothesis that the LPPLS confidence indicator can detect regime changes. Thus, it shows that the market is inefficient and future price patterns can be predicted based on the past price information, at least in pockets of predictability associated with the ends of financial bubbles.

We reached three important conclusions. First, based on extensive event studies in both the U.S. and Chinese markets, we found that the LPPLS framework can systematically detect unsustainable price increases and decreases (including bubbles) with only price data, ex-ante and causally. In this manner, we refuted the claims by Fama (2014) and Greenwood et al. (2019) that bubbles cannot be identified in real time.

Second, we found bubbles at the industry-group level in both China and the U.S. markets. We showed that a smaller LPPLS confidence indicator can detect a short-term continuation, while a larger indicator can detect a strong reversal. Particularly, the Chinese market showed stronger collective bubbles (followed by predictable price decline) that develop in different industries simultaneously, despite their different business cycles. However, stronger bubbles in the U.S. market (followed by a largely predictable price decline) are relatively evenly distributed in different industry groups over time, suggesting more decoupling. Moreover, both positive bubbles and crashes are significantly more extreme in the Chinese market than that in the U.S. market.

[132] An illustration is Lehman Brothers' closure on September 15, 2008.

Third, positive and negative bubbles are not symmetric, and the alarms obtained from the LPPLS confidence indicator do not always diagnose the occurrence of subsequent crashes. For positive bubbles, larger positive LPPLS confidence indicator values diagnose an overactive price behavior, leading to a peak followed by a crash. In contrast, a smaller LPPLS confidence indicator value predicts a regime change to a less extreme regime—just a plateau breaking the preceding accelerating price. For negative bubbles, the U.S. market shows a clearer rebound behavior following the price trough, relative to the Chinese bubbles. However, in both markets, the larger the amplitude of the negative alarm signals, the more volatile is the price after the critical time of the price peak.

Finally, we conclude that a simple classification of price regimes based on the LPPLS confidence indicator can predict price regime switching in both the U.S. and Chinese. Our model can also *unify* the overreaction and underreaction phenomena. Particularly, strong positive LPPLS confidence indicators predict a strong price decline following a large price appreciation, which, according to Fama's definition, is a bubble.

3.2.7 Appendices

Appendix 3A: The Construction of the LPPLS Confidence Indicator

We use equation (1.1) to detect financial bubble patterns in financial price time series, by fitting the model to data. Naturally, we need to check the goodness of each fit, that is, whether a fit qualifies a bubble signal. Moreover, since we are dealing with noisy financial data, it is better to do multiple fits at each time point to build a strong indicator, than simply to do just one fit. Based on these ideas, we used the LPPLS Confidence Indicator. We now discuss in detail the construction of the LPPLS Confidence Indicator, especially the two most important aspects of it, namely the goodness of fit and the multiple fits at each time point.

An important ingredient of the LPPLS Confidence Indicator is the manner of qualifying a good fit of the LPPLS model. The first thing one can imagine is the loss function, for instance, the mean squared error (MSE) between each element in the input log prices and the corresponding LPPLS fits. Thus, our first criterion of a good LPPLS fit is based on the MSE loss. In other words, if the MSE of a fit is larger than a threshold, the fit is considered bad, that is, it does not qualify a bubble signal. However, that does not mean that a low MSE fit alone qualifies as a good fit, because a bubble pattern has its unique characteristics, which leads to our next criterion for good LPPLS fits.

Our second criterion is the relative closeness of tc to t_2, where tc is one of the fitted parameters of the LPPLS model, indicating the time that a bubble, if it exists, will become unsustainable. Here, t_2 is the timestamp of the last data point in the price time series used to fit the model. The calibration is performed on the log-price data in a time window starting from the start time t_1 to the current time t_2. If t_c is far away from t_2, in the sense that $|t_c-t_2|/|t_2-t_1|$ is larger than a threshold, the fit does not qualify as a bubble signal.

For the third criterion, we first introduce an indicator called damping, which is defined as $|Bm|/|C\omega|$, and denotes the intensity of a bubble, if it exists. The indicator comes from the fact that, in the JLS rational bubble expectation formulation (Johansen et al., 1999; 2000), the derivative of the expected log-price is proportional to the crash hazard rate, and thus must remain positive by definition of a probability. The condition for this to hold is $|Bm|/|C\omega| > 1$ (Bothmer and Meister, 2003). This motivates us to define the “damping” parameter $|Bm|/|C\omega|$ and use its quantitative values for classification (while not imposing the strict lower threshold of 1). A good LPPLS fit is then such that the damping parameter is larger than a threshold.

The fourth criterion concerns parameter m, which should be between 0 and 1. This is to describe that, in a bubble phase, the prices usually accelerate before they correct. A value m=1 would correspond to a linear average log-price increases (i.e., an average exponential growth of the price) and values m>1 correspond to concave decelerating expected log-prices.

The fifth criterion concerns the number of oscillations of the fitted model, which is required to be larger than some threshold. If there are not so many oscillations, the probability that a bubble is mature or even exists is interpreted as low. The number of oscillations can be easily computed from the parameters of the LPPLS model, giving $\omega \log(|t_2-t_c|/|t_1-t_c|)/2\pi)$.

When a fit passes all the above criteria, it qualifies as a bubble signal. At the same time, we need to check the sign of parameter B. If B is positive, it detects a negative bubble and the confidence indicator takes a negative sign; otherwise, it detects a positive bubble and the confidence indicator takes a positive sign.

Another ingredient of the LPPLS Confidence Indicator involves multiple fits. As discussed above, for a time series from t_1 to t_2, we fit the log-prices in a series of historical time windows ending at t_2, which are $[t_2-30, t_2]$, $[t_2-35, t_2]$, …, $[t_1, t_2]$. We usually use a step size of 5 days to define increasing time window lengths from a minimum of 30 days to a maximum equal to t_2-t_1. This is a compromise between having sufficient statistics and robustness over many time windows while keeping computation efforts to a reasonable level. When we fit the log-price in all these time windows, we apply the aforementioned criteria to filter out fits that do not qualify as reliable bubble signals.

The LPPLS Confidence Indicator is thus the fraction of good fits among the fits spanning all time windows. We compute the median value of damping indicators of these qualified fits, which quantifies the severity of the bubble. It is clear that a large LPPLS Confidence indicator indicates a stably growing bubble found consistently across many time windows of increasing sizes, while a high median damping indicator of qualified fits indicates that the bubble has a significant amplitude.

The process of constructing the LPPLS Confidence Indicator can be summarized as follows:

1. We determine the size (number of time stamps) of the input time series, denoted by $T=t_2-t_1$ which is a fixed meta parameter, the threshold for the MSE denoted by err, the threshold for the closeness of t_c to t_2 denoted by t_{cd}, the threshold for the damping parameter denoted by d, the threshold for the number of oscillations denoted by osc.
2. For a price series from t_1 to t_2, we fit the LPPLS model and get the corresponding parameters A, B, C, m, ω, φ, t_c. With these parameters, we compute the MSE, the closeness of t_c to t_2, denoted by $|t_c-t_2|/|t_2-t_1|$, the damping indicator $|Bm|/|C\omega|$, and the number of oscillations $\omega\log(|t_2-t_c|/|t_1-t_c|)/2\pi)$. Only if all criteria of a "good" fit are met, that is, MSE<err, $|t_c-t_2|/|t_2-t_1|<t_{cd}$, $|Bm|/|C\omega|>d$, $0<m<1$, and $\omega\log(|t_2-t_c|/|t_1-t_c|)/2\pi)>osc$, then the fit will be qualified.
3. We apply step 2 to all n time windows $[t_2-30, t_2]$, $[t_2-35, t_2]$, …, $[t_1, t_2]$, where $n=[(t_2-t_1-30)/5]$, and obtain the number of qualified fits m.
4. The LPPLS Confidence Indicator is m/n.

Appendix 3B

Table 3B.1. Statistics of the LPPLS Alarm Events in the Chinese Market.

Chinese LPPLS Alarm Signal (Thresholds) —— Event Study					
Positive Alarm			Negative Alarm		
Thresholds	Total Events	Valid Events	Thresholds	Total Events	Valid Events
Confidence =1	31	30	Confidence =-1	3	3
Confidence >0.9	62	60	Confidence <-0.9	3	3
Confidence >0.8	79	77	Confidence <-0.8	9	9
Confidence >0.7	100	98	Confidence <-0.7	13	13
Confidence >0.6	138	136	Confidence <-0.6	23	23
Confidence >0.5	194	191	Confidence <-0.5	29	29
Confidence >0.4	292	289	Confidence <-0.4	44	44
Confidence >0.3	393	385	Confidence <-0.3	80	80
Confidence >0.2	576	566	Confidence <-0.2	154	154
Confidence >0.1	916	894	Confidence <-0.1	330	330
Confidence >0.0	1131	1108	Confidence < 0	383	383

Chinese LPPLS Alarm Signal (Interval) —— Event Study					
Positive Alarm			Negative Alarm		
Intervals	Total Events	Valid Events	Intervals	Total Events	Valid Events
Interval (1, 0.9)	92	90	Interval (-1, -0.9)	3	3
Interval (0.9, 0.8)	113	112	Interval (-0.9, -0.8)	6	6
Interval (0.8, 0.7)	87	87	Interval (-0.8, -0.7)	4	4
Interval (0.7, 0.6)	103	103	Interval (-0.7, -0.6)	10	10
Interval (0.6, 0.5)	121	120	Interval (-0.6, -0.5)	6	6
Interval (0.5, 0.4)	176	172	Interval (-0.5, -0.4)	15	15
Interval (0.4, 0.3)	241	240	Interval (-0.4, -0.3)	36	36
Interval (0.3, 0.2)	332	330	Interval (-0.3, -0.2)	74	74
Interval (0.2, 0.1)	458	445	Interval (-0.2, -0.1)	176	176
Interval (0.1, 0)	317	311	Interval (-0.1, 0)	53	53

Table 3B.2. Statistics of the LPPLS Alarm Events in the U.S. Market.

US LPPLS Alarm Signal (Thresholds) —— Event Study					
Positive Alarm			Negative Alarm		
Thresholds	Total Events	Valid Events	Thresholds	Total Events	Valid Events
Confidence =1	32	30	Confidence =-1	30	30
Confidence >0.9	76	74	Confidence <-0.9	36	36
Confidence >0.8	114	112	Confidence <-0.8	51	51
Confidence >0.7	137	134	Confidence <-0.7	60	60
Confidence >0.6	185	180	Confidence <-0.6	77	77
Confidence >0.5	237	231	Confidence <-0.5	88	88
Confidence >0.4	310	304	Confidence <-0.4	106	106
Confidence >0.3	372	366	Confidence <-0.3	134	134
Confidence >0.2	461	456	Confidence <-0.2	153	153
Confidence >0.1	525	520	Confidence <-0.1	167	167
Confidence > 0	546	541	Confidence < 0	173	173

US LPPLS Alarm Signal (Interval) —— Event Study					
Positive Alarm			Negative Alarm		
Intervals	Total Events	Valid Events	Intervals	Total Events	Valid Events
Interval (1, 0.9)	76	74	Interval (-1, -0.9)	36	36
Interval (0.9, 0.8)	38	38	Interval (-0.9, -0.8)	18	18
Interval (0.8, 0.7)	23	22	Interval (-0.8, -0.7)	14	14
Interval (0.7, 0.6)	48	46	Interval (-0.7, -0.6)	22	22
Interval (0.6, 0.5)	52	51	Interval (-0.6, -0.5)	18	18
Interval (0.5, 0.4)	73	73	Interval (-0.5, -0.4)	25	25
Interval (0.4, 0.3)	62	62	Interval (-0.4, -0.3)	34	34
Interval (0.3, 0.2)	90	90	Interval (-0.3, -0.2)	23	23
Interval (0.2, 0.1)	64	64	Interval (-0.2, -0.1)	15	15
Interval (0.1, 0)	21	21	Interval (-0.1, 0)	6	6

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Chapter 4

Polytope Fraud Theory

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Abstract

Polytope Fraud Theory (PFT) extends the existing triangle and diamond theories of accounting fraud with ten abnormal financial practice alarms that a fraudulent firm might trigger. These warning signals are identified through evaluation of the shorting behavior of sophisticated activist short sellers, which are used to train several supervised machine-learning methods in detecting financial statement fraud using published accounting data. Our contributions include a systematic manual collection and labeling of companies that are shorted by professional activist short sellers. We also combine well-known asset pricing factors with accounting red flags in financial features selections. Using 80 percent of the data for training and the remaining 20 percent for out-of-sample test and performance assessment, we find that the best method is XGBoost, with a Recall of 79 percent and F1-score of 85 percent. Other methods have only slightly lower performance, demonstrating the robustness of our results. This shows that the sophisticated activist short sellers, from whom the algorithms are learning, have excellent accounting insights, tremendous forensic analytical knowledge, and sharp business acumen. Our feature importance analysis indicates that potential short-selling targets share many similar financial characteristics, such as bankruptcy or financial distress risk, clustering in some industries, inconsistency of profitability, high accrual, and unreasonable business operations. Our results imply the possible automation of advanced financial statement analysis, which can both improve auditing processes and effectively enhance investment performance. Finally, we propose the Unified Investor Protection Framework, summarizing and categorizing investor-protection related theories from the macro-level to the micro-level.

The old wheel turns, and the same spoke comes up. It’ s all been done before, and will be again.

——————Sherlock Holmes

4.1 Introduction

Financial statement fraud has been, and remains, a significant concern worldwide. It affects many industries, countries, and communities. In the U.S., the total cost[133] of financial statement manipulation has been estimated at roughly 572 billion dollars per year (Perols, 2011). In addition to direct costs, this fraud also negatively impacts suppliers, clients, employees, creditors, and investors, because inaccurate financial information interferes with their decision-making processes. Accounting fraud not only reduces financial market efficiency, but also decreases market trust, since financial statements are critical for modern economic activities. Investors rely on financial statements to make value-enhancing decisions and allocate their capital to the right places; bankers access them to decide whether the bank should grant credit; suppliers use them to evaluate whether clients are reliable; and regulators, tax authorities, customers, and even employees rely on financial statements to obtain information about businesses. Thus, financial statements build bridges for corporate insiders and outsiders to communicate a company’s financial soundness, credit risks, business strategies, and future perspectives. However, despite strong national and international monetary regulations and oversight accounting, corporate fraud scandals such as Enron, Lucent, WorldCom, Toshiba, Wirecard, and Evergrande continue to rock the financial world with astonishing regularity.

A financial statement fraud is usually defined as making falsified financial accounting statements by overstating balance sheet items, revenues, and net earnings, misappropriating taxes, or understating financial liabilities, expenses, or losses. Young and Cohen (2013) distinguish between deliberate fraud and financial statement errors, attributing financial statement errors to (1) limits to measuring technology (i.e., the

[133] Perols (2011) estimated the total cost of financial statement fraud by assuming that the mean cost per case is equal to the median cost per fraud category. He used the number of cases times the mean cost per case to derive the total cost. The median cost as well as the number of cases are provided by the Association of Certified Fraud Examiners (ACFE, 2008).

difficulty of evaluating the technology "know-how" in dollar value), (2) randomness[134], and (3) the subjective "accounting choices" of management (i.e., managers intentionally delaying or advancing reporting revenue to tactically smooth earnings). Young (2020) proposes that:

$$\text{Financial accounting} = \text{Economic reality} + \text{Error}$$

In a comparison, accounting fraud is the intentional, material, perennial, and systematic misstatement of accounting reports, which might have serious consequences. Financial statement fraud is mainly related to inflating accounting numbers in income statements and balance sheets. We therefore borrow from the terminology of financial bubbles, which was used to describe the excess market prices above fundamental value, and we categorize the existence of two major types of fraud bubbles[135]: 'income statement fraud bubbles' and 'balance sheet fraud bubbles.' The above equation can therefore be rewritten as:

$$\text{Financial accounting} = \text{Economic reality} + \text{Fraud bubbles} + \text{Error}$$

'Income statement fraud bubble' refers to situations in which managers intentionally inflate the revenue or boost the net incomes[136] during some accounting periods. In contrast, a 'balance sheet fraud bubble' is the situation in which managers intentionally manipulate corporate leverage or increase net assets by inflating the assets' value, hiding unfavorable debt[137], or both.

An income statement fraud bubble accumulates over time and finance managers need to hide the inflated net incomes within other items in the balance sheet, or they have to boost expenses and costs to eliminate the inflated revenue over time. To hide inflated net incomes, they can either choose some items within the balance sheet to park the inflated income, or quietly spend the fake income through raw material purchases, Capex (capital expenditure) investments such as PP&E (property, plant, and equipment), or merger acquisitions (transforming the fake income into goodwill or intangible assets),

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[134] Randomness comes from manager estimates. For example, when a manager is estimating the cost of restructuring, it is impossible to predict exact cost outcomes before the restructuring occurs. The difference between actual cost and estimated cost is a typical source of randomness.

[135] We define a financial fraud bubble as a situation in which no reasonable fundamental reality can justify the (inflated) accounting number.

[136] Managers can artificially boost the net earnings by increasing revenue-related items, decreasing costs and expenses incurred, or both.

[137] For example, managers can artificially increase the assets' valuation, or conduct fake impairment tests on assets, or record less amortization cost of intangible assets.

depending on the situation and difficulties. However, if a company has accumulated too much inflated income on its balance sheet, the asset column on its balance sheet will become too bloated, and its financial ratios will be dragged down. After a while, such companies will need a "big bath" to clean the balance sheet to 'squeeze out the bubbles.'

Financial fraud is very challenging to discover since it is:

- hard to be confirmed: there is no clear and exact accounting rule to decide whether a company is committing financial statement fraud. In practice, auditors, based on experience, can accept small, non-material deviations between reported and tracked accounts to allow for accounting error. Additionally, auditors have some leeway to allow for different accounting practices, as some companies might use conservative methods to smooth earnings. However, financial fraud companies tend to have bigger differences (for example, Muddy Water Research focuses on companies whose reported numbers deviate by more than 50 percent from what would commonly be accepted as accounting reality).
- hard to detect: the traditional approach for detecting financial statement fraud is based on auditing procedures, which are time-consuming and sometimes unrealistic[138]. First, auditors usually lack the resources to apply sophisticated knowledge to identify financial fraud or prevent accounting malpractice. Second, due to the infrequent nature of such cases, in conjunction with the incentive structure of auditor remuneration, most auditors are incentivized to not notice accounting distortions. Third, corporate financial experts such as Chief Financial Officers (CFOs), financial managers, and accountants intentionally use their deep industry expertise to deliberately deceive internal or external auditors. Finally, corporate insiders and auditors might even conspire to manipulate accounting numbers due to principal-agent problems and lack of self-regulation (for example, the Enron scandal).

Investment firms and financial institutions[139] can be seen as financial statement data collectors, users, and processors, and their tasks require some degree of intensive and specialized data analysis. Since the quantity of data available for analysis has grown

[138] With limited time, it is almost impossible for auditors to correctly evaluate (1) the impairment rules of high-tech equipment; (2) the fair value of assets located among different countries or in some unknown rural areas; and (3) the market value of fishery resources and forestry resources, etc. in a very short period before the annual report is released.
[139] Such as loan associations, credit unions, mortgage companies, and commercial banks.

tremendously, improving the accuracy and consistency of data analysis and interpretation poses a formidable challenge to financial statement users. Generally, institutions can expand their workforce to handle more financial data. Still, with the limited number of appropriate financial experts and the complexity of the data, it is quite challenging to scale up effective and accurate business decisions. Thus, traditional auditing and financial analysis procedures are far from meeting the demands of investors and creditors, suggesting the need for additional advanced, automatic financial statement analysis tools or techniques.

Recent improvements in computational intelligence (CI)-based techniques, might present potential solutions. Applying statistical methods or machine-learning algorithms in financial statement analysis is a logical development. Much of the work comprises classification problems, such as financial statement fraud detection, bankruptcy prediction, crediting-rating evaluation, and so on. Machine-learning algorithms — which allow machines to uncover patterns without explicit specification of what to look for — are widely used in voice recognition (e.g., Siri), image recognition (e.g., self-driving cars), ranking systems (e.g., Google PageRank), and recommendation systems (e.g., Amazon's product recommendations). In accounting and finance, machine-learning algorithms have successfully been applied to risk assessments, creditworthiness checks, lending evaluations, fraud detection auditing, automation, and so on.

