THE UTILIZATION OF COMPUTATIONAL SOCIAL SCIENCE FOR THE BENEFIT OF FINANCE

by

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Doctor of Philosophy
Computational Social Science

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DEDICATION

To Lora, Téa, and Jenson I dedicate this dissertation you and thank you for all your support and understanding during this journey.

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While there is an “i” is dissertation, there is almost “team” in it as well. Therefore, I would like to acknowledge a great number of people for their assistance in the preparation of this document. The list starts with my adviser and committee chair, Prof. Rob Axtell. His wealth of knowledge and openness to discuss any number of issues was a vital ingredient in not only this document but also throughout my exploration of Computational Social Science. Next, is my dissertation committee, Rick Backstaber, Andrew Crooks, and Eduardo Lopez, for all their valuable input and insights. In addition, Andrew’s guidance as the programs Graduate Coordinator and his general assistance throughout my studies was invaluable.

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LIST OF ABBREVIATIONS

Agent-based Model	ABM
American Depositary Receipts	ADR
Capital Asset Pricing Model	CAPM
Chief Executive Officer	CEO
Complex Adaptive System	CAS
Computational Social Science	CSS
Cumulative Density Function	CDF
Dow Jones Index	DJI
Efficient Market Framework	EMF
Efficient Market Hypothesis	EMH
Global Financial Crisis	GFC
Heterogeneous Interacting Agents	HIA
Independent Cascade Model	ICM
Independent and Identically Distributed	IID
Initial Public Offering	IPO
Limited Liability Corporation	LLC
Long-Term Capital Management	LTCM
Natural Language Processing	NLP
Net Present Value	NPV
Net Income	NI
New York Stock Exchange	NYSE
Overview, Design, and Details	ODD
Public Disclosure Statement	PDS
Price to Book	PB
Price to Earnings	PE
Price/Earnings to Growth	PEG
Principal Component Analysis	PCA
Probability Density Function	PDF
Research and Development	R&D
Rest of the World	ROW
Return on Invested Capital	ROI
Social Network Analysis	SNA
Standard & Poors 500	S&P500
United Kingdom	UK
United States of America	USA
United States of America Federal Reserve	The Fed

ABSTRACT

THE UTILIZATION OF COMPUTATIONAL SOCIAL SCIENCE FOR THE BENEFIT OF FINANCE

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The ability to identify the mechanisms responsible for the behavioral characteristics of financial markets has remained an elusive pursuit. Further, the precise behavioral characteristics of financial markets remains a point of contention. Some practitioners proclaim that markets are efficient and the return profile of financial assets follow a Gaussian distributed random walk, while others suggest that markets are not efficient, with returns tending to be heavily skewed and markets record instances of extreme outlying events at a rate more than what the efficient school prescribes. A feasible explanation for why financial markets behave as they do is that they are a complex adaptive system (CAS), an approach where investors and firms are considered heterogeneous interacting agents (HIA), which contrasts against the single representative agent approach utilized in the efficient market (neoclassical economic) paradigm.

Firstly, this dissertation provides an overview of the basis of the efficient market framework (EMF) before presenting the need to pursue alternative methods. The principal alternative discussed is the utilization of Computational Social Science (CSS) tools to consider financial markets as a CAS. The primary impetus for the approach is the statistical imprint of a CAS – power-law distributions – are found in asset returns and various other economic variable related to financial markets, including the distributions of shareholders and firm size. Of the various CSS tools, the remainder of the dissertation presents two agent-based models aimed at addressing a variety of research, yet with a common theme of quantifying the effects of agents placing an increased focus on short-term factors, a phenomenon known as "short-termism."

The first model considers the effects of investors forming an information network with each other in an agent-based artificial stock market. In turn, agents try and improve their investment performance by adjusting their connections; a process that involves cutting ties with those agents who provide poor quality information and connecting to the better-performing investors. The crucial elements in the model are the timeframe over which the agents consider their performance; the interval between rewiring their connections; and their tendency to follow the advice of their connections over other information sources. Through varying the effect of these elements meaningful insights into the dynamics driving the behavior of the financial markets, with the presence of even a small proportion of short-term investors being responsible for a material increase in market volatility. A similar record occurred after reducing the interval between when investors adjust their information network.

An ambition research agenda underlies the implementation of the second model. The foundation for the model stems from the growing concern that the management of publicly listed firms is becoming preoccupied with the share price of their firm, thereby placing an increased, and non-optimal, focus on their short-term earnings. To address this issue required the expansion of the existing agent-based artificial stock market approach to include many firms who have their earnings endogenously influenced by the market. To achieve the required expansion, the model has firms maintain growth expectations which they adjust after factoring in their most recent performance against those expectations and the movement in their firm's share price. Firms also must allocate their limited resources between growing sales or margins. In terms of the investors, the model considers various investment styles, with individual styles and combinations responsible for generating greater volatility in the market and more extreme adjustments by management. Before undertaking the extensions, an extensive set of data relating to the size, growth, and performance of globally listed firms was collected and assessed. Consistent with previous research, the distributions, apart from growth, were heavily skewed. The growth distributions were found to be somewhat consistent with Laplacian distributions, which is the existing growth distribution benchmark.

1 THE FOUNDATIONS OF THIS DISSERTATION

1.1 Opening Remarks

Financial markets are an integral part of the modern economy, ensuring that firms can raise capital, and investors can diversify their risks widely (Stiglitz, 1989). Financial markets refer to marketplaces where investors trade (buy or sell) financial assets, such as stocks, bonds, debt, commodities, derivatives or foreign currency. However, while there are generally agreed principles as to how these markets should operate, at times they have performed in a manner that defies any ex-ante explanation. The cost to society in terms of lost income and increased debt of these “outlying events” is enormous (Reinhart & Rogoff (2008) provide a summary of the cost of the various financial crisis that have occurred since World War II) and identifying and understanding the mechanisms responsible for the behavior of financial markets has proven to be a problematic and frustrating pursuit. The papers presented in this dissertation leverage Computational Social Science (CSS) methods to uncover the mechanisms that can provide a feasible explanation for some of the outlying behavior in equity (stock) markets.

Figure 1 illustrates various two-way relationships between the entities (denoted by the arrows); thereby, defining the bounds of the financial markets’ ecosystem. These relationships indicate the possibility that feedback mechanisms may exist between the entities, which in turn may influence the behavior of individual agents, or give rise to an emergent system wide behavior. However, the relevance of these mechanisms is a subject of much debate, with some accepted theories either denying them or giving them little credence. Sections 1.3.2.2 and 1.4.4 discusses how these feedback mechanisms vital components in considering the economy in general, or financial markets explicitly, as a complex adaptive system (CAS) – a topic which is growing in its relevance and influence. Section 1.3.2 introduces the concept of a CAS and details their specific relevance to finance economics.

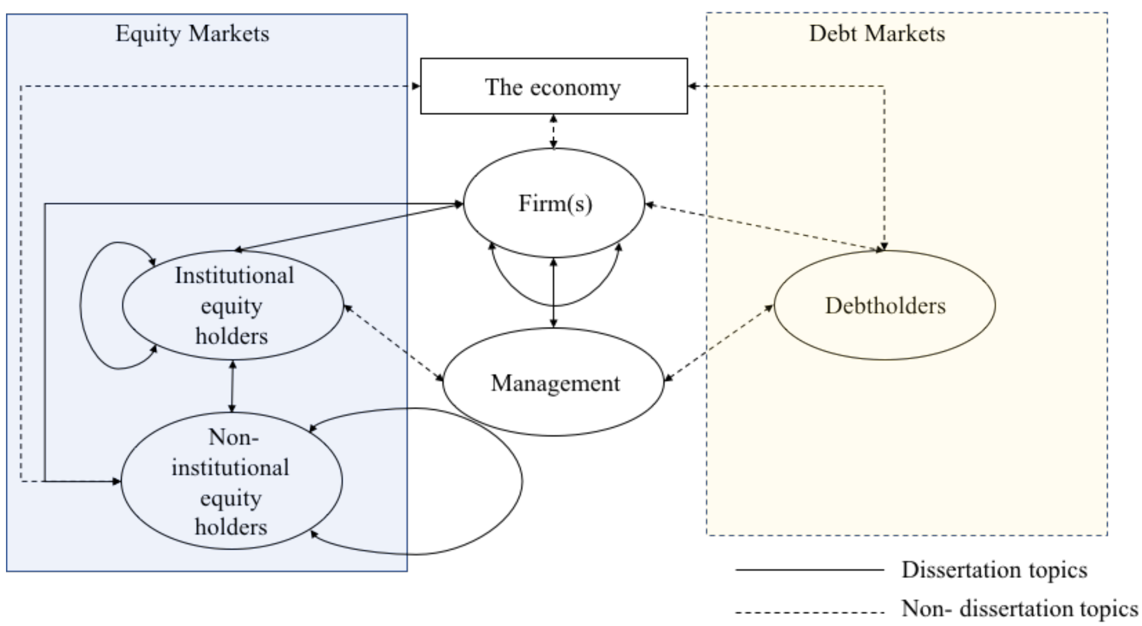

Figure 1: The financial market ecosystem

The areas of research relating to this dissertation are identified in Figure 1 by the solid feedback lines. Specially, these are the relationships between firms and investors through equity (stock) markets, firms and their management, and between investors. It is by investigating these relationships through the approaches justified in Chapters 2 and 3, this dissertation intends to meet its stated objective

The remainder of this chapter is structured in the following manner. Section 1.2 provides background regarding: the growth of finance, the role of financial markets, and how the established financial theories arose. The following section – Section 1.3 explores the need for, and growth of, interdisciplinary research, with a focus on CSS, before Section 1.4 provides more details as to how various CSS techniques – including agent-based models (ABMs) and network science – are utilized to address the research questions posed in Chapters 2 and 3. Finally, Section 1.5 provides a summary of the research papers addressing the research questions.

1.2 A Background to the Theories of Finance

1.2.1 A Brief Introduction

Given the significant amount of intellectual capital already employed in trying to understand financial markets, before exploring alternatives, the existing theories should be reviewed. This section provides such a review as well as highlighting the shortcomings that have given rise to the need to pursue alternative approaches. Section 1.2.2 describes how finance developed from a minor sub-branch of economics into a distinct discipline. Some of the vital areas that the new discipline addresses are the determination of the "correct" (or justifiable) price of financial assets, and how firms interact with shareholders. Section 1.2.3 discusses the importance of financial markets to the broader economy, especially the need for them to price assets correctly. The centerpiece of the established financial theory is the efficient market framework (EMF). Section 1.2.4 introduces the theory and, its repercussions and how it rose to become the dominant force in finance. Finally, Section 1.2.5 details the reality of how financial markets behave. The relevance of this section is that the behavior of financial markets is often outside of what the EMF predicts. Additionally, this section introduces other concepts to be utilized throughout the remaining chapters, including: how firms grow, how investors behave and evolve, and the relevance of networks to financial markets.

1.2.2 A Brief History of the Development of Finance

While the evolution of financial markets has been traced back to ancient Mesopotamia (Ferguson, 2008), the theories relating to how these markets operated remained a subset of economics until the 1950s. The behavior of financial markets and their associated instruments, for example, stocks, commodities, or options – were meant to comply with the concept of a stable equilibrium, where the demand of buyers met the supply of sellers just as with any other good or service. However, financial assets are intrinsically different from physical assets as they are a contractual claim over an asset (for example, a share is a contractual claim to share in the future profits of a firm), and do not necessarily have a tangible value. The field of finance grew in response to needing to establish a theory and process for valuing financial assets correctly, all of which were intended to aid investors maximize their investment performance. The early innovations were focused of asset pricing models, capital allocation and portfolio construction.

The standard economic approach persisted despite there being numerous episodes of investors acting with exuberant behavior on behalf of investors, resulting in the demand for financial assets materially outstripping their supply, causing a sharp increase in price (a boom) before the market corrected, or even overcorrected, causing a crash. White (2016) describes such episodes as asset bubbles, where a definition of a boom is the doubling of an asset's value (most commonly a given market) within a year, and a crash the halving of its value over the same period. Despite the progress made by mainstream finance to understand financial markets, as detailed in Section 1.2.4,there have been continued reappearances of asset bubbles and other "outlying events" that have been responsible for the loss of material economic wealth. These events are classified as outlying because they fall outside the expectations of what the newly established field of finance proposed. Section 1.2.5 details the gaps regarding how financial markets behave and what the newly established mainstream theory envisaged.

It was not as if the general behavior of financial markets did not go unnoticed by economists for example, several prominent 20th century economists published crucial insights that would later form the basis of financial theories, without specifying any formal theories. Keynes (1936) introduced the concept of "animal spirits" to describe the exuberant behavior on behalf of investors, which would later inform behavioral finance. Friedman (1953) who made the point that uninformed speculators (later these would be known as irrational traders) would be forced from foreign exchange markets because they would lose their capital to informed traders. This argument would underlie much of the EMF as discussed in Section 1.2.4.4. One exception to the lack of formal mathematical theories was Fisher (1925), who provided the mathematics required to solve for the equilibrium price of a risky asset, thus providing a framework for dealing with uncertainty in asset prices. Fisher's work was completed within the realm of economics and would eventually underwrite much of modern financial theory.

The marginalist approach remained the dominant theory within the economics of how firms and their management were meant to operate well into the 20th century. The impetus of the marginalist was to understand how markets alone operated. Within this framework, firms interact in the market to determine pricing and demand, with resources allocated to maximize net profits by setting the firm's marginal revenue equal to its marginal cost. The consequence of this approach was that the study of understanding why firms or organizations existed was nonexistent.

While the marginalist approach remains the foundation of neoclassical economics, numerous theories arose in the latter half of the 20th century that addressed why firms exist and the motivations of management and shareholders. Berle & Means (1991) provided the first work of consequence that addressed the issues and implications of the separation of ownership and control of a firm – an issue first raised by Adam Smith at the advent of limited liability corporations (LLCs). Section 1.2.4.7 details the issues relating to the ownership and control of firms. Another important work was that of Hall & Hitch (1939), which uncovered the fact that management did not operate under the rules prescribed by economic theory, but instead utilized heuristics in making management decisions. These issues underline the model presented in Section 3.

Notwithstanding the birth of finance as a stand-alone discipline having its origins in Europe, the universities and business schools of the United States of America (USA) in the 1950s were responsible for its growth. Fox (2009), MacKenzie (2008), and Lo

(2017), whose works inform Section 1.2.4.3, provide a detailed and informative description of finance's origins in probability theory dating back to the 1500s, through to Fama's (1970) Efficient Market Hypothesis (EMH). The finance theories and policy prescriptions that emerged in the 1950s, are classified under the efficient (or rational) market approach, and until recently were deemed the "generally accepted" theories of how financial markets operate. For clarity, the term EMH in this documents refers specifically to Fama's EMH, while the term efficient market framework (EMF) refers to the broad framework of research, models, and theories relating to how and why financial markets operate in an efficient manner. These terms are often used interchangeably in the financial literature. Additionally, the term rational markets implies that markets are efficient in the EMF sense. While the theories within the EMF (as described in Section 1.2.4.5) were beyond reproach, events such as the 2007 Global Financial Crisis (GFC), and the rise of interdisciplinary approaches (see Sections 1.3 and 1.4), have meant that credible alternatives are now developing and are steadily being recognized and accepted by the broader finance community.

Per MacKenzie (2008), there were three critical components to the new field of financial theory: capital structure, portfolio theory, and efficient markets. Lo (2017) proclaims the third component was the crown jewel in the theory of finance (Section 1.2.4 discusses this area in detail). From efficiency, which refers to: the informational content of asset prices and their random movement, comes the prescription that no investor can on a risk-adjusted basis outperform the market over the long-term, and prices are always right. These points have become contentious and be discussed in Section

1.2.5. In the event of the violation of efficiency, the question that underlies much of this dissertation is: how do markets operate? While this dissertation does not address the remaining components directly, the point of conjecture is that if markets are not efficient, the argument put forward in this dissertation, then many of the models and policies prescribed by remaining components are erroneous. Notably, the models developed under portfolio theory assume that the distribution of asset returns matches a Gaussian distribution, deemed by some as an assumption of convenience (Shiller, Fischer, & Friedman, 1984) to allow for the derivation of the various models. Section 1.3.2.1 discusses the presence of other possibilities, such as a power-law distribution.

1.2.3 The Role of Financial Markets

Financial markets are utilized by firms to raise capital through issuing shares, and for investors holders to diversify risk and gain exposure to potentially profitable investment opportunities. Different classes of assets including stocks(shares), debt, commodities, and derivatives trade on financial markets, with firms and investors having varying motivations for their involvement in the different markets. In general, all financial markets consist of a primary market where the issuance of financial assets occur and a secondary market where trading in those financial assets occur. This section relates solely to how firms and investors interact in the stock (share) market.

For the primary stock markets, the flow of capital from investors to a firm occurs through firms raising equity (capital) by issuing stock (also known as shares). Firms raise capital through either an initial public offing (IPO); which as the name suggests is the initial "floating" of the firm, or through subsequent capital raising, such as rights issues or share placements. Investors receive new, or additional, stock from the company – which recognizes the investors partial ownership of the company – in return for the funds they provide to the company. Public companies are those firms that raise capital through public markets, and are listed on a stock exchange (market); therefore, they are also known as publicly listed companies. Firms are also able to access capital through debt markets (the right-hand side of Figure 1). In contrast, debtholders have no direct claim of ownership in the company, although they may have claims over specific assets.

Public firms are limited liability firms, which provides a level of protection for equity holders because they are not liable for the debts of the company. If the company enters bankruptcy, an equity investor will not be required to meet the debts of the company. On the downside, the investor will lose the capital they invested in the firm. However, on the upside, an investor shares in any profits, through dividends and share price growth. Section 1.2.4.7 discusses the ramifications of this asymmetric relationship. While this dissertation does not address the primary stock markets and debtholders, investors in these markets will take pricing cues from the secondary markets, and, as discussed in Chapter 3, managements demand for incremental capital can be affected by the pricing behavior in the secondary markets.

Stock markets also facilitate the trade of the previously issued shares, via the secondary market between investors. In contrast to the primary market, the transactions in the secondary market do not directly affect the company as no capital flows back to them from the trading of their shares. However, the prices at which the shares trade provides valuable information to the management of the firm and to other shareholders. However, the importance of the price information is a source of much debate.

The primary objective of investors in the secondary market is to generate profits through buying a stock before selling it later for a higher price, and/or to collect dividends (a share of the company's profit) from the companies they trade. Traditional economic theory stipulates that through investors trading in the secondary market the equilibrium price for each company will be found. Also, under the sphere of the EMF (as expanded upon in Section 1.2.4.2), the equilibrium price of the company will be such that the net present value (NPV) of all future dividends will equal the current market value. The resulting value is known as the company's fundamental value, and if markets are efficient the market price should always match this value; that is, the "price is right." This expectation is a significant point of conjecture between those who think that markets are efficient, and those who feel otherwise. Suffice to say there have been numerous episodes where the price of companies, and the market in general, have deviated from fundamental values for extended periods. The most notorious recent example in the financial literature is the 2001 dot.com bubble (Brunnermeier, 2006). Shiller (1980) also provided evidence that shares prices movements are excessive in comparison to the earnings of companies. Section 1.2.5.1.2 provides a review of this research.

The justification for pursuing a greater understanding of the workings of secondary stock markets stems from the belief that the efficient pricing of assets is considered a desirable outcome, as price efficiency guides real decisions (Bond, Edmans, & Goldstein, 2011). The direct relevance of this is seen in stock market returns being a significant leading indicator for investment (an example of a real decision) by publicly listed companies (Barro, 1990), with the effects flowing into the broader economy. However, as discussed in Section 1.2.5, there have been periods, despite the continued argument that they are always efficiently priced (see for example an interview with Fama (Chicago Booth Review, 2016), where financial markets have not priced assets efficiently. The ramification of any phase where market prices deviate from their fundamental value for an extended period is that the economy will experience an over-or-under allocation of resources to investment, with economic growth affected. There is also a wealth effect for investors stemming from changes in the value of their investments. However, the wealth effect from changing house prices has been found to have a more significant effect on consumption (Case, Quigley, & Shiller, 2013).

Despite the previous points there is continued debate (as outlined in Bond, Edmans, & Goldstein (2011)) as to whether the secondary stock market is of actual value or merely a sideshow. Through the “financialization” of the economy (Krippner, 2005), equity markets, along with other financial markets such as derivatives, have in recent times managed to capture an unwarranted amount of attention and, more important, resources (Grilli, Tedeschi, & Gallegati, 2015). In turn, the increased allocation of resources to the financial sector has a potentially negative effect on society as it has been deemed partially responsible for the increased instability in financial markets (Grilli et al., 2015). The 2007 GFC serves as a clear example of the negative effects of “financialization.” Therefore, it has become imperative to gain an improved understanding of financial markets.

1.2.4 The Theory of Financial Markets

1.2.4.1 Economic Efficiency Versus Efficient Markets

There exists a vital link between the concept of efficient pricing (in the EMF sense) of a financial asset and economic efficiency. Bond, Edmans, & Goldstein (2011) capture the essence of the link by suggesting efficient asset pricing is desirable because it will ensure an efficient allocation of resources. The concept of economic efficiency underpins much of the justification for the implementation and acceptance of market-based economies. In general terms, economic efficiency refers to the fact that it is impossible to improve the position of one agent without lessening the position of another agent. In such a situation, resources have been optimally allocated as these is no waste; hence, the outcome is maximized for all concerned. The concept underpins many fields within economics, including welfare, trade, and competition.

Regarding the EMF, the concept of efficiency refers to the fact that an asset's current price contains all current and known information relating to it (Lo, 2017). Under this condition the future returns of assets are then assumed to follow a random–walk with their dispersion matching a Gaussian distribution (as discussed in Sections 1.2.4.2 through 1.2.5.5). Further, the more efficient the market, the more random, thus less predictable, price changes will be (Lo, 2017).

1.2.4.2 The Efficient Markets Framework (EMF) Introduced

When asked, what is the EMH, and how good a working model is it, the man responsible for it, Eugene Fama, replied: "It's a very simple statement: prices reflect all available information. Testing that turns out to be more difficult, but it's a simple hypothesis" (Chicago Booth Review, 2016). Despite the simplicity of the EMH, for the behavior of financial markets to be described in such simplistic terms took over 400 years of scientific endeavor. The hypothesis is ultimately a unique combination of a diverse selection of theories including: probabilistic models for understanding gambling; probability theory in general; the mathematizing of economics; the rise of positive economics (Friedman, 1953); and the rational expectations model (Muth, 1961). The increased availability of data aided the rise to prominence and dominance of the EMF and finance in the 1970s. However, in an ironic twist, the greater availability of data has enabled researchers to question the validity of the EMF, as discussed in Section 1.2.5.5.

1.2.4.3 Gambling and Random Walks

1.2.4.3.1 Technical Background

This section provides technical definitions for several vital concepts within the financial literature to assist the reader in gaining a greater appreciation of what the EMF implies, and what the possible shortfalls are. These concepts are: a random walk, including the geometric walk as derived by Samuelson (1965) and Osborne (1959); a Gaussian (or normal distribution); a "fat-tail" distribution; power-laws; and Brownian motion. Johnson et al. (2003) provide a detailed, and excellent explanation of these various concepts and how they relate to complexity in financial markets.

A random walk is such that for all T (the existing state) and t (the next step), the increment $Z(T+t) - Z(T)$ is independent of all previous values of Z inclusive of T. The state of the system (S_n) is then given by Equation 1. In the case of an un-bias binary event – for example, a coin toss – the expected value of S_n would be zero (assuming heads is equivalent to 1 and tails minus 1).

Equation 1: The equation defining a random walk

$$S_n = \sum_{t=1}^{n} Z_j$$

Figure 2a is provided to illustrate how a random walk evolves in a two-dimensional space, with S_x and S_y representing the two states. Starting at the coordinates, x=0 and y=0, as signified by the green dot, one of S_x or S_y is randomly chosen with their coordinates randomly increased or decreased by 1. The red cycle marks, after 1,000 iterations, the combined state of S_x and S_y. The steps executed to get there are traced out in the two-dimensional space.

The next concept utilized across the EMF is that of a Gaussian distribution (or normal distribution). The Gaussian distribution, which is a continuous probability distribution function (PDF), has several convenient properties that have seen it utilized across numerous disciplines when the population distribution is unknown. Its appeal is that its properties match closely with the central limit theorem, which states that the mean of a set of variables where the true distribution is unknown but has a finite mean and variance will tend to possess a normal distribution. Figure 2b illustrates the shape of the Gaussian distribution, with a mean of 0 and a standard deviation of 1.

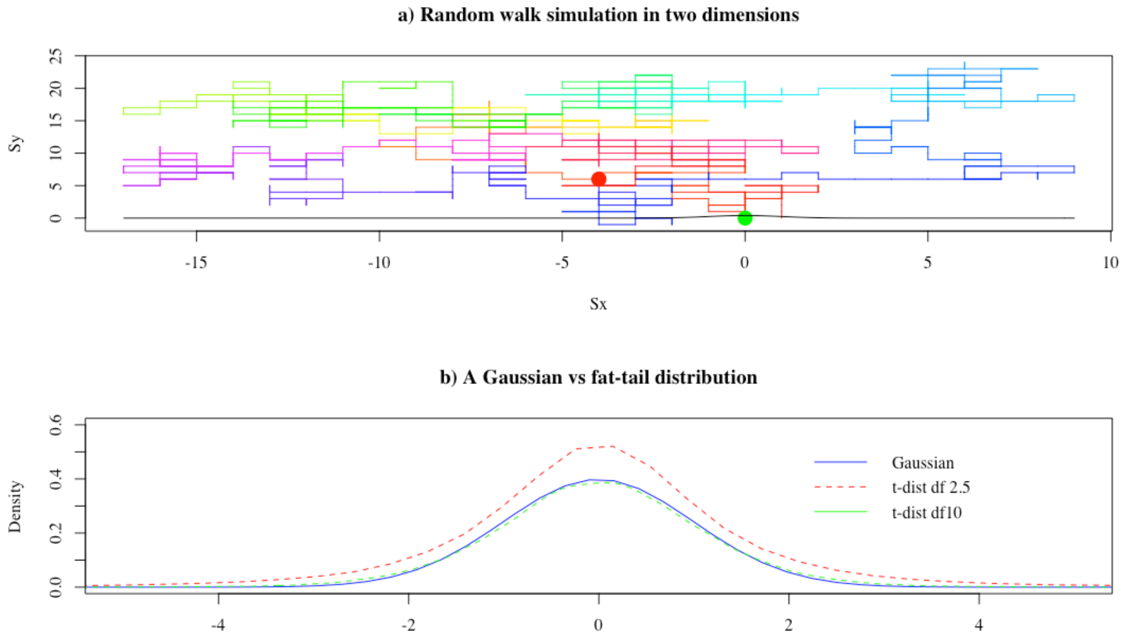

Figure 2: A random walk simulation and examples of PDFs. a) illustrates a two-dimensional random walk. Commencing at the location of the green dot, a 1 is either added or subtracted from either the x or y-axis. After 1000 steps the walk ends at the red dot. b) contrasts a Gaussian distribution with a t-distribution (a heavy-tail distribution), with 2.5 and 10 degrees of freedom.

The convenient properties of Gaussian distribution include: it is symmetric about its mean, thereby ensuring the mean, mode and median are equal; the area under the curve is equal to 1; within 1 standard deviation either side of the mean, 68% of the population is within the probability distribution; and within 2 (3) standard deviations 95% (99.7%) of the population is within the probability distribution. Further, the mean and standard deviation are assumed to be stable. The standard deviation is of particularly importance to finance as it is (as new approaches to financial modeling emerge, “is” is slowly becoming “was”) seen as the crucial measure of risk, in that it captures the extent by which an asset’s return can deviate from its mean. The first person to link the standard deviation of an asset’s return to its risk was Markowitz (1952) with his modern portfolio theory (MPT). Within this framework, an asset(market) with a higher standard deviation is considered riskier than one with a lower standard deviation, and therefore investors should be compensated with a higher expected return.

It is the assumption of returns matching a Gaussian distribution that provides one of the greatest contentions regarding EMF. At the heart of the issue is that a Gaussian distribution requires the observations to be independent and identically distributed (IID), which as discussed in Section 1.2.5.1 does not seem to match the reality of financial markets. The direct implication of assuming a Gaussian distribution is that the probability of an extreme/outlying event, such as the 1987 crash, is minuscule (1 in 50 billion) (Mandelbrot & Hudson, 2006).

The term "fat-tails" relates to a PDF where the area under the curve in the tails is greater than a Gaussian distribution. A common example of a fat tail is t-distribution with low degrees of freedom, noting that as the degrees of freedom for a t-distribution increase it becomes a closer approximation for a Gaussian distribution. Figure 2b highlights this point, with t-distributions with 2.5 and 10 degrees of freedom shown. By having a greater area in the tails, the PDF recognizes the higher probability of a large loss or gain occurring. The failure of modern financial practitioners to understand the risk in the tails of asset returns, even when including the use of t-distribution, has been a catalyst for the need to find alternate approaches and models to assess financial markets.

Numerous distributions exist that exhibit a broad distribution of data. The most extreme example is a power-law. Equation 2 provides a general definition of a power-law, where: $x > 1$ and α are constants; α is the power-law exponent and determines the length of the tail; and K is typically a non-material constant. A defining characteristic of a power-law is its scale invariance; that is by scaling *x* by the constant *K*, there will be a proportional scaling of the function *f.* This fact gives rise to the scale-free behavior, which means that the same mechanism is present across a range of scales and orders of magnitude. Figure 3a – with data generated through a user defined model, illustrates the characteristic of a power-law where the heavy-tail extends along the horizontal axis corresponding to underlying or extreme events.

Equation 2: The classical form of a power-law

$$f(x) = Kx^{-\alpha}$$

Within the power-law literature, there are two forms of the distribution function the continuous, and the discrete. The most well-known continuous form is the Pareto distribution. The basis of the Pareto distribution is that it provides the probability of observing an event greater than *x*; that is, it provides the cumulative distribution function (CDF). Specific to a Pareto distribution, the probability of the number of events greater than *x* is an inverse power of *x*. There is also a continuous PDF form of a power-law. The relevance of the continuous PDF is that it provides the expected number of observations meeting a specific condition. Within this form the probability of an event decays as a negative power of the event. In this instance, the scaling exponent is essential because it determines both the likelihood and size of the event.

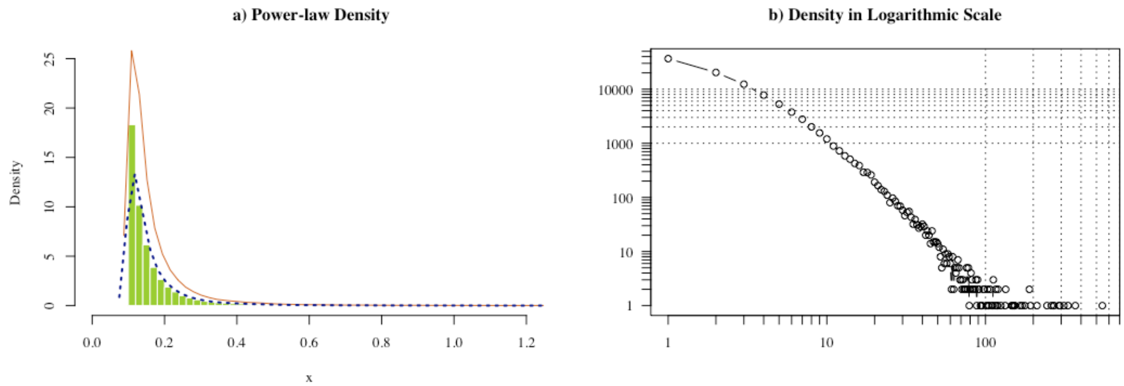

Figure 3: Illustration of a power-law distribution. a) illustrates the untransformed distribution, with b) illustrating how the distribution becomes linear after a log-log transformation. Source: user defined query.

In contrast, Zipf's (1949) law links the probability of observing a phenomenon – firm and city size and word count are classic examples – with its position within all observations of interest; that is, the observations rank. Therefore, per Zipf's law, the size of the *r'th* largest occurrence of a specified observation is inversely proportional to the rank's cumulative frequency (Delli Gatti et al., 2005).

Another characteristic of a power-law is that the function becomes linear following a log-transformation. More specifically, following the transformation it takes the form of Equation 3, where the exponent α produces a straight line with a slope of - α on a log-log plot. Figure 3b illustrates the corresponding log transformation from the data used in Figure 2a. Regarding finance, the distributions of asset returns typically match power-law characteristics in the tail of the distribution (Botta, Moat, Stanley, & Preis, 2015). Another implication of a CAS is that the coefficient in Equation 3 is stable and the intercept changes very slowly (Delli Gatti et al., 2005).

Equation 3: The log-log transformation of a power-law

$$\log f(x) = -\alpha \log x + \log K$$

The following equations (Equations 4-7) provides the interpretation of the random walk process and how it relates to financial assets. Equation 4 defines the gross return of an asset (R_t) over the period *t*. The return is the price of the asset at the *t* (P_t) divided by the price of the asset at *t-1* (P_{t-1}).

Equation 4: The calculation of the gross return for period*(t)*

$$1 + R_t = {}^{P_t}/_{P_{t-1}}$$

Equation 5 illustrates how to calculate the gross return if an asset over *k* periods. The gross return for *k* time periods is the product of the *k* single-period gross returns (from time $t - k$ to time *t*).

Equation 5: The calculation of the gross return over *k* periods

$$1 + R_t(k) = (1 + R_t) \dots (1 + R_{t-k+1})$$

By utilizing log laws, Equation 5 can be simplified as per Equation 6. The advantage of using log returns is that it allows the *k*-period log return ($r_t(k)$)to be the sum of the single-period log returns.

Equation 6: The calculation of log returns over *k* periods

$$r_t(k) = \log\{1 + R_t(k)\} = r_t + r_{t-1} + r_{t-k+1}$$

The final step is to make certain assumptions regarding the distribution of the returns. By invoking the assumption that returns are IID in a normal fashion the price of the asset (P_t) is distributed in a log-normal manner, with P_t given by Equation 7.

Equation 7: Determining the price at time *t* if the asset follows a random walk

$$P_t = P_0 * \exp(r_t + r_{t-1} + r_1) \ where\ k = t$$

Brownian motion is the theory that explains the motion of particles suspended in a fluid (a liquid or a gas) that results following their random collision with the molecules of the given fluid (MacKenzie, 2008). The motion that the particles take is one of a random walk in continuous time, where the dispersion of their movements matches a Gaussian distribution. The recognition for solving the problem of Brownian motion mathematically, as detailed in Section 1.2.4.3.2, generally goes to Albert Einstein, but the solution was first put forth with regards to financial markets by Bachelier ([1900] 2006).

Figure 4 illustrates the essence of Brownian motion and how it relates to financial assets. Figure 4a shows the result of simulating the returns of an asset over 100 days with the following characteristics: a mean return of 10% per annual with the standard deviation of the return being 25%. While some simulations have produced high and low returns, the resulting histogram (Figure 4b) displays the resulting symmetric distribution at the end of 100 days, with the expected price change being negligible. Further, the data is fitted with a density function (the blue curve), which is very close to the theoretical normal distribution (the red curve) given the previous parameters. While Figure 4 captures the essence of a random walk in financial markets, the history as to how and why it became the dominant theory in finance follows in Section 1.2.4.3.2.

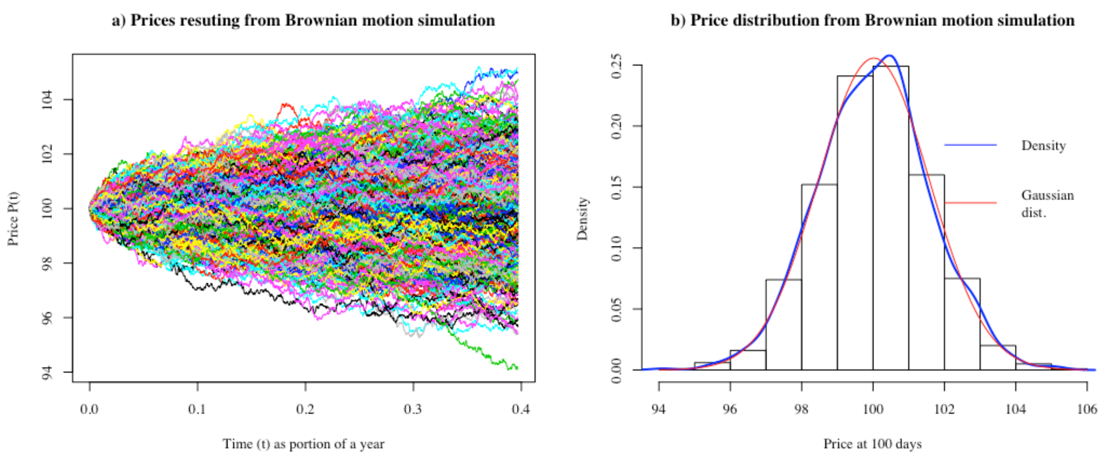

Figure 4: An illustrative Brownian motion simulation. a) illustrates the result of the Monte Carlo simulation over 100 days of a Brownian motion process. b) is the resulting histogram of asset prices at the end of the 100 days.

1.2.4.3.2 A Condensed History of Finance and Efficient Markets

The first step in getting to Fama's 2016 eloquent statement (see Section 1.2.4.2) regarding the behavior of markets was to establish a quantitative framework capable of capturing the behavior of financial markets. According to Lo (2017), the first step in this process originated in the 1560s with the establishment of the notion of a fair game (known more generally as a *martingale*) by Cardano ([1663] 2015). Gambling is a game of equality under this concept, where a gambler should only make (accept) a bet if they hold the same information and have the equivalent conditions as their opponent. From this stems a compelling concept, one that remains at the heart of EMF: if a bet is fair then the past win-loss performance of the two parties cannot be utilized to forecast the outcome (Lo, 2017). Given that the past provides no value for informing the future, the expected outcome of a future event is best described by a random outcome – in the case of a coin toss, heads or tails. (2015)

It is often assumed that French mathematical Louis Bachelier ([1900] 1964) dissertation is responsible for the next step in the evolution of the EMF. However, as detailed by Jovanovic and Le Gall (2001), this assumption overlooks the work of little-known French economist Jules Regnault. Many of the themes of Regnault's (1863) book *Calcul des Chances et Philosophie de la Bourse* remain intertwined with modern finance. The motivation behind the work, which occurred in the shadow of a ruined French economy due to John Law's various financial schemes and rampant speculative behavior in the French financial markets, was to identify the laws that dictated the behavior of the stock market (Jovanovic & Le Gall, 2001). In his attempt to identify these laws, Regnault pursued a scientific (quantitative) approach, thus giving rise to quantitative finance (Goetzmann, 2017). The defining feature of quantitative finance is the utilization of mathematical modeling to establish an explanation for the behavior of the markets.

From the original quantitative to finance approach, various aspects remain relevant today and are themes that reappear throughout this dissertation. These aspects include: individuals have bounded knowledge of the future, and therefore they can only approximate what the future will entail; there are short-term effects, which are the result of new and exogenous information; there are long-term effects which are the result of long-term trends that are continuously in play; the price of an asset contains all known information about that asset; news is assumed to arrive in a random fashion, so previous prices give no insight into future prices; and Regnault's work justifies the morality of short-term speculation (Jovanovic & Le Gall, 2001).

In the process of developing the his new of finance laws, Regnault introduced the concept of the random walk to finance. The premise was that when investors take the opposing side of a speculative trade, their expected payoff would be zero, as neither party has an information advantage (as per a martingale). Therefore, the outcome would be completely random, and independent of previous price movements – which is the essence of the random walk, as illustrated in Section 1.2.4.3.1. To ensure the expected outcome of short-term speculation was zero, the random walk model needed to be symmetrical. To achieve this, Regnault specified the assumption, one that remains today, that the evaluation of news by investors would follow a Gaussian distribution. Hence, price movements would follow a similar distribution.

Although Bachelier's (1900) work on the random walk followed Regnault's work, it remains a crucial component in the development of the EMF. A vital contribution of Bachelier was to frame the random walk in continuous time (MacKenzie, 2008), a step which was effectively equivalent to, and preceded, Einstein's theory of Brownian motion, a theory that would go on to have a substantial influence on finance following its rediscovery and utilization by Samuelson (1965) some 50 years later. The other contribution from Bachelier's work was that because asset prices undertook a random walk; that is, it is the dollar value of share price that changes, the resulting distribution of prices on the exchange would match a Gaussian distribution. In specifying the theory this way, the expected return of speculation would be zero, and it would be impossible to outperform the market over the long-run (Fox, 2009). These points remain significant components of the EMF, with their relevance discussed in Section 1.2.4.6.

Bachelier's work contains two warnings relating to its limitations. However, until the flaws in the concept of efficient markets became more evident these limitations remained unheeded. The first warning relates to the use of the Gaussian distribution. As discussed in Section 1.2.4.3.1, the distribution requires random and independent events. However, Poincare (Bachelier's adviser) highlighted human decision-making was not an independent event (Fox, 2009). Bachelier was aware of this issue, which gave rise to the second warning – the theory applied to only the next immediate occurrence in the future (Fox, 2009). Given that the theory was only meant to hold in the next occurrence, the possibility of an asset's price becoming negative was not a concern. However, the later iterations of the framework addressed the issue of negative prices, the issue of the theory relating to the next immediate occurrence was not.

Despite the importance of Bachelier's (1900) work, it remained relatively unknown for over 40 years. However, in the interim others were beginning to uncover patterns in financial markets, that would ultimately lead to the EMF. Firstly, Kendall (1953), utilizing the work of Working (1934) – which was meant to identify the presence of non-random effects in time series data, presented findings that indicated that the pattern of financial assets return (the percentage price change) showed little to no correlation from period to period, and were effectively random. A critical aspect of Kendall's work was that he assessed the percentage price change of an asset, rather than just the price. This modification ensured that the prices could not become negative – one of the flaws in Bachelier's theory. The change also addressed the issue that share prices, in general, had trended higher over time; that is, their mean was not stable, nor was the distribution normally distributed. Returns were now assumed to be distributed in a normal fashion around a mean, which did not have to be 0 after this change.