Machine-learning algorithms present three crucial advantages compared with traditional manual detection procedures:

1. They can uncover nonlinear or hidden relationships and complex patterns.
2. They show distinguishing-features extraction capability of large datasets without requiring specific knowledge of the input variables.
3. The algorithms are more scalable, standardized, and objective.

However, there are also some disadvantages[140] to using machine-learning algorithms:

4. The difficulty of dealing with missing data or inadequate datasets.
5. Proneness to overfitting.

[140] One of the more famous A.I. failures is Zillow Group Inc., an American online real-estate marketplace company that used A.I. technology to predict property prices. For more information, see https://www.wsj.com/articles/zillow-offers-real-estate-algorithm-homes-ibuyer-11637159261.

6. It can be challenging to interpret the model, because the result tends to be more numerical, and the relationships within elements of the model are very complex and multidimensional, leading to a “black box” situation.
7. Further investigation may be needed when the underlying situation changes substantially since the assumptions of the training regime might have been completely broken by the boundary conditions.
8. The quality of the output is highly dependent on the quality of the input data, and in many cases much of the effort is spent on bringing the data into a machine-readable, cleaned-up format.

Activist short sellers use their advanced accounting and analytical research skills, and specific information processing abilities to find potential short-selling targets. They not only short fraudulent companies but also overvalued companies; sometimes short sellers hold short positions because they simply follow a momentum-based strategy (short the ‘loser’ companies). In addition, the existence of activist short sellers partially balances a market dominated by long only funds and serves to ‘weed out’ the figurative ‘bad apples.’ This research studies fraudulent companies selected by prominent activist short sellers and focuses on the financial statements of those fraudulent companies. It looks for patterns in the financial characteristics of short-selling targets and attempts to lift part of the mysterious veil of the activist short sellers’ “black box”.

Short-selling targets and their annual financial reports are publicly available, and we can utilize this data in supervised learning to train algorithms to mimic the professional financial analysis experts. It is worth noting that sophisticated activist short sellers conduct extensive research to corroborate and validate their hypotheses[141]. This research complements their sharp business acumen, broad financial knowledge, and the accumulated experience that enables them to judge the financial health of businesses. This paper will focus on annual corporate financial statement data only. While there is extensive evidence embedded in the footnotes, management outlooks, and other public information sources, and so on that may suggest the potential financial fraud, we chose not to include these reports in our training dataset due to data limitation.

[141] It appears that activist short sellers conduct due diligence with suspected fraudulent companies, investigating their customers, suppliers, and competitors, and collecting information from the tax authority.

This paper contributes the following: (1) We manually collect the short-selling targets of eight prominent activist short sellers such as Muddy Water Research, GMT Research, Citron Research and so on, to label the dataset for training nine machine-learning algorithms. (2) We investigate whether including financial features from documented asset pricing factors, accounting models, and financial variables/ratios in the training data set contributes significantly to the performance of our models. These models include Logistic Regression, K-Nearest Neighbours, Decision Trees, Random Forest, Support Vector Machines, Artificial Neural Networks, AdaBoost, XGBoost, and LightGBM. (3) We propose the 'Polytope Fraud Theory' (PFT), which addresses common financial and accounting fraud issues. (4) We propose the 'Unified Investor-Protection Framework' (UIPF), which summarizes and categorizes macro-, middle-, and micro-level fraud prevention and investor protection theories.

The remainder of this paper is organized as follows: Section 2 presents a review of financial fraud detection, short selling, and machine learning in the accounting and finance disciplines. Section 3 outlines our data collection, preparation, and cleaning methods. Section 4 presents our methodology, and our empirical findings are described in Section 5. Section 6 outlines our Polytope Fraud Theory and the Unified Investor-Protection Framework, and Section 7 presents our conclusions.

4.2 Literature Review

4.2.1 Motivations for Fraud

The motivations for financial statement fraud vary, but generally fall into two categories: first, contracting incentives (especially management bonus programs that link to accounting outcomes), and second, capital market incentives – to obtain favorable financing terms or to inflate the value of an asset in the capital market to gain from insider trading (Young 2020). A rarer case would be intentional deflation of the perceived market value of a company, leading to favorable take-over conditions.

The presence of accounting-based compensation (e.g., EBIT, net income, revenue growth) tends to result in more accounting irregularities than the absence of such compensation. Healy (1985) showsed that the choice of accounting method and overstating or understating financial statements are determined by the management in large part, which is likely to have agency problem issues. Efendi et al. (2007) documented that the likelihood of "restatement" required by the U.S. Securities and

Exchange Commission (SEC) increases significantly when Chief Executive Officers (CEOs) have sizable holdings of in-the-money options. This implies that the direct link between senior executives' personal interests and stock price performance might lead to potential accounting malpractices to boost, or at least sustain, the stock price. Röell and Peng (2006) also indicated that the existence of executive options increases the likelihood of securities-related litigation. Call, Kedia, and Rajgopal (2016) reported similar findings.

The pursuit of desirable equity prices or favorable financing terms is another motivation. Dechow et al. (1996) revealed that a company might inflate its earnings to obtain a better price for new equity issuances or to lock in a lower interest rate. Burn and Kedia (2006) found that firms are willing to adopt aggressive accounting practices to reduce the costs of financial distress. Perry and Williams (1994) argued that if managers want to acquire the company/division through Management Buyout (MBO), they tend to understate the corporate earnings. Beneish (1999a) posited that net insider selling will appear when earnings are inflated. This suggests that managers might overstate their financial statements before they sell their shares. Röell and Peng (2006) uncovered similar results, showing that securities lawsuits increase when insiders are not selling. This implies that insiders anticipate that they might be charged with financial misconduct, so they sell more shares or options during class-action litigation periods.

4.2.2 Fraud Triangle Theory and Fraud Diamond Theory

There are various leading factors or conditions that most fraud events possess. The two most cited related theories are Cressey's (1953) 'Fraud Triangle Theory' (FTT), and Wolfe and Hermanson's (2004) 'Fraud Diamond Theory' (FDT). Donald Cressey, a criminologist and former student of Edwin Sutherland (Sullivan coined the term 'White-collar crime') proposed the foundation theory of fraud[142] based on (a) Pressures, (b) Opportunities, and (c) Rationalizations or Attitudes[143]. The major difference

[142] Cressey never referred to the three elements of fraud as the "fraud triangle". It is Albrecht (1991) who completed Cressey's trust violation theory and named it "the fraud triangle", as he considered the three elements of fraud similar to the "fire triangle".
[143] The three elements of fraud triangle theory can be explained as (1) Incentive: I want to, have to, or need to commit fraud; (2) Opportunity: the system has a weakness so that fraud is possible; (3) Rationalization: the assessment that committing fraudulent behavior is worth the risks.

between FTT and FDT is that FDT adds a fourth element to the FTT, which is the "Capability" to commit fraud[144].

FTT: Fraud = f (Pressure, Opportunity, Rationalization)

FDT: Fraud = f (Pressure, Opportunity, Rationalization, Capability)

Research shows that management is under pressure when it has to meet analysts' forecasts, confront poor performance, or source external financing. Loebbecke et al., (1989) and Bell et al., (1991) established that, if a company is experiencing growth that is below the industry average, management may manipulate the earnings to improve corporate output. Rosner (2003) pointed out that failing firms are more likely to inflate the income statement to hide financial distress based on accruals (decreased cash flows or more accounts receivables). Davidson (2016) concludes that managers commit balance sheet-related fraud when the market-wide default risk is high, and their firms are in greater financial distress. In addition, managers commit income statement-related fraud when their firms' stock price is sensitive to their idiosyncratic earning performance.

Opportunities for fraud arise in conditions of weak internal control (for example, poor corporate governance and lack of supervision), lack of external monitoring (auditors being undercompensated and overworked), and inadequate accounting policies (poor separation of duties and poor documentation of processes). Dechow et al., (1996) indicated that companies with fewer independent boards, more unitary structures for the chairman and CEO, and fewer outside block holders are more likely to manipulate earnings. Farber (2005) affirmed that fraudulent firms tend to have fewer independent board members, fewer audit committee meetings, fewer financial experts on the audit committee, and a higher percentage of CEOs as the Chairman than no-fraud firms. Research also shows that auditor tenure is related to earnings quality (Iyer & Rama 2004; Myers et al. 2003). Carcello and Nagy (2002) showed that auditor industry specialization and financial irregularities negatively correlate.

Rationalization indicates that the firm's management must accept immoral ideas before engaging in unethical behavior. Gillett and Uddin (2005) showed that the CFO's attitude toward fraudulent behavior influences accounting malpractices. Howe and

[144] The added fourth element in the fraud diamond theory, 'Capability', can be considered as 'I am the right person with the necessary skills and abilities to commit fraud'.

Malgwi (2006) argued that the gap between pressure and opportunity is filled when individuals rationalize behaviors, for example, employees' lack of personal integrity or moral reasoning (Rae & Subramanian 2008).

Capability – the fourth element in the fraud diamond – describes the necessary skills or abilities to commit fraud. Albrecht et al., (1995) found that capability is essential, especially for large-scale and long-term fraud. Albrecht et al. (1995) also argued that only a competent person who thoroughly understands the internal control and auditing process could implement the fraud. Wolfe and Hermanson (2004) similarly observed that position, intelligence, ego, and stress are the supporting elements of capability: individuals within an organization who are intelligent enough to understand where the weaknesses are can exploit them.

Abundance of opportunity also plays a large part in the psychology that motivates certain fraudulent activities, especially for "high capability" fraud[145]. Even when external deterrents are lacking, strong internal controls can prevent individuals with high capability from exploiting weaknesses (Murphy & Dacin 2011). Knowing that they might get caught and punished deters the "high capability" managers from committing fraud (Carland et al. 2001; Kassem & Higson 2012; Rose et al. 2015).

Albrecht and Albrecht (2003) categorize six signs of fraud: (1) accounting anomalies, (2) internal control weakness, (3) analytical anomalies, (4) extravagant lifestyles, (5) unusual behaviors, and (6) tips and complaints. Although these symptoms are observed frequently in fraudulent companies, it is still complicated to formulate an audit plan to uncover fraud.

4.2.3 Illustration with the Case Study of Enron

Based on the book Man-made catastrophes and risk information concealment: 25 case studies of major disasters and human fallibility (Chernov & Sornette 2015), we here summarize the case of Enron to illustrate the Fraud Triangle Theory and Fraud Diamond Theory.

Founded in 1985, Enron was one of the largest companies in the United States before filing for Chapter 11 bankruptcy, on December 2, 2001. Enron focused on

[145] Intuitively speaking, if the opportunity is very good (i.e., it is easy to implement the fraud), less capability is needed to commit the fraud. Similarly, if the opportunity is weak, the manager needs very strong capability to commit accounting fraud.

wholesale merchants, commodity markets, gas transmission systems, and retail energy services, and had around 3,500 domestic and foreign subsidiaries and affiliates. The annual revenue soared from 9 billion to 100 billion dollars between 1995 and 2000. After the Enron accounting fraud was uncovered, Enron's stock price plummeted from 90 dollars per share to less than 1 dollar, evaporating $11 billions of (59,000) shareholders' wealth. Several pension funds suffered 2-billion-dollar losses, and 20,000 creditors received just 14 to 25 cents on every dollar they lent to Enron. The Enron scandal, being the largest firm bankruptcy in American history, led to the dissolution of Arthur Andersen, one of the five largest auditing firms in the world.

According to the fraud diamond theory, we can conclude as follows:

Incentive: After two debt-financed merger acquisitions, Enron had an enormous debt of 4.3 billion dollars. What's worse, the deregulation of the energy sector in the late 1980s meant Enron lost its exclusive rights to the gas transportation pipeline in the natural gas market. These two revenue-impacting issues created huge pressure for Enron's management team, and the company reported a 79-million-dollar loss in the late 1980s. After Jeffrey Skilling became CEO, Enron's compensation structure was radically changed. The employees' pension fund was heavily invested in Enron's stock and Enron's aggressive payment structure motivated employees to increase Enron's capitalization — by any means. Senior management created Special Purpose Entities (SPEs) in their own names that could be used to hide the corporate debt and transfer the money into their pockets. As this enriched them as individuals through self-dealing, it presented a material conflict of interest with company shareholders.

Opportunity: The federal deregulation of the energy sector during George H. W. Bush's U.S. presidential term created opportunities to expand Enron's commodity trading business. Due to a strong tie[146] with the government, Enron successfully lobbied to remove regulations on over-the-country energy derivatives. In addition, the SEC's approval of the mark-to-market (MTM) accounting method for energy companies in 1992 allowed Enron to report expected benefits from future transactions into current income, inflating its revenue from $6.3 billion to $100.8 billion by 2000. Arthur Andersen, Enron's auditing firm[147], assisted Enron to implement aggressive accounting

[146] Enron's chairman Kenneth Lay was the co-chairman of Bush's 1992 re-election committee, and he had made large monetary contributions to the Bush presidential campaign. For more information, see https://www.economist.com/unknown/2002/01/11/bush-and-enrons-collapse.

[147] Arthur Andersen earned 1 million dollars per week for auditing, and its consultation services accounted for 70 percent of the total payment from Enron.

to increase revenue. Furthermore, Enron had no internal auditing department, and many of the financial managers of Enron were former executives of Arthur Andersen. The board directors received extremely high salaries (double the high end of an ordinary public company directors' remuneration) for serving on Enron's board, though they had little understanding of the business. Corrupt politicians, greedy auditors, and 'silent' board directors provided weak control and created ample opportunities for fraudulent activities.

Rationalization: Under the leadership of Jeffrey Skilling, Enron's corporate culture changed dramatically. Analysts argue that it became less of an energy company and more like an investment bank. It became known that Enron paid and promoted employees who brought in big new deals and put huge pressure on those who didn't. The remuneration system was redesigned to focus on making big deals, regardless of quality. The company hired aggressive and smart young graduates and gave them generous salaries[148], and reportedly fired those in the bottom 15 percent quantile. An auditor who dared to question Enron's financial reports was fired[149]. No one in the investment banks marked Enron as a "Sell" target because many banks had businesses with Enron. The culture of "success at any cost" and "report only good news" blinded internal employees and external financial institutions, distorting their professional ethics (Chernov & Sornette 2015).

Capability: Kenneth Lay (chairman of Enron, Ph.D. in economics), Jeffrey Skilling (CEO of Enron, Harvard University MBA), and Andrew Fastow (CFO of Enron, Northwestern University MBA) were all highly educated and intelligent. Andrew Fastow engineered a network of 3,000 out-of-balance special purpose entities (SPEs) to hide the enormous debt and transfer huge losses resulting from merchant investments to third-party companies. To accomplish favorable financial statement results they unconsolidated the unprofitable international subsidiaries and affiliates. They committed money laundering, filed fraudulent income tax returns, and transferred corporate assets to their own pockets through complex and opaque accounting structures. The Enron scandal was only uncovered after many years of fraudulent activities, through

[148] The base salary at Enron was 51 percent higher than its peer group. In addition, employees' bonus payments were 383 percent higher, and stock options were 484 percent higher (Chernov and Sornette 2015).

[149] Carl Bass, one of the auditors from Arthur Andersen, questioned the mark-to-market accounting method, but he was fired, and his CPA membership was canceled by the Texas State Board of Public Accountancy (TSBPA), which was under the leadership of Mike Conaway, mutual friend of both George Bush and Kenneth Lay.

one of their employees, Sherron Watkins, who became a whistle-blower in 2001. Before that, Enron was an award-winning company often cited as case study material for innovation in business schools across America.

The Enron scandal has led to a huge crisis of belief in the trustworthiness of the whole U.S. capitalist system, since it throws doubt on the accounting practices and financial reports of U.S. listed companies. Thus, the American Institute of Certified Public Accountants (AICPA) issued the Statement of Auditing Standards No.99 (SAS No. 99), and U.S. congress passed the Sarbanes-Oxley Act of 2002 (also known as the "Public Company Accounting Reform and Investor Protection Act"), in response to the collapse of the Enron empire (Skousen et al. 2009). The Sarbanes-Oxley Act aims to increase financial information accuracy, strengthen corporate governance, and increase the severity of financial fraud penalties for corporate management (Chen et al. 2015). The Act also created a new agency, the Public Company Accounting Oversight Board (PCAOB), to regulate and oversee accounting firms' independence and internal controls.

4.2.4 Market Efficiency Versus Inefficiency

Market pricing efficiency is a basic tenet of financial economics (Fama, 1970). In this spirit, Grossman and Miller (1988) stated that the stock price would move toward fundamental value due to arbitrage forces. Lee et al. (1997) also indicated that the stock price and fundamental value form a co-integrated system, and arbitrage will force them to converge. However, with the existence of various mechanisms (e.g., bounded rationality, limits of arbitrage, and noise), the price can deviate significantly from fundamental value for quite a long time. This is known as "mispricing." Dechow and Sloan (1997), Espahbodi et al. (2001), and Ang and Ma (2001), determined that analysts' earnings forecasts are generally over-optimistic. Black (1986) stated that noise trading contributes to the long-time divergence of price and intrinsic value, and unreasonable price movements. Hüsler et al., (2012) also revealed from laboratory experiments that the over-optimistic expectations on price would result in positive feedback favoring bubble formation.

Behavioral finance theory points to the limits of arbitrage and the presence of irrational investors as the major reasons the market is inefficient. Shleifer and Vishny (1997) proposed that arbitrage costs deter the price from approaching its intrinsic value. Specifically, there are three kinds of arbitrage costs: (1) trading costs: brokerage fees, order implementation cost, or other fees that are related to building or closing trading positions; (2) holding costs: the costs of sustaining the duration of the position, for example, short selling interest; and (3) information costs: costs associated with accessing, analyzing, and monitoring information. In addition, Edwards (1968) suggested that investors tend to undervalue new information when they update their information set. Barberis et al. (1998) indicated that the ‘conservative bias’, which means prices will slowly adjust to new information, might result in an underreaction by investors and generate a ‘momentum effect’. Daniel and Hirshleifer (2015) asserted that overconfident investors, including experts and professionals, contribute to excessive trading and disagreement between price and value. Various psychological biases lead to mispricing.

Sornette (1999) proposed that heterogeneous investors with repetitive interactions have the tendency to imitate others, which results in ‘herding’ and crowd effects. Cooperative herding and social imitation can emerge out of equilibrium properties. Sornette (2003) noted that self-reinforcing imitation among noise traders is one among many mechanisms in financial economics leading to nonlinear positive feedback, which leads to unsustainable super-exponential price dynamics – a hallmark of financial bubbles. For instance, these transient super-exponential price dynamics can be used with the LPPLS (log-periodic power law singularity) model to diagnose developing bubbles and forecast their end times (Sornette, 2003; Sornette & Cauwels 2015; Zhao & Sornette, 2021).

4.2.5 Agency Problem and Investor Protection

Agency theory, one of the oldest theories in management and economics literature, discusses problems due to the separation between the owners and managers of a firm (Daily et al. 2003; Wasserman, 2006). Adam Smith discussed in his book The Wealth of Nations that, if an organization is managed by a person other than the real owner, then the people might not work for the owner’s benefit. Berle and Means (1932) observed that many large U.S. firms had dispersed ownership, leading to the separation of ownership from control. They argued that self-interested agents might use the firm’s property for their benefits, creating conflicts between the principals and agents.

In the modern era, the agency problem is not limited to principals and agents – it extends to other parties such as creditors, major shareholders, and minor shareholders (Panda & Leepsa 2017). Researchers have categorized three agency problems: (1) an agency problem arises between the principal and agents due to information asymmetry and divergent risk-taking attitudes of the owner and the principal (Jensen & Meckling, 1976; Ross, 1973); (2) an agency problem exists between the major and minor shareholders (Shleifer & Vishny, 1997; Gilson & Gordon, 2003). Shleifer and Vishny (1997) indicated that an agency problem can also occur between outside investors and controlling shareholders, who have almost full control of corporate management; (3) Damodaran (1997) proposed that an agency problem can occur between owners and creditors: higher-risk investment decisions by owners can be unsupported by existing creditors.