Kendall's intention had been to uncover correlations between successive periods (that is, autocorrelation) in asset prices, but this was not the case. With a lack of correlation, Kendall concluded that price changes were random, any trend was an illusion, and price movements matched a Brownian motion, with a Gaussian distribution (MacKenzie, 2008). While Kendall's findings generated little interest amongst his peers in the United Kingdom (UK), the story was very different in the USA.

For the random-walk theory of asset pricing to progress from a trivial finding to become the keystone of finance required the combination of a well-established economist and a highly credentialed institute. This was achieved by Samuelson at MIT developing his proof of asset pricing in his paper *Proof that Properly Anticipated Prices Fluctuate Randomly* (Samuelson, 1965). The significance of the proof was that it explained *why* the asset returns followed a random walk, opposed to Bachelier who had established the process that explained *how* prices were randomly determined (Lo, 2017).

Samuelson's work recognized that it is not the dollar value of any change that is normally distributed, but it is the percentage change (the gross price return) in the price that is normally distributed. This change ensured that by chance, through the random walk, the price of an asset could not become negative, which was a significant flaw in Bachelier's work. The change also transformed the theory of the random walk from an arithmetic Brownian motion to a geometric one (MacKenzie, 2008). In making this change, it is assumed the changes in the logarithm of prices are normally distributed; thus, prices would be distributed per a log-normal distribution. Section 1.2.4.3.1 contains the mathematical specification of this point.

Another vital component of Samuelson (1965) was the explanation of *why* price changes were random. It was because like a martingale the current price of an asset must contain all information relating to past changes in an asset's price. Otherwise, it could be utilized to inform an investment decision, and any new information would appear in a random, unpredictable manner. These assumptions were sufficient to state that future price changes would be random. By linking the informational content of a current price and the randomness of future changes, the EMF was formalized, and born into the new field of finance. Interestingly, Samuelson was somewhat indifferent to the significance of the finding, stating "all or none of these may be true, but would require a different investigation" (Samuelson, 1965). The different investigation related to a more though empirical validation of the proof, a process undertaken by others.

A description of the rise of the EMF is not complete without acknowledging that, in isolation from Samuelson, Osborne (1959), came to the same conclusion regarding the movement of asset prices. The significance of Osborne's finding is the way he produced his result. Unlike Samuelson and his students at MIT, Osborne was not an economist but held a doctorate in physics. As described in Weatherhall (2014), Osborne had become curious about financial markets and approached the problem as an empirical scientist; that is, he assessed the available data and then determined a model that matched the data, thus overcoming the lack of empirical work in Samuelson's work. By utilizing the empirical approach, Osborne saw the failings of Bachelier's theory, and, like Samuelson, determined that it was the rate of return of an asset (the log price change of an asset) that was normally distributed, thus the distribution of prices matched a log-normal distribution. Since Osborne's work, the utilization of an empirically based research approach has grown significantly in finance with varying degrees of success.

1.2.4.4 The Rise of Positive Economics and Rational Expectations

As discussed in Section 1.2.2, as the field of finance developed it had three streams: the cost of capital; portfolio theory; and efficient markets. However, for the field to develop, and especially the portfolio theory stream, required necessary changes in the approach of economics. The first was the desire to mathematize the field, with Irvine Fisher (1925) being one of the pioneers, followed by Samuelson.

The next significant development in economics was the rise of Friedman's (1953) "positive economics." The principle component of the change was that economics became a study of "what is" as opposed to "what ought to be." The change, according to Krugman (2007), saw Keynes's plausible psychological theorizing, such as the presence of "animal spirits" in markets, replaced by more detailed and predictive analysis of what a rational decision-maker would do. The practical implication was that the focus of economics – and the developing field of finance – shifted from developing models on realistic assumptions and observation to creating models that have a superior predictive ability. Under this banner, an economic theory becomes better insofar as it made less plausible assumptions (Buchanan, 2014).

The next aspect in the evolution of finance was the corresponding rise of the "rational agent and the theory of rational expectations" model. While the rational agent theory had existed in economics for over 200 years, the influence of "positive economics" and the desire to mathematize economics saw its significance rise rapidly. The theory of rational agents implies that an agent's decision-making process involves determining, solely for themselves, subject to a budget constraint, an optimal level of benefit/utility after considering all future risks. The approach requires agents to employ top-down deductive reasoning, which is where conclusions are reached by reductively applying general rules that hold over the entirety of a closed system. A vital assumption of the approach was that the population holds homogenous expectations and beliefs. This assumption, in turn, allowed economists to utilize a sole representative agent that embodies the collective preferences of the population (Sornette, 2014). By allowing for the representative agent closed-form mathematical solutions for various financial models, all underwritten by the EMF, could be derived.

The theory of rational expectations (Muth, 1961) was a vital component in the development of the EMF and deals with how agents integrate their expectations into the decision-making process. The theory is somewhat simplistic, stating that the only expectation an agent (or investor) should hold is that the market will find its equilibrium point; that is, they should be rational in their expectations. More specifically, the agent's anticipated price will be equal to the expected price. This statement is predicated on the buyers and sellers understanding and implementing the behavior described by equilibrium/rational economics. Interestingly, as highlighted by Lo (2017), Muth never suggested that agents successfully performed the required utility maximizing equations, nor were their expectations perfect. In a similar manner to overlooking the warning in Bachelier's work, the interpretation of the theory was that agents always performed the required calculations successfully. The acceptance and utilization of the rational expectations theory according to Shiller (2003), was because economists could produce theories, with their assumptions "protected" by the idea of "positive economics," that interconnected speculative asset prices with economic fundamentals, thus linking finance and the entire economy. This fact prompted the rapid growth in the importance of, and resource allocation, to finance as a new discipline.

1.2.4.5 The Efficient Market Hypothesis

The final pieces in the evolution of the EMF were to establish: *what* information the price of a financial asset has incorporated in it, and whether that price *was* accurate. These considerations contrast with the previous work on efficient markets, which only described *why* and *how* prices moved. The predominant scholar in providing the answers to the final two questions, through his EMH, was Eugene Fama. Despite becoming synonymous with the EMH, and the ramification that the returns of financial assets should follow a Gaussian distribution, Fama (1963), working under Mandelbrot (Sections

1.2.5.5 and 1.3.2.2 discuss this work), uncovered evidence of asset returns exhibiting fat-tails (see Section 1.2.4.3.1 for a definition of fat-tails) (Lo, 2017). Despite this, it was Fama's contribution through the EMH that effectively allowed the EMF to side-step the presence of these fat-tails. This point is captured by Lux and Alfarano (2016), who state that Fama's EMH is "agnostic about the structure of the 'news process' driving returns, there are no direct implications regarding the prescribed nature of asset returns."

In the process of identifying the fat-tail returns, Fama (1965) reported that non-random patterns in the market disappeared rapidly. The rationale for this trait, which is in a similar vein to Friedman's (1953) theory of why the market would contain only rational investors, was that superior analysts would be able to identify these patterns rapidly and counter them. This process ensured that the price of an asset was the best estimate of its intrinsic value because the asset's price had all new information rapidly incorporated into it. In framing the theory in this manner, Fama's focus was on the speed and accuracy in which the investors reacted to any new information.

Fama defined three forms of the EMH relating to the information reflected in the price. As outlined by Jensen (1978) these are the: weak form, where the only information available to investors is past price history; semi-strong form, additional to the weak form, investors have access to all publicly available information; and strong form, where investors have access to all possible information. Event studies – that assessed how the market reacted to the arrival of news were undertaken to test the validity of the various forms of market efficiency. The general outcomes of these studies were that the market did a "good" job of reflecting new information (Fox, 2009). More specially, Jensen

(1978) suggests that the most widely accepted form of the EMH was the semi-strong form; thereby for investors trading solely on publicly available information, including the past price history, it is impossible to make an economic profit.

Whether the price was right once new information became available was the next question. For this to be true, investors were assumed capable of collecting all relevant information, have significant foresight, and have the computational power to incorporate this information correctly. The first attempts to provide affirmative support to these assumptions was to concurrently test the EMH with the Capital Asset Pricing Model (CAPM) (Sharpe, 1964). The initial tests provided positive evidence that the prices were indeed “right.” These findings led to the general acceptance of the EMF and the various rational expectation models in the broad finance community. However, as testing continued, contradictory evidence regarding the “rightness” of prices from the EMH and CAPM tests became overwhelming (Fama & French, 2004). However, proponents of the EMH regarded this as a failing of the CAPM and not the EMH. Indeed, Fama – with French, went on to develop a 3-factor risk model (Fama & French, 1993), and then a 5-factor model (Fama & French, 2015)) that was more supportive of the EMH and investors’ ability to get the price “right.” Elsewhere, as discussed in Section 1.2.5.5 others were finding evidence that prices were not necessarily “right” all the time.

1.2.4.6 The Repercussions of Efficient Markets

Several repercussions stem from the EMH implying that prices are always right, and returns are unforecastable (or at least “very” unforecastable, as discussed in Section 1.2.5.5). The first relates to individual investors, and specifically whether, systematically, investors can over the long-term generate risk-adjusted above-average returns? The EMF says not, with the answer popularized in the notion that there are “no free lunches” in the market. The explanation is that an asset’s price has all information rapidly reflected in it; thereby, there is no information that is not already incorporated into the price that can move the price; hence, prices are efficient. Additionally, it is assumed no investor holds a systematic advantage in obtaining and correctly processing new information. For investors to earn above, markets return they must expose themselves to greater risk, but with this comes the exposure to more significant losses. Section 2.3.4 discusses the performance of individual investors in greater detail. In short, despite the presence of outliers such as Warren Buffett (see Figure 5 for his relative performance compared to the S&P 500), Ed Thorpe, or David Shaw, there is little evidence to suggest that investors can outperform the market (Malkiel, 1999).

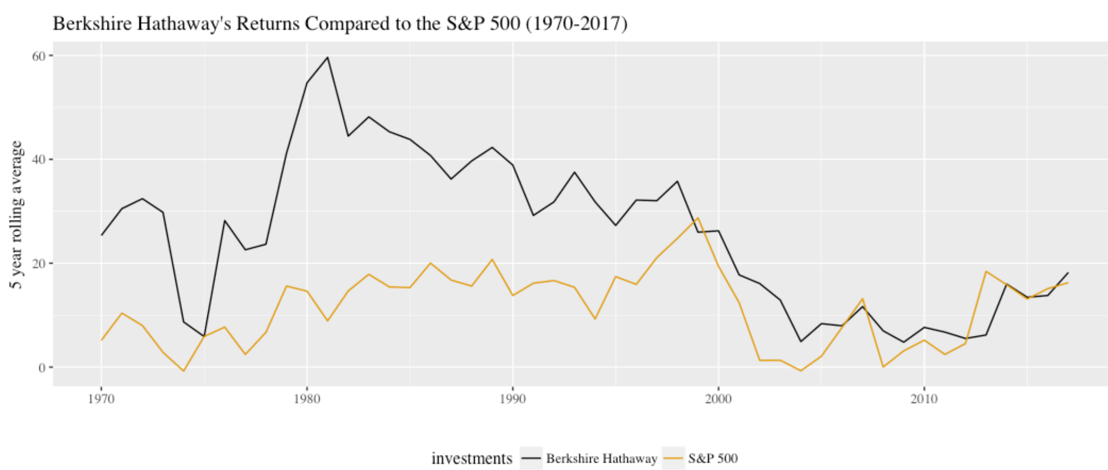

Figure 5: Comparative average 5-year rolling returns of Berkshire Hathaway (Warren Buffett’s investment company). Returns are compared to the S&P 500. Data source: 2017 Berkshire Hathaway Annual Report.

The second repercussion relates to the public implication of efficiency. Efficient pricing in the security markets is desirable because it provides the correct signals and incentives for the allocation of resources in the broader economy. The issues surrounding this point are the catalyst for the research undertaken in Chapter 3, with a though discussion relating to the allocation of resources based on signals from security markets detailed in that section. In short, if pricing is not efficient, by whatever means, then there will be a wasteful and inefficient allocation of resources in the economy.

Lastly, with the EMH implying that the market is always right, it has been considered unnecessary for regulators and investors to intervene in the market nor question whether financial assets (including residential housing) are over or undervalued. Fox (2009) highlights the various failed attempts of policymakers to identify and deflate previous bubbles, with the most infamous example being that of the Chair of the Federal Reserve (The Fed) Alan Greenspan, who, when asked if it was possible to establish when investors exhibiting "irrational exuberance" had inflated asset prices, conceded that it was pointless to fight market forces. However, in the fallout of the GFC this is no longer an acceptable position, explaining the reinvigorated search for an alternative explanation for the behavior of financial markets.

A significant negative externality of the ascendancy of the EMF was the stifling of other financial market research agendas. Before the rise of the efficient markets paradigm in the 1950s the market's psychology had been considered relevant following the identification, by Keynes (1936) of the "animal spirits" that drove consumers and investors alike. However, with no consideration of investor psychology in a rational agent environment, research into the psychology of the market was forced into the background until the rise of behavioral economics in the 1980s – which was ironically boosted by the failure of the markets to follow the EMH. In laying the foundation for behavioral finance, Shiller et al. (1984) highlights the mechanism by which the EMF does not consider market psychology. The mechanism is that if fads do influence the price then fads, and fads became predictable, prices would in turn become predictable –something considered impossible under the EMF.

1.2.4.7 Limited Liability Companies and Acknowledging Agency Costs

Figure 1 illustrated that firms (companies) are connected to numerous other agents in the economy, specifically: debtholders, management, and owners. One kind of firm is a limited liability company (LLC), whose management of the company (firm) is hired by the debt and equity holders to run the company profitably and achieve a mutually agreed-upon set of objectives. Likewise, equity owners have limited exposure to any debts of the company and other legal obligations. This scenario is attractive to investors because any potential liabilities are limited, yet the upside is somewhat unlimited. Harford (2017) suggests that the introduction of LLCs was one of the 50 most important contributions to the modern economy.

While the first instances of LLCs trace back to the 900s, the widespread use of them did occur until the 1600s, following the creation of the East India Company in the UK (Harford, 2017). Their general acceptance and growth had a difficult birth, with their proliferation perceived as one of the key contributors to the first global financial crisis, the South Sea Bubble. The ongoing existence and success of LLCs, was not guaranteed and their ability to be managed effectively was first raised by Smith ([1776] 1976), who suggested that it would be erroneous to expect the directors/managers of LLCs to manage them with the same vigilance, as if they were the owners of the company. The vital concern arises in that equity holders face potential losses or the underperformance of their investment if their incentives do not align with those of management. The problem is commonly known as the agency problem.

The concern raised by Smith, while acknowledged by many in economics, was not fully incorporated into a theory related to the ownership structure of a firm until Jensen and Meckling (1976) formalized agency theory. This theory included the vital recognition of agency costs. Jensen and Meckling's work, as discussed in Fox (2009), was the culmination of the ongoing debate regarding the behavior of firms, and whose interest the management of a firm is trying to maximize. Jensen (1986a) highlighted that firms with free cash-flow and low growth prospects were susceptible to incurring agency costs. The explanation for this is that management will be inclined to use the free cash-flow to invest in sub-optimal projects to accelerate the growth of the firm, enhance their reputation, and or compensation.

The essence of agency costs is that there is a cost to bear for the separation of ownership and control of a company; that is, it is all but impossible for the principal (business owner) to ensure that the agents (managers) take actions in their best interest. The cost manifests itself as: a monitoring cost by the principal; bonding costs (the cost incurred by the agent from taking actions in the principals' best interest, rather than theirs); or residual losses from inefficient activities. In a seminal paper Jensen (1986a) proposes several solutions to this issue, including how the greater use of debt can reduce agency costs by effectively focusing management.

An insight from Jensen's and Meckling's (1976) work, which was previously raised by Friedman (1970), is that the efficiency of the market would ensure that management would always act to maximize the value of the firm. This outcome occurs because the market would punish any non-conforming behavior. However, with markets failing to maintain their "efficiency," and the short-termism of market participants, the efficient behavior of management is questionable. Section 3.3.3 in Chapter 3 investigates the question, of whether the reactions of management to the market is responsible for feeding a positive feedback loop that results in even greater volatility in asset prices.

1.2.5 The Reality of How Firms Grow and Markets and Investors Behave

The purpose of this section is not to provide a detailed rebuttal – Malkiel (2003) provides a summary of the various rebuttals, or otherwise – Fama (1998) claims a pyrrhic victory for market efficiency, of the EMF but rather highlight the various aspects of the debate regarding the appropriateness of the EMF and the alternatives that now exist that have informed the different chapters within this dissertation. The issues that are raised are the non-Gaussian return characteristics of the market, evidence of the market not correctly valuing assets, behavioral issues of investors, and the investors appearing to ignoring universal laws relating to how firms grow.

1.2.5.1 The Characteristics of Market Return

1.2.5.1.1 The Stylized Facts

Figure 6 illustrates how financial markets have performed over the last 20 years. by showing both the cumulative movement in the S&P 500 index and its daily log returns between 1985 and 2016. The graph's characteristics are consistent with the statement that the EMF related models provide a rough approximation of financial market returns, but fail to explain outlying events (Kirou, Ruszczycki, Walser, & Johnson, 2008).

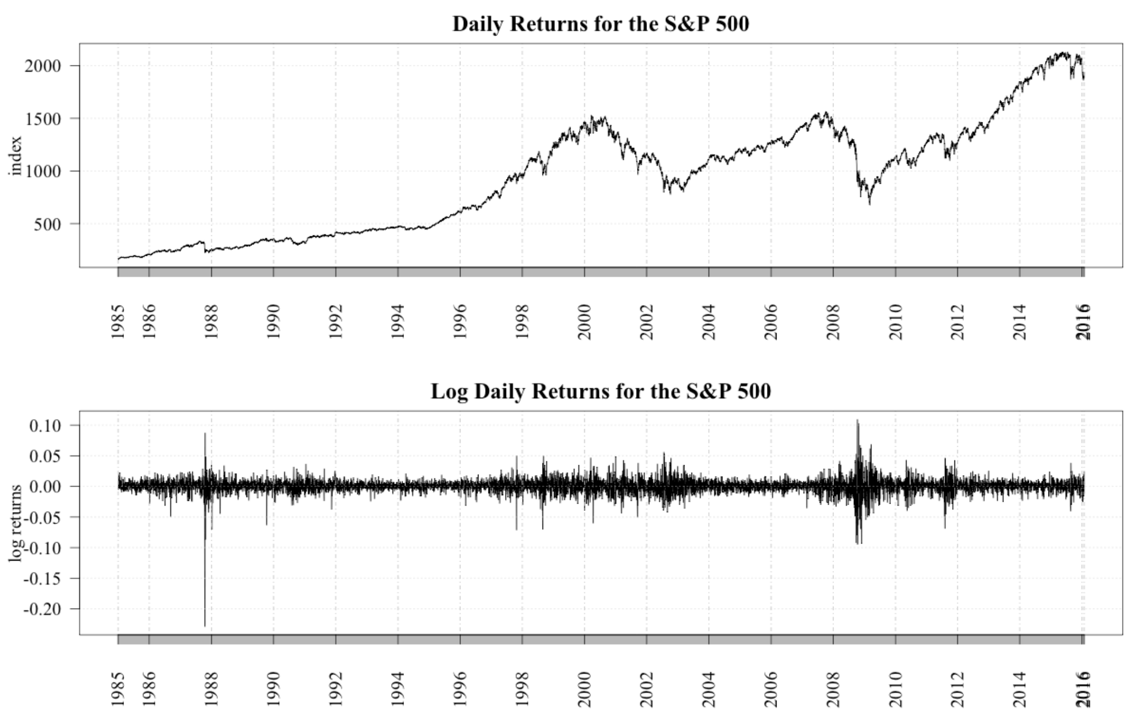

Figure 6: Daily returns of the S&P 500 between 1985 and 2016. a) shows the daily movements of the S&P 500 index from 1985 to 2019. b) illustrates the daily log returns over the equivalent period. Data source: Data extract from Yahoo Finance utilizing the R package quantmod (Ryan & Ulrich, 2017).

The return characteristics of financial markets have been found to demonstrate a specific set of stylized facts, that contradict the EMF informed Gaussian models. These facts, as summarized by Cont (2007) and Johnson et al. (2003), are: excess volatility – the existence of large movements not supported by the arrival of new news; heavy tails – returns exhibit heavy-tails or fat-tails indicating returns deviate more than anticipated and do not follow a Gaussian distribution; volatility clustering – large changes are followed by further large changes; and volume/volatility clustering – trading volumes and volatility show the same type of long memory. The replication of these stylized facts has been a significant focus for researchers trying to understand the behavior of financial markets, a matter discussed in Section 1.3.4.3.

Before preceding it is necessary to discuss the relevance of stylized facts. Kaldor (1961) originally defined stylized facts as stable patterns that emerge from multiple empirical data sources. Crucially, their formation requires a level of abstracting from the minutia of the evidence. The utility of stylized facts is that they enable the researcher to build a model capable of identifying, explaining, and communicate critical observations that require a scientific explanation without having the burden of explaining all variations in the empirical evidence (Heine, Meyer, & Strangfled, 2005).

Before the recognition of the now accepted stylized facts, Mandelbrot (1963) uncovered important observations regarding the characteristics of asset returns. These observations were that returns were non-Gaussian with broad tails, and that returns exhibited “time scaling,” which is to say that the distribution of returns across a range of time frames had a similar functional form. Based on these findings Mandelbrot proposed the theory that returns met the requirements of a Levy stable distribution. Mandelbrot's theory of fractal geometry provides a feasible explanation for the self-similarity of returns across timeframes. Self-similarity is a vital characteristic of scale-free distributions, with the system exhibiting similar characteristics regardless of the scale at which the observations are taken.

Additionally, Fama (1976) argued that it was only daily returns that were non-Gaussian distributed (he suggested the returns were skewed and highly leptokurtic), and monthly returns matched a Gaussian distribution. The ramification of this characteristic is that the outlying events that occur within a short-term horizon have only a modest effect on longer-horizon returns; therefore, investors should not be overly concerned with short-term volatility. However, with the advent of more granular data it has been discovered that rather than a Levy distribution, asset returns match a power-law distribution over extended time intervals (see, for example, Gopikrishnan et al. (1999) and Botta et al. (2015)). The implication for investors of returns following a power-law is that the risk of large losses is much higher than suggested by the EMF, and markets are more volatile.

Lux & Alfarano (2016) provide a detailed review of the empirical evidence supporting the existence of power-laws in financial markets. It is the existence of power-law returns that provides the crucial insight that financial markets may operate as a complex system. The discovery and implications of power-law distributions in other areas of economics is a growing research field, with the most relevant for this dissertation being the distribution of firm size and the degree-distribution of shareholders.

1.2.5.1.2 The Market is Found to be Priced Incorrectly

As outlined in Section 1.2.4.6, the EMF implies that prices are always right; that is, the fundamental value of an asset will always equal its market price. Section 1.2.4.5 outlined the basis for how the promoters of the EMF proclaim that, after a few adjustments, they have provided sufficient evidence that the market gets the prices of individual assets right. From the joint tests of the EMH and the various asset pricing models, a crucial implication arises in that the market's value is deemed to be "right" if the individual assets are correctly priced.

Rather than testing whether the price of individual assets was correct, Shiller (1980) investigated whether the market's value was "right." By returning to the work of Fisher, which stated that the intrinsic value of an asset is the NPV of its dividend stream, Shiller compared the volatility of the dividend stream of the S&P 500 index with the volatility of the index. The results were damning, suggesting that there were numerous episodes where the market had not got it "right" based on far greater volatility in asset prices than the dividends. As summarized in Fox (2009), these works were initially ignored by the newly established finance fraternity. However, from Shiller's (1980) work grew the antithesis to the EMF, behavioral finance. While the details of behavioral finance are beyond the scope of this dissertation, the work exposed vital investor behaviors such as overconfidence, overreaction, and a preference for the "now," that have helped explain the periods of "irrational" market behavior.

1.2.5.2 How Firms Grow

While not directly related to the EMF, it is appropriate at this point to mention two crucial stylized facts about the distribution of firm size and the growth rates of firms. The relevance of these facts is that they must inform any model explaining the growth and size of firms. Concerning the distribution of the firm size, it has generally accepted that the size distribution of firms within in an economy is highly skewed (Simon & Bonini, 1958), a fact that has been used to inform numerous theories in economics. However, more specifically it has been found that the size-rank distribution matches a Zipf-law (Axtell, 2001) (see Section 1.2.4.3.1 for an explanation of Zipf's law). This distribution has been found to robust over time, thus providing a much higher burden of proof for theories regarding firm growth.

The second fact is that the growth rate of the firms should match a Laplace distribution, as per Stanley et al. (1996) - this is to say that the distribution of the growth rates has an exponential form, or more specifically the growth rate frequencies exhibit Laplacian decay (Metzig & Gordon, 2014). The other vital finding was that the variance of growth rate scales with the size of the company. In general, this means that the growth rates for smaller or larger firms exhibit a larger or smaller or spread in growth rates.

Figure 7 is a stylized illustration of a Laplacian distribution, with different values of lambda, which is the variable that controls the variance of the distribution function. The classic tent-like shape of the distribution is evident for each of the distributions, as lambda increases the height (spread) of the distribution decreases (increases). As stated above, this is what is evident in the firm growth rates; thus, the lambda coefficient is akin to firm size, with 1 being the largest firms and 3 being the smallest firms.

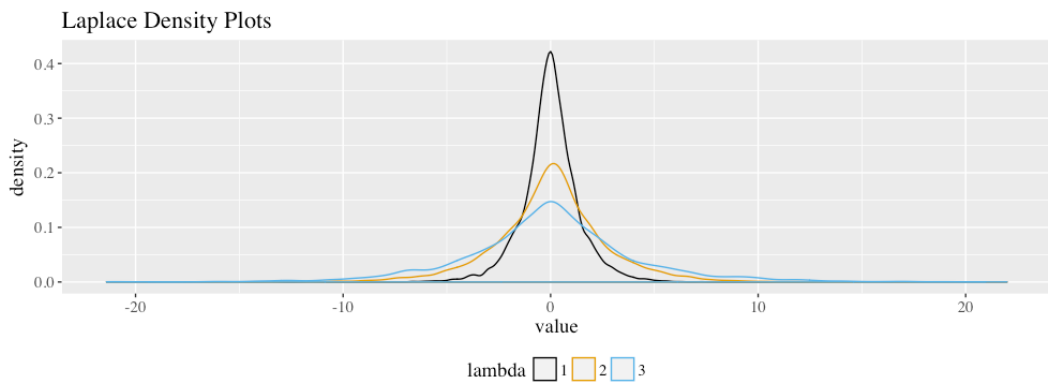

Figure 7: Stylized examples of Laplace distributions

The existence of the above distributions rendered Gibrat's (1931) and many of the original theories of firm growth inaccurate. This is because they assumed that any stochastic process involved in determining the growth of a firm was independent of firm size (Metzig & Gordon, 2014). The existence of the stylized facts, especially the Zipf-law distribution of firm size, is suggestive that firms operate in a CAS – noting that the stylized facts do relate to all firms and not just publicly traded firms. However, within the CAS it is entirely possible that the interaction between firms and investors, as subsystems, is at least partially responsible for the stylized facts. Section 3.2.1.1 discusses these stylized facts and their relevance to the various research topics.

1.2.5.3 Bounded Rationality and Representative Agents

One of the most meaningful rebuttals of the rational agent approach came from Simon (1955a), through the theory of bounded rationality. The concept behind the theory was that humans do not possess the computational power required of them to perform the necessary calculations of the fully rational agents. Therefore, they are forced to act as if they have such power, searching for and trying solutions that seem appropriate; that is, heuristics. Behavioral economics and agent-based modeling (ABM) have made extensive use of heuristics in models of a decision-making. On a side note, Simon was supportive of Muth's rational expectations model (Lo, 2017) but ultimately concluded that "I do not think it [rational expectations] describes the world correctly. Sometimes an idea that is not literally correct can have great scientific importance" (Simon, 1996).

The bounded rationality approach parallels with the thoughts of Keynes (1937). Keynes suggested that the decision-making framework of individuals contains the following elements: the present is more relevant than the past; investors and consumers should accept the current price until something new comes along; individual judgments are worthless, so it is best to fall back on the view of the rest of the world.

The continued defense of the representative agent across numerous economic fields by the neoclassical zealots raises many objections by non-believers. Kirman (1992) provides the foundations to the argument against the continued use of a representative agent, with the main objection being that the utilization of a representative agent is a "convenient fiction" used to provide micro foundations for aggregate behavior with the sole intent of solving for stable and unique equilibria. The paper also provides the impetus to consider the economy as a CAS, capable of delivering emergent outcomes, when he makes the point that "the sum of the behavior of simple economically plausible individuals may generate complicated dynamics." An alternative to the representative agent is discussed in Section 1.4.2, where prospect of investor classes is discussed.

1.2.5.4 Market Participants Exhibiting Short-termism

Davies, Haldane, Nielsen, & Pezzini (2014) make the point that one of the potential costs of modern capital markets is short-termism. The cost manifests itself with both investors, explored in Chapter 2, and management, as explored in Chapter 3, undertaking inefficient behavior that is detrimental to long-term wealth creation. Haldane (2011) defined short-termism as a situation where short-term factors are allocated a disproportionate weight at the cost of long-term factors. Alternatively, Kay (2012) identifies it as "the natural human tendency to make decisions in search of immediate gratification at the expense of future returns." The critical ramification for Kay is that short-termism may lead to hyperactivity by management, such as, frequent corporate restructures, mergers and acquisitions, and financial re-engineering. These activities in most cases do not generate a sufficient return on the investment associated with them.

The mechanism by which short-termism produces detrimental outcomes is that investors underestimate the value of medium to long-term cash flows, which in turn removes the incentive for management to invest in long-dated projects (Davies et al., 2014). The issue of short-termism has gained increased attention in the wake of the most recent financial crisis. In the USA, the issue has been raised by prominent investors and regulators (The Aspen Institute, 2009), while in the UK the government commissioned a report on the issue, *The Kay Review of Equity Markets and Long-term Decision Making* (Kay, 2012). The evidence cited by the Aspen Institute (2009) to support the argument that short-termism is increasing includes: reduced investment by firms due to their focus on meeting quarterly earnings expectations; reduced chief executive officer (CEO) tenure; the increased prevalence of short-term investors, such as hedge funds and high frequency trading; and the corporate culture of providing quarterly earnings guidance.

The economic cost of short-termism manifests itself at three levels in the economy. Firstly, at the investor level, excessive trading and the misalignment of investment horizons with return expectations, as detailed in Section 2.3.3, has proven to be detrimental. Next, at the corporate level, by taking a myopic view management teams under-invest in future growth projects, and determine business priorities on meeting the market's expectations, an issue at the heart of the model presented in Section 3. The final effect of short-termism occurs in the broader economy. This effect is seen in general underinvestment in Research and Development (R&D), leading to lower economic growth; a miss-allocation of resources due to the financial markets not operating in an efficient manner (as discussed in Section 1.2.4); and a general mistrust in the markets and the role they play.

1.2.5.5 Addressing the Relevacne of the EMH

Returning to the specific debate as to whether the EMH is the best way to describe markets, the conclusions has waxed and waned between yes and no, with arguments for and against filling numerous journals over last 40 years. At one end, Jensen (1978) proclaimed that "there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis," while at the other end, Shiller et al. (1984) state that the EMH is the "most remarkable mistake in the history of economic thought." The debate is likely to continue for some time, but there is no doubt that at times market traders are not correlated with economic reality (Topol, 1991). This raises the question "what are they correlated to?" A question addressed, in part, throughout this dissertation.

One of the underlying issues inflaming the debate about the EMH stems from the relative simplicity of it. As Fama states, "It's a very simple statement: prices reflect all available information. Testing that turns out to be more difficult, but it's a simple hypothesis." (Chicago Booth Review, 2016). Further, Fama indicates that the EMH is a model and one that provides a good approximation of the world. The point of providing a "good approximation" is addressed by Shiller (Shiller et al., 1984) when he suggests that while the EMF has shown that returns are not "very" forecastable, so have other theories, including some that have included fads and social influence in the decision-making processes of the investors. Therefore, it is incorrect to dismiss alternate theories.

A concern with the EMF is the way in which, while in the face of mixed evidence, the promoters of the theory, in a one-eyed fashion, influence policy and strategies on the pretense that the EMF will hold in its entirety. This point is captured by Buffett (1988) when he summaries the feelings of the non-believers by stating – "observing correctly that the market was frequently efficient, they (academics, investment professionals, and corporate managers) went on to conclude that it was always efficient, the difference is night and day." Ultimately, one should recognize that no model is ever 100% correct.

Therefore, debate regarding the pricing efficiency of the markets will continue. In the interim, with the advent of new research techniques and access to an almost endless supply of data, it is worth considering alternative explanations. The justification of this is further discussed in Section 1.3.

An obscure ramification of the EMF is that there should be little to no trading because, with all investors sharing the same information, no incentive exists to trade because the prices of the assets will reflect all current information. However, the reality is that trading occurs, and occurs at a rate that even proponents of the EMH struggle to explain (Farmer, 2002). Barber & Odean (2000) highlight two competing explanations regarding the observed level of trading. The first, which uses a rational expectations framework, is Grossman & Stiglitz (1980), who propose that trading will occur up to the point where the marginal benefit of trading equals the margin cost of gathering the information which informs the investors' decision-making. However, as the cost of gathering information is not homogeneous, the incentive to trade is heterogeneous for investors. The other alternative is that investors suffer from numerous cognitive biases, including overconfidence, and this leads to excess trading. This excessive trading comes at a cost to investors, with their net returns being well below the market (Barber & Odean, 2000). The effect of noise traders (De Long, Shleifer, Summers, & Waldmann, 1990) is another stream of research used to explain excessive trading.

1.2.6 Section Summary

This section justified why it is essential to understand the dynamics of financial markets and how the standard analytical approach of the EMF has been unable to provide an adequate explanation of the behavior of the markets. Section 1.2.2 summarized how finance developed from a minor sub-branch of economics into a distinct discipline. The section also identified the areas of most significant concern for the emerging discipline: the determination of the price of financial assets, and how firms interact with shareholders. Section 1.2.3 discussed the role of financial markets, highlighting the need for them to price assets correctly, which is meant to ensure an efficient allocation of resources in the broader economy. The following section, Section 1.2.4, introduced the theory of the EMF, its repercussions, and how it rose to become the dominant force in finance. Finally, Section 1.2.5 detailed the reality of how financial markets behave; that is, they exhibit behavior outside of what the EMF predicts. The section also introduced many concepts, such as how firms grow, and how investors behave and evolve, which underwrite much of the research focus in the remaining chapters.

Having developed the argument that financial markets operate in a manner inconsistent with the EMF, the question becomes: how should financial markets be analyzed? Section 1.3 details progress that interdisciplinary research has achieved and its relevance. The central focus is the use of the CAS framework, and the many ramifications it has. As explored in Section 1.3, these ramifications include feedback mechanisms, learning and adaptation, networks, and the diffusion of information throughout the population. Section 1.3 also introduces the field of CSS, and explain its relevance before proposing an alternative research method involving ABMs.

1.3 An Alternate Approach: Interdisciplinary Research

1.3.1 Introduction

The effect of the failure of EMF to explain outlying events and anomalies, along with the rise of parallel research methods have provided impetus for researchers to apply an interdisciplinary approach to economics and finance. This section explores the overarching ramifications of considering financial markets as a CAS. Section 1.3.2 justifies the reason for considering markets in this manner. The section also details many of the components of a CAS and highlights their relevance to the research questions proposed to address the behavior of financial markets. The field of CSS is experiencing a meteoric rise as many of its techniques are utilized to provide novel insights into CAS and the population in general. Section 1.3.3 details the relevant aspects of CSS, with Section 1.3.4 justifying the utilization of ABMs to analyze a CAS. This section also introduces the concept of artificial stock markets created with the use of ABMs. Finally, Section 1.3.5 summarizes the chapter.

1.3.2 Complex Adaptive Systems

To gain an understanding of why financial markets fail to comply with the prescribed behavior of the EMF, the use of a complex systems framework has become increasingly popular and relevant. For a system to be a CAS, it must contain some, if not all, of the following: feedback, non-stationarity, many interacting agents, adaptation, evolution, single realization, and be open (Johnson et al., 2003). The appeal of the CAS approach is that the dynamics and mechanisms behind endogenous changes are capable of being uncovered.

The direct link to financial markets is that a boom and/or crash are examples of self-generated (endogenous) changes. To understand why the boom and bust cycles of financial markets occur, despite the lack of top-down planning, Simon (1982) highlighted the importance of the bottom-up process of complex systems. Specifically, it is the interaction and adaptation of heterogeneous agents that is responsible for the emergent market outcomes. Viewing markets as CAS is consistent with the view of Sornette (2014), who concluded that to understand stock market returns one must consider imitation, herding, self-organized co-operativity, and positive feedbacks. If one is to accept that financial markets operate as a CAS, then one must accept that the behavior of the system is an emergent process based on the self-organized behavior of independently acting, self-motivated individuals (Farmer et al., 2012). Based on this, and related empirical findings, the need to consider components of the economy other than the financial markets as a CAS exists. In fact, this need has given rise to the field of complexity economics (Arthur, Durlauf, Lane, & SFI Economics Program, 1997).

1.3.2.1 Complex Adaptive Systems and Power-laws

The evidence of the power-law returns is one of the principal justifications for suggesting that financial markets operate as a CAS. In general, the presence of a power-law distribution is considered the statistical imprint of a complex system, with the self-organizing mechanism of a CAS being partly responsible for their existence (Sornette, 2009). As discussed in Section 1.2.4.3.1 power-laws are necessary and sufficient for identifying scale-free behavior, which is suggestive that a common mechanism is at work across a range of different scales (Farmer & Geanakoplos, 2008). Sornette (2009) provides further detail of their relevance when he states that “power-laws emerge close to special critical or bifurcation points separating two different phases or regimes of the system.” The identification of the critical points, and their cause, in the economy is a vital pursuit, given the significant cost of the economy suffering a financial collapse.

Other examples of power-laws in economics and finance include the distribution of firm size (see Section 1.2.5.2) and company shareholdings. Regarding shareholdings, Caldarelli et al. (2004) reported that the market graph, with regards to the number of owners of each company, was characterized by a power-law topology degree distribution.

1.3.2.1.1 How Power-laws are Generated

The characteristics of power-laws, and the behavior of systems that exhibit them, imply that there are specific processes responsible for generating them. Gabaix (2009) identifies numerous processes applicable to economics responsible for generating power-laws, including: proportional random growth; optimization; scaling considerations; and the “superstar” effect. In general, though, a power-law distribution occurs because the process influencing the system is a combination of chance and the systematic actions of the agents within the system (Delli Gatti et al., 2005). This contrasts to a simple random process that will most likely generate a Gaussian distribution, or at the extreme a mildly skewed distribution.

Of the possible mechanisms responsible for power-laws, the proportional random growth model is the most widely used. The process has a positive feedback mechanism (see Section 1.3.2.2) that results in the probability of a new element being added to a system, or attached to an existing element, being proportional to the abundance of the elements already existing in the system (West, 2017). This process is generally known as the rich getting richer. Of the other processes, the superstar effect (Rosen, 1981) is most relevant to the work within this dissertation. The process suggests that when faced with limited resources, the decision-maker will opt for the known superstar(s). Gabaix & Landier (2008) applied the superstar framework to explain the skewed distribution of executive remuneration, while it has also been used to explain why musicians and sportspeople with very minor differences in talent, record large variations in pay.

Section 1.2.5.3 described, in general, the shortcomings of the representative agent in economics. In a more technical rejection Delli Gatti et al. (2005), stated that the presence of the representative agent cannot occur in a system exhibiting power-laws. The rationale of the statement is that the dynamics of the system are the result of the interaction of heterogeneous interacting agents. In turn, and as detailed in Section 1.3.3.1, the consideration of interacting agents requires an alternative modeling approach, with CAS being a justifiable solution.

1.3.2.2 The Role of Feedback

A component of a CAS is the presence of feedback mechanisms. Their importance is explained by Sterman (2014), when he states that “the most complex behaviors usually arise from the interactions (feedbacks) among the components of the system, not from the complexity of the components themselves.” There are two types of feedback mechanisms: a positive feedback loop and a negative feedback loop. The crucial difference is that a positive loop is self-reinforcing, and will intensify the effect of any shock; that is, an increase(decrease) in a variable will see another variable increase(decrease), which in turn leads to an increase(decrease) in the original variable. Alternatively, negative loops are self-correcting and will dampen the effect of any shock.

Traditionally the relationship between the price/value of, and demand for, an asset is influenced by a negative feedback loop; that is, as the price of an asset increases above its intrinsic value, demand falls, and the falling demand, in turn, has a negative effect on the price. However, positive feedback loops have been identified in financial markets at certain times, with the implication being that an unchecked positive pricing feedback loop will ultimately result in exponential price growth.

Positive feedback loops make a significant contribution to the theory of CASs. Unstable equilibrium characterizes these systems; that is, the system will not settle permanently into a steady state. Therefore, if a small shock causes the positive feedback loop to generate sufficient velocity, the system can experience a significant shift in behavior as the feedback loop forces the system farther and farther from its starting position. However, potentially the feedback loop can abruptly stop forcing a dramatic correction. An example of this is an asset bubble.

1.3.2.3 Learning and Adaptation

One of the components of a CAS is the adaptation and evolution of the agents within it and the environment. The point is confirmed by Holland (2006) who stated that CASs are systems that “involve many components that adapt or learn as they interact.”

The process of learning and adaptation occurs as agents adjust after interacting with other agents and their environment (noting there may also be random changes as well).

The ability of learning and adaptation present unique issues in trying to understand the dynamics of CASs because of the dynamic nature of the system, which renders most analytical techniques of little value. For comparison, if one looks at a neoclassical economic model, such as the original rationale expectation model (Muth, 1961), traders “learn” instantaneously from any systematic errors and revise their expectations immediately. This process creates a stable equilibrium, with an external shock the only process capable of dislodging the equilibrium. However, this learning process is conditional on the agents knowing and expecting the market equation. For traders in a CAS, with learning and adaptation, their behavior should see the price converge to the equilibriums even if they do not know the correct price.

The utilization of interdisciplinary approaches to understanding CASs has led to numerous approaches being pursued to understand learning and adaptation within the system. The early approach was to allow agents to recognize patterns at which point they develop a hypothesis as to how and why and then act accordingly (Grimm, 2005). Within this approach agents can employ: adaptive learning – the agents use parameterized rule and update the rule as additional information comes in; evolutionary selection – the agents reduce the option of possible behaviors based on past outcomes, with one option becoming dominate; or they can use basic heuristics (Arthur, 1994). However, as the utilization of ABM expands, genetic algorithms, machine learning, learning classifier systems have been incorporated (Macal & North, 2010). In summary, these are all examples of inductive learning, which is the direct alternative to deductive learning which is used in the EMF.

1.3.2.4 The Influence of Network Science

This section provides a high-level overview of the utility of network science to CAS research, and the relevance of networks to financial markets and the investors within them. As mentioned in Section 1.3.2.5.3 networks and their structure (topology) have become a vital instrument in helping to explain the behavior of social systems. The justification is concisely provided by Strogatz (2001) when he states that "structure always affects function." Further, the attractiveness of network science is that graph theory, one of the underlying principles of network science, "provides a natural and very convenient framework to describe the population structure on which the evolution of cooperation is studied" (Santos & Pacheco, 2005), and according to Newman (2010) networks are "powerful means of representing patterns of connections or interactions between the parts of a system."

The origins of network science can be traced back to 1736, when Euler mathematically solved the "Bridges of Königsberg" problem, yet it was not until the 1980s that its growth accelerated. According to Barabási (2016), two critical factors led to the meteoric rise of network science. The first was that researchers lacked the necessary tools to capture and manage the data required to map large-scale networks. With the growth of computing power from the 1970s this issue disappeared. The second was that as researchers across multiple disciplines started to investigate the prevalence of networks in their field, there developed a standard set of organizing principles that allowed for a common mathematical approach.

The developments in network science have greatly assisted the understanding of CASs. The rationale is that behind a complex system lies a network that encodes how the components of the system interact, with this interaction giving rise to emergent outcomes (Barabási, 2016). The direct relevance of networks to economics (and finance) according to Schweitzer et al. (2009) is that the analysis of economic networks has become essential because the existing theories, and the policies associated with them, are inadequate for comprehending the interdependencies across global trade, supply chains, and investment networks, all of which are growing at an increasing rate.

Within CAS research, the social network of agents has been a significant focus of researchers. The value of social networks per Oremond (2012) is that people can reduce the use of their time dictated to decision-making by coping or imitating what their social connections do, or think. Therefore, networks can influence the spread of knowledge, behavior, and resources (Barabási, 2016). While the study of social networks is not new, the original analysis was confined to small data sets, something that is no longer an issue with the advent of data collection (Chen, Lakshmanan, & Castillo, 2014). The rationale to continue the expansion of social network analysis (SNA) is that by capturing how much and with whom an individual interacts has been beneficial in explaining the behavior of individuals, with this behavior potentially leading unforeseen global behavior. Section 1.4.7 discusses the role of social networks in financial markets.

1.3.2.4.1 Network Topologies

Within network science, there are four general network structures (topologies). These are: lattice, small-world, random, and scale-free (or preferential attachment) networks. Figure 8 provides a stylized illustration of the four generic network types. Each of these networks contains a unique set of characteristics of metric.

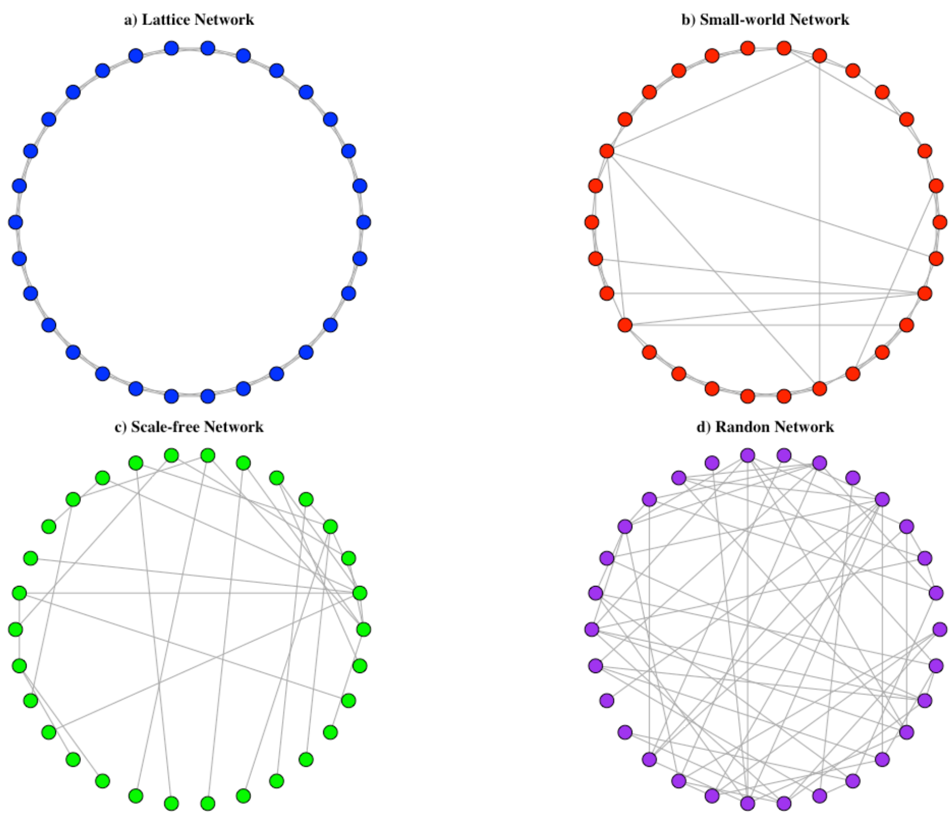

Figure 8: Stylized examples of the four generic networks topologies. Graphs generated in R by utilizing the igraph (Csardi & Nepusz, 2006) package.

The behavior of the agents within a system is affected by these characteristics. In turn, the individual behaviors are responsible for affecting the system in its entirety. The characteristic most relevant for this dissertation is the degree-centrality of an agent. The metric, assuming an undirected network, is given as the number of connections an agent has. If the network is directed, the degree-centrality is divided into in and out-degree. It is also important to assess the distribution of the population's degree-centrality as the four generic network topologies possess unique characteristics.

Another important characteristic is the clustering coefficient, which is defined as the measure of the interconnectedness of an agent's neighbors (Markose, Alentorn, & Krause, 2004). Its importance to understanding the structure and behavior of a network is that is defines how closely (or otherwise) agents are grouped together. Equation 8 provides the formula for the clustering coefficient. In Equation 8, $k_i(k_i - 1)$ refers to all possible directed links between agent *i* neighbors. E_i refers to the actual number of links between agent *i* neighbors. Therefore, the clustering coefficient is the ratio of the actual links between agent *i* neighbors and the possible links.

Equation 8: The formula for the clustering coefficient for agent *i*

$$C_i = \frac{E_i}{k_i(k_i - 1)}$$

Of the four network types, small-world and scale-free networks have the greatest relevance to the financial markets. Small-world networks have become synonymous with social networks since Watts & Strogatz (1998) generated a network structure that explained the tendency of humans to form social networks that are "clumpy" yet "compact" (Borgatti, Everett, & Johnson, 2013). In technical terms this means that small-network networks exhibit high clustering, yet have a low average path, which contrasts to a random network, which is considered to have low clustering and low average path links, suggesting the network has little structure. The ramification of the small-work network is that information can spread quickly due to the low average path. Given the social interaction required to develop and maintain a network between investors, a plausible expectation is that the investor network would potentially evolve to match that of a small-world network.

Scale-free networks have been found extensively across many domains in the real-world (Mitchell, 2006). A scale-free network earns its name from the fact that its degree distribution matches a power-law; that is there are a very few agents with many connections, known as a hub, and many agents with a very few connections, known as the spokes. The implication of the distribution is that the network is robust random strikes but not resilient if a hub fails. As discussed in Section 1.3.2.1.1, power-law distributions are generally found where the system contains a "rich get richer" process. Scale-free networks are no different, with Barabási & Albert (1999) proposing the mechanism of preferential attachment as being responsible for the growth of scale-free networks. The consequence is that large inequalities can grow and be locked in because through this process. Interestingly, scale-free and small-world networks share many characteristics, and as such some (but not all) small-world networks are scale-free (Mitchell, 2006).

The relevance of the scale-free network in finance is discussed further in Chapter 2 (see Section 2.3.2). In summary, financial markets contain multiple examples of scale-free networks. In the instance of an investor network, the direct implication is that if investors (the spokes) are blindly following a vital investor (a hub), then the capital allocated to a given investment may be excessive, thus leading to inflated prices.

1.3.2.5 The Flow of Information

Within the feedbacks mechanism of financial markets, information is a vital commodity, as it affects decision-making and the rate at which agents adapt within a system. As such, and in agreement with Kirman (1983), when an economic theory involves the use of information, it must as a minimum have an implicit view of how the information diffuses (or propagates) to individuals. This process is particularly relevant for the EMF, which assumes that an asset's price quickly reflects and fully incorporates any new information. A considerable volume of interdisciplinary academic work now exists that provides vital insights into how new information or behaviors diffuse through a community. Within the research of information diffusion, the issue of herding (information cascades) is of the greatest relevance to this dissertation. The work detailed in Section 1.3.2.5.2, was initially developed without the consideration of social networks. However, as detailed in Section 1.3.2.5.3, the field of network science has greatly enhanced the understanding of information diffusion.

1.3.2.5.1 Background

The process of information diffusion, which is the process by which new information spreads and reaches individuals, encompasses techniques from multiple scientific disciplines (Zafarani, Abbasi, & Liu, 2014). For diffusion to occur requires the following components: a sender, a receiver, and a medium by which the information flows. A classic example of information diffusion in financial markets would be an investment bank sending, via email, a company report to its clients. Important considerations in the diffusion process are: the extent by which users consider the new information; the speed at which they receive it; and where they source their information. As per Zafarani et al. (2014) agents will depend on either their local (immediate), or global (all their connections) sources in their decision-making process. Discussed in the following paragraphs, within this section, are the implications of these differences.

The preliminary work on the diffusion-of-information process occurred at the global level; that is, theories capable of explaining the aggregate level of diffusion within a population, and related to the diffusion of innovation. Specifically, the theories explained the flow of a new idea or concept, technical information, or actual practice within a social system (Wejnert, 2002). Rogers (1995) developed the seminal framework in the field, explaining how the rate of diffusion of an innovation within a population varied and evolved. The communication of information via either mass (a global dependence) or interpersonal (a local dependence) communication is a vital component of the diffusion process and has been investigated at length. The research was greatly assisted by the eventual integration of network science, as discussed in Section 1.3.2.5.3.

A key attribute of the diffusion-of-innovation framework is the S curve, which explains the rate of diffusion. The curve illustrates how an innovation diffuses slowly at the start, due to the novelty and a lack of understanding of the innovation by the population, before accelerating as a more significant proportion of the community becomes comfortable with the innovation, through observing its increasing prevalence and adoption. Growth eventually slows in the tails as the late adopters, who required extra time and information before adopting the process, finally join the fad – noting that there is no guarantee that they will adopt it. By utilizing the existing epidemiology models (therefore, connecting the concept of diffusion with that theory of contagion), the diffusion process was mathematically modelled by Bass (1969), in a framework that linked the rate of diffusion to the proportion of the population that had already adopted (or had been infected) via differential equations. A downside of these models were that they gave no insight into the expected behavior of individual members of the population.

In contrast to the diffusion of innovation models – which are restricted to assessing global patterns – the group of models within the informational cascade framework provide more granular detail into if and why an idea diffuses to the entire population. The basic premise of the informational cascade models is that a given agent's immediate neighbors will influence their decision – in other terms, their immediate network influences the decision-making process. The degree of influence will depend on the weight the agent assigns to their private information and the information of their neighbors. To derive this information agents, observe the behavior of their neighbors (Easley & Kleinberg, 2010). It is by assessing the decision-making behavior of individuals that the granular detail is exposed. The models can explain why a small initial shock can lead to a global shift, despite similar previous shocks causing no disruptions, thus exposing the robust yet fragile nature of complex systems (Watts, 2002). The ability of the theory to determine the origin of the fragile nature of a system makes it directly applicable to financial markets, which experience non-trivial and ex-ante unexplained boom and bust cycles.

There are two alternatives within the informational cascade framework based on how individuals are linked. The first, as detailed in Section 1.3.2.5.2, assumes that individuals are essentially link in a line. The other is to assume individuals connect through a network (most commonly a social network), where the network can take a variety of forms (topology), with some individuals having greater prominence in the network, as discussed in Section 1.3.2.5.3. In both cases the decision-making process unfolds in sequential order; that is, an agent can assess the decisions of previous agents. The sequential decision-making process is a principal component of the cascading process (Easley & Kleinberg, 2010).

1.3.2.5.2 Herding Models

This section relates to the herding model (or informational cascade models) as originated by Banerjee (1992) and Bikhchandani et al. (1992). These models explain why mass behavior occurs and why it is often fragile. Fragility refers to the fact that given relatively similar environments, the herding behavior may or may not occur, and the herding behavior may not be long-lasting. Fashion fads, investment bubbles, and localized conformity are all considered examples of herding.

The essence of these models is that people obtain information by observing the behavior of those around them, and use that information in combination with their private information in their decision-making process. Herding occurs when it becomes optimal for an agent to disregard their private information and merely follow the behavior of the preceding individual, a point at which the decision of each succeeding decision is uninformative (Bikhchandani et al., 1992). Herding is an example of a positive feedback mechanism (see Section 1.3.2.2), as the adoption of the new behavior by one agent sends a positive signal to the subsequence agents that they should adopt the same behavior.

A potential downside of herding is agents may pursue inefficient behavior, a point captured by Schiller's Dictum: “anyone taken as an individual, is tolerably sensible and reasonable – as a member of a crowd, he at once becomes a blockhead.” However, in the models mentioned above, it is assumed that the agents are still acting rationally; that is, they are drawing rational inferences from the limited available information. Section 1.4.6 discusses the direct relevance of herding to financial markets.

1.3.2.5.3 Adding Networks to the Diffusion Process

Valente (2005), comments that the diffusion of innovation research peaked in the 1960s before making a resurgence in the 2000s partly due to the rise of network science. Section 1.3.2.4 detailed the important fundamental concepts concerning network science that may have contributed to the resurgence of this research. Actors are implicitly limited to either a fully connected network or to local communities within the original herding model. The shortcoming of this assumption is that results, with particular reference to financial models, did not tend to be robust when the system was enlarged (Alfarano & Milaković, 2008). The importance of adding networks is that they provide the communication structure by which information flows to individuals, a structure that can be stochastic or deterministic (Kirman, 1983).

The utility of networks is seen in their ability to explain whether a cascade will or will not occur. As per Easley & Kleinberg (2010), a population level model, such as the Bass model, can only assess the effect of a cascade at a macro level. However, by introducing and integrating network science, a microanalysis of the diffusion process can be undertaken and it can be shown that a cascade can occur when only a small number of select individuals introduce a new behavior; alternatively, the cascade can cease due to the presence of clusters of non-conforming agents within the network. Further, the speed of a cascade can be affected by a social network because opinion change via the mass media is less than that produced by informal face-to-face communication of people within a person's social network (McGuire, 1985). Hence the need exists to analyze and understand the structure of the network, in particular social networks, with a focus on the centrality of individuals and the community structure.

1.3.3 Computational Social Science

Computational social science (CSS) is an emerging discipline that is at the intersection of social science, math, and computer science. CSS provides various numerical models and data analytics approaches to further the understanding of societal and human behavior. Therefore, it is the ideal discipline to apply to uncover the dynamics driving the economy, and financial markets.

The computational approaches within CSS present unique opportunities and methodological challenges compared to the traditional social science approaches of inferential statistics, axiomatic modeling, or interviews (Cioffi-Revilla, 2014). For example, how should adaptive behavior be introduced? How do we evaluate policies and outcomes when decision-makers exhibit bounded rationality? How are spurious inferences resulting from an over-analysis of data avoided? It is by combining formalized theories and empirical research that researchers can study and further develop their understanding of CAS via methods not available elsewhere.

Within the CSS framework, various computational and modeling tools have been, and continue to be, developed to understand and or make predictions regarding social science issues. Examples of the techniques employed are: ABM, SNA, machine learning, content analysis, and geographic information systems.

1.3.3.1 Agent-based Modeling

Assessing and gaining an understanding of the characteristics and dynamics of a CAS is problematic. By considering heterogeneity, feedback, non-stationarity, interaction, adaptation, and evolution, many of the traditional research methods, such as closed formed mathematical solution, are rendered ineffective. To avoid making the limiting assumptions, such as the representative agent, the utilization of computer simulation to understand CASs is becoming increasingly popular, and effective.

One simulation method that has been and continues to be extensively employed in the study of CASs is ABMs. According to El-Sayed et al. (2012) ABMs "are stochastic computer simulations of simulated 'agents,' or individuals, in simulated space, over simulated time." The utility of the approach comes from the capability of ABMs to address issues such as: heterogeneous expectations; out-of-equilibrium dynamics; the ramifications of a variable external environment (including shocks); and the adaptation and evolution of the agent population. In developing an ABM, a "bottom-up" perspective is taken, which allows for interaction between individual agents, with these agents acting and undertaking actions based on the context of their environment and basic rules. This process makes them ideal for assessing any emergent outcomes arising from micro-level behavior. ABMs can consider these factors because they do not rely on optimization so are not constrained to equilibrium conditions (Sornette, 2014).

The relative ease of including networks between individual agents or agent classes is another advantage of ABMs. As discussed in Section 1.3.2.5.3 and discussed further in Section 1.4.7, research utilizing network science has provided, and continues to provide, meaningful insight into critical social dynamics. However, to date, most SNA – the most relevant to an investor network – has concerned static networks, thus, not addressing the process of how networks form and evolve (De Caux, Smith, Kniveton, Black, & Philippides, 2014). ABM has proven to be a successful tool in understanding the dynamics of social network formation (see for example Hamill & Gilbert (2009)). However, per Fontana & Terna (2015) and De Caux et al. (2014), the benefits of combining network analysis and ABM are yet to be fully exploited.

1.3.3.2 The Rise and Rise of Data

The importance of collecting and utilizing data in the decision-making process is hardly a new endeavor. Simon (1955a) proposed that investors begin their decision-making process by collecting data. However, the generation, collection, and analysis of data have accelerated rapidly in recent years. The rapid rise of the phenomena captured under the "Big Data" paradigm is highlighted by IBM (2016), when they state that 90% of the world's data was created within the past 2 years. Financial markets are not immune from the rise of data. For example, the New York Stock Exchange (NYSE), the world's largest exchange, records a transaction ever 200 microseconds. The result of approximately 40-60 billion transactions per day is the generation of 15 terabytes of data. The rise of social media and the internet are two other examples of new sources of information that have fed the rise of "Big Data." However, it remains to be seen whether the new data holds any value or is "noise."

New data collection methods and processes have arisen with existing ones extended in response to the need to analyze the large volumes of data. CSS utilizes many of these methods, including machine learning, content analysis, natural language processing, and geographic information systems. The availability of the data has also proven beneficial for extending the reach of network science, as new networks are uncovered or expanded using the new data sources. Regarding ABM, the expanded availability of the data has had various positive effects. The new data sources inform research, thus allowing improved model specification, and the validation process – the process of matching the output of the model to actual data – has been enhanced as researchers can fine-tune their models.

Concerning financial markets, the use of data to gain an understanding of their behavior dates to Bachelier's (1900) work in the early 1900s (as discussed in Section 1.2.4.4). In that time, various financial models, informed by the available data, have achieved some levels of mild, positive predictive performance (Schumaker & Chen, 2009). However, the overreliance on data has seen some spectacular disasters, including the quant melt (Patterson, 2011) and the collapse of Long-Term Capital Management

(LTCM) (Lowenstein, 2011). While the exact nature of how data is used successfully (or otherwise) by modern investors are proprietary secrets, Huang, Lin & McMillan (2014) provide a comprehensive review of how various approaches have been used in the research environment to understand the movement of asset prices such as decision trees, neural networks, clustering, association rules, time series, and factor analysis.

1.3.4 Alternatives Utilizing an Interdisciplinary Approach

1.3.4.1 Combining Bounded Rationality with Complex Systems and Agent-based Modeling

As discussed in Section 1.2.5.3 it is questionable whether humans can perform the necessary calculations to be rational agents. Also, given that the stylized facts of the financial markets, which contradict the EMF, and the behavior of individual market agents cannot be explained using conventional decision models – especially their bias and attitudes toward risk – the need to pursue an alternative theory is required. However, this does not automatically justify the use of ABM. The validation for combining the theory of bounded rationality, complex systems, and ABMs was made by Arthur (1994) when he solved his El Farol Bar problem.

The link from the El Farol Bar problem to today's financial markets is: what occurs if humans cannot rely on other humans to act in a rational manner? The answer is that humans need to employ inductive (bottom-up) reasoning. Otherwise, if they maintain a top-down deductive approach, as utilized by rational expectations and normative economics, everyone would reach the same conclusion, but they would all ultimately be wrong. The inductive approach requires agents to form multiple belief models, act on the most credible, and then update or discard those that do not work. A key outcome of the approach is that while the system can reach a close to efficient outcome, it never settles into an exact equilibrium – which is a characteristic of financial markets.

Given the need for agents to have, maintain, update and possibly discard strategies, the model presented by Arthur (1994) was not mathematically tractable. Additionally, the agents were heterogeneous regarding their use of history, and the weights they applied to previous outcomes. To successfully solve the problem an ABM was employed, thus providing the proof of concept required to justify the use of not only the concept of bounded rationality but also an ABM to simulate and solve the problem.

A further justification for utilizing an alternate approach to understand financial markets comes from Tedeschi et al. (2012), who states that statistical analysis alone will not be sufficient to understand how the stylized facts of the financial markets arise. Indeed, Tedeschi et al. (2012) echo the sentiment of Epstein (1999), “If you didn’t grow it, you didn’t explain it,” by stating that there is a requirement to uncover the economic mechanisms that can explain the stylized facts of the financial markets. Utilizing ABMs is one method capable of uncovering the mechanisms in effect.

1.3.4.2 The Concept of Reflexivity

Thus far the concepts of a CAS (see Section 1.3.2) and feedback mechanisms (see Section 1.3.2.2) have been discussed, and their relevance to the research topics explained. While these concepts provide numerous avenues for research, it has been suggested by others (for example Beinhocker (2013) and Bookstaber (2017)) that the concept of reflexivity, per Soros's (2009) definition, provides an even more fertile ground for inquiry. The essence of the concept is that agents exist in a system where a self-referential feedback mechanism exists, with the mechanism governed by the principles of fallibility and reflexivity (Bookstaber, 2017). Before proceeding, per Beinhocker (2013), the need exists to acknowledge that there is significant overlap between a CAS and a reflexive system, in that the latter is a specific subset of the former. The need for the differentiation comes from the agents having the capability to adjust their internal mental models, and the interactive and dynamic complexity of the system within which the agents perform their tasks (Beinhocker, 2013).

The principle of fallibility sits at the core of reflexivity (Soros, 2013), and relates to the situation where an agent's perspective (internal model) with either be inconsistent or biased or both, opposed to reality. Thereby, agents will not (and cannot) consistently undertake the optimal behavior. Further, the agents will continuously update their erroneous models after assessing the outcomes of those models through their interactions with their environment and other agents. Regarding reflexivity, it specifically relates to how the previously formed imperfect views (or intentions) affect the system; thereby completing the feedback loop.

The relevance of reflexivity to the research undertaken in this paper is that when used correctly ABMs are inherently reflective models (Bookstaber, 2017). The foundation for this statement is that ABMs can match the dynamics of a reflexive system; that is agents maintain a cognitive function that allows them to perceive their environment by observing and receiving information, before assessing the alignments of their goals and the perceived state of their environment. Agents will then utilize their manipulative function to determine the best course of action to affect the environment such that their goals and the environment become better aligned. The actions of the agents as determined by their manipulative function, will, in turn, alter the environment, resulting in the need for further changes.

Bond et al. (2011), detail the direct relevance of reflexivity to financial markets within the body of research relating to how the information contained in prices affects the feedback mechanism between financial markets and the real economy. Examples of the dynamic is that management (decision-makers) gain information from market prices and use this in their decision-making process (e.g., whether to proceed with an investment); decision-makers care about their firm's price due in part to employment contracts, and this may impede them from making investments; and decision-makers may become irrationally anchored to the share price, thus inhibiting their thought processes.

While the models presented in Chapters 2 and 3 borrow from Soros's (2009) concept of reflexivity, they do not fully exploit the potential utilizing the framework. Section 4.3.2 addresses this shortfall by outlining possible remedial actions. In summary, the actions involve enhancing the cognitive function of the agents and allowing for a dynamic decision-making mechanism.

1.3.4.3 Artificial Stock Markets Utilizing Agent-based Models

Since the original ABM-based artificial stock market (see Arthur et al. (1997)) an assorted and rich vein of research attempting to uncover the dynamics of financial markets has developed. The models have developed along four lines (Cont, 2007): the heterogeneous arrival of information; evolutionary models; behavioral switching; and investor inertia. The following factors differentiated the approaches: how they handle agent preferences; the price-setting mechanism; whether evolution is allowed; and how to store strategies. Despite the differences, each framework has the common theme of utilizing heterogeneous agents regarding both expectations and investment strategies with the intention of: studying how agents act and prices change; reproducing the stylized facts of the markets; and, most important, understanding the influence of the market's microstructure. This underlying philosophical approach has resulted in the various implementations reproducing the stylized facts of financial markets, and identifying the conditions under which the return characteristics match the EMH or models that utilize it.

Within the artificial stock market literature there exist numerous options for establishing the price of the assets. The two main options are to create an order book and fulfil those orders through an auction process, or make use of a market maker who coordinates the market. Both models in this paper utilize the market-maker model. The rationale for the use of this model is that it ensures that the market does not become frozen due to a lack of liquidity or an inability to match orders, all of which are real-world considerations. To achieve the clearing process, the market maker provides liquidity by standing on the other side of all trades. This process guarantees that investors have their trades executed, thus a price is always struck at each step.

1.3.5 Section Summary

The purpose of this section was to justify the utilization of various CSS tools to address the research questions posed in the remaining chapter. Two viable CSS techniques – ABMs (Section 1.3.3.1) and network analysis (Section 1.3.2.4) – were highlighted. The use of CSS tools and an interdisciplinary approach, in general, is necessary to consider a system as a CAS, the primary criterion being that a CAS is characterized by non-equilibrium dynamics, as agents within the system interact, evolve, connect, develop feedback loops, and learn. Section 1.3.2.1 detailed that this behavior can create power-law distributions – with the returns of financial assets being evidence that financial markets operates as a CAS. This characteristic, in turn, creates a host of issues regarding how to avoid extreme events.

Having established the need to engage an alternate approach, Section 1.4 provides greater granularity concerning the research questions to be addressed in this dissertation. The topics that are discussed include: the social interaction between investors (Section 1.4.3); how the resulting social networks can affect financial markets (Section 1.4.7); whether they are responsible for herding (Section 1.4.6); the various potential feedback loops that can exist in financial markets (Section 1.4.4); and the existence and effects of irrational noise traders (Section 1.4.5).

1.4 Building out an Alternative Approach

1.4.1 Introduction

Section 1.3 provided the background arguments to support the use of alternative analytical methods and introduced and justified the most relevant ones. This section provides greater detail on various topics that are addressed by the research questions contained in Chapters 2, and 3. Section 1.4.3 discusses the need to consider the social interactions of investors. When social interactions are applicable, then the social network of those investors is relevant, while Section 1.4.7discusses the ramifications of investor networks. Figure 1 introduced the concept of feedback loops in financial markets. Next, Section 1.4.4 details the various potential feedback loops that can exist in financial markets, before Section 1.4.5 discusses the theory of noise traders and how they contribute to inefficient outcomes in financial markets. Finally, Section 1.4.6 expands on the herding topic raised in Section 1.3.2.5.2, with a summary of the research undertaken to understand herding in financial markets.

1.4.2 The Market Ecosystem and Microsystems

Within the CAS framework a research stream of untapped potential is the consideration of financial markets as an ecosystem. Farmer (2002) first proposed the concept of a market ecosystem to explain how the endogenous characteristics of financial markets can produce various phenomena, including excess volatility –which cannot be readily explained by the EMF. The genesis of the theory comes from the notion, and subsequent recognition through empirical evidence (see for example, Bouchaud et al. (2009)), that investors of varying investment strategies, or classes, co-exist in the market. In turn, the interactions of the various investor classes are deemed responsible for the observed behavior of the financial markets. Vitally, the recognition of the interaction of various investor classes invalidates the theory of the representative agents and supports the investigation of how these interactions may be affected by positive or negative feedback loops, and in turn how this influences the behavior of the market.

As detailed in Section 1.4.5, the original formalized recognition of alternate investor strategies was between fundamental and noise traders. The recognized investment strategies have now expanded to include: fundamental growth and value investors; and trend followers (the original noise traders). The existence of various investment strategies is used to inform the model presented in Chapter 3. While not discussed in detail in this dissertation, the reader should be aware of the ongoing debate within financial markets as to which investment strategies are optimal. Suffice to say there is yet to be a definitive answer, with the benefits of growth and value investing varying across time. Such a debate is irrelevant within the EMF because there is no possibility of heterogeneous investor strategies existing because: one, the market contains homogeneous representative agents; and two, any non-rational investors cannot survive.

The rationale for the development of Farmer's (2002) ecosystem approach was two-fold. The first was to acknowledge the interrelationships between financial agents and their environment. This included recognizing that investors are effectively "species" defined by their investment strategies. The basis of the second point was that to understand the market's behavior, it was deemed to optimal to observe the behavior of the species; that is, trading behavior of the investors, and explain what occurs, without attempting to explain why it occurs. Lo (2017) extended the ecosystem analogy in his theory of the adaptive market hypothesis. The essence of the theory is that certain investor classes can appear and prosper in the short-term despite utilizing trading strategies inefficient over the longer-term.

One of the greatest impediments of the ecosystem approach has been gaining sufficiently detailed data to fully explore the theory and exploit an interdisciplinary approach. However, this issue is slowly disappearing, with the recent work of Musciotto et al. (2018) highlighting the potential of utilizing data and CSS tools to uncover the inner dynamics of financial markets. A vital aspect of the research was to assess the potential role that the network topology of investors has on the volatility of financial markets.

1.4.3 The Role of Social Interaction

To arrive at the realization that heterogeneous investment strategies can co-exist, various alternative approaches needed to be considered. One such consideration is that investing in speculative assets is a social activity. With no broadly accepted, and followed theory existing regarding how to price speculative assets, Shiller et al. (1984), considered the possibility that stock prices were vulnerable to social movements. Another factor in this line of inquiry was that investors are unable to predict the consequence of changing their investments accurately; therefore, they cannot assess the accuracy of their decision. Under these conditions, it may indeed be considered optimal for investors to mimic, rather than to solve the problem for themselves. The essence of this argument underlies the EMH; that is, it is meant to crystallize the wisdom of the crowds (Lo, 2017).

The foundation of Shiller et al. (1984) was that the market has two types of investors, smart ones – those not influenced by social movements, and "dumb" ones – those that followed the social movement. This approach was used to inform the insight that the equity bull market of the second half of the 20th century had been driven by social movements, as more and more socially motivated investors joined the market in response to the profits of their peers. The vital component of this paper was the need to understand the extent to which smart money dominated the market and alternatively and under what conditions did it switch so that dumb money dominated the market. The importance of this dynamic is that it raised the need to understand the mechanism by which investing trends flowed between socially influenced investors; that is, did investors herd, and if so, how and why did it occur? Cont & Bouchaud (2000) identified the importance of this when suggesting that the high variability present in stock market returns may correspond to collective phenomena such as crowd effects or herd behavior. Section 1.4.6 discusses the literature relating to this.

Another factor highlighted in the Shiller et al. (1984) paper was the issue of the correct discount rate. In his response to the theory proposed in Shiller's et al. (1984), Fischer raises the point that under Samuelson's (1965) assumptions of efficient pricing in the stock market, it required the discount rate of investors to remain constant (Shiller et al., 1984). As discussed in Section 1.2.5.4, the issue of how investors assess their discount rate is an important one, and will be addressed further in 2.3.3. By relaxing the assumption of a constant discount rate, models such as Grossman & Shiller (1980), have been better able to explain the variability of the stock market.

1.4.4 Feedback Loops in Financial Markets

Figure 1 provided a stylized illustration of the various feedback loops in the financial ecosystem. In a significant step, the definition of the financial ecosystem is now extended beyond the one discussed in Section 1.4.2. Rather than solely considering investors, the bounds of the ecosystem is expanded to include investors – with their investor strategies, and firms (and their management) with their resource allocation strategies, thereby; the altering the objective of the research to observing and understanding how investors and firms interact and survive, or otherwise. To achieve an understanding of the behavior, two specific feedback loops are explored in this dissertation. Sections 1.4.4.1 and 1.4.4.2 discuss these specific relationships in detail.

1.4.4.1 Prices and Investor Behavior

As mentioned in Section 1.3.2.2, rising prices are meant to dampen demand for a product via a negative feedback loop. However, positive feedback loops have appeared on a semi-regular basis in financial markets. Mill (1865) provided an early illustration of how speculation can create a positive feedback loop that resulted in a price bubble in commodity markets. The explanation started with a general "impression" among the community that prices were going to rise due to either a poor crop, extra demand, or a supply restriction. The presence of the "impression" forces speculators to increase their stocks in anticipation of future price increases. Increased demand for the existing supply increases the price, and the price increase attracts further speculation, and more "speculators" enter the market driving the price higher again. At some point, the price level is not justifiable, and the subsequent slowing in price increases signals to speculators that further profits are unlikely and they begin the process of realizing profits. Next, speculators start to sell in unison, and the underlying demand for the product is not sufficient to maintain the existing price and the price collapses.

Augmenting the theory that a positive feedback loop can create an asset bubble, Shiller (2005) theorizes that bubbles arise because: "Initial price increases caused by certain precipitating factors lead to more price increases as the effects of the initial price increases feedback into yet higher prices through increased investor demand. The second round of price increase feeds back again into a third round, and then into a fourth and so on. Thus, the initial effect of the precipitating factors is amplified into much larger price increases than the factors themselves would have suggested."

De Long et al. (1989) formalized the positive feedback theory into a model capable of explaining asset price volatility. The significance of the model was that it introduced positive feedback investors (who would later become part of the noise trader literature) who would buy an asset as the price rose and sell when the price fell – a behavior that contradicted the standard economic theory. The presence of these traders was reported as destabilizing because rational speculators would be aware of the presence of positive feedback investors, and would anticipate their decisions and trade ahead of them. This process would commence the trading cycle and reinforce the expectations of the feedback investors, resulting in prices moving away from their fundamental value in the short-term before fundamental investors would reverse the process in the long-term. The model, therefore, captured the empirical evidence that short-term returns were negatively correlated with long-term returns.

1.4.4.2 Management Behavior and Prices

Another potential feedback mechanism exists between management and investors through the share price of the company. The influence of the direction of a company's share price over its management is a moot point within the realms of efficient markets. The basis of the argument is that the market will not be systematically fooled by the manipulative behavior of management; thus, a company's share price will solely reflect the long-term prospects of the firm (Stein, 1989). However, like much of the EMF, this expectation appears inconsistent with the actual behavior of the markets.

There is now a growing body of research relating to the possible feedback mechanism between the decision-making process of a firm's management, its effect on the earnings profile of a company, and the market's valuation of the firm (as explained in Bond et al. 2011)). Rappport (2014) even provides a guide as to how management can maximize the value of their firm by modifying, and enacting certain strategies. Importantly, this research does not touch on earnings management, which is a strategy employed by management to avoid disappointing shareholders. Soros's (2003) concept of reflexivity, (as introduced in Section 1.3.4.2) captures this feedback mechanism and implies that financial markets potentially affect the fundamentals (for example, earnings and investment decisions) they are meant to reflect solely.

1.4.5 The Arrival of Noise Traders

As became apparent that investors, and therefore the market, did not behave in accordance with the EMF, the question turned to how do they act? One possibility is that they act with bounded rationality, which may lead to inefficient outcomes such as herding. Another possibility, one that has gained considerable traction, is that a proportion of the investing population acts are noise trader, thus providing the spark to consider how heterogeneous investors may exist in a market ecosystem.

Friedman (1953) was the first to acknowledge the possible existence of the noise traders, but he theorized that the irrational (noise) investors would disappear from the market due to losing their money at the hands of the rational investors. Therefore, markets would tend to self-stabilize. This argument was extended and reinforced by Fama (1965). However, it has now become accepted that noise (irrational) traders can survive and they have the potential to destabilize markets (Tedeschi et al., 2012). Given their relevance, financial ABMs make extensive use of the concept of noise traders.

The concept of noise traders was introduced by Kyle (1985) when comparing the behavior of an investor with private information to that of investors who acted randomly – that is, noise traders. Following this, De Long et al. (1990) made the critical contribution that noise traders could survive and outperform in the market on the condition that the rational investors were risk-averse. The mechanism is that rational investors were too risk-averse and were not prepared to execute the arbitrage (riskless) trades required to force the noise traders from the market. This outcome meant that prices of financial assets would remain disconnected from their fundamental value for an extended period, hence making it difficult for rational investors to determine the fundamental value of an asset.

A proposed mechanism responsible for excess market volatility is the connection between noise traders and a positive feedback loop. The argument, which has developed since being proposed by De Long et al. (1989), is that noise traders generate price signals that investors mistakenly interpret as fundamental information. This error draws in more investors which in turn causes the price to move again, and the cycle repeats. By this stage investors have mistakenly interpreted noise for fundamental market information and their decisions are impaired. At the extreme, this cycle can lead to herding behavior, as discussed in Section 1.4.6.

1.4.6 Herding in Financial Markets

A definition of herding in a financial context is a group of investors following each other into (or out of) the same securities over a defined period (Sias, 2004). The importance of understanding investor herds is that their behavior has the potential to help explain market behavior, as the different groups should correlate differently with the market (Venezia, Nashikkar, & Shapira, 2011). According to Topol (1991), Shiller et al. (1984) was the first to introduce a model that integrated herding behavior into an asset pricing model. From this point, an extensive body of literature has developed, which includes noise traders, as discussed above, developed – Hirshleifer & Hong Teoh (2003) provide a detailed survey of the literature relating to herding in financial markets. The next step in the evolution of the subject matter was the uncovering of specific empirical evidence (see Scharfstein & Stein (1990), Grinblatt et al. (1995)) that supported the theories of herding. The overarching theme of the research is that investors tend to follow each other due to a positive feedback loop, where rising (decreasing) prices reinforce the current behavior of the investors.

Since the original empirical evidence of herding, the research has been divided between attempting to detect institutional herding by utilizing micro-data to uncover whether investors imitate each other's actions or by using aggregate data to understand how the market discriminates between different stocks (Galariotis, Rong, & Spyrou, 2015) and (Klein, 2013). Identifying institutional herding through utilizing the micro-data approach finds at best meaningful evidence of herding, and at worst only limited herding (see for example Lakonisok et al. (1991), Sias (2004), Nofsinger and Sias (1999), and Wermers (1999)). Regarding the market approach, Klein (2013) reported that the herding effect in stock markets increases during times of market turmoil, with the implication being that investors discriminate more strongly between single stocks than implied by rational asset pricing models.

1.4.7 Investor Networks

Since the formalized documentation of the existence of networks linking investors by Shiller & Pound (1989), there has been an extensive body of work developed to understand the implications of investor opinions and actions flowing across these networks. With their ability to explain the trading decisions of investors and their portfolio performance, understanding the relevance of investors networks is essential (Ozsoylev & Walden, 2011).

The existing work relating to network structures associated with stock markets has taken several forms. The first is forming network containing stocks, where the links are based on the correlation between individual stocks (see Preis et al. (2012), Bonanno et al. (2004), Boginski et al. (2006) and Kenett et al. (2010)). Alternatively, networks between investors have been created by implying the network based on trading patterns (see Ozsoylev et al. (2014)). Finally, empirically based investor network have been identified (see Shiller & Pound (1989), or Hong et al. (2005)). Many of these studies have involved the analysis of static networks, whereas ultimately greater insights will come from the analysis of temporal networks. However, Boginski et al. (2006) assessed the temporal dynamics of the US stock market network between 1998 and 2002 and found that the market network increased in density over time, a fact Boginski et al. (2006) attributed to increased globalization.

In another approach, Caldarelli et al. (2004) assessed a bipartite network between stocks and investors. A key finding was the characteristic of their resulting market graph, which matched scale-free topology, where the degree distribution of the stocks matched a power law distribution, providing further evidence that financial markets operate as a CAS. The authors highlighted that this result is inconsistent with the expected result of a constant in-degree, as inferred by the CAPM.

Network science has been utilized to understand the critical concept of herding behavior amongst investors. Cont & Bouchaud (2000), developed the first model to remove the sequential decision-making process, replacing it with a random network. However, Alfarano & Milaković (2008), highlight a potential issue with the models that use a similar framework to Cont & Bouchaud (2000). The issue is that these models rely on carefully tuned parameters, which place the model close to its critical point, without explaining how the system would self-organize to such a point.