Jensen and Meckling (1976) argued that a misalignment of interests between agent and the principal can lead to agency conflicts and related costs. There are three agency costs: (1) monitoring costs are the costs associated with monitoring and assessing the agent’s performance; (2) bonding costs are the costs incurred to set up and operate according to predetermined contractual obligations, and (3) residual costs are losses due to inefficient managerial decisions. Williamson (1988) claimed that residual cost is the key component of agency cost.

The lack of effective legal restrictions on the ability of corporate insiders (managers or controlling shareholders) to divert corporate wealth to themselves, known as ‘self-dealing’, is a major investor protection problem (Grossman & Hart, 1983). Much research indicates that differences in legal investor protection across countries (which restrict the ability of insiders to gain “private benefit of control”) determine investor confidence in markets, and consequently the differences in their development (Shleifer & Vishny, 1997; La Porta et al., 1997, 1998; Shleifer & Wolfenzon, 2002). Djankov and La Porta (2005) documented the differences in legislation between countries in protecting minority shareholders and creditors. They indicated that the ability of different legal bases to restrict the self-dealing problem impacts the development of the corresponding financial markets. Shleifer et al. (2002) also revealed that investor protection shapes external finance. In addition, Shleifer et al. (2008) proposed the ‘Legal Origin Theory’, suggesting that common law countries (U.K., U.S.A, Singapore, Hong Kong, etc.) protect outside shareholders and outside creditors better than civil law countries (France, Germany, Italy, Japan, China, etc.), and thus financial markets in common law countries become larger and better functioning, with more sources of external financing.

4.2.6 Short Sellers

Research on short selling indicates that short sellers are sophisticated investors. Typical short sellers include professional traders, hedge fund managers, portfolio managers, and so on, and they play important roles in the dynamics of price discovery, stock market efficiency, and corporate manager discipline (Boehmer et al., 2008; Christophe et al., 2004; Diether et al., 2009). Short sellers, based on the underlying economics or fundamental analysis of stocks, decide whether a stock is overvalued or not, and act accordingly. Studies suggest that short selling constitutes around 20-31 percent of trades in the U.S. market (Chen et al., 2019). The short seller's business model is based on the expectation of future drops in the target firms' stock price. Short sellers' profit from the strategy of "selling high and buying low", which means they buy back the securities at a lower price and return them to the broker they originally borrowed from at a higher price.

There are two types of short sellers: passive short sellers and activist short sellers. The basic difference is that activist short sellers declare their short position to the public, whilst passive short sellers keep quiet and tend to implement market-neutral arbitrage strategies. Portfolio managers may execute short selling of stocks to hedge against any downside risk of a long position (Ederington, 1979), or short the stocks of the acquiring firm while building the position of the target firm in merger and acquisition events (Baker & Savasoglu, 2002). Passive short sellers usually build positions without announcing their actions, even after they close their positions. In contrast, activist short sellers openly publicize their opinions about target companies through detailed public reports online, accusing the target firms of financial statement fraud (e.g., accounting irregularities, earning manipulations, fake transactions, and so on). Activist short sellers aim to push the stock price down, as their short positions have been built in advance. To draw down the prices, they not only acquire large short positions[150], but also persuade other long-side buyers, (mainly institutions), to cut their long positions[151].

In general, activist short sellers proceed with information more efficiently than passive short sellers, since activist short sellers often conduct extensive research, while passive short sellers often short stocks based on simple factors. In addition, activist short

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150 Activist short sellers might borrow a lot of stocks and suddenly dump them into the market to create panic among investors.

151 Activist short sellers disclose their detailed short-selling theory with conclusive facts and strict logic to persuade other investors to terminate their long positions.

sellers tend to create stock price declines themselves (i.e., they might create stock price crashes of some companies) rather than for tax or hedging purposes (Brent et al., 1990). Accordingly, activist short sellers, who are unconstrained by the supply in the equity-loan market, take more risks than passive short sellers.

There are three significant risks that activist short sellers face:

First, whether the stock price will decline enough to at least compensate for the additional costs (e.g., borrowing costs, transaction costs, and information costs) and corresponding risks (e.g., market risk). In addition, short sellers have to face the possibility of a "short squeeze," whereby the stock price increases instead of decreasing, so that they have to buy back the stock at a higher price than their selling price in order to return it to the broker. In this situation, they not only have to bear the costs, but also suffer from losses associated with their position[152]. In theory, a short sellers' maximum loss is unlimited since the stock price can increase to unlimited levels (Diamond & Verrecchia, 1987).

Second, whether the shorted company will sue the activist short sellers for misleading in a material respect (i.e., market manipulation). If the activist short sellers engage in market manipulation (intentionally misleading the public), they may face criminal prosecution. For instance, in the British jurisdiction, under Sections 89 and 92(1)(b) of the Financial Services Act (FSA), anyone who has engaged in market manipulation could be sentenced to a maximum of 7 years imprisonment and incur an unlimited fine (Durston, 2021).

Third, when short sellers "touch other people's cake", they may, of course, invite trouble into their personal lives. That is also why many activist short sellers refuse to reveal their identity – to protect themselves and their family members. Most of the sophisticated short sellers we reviewed have revealed their names and contact details. Consequently, some of them have received hundreds of emails threatening their lives or their safety, or that of their family members[153].

Research indicates that short sellers have abilities superior to auditors and financial analysts in detecting financial statement fraud by exploiting public information

[152] For example, short sellers had shorted GameStop (GME) stock since 2020, while the GameStop stock price increased more than 1700 percent from January 1, 2021, to February 2, 2021.

[153] For instance, after Citron released the short-selling report of GameStop, Andrew Left received anonymous threatening phone calls using fake voices and had strangers show up at his personal residence. Citron's twitter account was hacked. Thus, Andrew Left decided to stop issuing short-selling reports and his fund has turned to implementing long-only investment strategies since January 2021.

(Achert & Athanassakos, 2005; Aitken et al., 1998). Their existence in the financial market accelerates the discovery of overvalued stocks, increasing market efficiency, and restraining corporate managers from potential fraud activities (Boehmer et al., 2008; Christophe et al., 2004, 2010; Henry et al., 2015). They also play an essential role as a counterbalance to excessive market optimism (Keshk & Wang, 2018; McNichols & O' Brien, 1997). Research also indicates that short selling restrictions and constraints slow down the incorporation of negative private information and thus reduce market efficiency and hedging effectiveness (Brunnermeier & Oehmke, 2014; Choy & Zhang, 2019; Danielsen & Sorescu, 2001; Hasan et al., 2015).

Short sellers tend to target firms with a poor fundamental ratio, large market value, and high institutional shareholding (Dechow, et al. 2001). In addition, short sellers are more activist in high-growth and financially opaque firms, which are susceptible to overvaluation (Grullon et al., 2015). Dechow et al. (2001) found that short sellers heavily target companies with significant deterioration in their fundamentals. Kecskés et al. (2013) also demonstrated that stocks with lower credit ratings are more likely to have ratings downgraded or develop distressed situations – such stocks constitute desirable targets for short sellers. Desai et al. (2006) observed that short sellers tend to avoid small firms, a behavior that might be due to high liquidity risk and the difficulty in borrowing their stocks.

Current regulations in the U.S. relevant to activist short sellers mainly come from the Security Exchange Act of 1934. According to Section 78i, any "false or misleading statement" to facilitate stock transactions is considered "manipulation of security prices." The Act grants the SEC the power to investigate and issue severe penalties to punish anyone suspected of manipulating stock prices through a "false or misleading statement". However, the burden of proof lies with the SEC to demonstrate reasonable grounds that the short sellers were using false and misleading information to gain special advantages over transactions.

4.2.7 Financial Statement Fraud Detection

Machine-learning models have been proven effective and accurate in classifying performance (Feroz et al., 2000; Kotsiantis et al., 2006; Perols, 2011). Their decision-making process is more objective, and more data can be efficiently processed. Unlike traditional statistical models that require time-consuming and expensive manual detection, machine-learning algorithms such as logistic regression, artificial neural networks (ANN), fuzzy logic, and ensemble-based methods have more computing power and can find subtle non-linear relationships among data (Green & Choi, 1997; Lin et al., 2003; Kirkos et al., 2007; Lokanan & Sharma, 2018; Perols, 2011). Yue et al. (2007) reviewed the existing literature on machine learning applied to fraud detection before 2006 and claimed that the most researched methods of fraud detection are classification-based, which Sharma and Panigrahi (2012) and West and Bhattacharya (2015) confirmed in more recent literature reviews.

A common thread in previous research is to find indicators related to potential fraud, known as 'Red Flags' (Cecchini et al., 2010). However, Green and Choi (1997) indicated that there are no formal theoretical indicators of fraud – people usually choose some financial attributes using expert judgment but, on an ad-hoc basis. Green and Choi (1997) used 46 fraudulent and 49 non-fraudulent companies to train their ANNs to identify financial statement fraud, with five revenue-related ratios from previous audit assessments research. They obtained a 72 percent accuracy. The major limitation of their study is that the neural network is a "black box" approach providing little insight, and the researchers ignored the unbalanced nature between fraud and non-fraud companies within the sample. Summers and Sweeney (1998) used 51 fraudulent and 51 non-fraud companies to train the cascaded logit model with financial variables and obtained the same 72 percent accuracy. The main weakness of their work was the lack of out-of-sample validation. Kotsiantis et al. (2006) used Decision Trees, ANN (Artificial Neural Network), SVM (Support Vector Machines), and nearest-neighbor methods to classify 164 Greek firms (41 fraud and 123 non-fraud) with financial statement data and variables and achieved above 90 percent accuracy. However, Kotsiantis et al. (2006) did not conduct out-of-sample tests.

Hoogs et al. (2007) introduced a genetic algorithm to classify 51 fraud companies (using SEC accusation data) from 339 peers with similar industry and size (revenue) using 76 comparative financial metrics and ratios. Their genetic algorithm correctly classified 44 percent of the allegedly fraudulent companies (True Positive). Dechow et al. (2009) implemented a logistic regression model to study 293 fraud and 79,385 non-fraud cases, and their model was able to classify 70 percent of the fraud firms (True Positive) and 84.9 percent of the non-fraudulent firms (False Negative) in the testing sample. Cecchini et al. (2010) used an SVM to classify the 137 fraudulent company years and 3,187 non-fraudulent firm years using SEC restatement data from

1991 to 2000 and obtained 80 percent of fraud cases (True Positive) and 90.6 percent of non-fraud cases (False Negative) in the testing set.

Sharma and Panigrahi (2013) examined and compared data mining applications and fraud detection systems in the literature and found that Logistic Models, ANN, Bayesian Networks, and Decision Trees data mining techniques are most widely applied to provide solutions to the problems of identification and classification of fraudulent data. West et al. (2015) categorized the research from 2004 to 2015 and discovered that supervised learning tools are more frequently used than unsupervised learning tools. Albashrawi (2016) reviewed 41 financial statement fraud articles and found that Logistic Regression, Decision Trees, SVM, NN, and Bayesian Networks have been widely used (in more than 50 percent of the studies) to detect financial fraud.

There are two common problems for most of the previous machine-learning research that focused on fraudulent financial statements: missing values and sample imbalance. First, deletion is a general method to handle the missing-data samples. That is, if the financial features of a target firm are missing, researchers tend to remove incomplete sample firms, which might lead to biased or incomplete conclusions. Deletion is also the primary reason for the small number of samples used in research. Second, due to the infrequent nature of fraudulent cases, the fraud to non-fraud ratio is actually very small, and there exists a highly imbalanced problem in the real world. However, much of the previous research used a fraudulent to non-fraudulent ratio close to (1:1) (Ye et al., 2019). Therefore, small samples and unrealistic fraud ratios are the two "Achilles' heels" of otherwise excellent machine-learning results.

There is an alternative way to detect financial statement frauds, namely, using statistical properties of the reported numbers in financial statements (Sornette, 2004). Frank Benford (1938) noticed a pattern in Newcomb's (1881) dataset: that the digits 1 to 9 are not equally distributed in "natural" sets of numbers, for instance in an encyclopedia, and the lower digit numbers appear more frequently than higher digit numbers. The distribution of numbers follows the so-called Benford's law, which derives from the log-periodicity inherent in the number theory; for instance, the base-10 decimal system exhibits a log-periodicity with a preferred scaling ratio of 10 by construction (Sornette, 1998). Researchers collected 20,000 first digits from various sources, including river area, population, constants of physics, newspapers, addresses, death rates, and so on. They found that Benford's law is widespread in the natural world. Research also shows that Benford's law appears in the finance and accounting disciplines. Nigrini and Mittermaier (1997) and Guan et al. (2006) showed that Benford's law can also be used in auditing and taxation to detect "cosmetic earnings management" and accounting fraud. Kossovsky (2014) showed that Benford's Law can be applied in forensic fraud detection, tax fraud in international trade, and market collusion.

4.2.8 Asset Pricing Factors and Accounting 'Red Flags'

One way to reduce the overfitting problem is to use domain expert knowledge. The accounting literature indicates that some accounting ratios can be used to detect financial statement fraud, and asset pricing theories show that some factors can be used to construct long/short portfolios. We include these accounting models and quantitative factors in our machine-learning features.

Beneish (1999b) showed that sales growth, accruals, leverage, and so on can be used to detect financial anomalies such as earning manipulations, and he created what is now called the Beneish M-score to classify fraudulent firms. There are eight financial features that the model covers. Summers and Sweeney (1998) also demonstrated that disparities between inventories, return on assets, and so on can be used to detect financial fraud. Montier (2008) observed that firms manipulating their financial statements might have lower future earnings and expected returns. Therefore, he created what is now known as the Montier C-score, using six accounting red flags to detect earning manipulations that frequently appear in financial practices. Dechow et al. (2011) developed a fraud score (F-score) model, a more recent variant of the Beneish M-score. Their model evaluates fraudulent activities of companies in five areas: accrual quality, financial performance, nonfinancial measures, off-balance-sheet activities, and market-based measures.

To understand how activist short sellers systematically measure the financial position of fraudulent firms, we also included many well-known asset-pricing quality factors that have predictive power for expected returns and reflect corporate financial strength. For instance, Altman (1968) created a Z-Score that can be used to detect the bankruptcy risk of a business, which is calculated using financial ratios from financial statements. It is also documented that firms with higher credit risks tend to underperform their market peers in stock price return (Campbell et al., 2008; Ohlson, 1980).

Ou and Penman (1989) indicated that some financial ratios can lead to expected earnings. Sloan (1996) showed that high-accrual[154] firms are more likely to have downside earnings surprises and that low-accrual firms tend to outperform their competitors. Piotroski (2000, 2012) found that the F-score, which combines nine binary financial ratios (covering profitability, efficiency, and leverage in financial statements), can be used to construct portfolios that generate excess return. Back-testing results show that portfolios consisting of higher F-score stocks can persistently generate excess returns after transaction costs. In addition, portfolios that contain lower F-score stocks tend to underperform the benchmark. Mohanram (2005) created a G-score by comparing eight accounting ratios with the correspondent sector medians. Li and Mohanram (2019) showed that portfolios with higher G-scores tend to have more competitive advantages in relative fundamental strength and can generate excess portfolio returns. Chanos (2003) used "ROIC-WACC" (value-added economic model) to predict the Enron fraud and set up a short position against Enron and made a fortune with it. Novy-Marx (2013) showed that firms with higher gross profitability, defined as revenue minus COGS (cost of goods sold) scaled by total assets tend to outperform firms with lower gross profitability. Asness et al. (2014) combined 21 financial features to create the Quality-Minus-Junk (QMJ) factor. Their research shows that high-quality stock portfolios beat low-quality stock portfolios. We added standard accounting red flags (e.g., short-term debt as a percentage of total debt and so on) and financial ratios (e.g., ROA, gross margin and so on) to the features inputs and utilized 89 financial features for training the machine-learning algorithms.

The above accounting-related factors, ratios, and variables are well-known in the asset-pricing and accounting literature. In addition, many of the famous quantitative long/short hedge funds[155] or asset management companies use the mentioned factors to construct investment strategies, by building long or short positions based on the rankings of the stock according to those factors[156]. In the present research, we include these passive short-selling accounting factors, accounting red flags, and fraud detection models, trying to unveil some of the hidden recipes of the activist short sellers.

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[154] Sloan's Accrual Ratio is defined as: (Net Income - Cash Flow from Operating activities - Cash Flow from Investing activities) / Total Assets.

[155] Such as AQR Capital Management's core equity funds, DFA's growth funds, the Guggenheim defensive equity fund, the MSCI high-quality fund, and so on.

[156] Many of the well-known factors are used to the effect that any stock that ranks with relatively low factor loadings will be automatically shorted, while those that rank relatively high will be automatically longed by the multifactor hedge funds or financial institutions.

4.3. Data Preparation, Data Cleaning, and Features Selection

4.3.1 Data Preparation and Data Cleaning

To avoid sample bias, we chose eight well-known activist short sellers (Muddy Waters Research, GMT Research, Citron Research, Hindenburg Research, Gotham City Research, J Capital Research, MOX research, and Glaucus Research), and we manually collected the list of fraudulent firms from their websites. The fraudulent targets detected by these short sellers spanned the period from 2010 to 2020. We observed that many of the short-selling targets were shorted by more than one short-selling company, and most of their short-selling reports contained abundant evidence, strong logic, and solid reasoning. The fraud types included outright fraud, improper application of GAAP, fake businesses, inflated revenue, profit manipulations, hidden debt, fake assets, self-dealing and so on.

The goal of our research is to use training datasets to train the machine-learning algorithms so that they could be used to distinguish short-selling targets from non-fraud samples in the test set. We downloaded all of the short-sell targets' annual financial statement data from the Thomson Reuters - Refinitiv Eikon database.

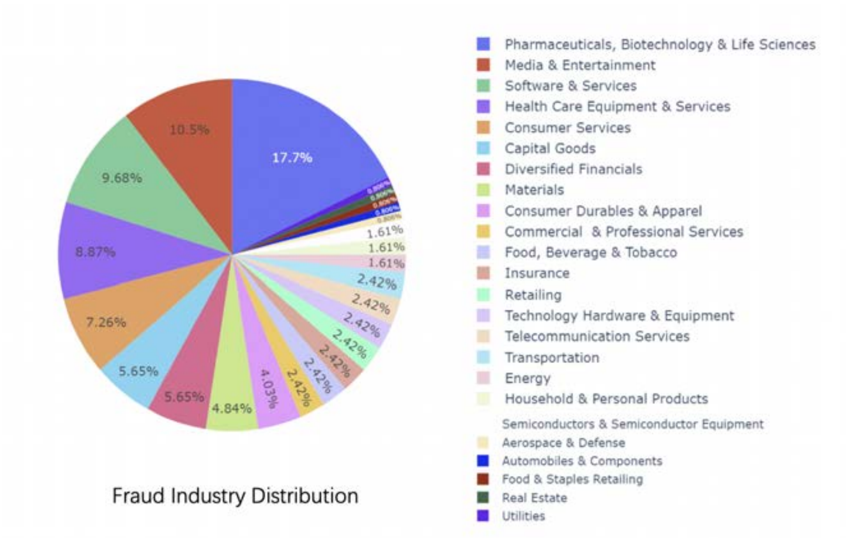

Figure 4.1. *Plot of MSCI GICS Industry Group distribution of 131 fraudulent companies. The fraudulent companies were defined by the short sellers, spanning the period 2010 to 2020. We manually collected the data from the websites of the short sellers listed in the main text.*

There are a total of 131 companies listed in the U.S. market that were reported as fraudulent by the eight mentioned short sellers from 2010 to 2020 (Figure 4.1). Some of the companies were registered as fraudulent and were shorted by one of the eight financial investigating institutions, while some were reported as fraudulent by many of the investigating institutions. Since the corporate fraud spans several years (Cecchini, et al. 2014), we assumed that all of the shorted target companies committed fraudulent activities for the whole company life. To calculate total financial ratios, we analyzed 14 years of annual financial statement data of the 131 targets from 2007 to 2020[157], and treated every individual year of the selected companies as a "company-year".

We treated huge and tiny values as outliers, in the sense that the top 1 percent and the bottom 1 percent of financial feature values were replaced by their corresponding 99 percent higher-bound and 1 percent lower-bound of the corresponding financial feature values. Infinity values were substituted with NaN (interpreted as a missing value) and treated in the same way as the missing values. Then the missing values were replaced by the dataset median value. If a company-year sample had over 40 percent of missing values, this sample was removed from the dataset.

Some shorted companies were delisted during the 2010-2020 period. We only analyzed the company-year financial data before delisting, i.e., the company-year of the short-selling targets after the delisted year was deleted due to lack of data.

After data cleaning, preprocessing, and labeling, we ended up with a dataset comprising 1,037 short-selling company-year samples and 6,305 non-fraudulent company-year samples. The ratio of fraudulent to non-fraudulent company-year data in our sample is approximately 16.5 percent. We split the original financial dataset into two parts: 80 percent of sample data for model training and validation, which included 830 short-sell targets company-year samples, and 5,044 non-fraudulent company-year samples; 20 percent of the data were set for model testing, which included 207 short-selling targets company-year samples and 1,261 non-fraudulent company-year samples. We then labeled all the company-year annual financial data of short-selling targets as "1", and we labeled company-year annual financial data of other non-fraudulent firms as "0" for machine-learning training, cross-validating, and testing purposes.

[157] For calculating financial metrics, for example the G-score, we selected the data from 2007, since some financial metrics require a time span of two to four years. However, the dataset of "company-year" in training and testing samples starts from 2010.

4.3.2 Features Selection

Based on the literature review presented in Section 2.6, we only included the financial statement data to generate accounting ratios, binary data, and other accounting factors. We include several well-known accounting models, financial scores, and red flags (as well as their corresponding ingredients), see below (also see Appendix B for more explanations):

- Beneish's M-Score for detecting earning manipulation.
- Montier's C-Score for detecting "Cooking the Books" shenanigans.
- Dechow Fraud Score for detecting financial fraud.
- Piotroski F-Score for measuring financial strength.
- Mohanram G-Score for measuring competitive advantages.
- Altman Z-Score for predicting bankruptcy risks.
- Ohlson O-Score for predicting bankruptcy risks.
- "ROIC-WACC" for measuring economic value added.
- Red flags and other accounting variables.

4.4 Methodology

4.4.1 ANOVA F-test

Before running the models, we need to reconsider the financial features. We calculate the correlations between each pair of features and built up a 'correlation matrix' based on the correlations (Figure 4.2). Each small square in the matrix represents a correlation between two variables. We can observe that there are some squares that are dark blue or dark red, representing very high or very low correlations. The reasons for this can be: (a) Some financial metrics are calculated with similar financial statement components or in a similar way (for example, Z-score-RTA and Z-Score have a very high positive correlation), and (b) there is an accordance or a trade-off between some financial metrics[158].

[158] For example, holding all other variables equal, an increase in Current Liabilities leads to a higher CLCA and a lower Z-score-NWCTA.

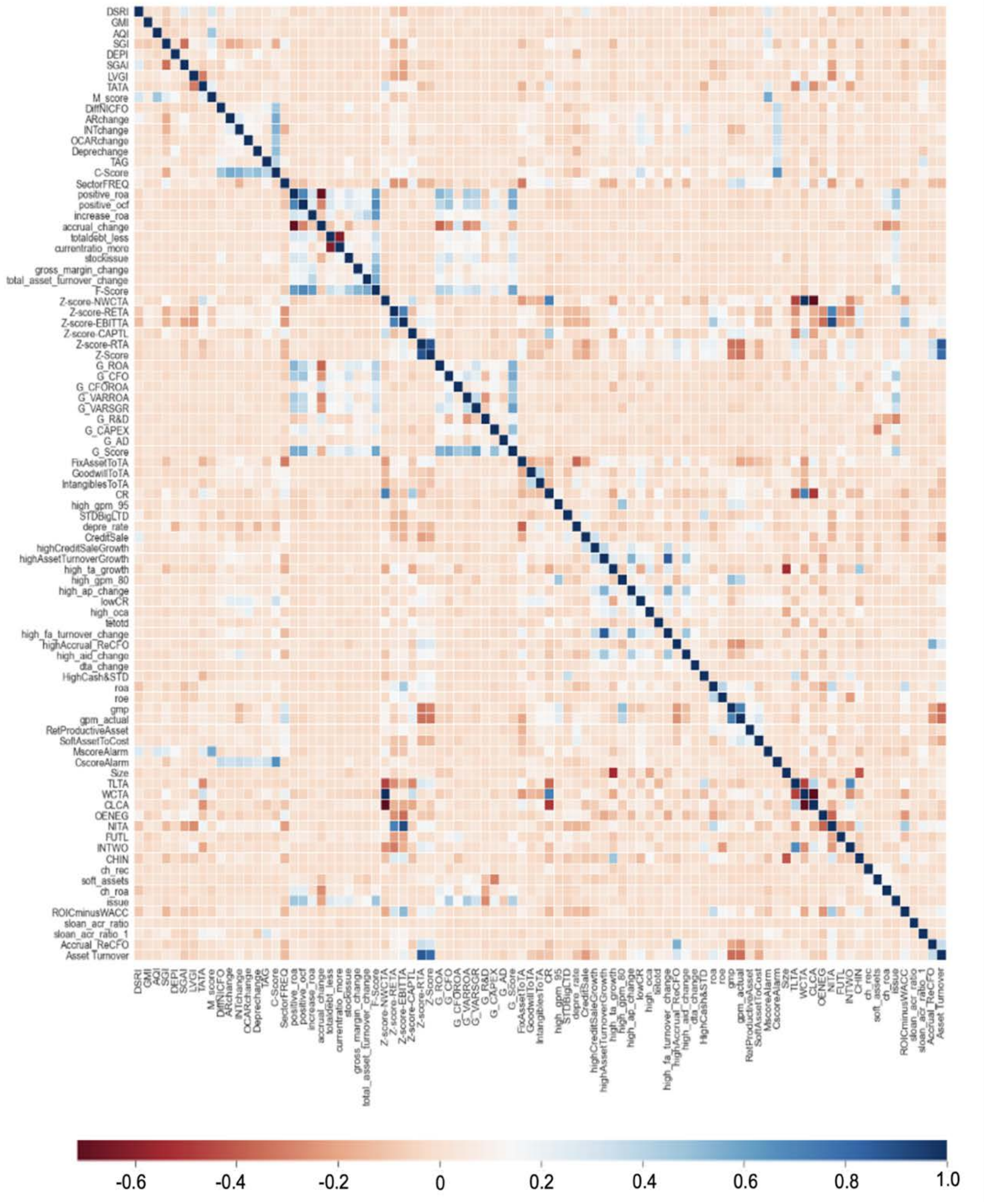

***Figure 4.2**. Correlation matrix of 81 financial features. We included all the accounting models, financial scores, and red flags, as well as their corresponding ingredients. The data range was from 2010 to 2020.*

A strong positive (or negative) correlation leads to a high multicollinearity, which can unnecessarily increase the complexity of the model with redundant features. It is preferable to have a sufficiently good model with fewer variables, we don't need to put more into our model. Another concern is that some features might not be so important for the results, that is, we need to consider the statistical significance of the features. Based on these considerations, we used the ANOVA F-test to judge the importance of the different variables.[159] ANOVA, short for "Analysis of Variance", analyzes variations between and among the group means in a particular sample (Dhal and Azad 2021). Features with larger F-test values (along with smaller p-values) have a larger significance. Following Kumar et al. (2015), the formulae of the ANOVA F-test value are summarized as:

$$Between\ sum\ of\ squares\ (BSS) = n_1(\bar{X}_1 - \bar{X})^2 + n_2(\bar{X}_2 - \bar{X})^2 + \cdots \quad (4.1)$$

$$Between\ mean\ squares\ (BMS) = BSS/df \quad (4.2)$$

$$Within\ sum\ of\ squares\ (WSS) = (n_1 - 1)\sigma_1{}^2 + (n_2 - 1)\sigma_2{}^2 + \cdots \quad (4.3)$$

$$Within\ mean\ squares\ (WMS) = WSS/df_w \quad (4.4)$$

$$F = BMS/WMS \quad (4.5)$$

where df = degrees of freedom, df_w = $(N - k)$, σ_k = standard deviation of the samples in group k, N = Number of samples, k = Number of groups, and n_k = number of samples in group k.

The test statistic F is thus calculated using formula (4.5). With the idea of univariate feature selection, we aim to find out features which are statistically significant and drop the variables with relatively small F.

4.4.2 Evaluation Metrics

Since we are constructing binary classification models, there are four possible results that our models will generate. In the cases where the activist short sellers did not short stocks, our model could either correctly predict that they are non-fraud stocks, yielding a true negative (TN), or falsely predict that these are fraud stocks, yielding a false positive (FP). In contrast, for the cases where the activist short sellers shorted stocks, our models could either correctly classify them as a short sellers' picks, yielding a true positive (TP), or falsely classify some of them as non-fraudulent companies, yielding a false negative (FN). These four results can be categorized into a 2×2

[159] In the Python package sklearn, we used the function "SelectKBest" to select k variables using the ANOVA F-test value (for classification) and selected the most significant features for our further experiments (Pedregosa et al., 2011).

contingency table, also known as a 'confusion matrix'. From the four outcomes, there are three evaluation metrics that we considered: Precision, Recall, and F1-score.

$$Precision\ (P) = \frac{TP}{TP + FP} \tag{4.6}$$

Precision thus measures the fraction of true positives among all positive samples.

$$Recall\ (R) = \frac{TP}{TP+FN} \tag{4.7}$$

Recall quantifies the classifiers' completeness.

The F1-score, often also called F1-measure, is a particular case of the F_{beta}-measure (Sasaki 2007) and is defined as follows:

$$F1\ score = \frac{2PR}{P+R} = \frac{TP}{TP+\frac{1}{2}(FP+FN)} \tag{4.8}$$

We do not include the accuracy, defined as $\frac{TP+TN}{TP+TN+FP+FN}$, because in the real world, the ratio of fraud firms to non-fraud firms is too small (less than 5 percent detected fraud cases). With such a severely imbalanced dataset, if the model classifies all firms as non-fraud, the accuracy is still around 95 percent, which generates meaningless interpretations. Some of the previous research uses accuracy as one of the evaluation metrics, which provides misleading results. The Receiver Operating Characteristics (ROC) graph illustrates the trade-off between recall and loss of specificity in the classification analysis. The discrete classifiers can be plotted as single points in a graph according to their true positive rate (TPR) and false positive rate (FPR), both of which range from 0 to 1.

Varying the decision thresholds yields a probability curve on the ROC graph, in which FPR and TPR are defined as x and y axes, respectively. According to Fawcett (2006), the ROC curve for evaluating model performance is advantageous in that the ROC curves do not change when the class distribution of the predicted targets changes.

The Area Under the Curve (AUC) is the area under the ROC curve. The AUC represents the degree or measure of separability, showing how well the model can classify the two classes. The AUC can take values between 0 and 1, and the closer the AUC is to 1, the closer the model is to a perfect classifier. In contrast, the closer the AUC is to 0, the worse the model is at separating the classes, (in fact, an AUC of 0 means that the model predicts exactly the opposite of a perfect classifier). When the

AUC is 0.5, the model cannot separate the classes and is performing at the same level that a random classifier would.

In the real world, misclassification costs (of false positives and false negatives) are different. For investors and auditors, a false negative error (misclassifying fraudulent firms as non-fraudulent firms) usually costs much more than a false positive error (misclassifying non-fraud firms as fraud firms), since a false negative will lead to substantial capital losses, or potentially disastrous litigation costs (while the cost of a false positive can be priced at the cost of the human labor needed for further investigations). Thus, recall and F1-score are the metrics that are more relevant to the goals of this paper.

4.4.3 Models Used

4.4.3.1 Logistic Regression

We use Logistic Regression, as its historical pervasiveness makes it a well-established baseline performance measure for all the other models we evaluate. Binary Logistic Regression solves the problem of translating Linear Regression predictions into a class likelihood:

$$P(c = 1 \mid x) = \frac{1}{1 + e^{a_0 - \sum_i a_i x_i}} \tag{4.9}$$

In our case, c is the outcome of a single sample and x is the data describing this sample. $P(c = 1 \mid x)$ denotes the probability of the firm being involved in fraud given the data x, while $a_i, i \in 1 \dots n$ are the underlying linear model coefficients and a_0 is its intercept. In the following steps, we denote $\sigma(x) := \frac{1}{1+e^{-x}}$ and $a^T x := \sum_{i=0}^{n} a_i * x_i$ with $x_0 = 1$ for ease of notation. To train our model, we additionally formulate the complement likelihood,

$$P(c = 0 \mid x) = 1 - \sigma(a^T x) \tag{4.10}$$

leading to the general expression for a single sample:

$$P(c \mid x) = \sigma(a^T x)^f (1 - \sigma(a^T x))^{1-f} \tag{4.11}$$

where f describes the outcome, with $f = 1$ for fraud cases and $f = 0$ for non-fraud cases. The expression for the likelihood for the model parameter vector a over the whole training dataset with m samples thus becomes

$$L(a) = \prod_{j=1}^{m} P(c = f_j \mid x) = \prod_{j=1}^{m} \sigma(a^T x_j)^{f_j} (1 - \sigma(a^T x_j))^{1-f_j} \tag{4.12}$$

It is convenient to work with the logarithm of the likelihood

$$logL(a) = \sum_{j=1}^{m} f_j * ln(\sigma(a^T x_j)) + (1 - f_j) * ln(1 - \sigma(a^T x_j)) \qquad (4.13)$$

Since we want to maximize the likelihood and, by extension, the log-likelihood, this corresponds to equating to zero for all partial derivatives with respect to the model parameters

$$\frac{\partial logL(a)}{\partial a_i} = \sum_{j=1}^{m} (f_j - \sigma(a^T x_j)) * x_{i,j} \qquad (4.14)$$

As no analytical solution is available, we solve this set of equations computationally by using, for example, gradient ascent. For this, we set the initial parameters $a_{i,t=0}$ to random values and perform the updating step

$$a_{i,t+1} = a_{i,t} + \varepsilon * \frac{\partial logL(a_t)}{\partial a_{i,t}} \qquad (4.15)$$

for a small enough ε until some predefined stopping criteria have been met. A modern implementation of Logistic Regression can be found in Logistic Regression for Data Mining and High-Dimensional Classification (Komarek, 2005).

4.4.3.2 K-Nearest Neighbors

The main virtue of the K-Nearest Neighbors method is that it does not rely on any parameter, and it needs only a few (namely k) meta-parameters, relaxing the need for tight training supervision in the training and model selection process. First expounded by Altman (1992), it builds on the idea that samples that are close together in the variable space are more likely to be part of the same class. As this method does not rely on any parameter, there is no need for a training phase to optimize them. Or put differently, training consists of saving the training data in an appropriate data structure. If, for example, $k = 1$, to predict a new sample i having the variables $x_j, j \in 1 \dots n$ with n being the dimension of our variable-space, our model looks at the one neighbor in the training set that is nearest according to a predetermined distance metric $(d: X \times X \rightarrow [0, \infty), X \in R^n)$ to this sample, and returns the class of this neighbor. The distance metric d, is used as a similarity measure (Hu et al., 2016) for different data sets.[160]

[160] Consider the feature vectors $A = (x_1, x_2, \dots, x_m)$ and $B = (y_1, y_2, \dots, y_m)$, where m is the dimensionality of the feature space. To measure the distance between A and B, one often uses the normalized Euclidean metric defined by $d(A,B) = \sqrt{\frac{\sum_{i=1}^{m}(x_i - y_i)^2}{m}}$.

However, if k is larger than one, this method might cause conflicting predictions. A simple way of resolving them is by majority vote amongst the k neighbors. In some cases, this leads to predictably problematic situations, for example, when the sample to be predicted is situated on the outcrop of a well-separated cluster, which leads to it being surrounded by out-of-class neighbors. When a prediction is arbitrated by simple majority vote, this example would result in a false classification. A way to solve this problem is by weighing the influence of the neighbors into consideration by a function that inversely relates to the distance d, for example $\frac{1}{d}$. As we used the sklearn implementation (Pedregosa et al., 2011), the execution of the method depends heavily on additional intricacies detailed in Neighborhoods Component Analysis (Goldberg et al., 2004).

4.4.3.3 Decision Trees

We included Decision Trees (Quinlan, 1993) among the models we evaluated for performance, because of their long-standing relevance (survey from 2007) that continues into present-day considerations of powerful algorithms (Sarker, 2021).

A Decision Tree is constituted by a set of decisions organized in the form of a tree. These decisions consist of several steps: first, one selects a single variable from the data, then one introduces a discriminative criterion – usually by introducing a threshold into real-valued (or integer-valued) variables or associating the samples to binary-valued variables – that splits the whole dataset into two parts. Choosing a variable can be based on various criteria; and the information gain is the most widespread one in use (Quinlan, 1986). Finally, for each part of the newly segmented dataset, one can either pick a new discriminative criterion, or stop the recursion and return a final prediction – in our case: we want to decide whether a company's stocks should be shorted or not.

Note that one might encounter the same variable multiple times along the tree. If there were no stopping criterion to the recursion, we would end up placing every single sample in a leaf node of its own, overfitting the model to the data to the maximum degree possible. A common remedy is to specify a maximum depth to the tree, a minimum-required information gain to be allowed to further split a node, or a minimum number of samples a leaf node should contain.

Predicting the class of a single sample is achieved by traversing the trained tree from the root node, comparing the sample's value of the sample variable to be predicted against the thresholds specified by the node of the decision tree, and proceeding to its child node according to the comparison outcomes. This procedure is repeated until a leaf node is reached, and the prediction returned by the model is the one specified in this leaf node.

Using Decision Trees is very useful to determine the “variable ranking”: based on the full set, we can calculate all conditional probabilities of subsets dependent on every variable. Then, we select the variable that can provide the highest purity[161] as the first binary node of the tree. We keep repeating this process to split child groups. Based on this “recursive partitioning” process, we can conclude that the most critical variable is the one placed at the root of the tree, and the further away the children’s nodes to the root, the less purity the corresponding discriminative variables have.

4.4.3.4 Random Forest

A drawback of Decision Trees is their susceptibility to overfitting. Rather than optimizing the tree hyper-parameters, one can opt for using a Random Forest instead, which gives better guarantees regarding their generalization error (Breiman, 2001).

A Random Forest combines several Decision Trees into an ensemble. If all trees were trained using the same training data, their predictions would be highly correlated, as training a Decision Tree is a deterministic process. For this reason, a process needs to be introduced that guarantees that the single predictors – the Decision Trees – behave less correlated to each other. Modern Random Forests rely on the procedure advanced by Breiman (2001), that combines bootstrap aggregation of the training samples (drawing several training samples from the whole training set), training a single tree on this selection, with variable sub-sampling (at each node split, instead of considering every variable, only a randomly selected subset of variables is considered). Note that by using bootstrap aggregation, each single tree has access to its own “cross-validation” dataset. It has been shown (Breiman, 2001) that the average scores on the out-of-bag samples serve as a robust estimate of Decision Tree performance on the test dataset.

Since straightforward prediction is hampered by the generation of multiple predictions by multiple trees, a final decision is made by the majority vote over all trees in the ensemble. Deciding on variable importance cannot be done directly, but rather uses the out-of-bag score estimate as a proxy. For each variable, the predictions on the

[161] Purity is a concept that is based on the fraction of the data elements in the classification that belong to the subset. Purity can be defined as the frequency of its most common constituent. The variables that provide the clearest divisions of subsets will be selected as the branch nodes.

training set are re-run, but with that variable replaced by random noise. If this variable contributed in any way to the predictive performance of the Decision Forest, one would expect a performance degradation, were this variable randomized. By comparing the relative performance loss of all variable randomizations, an approximation to variable importance can be constructed.