In general, the relevance of networks to the herding process is that if and when investors herd their information network becomes a vital consideration (Ozsoylev & Walden, 2011). The information network of investors contains numerous inputs, including but not limited to their social network – formed from their interactions with other investors, public information from either the company or media sources and semi-public information, which is provided on a selective basis based on the relationship between the investor and the source.

1.4.8 Section Summary

The purpose of this section was to define and justify the specific topics addressed in the following two chapters. Section 1.4.2 introduced the concept of the market ecosystem and connected it to various feedback loops. Next, Section 1.4.3 examined the concept that investing has a significant social element. Therefore, rather than reducing financial markets to a market of a single rational investment, the theories of financial markets need to consider the consequences of social interaction and fallibility of human decision-making. To extend the discussion of the implications of social interaction in financial markets, Section 1.4.4 discussed the existence of, and the effects of, positive feedback loops in financial markets. Two loops of relevance are a loop between investors, and one between management and the markets where their firm’s stocks trade. Next, Section 1.4.5 discussed the relevance of noise traders and how their ongoing presence in markets can help explain the stylized facts of price movements in financial markets. Section 1.4.6 drew the link between the general theory of herding and herding within financial markets, along with a review of the empirical evidence of herding. Finally, Section 1.4.7 introduced the methods and empirical work regarding investors forming and relying on a network with other investors.

1.5 Summary of Papers

This section provides the abstracts for the two chapters that implement ABMs to fulfill the research goal of identifying novel outcomes by considering financial markets as a CAS. The theme of both papers is that financial markets are not efficient and agents co-exist in an ecosystem, where their interactions affect the behavior of the system. The first model looks at how an endogenously formed investor network affects the characteristics of an artificial stock market's returns. This model also assesses the implications of short-term investors. The second paper looks at the interaction between investors and management, with a focus on whether the price signals from the market affects the behavior of the market.

1.5.1 Understanding how Short-termism and a Dynamic Investor Network Effects Investor Returns: An Agent-Based Perspective

With financial markets exhibiting periods of unforeseen volatility it has become necessary to improve the understanding of investors behavior. Specific points of interest are whether investors rely on other investors to inform their decisions and the extent that they react to new stimulus. If investors become dependent on other investors, then their network of advisers will become a vital factor in determining their actions. This chapter implements an ABM where investors connect in a network – which they in turn utilize to inform their investment decisions. Over time the investors update the trust they have in their information sources and evolve their network by connecting to investment Oracles and discarding poor advisers. The magnitude by which investors update their trust is influenced by the consideration that the investors give to past price movements and the fidelity of the advice they receive. The stock market is found to be materially affected by how often investors revise their advisers and their sensitivity to the past behavior of the stock market.

1.5.2 Quantifying the Concerns of Dimon and Buffett with Data and Computation

There are growing concerns that by the management of firms giving too much consideration to the movement of their share price their decision-making processes are adversely affecting the long-term performance of the firm. This concern implies that there may be a positive feedback loop between firms and investors. The danger of the loop is that it may prejudice the way management allocate their resources, with their growth adversely affected. While the determinants of firm growth have not been definitively identified, a set of stylized facts relating to the distribution of firm size and growth have, and their characteristics are suggestive that firms evolve in a complex system. Additionally, various financial market metrics are also found to exhibit the statistical imprint of a complex system. To investigate the issue of a feedback loop existing, and its ramification on firm growth, this chapter implements ABM where firms have the option to react to recent changes in their share price when deciding how to allocate their resources. The results highlight an adverse outcome – regarding capital growth if management considers the market's movement. The type of investors in the market is also found to affect the performance of the firms through the volatility they generate. The model also presents insights into how and why the extent of that agents consider past outcomes in their decision-making process become influential.

2 UNDERSTANDING HOW SHORT-TERMISM AND A DYNAMIC INVESTOR NETWORK EFFECTS INVESTOR RETURNS: AN AGENT-BASED PERSPECTIVE.

2.1 Introduction

Secondary equity markets are an instrument that provides participants (investors) with the opportunity to increase their wealth. However, the behavior of these markets has proven difficult for most investors to master. The principal issue facing investors is that these markets at times have behaved in a manner inconsistent with the efficient market framework (EMF), thereby providing investors with little guidance as to how to respond to the behavior of the markets. The behavioral characteristic of greatest concern for investors is when markets demonstrate excess and clustered volatility; that is, prices fluctuate excessively within a short-period. The ramification of this behavior is that it amplifies any poor investment decisions and investors can experience material wealth destruction. In some instances, investors may be responsible for feeding market volatility as they pursue short-term profits or forgo reliable information sources and follow a short-term trend. However, in yet another quandary for investors, following the crowd and gaining from its wisdom has been proposed as an optimal solution by many.

Within the standard EMF, there is no room for investor emotion or irrational (non-optimizing) behavior. Within this framework investors take the form of a single representative agent who, with perfect foresight, can make optimal long-term investment decisions. The introduction of any divergent behavior renders the EMF obsolete and raises numerous questions as to how investors behave. For this chapter, the research addresses the possibility that investors: can receive information from selected invested; varying the time horizon of which they consider past information; are influenced their environment, that is a feedback loop exists; and, learn and adapt to their environment. The consideration of financial markets as a complex adaptive system (CAS) addresses these issues, and more. The use of the CAS framework to analyze financial markets is becoming more accepted, with researchers uncovering many dynamics driving the excess volatility in the financial markets.

By allowing investors to receive information from other investors, and more specifically select their preferred advisers, is to allow them to form an information network. In this instance the network is a socially based. The consideration of an investor's network has become essential, as social network analysis (SNA) has become a fertile field of research providing numerous insights across a variety of fields. Before the rise of SNA, many of the relationships between agents that are responsible for the behavior of an overall system remained hidden.

The standard analytical tools that underlie much of standard financial analysis become redundant in the realm of a CAS. One possible solution is to utilize agent-based models (ABMs). This approach allows researchers to build a simulation from a bottom-up perspective, with the agents interacting with and adapting to their environment. The interaction includes contact with their other agents. By allowing the interaction between agents the topology of the agent's social network becomes a vital consideration, with feedback loops having the potential to operate across the network.

The model presented in this chapter implements an artificial stock market utilizing an ABM with investors linked in a network. The investor population is divided into long-and short-term investors, with the difference in the sub-population being how the investors factor in the prior movements in the risky asset's price. Long-term investors consider a greater length; therefore, they will be less reactionary to recent price movements, while short-term investors will be more reactionary. This feature intends to assess whether short-termism on behalf of investors leads to more trading, which in turn contributes to excess volatility in the stock market. The investor network is dynamic as investors select (and cut) the neighbors they receive information from (advisers) at fixed intervals. In selecting their new advisers, investors seek out the better performing investors, investors known as Oracles. The intention of the process is for investors to enhance their investment performance by receiving the highest quality of information. The implementation of this process is intended to provide insights into how the dynamics of an investor's social network can affect the behavior of the stock market.

Section 2.2 develops the foundation for this chapter. Followed by Section 2.3, which provides a literature review that expands upon the relevant concepts from Chapter 1. Next, Section 2.4 details the implemented model with its results presented in Section 2.5. Finally, Section 2.6 provides a summary and concluding comments.

2.2 Chapter Foundations

2.2.1 Background and Motivation

Figure 9 illustrates the actual and inflation-adjusted growth of the S&P 500 index. The message from the chart is that equity markets have provided astute investors the opportunity to increase their wealth. For example, a dollar invested in the index at its inception would have generated an annual return of 4.45% per annum (p.a.) (2.3% p.a. inflation adjusted). The return increases to 9.68% p.a. (6.87% p.a. inflation adjusted) if dividends are re-invested. However, most of the growth in the index has occurred post-World War II; for instance, the per annum return with dividends reinvested since 1945 is 11.12% p.a. (7.19% p.a. inflation adjusted).

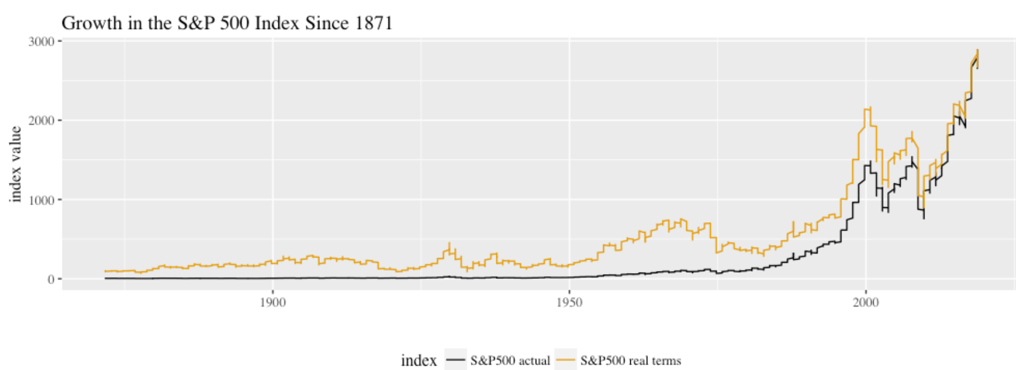

Figure 9: The growth in the S&P 500 index since 1871. Data source: (Shiller, 2019)

It is also apparent that the growth has not been smooth, with numerous examples where the index has experienced periods of material acceleration in growth before subsequent reversals. These episodes include the Black Monday crash in 1987, 2001's dot.com crash, the global financial crisis (GFC) correction in 2008, and the extended bear market from the 1970s until the early 80s.

This chapter investigates two specific implications of Figure 9. The first is to explore possible causes of volatility in the markets and the second is to understand what, if any, are the characteristics of investors who generate higher returns than the market. Under the umbrella of EMF this analysis is redundant as: noise traders will fail to survive (Friedman (1953)), thereby reducing the market to rational long-term investors; and no investor is deemed capable of outperforming the market on a risk-adjusted basis over the long-term. While there is supporting evidence that on average mutual fund managers have been unable to outperform the market (see for example Cuthbertson, Nitzsche, & O'Sullivan, 2008 and Malkiel (1999)), there is also evidence that some investors have achieved and maintained a material positive performance differential over the market (see Lo (2017) and Weatherall (2014)). This fact raises the research questions as to what makes these investors unique, and what are the consequences of other investors attempting to replicate their strategies. The latter question can be addressed by linking investors across a network, with trading information flowing across it. Chapter 1 provided a general overview of these issues; however this chapter will specifically address how investor networks contribute to the behavior of the market and the investors within it.

As discussed extensively in Chapter 1, the reality of the market's erratic behavior has forced some to consider the financial markets as a CAS. This approach, by considering factors such as feedback, non-stationarity, many interacting agents, adaptation, evolution, single realization, and an open system, has produced viable explanations for the return characteristics of financial markets. Within the CAS framework, the exploration of the possibility and implications of investors sharing a social network continues. The critical implication is that these networks can produce herd-like behavior, and therefore excess volatility in the markets. An advantage of using a CAS framework in assessing financial markets is that investors can possess heterogeneous attributes. In turn, this approach creates a market ecosystem, a system that reacts to the whim of investor behavior and expectations. The relevance of the assessing a market ecosystem, as detailed in Section 1.4.2, is that agents of differing species interact and these interactions, and the agents' response to these interactions, are responsible for generating system level behaviors, some of which result in large shocks.

A vital component of an investor's decision-making mechanism is the investment horizon, an issue addressed in this chapter. In the neoclassical economics and finance literature investors are assumed to have perfect foresight and they utilize this quality to make investment decisions over a long-term time horizon. However, lessons from the various market disruptions provide evidence of contrary behavior, with investors exhibiting a tendency for short-term profit-taking. Section 1.2.5.4 contains a more detailed discussion on "short-termism" in financial markets. The acknowledgment of the harmful effects of investors exhibiting a focus on short-term factors has existed for some time (see for example Keynes (1936)), but the issue has gained greater prominence in recent years (see for example Kay (2012)).

Another negative side-effect of short-termism that is relevant to this chapter is excessive trading by short-term investors. The vital concern of excessive trading is that it can disrupt the functioning of the capital markets (Stiglitz, 1989). Another issue is that while in some instances it is rational for investors to employ short-term trading strategies, which result in excessive trading, in general this approach produces inferior wealth generation (see, for example, Barber & Odean (2000)). Section 2.3.3 discusses why investors trade excessively, an issue that remains open, in more detail.

Within financial markets it has been recognized that investors form networks. The relevance of investor networks is their ability to explain trading volumes and performance of investors (see for example Ozsoylev & Walden (2011) and Ozsoylev et al. (2014)). Within finance, researchers have either analyzed (or implied) actual networks or simulated the networks. Yet to date much of this analysis and SNA, in general, has utilized static networks. However, the pursuit of understanding the dynamics of networks through time is a burgeoning avenue of research. ABMs have proven to be a successful tool in understanding the dynamics of network formation (De Caux et al., 2014). However, according to Fontana & Terna (2015) and De Caux et al. (2014), the benefits of combining network analysis and ABM are yet to be fully exploited. The model described in Section 2.4 and the results detailed in Section 2.5 demonstrate the fertile research achieved by combining the two fields.

As discussed in Section 1.3.4.3, agent-based artificial stock markets have made substantial inroads into explaining the observed behavior of financial markets. These models have uncovered, and continue to uncover, mechanisms that can generate the many stylized facts observed in the financial markets (discussed in Section 1.2.5.1.1). ABMs are well-suited to this role because their role in research is to develop an explanation of how and why the elements of the system generate emergent outcomes. This contrast with the standard analytical approach which makes precise predictions regarding a specific variable, for example a stock price in the instance of an asset pricing model like the CAPM. The foundation of these ABMs was the behavioral heterogeneity of the agents. However, according to Alfarano & Milaković (2008) the approach can be enhanced by introducing structural heterogeneity. The purpose of structural heterogeneity is to allow for various social and institutional relationships, and to provide the feasibility of agent interaction. Structural heterogeneity manifests itself as a network between investors.

2.2.2 Overview of Approach

To address the research question posed in Section 2.2.3, an artificial stock market implemented via an ABM, with investors linked in a network as detailed in Section 2.4 is utilized. The model's functionality is that investors have access to three sources of information: public, private, and trading intentions – that is, to buy, hold or sell the risky asset – of their network links (neighbors). An investor considers these neighbors as advisers. Each investor combines these information sources to decide whether to buy, hold, or sell the risky asset. Investors adjust their trust in the various information sources based on its past ability to correctly (or incorrectly) predict the movement of the risky asset's price. In assessing their trust in the information sources, the agents utilize varying lengths of historical results based on whether they are long or short-term investors. The intention is that a short-term investor will adjust trust more rapidly, based on fewer data points. Section 2.4.3.2 provides a more detailed explanation of the process. Finally, investors will, at varying intervals, discard untrustworthy neighbors and search for better-performing ones; thus, the network evolves endogenously. 2.4.3.1 details the process and the parameters regarding the actions of the investors.

After delivering verifiable results, several variables are varied to understand the effect they have on the market and investor wealth creation. A focus of the various experiments, as outlined in Section 2.5.2, is to understand how the composition of the investor population affects the market's behavior, with an emphasis on understanding the ramifications of short-term behavior and an endogenously evolving network.

2.2.3 Research Questions

To assess the consequences, if any, at the market and agent level of a dynamic investor network and differing investment horizons, several questions are addressed in this chapter. Specifically, what are implications for the market of providing agents with the ability to be selective in their choice of advisers(neighbors)? Additionally, by providing agents with this flexibility, what form does the resulting network topology take, and how long does it take to become stable, if at all? Lastly, the effect of allowing investors to take a myopic approach is assessed to judge whether it amplifies or nullifies the dynamics of systems. At the agent level, the critical question relates to establishing whether specific agents are more successful in generating excess returns than others, and if so what are their characteristics? In short, what are the characteristics of an Oracle? The intention is to see if it is possible to grow a Warren Buffett in silico.

2.2.4 Section Summary

This section provided a general introduction, covering the motivation for the research (Section 2.2.1), the chosen approach (Section 2.2.2), and the research question (Section 2.2.3). The motivation is that the financial markets consistently exhibit behavior outside of the standard theories, such as the EMF, thus providing an impetus to consider alternatives. One alternative is to consider financial markets as a CAS and deploy an ABM to simulate the behavior of investors. Section 2.2.3 summarized the research question addressed in this paper, which is: what are the effects of investors considering the actions of their neighbors and possessing a myopic view regarding the past performance of the market.

Section 2.3 is divided into distinct sections to effectively communicate the rationale for and the results of the research questions. First, Section 2.3.2 provides greater detail about the significance of investor networks and the case for the greater exploration of their contribution to explaining the behavior of financial markets. Next, Section 2.3.3 presents the literature relating to trading frequency and Section 2.3.4 provides a summary of the investor performance research. While Section 1.3.4.3 provided a general history of agent-based artificial stock market, Section 2.3.5 provides a review of the literature relating to the specific model in this paper.

2.3 Literature Review

2.3.1 Background and Introduction

The model presented in Section 2.4 is informed by multiple sources of theory and research with each dealt with separately in the following sub-sections (Sections 2.3.2 to Section 2.3.5). Having investors linked in a network, the consequences of the network, and utilizing the network to inform trading decisions underpins the model. Section 2.3.2 reviews the literature relating to investor networks. Regardless, of whether investors form a network, there is evidence that they exhibit heterogeneous characteristics regarding their investment horizon and trading behavior. Section 2.3.3 discusses the evidence and the ramifications of this theme. The EMF implies that no investor can outperform the market over the long-term. While there has been considerable evidence to support this (see for example Malkiel (1999)), contrary evidence exists (see Lo (2017). Section 2.3.4 discusses this research. The final section, 2.3.5, provides the rationale for utilizing an ABM to create an artificial stock market, and the history of the different approaches.

2.3.2 Volatile Markets, Herding and Investor Networks

Section 1.2.5.1 provided clear evidence that financial markets do not conform to the characteristics prescribed by the EMF. A viable explanation for the observed behavior was that financial markets are a CAS, with investors potentially forming herds because of positive feedback loops influencing investment decisions. Section 1.4.6 summarized the significant body of research, both theoretical and empirical, that addresses the herding behavior of investors. Additionally, as the CAS perspective has evolved, the effects of investor networks on investor behavior has become a fertile field of research as network analysis has been able to explain the trading activity of investors and their portfolio performance (Ozsoylev & Walden, 2011).

The original empirical evidence (with no direct mentions of networks) of herding in financial markets first appeared in the 1990s. As defined by Sias (2004), herding is where a group of investors follow each other into (or out of) the same securities over a defined period. The importance of understanding investor herds is that their behavior has the potential to help explain market behavior, as the different groups (herds) should correlate differently with the market (Venezia et al., 2011). Since the original evidence of herding, the research has either attempted to detect institutional herding by utilizing micro-data to uncover whether investors imitate each other’s actions, or aggregate market data to understand how the market discriminates between different stocks (Galariotis et al., 2015) and (Klein, 2013).

Despite the awareness of the detrimental effect of group behavior being recognized in the 1800s (see Mackay(1841)), the formal connection to the relevance of networks did not occur until the 1980s. Since the formalized documentation of the existence of networks linking investors by Shiller & Pound (1989), there has been an extensive body of work developed to understand the implications of investor opinions and actions flowing across these networks. The relevance of networks to the question of financial market volatility is that, if and when investors herd, their information network becomes a vital consideration (Ozsoylev & Walden, 2011). Cont & Bouchaud (2000) were the first to model and interpret the implications of investors connecting in a network herding and herding on the returns of financial markets.

The information network of investors contains numerous connection possibilities, including but not limited to: their social network – other investors that they interact with; public information from either the company or media sources; and semi-public information. An example of semi-public information would be broker research – research distributed on an "exclusive" basis to the client base of the broker. The role of the model implemented in this chapter is to investigate the various permutations of the social network of investors. The justification for the focus on the social network of investors is provided by Oremond (2012), who stated that people often copy or imitate what their social connections do or think. Further, in times of greater uncertainly, researchers suggest that imitation may be the optimal solution.

Financial markets consist of both professional institutional investors and private investors. These populations, while sharing the common goal of increasing their wealth, pursue different agendas. A critical difference is how they assess performance, with institutional investors more concerned with their performance in comparison to their peer group and to the market – that is, their relative performance – and private investors concerned about wealth creation. This issue relates to how institutional investors utilize their performance records to attract investors, a step not required for private investors. This asymmetry in incentives has been used to explain herding by institutional investors (Chevalier & Ellison, 1995). In differentiating between investors, another question is whether institutional investors are more reliant on their networks than private investors.

This issue again relates to the needs of institutional investors to maintain a superior record within their peer group.

2.3.3 Trading Behavior and Short-termism

An obscure ramification of the EMF is that there should be little to no trading because, with all investors sharing the same information, no incentive exists to trade because prices of the assets will reflect all current information (Grossman & Stiglitz, 1980). However, the reality is that trading does occur and occurs at a rate that even proponents of the EMF struggle to explain (Farmer, 2002). Barber & Odean (2000), highlight competing explanations regarding the empirical level of trading. One, which uses a rational expectations framework, is from Grossman & Stiglitz (1980), who proposed that trading will occur up to the point where the marginal benefit of trading equals the marginal cost of gathering the information which informs the investors' decision-making. However, as the cost of gathering information is not homogeneous, investors develop varying motivations to trade. Barder & Odean (2008) provide a prime example of this issue by assessing the different trading outcomes due to investors having a limited attention span concerning evaluating company announcements. Another explanation is that investors suffer from numerous cognitive biases, including overconfidence, leading to excessive trading. Excessive trading comes at a cost for investors, with their net returns being well below the market (Barber & Odean, 2000).

The presence of noise traders (De Long et al., 1990) is another stream of research utilized to explain excessive trading. Section 1.4.5 provided a review of the broader noise trader research. The presence of noise traders is an important feature of not only artificial stock markets but all financial models. By way of background, following the argument put forward by Friedman (1953), neoclassical economic assumed that irrational (noise) investors would be forced from the market due to losing their money to rational investors. This argument is based on investing being a zero-sum game; that is, the wealth of the irrational investors is transferred to the rational investors. However, it has now become accepted that noise traders can survive and they have the potential to destabilize markets (Tedeschi et al., 2012). ABMs have and continue to assess the effects of noise traders.

Another feasible explanation for the excess trading is that investors have a short-term focus and this leads to excessive speculative trading (The Aspen Institute, 2009). Short-termism is where investors maintain a preference for near-future cash flows over longer-term cash-flows. This preference is a result of hyperbolic discounting, the phenomenon of discounting future gains at a higher rate, and therefore preferring smaller and sooner payoff to larger and later ones. Investors are thereby underestimating the value of medium to long-term cash flows, which removes the incentive for management to invest in long-dated projects (Davies et al., 2014) (Section 1.2.5.4 explored this point). The undesirability of short-termism also comes from the inefficiency that occurs with firms (and management) becoming preoccupied with short-term returns and meeting market expectations (Dimon & Buffett, 2018), a point discussed in Chapter 3.

An implication of the representative agent approach employed by the EMF is that the composition of the investor population is inconsequential to the performance of the market. However, there is abundant anecdotal and empirical evidence, as discussed above, to refute that. As to the effect of the trading horizons of speculators on the efficiency of financial markets – that is, whether asset prices reflect the intrinsic value of those assets – Froot, Scharfstein and Stein (1990) specified an analytical model to determine whether a market became more or less efficient when there was a greater (or lesser) presence of short-term investors. Their findings were that if speculators have a shorter investment horizon, it could lead to herding as investors attempt to learn what informed traders know. Therefore, the market would become informationally inefficient, with multiple equilibriums possible.

A final explanation for the excess short-term trading is put forward by Shleifer & Vishny (1990). They reason that given the costs and risks of exploiting long-term arbitrage opportunities (a situation where an asset's market price is not equal to its fundamental value, as given by the net present value (NPV) of all its future cash flows), it is optimal for investors to pursue short-term investment opportunities. The costs and risks can be exacerbated by noise traders who can extend the period of mispricing beyond the resources of the arbitrage, a scenario captured by the following quote attributed to Keynes (1936), "The market can remain irrational longer than you can remain solvent*."* The state in which it is justifiable for investors to pursue short-term strategies is explored via an ABM in LeBaron (2013), with the conclusion being that in volatile markets investors are indeed better served by considering less rather than more.

2.3.4 Investor Performance

The growth of financial markets, and their associated services, now contributes over 8% towards the gross domestic product (GDP) of the US economy. Asset management and trading profits are responsible for close to 50% of that contribution

(Greenwood & Scharfstein, 2013). Given the vast amounts of income generated by actors within the financial system, a vital question is how and whether agents within the system are adding value or merely rent-seeking. The performance of asset managers, and whether they can add value by outperforming their benchmarks, remains an ongoing focus for market participants, with their performance extensively scrutinized by both scholars and investors in attempts to affirm the efficiency of the markets.

The most common way to assess the performance of professional investors is through the performance of the various classes of mutual funds. Concerning this, Cuthbertson et al. (2008) summarize the relevant literature when they comment that on balance the average net (after expenses) risk-adjusted performance of funds in the US and the UK is negative. Additionally, any outperformance is not maintained. Figure 10 provides graphical evidence of this statement, with graph a illustrating the percentage of managers that are unable to outperform their benchmark in any given year. By way of explanation the data is divided into classes which are reflective of the asset manager's investment strategy. For the domestic funds; that is, only investing in USA listed companies, the data is further divided into the market capitalization (size) of the companies. The global funds, international, emerging market funds relate to companies listed outside the USA. Of note are the following: in general, more than 50% of managers cannot outperform their benchmark in each year; and the percentage of underperforming managers increases significantly in years of material market dislocations such as 2008.

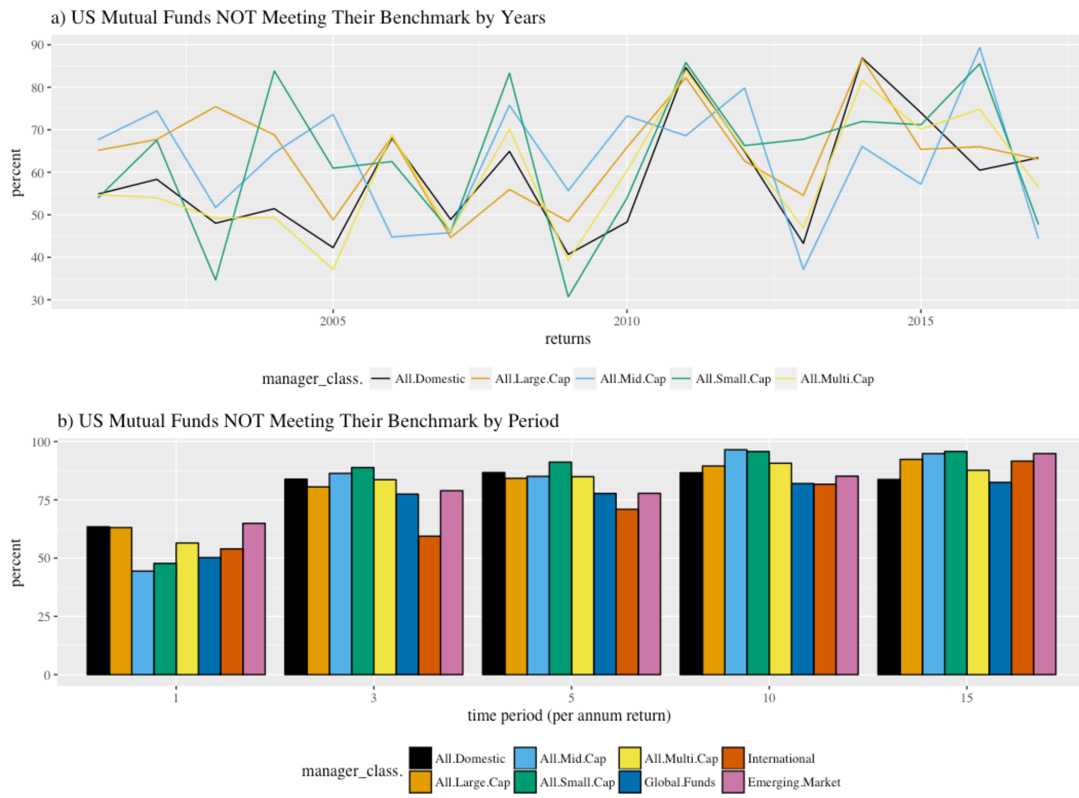

Figure 10: USA mutual fund managers' performance against their benchmark. (Date Source: Thomson Reuters Lipper.)

The other issue relating to manager performance is the ability of a manager to outperform over an extended period. Malkiel (1999) evidences this point by highlighting that since 1970 only 4 funds, starting with a sample size of 358, have delivered annualized returns in excess of 2% over the benchmark. While the distribution of performance in Malkiel's analysis appears normally distributed it does suffer from survivorship bias – the issue of poor performing managers tending to disappear over time – with only 84 of the original funds surviving. If the failed managers were to be included, the distribution of performance would become skewed. The ramification is that the performance of managers is most likely worse than what the research reports. This issue reinforces the fact that being a successful investor is a difficult task and it may ultimately be easier and more successful to track the market. In further supporting evidence that fund manager cannot outperform, Carhart (1997), using a data free of survivorship bias, concludes that common factors in stock returns and investment costs explain much of a manager's performance; thus, leaving little to no room for stock selection skills.

Figure 10b provides additional characteristics of manager performance by illustrating the percentage of managers whose annual performance does not exceed their benchmarks. The chief observation is that the percentage of underperforming managers increases as the performance horizon extends. Figure 11 demonstrates the dynamics behind managers being unable to maintain their outperformance. For a given year, in this instance the performance of Australian equity managers (chosen due to the availability of the data), there is a broad distribution of performance, with some outliers at either end of the spectrum. However, over a 3-or 5-year period, the dispersion in performance decreases materially, with managers being narrowly dispersed around the mean – which happens to match the performance of the market, which is a result consistent with the more extensive findings from the likes of Carhart (1997). This phenomenon is symptomatic of herding, with managers not wanting to risk their reputation by taking excessive investment risks. Thereby, ensuring the optimal behavior for managers is to mimic the market, with a slight tilt toward a given investment style.

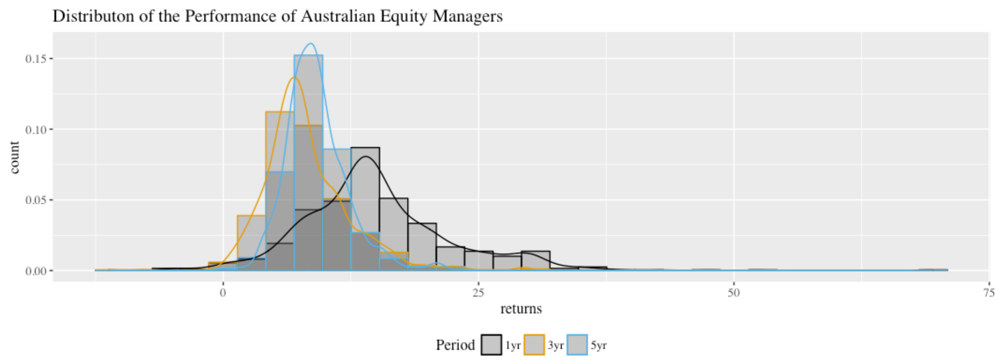

Figure 11: The distribution of the performance of Australian equity managers. (Data source: Morningstar Australia).

Despite the inability of most managers to outperform the market regularly over the long-term, there are examples of those who have consistently done so. Lo (2017) names Warren Buffett, Peter Lynch, and George Soros as examples, with Weatherall (2014) highlighting the clear outperformance of James Simons's Renaissance Technologies. There are undoubtedly more investors who have managed to beat the market, but their records remain obscured from public view. Therefore, the question is what makes these investors unique and what are the consequences of other investors following their actions? Alternatively, one needs to consider the consequence of investors following managers who have had a "run" of outperformance that ultimately is not sustainable. The model presented in Section 2.4 intends to assess such issues.

2.3.5 Artificial Stock Markets, Agent-based Models, and Networks

The inclusion of networks within the various agent-based artificial stock markets is now a growing field of research. The belated use of this technique most likely resulted from the following factors: the work on artificial stock markets predated the meteoric rise in the applications of network science in the 2000s; and as per Alfarano & Milaković

(2008), the models were able to explain a great deal without the use of networks. The benefits of ABMs have become evident, with important research including: the replication of real-world market returns by a model that utilized social interaction amongst investors (Hoffman, Jager, & Von Eije, 2007); the identification of how the network structure of investors influences the stability of, and the fluctuation of, an asset's price (Panchenko, Gerasymchuk, & Pavlov, 2013); and how bubbles can emerge as a result of agents considering different information sources, including the expected actions of their neighbors (Harras & Sornette, 2011). These models shared the common theme of exogenously imposed static investor networks.

There also exists a body of work, which forms the foundation for this chapter, that implement models that endogenously form networks between investors (see Markose et al. (2004) and Tedeschi et al. (2012)). Section 1.3.2.4 discussed the importance of this process and assessing dynamics of and on a network. The rationale for the approach was to include the role of dynamic learning amongst the agents as they decided from whom to take investment advice (Markose et al., 2004). The central plank of these papers was investors attempting to locate and then form a connection with "gurus" (defined as agents with superior investment performance). Following the connection, agents would attempt to align their market expectations with those of their "gurus."

A vital finding of the guru models was that the networks formed by the investors exhibited a high level of clustering; that is, the population was highly inter-connected through their common connection to gurus. Markose et al. (2004) suggest this is evidence of a small-world network, while Tedeschi et al. (2012) indicate that when imitation is large, the investors form a scale-free network. The relevance of the difference in the network topology according to Panchenko et al. (2013) and Oldham (2017a & 2017b) is that the network topology of the investors is capable of affecting the behavior of the market, with the critical finding being that a scale-free topology results in higher levels of price volatility for the risky asset.

The connections mechanism in the guru models explained how agents formed herds based on common market expectations. Changes in the expectations of these herds were responsible for the returns of the risky asset exhibiting return profiles consistent with the stylized facts of the real-world financial markets detailed in Section 1.2.5.1. The model of Tedeschi et al. (2012) produced meaningful insight into the ability of noise traders and "fully informed" investors (whose who consider the expectations of noise traders and fundamental factors) to outperform fundamental investors and the market.

2.3.6 Section Summary

This section ultimately justified the use of ABMs, such as the one implemented in Section 2.4 to uncover the dynamics within financial markets. Section 2.3.2 highlighted the volatile nature of financial markets and how herding and investor networks potentially contribute to that volatility. The preceding section, 2.3.3, discussed how short-term behavior and memories also contributed to the volatility, with a focus on excess trading. Next, Section 2.3.4 highlighted the characteristics of the distribution of investor performance. Finally, Section 2.3.5 provided the background of, and the justification for, the utilization of an artificial stock market, implemented through an ABM to analyze the behavior of financial markets. More specifically, it provided evidence of the benefits of including investor networks within the models.

Section 2.4 provides a detailed description and justification of the model used to produce the results presented in Section 2.5. In summary, the model was successful in having investors consider the actions of their neighbors, evolving their social network, and having two classes of investors, who varied in the manner they considered past performance. Section 2.4.3 provides the details of the various agent classes, while Section 2.4.4 details how the model operates.

2.4 Approach and Model Design

2.4.1 Introduction

This section provides a detailed description of the model that was implemented to address the research questions as detailed in Section 2.2.3. Section 2.4.2 justifies and summarizes the use of the model that formed the foundation for the implemented model, with Section 2.4.3 detailing the agent classes and their relevance to the research question. As the implemented model extends the model presented in Oldham (2017a), Sections 2.4.3 through 2.4.5 provide the details of only the model extensions. An interested reader can refer to the overview, design, and details (ODD) document (Grimm et al., 2010) for further insight into the model. The document is found at http://www.openabm.org/model/5203/. The rationale for providing both the model and the ODD document is to allow for the replication of the results and dissemination of the model into the broader modeling community with the intention of motivating additional extensions. The final two sections of the chapter detail the verification steps undertaken to ensure the model performed as intended and the outputs that the model created.

2.4.2 Model Background

The model of Harras and Sornette (2011) (H&S hereafter) underwrites the implemented model, with the model of Tedeschi et al. (2012) serving as the motivation for various extensions. The extensions, all designed to address the research questions, include: the ability of investors to select their neighbors; investors establishing directed links, implying they only listen to who they want to; and investors having either short-or-long term investment horizon. Equation 9 illustrates the intent of the model, which is that investors have access to three sources of information that inform their investment decisions. The sources are the actions of their neighbors, a common public source, and a private source. An investor's neighbors are those with whom the investor has explicitly decided to link with, or more explicitly those from whom they choose to receive information from. In the H&S, these links are assumed to be fixed and undirected, which implies that an agent will listen to all their neighbors and their neighbors remain fixed. Section 2.4.3.1 describes the alteration of the implemented model, which introduces a dynamic network with directed links.

Equation 9: The general intent of the agents' decision-making calculation

$$Decision\ score = Network\ Information + Public\ Information + Private\ Information$$

Equation 10 provides granular detail as to how agent j combines the three sources of information to determine a decision metric (ω_{ij}) for asset i. The decision metric determines whether the agents buys more, holds, or sells a proportion of their holding in the risky asset. The information sources are the expected actions of their neighbors ($E_{ij}[a_{ik}(t)]$); public information ($pi_i(t)$), and private information ($\epsilon_{ij}(t)$). Once investors make their decision, trading occurs and a new price is endogenously determined for the risky asset. Investors utilize the pricing outcome to update various beliefs, including trust in the neighbors (advisers). The previously mentioned ODD provides a detailed description of the various steps, while Sections 2.4.4 explains how the current iteration of the model operates.

Equation 10: The decision-making equation used by the agents (investors)

$$\boldsymbol{\omega_{ij} = c_{1ij}\left(\sum_{k=1}^{K} nt_{jk}\,(t-1)E_{ij}[a_{ik}(t)]\right) + \ c_{2ij}pt_i(t-1)pi_i(t) + c_{3ij}\epsilon_{ij}(t)}$$

Equation 10 also explains how the influence of each information source is weighted by additional variables. For the public and network information one of the variables is fixed while the other variable is updated as the investor reacts to the market and the quality of the information. The fixed values are given by c_{1ij}, c_{2ij} and c_{3ij}, while the variable coefficients are network trust (nt_{jk}) and public trust (pt_i). The fixed variables are uniformly distributed among the investors, with the lower limit being 0 and the upper limit determined by the user. By altering the upper limit of the global coefficients (c_1, c_2 and c_3), different dynamics are generated. A crucial result – asset bubbles in the risky asset's price – appear when c_1 is set at 4. Given this, all parameter sweeps of the implemented model will include values of c_1 ranging from 1 to 4. The justification for utilizing the H&S model as a foundation for the implemented model were, that it:

- provided a framework where information that effected investment decisions flowed across a network;
- it considered the processes of adaption and evolution through investors continually reassessing and adjusting trust in each of their information sources;
- showed that price movements were affected by how strongly the agents are influenced by their neighbors; and
- generated asset returns that matched the stylized fact of fat-tailed returns, which did not match the Gaussian distribution of the public and private information.

The first step in the modeling process was to implement the model so that it could successfully replicate the results of H&S. This process formed a vital part of the verification process for the model (see Section 2.4.5). The following metrics and behaviors were replicated in the verification process: the return characteristics of the risky asset, including its volatility and range; and the range of, and variability in, the level of network and public trust.

Two model extensions were required to address the research question. The first extension was to divide investors into two classes – long and short-term investors. Section 2.4.3.2 provides the full details of this extension; briefly stated, the extension relates to how investors assess the performance of their peers, and to the distribution of the investor's decision threshold (ω_{ij}). The more significant change, as inspired by

Markose et al. (2004) and Tedeschi et al. (2012) is to have investors adjust their network as the system evolves. Section 2.4.3.1 details this extension.

NetLogo 5.3 (Wilensky, 1999) was select as the programming langue to implement the model. Having selected NetLogo, its network extension functionality was utilized to help generate the network and calculate various network statistics. Agent initialization is per the NetLogo default of a random asynchronous order. A step in the model is assumed to be a day because information arrives at each step and is not specially related to an earnings announcement; and daily price movements and trading decisions is a close approximation for the actual markets. Figure 14 illustrates how the model flows, with Section 2.4.4 providing the details of each step.

2.4.3 Agent Classes

This section details the various classes utilized in the model. While the classes remain the same as the H&S framework, there are numerous changes, which are highlighted in the appropriate section. The investor class is the most important class. However, the changes to the network functionality has several implications for the investors. Therefore, the changes to the network are explained first (see Section 2.4.3.1), followed by an explanation of the various changes to the investor (see Section 2.4.3.2) and asset class (see Section 2.4.3.3).

2.4.3.1 The Network

The H&S framework had investors connected in an undirected static lattice network. The central extension for the implemented model involves allowed investors to select their neighbors, which in turn necessitated the need for investors to form directed links. The use of directed links is in line with Markose et al. (2004). The utilization of directed links allows the investor population to perform two roles: advisers providing information to those agents who choose to connect to them, and followers – receiving information from their advisers. The information in this instance is the investment action (buy, hold or sell) that the adviser intends to implement in the current time step. Agents, if required, perform both tasks concurrently.

Directed links imply that an investor only receives information from those with whom they form a direct link. The selected investors are known as advisers, and they do not seek information from those investors who connect to them. This modification allows many agents to seek the actions from an Oracle but for the Oracle to ignore the actions of its followers. The justification for this functionality comes from combining the facts that investors (followers) become disciplines of superstars, with these superstars maintaining a disciplined investment approach. This is clearly illustrated by how the attendance at the annual Berkshire Hathaway – Warren Buffett's investment vehicle, annual meeting grew as his investment performance grew in status (Oyedale, 2018), while Buffett's investment style remained predicated on his concentrated value style (Gergaud & Ziemba, 2012). Indeed, from Gergaud & Ziemba (2012), there is no suggestion that star performers are directly influenced by the investment decisions of other investors. Further confirmation is seen with George Soros (another world-renowned investor) having over 200K Twitter followers but he follows only 4 accounts.

The model does track the number of followers each agent has, but advisers do not utilize the information in any manner. The direct-linked process does not preclude a pair of investors sharing information. Figure 12 summarizes the various relationships where: Agent A has two followers (Agent B and C) but does not seek information from any investors; Agent B has two advisers (Agent A and C) but has no followers; and Agent C has one adviser (Agent A) and one follower (Agent B). As discussed in Section 2.4.3.2 the model tracks the number of followers investors have and the number of investors from whom they seek information (known as advisers). The expected result is that under certain conditions there will be a skewed distribution regarding the number of followers some investors have.

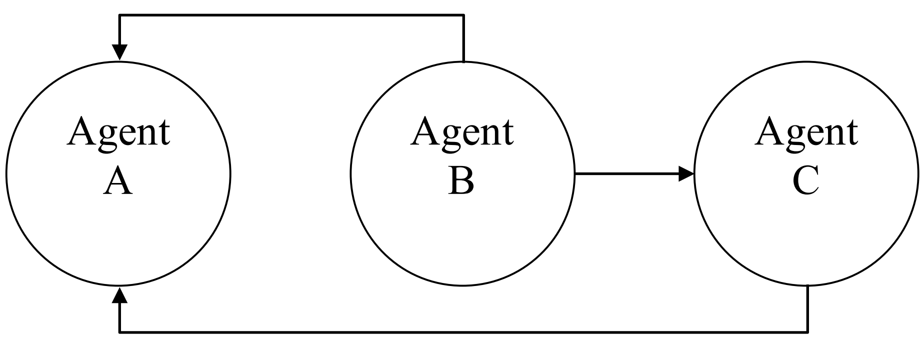

Figure 12: A stylized directed investor network

The introduction of directed links in the network alters the network formation process from the one described in the previously mentioned ODD. The primary difference is that the number of links created is double the amount in the undirected case. The process for creating links is that first a sequential list of investors is formed, where their identification number determines their place in the list, then investors select a user-determined number of agents to their immediate right and their immediate left and form a directed link with those investors. The user sets the number of immediate neighbors by the *Ring_M* parameter, with the number of advisers for each investor at initiation being double the setting for the *Ring_M* parameter. At the end of the link formation process, investors register how many investors are following them. At initiation, this relationship is symmetrical, with each investor having double the *Ring_M* parameter setting in followers and advisers. The followers and advisers at initiation are equivalent to neighbors in an undirected network. The critical element of the model is how the rewiring process alters these relationships, and under what conditions they change.

Sections 2.4.4.6 through to 2.4.4.8 provide the details relating to how the network rewiring process occurs, with Sections 2.5.3.2.1 through 2.5.3.3 detailing the results. In summary, the rewiring process occurs at intervals decided by the users, via the *rewire* variable. In calling the procedure investors will assess: the trust they have formed in each of their advisers (their outbound directed-links); their performance relative to the market; and their aggregate trust in the information they receive from their advisers. Table 2 summarizes the actions an investor will take based on this assessment. If an investor decides to cut an adviser, the direct link is cut; alternatively, if an Oracle is selected the investor creates a directed link to the Oracle. It is by this process the network evolves. The selection of an Oracle is in line with the preferential attachment process as proposed by Barabási & Albert (1999).

A crucial component of the rewiring process is agents identifying, and possibly selecting, Oracles as advisers. While Section 2.4.4.6 details how Oracles are selected, the relevant detail is that the user selects, via the *Oracle_option* variable, the number of investors classified as Oracles, with Oracles being the better-performing investors. Given there is a single risky asset in the implemented model, performance relates to the way an investor allocated their assets, that is, their asset allocation. The alternative measure of performance – typically used in the actual financial markets, relates to stock selection, which refers to whether an investor was successful in selecting stocks that outperformed the index in which they are constituents. When assessing an investor's asset allocation performance, out (under)performance occurs when the investor is over (under)weight – in this instance their holding in the risky asset is greater than 1 – when the risky asset's price increases. The situation reverses when the risky asset's price decreases. Table 1 summarizes the performance scenarios.

Table 1: How to determine and classify performance

	Overweight (risky asset holding >1)	**Underweight (risky asset holding <1)**
Risky asset price increases	Outperformer	Underperformer
Risky asset price decreases	Underperformer	Outperformer

Long-term investors define an Oracle as an investor who is amongst the highest ranked at growing their portfolio more than what the market has achieved since initiation. In contrast, short-term investors seek out those investors who have outperformed the market since the last rewiring process. The rationale of this assumption is that short-term investors are myopic in assessing all elements of the market ecosystem; that is, information sources, returns, and the value of their advisers. Kay's (2012) identification of the "hyperactivity" of short-term investor provides the foundation for this approach.

Table 2: Investor network behavior scenarios

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="2">Outperformer?</th></tr>
<tr><th>Yes</th><th>No</th></tr>
<tr><td rowspan="2">Positive aggregate trust in your network information?</td><td>Yes</td><td>Keep all advisers and add an Oracle</td><td>Cut bad advisers and add an equivalent number of Oracles</td></tr>
<tr><td>No</td><td>Do nothing</td><td>Cut bad advisers without adding new advisers</td></tr>
</table>

The basis for Table 2 is that investors are assessing their environment and deciding the best course to improve their investment performance. While the rewiring process occurs at discrete intervals, investors are updating their trust in their information sources at each step. Therefore, investors may have little, or negative, trust in an individual adviser at the time of the rewiring process, meaning that they are not following their actions at each step but may, based on the overall environment, choose to maintain the relationship, expecting it to improve. Table 3 details the rationale for each behavior.

The implemented model has several differentiated network formation characteristics to the models of Markose et al. (2004) and Tedeschi et al. (2012), the first is the use of a lattice network at initiation. The rationale for this approach is that Watts and Strogatz (1998) also commence with a lattice network in their theory of the evolutionary process of a small-world network, which is consistent with the aim of assessing the network topology as it evolves. The use of the lattice network also allows for more accurate verification against the H&S framework.

Table 3: The rationale for the network rewiring process

Outperformer?	Positive network trust?	The rationale for their behavior
Yes	Yes	These investors judge that their advisers are a significant overall source of outperformance. Therefore, they are willing to overlook the individual performance of their advisers (noting that they already adjust their trust) in the rewiring process and simply look to add an Oracle in the expectation of improving their incoming information.
Yes	No	These investors are attributing their outperformance to the other information sources. That is, there is not a strong belief that advisers can aid performance. They have already adjusted the trust in each neighbor; thereby, they would be already ignoring the advice, so do not see the need for change.
No	Yes	These investors have underperformed but given the positive level of trust in their network information assume that removing poor advisers and adding Oracles will reverse their underperformance. This mechanism contrasts to outperformers who are prepared to forgive poor advisers.
No	No	These investors are effectively attributing their underperformance to their network information and to turnaround their performance will cut ties with their advisers and not seek new advisers. In the extreme, these investors will only use just public and private information.

The model rewires the network at discrete intervals while in the other models this step occurs at each interval. The justification for this change is that investors do update their trust at each step so investors can effectively “cut” a link by not assigning weight to the available information from their adviser. The introduction of discrete intervals means investors are more forgiving and considered in their actions. The implemented model also allows for multiple outbound links from an investor.

The ability of a network's topology to help explain the dynamics of complex systems (see Section 1.3.2.4 for more details) has played a significant role in the meteoric rise of network science. Of the various network metrics that help determine the appropriate stylized network that a network may fit, the degree distribution (degree centrality), closeness centrality, and clustering coefficient are of greatest interest in the research questions of this chapter. The relevance of the three metrics is that they will provide insight into whether the way investors are linked in the network effects the macro behaviors of the environment; that is, the price behavior of the risky asset.

Degree centrality – defined as the number of links an agent (an investor in this instance) has – is the most straightforward of the network metrics. Given the implemented model has directed links each agent has a degree distribution related to their in-and out-degree. These metrics explain two very different things. In-degree explains the popularity (or prominence) of an agent, determined by the number of people that are following the agent. For the implemented model the in-degree relates to how many people are following the actions of a given investor. In the general case, out-links explain the ability of an agent to disperse something such as information. However, in the case of the implemented model, out-links indicate how many advisers an investor is following. Figure 12 illustrated this point. An important consideration is the degree centrality of an agent compared to the degree distribution of the population. As discussed in Section

1.3.2.4.1 the degree distribution is utilized to define the network topology – for example, the degree distribution of a lattice network matches a uniform distribution while a scale-free network meets a power-law distribution.

Along with the evolution of the degree distribution, changes in the clustering coefficient (also detailed in Section 1.3.2.4.1) will reveal vital information. The clustering coefficient measures the interconnectedness of an agent's neighbors (Markose, Alentorn, & Krause, 2004) an allows an assessment of how tightly, or otherwise, a population is grouped. For reference, a lattice network maintains a higher level of clustering than the other network topologies, so the question to be addressed is whether, and under what conditions, the initiated lattice network can maintain its structure.

2.4.3.2 Investors

Equation 10 provided the mechanism by which investors combine variables to make their investment decisions. Investors are either initiated with a fixed value for these variables or update them at each step. The implemented model made several changes relating to how agents are either imitated with the fixed variable or update them. The most significant modification is the introduction of two investor classes. The investor population, which the user sets via the $number\_of\_investors$ variable, is assigned to either the short-or-long-term investor class. The user determines the proportions of each class through the $\%\_longterm$ variable. The investor's class has two effects: the amount of history the investor considers, and the distribution of the decision threshold value. Per Section 2.4.3.1, the investor population is also divided into out under-and outperformers based on criteria dependent on the investment horizon of their investor class.

The investors utilize history to update their trust in their neighbors and public information. Using past information, and how much of it, is a vital component in the discipline of building artificial financial markets (LeBaron, 2001) To allow for the two classes the $short\_term\_diff$ variable was introduced. Equation 11 summarizes how the $short\_term\_diff$ variable affects the amount of history that an investor considers – which is simply an amount less than the long-term investors. Section 2.4.4.4 provides the detail as to how investor *i* considers history through their memory weight variable α_i.

Equation 11: Determining an investor's memory weight

$$\alpha_j = memory\_weight - \ short\_term\_diff$$

With the time-scale by which past information continues to influence various metrics given by $\frac{1}{|\ln(\alpha_j)|}$, any positive value for $short\_term\_diff$ reduces the length of time that past performance affects current decision-making. For a long-term investor, $short\_term\_diff$ is set to 0, and for a short-term investor $short\_term\_diff$ is greater than 0. For the experiments reported in Section 2.5 the difference was set at .05, which is equivalent to 10 periods. The second modification to the model relates to the distribution of the decision-score metric. Table 4 defines how an investor's actions are determined. In the H&S framework, $\overline{\omega}_j$ was distributed in a uniform manner between 0 and 2. The implemented model assumes that a short-term investor will, besides considering less history, in general possess a lower trading threshold. The rationale for this approach is that investors are assumed to have a higher propensity to act on the most recent information. A prima facie argument could be made that this assumption will simply see short-term investors trade more. However, this result might not necessarily arise because short-term investors may struggle to maintain sufficient trust in any of their information sources; hence they will become indifferent to trading.

Table 4: The decision thresholds for the agents

Scenario	**Action**	**Variable**	**Trading Volume**
$\boldsymbol{\omega_{ij}(t) > \bar{\omega}_j}$	Buy	$a_{ij}(t) = +1$	$v_{ij}(t) = tr * \frac{rf_j(t)}{p_i(t-1)}$
$\boldsymbol{\omega_{ij}(t) < \bar{\omega}_j * -1}$	Sell	$a_{ij}(t) = -1$	$v_{ij}(t) = tr * holding_{ij}(t)$
Otherwise	Hold	$a_{ji}(t) = 0$	Not applicable

Rather than a uniform distribution, an exponential distribution determines the allocation of the $\boldsymbol{\bar{\omega}_j}$ variable. The distribution remains bounded between 0 and 2, with the long-term investor distribution given by 2 minus the value from the exponential distribution. Alternatively, the threshold for the short-term investors takes the value of the exponential distribution, noting a value of 0 is increased to 0.1. Figure 13 illustrates a typical distribution of the $\bar{\omega}_j$ variable for an equally divided population.

Section 2.4.3.1 discussed the technical aspects of the network and how investors are connected in the network. To allow investors to assess the actions of their advisers, and update their trust in them, they maintain a list of their outgoing links. Investors also track the number of investors following them and the maximum and minimum number of followers and advisers they have has at any point in the simulation. This data is assessed to understand the dynamics of the investors behavior.

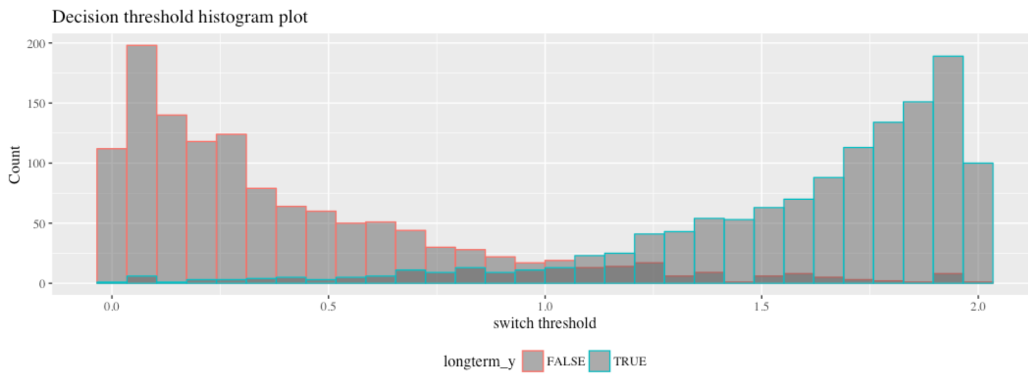

Figure 13: The distribution of the investor decision thresholds

2.4.3.3 The Risky Asset

The risky asset class encompasses a single asset i. The asset has passive role, with its price movements being the primary variable of interest. This approach is somewhat inconsistent with most approaches within the realm of agent-based artificial stock markets, where the asset has a stochastic earnings process, which investors use to determine their investment decisions. While there is no direct earnings component in the implemented model, investors do receive both private ($\epsilon_{ij}(t)$) and public information ($p_i(t)$) about the asset, at time t, which is in turn utilized to inform their decision-making process. Therefore, the information is broader than, yet not as specific as an earnings stream. This approach is consistent with the H&S framework, with the rationale of the approach being that it will ensure that the dynamics reported in Section 2.5 relate solely to the behavior of the investors.

As part of data collection process, the model records the asset's returns and standard deviation. The data is collected to enable the asset's price movements to influence the investors' behavior. This process occurs when the market clears, as per Section 2.4.4.3. As discussed in Section 2.4.3.3 investors use the asset's return and standard deviation in updating their trust in their public and network information sources.

2.4.4 Model Steps

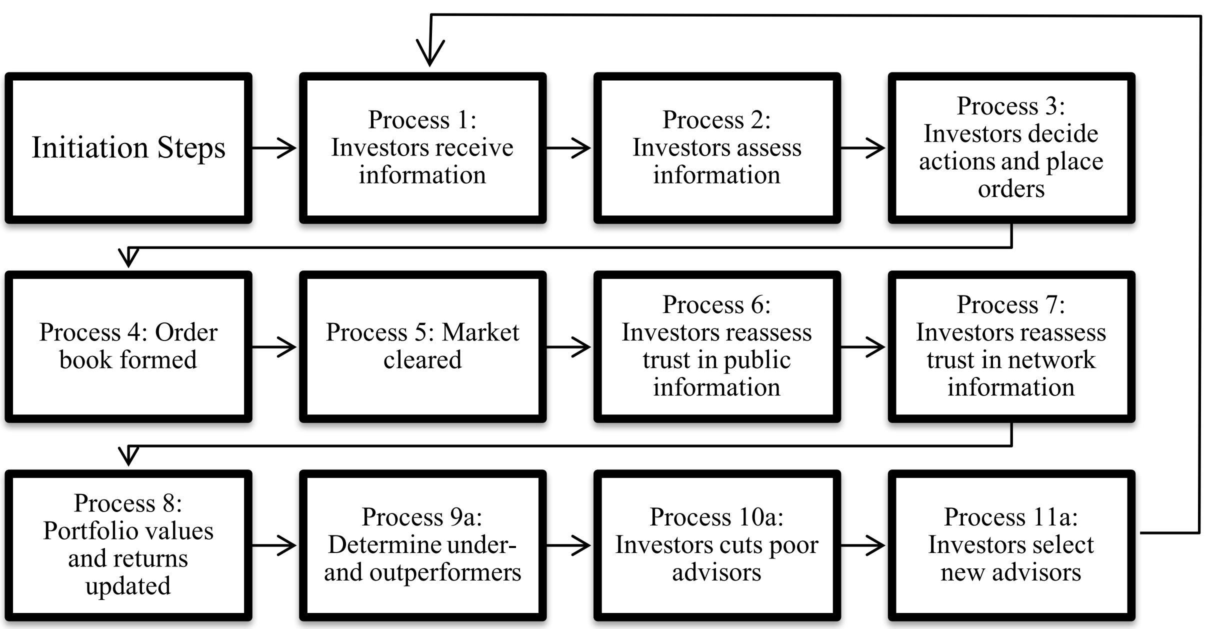

Figure 14: Representation of the model's processes

Figure 14 provides the steps for the implemented model. The model has the identical steps – up to Step 7 – as the model described in the ODD document. Steps 8a through to 10a occur only when the step number matches, or is divisible by the *rewire* variable; for example, if the *rewire* variable is set at 500 the model will call the rewire procedure at step 500, 1000, 1500, etc.

2.4.4.1 Receiving Information

The first ongoing step of the model has the investors receive information. At time *t,* the private information (ϵ_{ij}) is allocated the value of a random variable, normally distributed with a mean of 0 and a finite variance – in all instance of this implementation this is 1. A positive (negative) value provides an impetus to the investor to buy (sell). Equation 10 implies that a higher value of ϵ_{ij} will, *ceteris paribus*, have a more material effect on the investment decision. Given the random nature of the private information, there should be no serial correlation between the private information of the investors. The role of the private information is to have investors receive differentiated information that may be of some value in their decision-making process. Investors do not adjust their trust in their private information, with its influence fixed at initiation.

In this implementation of the model, the public information for asset i (pi_i) at time *t* is generated in the same manner as the private information. The one difference is that the population shares the same information. However, investors will have varying inclinations toward following the data due to their independent trust (pt_i) in the source and their specific influence parameter (c_{2ij}).

To generate their network information, investors poll the intended actions of their advisers. The $E_{ij}[a_{ik}(t)]$ variable from Equation 10 captures the expected actions of an investor's neighbors. Table 4 provides the possible values of $a_{ik}(t)$ (1, 0 or -1), and the conditions responsible for those values. The justification for following the actions of an adviser is that when an investor can only employ bounded rationality it becomes optimal to follow neighbors (see Sections 1.4.7 and 2.3.2). The information received from advisers are not weighted equally, with an investor consideration based on the trust in the given adviser (nt_{jk}) generated in the prior period *(t-1)*. Finally, investor sum the weighted actions of their advisers before multiplying the value by their fixed influence term (c_{1ij}).

Having assessed their information sources, investors combine the information to decide their action. As per Equation 10, this is a straightforward summation, with the investors' actions determined per Table 4. The inference from the information-gathering process is that investors are more inclined to follow their information sources only when they have sufficient trust in them. Additionally, connecting with a larger number of advisers will increase the given investor's tendency to follow their network's behavior. In a similar vein to Markose et al. (2004), by measuring the accumulated actions of the population, the herding tendency of the population can be assessed. The ratio of the population buying/selling to the total population provides the herding tendency, with a higher number indicating the possibility that herding is occurring.

2.4.4.2 Finalizing the Investment Decision

After determining their preferred action, investors must firstly check they have the required resources to undertake the desired action and secondly decide how much to trade. The need for the former comes from the assumption that there is no leverage or short-selling. Therefore, investors must have a positive balance of the risk-free asset at time *t* ($rf_j(t)$) to buy more of the risky asset and must hold a positive quantity of the risky-asset ($holding_{ij}(t)$) if they intend to sell. If investors meet the requirements they trade per Table 4. If an investor does not meet the trading requirements, the investor must sit out of the market. Despite this, followers still assess their actions.

To determine the actual trading volume ($v_{ij}(t)$) of asset *i* at time *t*, the model utilizes the transaction ratio variable (tr). The user sets the *transaction_ratio* parameter at initiation, with it being fixed and homogenous for the population. The ratio represents the fraction that an investor is willing to trade. Future research should look to vary the ratio based on the conviction an investor has in the investment decision. An important point is that when deciding how much to invest ($v_{ij}(t) > 0$), investors do not attempt to forecast what the price will be at the completion of the trade $(p(t))$; rather, they use the existing price. Harras & Sornette (2011) indicate that this does not affect the results.

2.4.4.3 Clearing the Market

In the implemented model the investors' orders are combined to determine the asset's return (see Equation 12) and a new price (see Equation 13). Section 1.3.4.3 discussed the two-alternate market clearing processes – a market-maker and a formal auction market. In line with the H&S model, a market maker model is employed. Tedeschi et al. (2012) in contrast utilized an auction market, but their model was implemented with 150 investors in comparison to the 2,500 implemented in the H&S model. The orders are combined through the $\sum_{j=1}^{N_j} a_{ij}(t) * v_{ij}(t)$ portion of Equation 12, with the J being the number of investors and λ adjusting for the market's depth. Farmer (2002) provides a detailed rationale for the market depth term. The value of $\sum_{j=1}^{N_j} a_{ij}(t) *$

$v_{ij}(t)$ provides an important insight into the behavior of the population. A positive (negative) value indicates a surplus (deficit) in demand, which results in a positive (negative) price and return for the period. Additionally, the larger (smaller) the surplus (deficit) the larger (smaller) the price movement. Large price movements are indicative of herding, with the effect of large changes discussed in Section 2.4.4.4.

Equation 12: Return determinant for asset *i* at time *t*

$$r_i(t) = \frac{1}{\lambda * J} \sum_{j=1}^{N_j} a_{ij}(t) * v_{ij}(t)$$

Equation 13: Price determinant for asset *i* at time *t*

$$\log[p_i(t)] = \log[p_i(t-1)] + \frac{1}{\lambda * J} \sum_{j=1}^{N_j} a_{ij}(t) * v_{ij}(t)$$

2.4.4.4 Trust Updating

Once investors become aware of their returns, they utilize that information to adjust the level of trust they have in the information provided by their network (nt_{jk}) and public sources (pt_j). This process consistent with Harras & Sornette (2011), with the approached based on the assumption is that while the variables have initial values of 0 – meaning no trust – investors begin to place greater trust in a source if it provides the correct advice. That is, if the agent receives a buy (sell) signal from the information source, and the price subsequently increases (decreases), then the weight (trust) increases. This updating process is the point at which the difference in the short-and long-term investors manifests itself.

Equation 14 is the process that investors utilize to update their public trust, while Equation 15 is the mechanism by which investors utilize to update their network. The essence of the two equations is the same, with the first term in the equation discounting the previous trust value variable by the variable α_i. However, per Equation 11 this variable differs for the two investor classes. Therefore, the two classes discount past values at different rates, with $\frac{1}{|\ln(\alpha_i)|}$ providing the length of time past value affects the current value. The second part of the equation adds the assessment of the immediately preceding information, which has been discounted by (1- α_i) after the $\frac{r_i(t)}{\sigma_{ir(t)}}$ term multiples it. From these equations, a lower value of α_i increases the influence of the most recent history.

Equation 14: The public trust updating process

$$pt_i(t) = \alpha_i pt_i(t-1) + (1-\alpha_i) pi_i\ (t-1) * \frac{r_i(t)}{\sigma_{ir}(t)}$$

Equation 15: The network trust updating process

$$nt_{jk}(t) = \sum_{i=1}^{I} \alpha_i nt_{jk}(t-1) + (1-\alpha_i) E_{ij}[a_{ik}(t-1)] * \frac{r_i(t)}{\sigma_{ir}(t)}$$

The $\frac{r_i(t)}{\sigma_{ir(t)}}$ term normalizes the past return of an asset $(r_i(t))$ by the standard deviation of its past returns $\sigma_{ir}(t)$. H&S provide the rationale: a larger return scaled by its volatility enhances trust to a higher degree. The trust-updating process provides the potential mechanism for the development of a financial asset bubble, which is that investors will place more and more trust in an information source as it provides greater profits (or saves losses). This process in turn feeds the positive feedback loop responsible for investors becoming more aligned to the advice of their most trusted advisers, with other investors quickly becoming aligned with a common investment strategy.

Equation 16 shows how the ensemble variance $\sigma_{ir}(t)^2$ is calculated, and takes account of the two investor classes. In a somewhat similar manner to the trust variables, the most recent result is weighted by $(1-\alpha_i)$ and the past information is weighted by α_i. The $\langle r_i(t)\rangle$ *and* $\langle r_i(t-1)\rangle$ terms represent the ensemble average of the return series, where the ensemble average is defined as the expected outcome of the stochastic process.

Equation 16: The variance and ensemble average of an asset's return

$$\sigma_{ir}(t)^2 = \alpha_i * \sigma_{ir}(t-1)^2 + (1-\alpha_i) * (r_i(t) - \langle r_i(t)\rangle)^2$$

Where $\langle r_i(t)\rangle$ is given by:

$$\langle r_i(t)\rangle = \alpha_i * \langle r_i(t-1)\rangle + (1-\alpha_i) * r_i(t)$$

2.4.4.5 Portfolio Updating

The next step in the process involves updating the investors' holdings to reflect the outcome of the market-clearing process. The step is straightforward bookkeeping, updating the investors' balances of the risk-free and risky-asset. The balance of risk-free asset (rf_j) is increased by the proceeds of any sales and decreased by the cost of any purchase. The risky assets, balance is updated similarly. At this point, there is no need for the investors to calculate the value of their portfolio, or their performance against the market, because between the rewiring intervals investors are concerned with only the direction of the price in comparison to the information they received.

2.4.4.6 Determining Under-and Outperformers

While investors assess their trust in their information sources on a continual basis, a more detailed assessment occurs when they decide to keep and/or seek new advisers. The assessment occurs as part of the rewiring process, which is called at a fixed interval, as determined by the user. The first step in the process is for investors to determine the value of their portfolio, which is a matter of multiplying their holding in the risky asset at time *t* by the price of the risky asset at time *t*. Next, the total value of the portfolio is determined by summing the holding in the risk-free asset with the value of their holding in the risky asset. The model then stores the value of the portfolio in a list.

Having determined the value of their portfolio at time *t*, investors compare it to the value of their portfolio at the previous rewiring step and calculate the return over the period. Equation 17 defines this calculation, including the calculation of the portfolio value. From Equation 17, $pr_j(t)$ refers portfolio return for agent *j* at time *t;* $pv_j(t)$ is the portfolio value of agent j at time t; and $pv_j(prw)$ is the portfolio value of agent j at the time of the previous rewiring step. The model also calculates the global variable *n_step_return* at this step, which is the return of the risky asset over the rewiring interval. This is the benchmark by which short-term investors judge their performance.

Equation 17: Portfolio return calculation

$$pr_j(t) = \frac{pv_j(t)}{pv_j(prw)} - 1 = \frac{rf_j\ (t) + holding_j(t) * p_i(t)}{rf_j\ (prw) + holding_j(prw) * p_i(prw)} - 1$$

Having calculated their return between the rewiring intervals, investors determine whether they have out-or underperformed the market by comparing their performance to the appropriate benchmark. The two investor classes assess this on different criteria, with their *outperformer?* variable updated accordingly. The long-term investors compare the growth in their portfolio value to that of the markets since inception. Therefore, it's a matter of comparing $pv_j(t)$ to the price of the asset i plus one (which represents the initial endowment of the risk-free asset). The rationale for adding the risk-free asset is that, per Table 1, investors are assessing whether they made the correct allocation between the risky and risk-free asset.

In contrast the short-term investors compare their most recent portfolio return $pr_j(t)$ with the *n_step_return.* Investors consider themselves out (under) performers if they have exceeded-or underperformed this metric. It should be appreciated that the selection of an appropriate benchmark, and the timeframe performance is assessed over, is a non-trivial issue (as discussed in Morey & Morey (1999)). However, within the context – and intent – of the model it is justified to assume that short-term investors can be differentiated from long-term investors based on a shorter-term benchmark. Table 1 details the conditions under which investors will out (under)perform the market. In summary, an investor over (under) weighting the risky asset in a rising (decreasing) market will outperform.

The final step of this procedure is to select the best-performed investors. Given the difference in the performance criteria for the long-and short-term investors, there are separate lists of investors with the largest portfolio values and one with the largest *n_step_return*. Given their outperformance the selected investors are deemed Oracles, and investors may seek to select them as advisers (see Section 2.4.4.8) The *Oracle_options* variable dictates the list lengths, with the user setting the value. It may be the case that the same investors are on both lists, but they are there on different criteria.

2.4.4.7 Cutting Poor Advisers

From Table 2 it is seen that underperformers (identified in Section 2.4.4.6) will cut the advisers– a process where investors review the level of trust they have in each of their advisers. An adviser is added to a list, named *stayorgo,* if the investor's trust in the adviser is negative. After reviewing all their advisers, the length of the *stayorgo* list is utilized to update the *p_new_ad* variable. The purpose of the *p_new_ad* variable is to record the possible number of new advisers the investors will select in the next step. Having identified the advisers, they have lost trust in, the investor will cut the links to those advisers and remove them and their trust record from the relevant lists.

2.4.4.8 Selecting New Advisers

Table 2 details the scenarios which see investors select a new adviser(s). The overarching process is that an investor will access the relevant list of outperformers and select at random the required number of advisers. An outperformer with overall positive trust in their network information will select a single Oracle. Next, an underperformer with overall positive trust in their network information will determine how many Oracles they choose based on the value of their *p_new_ad* variable as determined in the previous step. Having chosen an Oracle-or Oracles, the investors form a directed link to that investor. The investor also updates the various lists that contain the identity of their advisers and the trust they have in them. New advisers have an initial trust level of 0.

At the completion of the process, investors count the number of advisers (out-links) and followers (in-links) and update the variables which record these values – *num_advisers* and *num_followers* accordingly. Next, a comparison between these variables and the previous maximum and minimums that the investor has recorded for these variables occurs. If required, the maximum or minimum values were updated. The final step in the process is for the closeness, betweenness and clustering coefficients for the rewired network to be calculated. The in-built NetLogo functions perform this task. These variables are recorded to allow an analysis of the possible contributors to the performance of the investors and the overall behavior of the system.

2.4.5 Verification

While ABMs provide the researcher with great flexibility, there exists a considerable risk of the model not being implemented as intended. This risk predicates the need for the verification process. This step is utilized to ensure the design intentions of the model are met. This step does not involve an ex-ante assessment of the results, but rather several distinct review steps. The steps undertaken for the model and the analysis performed in this chapter were: the model matched the baseline output of the previous work that utilized the H&S framework; an electronic journal, which recorded the output of various, was utilized. In turn, this allowed manual calculations to be undertaken to ensure calculations were correct; there was a visual inspection of various charts plotting the behavior of the variables; a code walkthrough was undertaken to ensure no coding errors were made and to produce flow charts to ensure the code implemented the intended model; and parameter sweeps were made of the extreme values.

2.4.6 Model Outputs

Given the objected-oriented foundation of ABMs, the researcher can collect extensive data at both the agent and system level (Section 2.5 provides the analysis of the data generated by this model). At the system level, the focus is the price and volatility of the risky asset. The intent is to gather data to assess under what conditions greater volatility occurs. Other price-related metrics include: the maximum draw-up and draw-down of the price, and the maximum and minimum prices achieved.

At the agent level, to propose possible causes of investment outperformance, a host of data is collected. In Section 2.5 the agent data is aggregated to establish population characteristics and assessed at the agent level. As discussed in this section the records of the investors, holdings, their portfolio values, number of advisers and followers and their trust levels, are recorded at each step. The model also records the investors’ fixed values, including their investment horizon, decision threshold, and tendency to follow the various information sources. At the rewiring step, the model also updates and captures the investors, performance class, and network metrics.

2.4.7 Section Summary

This section provided the details of the implemented model, with a focus on the extensions applied. The purpose of the extensions was to provide more insight into how financial markets operate and why some investors do better than others. In summary, the extensions were, the introduction of two investor classes – with associated changes in the decision-making and trust updating processes –, and an endogenously formed investor network. Section 2.5.3.2.1 through 2.5.3.3 report on the various experiments implemented to test the implications of the extensions.

2.5 Results and Findings

2.5.1 Introduction

Given the variety of research questions detailed in Section 2.2.3 and the ability of ABMs to generate agent and system level data, this section contains multiple components. The components explore specific issues but share the common purpose of highlighting the potentially critical role that short-termism and investors’ networks have on market volatility. Section 2.5.2 provides the details of the various experiments undertaken to derive the results presented along with a general explanation of presentations of the results. Next, Section 2.5.3.1 serves two purposes the first to provide a level of validation of the model, and the second to report on the effects of introducing short-term investors. The following section, 2.5.3.2, provides the results from allowing the investors to select their neighbor; that is, the network is rewired, per Section 2.4.4.7. The section has two sub-sections, with Section 2.5.3.2.1 detailing how and why the rewiring process influenced the price of the risky asset, and Section 2.5.3.2.2 illustrating how the network evolved under the various scenarios. Section 2.5.3.3 delivers the results regarding identifying the characteristics of the more-and less successful investors. Finally, Section 2.5.4 summarizes the results and their importance.

2.5.2 Experimental Settings and Result Summary

The research questions, namely establishing the effect of short-termism on behalf of investors and a dynamic investor network on the market's behavior, informed the design of the experiments presented in this section. Table 5 provides a summary of the common baseline settings utilized. The baseline settings were chosen to ensure a level of consistency and comparability not only between the experiments of this chapter but also with those of Harras & Sornette (2011) and Oldham (2017a, 2017b).

Table 5: Baseline parameter settings

Variable	Settings
Steps per run	2,999
Runs per setting	60
Number of investors (J)	2,500
Market depth (λ)	0.25
Transaction ratio (tr)	0.02
Memory for long-term investors (α)	0.95
Memory differentiation	0.05
Potential oracles	10
Number of original neighbors	4

Table 6 provides an overview of the main components of the two classes of experiments and a summary of the findings. In combination with Table 5, the reader should note that as each model run was 2,999 steps a final rewiring did not occur; that is, for a rewiring set of 1,500 (250) the network rewired once (11 times). The rationale for this decision was to allow an analysis of the network and agent characteristics without the interference of a final rewiring process. The methodology put forward by Lee et al. (2015) was utilized to decide the number of runs. The approach suggests that number of runs should be such that the coefficient of variation for selected variables should demonstrate sufficient stability.

The charts presented in this section, were all created using the ggplot2 (Wickham, 2016) package and were implemented in R (2017). Figure 15 through Figure 32 apply the same color-coding for the percentage of short-term investors in the population, with the variable of interest plotted on the y-axis. The facets for Figure 15 through Figure 18 reflect the different levels of the network influence variable (c1). Figure 19 through Figure 32 are arranged in a facet grid, with the setting for network influence variable (c1) described by the vertical facet, and the rewiring setting represented by the horizontal facet. Additionally, the network influence variable facets have the prefix of 1) through 4), while the rewiring facets have the prefix of a) through e). Therefore, when referenced a facet will be described by its coordinates; for example, facet b3 refers to a rewiring setting of 500 and a level of network influence equal to 3.

Table 6: Experimental design and result summary

Model Setting	Key Components	Summary of Findings
Varying network influence (c1) and short-term investors	The initial network for the investors is a lattice network. The following variation in parameter were used: network influence (c1) [1,2,3 and 4]; percentage of short-term investors [0%, 25%, 50%, 75%, 100%]	The introduction of the short-term investors resulted in greater volatility and the earlier synchronization of investor strategies, meaning the system tipped into bubble territory earlier. Also, bubbles appeared under conditions that did not previously result in bubble. On note was that only a small low percentage of short-term investors was required to increase the activity in the system.
Varying network influence (c1), short-term investors, rewiring	As above with the exception that the investor network is rewired in increments of: [250, 500, 1000, 1500] steps, meaning rewiring occur: [11, 5, 2, 1] times.	The rewiring process resulted in even greater variations in the behavior of the system. This was witnessed by previously dormant markets – containing only long-term investors produce volatile behavior. Thereby, identifying the fact that the presence of Oracles can destabilize the market The wealth distribution was extremely skewed under the conditions responsible for severe price movements, with short-term investors gaining off long-term investors.

In Figure 15 through Figure 32 employ two types of graphs – time-series plots, and summary statistics plots. The time-series plots provide a temporal aspect concerning how the behavior of a given variable evolved throughout across runs of a given setting. A loess smoothing technique is used to enhance the value of the time-series plots. The benefit of this process is that it provides a stylized representation of how each combination of parameters affects a given variable and removes unnecessary noise. Summary statistics plots – either Box-plots, range plots or bar graphs – are utilized to illustrate the variation within a given set of parameters. It is only by assessing how the data evolved across and within runs that a proper judgment can be formed regarding the underlying dynamics of the system.

2.5.3 Detailed Results

2.5.3.1 Introducing Short-term Investors

The benchmark by which to judge the effect of introducing short-term investors comes from the findings of Harras & Sornette (2011), which were confirmed and extended in Oldham (2017a, 2017b). The relevant benchmark is that as the variable that determines the inclination of investor to be influenced by their network – denoted by c1 – increases the price series begins to experience increased periods of volatility. An elevated level of network influence ultimately results in a phase transition once the setting is equal to or exceeds 3. The phase transition ensures that the positive feedback loop between investors generates sufficient weight for "herding" to occur; that is, following the actions of their most trusted adviser becomes common practice within the populations, and the price of the risky asset no longer moves randomly, per the arrival of private and public information. Furthermore, at a network influence setting of 4, the system becomes "excitable," with asset bubbles appearing. The boom portion of the bubble results in the risky asset's price approaching 8, a value well beyond its fundamental value, which remains around 1 throughout the simulation. The catalyst for the collapse of the boom, thus completing the bubble, is that investors have insufficient funds to maintain the buying momentum, thus slowing the positive feedback loop, which in turn sees investors begin to lose trust in their neighbors' investment advice.

Figure 15 presents the stylized price dynamics of the various settings across time. The y-axis represents the range between the maximum and minimum price of the risky asset at each step. The price range was chosen over other variables, such as the maximum value, median, or standard deviation as it provides a concise illustration of the variation between the extremes within the various combinations across time. Unlike the remaining charts in this section, Figure 15 provides a level of validation by plotting the equivalent price series from the original model, with the data coming from Oldham (2017a).

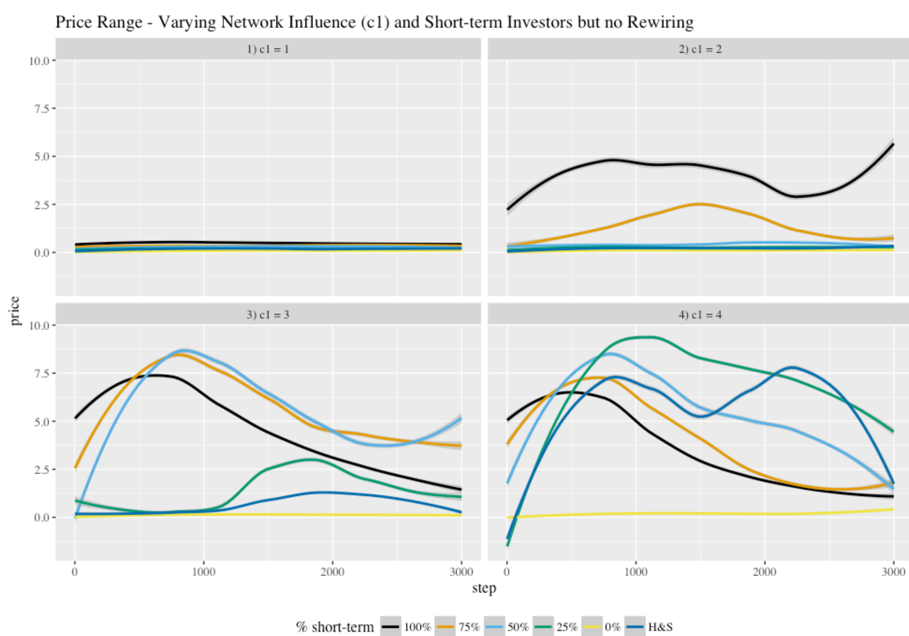

Figure 15: The temporal price behavior of the risky asset with no rewiring. The facets are differentiated by the setting for the c1 variable – the variable that effects the initial inclinations of investors to follow their neighbors' actions. The lines represent the temporal evolution of the asset for the various combination of short and long-term investors.

Regarding validation, the ex-ante expectation was that a population comprising a 50:50 mix of short-and long-term investors would produce similar results to the original model. The results of facet 1 and facet 2 provide a level of confirmation for this hypothesis. However, from facet 3 and facet 4 it appears that a population comprising a 25:75 mix produces a comparable result. The likely explanation is that in the case of a 25:75 combination, despite being in the minority, short-term investors have sufficient mass to draw the long-term investors into a buying herd, resulting in a material movement away from its fundamental value for the risky asset.

Overall the introduction of short-term investors produces several new dynamics. The magnitude of these dynamics is dependent on the composition of the investor population. The first observation, as illustrated in Figure 15 facet 1, is that it is only when the level of network influence exceeds 1 that there is any material change in the price dynamics. Next, when there is a high proportion of short-term investors the system does not require the level of network influence to be as high for the system to show more extreme price movements. Figure 15 facet 2 demonstrates this point.