4.4.3.5 Support Vector Machines

A Support Vector Machine, or SVM, introduces a linear boundary in the hyper-space representation of the data, making it work similarly to the logistic regression model mentioned earlier. The data can be transformed to accommodate nonlinear class boundaries before finding an optimal boundary. These boundaries are found by constructing an optimal hyperplane separating positive from negative samples. This is done by minimizing the function

$$\frac{1}{2} * v^T * v \ + \ C * \sum_{j=1}^{n} \xi_j \tag{4.16}$$

where v is a normal vector to the optimal hyperplane, and C is a freely selectable penalty weight for the slack – i.e., mathematically necessary to guarantee convergence, but not a meaningful part of the final predictive model - variables ξ_j.

wrt. the constraints

$$y_j\left(v * x_j + b\right) \geq \ 1 \ - \ \xi_j \, \forall \, j \ \in \ 1 \ldots n \tag{4.17}$$

where b is a constant.

$$\xi_j \ \geq \ 0 \, \forall \, j \ \in \ 1 \ldots n$$

with

$$v_k \ = \ \sum_{j=1}^{n} {\alpha_j}^k * y_j * x_j \tag{4.18}$$

where α_i is a normal vector to the optimal hyperplane, ξ_j is a slack variable, $y_j \ and \ x_j$ are elements of input vectors y (sample class) and x (sample data).

Transforming our features into an N-dimensional vector by applying the function $\varphi: \mathbb{R}^n \ \rightarrow \ \mathbb{R}^N$, we transform all instances of x_i with $\varphi(x_i)$. This (feature-transformed) minimization problem has the dual quadratic optimization problem

$$\sum_{i=1}^{N} \alpha_i - \frac{1}{2} * (\alpha^T * D * \alpha \ + \ \alpha_{max}^2 / C) \tag{4.19}$$

wrt. the constraints

$$\alpha^T * y \ = \ 0 \tag{4.20}$$

$$D_{ij} = y_i * y_j * K(x_i, x_j) \tag{4.21}$$

where D_{ij} is an element of matrix D, and $K(x_i, x_j)$ is a function that determines the convolution of the dot-products (Cortes & Vapnik, 1995).

While the SVM does not directly give a probability estimate, a good surrogate is the distance to the decision boundary. A common amelioration is to introduce another round of training, applying logistic regression to the output of the SVM, as e.g., described by Platt (2000).

4.4.3.6 Artificial Neural Network

A neural network consists of several layers that are made up of so-called neurons, a layout inspired by early research into how the human brain might work. These neurons are (quasi-)differentiable functions that map an m-dimensional space to a scalar, where m is the dimension of the last layer. The input of each neuron generally comprises the weighted sum of the output of the previous layer, plus a bias term. The first layer of neurons gets its inputs from the data, while the last layer outputs the corresponding decision.

Training is done by iteratively propagating the input through each successive layer (feed-forward), and then comparing the output of the final layer and the pick decision via a loss function giving an error. In the second step, this error is then differentiated with respect to the weights and biases of the previous layer, which indicates the general direction of updating. These differentiations can then be done layer-wise, going from the last to the first layer (Cross et al., 1995). Different methods to implement or approximate this gradient descent exist. As the goal is to use existing implementations of well-known algorithms efficiently, the NAdam optimizer (Dozat, 2015), as implemented in Keras, was used. Since the prediction target is binary, the final layer should produce a single real scalar ranging from 0 to 1, corresponding to the probability of the sample being shorted.

4.4.3.7 Boosted Ensembles

'Boosting' works by iteratively adding a weak learner — that is, a model with relatively few parameters and a correspondingly high error rate — to the current model in combination with the intention to correct the error of the ensemble of previous weak learners. The reason for using learners with substantially high error rates is twofold: (i) to make the overall training times reasonable, the training time for a single learner has to be comparatively short; (ii) to reduce the correlations between the predictions of different learners (if the learners were more complex, the risk that their predictions are highly correlated would rise significantly, making the ensemble model less robust).

To define the learning process more formally, let m be the m-th stage of an ensemble learning process and $f_m(x)$ a weak learner, for example, ${\beta_m}^T * X_{train}$ for a linear model. Instead of fitting directly to y_{test}, one fits $f_m(x)$ to $y_{m-1} - f_{m-1}(x)$ yielding y_m (Hastie, 2017). The first working implementation described for ensembles of this kind was AdaBoost (Adaptive Boosting), using an ensemble of decision trees of height 1 (Freund, 1997).

Another implementation is offered by XGBoost (Chen & Guestrin, 2016), which belongs to the class of gradient boosting algorithms, whereas the residual between the last prediction and the outcome is differentiated to train the next predictor. LightGBM takes a similar approach (Ke et al., 2017), where the single structural difference between the two learners lies in the ways their decision trees are built. XGBoost builds decision trees level by level, while LightGBM builds them by adding single leaves.

4.3.3.8 Cross-Validation and Hyperparameters

While training the above-mentioned models, most will necessitate tuning parameters to account for the differences in the way they represent reality. The models will most likely over-fit if these parameters are adjusted according to their performance on the training dataset since many of these parameter spaces are overly rich. Therefore, the training dataset is split into n folds – such that each fold contains the same proportion of positive to negative samples, and the models, with varying parameters, are trained n times on $n - 1$ folds, while holding back the n-th fold for validation. Averaging the scores across the n folds will deliver a robust estimate of the relatively best parameter set, while greatly reducing the risk of overfitting and selection bias. See more on cross-validation in Stone (1974).

4.5 Empirical Results and Analysis

4.5.1 Results and Analysis

Figure 4.3 shows the process that we followed in our research.

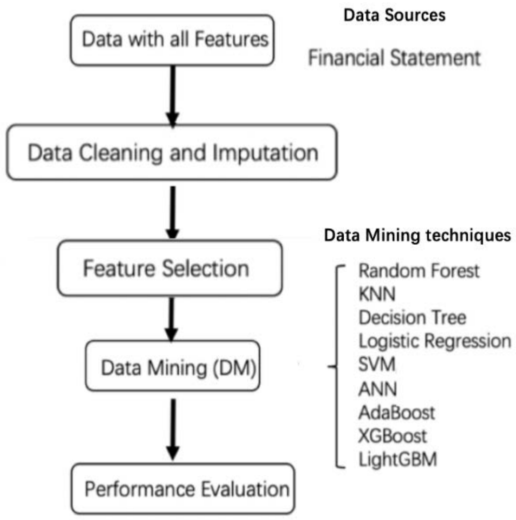

Figure 4.3. *Flowchart of our financial statement fraud detection approach step by step.*

We rank all financial features according to the variations between and among the (fraudulent and non-fraudulent) group-means detected by the ANOVA F-value. Then, we gradually add the number of financial features (from only one feature to all features according to the ranking) to train the nine machine-learning algorithms. Figure 4.3 gives the dependence of the F1-score performance as a function of the number of financial features. With more financial features added into the algorithms, the F1-score first improves rapidly and then tends to saturate, or grow slowly, beyond typically 20 features for all machine-learning algorithms. Thus, we shall use the top 20 financial features selected by the ANOVA F-value method for further investigations. The ensemble methods (XGBoost and LightGBM) are the best machine-learning algorithms among the nine methods, and XGBoost (XGB) can even reach 88 percent when using the full set of 81 financial features. The F1-score data shows that most of the nine models can obtain a reasonably accurate classification of the fraudulent and normal firms.

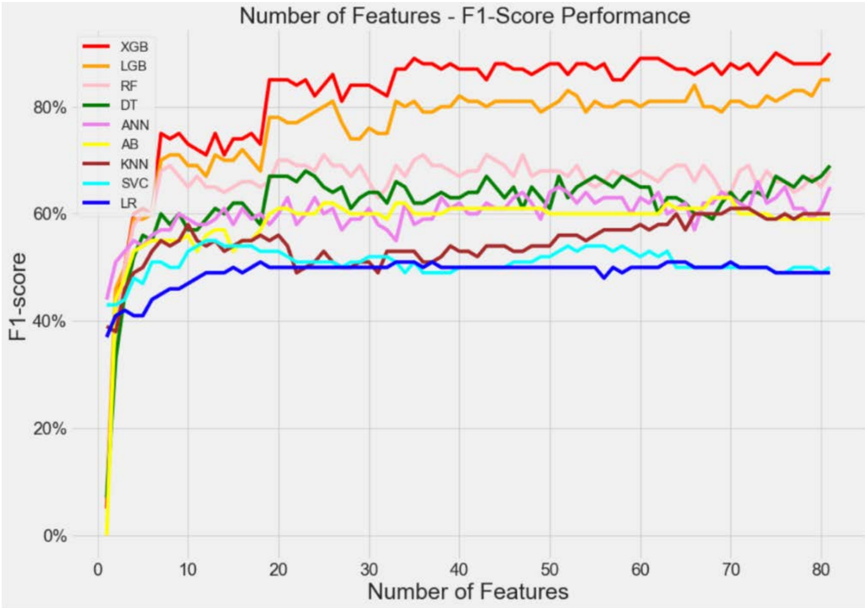

Figure 4.4. *Dependence of the F1-score Performance as a function of the number of features for the nine machine-learning algorithms. The order of features is determined according to the ANOVA F-value.*

Table 4.5 provides the scores of the nine models, which indicate that the majority of the models performed quite well with the top 20 financial features. The XGBoost (XGB) had an F1-score around 85 percent, with recall 79 percent and precision 91 percent. LightGBM (LGB) had the second highest F1-Score, around at 78 percent, with 72 percent recall and 86 percent precision. Linear Regression (LR) performed the worst among the nine algorithms, with an F1-score of 50 percent, recall 72 percent and precision 38 percent.

	Method	Accuracy	Precision	Recall	F1 Score
1	XGB	0.96	0.91	0.79	0.85
2	LGB	0.94	0.86	0.72	0.78
3	RF	0.93	0.82	0.62	0.70
4	DT	0.90	0.63	0.71	0.67
5	AB	0.90	0.68	0.56	0.61
6	ANN	0.86	0.50	0.74	0.60
7	KNN	0.90	0.72	0.46	0.56
8	SVC	0.82	0.42	0.69	0.53
9	LR	0.79	0.38	0.72	0.50

Table 4.5*. Scores of the nine machine-learning models.*[162] *A higher score value means a higher performance of the model. The values are rounded to two decimal places as a lower bound for the uncertainty that can be attributed to each score.*

Figure 4.5 shows that among the selected models, XGBoost (XGB) and LightGBM (LGB) have the highest AUC of 98 percent, while Decision Trees (DT) has the worst AUC, at 82 percent. The confusion matrices (see Appendix 4C) also confirm that many of our models can tell the difference between fraudulent and non-fraudulent firms well.

162 *Accuracy = (TP+TN)/(P+N);*
Precision=TP/(TP+FP);
Recall=TP/(TP+FN);
*F1-score =2 Precision*Recall / (Precision +Recall).*

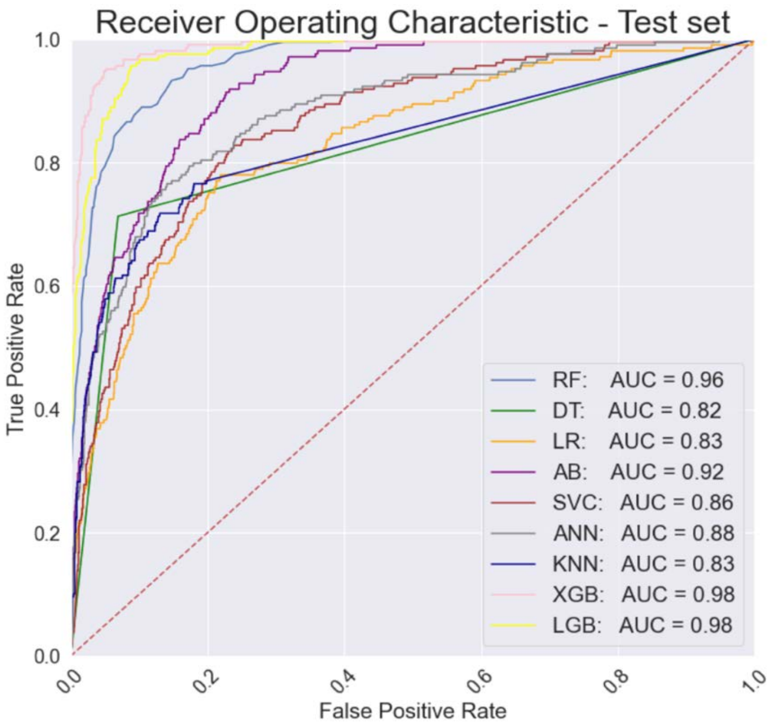

Figure 4.5. *ROC graph and AUC values based on the data of the test set for the nine machine-learning algorithms. The curves show the ROC of each model, and the AUC scores are shown at the bottom right. ROC: receiver operating characteristics; AUC: area under the curve (of ROC).*

4.5.2 Features Ranking List and Feature of Importance

It is worth identifying which features are more important in the decisions of the supervised machine-learning algorithms. Random Forest, Decision Trees, XGBoost and LightGBM algorithms have "feature of importance" functions, which can help determine which financial ratios or variables are of importance.

We selected the top 20 important features for each model, then ranked them according to their importance. Table 4.6 gives the list of feature importance for the Random Forest (RF), Decision Trees (DT), Logistic Regression (LR), XGBoost (XGB), and LightGBM (LGB) models.

	RF	DT	LR	XGB	LGB
1	FUTL	CHIN	CHIN	OENEG	ch_rec
2	ROICminusWACC	ch_rec	high_ta_growth	high_ta_growth	ROICminusWACC
3	CHIN	SectorFREQ	FUTL	lowCR	CreditSale
4	ch_rec	roa	OENEG	CHIN	FUTL
5	CreditSale	FUTL	lowCR	roa	depre_rate
6	roa	depre_rate	STDBigLTD	SectorFREQ	SectorFREQ
7	SGAI	CreditSale	depre_rate	ch_rec	Z-score-NWCTA
8	SGI	ROICminusWACC	INTWO	STDBigLTD	CR
9	depre_rate	OENEG	SGI	FUTL	SGI
10	CR	SGI	SGAI	ROICminusWACC	CHIN
11	SectorFREQ	CR	WCTA	SGAI	roa
12	WCTA	LVGI	Z-score-NWCTA	SGI	SGAI
13	Z-score-NWCTA	SGAI	ROICminusWACC	depre_rate	LVGI
14	LVGI	WCTA	MscoreAlarm	CR	high_ta_growth
15	high_ta_growth	Z-score-NWCTA	roa	Z-score-NWCTA	STDBigLTD
16	OENEG	high_ta_growth	SectorFREQ	LVGI	OENEG
17	STDBigLTD	STDBigLTD	LVGI	CreditSale	lowCR
18	MscoreAlarm	lowCR	ch_rec	INTWO	INTWO
19	INTWO	MscoreAlarm	CR	MscoreAlarm	MscoreAlarm
20	lowCR	INTWO	CreditSale	WCTA	WCTA

Table 4.6. *Ranking of the Feature Importance for five different models. The feature importance is derived by the corresponding functions in the machine-learning algorithms. The numbers in the left column show the ranks, based on which the machine-learning algorithms classify the fraud and non-fraud companies. See Appendix 4B for explanations of the features.*

From the feature importance ranking lists of the five algorithms, we can achieve a broad understanding of the machine-learning decision rules. According to Table 4.5, XGBoost (XGB) and LightGBM (LGB) are the first- and second-best machine-learning algorithms to classify the fraud and non-fraud firms in our research, with 85 percent and 78 percent F1-score performance, respectively. It is interesting that the components of Altman's Z-score, Ohlson's O-score, Beneish's M-score, and Dechow's Fraud score rank highly in all the lists, suggesting a convergence of the fraud companies' characteristics. Z-score, O-score, M-score, and Fraud-score are well-known classical leading indicators to detect financial distress or financial manipulations.

Since the XGBoost (XGB) and LightGBM (LGB) have the highest F1-score, Figure 4.6 shows the importance of each feature as determined by these two algorithms. XGBoost and LightGBM have different weightings of the top 19 features of greatest importance. It seems that the XGBoost algorithm weights more on balance sheet-related items, while LightGBM pays more attention to income statement-related items. Appendix D gives the importance of each feature as determined by Random Forest (RF), Decision Trees (DT), and Linear Regression (LR).

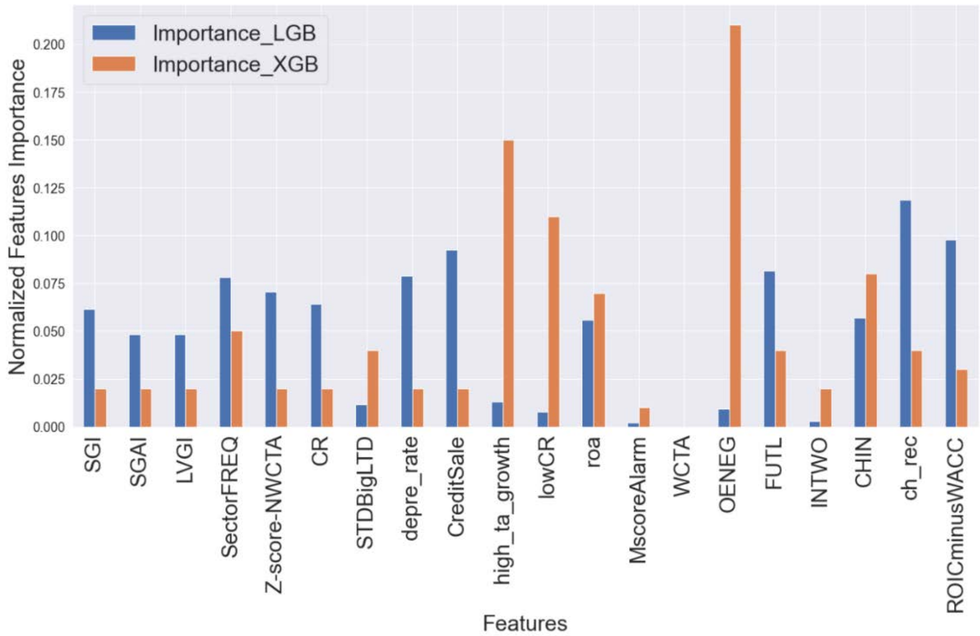

Figure 4.6. *Top 20 features of importance for the XGBoost and LightGBM models. The amplitude of each bar encodes the importance of the corresponding feature. The ranking of the features from left to right represents variations between and among the (fraudulent and non-fraudulent) group means, from highest to lowest of the top 20 features detected by the ANOVA F-value.*

The outstanding performance that we report suggests that activist short sellers may well pay special attention to 19 of the top 20 features ranked by the ANOVA F-value. The financial characteristics of these 19 financial features are described in the following section (see Appendix 4B for more detailed explanations of the financial features):

- Financial distress firms (LVGI, LowCR, Z-score-NWCTA, CR, OENEG, INTWO).
- Companies with pressure on net earnings (CHIN) and with signs of earning manipulations in some accounting items (MscoreAlarm, depre_rate).
- Firms that have fast asset growth as a proxy for acquisitions (high_ta_growth).

- Firms with inefficient asset utilization (roa) and suspicious debt structure— overly relying on short term debt (STDBigLTD).
- Businesses with low operating cash flow to cover the total liability (FUTL).
- Companies with high accruals (ch_rec, CreditSale) and high sales growth (SGI).
- Businesses in some special industry (SectorFREQ).
- Inconsistent growth in SG&A (Sales, general, and administrative expense) expenses over sales (SGAI).
- Value destruction activities (ROICminusWACC).

4.6 Polytope Fraud Theory and Unified Investor-Protection Framework

4.6.1 Polytope Fraud Theory

Based on the financial features selected by the algorithms outlined above and the contents of the activist shorts sellers' reports, we propose the Polytope Fraud Theory (PFT), indicating that fraudulent cases share many of the same financial characteristics[163]:

1. **Income statement fraud bubble**: Many companies that commit financial statement fraud aim to inflate their revenue or net earnings (higher EPS) through fake income such as high accruals[164], hidden costs or expenditure, or both. Usually, the management board of fraudulent companies intentionally fabricates sales or significantly increases credit sales, which might lead to abnormal profitability[165] compared to its industry peers. In addition, companies tend to have inconsistent revenue and net earnings patterns. Sometimes, they may have smaller dividend payout ratios [166] compared with industry peers or with their own history. Thus, investors are advised to also pay special attention to high growth companies with

[163] We summarize the ten accounting commandments as a checklist for financial analysts to judge whether a listed business has committed fraud.
[164] Due to the strict internal controls of the banking systems, it is very difficult for banks to collude with fraudulent companies in committing fraud. Thus, many fraudulent businesses record a high revenue whilst they can do little to improve real cash flow, leading to a high accrual increase or large percentage of credit sales (i.e., high accounts receivable).
[165] Fake revenue with hidden costs and expenses lead to overly high profit margins, while fake revenue and fake costs and expenses result in relatively low profit margins, compared to industry peers.
[166] If revenue is inflated and there is a lack of operating cash inflow, the discontinued dividend policies might provide some hints.

inconsistent revenue growth, rapid increases in receivables, and once-off disposal of assets, or companies with unreasonable dividend payout policy changes.