Once the network influence is equal to or greater than 3, the effect of the short-term investors becomes more evident. From Figure 15 facet 3 and facet 4 higher a proportion of short-term investors leads to a more rapid expansion and deflation of the risky asset's price. The most likely conclusion is that the short-term investors take less time to form herds, which create the asset boom sooner, thus exhausting the investable funds of investors at a more rapid rate. This feature, in turn, causes a reversion in the risky asset's price because the slowing price growth impairs the trust investors have in each other, and they become more inclined to follow the alternative information sources. The narrative for Figure 17 and Figure 18 extends the discussion on this topic.

The final point of the initial analysis is the behavior of a population comprised entirely of long-term investors. From Figure 15 it is seen that under no circumstances does the price series become excitable. The conclusion drawn from this is that considering more price points, and not being able to change advisers, is sufficient to restrict the behavior of investors as the conditions do not allow the formation of the positive feedback loop.

From the analysis of Figure 15, the question arises about how consistent the behavior of the system is under the various scenarios. Figure 16 provides an insight into this via boxplots of the standard deviation of prices at each step for each scenario. A low standard deviation is indicative of consistent behavior and/or small price movements. Facet 4 provides an important finding in that the median standard deviation increases as the percentage of short-term investors decreases, the exception being when there are no short-term investors. Coupled with Figure 15, this suggests that the hastened extreme price movements seen with a higher proportion of short-term investors occurs because the behavior of the system is more uniform as investors become more easily synchronized in their investment decisions thereby initiating the positive feedback loop more consistently and, as confirmed in combination with Figure 18, more rapidly. When the population is comprised entirely of short-term investors, there is a broader range in the standard deviation, including a higher number of extreme events, which suggests the behavior of these investors is more volatile.

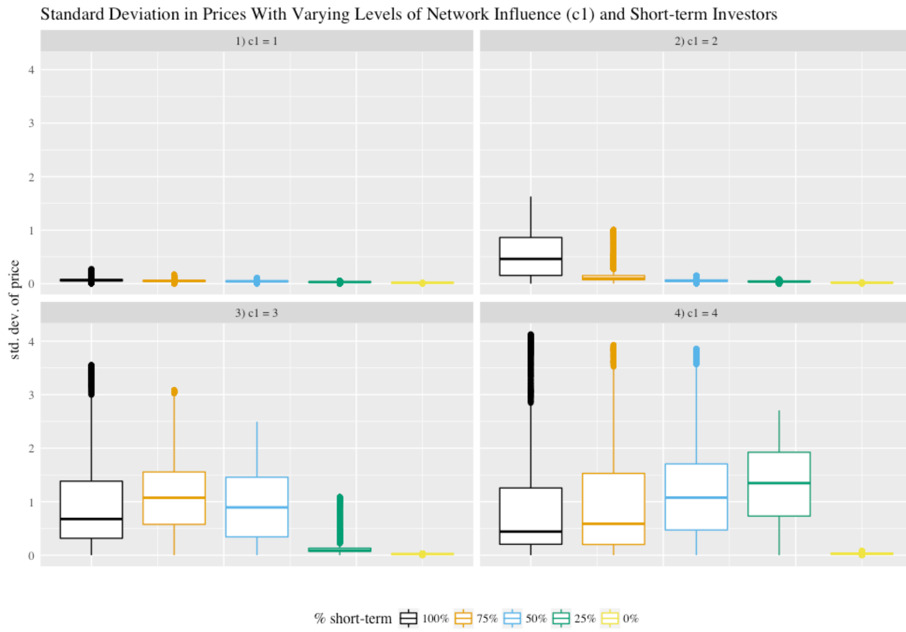

Figure 16: Analysis of price volatility and behavioral commonality. The result is shown for the various settings of c1 with no rewiring. The boxplots illustrate the median, variance and outlining behavior. Plots are provided for each combination of the experimental settings applied. Greater variance is seen in facet 4 compared to 1.

It is apparent that the introduction of short-term investors has a material effect on the market. The logical conclusion is that as these investors have, on average, a lower decision threshold (Figure 13), they are merely trading more often, and this is responsible for the excessive price movements. However, given the Gaussian distribution of private and public information, with a mean of zero, the investment decisions of the short-term investors should, in most instances, cancel each other out resulting in a random walk with the risky asset's price fluctuating in a tight band around its fundamental value. Notably, there should be no significant and predictable pricing behaviors; however, this appears. The alternative explanation is that short-term investors are more inclined to form herds because they tend to update the trust in their advisers at an accelerated rate. Therefore, the market experiences more substantial fluctuations.

The first area of inquiry into identifying the process driving greater price volatility seen with a population containing a higher proportion of short-term investors is to understand if, and how, short-termism affects how investors update trust. The rationale for this line of investigation is the established relationship between the level of trust and the movement in the risky asset's price (Harras & Sornette, 2011). The second area of inquiry is then to establish the connection between the dynamics of investors' trust in their neighbors and herding. Herding is the percentage of investors undertaking the most common activity, at each step for each scenario, noting the action may be buying, holding or selling. This analysis establishes a connection between the implemented model and the result presented in Tedeschi et al. (2012).

Section 2.4.4.4 details the process by which investors update trust in their neighbors. In summary, investors will increase (decrease) the level of trust in their neighbors when they provide the correct (incorrect) investment advice, with the process amplified by larger price movements. Therefore, once investors effectively forgo their other information sources and follow their neighbors' advice, herding commences. Which in turn increases the probability of the movement in the risky asset's price confirming the original advice, thereby resulting in the trust an investor has in the adviser who provided the advice increasing. Also, and just as important, short-term investors vary their trust at a faster rate due to considering less history. This process implies that the dynamics of the level of trust investors have in their neighbors parallels the herding dynamics. Figure 17 confirms the expectation that the dynamics of the level of trust investors have in their neighbors parallels the price movements of the risky asset (see Figure 15). The y-axis of the charts is the standard deviation of the trust coefficient.

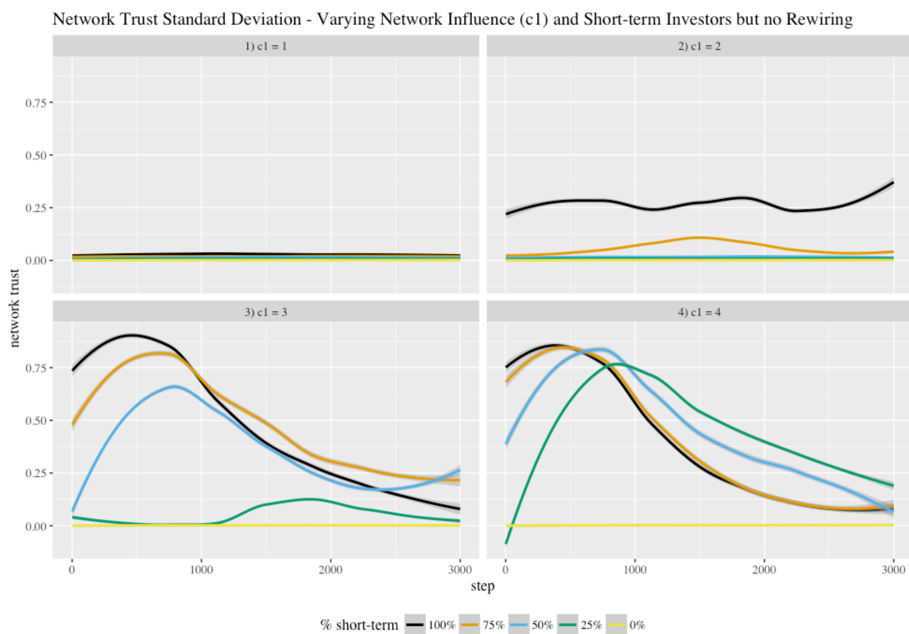

Figure 17: Temporal variation network trust coefficient with no rewiring. The facets are differentiated by the setting for the c1 variable. The lines represent the temporal standard deviation of the population trust in their network at each step for the various combination of short and long-term investors.

Figure 18 confirms the connection between the level of herding in the population and the level of trust investors have in their neighbors. The herding coefficient captures both the inflation and deflation of an asset bubble, as investors enter the buying herd before switching to the selling herd at later stage. The common theme is that a population with a higher proportion of short-term investors will herd earlier and, except for when the network influence variable is 4 (see facet 4)), record higher levels. Of note is the fact that under no condition does a population with no short-term investors experience herding and as previously noted no extreme price movements occur.

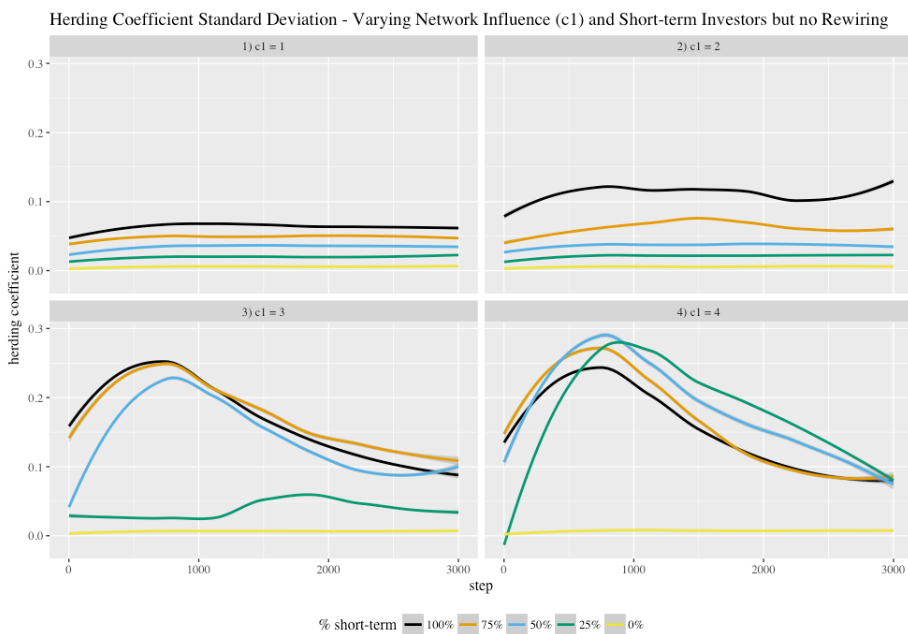

Figure 18: Temporal variation of the herding coefficient with no rewiring. Facets are differentiated by the setting for the c1 variable. The lines represent the temporal standard deviation of the herding coefficient at each step for the various combination of short and long-term investors.

A further observation regarding the herding coefficient is that it peaks and then declines monotonically in the later periods. This observation implies more varied and extreme behavior in the early stages of the simulation, before greater commonality returns. The mechanism by which asset bubbles deflate explains this characteristic. Namely, the positive feedback loop, which feeds the upward price movements, loses momentum as investors exhaust their investable funds. As the price momentum slows, investors begin to lose trust in their neighbors, which eventually leads to some investors beginning to leave the buying herd and decrease their holding in the risky asset. This dynamic eventually creates a selling herd. The critical element is that as investors start to sell in a down market the average (and below-average) investors generate material trading losses because they bought in the inflated market and are late in reducing their exposure to the risky asset. These losses culminate in a concentration of wealth with certain investors. This process impairs the ability of the system to create further extreme prices because most investors have insufficient funds to return to the market.

This section provided evidence as to the effect of, and the reason, short-term investors creating greater volatility. The first inference was that as the proportion of short-term investors grew in the population, this decreased the time taken for investors to build trust in their neighbors, which led to more rapid herding and price fluctuations. Additionally, as the network influence variable increases, it amplifies the dynamics of the short-term investors, a finding which is consistent with the previous papers that utilized the underlying model. The direct implication is that the composition of the investing population, and the predisposition of those investors to favor the advice of their neighbors over fundamental information, significantly affects the behavior of the market.

Having assessed the implications of varying the proportion of short-term investors embedded in a static network, the next stage is to evaluate the effects of a dynamic investor network. Section 2.5.3.2 addresses this question. The ex-ante expectation relating to the dynamic network – that is, agents having the ability to select (ignore) the agents they receive advice from – will increase the likelihood of herding. The intuition for the expectation is that agents will tend to find mutual high performing advisers

(Oracles) and follow their decision, thus creating a common strategy across the population. Section 2.4.4.8 describes the process of how investors select their neighbors. In summary, they look to those investors who have a superior investment record.

2.5.3.2 Short-term Investors and Rewiring

With the introduction of the dynamic network, there is the need to assess the dynamics of both the financial market and the investor network – more specifically, if and, in what form the investors evolve the topology of their network. The relevance of this outcome is that the topology of investor networks has been found to affect the behavior of the market materially. The first stage of the analysis (Section 2.5.3.2.1) presents an assessment of the system's response to the conduct of the risky asset's price and the dynamic variables driving it. The second component (Section 2.5.3.2.2) then assesses the meso-level element of investors arranging themselves in their network.

2.5.3.2.1 Price Behavior

Figure 19 illustrates the price behavior of the risky asset. The chart provides sufficient evidence that rewiring does have a positive effect on the price movements of the risky asset given the initial conditions that the network influence parameter is greater than 1. This statement is supported by the lack of movement in the price series in facets a1 through e1 compared to the other facets. This finding implies that the markets may well follow a random walk when investors are not inclined to follow the advice of their neighbors over their other information sources. Therefore, short-termism may well be an irrelevant concern if investors can maintain a balanced perspective regarding where and how they assess the information that determines their investment decisions.

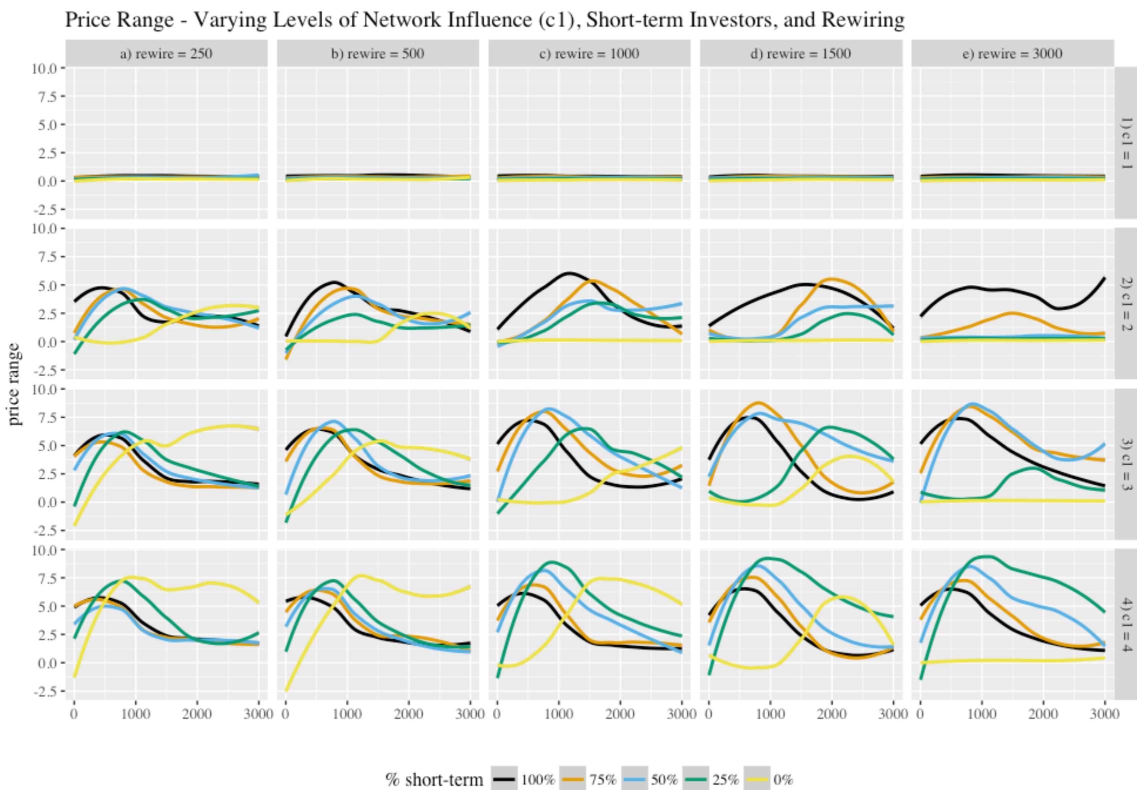

Figure 19: Temporal behavior of the risky asset's price with rewiring. Facets now differentiate for the rewire intervals (columns) and the c1 variable (row). The lines represent the progression of the asset's price for the various combination of short and long-term investors.

However, if investors are inclined to favor advice from advisers – seen with a c1 variable setting higher than 1 – the model produces multiple implications. The first implication is that given the ability to select their advisers, another otherwise "non-volatile" market – that is, extreme price movements do not occur – becomes volatile. Facets a3 through e3 are clear indications of this, with the most evident example being a population with no short-term investors. Facet e3 shows that with no rewiring and no short-term investors the price series is dormant. In contrast, the remaining facets record material movements in the price immediately following the rewiring set, noting that the LOESS smoothing will spread the action before and after the actual rewiring step. More generally, when comparing the facets in column e to those of a through d, the effect that the rewire interval has on bringing forward the upward trajectory of the risky asset's price is evident. The crucial finding from Figure 19 is that it appears that even long-term investors are susceptible to herding, given the ability to select their advisers.

Figure 20 are boxplots that illustrate the effect of rewiring on the volatility and commonality of the risky asset's price behavior. The y-axis, in a similar manner to Figure 16, shows the standard deviation of the prices across each run at each step for each scenario. The first observation is that for the lower levels of network influence (facets 1 and 2), the price series is relatively subdued and uniform. The second and more important observation is that as the intervals between rewiring increase – that is, moving from facet a to e – the level of uniformity decreases – with the justification being that the median standard deviation increases as the interval increase. This behavior occurs because the longer gaps between rewiring impede the ability of the population to find, and settle, on a set of common Oracles, thus delaying the synchronized behavior of the population.

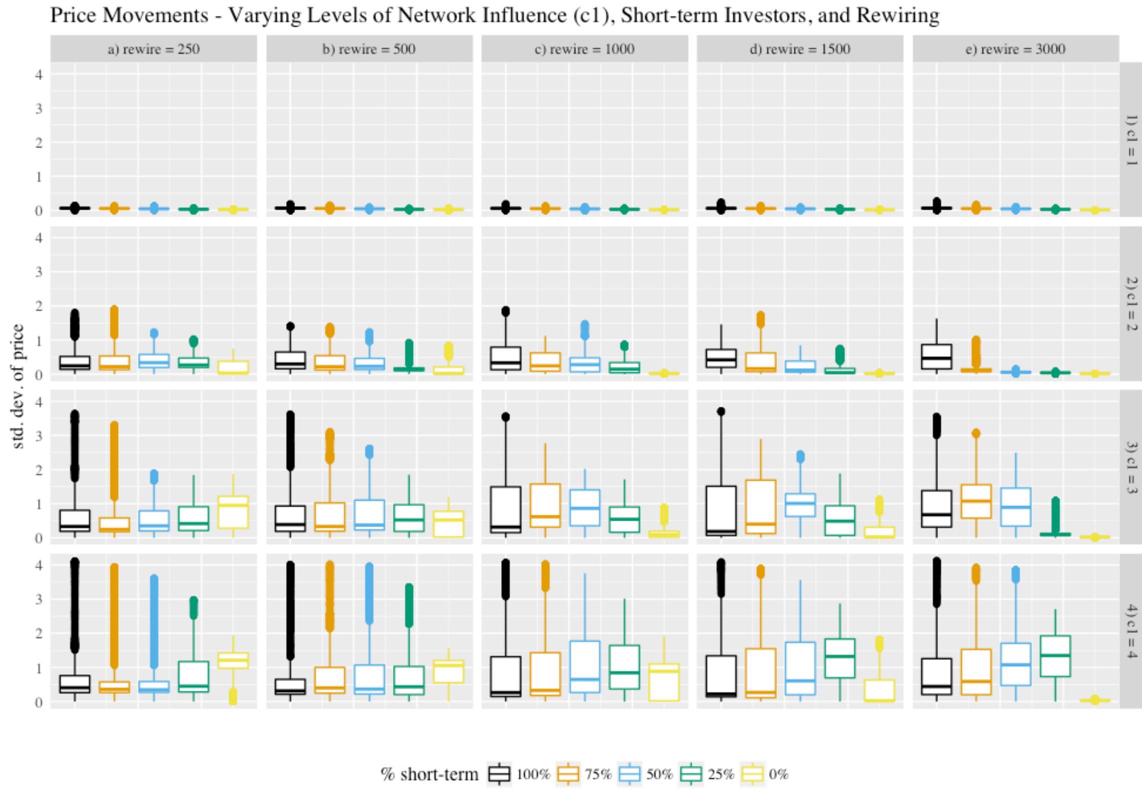

Figure 20: A representation of the price volatility and commonality with rewiring. The boxplots still illustrate the median, variance and outlining behavior.

While Figure 19 provides a stylized representation of the temporal aspect of the risky asset's price behavior, Figure 21 provides a more specific illustration of the price movement. The chart utilizes the concept of maximum drawdown-and-up. A draw-down –or up is the value of each consecutive uninterrupted downward (upward) streak of price reductions (increases). The maximum is the largest upward and downward streak. The advantage of these metrics is that the number of time steps in the simulation does not influence the magnitudes of these variables as they represent a specific subset of the data; that is, an uninterrupted streak of the price. Given the symmetrical nature of the charts, the metrics capture the inflation and deflation of an asset bubble and represent the potential gains (losses) an investor can experience. Figure 21 plots the median maximum draw-down-or up with the standard deviation illustrated by the bars.

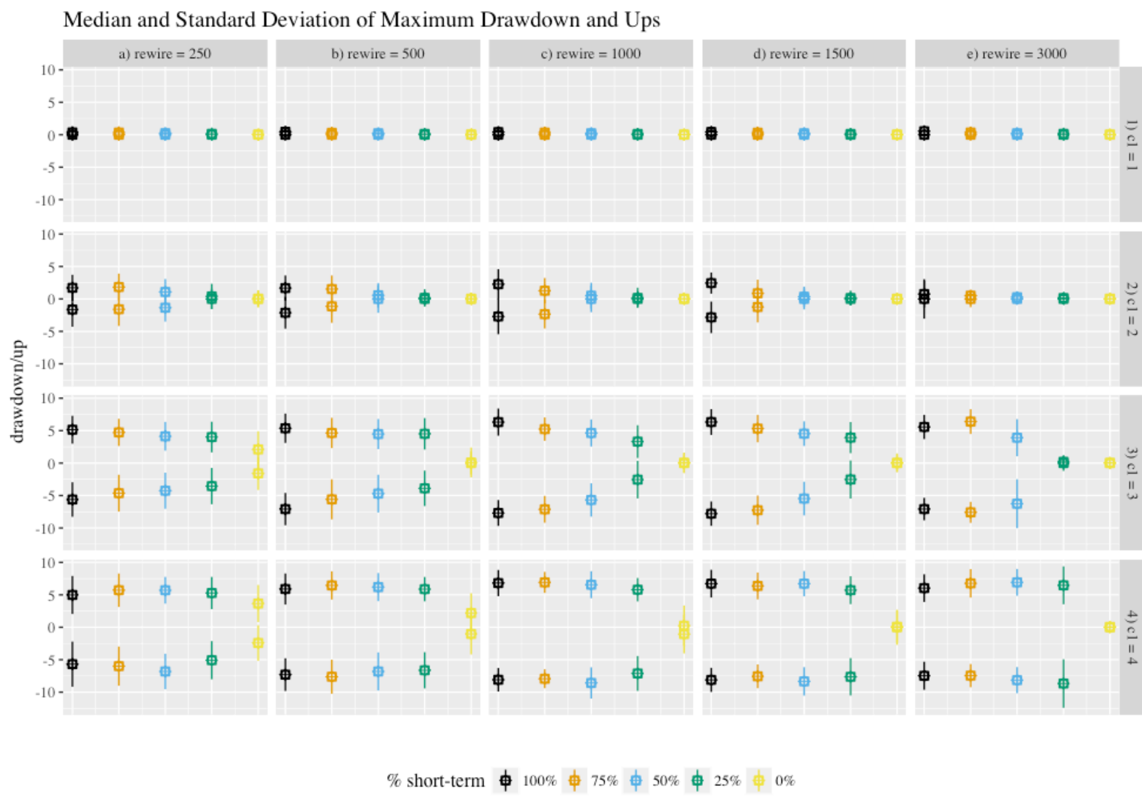

Figure 21: The maximum draw-downs, and draw-up statistics for all settings. The boxes represent the median, while the lines represent the upper and lower maximums recorded for each combination. Plots are provided for each combination of the experimental settings applied.

Consistent with the other findings reported thus far, the rewiring interval and the network influence have a noticeable effect on the draw up (down) variables. Facet rows 1 and 2 show that for the lowers levels of the network influence variable the maximums are not as large as for the higher levels of network influence. This observation tends to confirm that higher levels of network influence are responsible for instigating the positive feedback loop that results in the more extreme price movements. The second facet rows provide the initial evidence that the combined effect of shorter rewiring intervals and a higher proportion of short-term investors results in large price movements. This point can be seen with the points “jawing” open; that is, the gap between the maximum drawdown and up increases as the interval decreases, a population with no short-term investors serves as an anchor point.

The combined effects on the draw-down-or up variable of a shorter rewiring interval and a higher proportion of short-term investors are seen in facet rows 3 and 4. The first observation is that the jaws open farther, including some instances with no short-term investors experiencing material draw-downs-and ups (for example, facet a4 and b4); thus supporting the concept that even long-term investors can herd and cause excessive price volatility when they change their advisers at more regular intervals. The second observation is that jaws open in a linear fashion in facet row 3, while in facet row 4 the width of jaws is constant, except for when the rewiring process does not occur. This finding implies that the inclination of investors following neighbors, given by the c1 variable, has a more significant effect than do the rewiring intervals.

Section 2.5.3.1 established the connection between the behavior of the risky asset’s price and the level of network trust and herding coefficient. To conclude this line of investigation Figure 22 and Figure 23 illustrate the variation in network trust and the herding coefficient across the various experimental settings. Figure 22, which represents the temporal aspect of network trust, is consistent with the previously reported findings in that there is a transition in the system’s behavior once the level of the network influence exceeds 2. Additionally, shorter rewiring intervals and a higher proportion of short-term investors hasten the establishment of trust amongst investors.

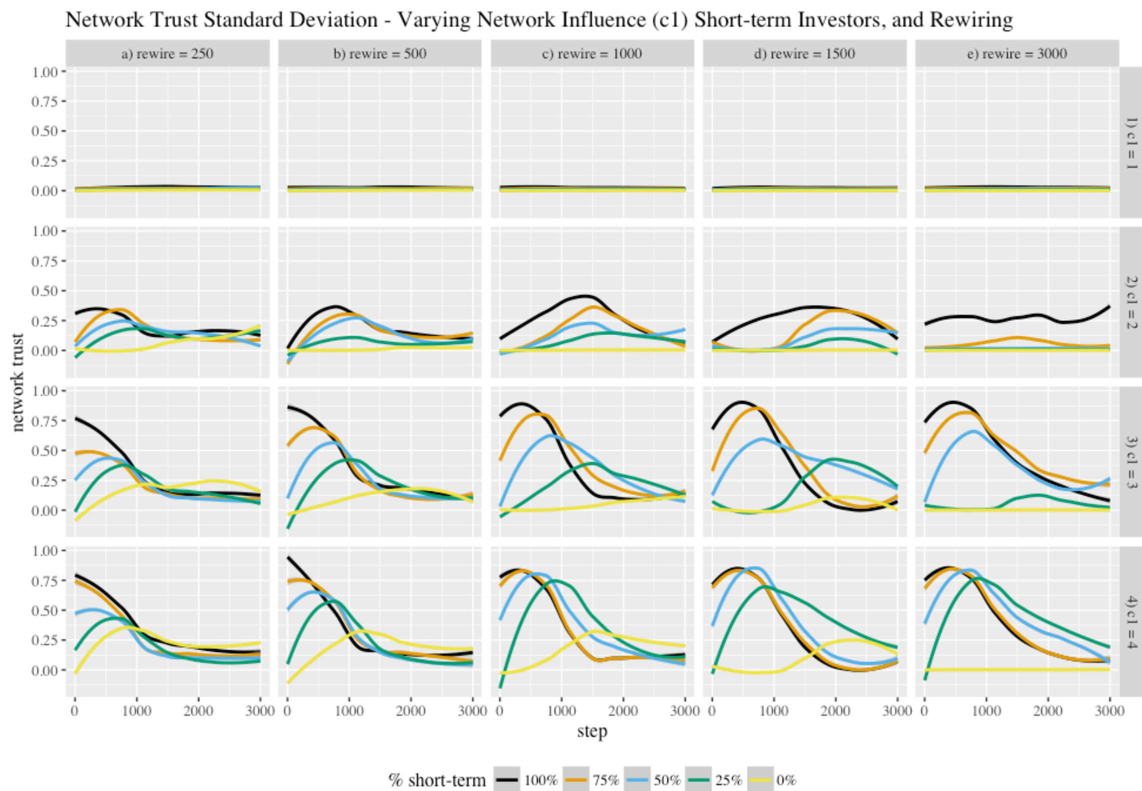

Figure 22: Evolution of network trust coefficient with rewiring. Facets now differentiate for the rewire and c1 variables. The lines represent the temporal adjustment of the standard deviation of the populations' trust in the network for various combination of short and long-term investors.

Figure 23 provides the final piece of evidence linking if, when, and how an investor network affects the pricing behavior of a risky asset. Consistent with the argument related to Figure 18, the increased levels of trust amongst neighbors parallels the characteristics of the herding coefficient. The introduction of rewiring does not affect the relationship.

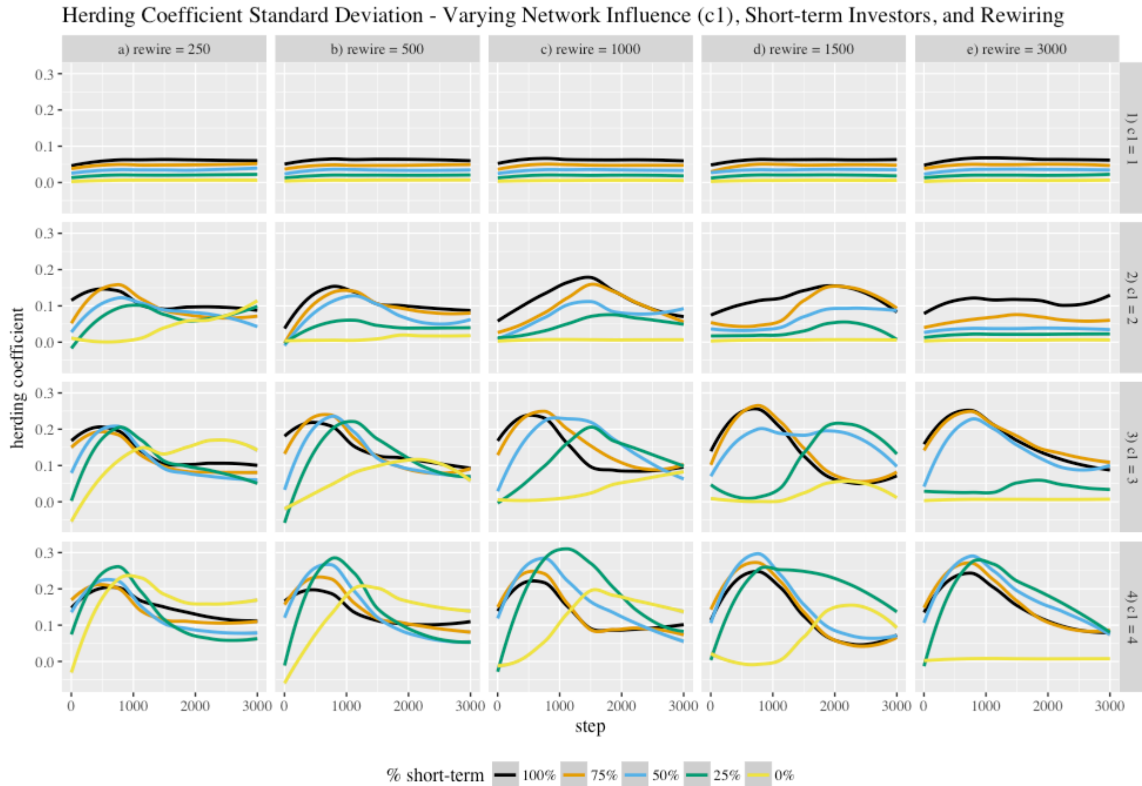

Figure 23: The evolution of the herding coefficient with rewiring. The lines represent the temporal changes of the standard deviation of herding coefficient for various combination of short and long-term investors.

Apparent implications arise from the analysis of how the interaction of investors of varying characteristics affect the behavior of the artificial stock market. The first is that a higher proportion of short-term investors will increase the volatility of the market because these investors are more reactionary and built trust in their advisers at an accelerated rate. The second is that by allowing investors to choose whom they receive information from hastens the building of trust and ultimately accelerates the realization of extreme price movements. The size and timing of these movements are also affected by the population's preference for following advisers (the network influence variable). If investors do not prefer any information source – that is, $c_1= c_2= c_3= c_4=1$ – these interactions become irrelevant. In summary, if investors and regulators are to understand the dynamics of the market entirely, they must comprehend the intentions and investment methodology of the investment population.

At this point it is worth considering the implications of trading volumes from the varying experimental settings. Section 2.3.3 detailed the research that highlighted first the increased trading volumes as the prevalence of short-termism increases, and second the detrimental effect excessive trading has on the accumulation of investor wealth. Figure 24 illustrates the median trading volume for each investor class for each experimental setting. Given the median is utilized the reader should be aware that total volume will be a function of the proportion of each investor class: that is, from facet a1, the total trading volume would be significantly higher when the population is comprised entirely of short-term focused investors. In contrast to the previous charts, an additional facet, which provides the data separately for the long and short-term investing communities, is added. It is denoted by i) and ii) for short-and long-term investors.

The obvious conclusion from Figure 24 is that, as expected, short-term investors are more inclined to trade. Yet, there is a marginal reduction in this tendency when there is a higher presence of long-term investors. For the long-term investors, it is apparent that a greater presence of short-term investors draws them into the market. They are also drawn into the market when they have a higher prevalence of listening to their neighbors (see facet rows 3ii and 4ii). This behavior is consistent with the larger price fluctuations seen with the equivalent experimental settings.

Figure 24: The volume of trading recorded by each sub-class of investor. The data comes all experimental combinations. The bars represent the average trading volume of an investor.

2.5.3.2.2 Network Behavior

The purpose of this section is to establish how the characteristics of the investors and the environment affect the evolution of the investor network. The network evolves as investors alter whom they are willing to receive information from based on their investment performance and their trust in other investors. Table 2 details the basis by which investors adjust from whom they receive information; that is, the maintenance of and selection of Oracles. In summary, investors who are outperforming their benchmark will, based on their overall level of trust in their neighbors, either add advisers or do nothing, whereas underperformers will sever ties with neighbors, who they no trust. Whether a replacement is selected is dependent on the investors overall trust their adviser network. The benchmarks for the two investor classes differ, with long-term investors comparing themselves against the market since the initiation of the market and short-term investors judging their performance against the market since the last rewiring process.

Figure 25, which splits the short-and long-term investor results, represents the evolution of the median number of outperformers. The arbitrary assumption was made that at initiation the median percentage of outperformance was 50%. The first observation of consequence is that once the network influence variable exceeds 1, long-term investors have difficult outperforming the market over the entirety of the simulation, yet have some success in the early portion of the simulation – see facets rows 2ii, 3ii, 4ii. By combining the insights from Figure 19, it becomes apparent that long-term investors can outperform the market as the risky asset experiences a material upward shift because they adjust their asset allocation to being overweight the risky asset at initiation of the boom. However, once the price reverses, they underperform because they cannot reduce their overweight position quickly enough due to their less reactionary nature. The long-term investors, in general, are then unable to recover their wealth and become perennial underperformers.

Figure 25: Proportion of outperformers within each investor sub-class. Facets now differentiate for the rewiring and c1 variables, and the investor sub-classes. The lines represent the temporal evolution of the proportion of outperformers for the various combination of short and long-term investors.

An acute observation is that it becomes evident that a higher proportion of short-term investors accentuates the poor performance of the long-term investors. The rationale for this point is that the short-term investors are early to join(leave) a significant price upswing(downswing) and early to exit(join) the downward(upward) correction. The opposite holds for long-term investors, who in colloquial terms are "left without a chair when the music stops." The implication is that investors can be taken advantage of if they are not mindful of the intentions of other investors in their environment.

A review of the performance of the short-term investors also provides some interesting observations. First, the short-term investors, in general, appear better equipped to match or exceed their performance standard over a given interval. Crucially, the ability to match or exceed the market appears dependent on shorter intervals between reassessing and selecting their advisers. This point is most evident when comparing facet a4i and e4i. In another significant finding, the median number of short-term investors outperforming declines when then there is a higher proportion of short-term investor, albeit, with the ability to rewire, this differential is reduced. The implication from this observation is that without long-term investors to "feast" off, short-term investors struggle to outperform. They can correct this situation by rewiring their investor network, a process which may involve ignoring the advice from other investors.

Figure 26 through Figure 32 establish the connection between investment performance, investment horizon, and the dynamics of the investor network. The following metrics have been chosen to describe the evolution of the network: the number of links and their distribution; the clustering coefficient; and the average closeness of the investor population. The rationale for assessing the number of links is that it provides evidence of whether investors, on average, are inclined to add or reduce the number of advisers. More links indicates a denser network, with investors on average utilizing a higher number of advisers. The distribution of the links provides an indication as to how the network evolves and whether some investors become more critical than others.

The clustering coefficient indicates the structure of a network, with a higher clustering coefficient indicative of investors remaining in tightly closed groups, while a lower clustering coefficient is suggestive of a more open structure. The combination of the clustering coefficient and the number of links and their distribution allows one to determine into which stylized network the lattice network may have evolved. Given the rewiring process namely, the ability to select Oracles, it was expected that the model will evolve into a scale-free network. This finding would be consistent with Tedeschi et al. (2012). Alternatively, the network may be unable to maintain its structure; that is, it becomes random as the volatility of the market will result in investors losing faith in the information coming from their network. The difference in the two processes would see the scale-free network maintain an intermediate level of clustering as investors connect to Oracles, while the random network would have a low level of clustering as investors either do not connect to any advisers or Oracles consistently change.

The closeness coefficient, which is a measure of the shortest distance between investors, provides a measure of whether investors are coming closer together by selecting higher performing advisers. The relevance of a higher closeness coefficient is that information potentially diffuses at a faster rate through the network. The connection to financial markets is that the advice of higher performing investors will find its way to the population at a faster pace, which in turn may hasten "herding" as the population shares and acts on the same information.

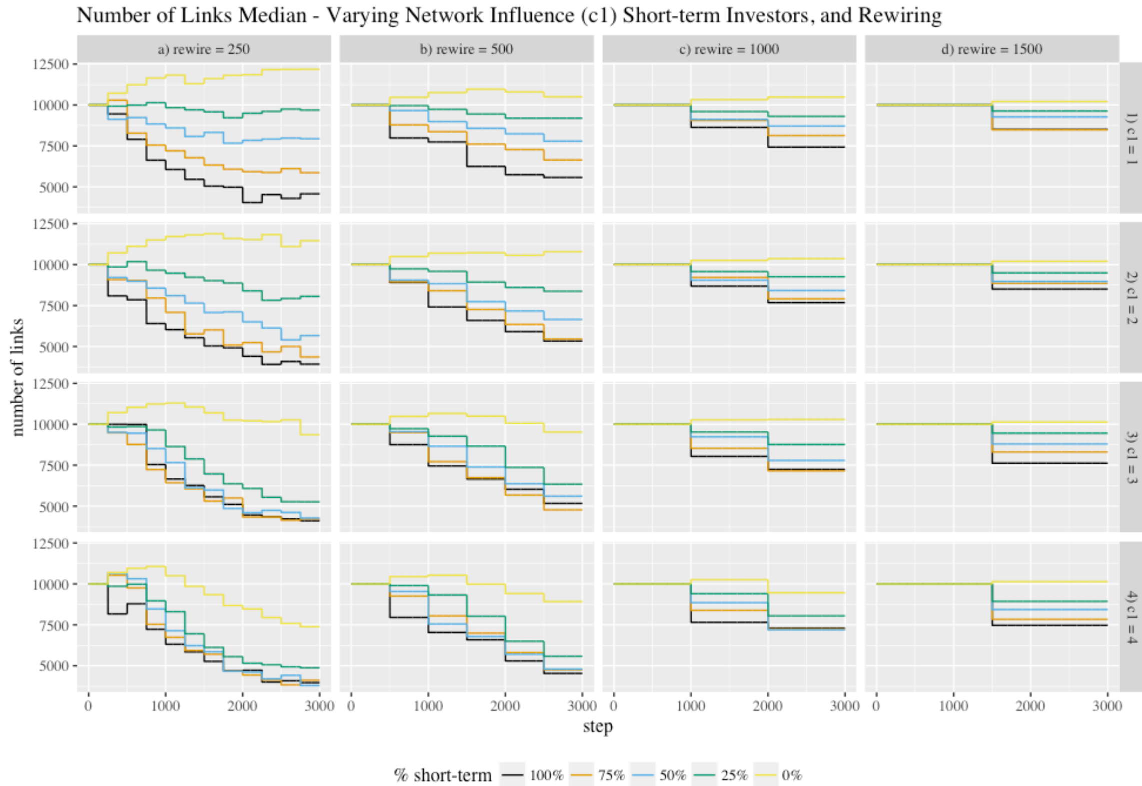

Figure 26: Temporal evolution of the median number of links with rewiring. With rewiring occurs a discrete step, the evolution of the metric appears "jagged." More frequent rewiring impairs the network.

Figure 26 illustrates the evolution of the median number of links in the network. The first observation is that in general the number of links declines through time. The one important exception is when the population has no short-term investors (see facet row 1 and 2). A decline occurs because investors cut and do not replace links. This scenario results from an investor's aggregate level of trust in advisers becoming negative and underperforming the market. The second observation is that the rate of decline becomes progressively faster the higher the proportion of short-term investors in the population. This point mirrors the price movements, which saw higher and more volatile prices when there was a higher proportion of short-term investors.