2. **Balance sheet fraud bubble**: For every fake dollar of net earnings from income, there must be somewhere to park it in the balance sheet. Thus, a long-term fraud company tends to have a swollen and 'filthy' balance sheet, leading to a small return on assets (ROA), or a suspicious debt structure, such as an over-reliance on short-term debt. Financial managers might use more than one balance sheet item (i.e., cash, accounts receivable, inventory, and so on) to hide fake net income produced from an income statement fraud bubble. However, the accumulation of fake net incomes will deteriorate some operating ratios and trigger many accounting irregularities[167].
3. **Value destruction activities**: Business is for profit. A normal business is designed to make more profit than the costs incurred undertaking the business' activities, creating positive Economic Value-Added (EVA) ($ROIC - WACC > 0$) for its stakeholders (shareholders and creditors).Therefore if a business consistently returns a low economic value ($ROIC - WACC < 0$), investors need to question the business model.
4. **Financial distress, 'Bet-on Agreement', or overreliance on financing cashflows**: Many companies falsify their financial statements to obtain gains such as stock price increases or high remunerations. In addition, companies with high leverage or low current or quick ratios tend to boost their net earnings to falsely enhance their financial statements, to obtain better credit ratings[168]. Managers of fragile businesses may only need to conduct limited fraud to significantly boost the stock price, since minimal positive signs may be enough to mislead investors. Investors should therefore pay special attention to companies that show signs of financial difficulties[169], or have 'Bet-on Agreements', or overreliance on financing

[167] There are some alarm scores that can provide insights about the accounting irregularities in both income statements and balance sheet statements, such as the Beneish M-score, Montier's C-score, Dechow's Fraud score, and so on. Investors are also advised to pay attention to items that have experienced abnormal increases.
[168] With higher credit rating, companies can raise funds more easily.
[169] Investors should compare a company's Altman's Z-score, Ohlson's O-score, interest coverage ratio, current ratio, quick ratio with other companies in the same industry to get more insights.

cashflows[170], as investing in fraud companies with fragile conditions can damage investor capital irreversibly if the company goes bankrupt.

5. **Suspicious internal transactions and self-dealing:** It is generally not easy for company management to gain assistance internally to inflate revenue, hide costs, or create fake transactions. Therefore, many company insiders create shield companies to inflate revenue or hide costs or expenses. In addition, there is a high risk that the management or controlling shareholders might conduct 'self-dealing' through internal transactions. Thus, if a large percentage of transactions are between the company and its internal parties, investors are advised to validate whether such transactions are detrimental to shareholder value.
6. **Aggressive remuneration and disconcerting corporate culture**: If (i) a company experiences unrealistic revenue or expense changes compared with industry peers; (ii) or has pressure to increase earnings growth (e.g., negative net earnings or decrease in net earnings); (iii) or has aggressive remuneration for management or employees, such as huge bonuses, large company options, and so on; or (iv) the managers of the company display 'unreasonable behavior' in public, investors should pay attention to the corporate culture. If the company leaders express the attitude of "success at any cost" or "report only good news", or are hostile to people who ask questions, the corporate culture might blind its employees or distort their ethics.
7. **Unreasonable mergers and acquisitions (M&As)**: Strategic management evidence suggests that it is challenging to generate synergy from M&As, as around 83 percent of mergers fail to produce any business benefit for shareholders (KPMG, 1999). When a company conducts frequent M&A activities without appropriate impairments or asset write-down, shareholders should be cautious about the company's strategic management goal. In addition, if the company does not conduct appropriate impairment tests or asset write-downs, investors should focus on the quality of the assets, especially reputation, goodwill, and other intangible assets. Revenue or net earnings growth created by external mergers and acquisitions cannot overcome weak internal operations over time.

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[170] Good companies rely on their operating cashflows. If a company's financing cashflow is much higher than its operating cashflow over many years, investors need to validate the cashflow against the business features.

8. **Special industries or income sources from offshore affiliates**: In some industries it is naturally easier to conduct fraudulent activities and more difficult to audit them, suggesting greater opportunity for fraudulent activities. In addition, if a firm is doing business in many foreign countries, it may be very difficult for auditors to collect and validate accurate accounting data from foreign affiliations within a limited auditing timeframe. Thus, it is easier to "cook the books" for companies doing business abroad, especially in countries with weak investor protection jurisdictions.
9. **Insiders' and auditors' behaviors**: If (i) the CEO or CFO resigns for no apparent reason, or (ii) auditors resign during the auditing period, or (iii) a rapid turnover occurs in the management team, or (iv) management has any history of illegal activity, or (v) insiders sell a large number of stocks, then investors are advised to pay special attention to upcoming financial reports. If a listed company has no internal audit department or lacks an audit committee, the company has more opportunities to commit fraud. In addition, if the auditor does not give an unmodified opinion, or resigns after auditing the accounting report, the investor should consider such behavior as an "accounting alarm"[171]. Moreover, internal management's stock-selling behaviors can be considered an indicator of insider confidence.
10. **Complex corporate structure, inappropriate accounting rules, and opaque information**: If a business has a very complex group structure (i.e., hundreds of subsidiaries or many unrelated businesses, like a conglomerate), or employs inconsistent accounting rules, or provides little detail to explain important information such as investments in affiliations, then it may be easier for the management to manipulate financial statements, because auditors have limited resources and time to validate the information.

Some of the above financial and accounting characteristics can be classified using the specific descriptions of the Fraud Diamond Theory: 4 and 5 can be regarded as "Motivation", 6 as "Rationalization", 7, 8, and 9 can be classified as "Opportunity", and number 10 can be attributed to "Capability." However, characteristics 1, 2, and 3

[171] It is litigation risk that might lead to such unusual behavior.

cannot be allocated to any of the four elements of the Fraud Diamond Theory. Thus, we propose an additional element: "Accounting Anomalies", which can describe any accounting irregularities appearing in balance sheets or income statements (characteristics 1 and 2, above), and the value destruction activities described in characteristic 3.

The Fraud Triangle Theory and Fraud Diamond Theory describe the theoretical elements of fraud. Complementarily, Polytope Fraud Theory describes the practical and detailed fraudulent activities or unreasonable behaviors that might occur in financial statement fraud. In addition, the Polytope Fraud Theory proposes a new aspect of fraud, which considers the many "accounting alarms", or red flags, that may be found in a fraudulent company's financial statements. The following case study of one of the largest bankruptcies in U.S. history, the collapse of Enron in 2000, illustrates how the PFT identifies these common financial and accounting red flags.

4.6.2 Illustration with the Case of Enron

1. **Income statement fraud bubble:** Enron created "hyper-inflated" revenues through two methods. First, it adopted mark-to-market (MTM) accounting for its wholesale energy contracts. The MTM accounting method treats energy contracts as financial derivative contracts, which can be used to overestimate future unrealized revenue based on hypothetical total net present value of the deal. However, MTM accounting also indicated that the market prices, which were used to value the unrealized gains or losses from of the financial derivatives as revenues, should "reflect management's best estimate"[172]. Second, the "Enron Online" trading platform used the so-called "merchant model" of revenue, instead of the "agent model"[173]. The "agent model" only records the brokerage fee earned from a deal as revenue, while the "merchant model" records the whole deal as its own revenue. In other words, Enron bought the financial derivatives and then resold them to its clients. The combination of the "merchant model" accounting treatment of deal

[172] Emphasis added, from Page 43 of Enron's 1998 Annual Report, found here: https://picker.uchicago.edu/Enron/EnronAnnualReport1998.pdf

[173] The major difference is that the "agent model" does not bear the risks of the asset, while the "merchant model" bears the asset risks, so it must take the asset rights. Financial institutions such as Godman Sech adopt the "agent model" since they only consider the brokerage fees of the transactions as their revenues. For example, a deal is $100, and the brokerage fee is $1. Under the "agent model", Goldman Sech only records $1 as its revenue, while Enron records $100 as its revenue and $99 as its costs, so the net profit of Enron is $1, which is around 1 percent net profit margin.

transactions and mark-to-market financial derivatives prices significantly boosted Enron's unrealized and non-cash revenues. In the short four years between 1996 and 2000, Enron's revenue surged by more than 750 percent, from 13.3 billion dollars in 1996, to $100.8 billion in 2000. In fact, from 1999 to 2000, the growth rate of revenue reached more than 150 percent. Enron ranked 7th in the world in revenue in 2000 according to Fortune Global 500 (Dharan & Bufkins, 2003)。

	1996	1997	1998	1999	2000
Revenues	$13,289	$20,273	$31,260	$40,112	$100,789
Gross Profit	$2,811	$2,962	$4,879	$5,351	$6,272
Gross Profit Margin	21.2%	14.6%	15.6%	13.3%	6.2%
Net Income	$584	$105	$703	$893	$979
Net Income Margin	4.4%	0.5%	2.2%	2.2%	1.0%

Table 4.7. *Gross profit and net profit margin of Enron, 1996-2000 (dollars in millions).*

Table 4.7 shows an opposite trend of net profit margin against rapid revenue growth from 1996 to 2000[174]. The gross margin dropped by around 15 percent from 1996 to 2000, which was mainly due to the rapid increase of the wholesale segment. The wholesale segment of Enron made little income since the net profits of the wholesale segment were only some small brokerage fees. As a result, the net profit margin declined, from 4.4 percent in 1996 to 1 percent in 2000. However, Enron's management team refused to explain why the rapid revenue growths were accompanied with low gross profit margins, which raised concerns of analysts[175].

[174] Enron Annual Reports, 1997-2000, see:
https://people.ischool.berkeley.edu/~hal/footprint/10K/Enron-1997-10-K-d.htm;
https://picker.uchicago.edu/Enron/EnronAnnualReport1998.pdf;
https://picker.uchicago.edu/Enron/EnronAnnualReport1999.pdf;
http://picker.uchicago.edu/Enron/EnronAnnualReport2000.pdf.

[175] See the report, *Is Enron Overvalued?* by Bethany McLean, Fortune Magazine: https://www.anderson.ucla.edu/documents/areas/adm/loeb/02d21.pdf.

	Logistics	Wholesale	Retails	Broadbank	Other
Segment Revenue	$2,955	$94,906	$4,615	$408	($2,095)
% of Total Revenue	2.9%	94.2%	4.6%	0.4%	NA
Operating Income (loss)	$565	$1,668	$58	($64)	($274)
% of Total Revenue	28.9%	85.4%	3.0%	-3.3%	NA
Operating Margin*	19.1%	1.8%	1.3%	-15.7%	NA

*Operating Income as % of Segment Revenue

***Table 4. 8**. Revenue and operating income by segments in 2000 (dollars in millions).*

In Table 4.8, the whole-sale segment accounted for 94 percent of the total revenue stream, while it only generated 1.8 percent of the operating margin in 2000, due to the small brokerage fee mentioned above. The most profitable business was the logistics segment, including transportations and distributions, while it only accounted for 2.9 percent of Enron total revenue. In addition, Enron reported $979 million dollars net income with $1.4 billion non-cash revenue in 2000. The rapid revenue growth alongside big non-cash unrealized gains led to low operating cash flow, which resulted in substantial negative free cash flow of operating activities. These accounting alarms show strong red flags for the Enron fraud.

2. **Balance sheet fraud bubble**: After years of accumulation of fake net incomes, Enron's balance sheet became very swollen. Thus, we can see deteriorations in some financial ratios. In table 4.9, we can see that the Return on Assets (ROA), debt level and Return on Equity (ROE) all deteriorated from 1996 to 2000. The Asset Turnover Ratio doubled during the same period, indicating the very fast increase of revenue over the total asset of Enron, which is suspicious.

	1996	1997	1998	1999	2000
Net Profit Margin	4.4%	0.5%	2.2%	2.2%	1.0%
Asset Turnover Ratio	0.82	0.90	1.07	1.20	1.54
Return on Assets	3.6%	0.5%	2.4%	2.7%	1.5%
Debt Ratio	76.9%	75.1%	76.0%	71.3%	82.5%
Return on Equity	22.6%	1.9%	10.2%	10.6%	9.5%

***Table 4. 9** Financial ratios, 1996-2000.*

In Enron's balance sheets, the item "Investments in and advances to unconsolidated equity affiliates" increased from $1.7 billion dollars in 1996 to $5.3 billion in 2000, indicating a 211 percent increase within four years. "Goodwill" soared from $ 0.87 billion in 1996 to $3.6 billion in 2000. "Other Investments" surged from $1.6 billion to $5.5 billion within the same period. Moreover, compared with other major global energy competitors (Dharan & Bufkins, 2003), Enron's Return on Assets (ROA) ranked in the bottom quantile (see Table 4.10). Fast balance sheet expansion with high leverage and low business efficiency is a clear red flag for Enron[176].

	Revenue in 2001	Profit Margin	Return on Assets
ExxonMobil	$191,581	8.0%	10.7%
BP	$174,218	4.6%	5.7%
Royal Dutch/Shell	$135,211	8.0%	10.0%
Enron (2000 data)	$100,789	1.0%	0.4%
ChevronTexaco	$99,699	3.3%	4.2%
Total Fina Elf	$94,312	7.3%	9.0%
American Elec. Power	$61,257	1.6%	2.1%
Duke Energy	$59,503	3.2%	3.9%
El Paso	$57,475	0.2%	0.2%
ConocoPhillips	$56,984	5.7%	5.1%
Petròleos de Venezuela	$46,250	7.9%	6.0%
Reliant Energy	$46,226	2.1%	3.1%
ENI	$44,637	15.5%	6.0%
Dynegy	$42,242	1.5%	2.6%

***Table 4.10**. Data from global energy companies (dollars in millions).*

3. **Value destruction activities**: In James Chanos's (2003) statement[177], he discussed the reasons why he shorted Enron stocks. A major reason he gave was that Enron's cost of capital was above 7 percent (at close to 9 percent), while its return on

[176] A group of students at Cornell University identified Enron's potential earnings manipulation in 1998 using Beneish's M-score, a statistical way to detect earnings manipulations. (For more information, see: https://pdfslide.net/documents/cornell-research-report-on-enron-1998.html). MacCarthy (2017) also confirmed that Enron's M-scores were abnormal in 1996, 1998, 1999, and 2000.

[177] The statement of James Chanos: https://www.sec.gov/spotlight/hedgefunds/hedge-chanos.htm.

invested capital was around 7 percent. The negative ROIC-WACC indicated Enron was destroying the invested capital. Thus, he had been shorting Enron stock since November 2000. In addition, based on Enron's annual reports (1996-2000), the U.S. risk-free rates for the same period, and Enron's debt structure, we calculated the Weighted Average Cost of Capital (WACC)[178] and Return on Invested Capital (ROIC) as shown in Table 4.11. We can see that the economic value-added from Enron business were close to or less than the weighted average cost of capital of Enron, indicating that Enron had not created any reasonable economic value for the stakeholders between 1996 to 2000.

	1996	1997	1998	1999	2000
Operating Income	690	15	1,378	802	1,953
Short-term & Long-term debt	6,254	6,254	7,357	8,196	10,228
Total common shares & Minority Interest & Preferred securities	5,070	7,758	3,103	13,000	14,788
Invested Capital (Debt & Equities)	11,324	14,012	10,460	21,196	27,194
Return on Invested Capital (ROIC*)	6.1%	0.1%	13.2%	3.8%	7.2%
Proxy Interest rate (10yr Bond Rate)	6.4%	5.7%	4.7%	6.4%	5.1%
Debt to Asset Ratio	76.9%	75.1%	76.0%	71.3%	82.5%
Cost of Capital	12%	12%	12%	12%	12%
Weighted Average Cost of Capital (WACC)	7.7%	7.3%	6.5%	8.0%	6.3%
ROIC-WACC	-1.6%	-7.2%	6.7%	-4.2%	0.9%

ROIC*is calculated as Operating Income as % of Invested Capital

Table 4.11 *Conservative calculations of Enron's ROIC-WACC, 1996-2000 (dollars in millions).*

4. **Financial distress, 'Bet-on Agreement', or overreliance on financing cashflows**: In Enron's year 2000 annual report, management highlighted the debt problem, emphasizing the importance of retaining an investment-grade credit rating, since it was critical to maintaining adequate liquidity[179] (Page 27 of the 2000 annual report). On December 31, 2000, Enron had around 2,112 million dollars of long-term debt matured, accounting for close to 25 percent of its total long-term debt. Thus, the urgent need to refinance the matured debt at the end of 2000 provided a strong incentive for management to maintain the debt covenants, since the debt ratio in 2000 had reached a five-year high of 82.5 percent. Thus, Enron management

[178] Enron's cost of equity was assumed to be 12 percent (Healy and Palepu 2003).
[179] Enron: 2000 Annual Report: http://picker.uchicago.edu/Enron/EnronAnnualReport2000.pdf.

created a 'Byzantine structure' to shift the debt off its balance sheet and onto its unconsolidated affiliates, i.e., SPEs (Special Purpose Entities). In addition, Enron had significant negative free cash flow from operation from 1996 to 2000 due to the non-cash revenue over the years, which means Enron had to seek substantial external capital such as equity and debt to support the operation of the business.

5. **Suspicious internal transactions and self-dealing**: Enron had hundreds of SPEs by 2001 (Healy & Palepu, 2003), many of which were used to fund the purchase of derivatives contracts with gas producers under long-term fixed contracts[180]. We noticed many suspicious internal transactions red flags in Enron's 2000 annual report: Enron used the equity method (Page 37) to treat the unconsolidated affiliates to avoid consolidation (shift the debt out of Enron), and the transactions between the corporation and the unconsolidated companies could be recorded as revenue for Enron. The annual report also revealed that it guaranteed (Page 48) and held exactly 50 percent net voting interest[181] in many of the unconsolidated affiliates, such as Citrus, JEDI, JEDI II, SK-Enron Co. Ltd, Whitewing Associates, and so on (Page 42). Moreover, Enron had some of its key employees, including its CFO Andrew Fastow, work as partners of those affiliates (Page 47), indicating that these SPEs were not independent at all.
6. **Aggressive remuneration and disconcerting corporate culture**: Enron linked the compensation of key executives to its revenue size. In proxy statements from 1997 and 2001, the pay targeting policies indicated that the pay level of the CEO and senior management should be informed by those of companies with comparable revenue size, while the bonus levels should be also informed from that of high performing companies. This indicated that the revenue size was a factor that determined the management remunerations. In addition, the proxy statement of 2001 also outlined that within 60 days of the proxy date, stock options (13 percent of common shares outstanding) were granted to the senior management team without any restrictions on subsequent sale of stocks acquired. As for its employees, Enron also implemented an aggressive renumeration system designed by CEO

[180] See Tufano (1994) for a detailed description of the structures.
[181] If the voting power is above 51 percent, then the balance sheet of the affiliates should be consolidated to Enron according to the rule of acquisition method.

Jeffrey Skilling[182]. Furthermore, analyst who questioned Enron were fired[183], and anyone who asked the management team to elaborate on the business model were blocked or ignored[184].

7. **Unreasonable mergers and acquisitions (M&As)**: Enron conducted various mergers and acquisitions from 1996 to 2000 without disclosing related information (Savage & Miree, 2003). In Enron's balance sheet, the "Goodwill" and "Other" items increased significantly. In 2000, the combination of "Goodwill" and "Other" accounted for 14 percent of Enron's total assets. In late 2001, Enron announced a series of asset write-offs: $287 million for Azure, $180 million for broadband investments, and $544 million for other investments. Later, Enron sold Portland General Corporation with a 1.1 billion-dollar loss. These buys and sells suggested that Enron had opaque and unreasonable M&A activities, and low balance sheet quality.
8. **Special industries or income sources from offshore affiliates**: To achieve further growth, Enron implemented a diversification strategy. It extended its natural gas business to the financial market, becoming a derivatives trader and market maker in the electric power, coal, steel, water, and broadband sectors. By 2001, Enron had become a global conglomerate with businesses located. In Central and South America, Eastern Europe, Africa, the Middle East, and India. In India, the Enron's Dabhol power station project was halted by the Maharashtra state government on 3 August, 1995, due to "lack of transparency, alleged padded costs, and environmental hazards" (Mehta 2000).
9. **Insiders' and auditors' behaviors**: In early 2000, $924 million dollars in shares and $1.26 billion dollars in convertible debt securities were sold by company 'insiders'[185]. Over the next 18 months, 68 of Enron's senior executives

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[182] The base salary at Enron was 51 percent higher than its peer group, bonus payments were 383 percent higher, and stock options were 484 percent higher. In addition, the bottom 15 percent quantile employees would be fired.

[183] On 21 August, 2001, Chung Wu of UBS PaineWebber expressed concerns about Enron's financial future and advised his clients to sell Enron stocks. He was fired the same day. Daniel Scotto of BNP Paribas lowered his recommendation on Enron stock on 23 August, 2001, and was fired shortly thereafter.

[184] During the 17 April 2002 Enron's conference call, Richard Grubman of Highfield Capital asked Jeffery Skilling, the CEO of Enron, to explain what the price-risk-management asset in the balance sheet is, Skilling did not provide any detailed information, and after the conversation, Skilling complained about Grubman in foul language with an unmuted Microphone.

[185] For more information, see https://ssqq.com/archive/cheatinginsidertrading.htm.

resigned[186]. On 12 February, 2001, Kenneth Lay stepped down as the CEO of Enron, but remained Chairman. On 14 August, 2001, Jeffery Skilling, Lay's replacement as CEO, unexpectedly resigned and sold almost 60 million dollars' worth of Enron shares. On 24 October that year, CFO Andrew Fastow was replaced by Jeffrey McMahon. Furthermore, in 2000, Enron paid Arthur Andersen 25 million dollars in audit fees, accounting for 27 percent of total audit fees of Arthur Andersen's Houston office. The same year Enron paid 25 million dollars in consulting fees.

10. **Complex corporate structure, inappropriate accounting rules, and opaque information**: Enron refused to explain the mark-to-market (MTM) method in detail in the financial statements and did not provide appropriate disclosure regarding merger and acquisitions activities, nor the impairment rules to test the quality of those assets. Management refused to explain the details of the price-management-asset in the balance sheets, the earnings sources, and the M&As (Savage & Miree, 2003). In addition, Enron had mysterious unconsolidated affiliates and hundreds of SPE structures (Dharan & Bufkins, 2008). Thus, analysts claimed that Enron was a "black box", and a reporter from Fortune Magazine wrote an early warning report[187] in March 2001 to raise questions about Enron's business model and valuation.

In summary, the application of the ten accounting criteria of the checklist proposed by the Polytope Fraud Theory would have allowed financial analysts to conclude with reasonable conviction that Enron had committed serious frauds before its collapse revealed their full extent. This is a case-in-point illustrating that many fraudulent cases share many of the same financial characteristics.

4.6.3 Unified Investor-Protection Framework

Borrowing the theoretical classification framework from earthquake prediction (Sykes et al., 1999), we summarize and categorize the investor protection theories and fraudulent action theories and propose the Unified Investor Protection Framework (UIPF).

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[186] For more information, see https://www.latimes.com/archives/la-xpm-2002-jan-26-mn-24913-story.html.

[187] See the report Is Enron overvalued? by Bethany McLean, Fortune Magazine: https://www.anderson.ucla.edu/documents/areas/adm/loeb/02d21.pdf.

Term	Cover Time	Scientific Theory
Long-term	Few centuries	Legal Origin Theory; Berle-Means Corporation Theory; Agency Theory, etc.
Middle-term	Decades/Years	Fraud Triangle; Fraud Diamond, etc.
Short-term	Yearly	Polytope Fraud Theory, etc.

***Table 4.12**. There are three levels of theories that relate to investor protection from a financial fraud point of view. Macro-level theories are related to the classical finance law and corporate governance theories, based on which the financial market has evolved for hundreds of years. Middle-level theories relate to financial criminology, abstracting general financial characteristics of fraudulent behaviors. Micro-level fraud detection theories summarize the associated phenomena from daily practices, which gives more detailed accounting and operating alarm signals.*

Although some of the most notorious fraud cases (Enron, WorldCom, etc.) occurred in the U.S. market, common law countries still have a generally superior investor protection system to that of civil law countries. As a plausible measure of this superiority, the average financial market capitalization to GNP ratio of the Commonwealth countries is much larger than that of civil law countries (La Porta et al., 2008).

Due to the flexibility of the common law system, common law countries have better shareholder rights protection, while civil law countries — where investors rely more on financial intermediaries such as banks to collect information and conduct financing activities, rather than direct investing — have less well-functioning financial markets (Graff, 2005). Besides, common law countries rely on the civil law system to address social problems. For instance, the U.S. SEC introduced in 2002 the Sarbanes-Oxley Act, based on the fraud triangle theory, to reinforce investor protection in the financial market, responding to failures due to financial fraud (e.g., the Enron Scandal). Chen et al. (2015) showed that the Sarbanes-Oxley Act reduces fraudulent financial reporting and increases investor protection.

No legal system is ever perfect, and there are always fraudulent behaviors occurring in financial markets. We surmise that the existence of activist short sellers complements the legal system for investor protection owing to their use of sophisticated accounting expertise to detect fraudulent listed firms. In other words, their hunting for fraudulent firms – like Batman in Gotham city – increases the risk for firms who are conducting financial fraud.

4.7 Conclusions

We have investigated the performance of various supervised machine-learning methods in detecting financial statement fraud using published accounting data. This work is the first to label companies shorted by activist short sellers (that were manually collected) and train algorithms to classify these fraud companies against non-fraud companies. This paper is also the first to combine well-known asset pricing factors (mainly used by passive short sellers such as hedge funds) with accounting red flags (from accounting expertise) in financial features selections.

Missing data is a significant issue that previous research has struggled to manage. Rather than deleting valuable short-selling target companies just because of missing values, as is generally done in other works, we have set a 40 percent threshold for company-year data, that is, we only deleted company-year data if more than 40 percent of the financial features of that financial year were missing. The missing values were completed with the dataset median to keep as many financial features as possible.

After careful reverse engineering, the algorithm was able to effectively detect the financial statement patterns of fraud firms selected by the sophisticated activist short sellers. We consider the high performance of our methods a result of the excellent accounting insights, tremendous forensic analytical knowledge, and sharp business acumen of the short sellers. Our results suggest that the leading activist short sellers use consistent fraud detection methods, demonstrating that they are selecting short-selling targets based on solid accounting rationale.

In terms of performance, we found that ensemble methods such as XGBoost and LightGBM algorithms outperformed the SVM, ANN, Logistic Regression, and other machine-learning models. Using only the top 20 financial features, the F1-score reaches 85 percent and 78 percent respectively for XGBoost and LightGBM, while for the Logistic Regression, KNN, DT, Random Forest, SVM, ANN, and AdaBoost, the F1-score ranged between 50 percent and 70 percent.

Our results imply that it could be possible to automate the processes derived from the advanced financial statement analysis skills of short sellers, which could not only improve auditing processes, but also could effectively enhance investment results, avoid ‘torpedo stocks’ in portfolio management, and find short-selling targets. In addition, the list of features of importance we collated indicates that fraud companies that might be short-selling targets share many similar financial characteristics: bankruptcy or financial distress risk, clustering in some industries, inconsistency of profitability, high accrual, and unreasonable business operations. All these characteristics are in line with existing fraud theories.

Our research highlights can be summarized as follows. (1) We have proposed the Polytope Fraud Theory (PFT), summarizing ten abnormal financial practice alarms that a fraudulent firm might trigger. (2) We proposed the Unified Investor Protection Framework (UIPF), summarizing and categorizing investor-protection related theories and fraud detection theories from the macro-level to the micro-level.

For future research, three extensions could be explored:

1. Since we only included financial statement features (mainly accounting models, ratios, and quality factors), further research might utilize non-structured texting data (e.g., annual report footnotes, management outlook, and news), valuation data (e.g., PE ratio, EV/EBIT, PS ratios, PB ratios) and alternative data (e.g., market sentiments) as complementary to the accounting data.
2. Only U.S. fraud companies shorted by global activist short sellers were investigated, so our labeled target only follows the U.S. GAAP. Researchers might add short-selling targets from Australia, the U.K., Germany, Hong Kong, Switzerland and other countries or regions that follow different accounting principles and standards (e.g., IFRS) to develop more comprehensive and universal models.
3. There are many other supervised machine-learning algorithms, and even semi-supervised, and ‘reinforcement learning’ machine-learning algorithms, that we have not tested. In addition, there are various other financial features that we also have not considered. Researchers might test different algorithms with different features as well as different fraud and non-fraud sample datasets.

4.8 Appendices

Appendix 4A: Descriptions of the financial investigating institutions and their websites, where we manually collected the fraud company list mentioned in section 4.3.

1. Muddy Waters Research, a private-owned hedge fund, is based in the U.S. and activistly conducts research while also taking positions that are in line with their research (mainly short-selling its targets). Usually, it tries to identify fraudulent public listed firms in Asia, Europe, and North America by using forensic accountants, trained investigators, and valuation experts to carry out due diligence reports, which are released online to the public. The CEO of Muddy Waters Research is Carson Block.
   Website: https://www.muddywatersresearch.com/research/.
2. GMT Research is a Hong Kong-based accounting research firm. It conducts deep fundamental accounting research on global listed firms and issues reports to uncover financial anomalies and accounting misbehavior. It issues reports to subscribing financial institutions (i.e., hedge funds and long-only investors) and does not take positions on the companies it investigates. The company is made up of a group of forensic experts led by Gillem Tulloch.
   Website: https://www.gmtresearch.com/en/about-us/hall-of-shame/?offset=0&limit=20.
3. Citron Research, a privately-owned American hedge fund, publishes online reports on listed firms that are engaged in fraud. The reports are produced by a team of forensic investigators led by Andrew Left. The company mainly focuses on the U.S. market, and not only holds long side investments, but also short sells fraudulent firms before it issues reports on its website.
   Website: https://www.citronresearch.com/.
4. Hindenburg Research, an American investment research firm, focuses on activist short-selling research, specializing in forensic financial research. It releases public reports online targeting fraud, accounting irregularities, illegal/unethical businesses, undisclosed internal transactions, etc. The company was founded by Nate Anderson.
   Website: https://hindenburgresearch.com/.

5. Gotham City Research, a diligence-based American investing firm, focuses on companies which seem to have systematic patterns of fraud, and issues a series of reports to uncover hidden wrong-doing. Based on its publication it builds long or short equity positions. Gotham City Research was founded by Dan Yu, a previous hedge fund trader.
   Website: https://www.gothamcityresearch.com/main.
6. J Capital Research, a U.S. investment advisory company, publishes research reports on public companies. While J Capital Research has expertise in Chinese markets, it also locates short-selling targets throughout the world. The company relies on its deep, independent, and quality primary research and publishes free reports to small, unaffiliated investors. The company is led by Anne Stevenson-Yang and Tim Murray.
   Website: https://www.jcapitalresearch.com/reports.html.
7. MOX Reports, a private short seller's website, focuses on reverse engineering fraudulent activities such as problematic capital structure and outright fraud. Its approach is to hunt down potential fraud and explain "exogenous elements" that drive irrational price distortions against the corporate fundamentals. Richard Pearson, an ex-investment banker and founder of the website, builds long or short positions based on his research reports published on the website.
   Website: https://moxreports.com/research-topics/
8. Glaucus Research, a U.S. investment firm, conducts investigative research on listed companies in Asia Pacific, Europe, and North America. Its team have expertise in forensic accounting, law, and investigative reporting. The firm hold long or short positions based on their research. Recently the company was separated into Blue Orca Capital, led by Soren Aandah, and Bonitas Research, led by Matthew Wiechert. Both companies focus on short selling listed fraudulent firms as per Glaucus Research's previous activities.
   Websites: https://www.blueorcacapital.com/short-activism;
   https://www.bonitasresearch.com/research/

Appendix 4B: Formulae Used for Financial and Accounting Features

Note: The positive_roa, ROE, Z-score-EBITTA, Z-score-RTA, Size, NITA, WCTA, rsst_acc, and ch_cs ratios are deleted to avoid multicollinearity due to high correlations.

Feature	Type	Formula
DSRI	Ratio	$\frac{Receivables_t / Sales_t}{Receivables_{t-1} / Sales_{t-1}}$
GMI	Ratio	$\frac{(Sales_{t-1} - Cost\ of\ goods\ sold_{t-1}) / Sales_{t-1}}{(Sales_t - Cost\ of\ goods\ sold_t) / Sales_t}$
AQI	Ratio	$\frac{(1 - Current\ Assets_t + PP\&E_t) / Total\ Assets_t}{(1 - Current\ Assets_{t-1} + PP\&E_{t-1}) / Total\ Assets_{t-1}}$
SGI	Ratio	$\frac{Sales_t}{Sales_{t-1}}$
DEPI	Ratio	$\frac{Depreciation_{t-1} / (Depreciation_{t-1} + PP\&E_{t-1})}{Depreciation_t / (Depreciation_t + PP\&E_t)}$
SGAI	Ratio	$\frac{Sales, general, and\ administrative\ expense_t / Sales_t}{Sales, general, and\ administrative\ expense_{t-1} / Sales_{t-1}}$
LVGI	Ratio	$\frac{(Long\ Term\ Debt_t + Current\ Liabilities_t) / Total\ Assets_t}{(Long\ Term\ Debt_{t-1} + Current\ Liabilities_{t-1}) / Total\ Assets_{t-1}}$
TATA	Ratio	$\frac{\Delta Current\ Assets_t - \Delta Cash_t - \Delta Current\ Liabilities_t - \Delta Current\ Maturities\ of\ LTD_t - \Delta Income\ tax\ payable_t - Depreciation\ and\ Amortization_t}{Total\ Assets_t}$
M_score	Ratio	$-4.84 + 0.92\ DSRI + 0.528\ GMI + 0.404\ AQI + 0.892\ SGI + 0.115\ DEPI - 0.172\ SGAI + 4.679\ TATA - 0.327 LVGI$

***Table 4B.1**. Beneish's M-Score for detecting earning manipulations.*

Feature	Type	Formula
DiffNICFO	Binary	1 if there is a growing difference between *net income and cash flow from operations*, 0 otherwise
ARchange	Binary	1 if *Days of Account Receivable* is increasing, 0 otherwise
INTchange	Binary	1 if *Days of Inventory* is growing, 0 otherwise
OCARchange	Binary	1 if *other current assets to revenues* is increasing, 0 otherwise
Deprechange	Binary	1 if there are declines in *depreciation* relative to *gross property plant and equipment*, 0 otherwise
TAG	Binary	1 if there is a high *total asset growth*, 0 otherwise
C-Score	Number	*DiffNICFO + RD + ID + OCARchange + Deprechange + TAG*

***Table 4B.2**. Montier's C-Score for investigating "cooking the books" activities.*

Feature	Type	Formula
positive_roa	Binary	1 if *net income before extraordinary items i*s positive in the current year, 0 otherwise
positive_ocf	Binary	1 if cash flow from operations is positive, 0 otherwise
increase_roa	Binary	1 if *net income before extraordinary items* of the current year less the one of the prior years is positive, 0 otherwise
accrual_change	Binary	1 if *cash flow from operations* is larger than *net income before extraordinary items*, 0 otherwise
totaldebt_less	Binary	1 if the firm's *leverage ratio* fell in the year preceding portfolio formation, 0 otherwise
currentratio_more	Binary	1 if the historical change in the firm's *current ratio* between the current and prior year is positive, 0 otherwise
stockissue	Binary	1 if the firm did not issue common equity in the year preceding portfolio formation, 0 otherwise
gross_margin_ change	Binary	1 if the firm's current year's *gross margin ratio (gross margin scaled by total sales)* less the prior year's *gross margin ratio* is positive, 0 otherwise
total_asset_ turnover_change	Binary	1 if the firm's current year *asset turnover ratio* less the prior year's *asset turnover ratio* is positive, 0 otherwise
F-Score	Number	*positive_roa* + *positive_ocf* + *increase_roa* + *accrual_change* + *totaldebt_less* + *currentratio_more* + *stockissue* + *gross_margin_change* + *total_asset_turnover_change*

Table 4B.3. *Piotroski's F-Score for measuring fundamental strengths.*

Feature	Type	Formula
Z-score-NWCTA	Ratio	$Working\ Capital\ _t / Total\ Assets_t$
Z-score-RETA	Ratio	$Retained\ Earnings_t\ /\ Total\ Assets_t$
Z-score-EBITTA	Ratio	$Earnings\ Before\ Interest\ and\ Tax_t\ /\ Total\ Assets_t$
Z-score-CAPTL	Ratio	$Market\ Value\ of\ Equity_t\ /\ Total\ Debt_t$
Z-score-RTA	Ratio	$Revenue_t\ /\ Total\ Assets_t$
Z-Score	Ratio	$0.012\ ZscoreNWCTA\ + 0.014\ ZscoreRETA + 0.033\ ZscoreEBITTA + 0.006\ ZscoreCAPTL + 0.999\ ZscoreRTA$

Table 4B.4. *Altman's Z-Score for predicting bankruptcy risk.*

Feature	Type	Formula
G_ROA	Binary	1 if ROA_t ≥ Industry Median ROA_t, 0 otherwise
G_CFO	Binary	1 if $\frac{Cash\ Flow\ from\ Operation_t}{Average\ Total\ Asset}$≥ Industry Median $\frac{Cash\ Flow\ from\ Operation_t}{Average\ Total\ Asset}$, 0 otherwise
G_CFOROA	Binary	1 if $\frac{Cash\ Flow\ from\ Operation_t}{Average\ Total\ Asset}$>= ROA_t, 0 otherwise
G_VARROA	Binary	1 if $ROA\ variance_t\ of\ 4\ years$<= Industry Median $ROA\ variance$ of 4 years, 0 otherwise
G_VARSGR	Binary	1 if $Revenue\ Growth\ variance$ of 4 years<= Industry Median $Revenue\ Growth\ variance\ of\ 4\ years_t$, 0 otherwise
G_R&D	Binary	1 if $R\&D_t/Total\ Assets_t$ >= Industry Median $R\&D_t$ / $Total\ Assets_t$, 0 otherwise
G_CAPEX	Binary	1 if $CAPPEX_t$ /$Total\ Assets_t$>= Industry Median $CAPEX_t$ / $Total\ Assets_t$, 0 otherwise
G_AD	Binary	1 if $Adverting_t/Total\ Assets_t$>= Industry Median $Adverting_t$ /$Total\ Assets_t$, 0 otherwise
G_Score	Number	Sum of *G1 - G8*

Table 4B.5*. Mohanram's G-Score for judging competitive advantage.*

Feature	Type	Formula
Size	Ratio	$log\ (\frac{Total\ Assets_t}{GNP_t})$
TLTA	Ratio	$\frac{Total\ Liabilities_t}{Total\ Assets_t}$
WCTA	Ratio	$\frac{Working\ Capital_t}{Total\ Assets_t}$
CLCA	Ratio	$\frac{Current\ Liabilities_t}{Current\ Assets_t}$
OENEG	Ratio	1 if $Total\ Liabilities_t > Total\ Assets_t$, 0 otherwise
NITA	Ratio	$\frac{Net\ Income_t}{Total\ Assets_t}$
FUTL	Ratio	$\frac{Funds\ provided\ by\ Operations_t}{Total\ Liabilities_t}$
INTWO	Ratio	1 if net income was negative for the last two years, 0 otherwise
CHIN	Ratio	$\frac{Net\ Income_t - Net\ Income_{t-1}}{\lvert Net\ Income_t \rvert + \lvert Net\ Income_{t-1} \rvert}$
O-score	Ratio	$-1.32 - 0.407\ Size + 6.03\ TLTA - 1.43\ WCTA$ $+ 0.0757\ CLCA - 1.72\ OENEG - 2.37\ NITA$ $- 1.83\ FUTL + 0.285\ INTWO - 0.521\ CHIN$