The conclusion from Figure 26 is that when there are more short-term investors, the population is less inclined to rely upon advisers for their investment advice. Now the question becomes: which investor class is disregarding the information available from their neighbors? A greater understanding of why the median level of links varies comes from an assessment of the distribution of out-degree of the investors – the number of advisers an investor utilizes. Figure 27 provides details of this relationship for the various experimental settings. The rationale for this analysis is that it will provide evidence for the conditions responsible for investors having a higher inclination, or otherwise, for seeking advice. Investors increase their number of advisers when they are outperforming the market and have positive trust in the network information and cut advisers when they have negative trust in their network information and underperform the market.

Figure 27 shows the dynamics of the median out-degree of the various investor classes. The dynamics appear to strongly parallel those that were evident when assessing the relative performance of the investor class (see Figure 25). Namely, the composition of the population and the rewiring interval affects how many advisers each investor utilizes. The central dynamic is that when long-term investors are forced to compete in an environment rich with short-term investors, they suffer poor performance. This outcome, in turn, leads to an accelerated loss of trust and a greater decline in the number of advisers they maintain. A critical condition for this process, as seen in facet rows 2ii through 4ii, is that the level of network influence must be higher than 1 – a setting proven to generate excess price volatility. Otherwise, consistent with Figure 25, long-term investors are capable of outperforming under the right conditions, namely when there is a higher proportion of long-term investors. Under these conditions, long-term investors are less inclined to reduce advisers and are even inclined on average to add them.

Figure 27: The development of the median number of advisers. The facets are split by the investor sub-classes, and the various other settings, to highlight the different behavior of the two classes, with the lines representing the median.

It is also vital to understand how investors are selecting their neighbors. This variable is defined as the number of followers per investor. Figure 28 illustrates the median and the upper and lower range for the number of followers each investor has, which are the investors in-links, and represents how many people are seeking advice from a given investor. The expectation is that the distribution will be highly skewed given the process of investors seeking Oracles. However, by what degree is important, as investors only search for Oracles under certain circumstances, as defined in Table 2.

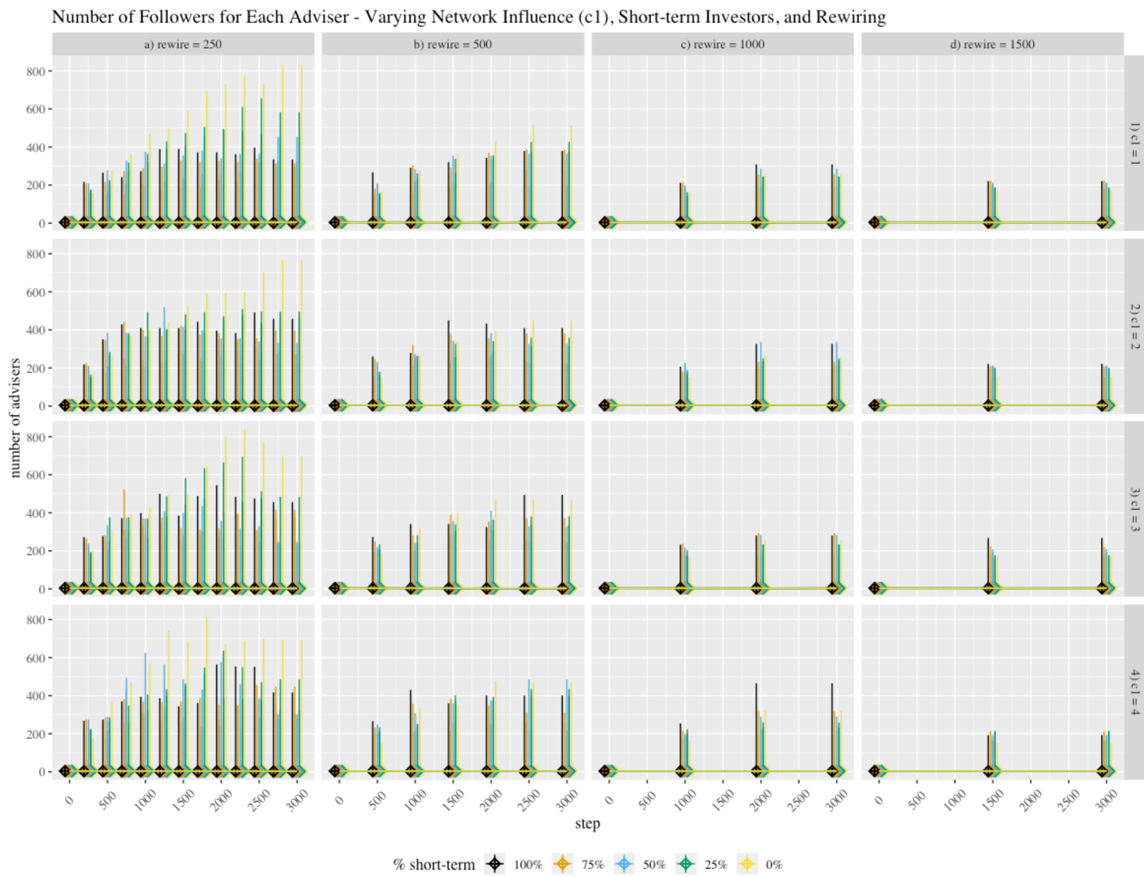

Figure 28: The dynamics for changes in the range of followers per adviser. The lines represent the range while the squares represent the median. The range is updated at the completion of each rewiring step.

The immediate impression from Figure 28 is, as expected, evidence of a highly skewed distribution. More important, meaningful differences across the various settings appear. From facet column a, the first difference of note appears with the skewness increasing as the proportion of short-term investors decreases. The other point from facet column a is that when comparing facet a4 to the others, it appears the that upper range peaks before declining in the latter portion of the simulation. Noting the similar extreme price characteristic for facet a4 and the ability of investors to rewire on a more regular basis, this suggests that investors tend to lose faith in taking advice from other investors, a point confirmed by the corresponding facet in Figure 22.

Figure 29 provides an alternate view of the in-degree distribution for the investors, by providing the standard deviation of the maximum number of advisers maintained by investors. The relevance of the standard deviation is that it provides a measure of the spread of the degree distribution and can be used in conjunction with Table 7 to estimate the network topology of the network. The consistent theme from Figure 29 is that a population with 25% short-term investors produces the largest standard deviation. Also, the standard deviation levels are generally higher the shorter the rewiring interval. From Figure 28 and Figure 29 it can be inferred that the higher standard deviation arises from a combination of some investors dismissing advisers and others adding advisers.

Having established the facts that investors, in general, have difficulty maintaining their original number of advisers, the next questions relate to how to classify the evolved network topology. Table 7 provides the network metrics for the original lattice and the alternative network topology with comparable initiation parameters; albeit the statistics come from an undirected network. Utilizing Table 7 in combination with Figure 28 through Figure 30 delivers an insight regarding the network topology. The importance of the topology of the network comes from Ozsoylev and Walden (2011), who proposed that markets would record higher volatility when there was an intermediate level of connectedness between investors, yet lower in markets with higher or lower connectedness. Therefore, from Table 7, if investors form a scale-free network the volatility of the market should be higher. The rationale for this dynamic is straightforward, in that many investors would tend to follow the decisions of a few Oracles, resulting in a higher prevalence of herding and more substantial price changes.

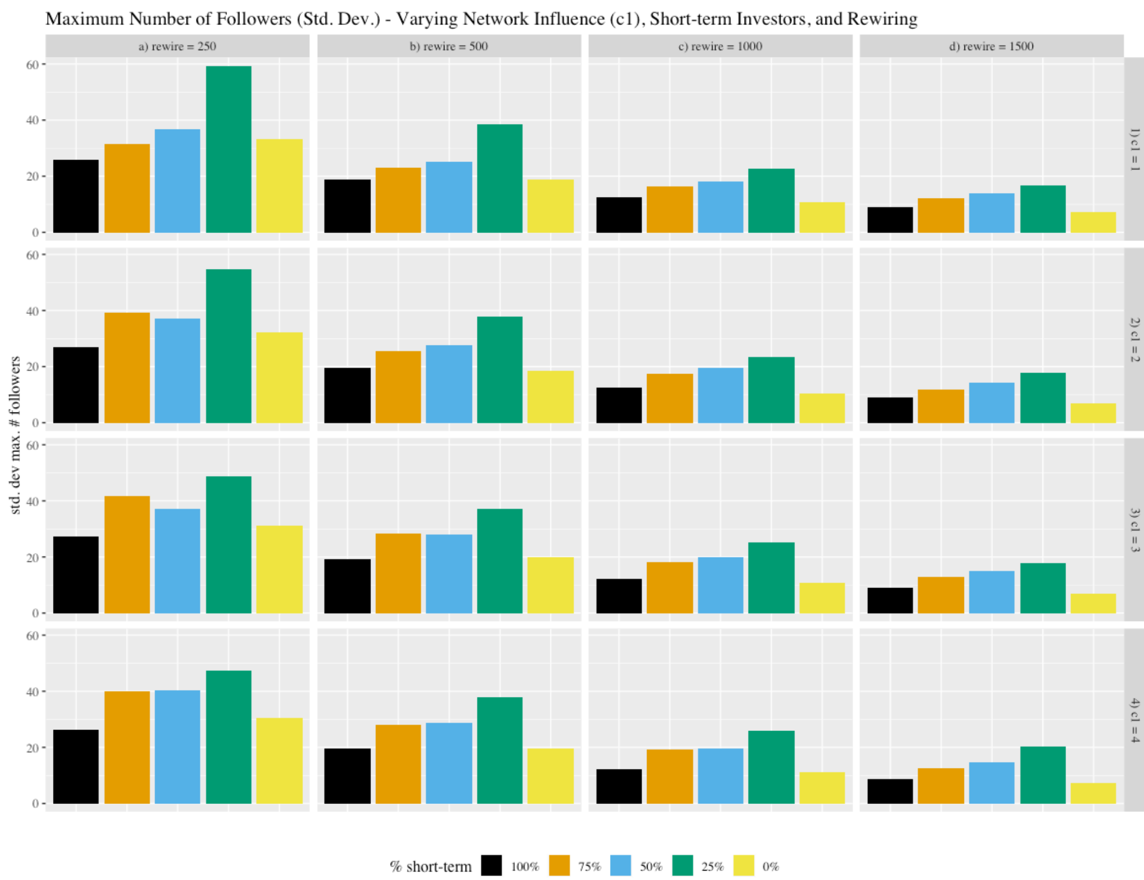

Figure 29: The standard deviation regarding the followers each agent attracts. The data and metrics were generated from the various runs with the previously discussed experimental settings. The purpose of the figure is to summarize the variations reported in Figure 28.

Table 7: Benchmark network metrics

	Original network	Scale-free	Small-world	Random
Mean clustering coefficient	0.5000	0.1412	0.3800	0.002
Mean closeness coefficient	0.0032	0.3361	0.0976	0.172
Standard Deviation in degree distribution	0.0000	31.774	0.6204	2.012

Figure 30 illustrates the temporal evolution of the median clustering coefficient for the investor network. It is immediately evident that investors do not remain in tight community clusters. This characteristic is an expected result given that investors can search the entire population for higher performing investors or choose to reduce their connectivity by not selecting new advisers. The reduction in the clustering coefficient occurs consistently across the various experimental setting, with a sizeable immediate drop followed by more gradual reduction as the simulation evolve.

Consistent with the behavior of other variables, a population consisting of a larger contingent of short-term investors records a more significant and faster change in the clustering coefficient. From facet column a, it also appears that the network finds a steady state, also seen in Figure 26. The range of the clustering coefficients in combination with the standard deviation relating to the number advisers per investor suggests, depending on the level of short-term investors in the population, that the investors' network ranges between a scale-free network, when there is a lower proportion of short-term investors, to a random network, when there is a higher proportion of short-term investors. The implications of the result are that in a more volatile market Oracles themselves have trouble maintaining their status, and investors tend to disregard actions of other investors.

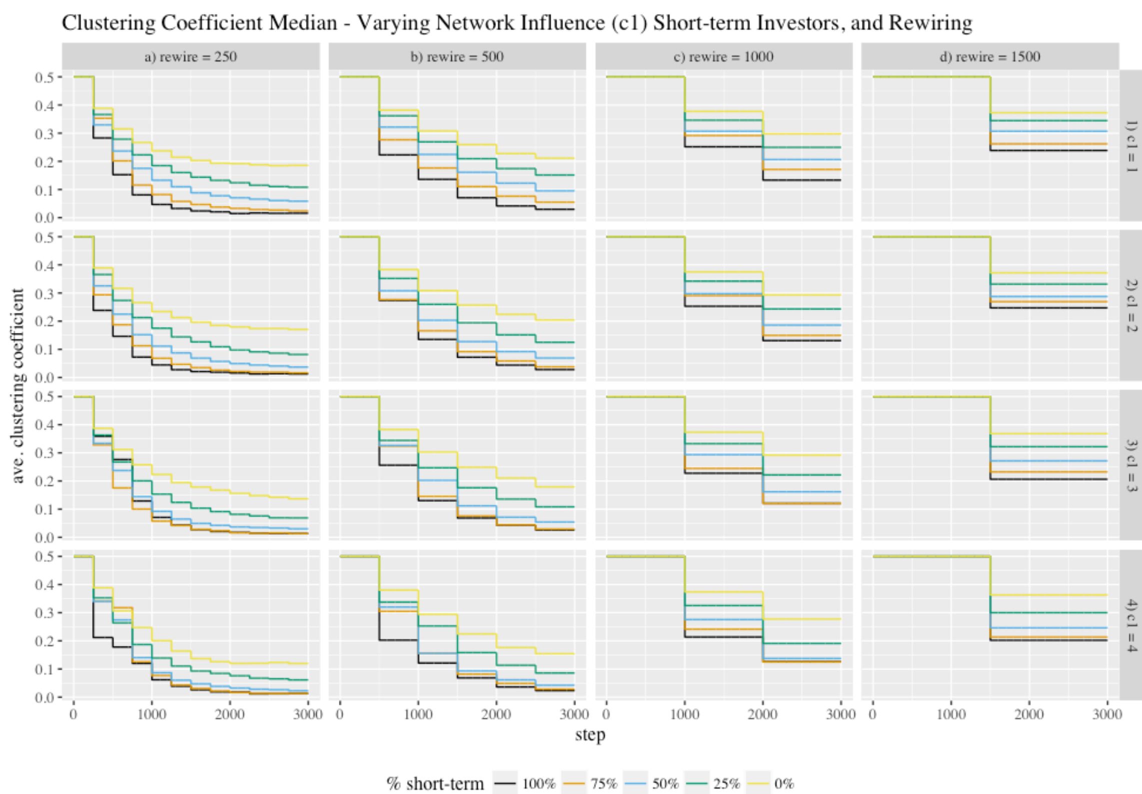

Figure 30: The evolution of the median clustering coefficient after rewiring. The lines represent the temporal changes in the coefficient for the various combination of short and long-term investors.

The evolution of the network provides several insights. The first, which agrees with Ozsoylev and Walden (2011), is that a system records its most active price changes in a period where the clustering coefficient is elevated. The second is that the more rapid deflation of the risky asset's price appears to cause a rapid decline in the clustering of the network. This phenomenon is likely to be caused by investors underperforming as they are caught in the price correction, thus forcing them to cut ties with investors and either seek an Oracle or opting not to receive information from other investors.

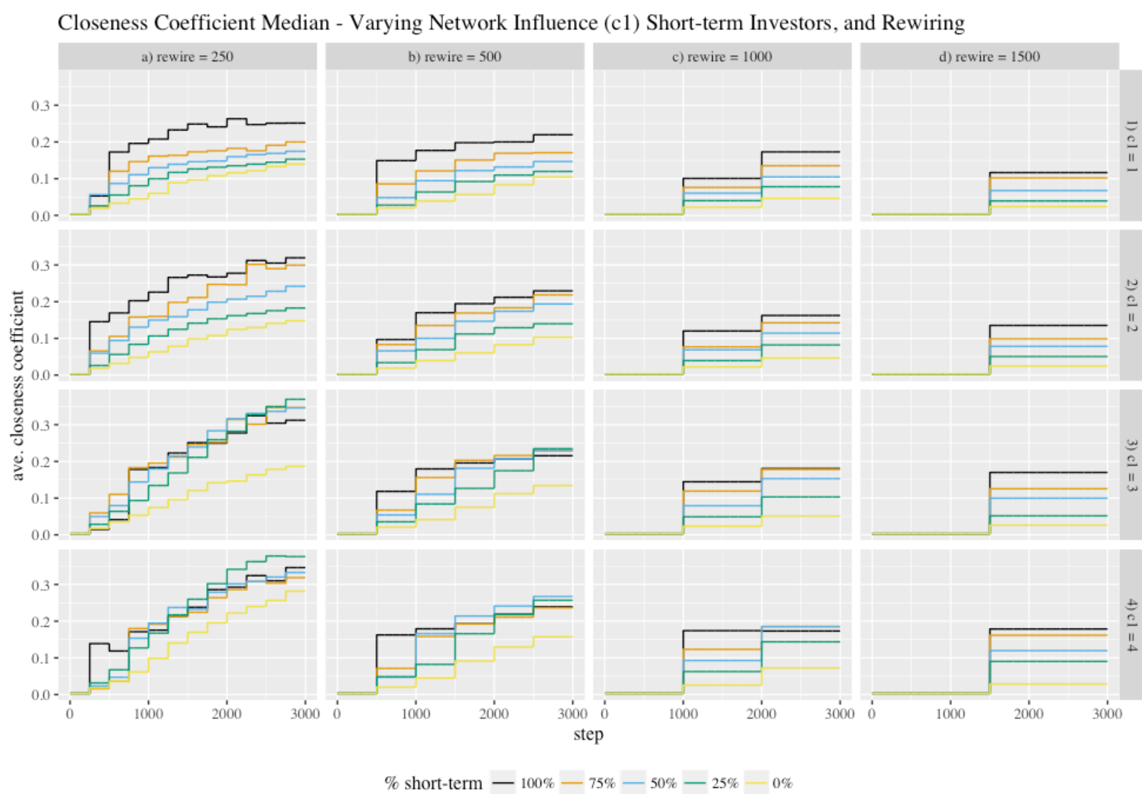

Figure 31: Changes to the median closeness coefficient after rewiring. The lines represent the temporal variations in the coefficient for the various combination of short and long-term investors.

Figure 31 provides the final macro-level observations of the investor network. The common theme is that investors increase their closeness through the rewiring process. This observation is consistent with investors breaking from their initial tight clusters and finding a mutual set of better performing investors, thereby rewiring the population into a closer formation. Another observation is that the closeness coefficient does not appear to settle on a steady state like the other network variables. The range in the closeness coefficient is supportive of the argument that the network evolves to a topology somewhere between a scale-free and random network.

2.5.3.3 The Hunt for Oracles

The previous sections identified the factors that influenced the behavior of the system and how that affected the various investor classes. The findings made it very clear that investors need to be aware of the environment they are engaged in because the system behaves in significantly different ways. Investors need to be particularly mindful of whether short-or long-term investors hold sway in the market and whether investors are predisposed to seek advice from other investors. As detailed in Section 2.3.4, the performance of individual investors presents a unique set of characteristics, including a tendency to be highly skewed over the short-term, yet normally distributed over the longer term. This section attempts to uncover the attributes of the more successful investors identifying the secrets of investment Oracles.

While Figure 25 indicated whether investors could outperform their benchmark, it did not provide evidence of the extent of outperformance, or what shape the distribution of outperformance took. Figure 32 presents the median portfolio value of the investors and the range of the various portfolio values at each rewiring stage. Therefore, the graph does not capture any wealth that may accumulate and then disappear within a rewiring interval, which would occur as asset bubbles can come and go within a rewiring interval.

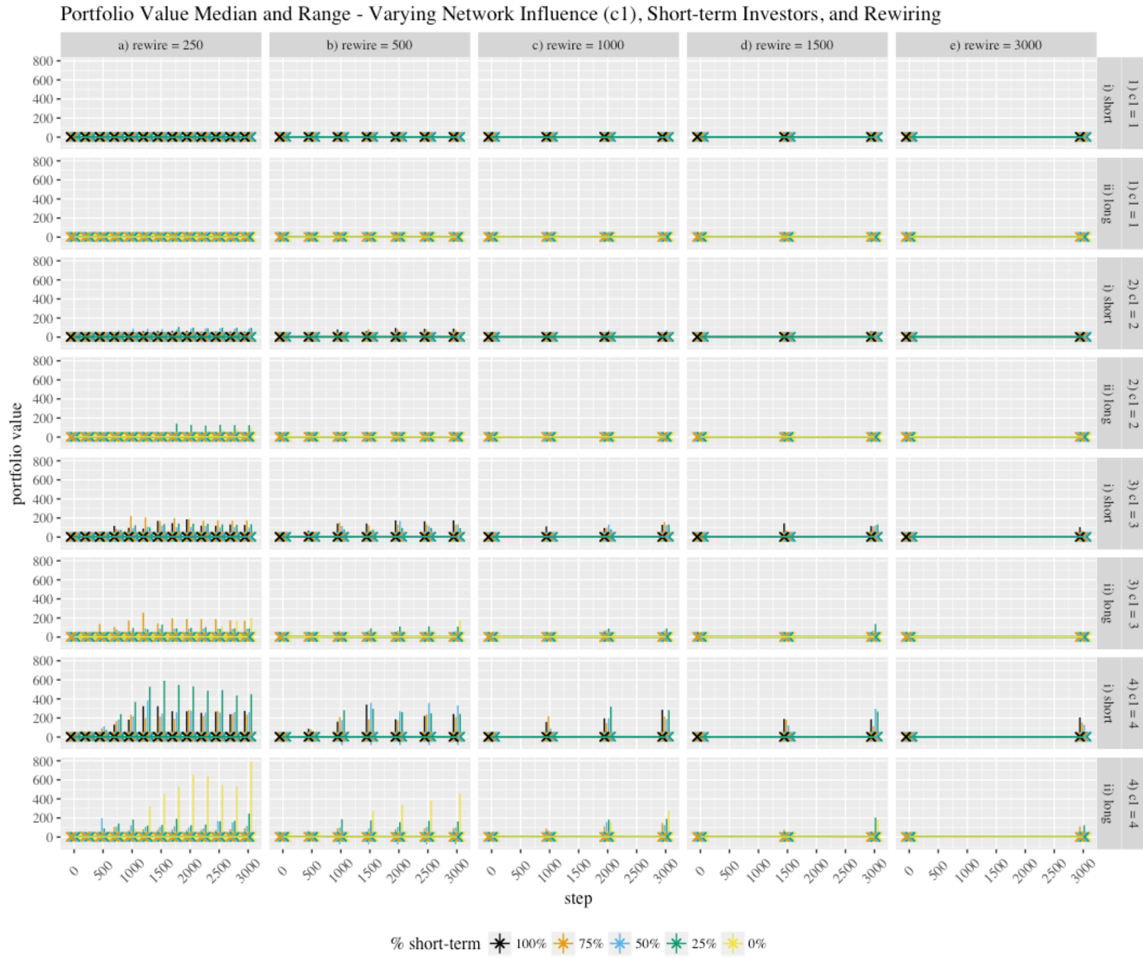

Figure 32: The dynamics of wealth creation. The plot shows summarize the distribution of wealth across the investor population. The lines represent the range while the stars represent the median. The range is updated at the completion of each rewiring step. Wealth becomes heavily skewed under certain conditions.

The most striking result is facet aii4 – where the relevant parameters see an asset bubble appear, with the instigation of the boom brought forward by the network rewiring process. What is striking is the extreme skewness in the wealth distribution when the population is comprised entirely of long-term investors. This finding suggests that even long-term investors can take advantage of other long-term investors by being ahead of the market. The extreme result occurs because a given investor starts the positive feedback loop, most likely because they have a relatively low threshold, and as more investors follow that investor's actions the bubble inflates, and long-term investors build higher, and sustainable trust in the original Oracle. The investor is then the first to leave the buying herd while the other long-term investors slowly adjust and start selling well after the original Oracle. The slow adjust provides the Oracle ample opportunity to sell at the top of the market. Therefore, the original Oracle achieves the perfect combination of buying low, instigating a herd which creates the boom, and selling high. This relationship is most pronounced with shorter rewiring interval but does hold with longer intervals.

The previously identified situation of short-term investors gaining wealth at the expense of long-term investors is also evident. Again, in the lower facet rows, the outperformance of at least one short-term investor over the highest performing long-term investor is clear. The gap also increases as the percentage of short-term investor decreases, which is indicative of the advantage short-term investors have in being able to adjust more quickly to the market. The final point of note is that material inequality only occurs when the network influence variable is greater than 2. Under this scenario, it is again short-term investors interacting with a more substantial proportion of long-term investors that produces the outcome.

Having identified that in a highly skewed manner some investors are capable of dramatically outperforming their peers, an attempt has been made to quantify the contributing factors. Figure 33 provides the first step in this process by presenting a correlation plot of the relationships between the log portfolio values (the log value was due to the skewed distribution of wealth) of investors and the numerous other variables of interest. However, unless noted, the relationships were not statistically significant at the 5% level. Commencing with the negative correlation coefficients, the global network influence variable (and the investor specific value) and the number of times an investor switches advisers both appear influential and are statistically significant. The dynamic responsible is that the higher the network influence, the higher the probability of extreme price movements due to investors herding more consistently. Naturally, all investors can benefit if they remain in a buying herd. However, with finite funds, this is an impossibility, and the asset boom is unsustainable. The switching variable appears to indicate that there is no value in continually switching advisers, a result consistent with the expectation that no investor can outperform the market over the long-term.

The positive influences on wealth are not as influential; however, there are several observations that are consistent with previously discussed results. The first is that the higher the proportion of long-term investors – as given by the *lt* variable – the higher the wealth of an adviser, with no indication of the class of the investor. An important observation is that investors who have a higher inclination to follow their private information appear to do better. The vital fact is that by following a source of information not common among other investors (public information), and not being influenced by the action of others (network information), an investor's chances of outperforming improve, albeit marginally. This statement is contradicted somewhat by the fact that increasing the number of advisers maintained by an investor, and having more followers, enhances the probability of outperforming. The final comment relates to trading, which makes a positive contribution to improving wealth accumulation. While this finding is inconsistent with the empirical results, it is consistent with the dynamics of the model, in that short-term investors generally have superior performance.

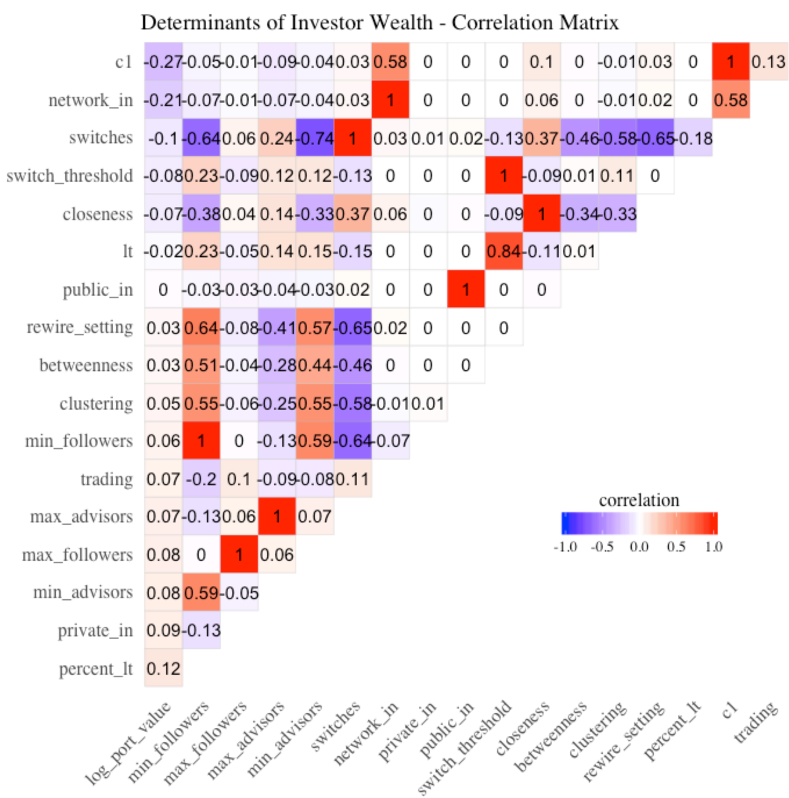

Figure 33: The correlation matrix summarizing the factors affecting wealth creation.

Given the model's broad parameter space, a principal component analysis (PCA) is a valuable process to investigate the influences of the model's behavior. PCA extracts information from multidimensional data by compressing the data into a reduced number of new variables called principal components. The benefit of PCA is that allows multivariate data sets to be summarized and visualized through these new components. Understanding the composition of the most critical components allows insights into the dynamics of the data to be derived, in this instance what variables are most influential in affecting the price of the risky asset – and ultimately the wealth of the investors.

The PCA provides several insights into how to succeed as an investor. Figure 34 identifies variables that made the largest overall contribution to the first two components and separately to the first and two components. An analysis of the critical factors of the first component (see Figure 34a), suggests it relates to the dynamics of the network. Within this component, the rewire setting makes the highest contribution to explaining the variation. From the previously examined results, this was an expected result, because allowing agents to rewire, or not, affects pricing dynamics of the risky asset. This dynamic was seen in Figure 19, where decreasing the rewiring interval increased the activity of the system, ceteris paribus. Logically, as the rewire setting increases, the minimums for the number of advisers and followers also increase. This outcome is because investors have less opportunity to reconfigure their network, a finding confirmed by the negative correlation the switch variable has with the rewiring setting. The other variables from component 1 relate to characteristics of how the network evolved.

The second component (see Figure 34) relates to the investment decision-making process of the investors, especially their decision threshold (the *switch_threshold* variable) and the structure of the population; thereby confirming the previously inferred importance of the investment horizon of investors and the composition of the population. The justification for this statement is the substantial contribution that the switch threshold variable makes to the behavior of the system, and the fact it is positively or negatively correlated with the percentage of long or short-term investors in the population. Trading volumes, which make a significant contribution to the second component, are negatively related to the switching threshold, meaning that as this threshold increases, trading declines, as seen in Figure 24.

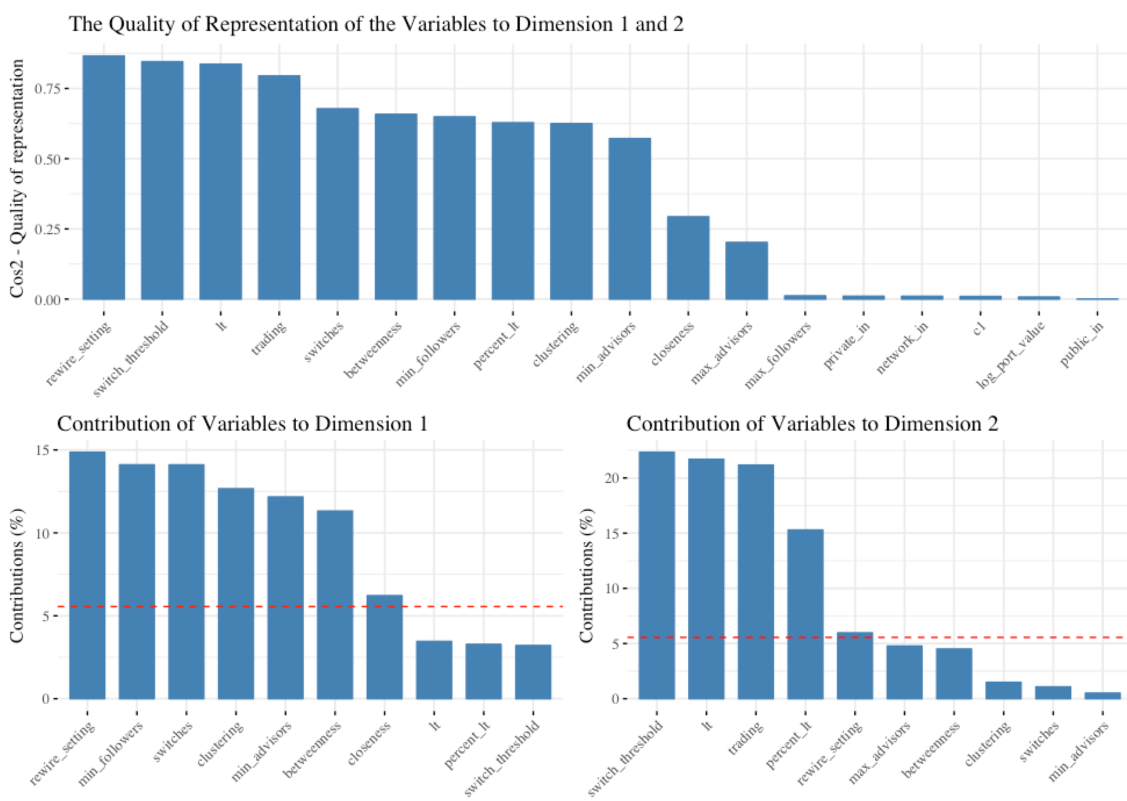

Figure 34: A summary of the PCA results. The PCA was used to assess the determininants of wealth creation.

2.5.4 Section Summary

Through an extensive set of figures and accompanying analysis, a clear narrative appeared regarding how the market ecosystem operates and evolves. From this analysis, it became apparent that the composition, and predispositions of the population have significant ramifications for investor performance. However, more important, the price of the risky asset, or at least its return characteristics, became highly predictable, and in some circumstances differed significantly from a random walk. The process responsible for the predictability was whether, and to what extent, the positive feedback loop accountable for investors following a common investment strategy developed.

Concerning the effect of specific variables, the setting of the network influence variable (c1) remained a vital component. Only by setting the value of this variable to more than 1 does the system begin to exhibit non-random behavior. The extent of this non-random behavior was, in turn, affected by the composition of the population and the ability of the investors to choose their advisers. When there was a higher prevalence of short-term investors the extreme price movements occurred earlier, as investors took less time to converge onto a common strategy. The process of allowing investors to choose their advisers instigated a predictable pricing pattern in otherwise comparable scenarios where the pricing pattern remained random. The underlying mechanism behind this phenomenon was the evolution of the investor network from a lattice network to one with a far broader degree distribution, which resulted from investors searching for Oracles.

The analysis provided a roadmap for how an investor may outperform peers. The most telling point was that the relevant roadmap was dependent on the environment in which the investor operated. The presence of short-term investors generally means that long-term investors need to be nimbler in their investment decisions. This requirement is amplified when the population tends to favor the investment information coming from their neighbors and adjust their advice network more regularly. When not faced with dealing with short-term investors, long-term investors can prosper. However, they still need to move ahead of the market.

2.6 Discussion and Conclusion

2.6.1 Introduction

Section 2.5.4 provided a concise summary of the findings. These findings highlight the flexibilities that ABMs provide in implementing bespoke models to investigate research questions and collect data ranging from the micro level up to the macro level and that is used to unravel the dynamics instigating the behavior of the model. The identified dynamics can then be utilized to inform responses by financial market stakeholders. Section 2.6.2 discusses in more specific details the implications of Section 2.5.4, with Section 2.6.3 outlining possible avenues for future extensions. Finally, Section 2.6.4 provides concluding remarks.

2.6.2 Implications Steeming From the Model

The overarching aim of this chapter was to utilize several well-founded qualitative and quantitative features of real-world financial markets to inform an ABM to understand why stock markets can display non-random behavior. The differences in where investor sourced information and their investment horizon adequately explained these non-random movements. Therefore, it is essential that investors are aware of the environment in which they operate and how it may change. The first point of concern is the information sources investors utilize. While the number of investors was fixed in this model, in reality new investors are likely to enter the market and these investors if they have a higher inclination for following the actions of other investors, it means the behavior of the market can shift dramatically. This point echoes Keynes (1936), who, long before the argument of whether markets followed the EMF, suggested markets were more efficient when controlled by "professional" investors who assessed stocks purely on fundamental grounds and avoided his so-called "beauty pageant" approach.

While Section 2.3.3 discussed the detrimental effects of short-term trading, the benefit of the model was its ability to pinpoint the dynamics by which a short-term focus can be destructive. Short-termism reaps its greatest rewards by exploiting the lumbering long-term investors who take longer to adjust to the changing conditions of the market. This issue is further pronounced if the market experiences a phase transition. However, this trait only appears when investors tend to disregard their other information sources, leading to the excess price movement. More specifically, when markets do not experience excessive price movements, short-term investors do trade excessively in the futile attempt to find non-existent profits. Alternatively, in an environment where excessive price movements appear, it seems to be optimal to employ a short-term approach. This outcome parallels the finding of LeBaron (2013), who reported that in volatile markets investors were better served by placing more weight on short-term parameters.

By introducing a dynamic investor network, several new implications became apparent, but these implications are dependent on the ability of investors to search the entire population and successfully identify the leading investors. Given the availability of past performance data, usually at monthly time steps, this assumption is valid; however, trading and investment performance data on shorter intervals are more difficult to obtain.

Regardless, under conditions identified as benign, the introduction of the dynamic process created disproportionate price movements. Critically, rewiring at more regular intervals accelerated the more extreme price movements. Therefore, a negative externality arises, in that it may be optimal for any one investor to rewire their investment network. However, when the entire population does so, it leads to a homogeneous approach appearing, with predictable excessive price movements resulting.

The ability of the investor network to remain relevant fluctuates with the characteristics of the investors. At one extreme, where there is a more significant presence of short-term investors who rewire regularly and have a higher inclination for initially following their neighbors, the network is impaired as investors react to the upheaval of a highly volatile market. Alternatively, in a more stable environment, the investor network remains integral with investors finding and maintaining connections with the Oracles, an outcome that leads to larger price movements. The rise of passive investing in the real world is a comparable phenomenon to these implications; that is, in the aftermath of the GFC, investors lost faith in active management and were prepared to sacrifice upside gains for the benefit of lower risk and matching the market.

The final insight relates to how investors can best navigate the environment to maximize wealth. They must understand the context that they are facing. If there is a higher prevalence of short-term investors, then it becomes optimal to act like the masses. Also, if investors prefer the advice of their cohort, then it may be best to find the leading investors and ride on their coat-tails. However, there is an essential caveat to this advice: the sharper the market rises, the more severe the fall, and to succeed an investor will need to know when to switch ahead of the greater population. This conclusion returns the issue to one of timing the match, an activity that has proven frivolousness over the years. This point is best made by Keynes (1936) who stated that “the market can stay irrational longer than you can stay solvent.”

Therefore, investors appear to have two clear options: determine how to remain just ahead of the market at times, or take the contrarian position and be patient. Another alternative, inline with the second option, and one that is proposed by the likes of Warren Buffett, is to find a sustainable investment strategy and stick to it. In certain conditions, this may be just to follow the market. This finding correlates with Lo’s (2017) Adaptive Market Hypothesis, which suggests that sub-groups of investors can survive and prosper in the market and, more important, can influence the market, even though their strategy is not optimal over the long-term.

2.6.3 Further Extensions

The most pressing shortfall for this model, which is common for most agent-based artificial stock markets is that new funds do not enter the market; that is, investors are reallocating their initial, and accumulated, wealth across the simulation, rather than investing new funds. Indeed, in the implemented model, a relaxation of this condition could cause an infinite asset boom. For ABMs is general to achieve greater acceptance, this issue remains a high priority. To extend the current framework, the decision-making process of the investors should be enhanced. Especially, given the predictability of the market, investors would most likely develop alternative decision-making strategies faced with certain circumstances. Given the predictable nature of the market, they could learn to recognize the conditions that feed the positive feedback loop and adjust their investment approach.

While not an extension of the model, efforts to calibrate and validate the model against real-world data should be pursued. The impediment to this pursuit is identifying real-world investor networks. There has been promising work in the area (see for example Ozsoylev et al. (2014) and Musciotto et al. (2018)), but the challenge is how to capture sufficiently detailed data in a time-sensitive manner. This challenge includes gathering accurate data on how investors make their investment decisions.

2.6.4 Final Word

The flexibility and utility of ABM were extensively used to gain insight into how the interaction of investors can influence the behavior of financial markets. the environment in which the investors operate has a material effect on the actions of the population, and therefore the market and individual investors. Integral to establishing the central insights was the utilization of a network, and an understanding of its behavior. Thus, the combination of ABM and network science has much to offer in establishing a more in-depth explanation for the conduct of financial markets. This chapter has contributed to this understanding and has provided adequate insight into the direction of future research.

3 QUANTIFYING THE CONCERNS OF DIMON AND BUFFET WITH DATA AND COMPUTATION

3.1 Introduction

"In our experience, quarterly earnings guidance often leads to an unhealthy focus on short-term profits at the expense of long-term strategy, growth and sustainability."

(Dimon & Buffett, 2018)

The above statement by investment market heavyweights Jamie Dimon (Chairman and Chief Executive Officer (CEO) of J.P. Morgan) and Warren Buffett (Chairman and CEO of Berkshire Hathaway) implies that there are serious concerns relating to the operational efficiency of the secondary equity market in the USA. The issues relate to the participants in the secondary equity market (both management and investors) allocating a disproportionate weight to short-term factors over long-term factors; that is, they are exhibiting short-termism (see Section 1.2.5.4 for a detailed discussion). The primary concern with short-termism is that economic growth may suffer because resource allocation is not efficient. Additionally, short-termism may also be responsible for excess volatility in the financial markets because of unnecessary trading.

The delayed recognition of short-termism is possibly due to the generally accepted proposition of the efficient market framework (EMF), which is that there is no place for short-termism. The premise of the EMF is that a representative rational agent can access all necessary information about companies, correctly evaluate the long-term prospects of these companies, and make the optimal long-term investment decisions. The theory implies investors only consider those strategies that affect the long-term growth prospects of the firm. Implicit within this process is the punishment of firms who pursue short-term growth at the expense of long-term growth. In turn, the theory assumes that management is aware of their investor's mindset and decision-making process. This in turn is meant to ensure the efficient allocation of resources by management; that is, firms will abandon short-term earnings accretive activities in preference for long-term growth actions. However, per Dimon & Buffett (2018), it is becoming apparent that short-termism is disrupting this process. This issue in turn raises the question of how it is affecting the growth and size of firms – a problem that forms the basis of this chapter.