Table 4B.6. *Ohlson's O-Score for predicting bankruptcy risk.*

Feature	Type	Formula
rsst_acc	Ratio	$change\ in\ (\frac{Shareholder\ Equity - Pre\ Stock - \ Cash\&equivalents}{Average\ Total\ Asset})$
ch_rec	Ratio	$\frac{Change\ in\ Receivable}{Average\ Total\ Asset}$
ch_inv	Ratio	$\frac{Change\ in\ Inventories}{Average\ Total\ Asset}$
soft_assets	Ratio	$\frac{Total\ Assets - net\ PP\&E - \ Cash\&equivalents}{Average\ Total\ Asset}$
ch_cs	Ratio	*Change in (Revenue − change in Receivables)*
ch_roa	Ratio	$change\ in\ (\frac{Net\ Income}{Average\ Total\ Asset})$
issue	Binary	1 if company issued long-term debt or common and/or preferred equity, 0 otherwise

Table 4B.7*. Dechow's Fraud-score for judging financial fraud.*

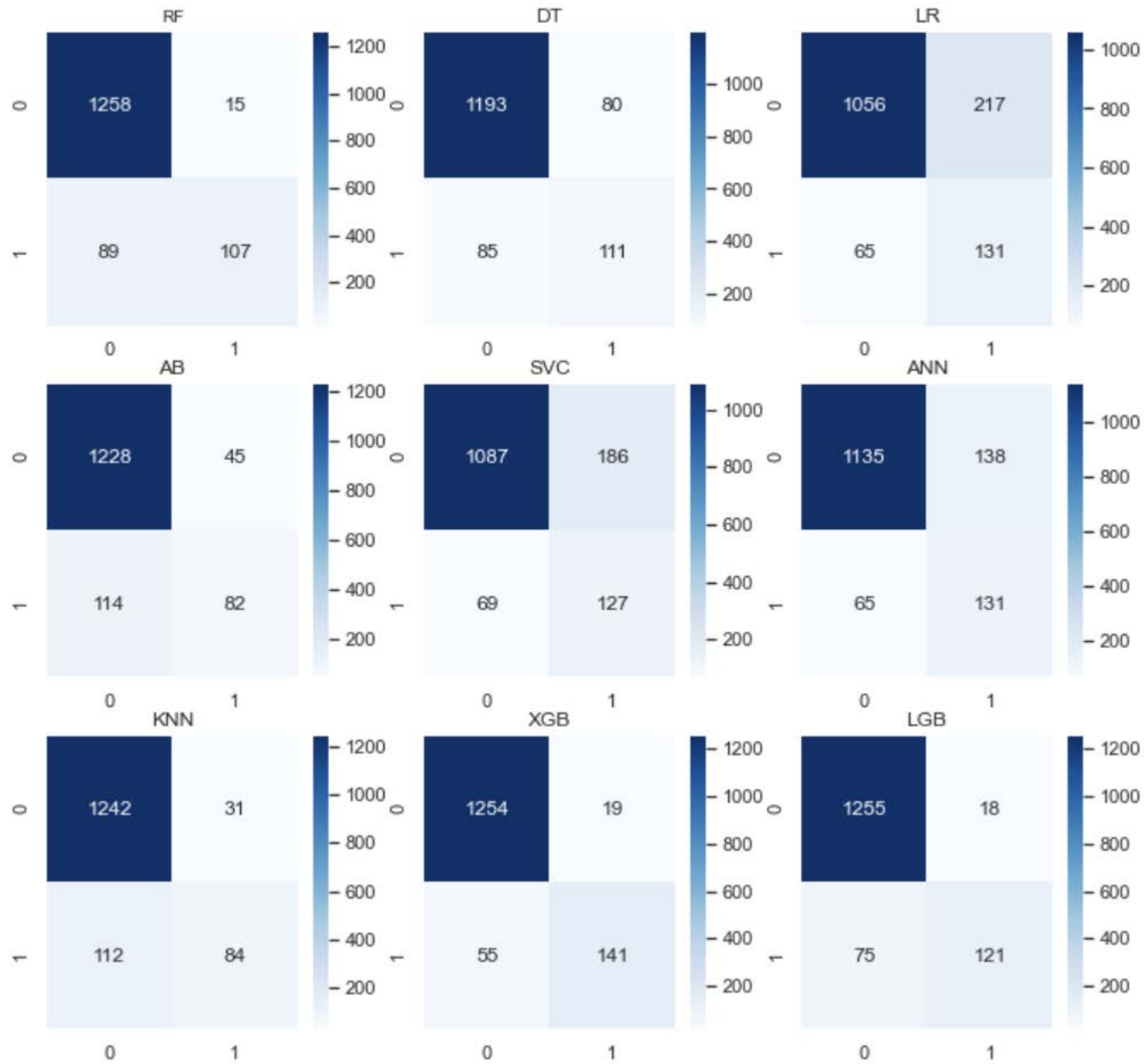
Feature	Type	Formula
SectorFREQ	Ratio	The frequency of the firm's industry appears in the list of shorted companies over the total fraudulent samples.
FixAssetToTA	Ratio	$Total\ Property, Plant\ And\ Equipment_t\ /\ Total\ Assets_t$
GoodwillToTA	Ratio	$Goodwill\ Actual\ Value_t\ /\ Total\ Assets_t$
IntangiblesToTA	Ratio	$Intangibles\ Gross_t\ /\ Total\ Assets_t$
high_gross_profit_95	Binary	1 if the *gross profit* of the firm is in top 5 percent of its industry, 0 otherwise
STDBigLTD	Binary	1 if $Short\ Term\ Debt_t\ /\ Current\ Liabilities_t$ > 0.75, 0 otherwise
depre_rate	Ratio	$Depreciation\ _t/\ (Depreciation_t\ +\ Fixed\ Asset_t)$
CreditSale	Ratio	$Net\ Accounts\ Receivable_t\ /\ Revenue_t$
HighCash&STD	Binary	1 if $Short\ Term\ Debt_t\ /\ Total\ Asset_t$> 0.15 and $Cash\&equivalent_t/Total\ Assets_t$>0.15, 0 otherwise
highAssetTurnover Growth	Binary	1 if the absolute value of *Asset Turnover change ratio* > 0.1, 0 otherwise
high_ta_growth	Binary	1 if *Total Asset Growth* > 0.1, 0 otherwise
high_gpm_80	Binary	1 if the growth of *Gross Profit Margin* is in top 20 percent of the industry, 0 otherwise
Accrual_ReCFO	Ratio	$Revenue_t\ /\ Cash\ Flow\ from\ Operation_t$
highAccrual_ReCFO	Binary	1 if $Revenue_t\ /\ Cash\ Flow\ from\ Operation_t$ is in top 20 percent of the industry, 0 otherwise

high_ap_change	Binary	1 if the absolute change of $Accounts\ Payable_t$ / $Revenue_t$ > 0.1, 0 otherwise
lowCR	Binary	1 if $Current\ Ratio_t$ < 1, 0 otherwise
highCreditSaleGrowth	Binary	1 if $Accounts\ Receivable_t$ / $Revenue_t$ > 0.1, 0 otherwise
high_oca	Binary	1 if the change of $Other\ Current\ Assets_t$ > 0.1, 0 otherwise
tetotd	Ratio	$Total\ Equity_t$ / $Total\ Debt_t$
Asset_Turnover	Ratio	$Revenue_t/Total\ Asset_t$
high_aid_change	Binary	1 if the change *of Inventory Days* > 0.1, 0 otherwise
dta_change	Binary	1 if the change of *Deferred Tax Assets* > 0.1, 0 otherwise
MscoreAlarm	Binary	1 if *M_score* exceeds -1.78, 0 otherwise
roa	Ratio	$Return\ On\ Assets_t$
roe	Ratio	$Return\ On\ Equity_t$
CscoreAlarm	Binary	1 if *C-Score* exceeds 2, 0 otherwise
gmp	Ratio	$Gross\ Margin_t$
RetProductiveAsset	Binary	1 if $Operating\ profit_t$ / $(PP\&E_t + Inventory_t)$ is in the top 10 percent quintile, 0 otherwise
SoftAssetToCost	Binary	1 if $(Total\ assets_t - PP\&E_t + Inventory_t)$ / $Cost\ Of\ Goods\ Sold_t$ in the top 10 percent quintile, 0 otherwise
ROICminusWACC	Ratio	$Return\ On\ Invested\ Capital_t - Weighted\ Average\ Cost\ of\ Capital_t$

Sloan_accruals	Ratio	$(change\ in\ Current\ Assets - change\ in\ Cash) - (change\ in\ Current\ Liability - change\ in\ Short\ Term\ Dedt - change\ in\ Tax\ Pabable) - \ depreciation$
Sloan_acr_ratio	Ratio	$(\frac{Income\ from\ Operation_t - \ Sloan\_accruals}{Average\ Total\ Asset})$
Sloan_acr_ratio_1	Ratio	$(\frac{Net\ Income_t - Cash\ Flow\ from\ Operation_t - \begin{matrix} Cash\ Flow \\ from\ Investment_t \end{matrix}}{Total\ Asset_t})$

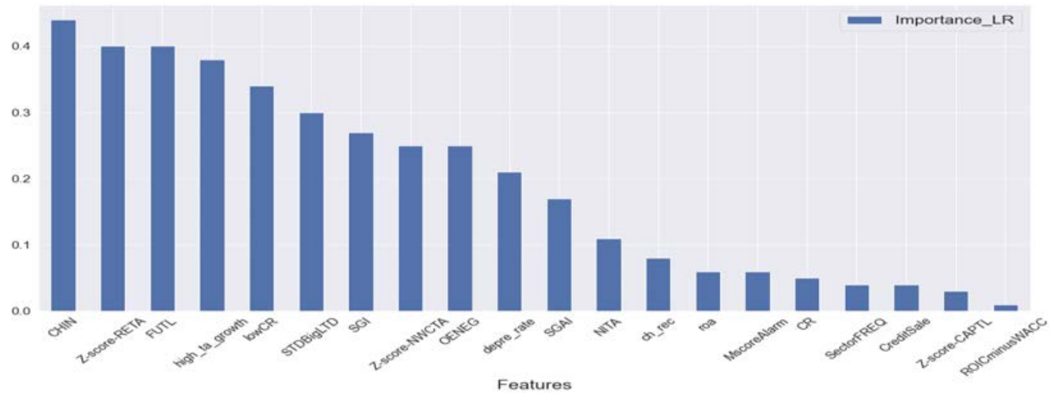
Table 4B.8. *Red flags and financial variables.*

Appendix 4C: Confusion Matrices Derived by Each Model

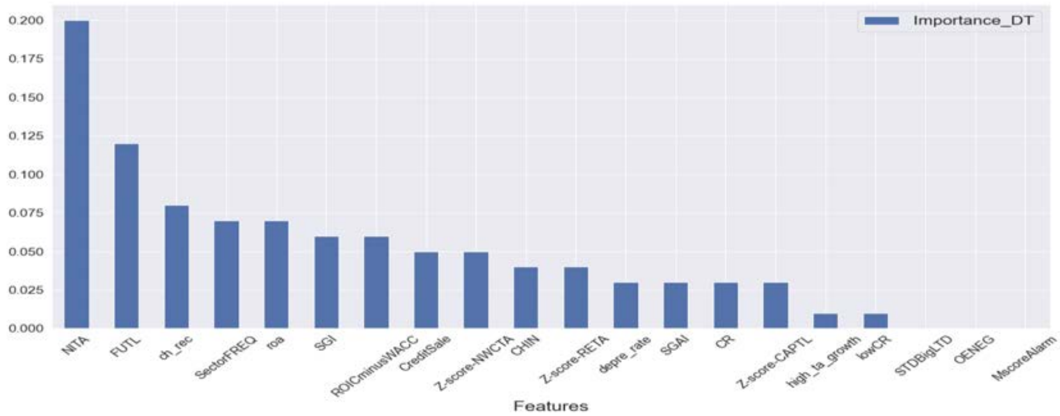


Note: For each confusion matrix, each matrix entry stands respectively for: True Negative (top left), False Positive (top right), False Negative (bottom left) and True Positive (bottom right). The number in each box stands for the number of rows in the test set.

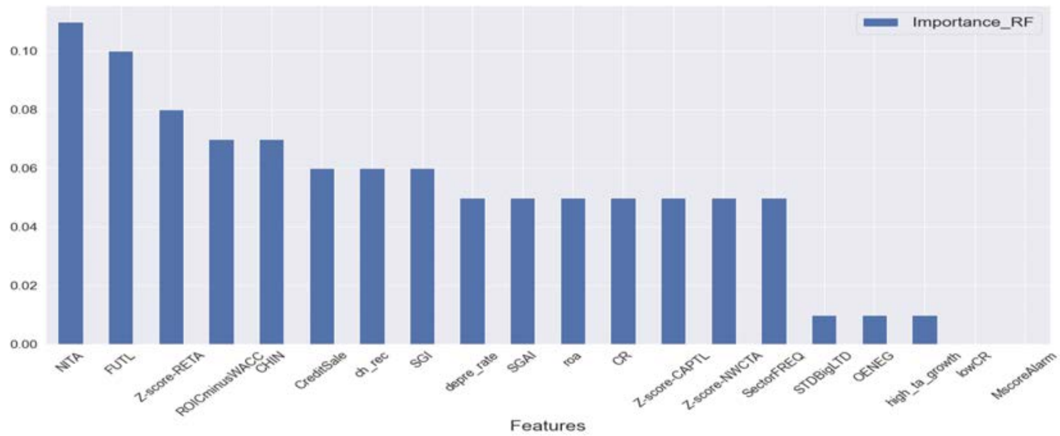
Appendix 4D: Ranked Importance of the 20 Top Financial Features



Graph 4D.1. *Importance of the top 20 features for the Logistic Regression model.*



Graph 4D.2. *Importance of the top 20 features for the Decision Tree model.*



Graph 4D.3. *Importance of the top 20 features for the Random Forest model.*

Note: These graphs are included because we believe that while the models do not show the best performances (according to the computational results), these results can be utilized as complementary material to our main results, and further hyperparameter tuning might have promising outcomes. Note that higher bars represent more important features.

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Chapter 5

Conclusion and Outlook

5.1 Summary of This Thesis

The focus of this PhD thesis is to understand the mechanisms behind economic bubbles so that we may potentially diagnose bubbles in advance. We first review the debate of market efficiency and some alternative hypothesis theories. Then, we propose a social bubble framework, which includes the financial bubbles. We further split the financial bubbles into macro and micro groups. For macro-level bubbles, we discuss the characteristics shared by all macro-level bubble-and-bust cycles and proposed the 'Bubble Triangle Theory' (BTT), which can provide guidance and a framework for financial analysts, economists, and scholars to quickly simplify the economic skeleton from complex social phenomena. For the micro-level price-related bubbles and fundamental-related bubbles, this research uses 'Log-periodic Power Law Singularity' (LPPLS) models and machine learning algorithms to identify them respectively. In addition, we define a price bubble as "super exponential price increase followed by a crash", and define a fundamental bubble as financial statement fraud bubbles that no fundamental reality can justify. Moreover, for the fundamental bubble research, we further propose the 'Polytope Fraud Theory' (PFT) and 'Unified Investor Protection Framework' (UIPF).

5.2 The Bubble Triangle

To discover the causes and features of macro-level financial bubble-and-bust cycles, we analyzed the 20 major economic bubbles in global history. We found three essential general characteristics: (1) *Disruptive Novelty* such as New Products, New Market, Changes of Economic Policies, and Catastrophe Events; (2) *Abundant Liquidity and Credit* from either domestic credit expansion, or international capital inflows—or a combination of both; and (3) *Social Bubble Spirit*. In each of the 20 major bubbles, we identified at least one of the three bubble elements. Additionally, we collected six fundamental summaries based on a detailed study of the individual cases.

5.3 Price Bubble Detection

We first utilized market-index level data to illustrate that (a) the LPPLS model is a useful market timing method and (b) the bubble that ended with the Corona Pandemic Crash during early 2020 has been diagnosed in real time, as it developed due to the endogenous processes unfolding over the preceding years. Thus, LPPLS should be a new way to understand bubble and tail risks for portfolio managers. We also proposed using dynamic risk management strategies to hedge against crash risks in the market.

To test whether price bubbles can be systematically detected *ex-ante*, we used the 'Event Study' methodology to examine the predictive power of the 'LPPLS Confidence Indicator', using industry-group level data of both the U.S. and Chinese markets. Our empirical results indicate that the LPPLS Confidence Indicator can efficiently diagnose the price regime change in real time. The results also identify two different types of bubbles, depending on the magnitude of signals: (1) a 'mild bubble' that is an *apparent* bubble and does not lead to a crash; and (2) an 'aggressive bubble' that is a *real* bubble, displaying transient faster-than-exponential ("super-exponential") price growths followed by crashes, which is a particular kind of unsustainable, irrational price movement. The bubbles end in a well-defined break of the pre-existing dynamics, which is in contradiction to Fama and Greenwood et al.'s claim (Greenwood et al., 2019) that bubbles cannot be identified in real time. In addition, negative bubbles are not symmetric to positive bubbles: the stronger the negative alarms from the LPPLS Confidence Indicators, the more volatile later price patterns will be. The research shows that investors can use the LPPLS model to efficiently detect the tail risks and avoid them. The thesis also contributes to the literature by summarizing and categorizing the bubble-related literature, including the LPPLS-related literature.

5.4 Fundamental Bubble Detection

To diagnose the fundamental bubble, we manually collected 131 fraudulent companies on the U.S. stock market, selected by eight prominent activist short sellers, spanning from 2010 to 2020. We pooled the 131 fraud targets with 623 non-fraudulent companies and select their annual financial data spanning from 2010 to 2020, and split the collected samples into a 'training set' and a 'testing set'. We then incorporated 81 financial features, including asset pricing, financial accounting, and important financial ratios according to the literature, to train nine machine-learning algorithms, and test the model outcomes. The research showed that the nine machine-learning algorithms could learn the pattern of sophisticated short sellers in judging whether a company is fraudulent or not in the testing set, using only financial statement data.

The results suggest an exciting opportunity to fully automatize the financial analysis that complements human auditing work in the future. In addition, based on our investigations and the short selling results, we summarized ten fraudulent accounting points that can be used by financial analysts to judge whether a company is conducting accounting 'shenanigans' or not. Furthermore, we use the famous Enron case to illustrate the Polytope Fraud Theory, concluding a reasonable conviction that Enron had committed severe accounting fraud before it collapsed. Additionally, based on time scale we categorized investor protection-related theories into a framework that can be a studying material for investors to diagnose the fundamental related risks and avoid them.

There are some limitations of the research. First, we have not built trading strategies that uses the LPPLS models to detect price crashes or trading strategy that implements financial fraud detection methods to avoid the "torpedo stocks". In future research, we will build robust investment methods that can help decision-makers avoid the severe economic consequences of stock price crash risks and companies' fundamental collapse risks. Second, we only tested the fraudulent cases and non-fraudulent cases that adopt the U.S. GAAP accounting policies. In future research, we need to test the accounting fraud detection methods in different countries that have different accounting rules or policies. Third, the different machine-learning algorithms have slightly different empirical result, so there might be some reasons to explain the differences. However, we have not conducted deeper research about what might cause these differences. In future research, researchers can try to uncover the reasons that lead to these differences.

This work contributes to further understanding bubble phenomena. We presented the social bubble framework, the development of financial instabilities, the financial statement analyzing summaries, and general investor-protection framework. We also introduced the idea of 'Bubblenomics' to counterbalance the defects of 'equilibrium economics' analysis and draw attention to *out-of-equilibrium* phenomena, which standard supply-demand analytical frameworks do not address. We envision this manuscript to be an interesting piece that presents new ideas to scholars and investors and reveals new directions for bubble-related research and portfolio risk management.