Alternate approaches to the EMF have appeared, and continue to develop, that can provide meaningful insight into effects and causes of short-termism. The theories that have attempted to explain short-termism have are divided between those that focus on the cognitive failings of humans to correctly evaluate complex problems over the longer term or positive feedback mechanisms. Laverty (1996) discusses the issues surrounding the debate regarding short-termism, including outlining the various cognitive failings. The role of a positive feedback loop was discussed extensively in Section 1.3.2.2.

Considering financial markets as a complex adaptive system (CAS) with a specific recognition that feedback mechanisms exist within a financial market ecosystem has been, and continues to be, a fruitful research field (as discussed in Section 1.3.2). The relevance of the feedback mechanisms is that they become more relevant when actors exhibit short-term behavior, as it tends to amplify positive feedback loops, thus creating unstable outcomes (De Long, Shleifer, Summers, & Waldmann, 1989). Concerning the positive feedback loop between investors and firms, it remains ambiguous whether the critical driver in the relationship is management reacting to share price movements or investors responding to the short-term earnings outlook of a company. This theme opens an even broader question, one this chapter addresses: is the excessive volatility observed in financial markets a direct consequence of the positive feedback loop of management trying to meet the short-term earnings expectations of their investors?

The genesis of the questionable behavior of management is the separation of ownership and decision-making for all but a few publicly listed companies. This inefficient behavior is likely to be influenced by a positive feedback loop between the parties (Bond, Edmans, & Goldstein, 2011). The separation of ownership creates a significant conflict of interest for both parties as they are likely to maximize the outcome for themselves ahead of the other party. As discussed in Section 1.2.4.7, Adam Smith's – *An Inquiry into the Nature and Causes of the Wealth of Nations* ([1776] 1976) identified the issue of management not acting in the best interest of shareholders at the onset of growth in limited liability companies (LLCs), with Jenson & Meckling (1976) eventually proposing a response to the issue through their theory on agency costs. Additionally, shareholders are not blameless, as a subset of investors trade in search of short-term profits – conduct inconsistent with the EMF – is responsible for sending unreliable signals to management. This practice highlights how a positive feedback loop between management and investor behavior can magnify inefficient behavior.

A central consideration for any theory/model that proposes to explain the growth and size of firms is the need to rationalize the presence of a set of empirical facts. These facts – as discussed in Section 1.2.5.2, and discussed further in Section 3.2.1.1 – are that the distribution of firm size matches a Zipf distribution (Axtell, 2001), while their growth matches a Laplace distribution (Stanley et al., 1996). With such definitive empirical facts, it follows that if the stock market is priced efficiently – that is, the price is right – then the distribution of various valuation metrics will be stable and consistent. Section 3.4 explores this hypothesis.

The approach employed in this paper will be to investigate, through an agent-based model (ABM), how management alter their strategy in response to the price signals from an artificial stock market. A vital component of the artificial stock market is that it is populated with a mixture of long- and short-term investors who either trade on fundamental information, or noise. The basis for assessing these components comes from the previously discussed (see Sections 1.2.5.4 and 1.4.5) negative effects of short-term investors and noise traders. In summary, per the research stemming from De Long et al. (1990), the presence of short-term investors can be destabilizing for financial markets, and results in outcomes contrary to the EMF. The implemented model makes a significant contribution in that it broadens the scope of assessing financial markets as an ecosystem to include firms and investors and not just investors, per the original definition of Farmer (2002). See Section 1.4.2 for a discussion of the current definition of the financial market ecosystem. The relevance of the implemented approach is to assess how inefficient management decisions may result from management misinterpreting the price signals from the market, caused by the short-term investors, or by placing too much consideration on the behavior of the market at the expense of their judgment.

The remainder of this chapter is organized in the following manner: Section 3.2.1 develops the background and motivation for this chapter; Section 3.3 provides a literature review that expands upon the relevant concepts of Chapter 1; Section 3.4 explores the empirical facts relating to the distribution of firm valuation metrics; Section 3.5 provides details of the implemented model; Section Section 3.6 presents the results; and finally, Section 3.7 provides a summary, concluding comments, and identifies area of further work.

3.2 Chapter Foundations

3.2.1 Background and Motivation

The detrimental effects of short-termism and excessive volatility in financial markets exist outside the realm of the EMF. And, as discussed in Section 1.2.5, the behavior of financial markets is somewhat inconsistent with the EMF. The growing prevalence of short-termism as a valid concern (as detailed in Section 1.2.5.4) and ongoing bouts of excessive volatility justify the search for alternative approaches. As outlined in Sections 1.3 and Chapter 2, considering financial markets as a CAS allows one to address numerous anomalies regarding the behavior of the markets and the agents within it. The focus of this chapter is how the conduct of firms and investors evolves in a market ecosystem, thereby generating a vibrant, dynamic insight into the behavior of financial markets. Regarding the process of management decision-making, the consideration of a positive feedback loop between their strategies and the direction of their firm's share price is a fertile ground of investigation. The importance of understanding the positive feedback mechanism is that, left unchecked, it will strengthen, and amplify sub-optimal decisions of investors and management alike.

The issue of a company's share price influencing its management is a moot point within EMF. The basis of the argument is that the manipulative behavior of management will not systematically fool the market; thus, a company's share price will solely reflect the long-term prospects of the firm (Stein, 1989). Jensen (1986b) articulates the importance of this point by stating that the market, with its investors acting rationally, serves as a disciplinary device, thus ensuring that management decisions are solely in the best long-term interest of shareholders. Further, Jensen (1986b) states that short-term managerial behavior arises when management has too little regard for their share price. However, in the aftermath of the dot.com bubble and the Enron scandal, Jensen (2005) conceded that high valuations could lead to destructive behavior by management.

A critical point in Jensen's (2005) concession is that if a firm is overvalued – that is, the firm's stock price is higher than its fundamental value – then is it only through chance that management will continue to meet the expectations of the markets. The rationale for Jensen's (2005) argument is that management mistakenly attributes a streak of good performance to their skills rather than recognizing the role that chance played in the process and so they continue their current practice. The realization of an adverse streak of performance, which again results by chance, will therefore quickly reverse the share price of a company, with management left questioning what changed. The issue of misplaced attribution is utilized by Aghion and Stein (2008) to inform a model, and as such informs the model implemented in this chapter. Further, in the event investors conclude in a synchronized fashion that a company's superior performance has been the result of luck, then the company's share price may potentially collapse. Additionally, if a sector or the market is in a similar situation, then a systematic collapse is a possibility. Section 3.2.1.1 revisits the importance of a stochastic process in the performance of a firm, with it being an essential consideration in some theories of firm growth.

The final relevant part of Jensen's (2005) concession relates to what occurs if management assesses their firm as being overvalued. In this instance, management may take advantage of the situation by engaging in behavior aimed at boosting short-term earnings for the purpose of prolonging the period of overvaluation, so as to gain financially or to boost their reputation as a superior manager. This behavior – which includes using the overvalued script to pursue merger and acquisitions, buying back shares or raising equity for speculative expansions – has proven to be value destructive in the long-run (see Section 3.3.3). When these short-term activities have eventually proven fruitless, shareholders are left holding diluted equity in a firm with inferior growth prospects; that is, investors, if they have not recognized the flawed strategies of the firm in question, are left owning one of the least attractive investment possibilities.

Bond et al. (2011) highlight that one consistent theme in the EMF and the broader research into the behavior of financial markets has been to consider the actions of the firms as exogenous. Aghion & Stein (2008) object to this assumption, instead suggesting that it is the strategies of the firms that drive the valuation model, and therefore the market. In this context, the valuation model refers to the factors (metrics) that investors consider essential in valuing a company. Aghion & Stein (2008) provide the example of how investors interpret the strategic direction and results of Amazon through the lens of a growth company, and therefore are more tolerant of lower margins, but are not willing to tolerate low revenue growth. This scenario results in firms with high sales growth trading on higher price-earnings (PE) ratios relative to the market. Nonetheless, this scenario is highly conditional on those firms consistently meeting the revenue growth expectations of the market. Failure to do so will usually see the stock price and PE ratio of the offending firm fall dramatically. The tolerance of the market will be influenced by the investment horizon of investors, with short-term investors being less tolerant of any failure to meet expectations. Firms signaling a focus on margin growth face a similar situation of needing to meet the market's predisposed expectations. This insight is utilized to inform the model described in Section 3.5.

An additional shortfall of considering the market valuation model as exogenous is to ignore the possible feedback mechanisms (Section 1.3.2.2 provides a general overview of the role of feedback) between the decision-making process of a firm's management, its effect on the earnings profile of a company, and the market's valuation of the firm. George Soros's (2003) concept of reflexivity captures this feedback mechanism by implying that financial markets potentially affect the fundamentals (for example, earnings and investment decisions) the markets are meant to reflect solely.

If one is to accept that a feedback loop exists between investors and company management, one must also question the behavior of the investors. The EMF assumes that investors, or at least the representative agent, employ a fully rational decision-making framework (Kirman, 1992). The ramification of this assumption is that the price of any financial asset will match its intrinsic value; that is, the "price is right" (Shiller, 1980). However, what are the consequences of investors not acting in such a manner? As discussed in Section 1.4.5, it is now a well-established fact that "noise" traders cannot only survive but can prosper in the market. Therefore, if these traders or Shiller's et al. (1984) dumb money traders, see Section 1.4.3) gain the ascendency in the market, how should management react, and how do they differentiate the behavior of rational and irrational investors? Likewise, management should be aware whether a certain investment strategy (for example, growth or value) is "in vogue" amongst investors and therefore influencing the direction of the market at any given time.

In summary, the overarching message from the likes of Dimon and Buffett (2018) is that firms should not attempt to meet the expectations of the market. The wider population will feel the ramifications of firms falling into this trap through inferior economic growth. Despite this advice, it is essential to understand the mechanism by which erroneous prices signals can disrupt the allocation of resources and the sensitivity of management to these signals.

3.2.1.1 The Role of Stylized Facts

Since Kaldor (1961) introduced the concept of stylized facts (as discussed in Section 1.2.5.1.1), they have become invaluable in enhancing the acceptance of simulations to address vital research issues. Regarding these facts and this chapter, Section 1.2.5.2 highlighted the unique characteristics of the stylized facts relating to the distributions concerning the size of firms and their growth. These characteristics should ultimately affect the investment decisions of investors and growth strategies of firms. However, there is little evidence suggesting that these facts have been explicitly considered, or even recognized, in financial theory. The first point that should be considered is that if the distribution of firm size matches a Zipf-law, then the market (investors and analysts) should ensure that their growth projections do not result in a violation of this distribution; that is, investors must not predict too many large firms or not enough small firms. Next, the growth projections of the individual firms in the market must fit a Laplace distribution over the short-term, before becoming more Gaussian over the longer term. Additionally, the size of the firm will affect the viable range of growth for firms – per Stanley et al. (1996) – with larger firms having a smaller dispersion in the distribution growth rates. Furthermore, the age of a firm has been found to affect its growth (Coad, Segarra, & Teruel, 2013). Finally, the theories relating to the growth of firms must contain a significant stochastic component – something investors must consider. This final point is consistent with the thoughts of Jensen (2005), who suggested investors must be aware of, and not fooled by, randomness.

The question remains open that if investors consider the previous points, and stock prices are efficient, what would this mean for the return distribution of firms? Miyano & Kaizoji (2017), highlight that the distribution of share price and various valuation metrics match a Zipf distribution, and provide a simple stochastic model that can replicate these findings. However, the model offers no insight as to why markets tolerate such an extreme distribution of investment fundamentals. Additionally, it is questionable whether the share price of a firm provides a meaningful insight because it is dependent, among other things, on the number of shares on offer. The market capitalization is a superior indicator as it combines the share price and the number of shares on offer to give the market's deemed value (size) of the company. Further, the distribution of share price movements has also been found to exhibit power-law characteristics (see Section 1.2.5.1.1). Additionally, there is also the common behavior of their distributions being skewed over the short-term yet normally distributed over the long-term. These findings raise the question as to whether the dynamics driving firm growth and size are somehow connected to the stock markets returns. Section 3.4 addresses these issues and reports on the analysis of various financial metrics for global publicly listed firms.

3.2.2 Overview of Approach

To address the issues raised in Section 3.2.1, an analytical framework that allows for temporal evolution, the existence of feedback loops, learning and adaptation, and heterogeneity preferences is required. Considering the market ecosystem as a CAS, modeled by utilizing an ABM, is a viable solution. Section 1.3 provides a general justification for this proposition. The expectations for the specific model implemented to address the research questions is that it will provide meaningful insights into how, and under what conditions, "noisy" price signals can influence the allocation of resources by management, and how this may affect the growth and size distribution of firms.

While ABMs have been extensively used to create artificial stock markets to comprehend the behavior of financial markets (as discussed in Section 1.3.4.3) the approach implemented in this chapter is novel. As explained in Dieci & Xue-Zhing (2018) the traditional agent-based artificial stock markets have seen many agents decide how to allocate their wealth between cash (a proxy for a risk-free asset) and a risky asset. This process results in the price of the risky asset being endogenously determined, with the stylized facts of the financial markets evident in the results. The earnings and or dividend stream of the risky asset, which the agents utilize to varying degrees in their decision-making process, is exogenously determined through a stochastic process. However, with the flexibility afforded through ABMs, an alternate approach is employed in this chapter, where there are multiple companies traded, with their earnings stream determined endogenously.

The ABM implemented in this chapter (see Section 3.5) will utilize an artificial stock market that has the management of firms contemplating – to varying degrees – price signals from the stock market when deciding how to allocate their resources between sales growth and margin improvement. In turn, investors react to a firm's performance based on the firm's growth objective; that is, whether they are intent to grow sales or improve margins. This approach therefore overcomes the objections of Aghion & Stein (2008) by internalizing the market valuation model as investors are aware of the general strategy of the firm and assess a firm's results accordingly. Regarding the ability (skillset) of firms, this is heterogeneous across the population, with a stochastic element also affecting a firm's ability to generate growth. To assess the effects of short-termism, investors and firms utilize varying lengths of past performance in their decision-making process. The rationale is to evaluate where a short-term view creates more or less volatility in the market and the growth of firms.

Evidence supporting the applicability of an ABM to this research topic comes from Delli Gatti et al. (2005) and Vitali et al. (2013). These models considered the interaction between debtholders (as opposed to shareholders), firms, and the decisions made by the firms' management. Both models produced several stylized facts relating to firm size, growth, and age, as discussed in Section 1.2.5.2, which the implemented ABM must reproduce if it is to be considered a success. Also, these models created cyclical movements in real economic variables endogenously, thus demonstrating the links between financial markets and the real economy.

3.2.3 Research Questions

This chapter justifies and reports on the implementation of an ABM that delivers insights into the effects of a feedback mechanism between management and the stock market, with a focus on how this mechanism affects the growth profile of firms. With the existence of learning and incentive channels between a firm's management and investors, which operate via the stock market, the model will assess how management allocates their effort towards meeting their growth expectations. Also, the model will assess how management's perceived view of investors' expectations regarding their firm affects this resource allocation and future growth objectives.

The essence of the model presented in this chapter is to combine the framework of Delli Gatti et al. (2005) with an "agentized" version of an existing analytical model. Agentizing is defined by Guerrero and Axtell (2011) as the process of rendering neoclassical economic models into computational ones, a process which sees the contrived assumptions of neoclassical become more realistic. In summary, the benefit of agentizing a model is that it allows for greater heterogeneity amongst agents, and provides for greater flexibility in uncovering the dynamics producing the outcome, including various temporal aspects. Axtell (2007) provides an extensive treatment of the benefits agentizing neoclassical models. The analytical model in question, as detailed in Section 3.3.5, is that of Aghion & Stein (2008). The basis of the model is that management must decide between pursuing either a sales growth strategy or profitability strategy. The relevance is that management can grow profits (revenue – costs) through either growing sales at a higher rate than expenses, or by increasing margins (reducing costs). While there is no prior expectation as to which strategy is more attainable, market conditions and a firm's resources will have some bearing on what is achievable.

A vital factor in constructing the model is how a firm assesses their performance against internal expectations and in respect to the market's reaction to their results. The relevant point from Aghion & Stein (2008) is that by trying to meet the expectations of the market, greater volatility in real variables, including sales and output, were found. Despite this finding, the paper does not attempt to assess the likely effect on the share price of the firm, something explored through this chapter. Section 3.3.4 discusses the issue of firms trying to meet the expectations of the market, a topic linked to the concern of Dimon and Buffett (2018), that firms are predisposed to matching the desire of the market at the expense of future growth.

The model presented in this chapter reverses the traditional artificial stock market approach, with many firms having their stock traded by multiple agents: a representative rational growth investor; a rational value investor; a noise trader (as discussed in Section 1.4.5) who follows price trends; and a noise trader who follows earnings trends. These investors have the capability of taking a myopic or long-term view. While the use of four representative agents may be surprising, it is an overly complicated process to have many agents trading many securities and is something that the current ABM literature does not explore. Regardless, the focus of the research is to understand the behavior of the firms and how the shifting weight of money between the rational and irrational investors affects the dynamics of the environment. Moreover, the specific issue to be addressed in this chapter is: how will the behavior of traders manifest itself with the actions of management and will it lead to higher volatility in asset prices?

3.2.4 Section Summary

This section provided a general introduction, which covered the motivation for the research (Section 3.2.1), the chosen approach (Section 3.2.2), and the research question (Section 3.2.3). The motivation for the research is that a positive feedback mechanism influences the relationship between firm owners (investors) and management, and greater details regarding its operation are required. Details discussed include the time horizon of investors and management, and the factors affecting the consideration the parties give to the stock market. Further, Section 3.2.1.1 summarized the various stylized facts regarding firm size and growth – facts which are yet to be fully explored. Next, Section 3.2.3

summarizes the research question addressed in this paper, which is to assess the dynamics of the feedback cycle and what are the most significant influences on the loop.

Section 3.3 has distinct parts summarizing the literature relating to the research, with Section 3.3.1 introducing the various concerns this chapter considered. Subsequently, Section 3.3.2 provides greater detail regarding the stylized facts of firm size and growth and summarizes some of the past and present theories relating to the stylized facts of firm growth. Next, Section 3.3.3 discusses the issue of agency further, with Section 3.3.4 detailing how the matter of agency creates the positive feedback loop between investors and management. Following this is Section 3.3.5 which provides a summary of the literature relating to short-termism. Finally, Section 3.3.6 explains why an ABM approach is required.

3.3 Literature Review

3.3.1 Background and Introduction

Secondary equity markets (stock markets) are the markets where investors trade previously issued stocks in the hope of generating a sufficient return on their investments. In attempting to identify attractive investment opportunities, some investors – fundamental investors – will consider, and attempt, to forecast the future growth prospects of the firms in the market. The time horizon of the investors affects this forecasting process in several ways, including: how much past performance they have considered; their forecasting horizon; their tolerance for any underachievement of a forecast; or the extrapolation of positive results.

The determinants of growth of firms and the connection to share price movements of those firms remains an elusive topic. More precisely, Malkiel (1999) suggests that since Little (1962) proclaimed that it was useless to estimate future earnings from various past financial metrics, and those metrics should not influence the share price, the professional realm is no closer to understanding the growth profile of firms. Despite this, as discussed in Section 3.3.2, progress regarding the understanding of the growth dynamics of firms has been made.

Interwoven into the need to understand how firms grow is the need to assess how human decision-making affects the process. While economics (and finance) were slow to address the issue of management decision-making (discussed in Section 1.2.2), it has since developed a response and now recognizes the conflicts that exist between the owners of a firm and the management of that firm, as captured in literature related to Jenson's & Meckling's (1976) agency costs. Section 3.3.3 discusses in greater details the issue of agency and how it relates to the operation of a firm. The conflict of interests between management and investors raises the questions as to what information management and investors should utilize to assess the performance of the firm, and how either party reflects their satisfaction in the performance of the firm. A firm's share price is one information source that provides an answer to this question. Therefore, it has become essential to understand the potential effects either party has on the direction of a firm's share price. Section 3.3.4 discusses the possibility of how a feedback loop between management and their firm's share price may present itself. Section 3.3.5 discusses the literature relating to how the time-horizon of investors and management may affect this feedback loop, with a focus on the implications of short-termism on behalf of each party.

3.3.2 The Size of Firms and How They Grow

Sections 1.2.5.2 and 3.2.1.1 highlighted the critical stylized facts regarding the size and growth of firms. However, these facts took some time to be discovered, and a precise explanation remains an open question. The original expectation was that both the firm size and growth of firms would match a log-normal distribution (see Gibrat (1931) and Hart & Prais (1956)). Gibrat's (1931) law of proportionate effect – which was one of the earliest explanations of the skewed distribution of firm size – assumed that a firm's growth was the result of a random process and growth rates were independent of firm size (Axtell, 2001). The justification for this law, according to Simon and Bonini (1958), was that: 1) it did agree with empirical findings of the time; and 2) if firms do operate under constant returns to scale it was not unreasonable to expect that a firm's growth, regardless of size, had an equal probability of increasing or decreasing in percentage terms – that is, their growth would be proportional to their current size.

Conversely, as explained in Section 1.2.5.2, with the availability of improved data, Gibrat's law ultimately proved inadequate. This issue forced researchers to pursue alternative explanations, with Simon (1955b) providing the first adequate explanation for the presence of the Zipf-law firm size distribution. From Simon's (1955b) original work have come numerous works that utilize ABMs and complex systems to explain the existence of the stylized facts. The rationale for the utilization of an ABM is that it allows for the interaction of the firms in an evolving environment. The common element of the new approaches was to dismiss the assumption that the stochastic process involved in determining the growth of a firm was independent of firm size (Metzig & Gordon, 2014).

The implication of firm growth matching a Laplace distribution means that investors need to be mindful that their growth expectations must meet this form, and not a Gaussian form; otherwise they will be overestimating growth. Another consideration is that the expected variance of growth rate needs to scale with the size of the company. In general, this means that the growth rates for smaller (larger) firms exhibit a larger (smaller) spread in growth rates.

As discussed in Bottazi & Secchi (2006) and Chang & Harrington Jr (2006) various approaches, including employee effort, organization norms, and technological have been utilized to consider firm growth. The model described in Section 3.5 takes its cues from the model of Delli Gatti et al. (2005), whose appeal comes from its exploration of the link between the power-law distribution of firms' size and the Laplace distribution of firm growth in combination with business cycle fluctuations and the financial fragility. However, the financial fragility only related to the banking system and not the stock market; hence numerous modifications, per Section 3.5, were undertaken.

3.3.3 The Role of Agency

Section 1.2.4.7 introduced the issue of the management and owners of firms not sharing the same incentives. Jensen and Meckling (1976) encapsulate the issue in their agency cost theory. While the theory has far-reaching implications, the focus of this chapter relates to management's concern with the share price of their firm and how a positive feedback loop influences the levels of concern, and the actions of management.

Management's concern with their firm's share price manifests itself in several ways, including: 1) the value of any options issued for past performance; 2) the achievement of current incentives; and 3) reputational enhancement (Jensen & Meckling, 1976). The first two issues arise due to share-based remuneration becoming an increasing portion of management remuneration to align management's incentives with those of shareholders. A partial justification for the approach according to Belghitar & Clark (2015) is that option-based remuneration is well-suited to lower agency costs because "the convex payout profile of stock options can offset the concavity in the manager's utility function."

While increased share-based remuneration is intended to alleviate the lack of alignment in objectives between shareholders and management, other issues have arisen. Mainly, management become preoccupied with their firm's share price. The relevance of this issue is raised in Aghion & Stein (2008) and Stein (1989) when they present models that predict unfavorable behavior coming from management considering the share price of their firm. The model of Aghion & Stein (2008) serves as a vital stimulus for the model implemented in Section 3.5. The primary problem relating to management's heightened concern over their share price is that they will engage in actions aimed at boosting the share price in the short-term, at the expense of long-term growth. As mentioned previously, the EMF does not consider this an issue, because any manipulative behavior of management will not fool the market. However, in a topic discussed in Sections 1.2.5.4 and 3.3.5, short-termism is a growing concern in financial markets.

3.3.4 Positive Feedback Loops in Financial Markets

With the apparent negative issues stemming from the separation of ownership and control of publicly listed companies, the need to better understand the dynamics of this relationship exists. An essential approach, as discussed in Section 3.2.1, is the need to consider the market valuation model as endogenous. Soros's (2009) principle of reflexivity captures the core of the issue. The basis of the theory is that investors (not the EMF's rational investors) form subjective models of how financial markets operate and how to value financial assets. The investors' action, driven by their subjective models, then affect the objective structure of the market. This process, in turn, forces adjustments in the investors' subjective models. The cycle will continue until a significant disruption in the market forces investors (and management) to abandon those models, thereby providing a classic example of the detrimental effects of a positive feedback loop.

In more general terms, Bond et al. (2011) summarize the body of research relating to how the information contained in prices affects the feedback mechanism between financial markets and the real economy. The processes by which the feedback loop affects the economy include: management (decision-makers) gaining new information from market prices and using this in their decision-making process (for example, whether to proceed with an investment); decision-makers caring about their firm's share price due in part to employment contracts, which may impede them from making investments; and decision-makers becoming irrationally anchored to the share price, thus inhibiting their decision-making process. It is these negative consequences that justify the research focused on treating the market valuation model as endogenous; that is, the secondary stock market plays a vital role in facilitating the feedback mechanism between management and investors.

Another issue relating to the price signals from the market and management is whether management interprets the messages correctly. Bond et al. (2011) raise the point that even if stock market prices are efficient as per the definition of the EMF – that is, they reflect the net present value (NPV) of future cash flows – they may not convey the information required for efficient decision-making. An example of this issue is provided by Dow & Gorton (1997), who specify an analytical model where management, after deciding that the price of their stock is random and therefore follows the EMF, ignores the behavior of their share price and do not invest for future growth. In turn, investors (speculators) detect the firm's strategy and do not invest in the stock, thus completing the feedback loop resulting in an inefficient level of investment by the firm.

3.3.5 The Issue of Short-termism

Under the EMF, a correctly priced financial asset will reflect the NPV of all future cash flows, with management expected to implement strategies to maximize this value. However, as discussed in Section 3.3.4, various incentives exist for management to concentrate on lifting the short-term earnings of their firm. Section 1.2.5.4 outlined how this short-termism may lead to hyperactivity in behaviors such as corporate restructures, mergers and acquisitions, and financial re-engineering. These activities in most cases do not generate a sufficient return on the investment associated with them (Jensen, 2005). Therefore, short-termism amplifies the effects of the feedback loop between investors and management, with the detrimental effects of economic growth augmented.

Section 2.3.3 discussed in detail the issue of investors exhibiting short-term tendencies. The direct relevance of this issue for this chapter is that investors will consider varying lengths of historical performance of each company. A long-term investor will form expectations utilizing more information, with the hope that this will lead to less market volatility. This characteristic raises the additional question that if investors are overly tolerant, will this lead to management maintaining inefficient behavior for an extended period because the market is providing insufficient signals? This issue, in turn, may eventually result in substantial correction because management's non-optimal behavior results in a collapse in earnings.

3.3.6 Why Utilize Agent-based Modeling

To achieve the goals of this chapter, the implementation of an ABM is required to allow for heterogeneous interacting agents (HIA), with their behavior based on micro-foundations. ABMs can consider these factors because they do not rely on optimization, thereby not constraining them to equilibrium conditions (Sornette, 2014). Delli Gatti et al. (2005) outline the rationale for this approach over the traditional reductionist approach, which justifies the representative agent by stating that the conventional economic approach relies on linear relationships between variables and no interaction between agents. These assumptions are inadequate in explaining the empirical evidence relating to much of economics and finance because the presence of a power-law-like distribution is indicative of non-linear interactions.

3.3.7 Section Summary

This section justified the modeling solution to the research question relating to the feedback loop between investors and management. Section 3.5 will provide greater detail of the implemented model. Within Section 3.3.2 specified the stylized facts regarding firm size and growth, including a discussion on the past and present theories relating to those facts. Section 3.3.3 discussed the relevance of agency theory to the research question, with Section 3.3.4 justifying the linking between agency theory and the positive feedback loop. Next, Section 3.3.5 discussed how short-termism on behalf of both management and investors could affect the feedback loop. Finally, Section 3.3.6 explains why an ABM approach is required.

3.4 Empirical Facts Related to Firms and Markets

Before proceeding to the details of the implemented ABM, various empirical facts are presented that explore the size and growth distributions of global firms between 2007 and 2017. The unique contribution of this section is that the data includes all the publicly listed companies worldwide, which numbered 56,891, as detailed in Section 3.4.2. The motivation for collecting the data is to inform a set of stylized facts that can inform the model. Section 1.2.5.1.1 discussed the rationale and the benefit of utilizing stylized facts. The collection of all publicly listed companies varies from work to work, for example Axtell (2001) who explored all USA firms, Stanley et al. (1996) used all publicly listed firms in the USA, and Williams et al. (2017), who used a proprietary database with 13,342 global firms. Support for the approach comes from Chaieb, Langlois & Scaillet

(2018), who made use of the Compustat database to investigate the variation in risk premiums across the global financial markets.

3.4.1 Background

Section 3.2.1.1 highlighted the discovery of the two stylized facts relating to the distribution of firm size and growth. The increased availability of detailed data, which has allowed a broadening of geographic analysis, and the desire to identify the determinants of firm growth have ensured that research into understanding the robustness and origins of the stylized facts relating to firms continues. However, a complete global picture is yet to appear; therefore, the challenge exists to see if these relationships hold in their entirety across the globe and, if not, whether specific regions exhibit varying characteristics. This analysis has not been performed to date – at least to the best of the author's knowledge – most likely because of the availability and reliability of the data. Section 3.4.2 discusses the specifics relating to the data, but in summary, given these data issues, the presented analysis is restricted to a high-level exploratory assessment.

Another inspiration for this section is to try and establish whether the stylized facts exhibited by firms and the stock market are in any way connected. Given that both investors and firms co-exist in the same ecosystem the possibility is not fanciful. Indeed, Miyano & Kaizoji (2017) provide evidence that the distribution of certain investment fundamentals exhibits power-law distributions.

3.4.2 The Data

The Compustat - Capital IQ database (2018), retrieved from the Wharton Research Data Services (WRDS) website, was the source of the financial and price data for the companies/securities used in this section. The data collection processed required accessing four separate databases: one for the share prices of the USA and Canadian stocks; another one for their financial data; and, one, for the share prices for the rest of the world (ROW) and another one for their financial data. To assess the most relevant data, firms not classified as common or ordinary stocks were filtered out. Other data filtering steps include removing American Depositary Receipts (ADRs) and subsidiaries, and securities that only appeared in the data once in the 11 years (noting the data was taken from 2007 – 2017). These steps were deemed sufficient for the exploratory nature of the analysis but future studies may require further data cleansing. An example would be ensuring that a security is in at least 5 consecutive periods. Through the data gathering process, data for 56,891 unique firms was collected.

Another major data preparation step was converting all the data into their USA dollar (USD) equivalent, with Compustat the source of the currency conversion rates. Without this step, a common analysis across regions would not have been possible. R (2016) was used to perform the conversions and undertake the exploration reported in this section. While the transformation was not technically challenging, it did highlight data issues relating to erroneous data including the misreporting of the reporting currency and the number of shares on offer. These issues were mainly associated with securities from Zimbabwe and Venezuela, and were removed from the data. The appendix provides a list of all exclusions and modifications to the data.

The next data processing step involved the calculation of various financial metrics. The most significant of these was to calculate the market capitalization of the ROW stocks. Compustat provided this data for the USA and Canadian firms. A firm's market capitalization is obtained by multiplying its end-of-year stock price with the number of shares the firm had on offer, a figure provided in the Compustat data. The other calculated metrics included the price earnings (PE) ratio, price to book (PB) ratio, return on invested capital (ROI), and net income (NI) margins. The growth for a variety of financial metrics, as reported in Sections 3.4.3 was then calculated. The calculation utilized the *delt* function in the *quantmod* (Ryan & Ulrich, 2017) package, with the log difference calculation utilized.

The last data processing step was to divide the stocks into sub-groups based on geography and economic factors, such as market regime and development status. The determination of these user-defined geographic regions utilized the country of incorporation code supplied in the data. The sub-groups are Northern America, Eastern Europe, the Middle East, Southern and Eastern Asia (including Japan and China), Africa, Latin America and the Caribbean, Oceania, and Western Europe. The rationale for forming the sub-groups was to assess whether the various scaling behaviors remained consistent across the globe. While regional location determines a firm’s sub-group, a firm potentially generate sales, and profits, in a variety of regions. For example, a company such as Apple sells its products across the globe and, hoards its cash offshore, yet its results are allocated to the Northern America sub-group.

3.4.3 Findings and Analysis

Given the volume of data collected, a select number of results are presented. The remainder of the results, along with their commentary, can be found in the appendix to this chapter. The three figures (Figure 35 to Figure 37) best represent the intention of the ABM presented in the following section and are the results of most interest. With this analysis focused on publicly listed firms, the obvious metric to assess the size of a company is its market capitalization. Under the EMF, the market capitalization is an accurate representation of the market's expectations regarding the future cash flows of the company. Factors that may affect the distribution of the market capitalization include the functionality of the region's capital markets and the general economic health and stability of the region. In turn, these factors will affect where companies choose to incorporate. For example, the USA is an attractive market to incorporate given the country's stable legal system and strong economic status; alternatively, some African nation will be less attractive for the opposite reasons.

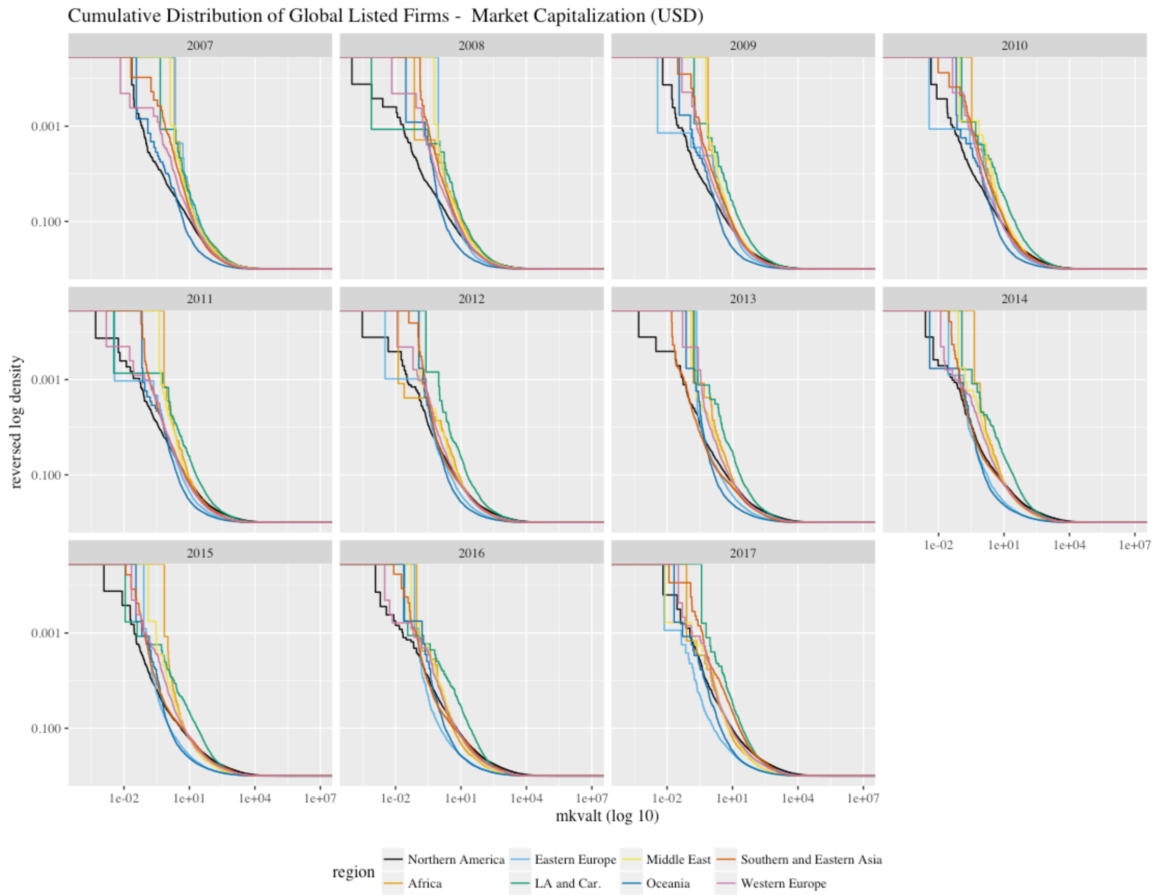

Figure 35: The distribution of market capitalization of firms across regions and time. The distribution is represented by CDF, in log form. A "straight" line is indicative of a power-law distribution. Data source: Compustat - Capital IQ database (2018).

The impression from Figure 35 is that the market capitalization of firms consistently matches a power-law-like distribution across regions. The justification for the statement is that the cumulative density function (CDF), which is also inverted, are linear following a log transformation. The slopes of the fitted functions range between 1.42 and 2.10 (Table 18 in the Appendix), which is close but not entirely consistent with previously reported results. Concerning the variation between regions, the more developed markets – North America and Asia – exhibit flatter slopes, which is indicative of a broader spread in terms of firm size. This result was to be expected as these regions have developed financial markets; therefore, companies are more likely to incorporate in these regions to gain access to capital. The implications for investors of this finding is that they will, not surprisingly, have more opportunities in these markets. A curious result was that Western Europe exhibited the steepest slope, which is indicative of a more limited range of firm size. This result is consistent with the comments of Bancel & Mittoo (2009), who noted that numerous studies have reported that European companies tend to IPO later in the firm's life cycle compared to those in the USA.

The next variable of interest is the ROI of the firms. Financial theory dictates that a firm's ROI should at least match its weighted average cost of capital (WACC). Several crucial factors influence the WACC of a firm, including its risks relative to the market, the risk-free interest relevant to the firm, and the equity risk premium. In straightforward terms, a riskier company in a riskier country will have a higher WACC. Figure 36 provides the distribution of the ROI of the global firms. There were two data issues related to this metric: missing values for the invested capital of the firms – in this instance no effort was made to impute a value; and a firm recording a net loss for the year, in which case the log transformation fails. To address the issue of the log transformation, negative numbers were replaced with the average of the current period (the period of the net loss) and the result from the prior period. If the imputed ROI was negative, it was removed from the sample because the log transformation of the data point fails.

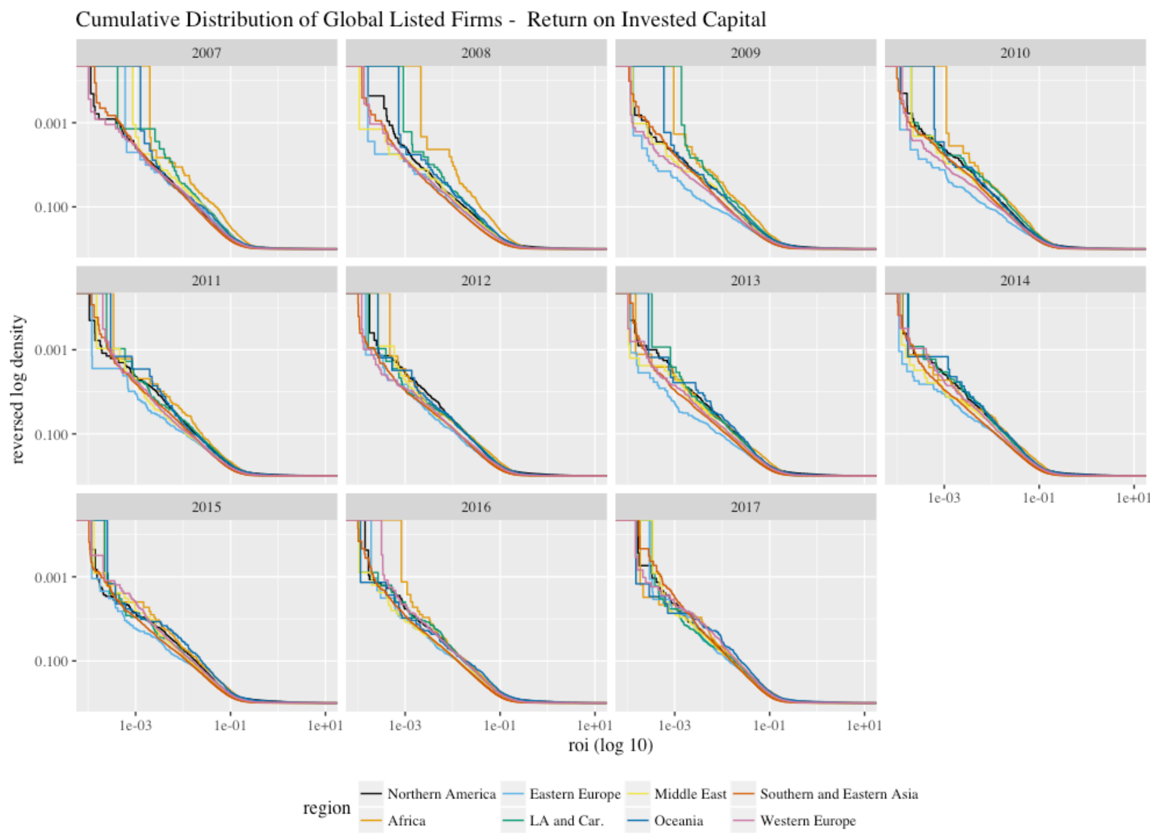

Figure 36: The distribution of the ROI of firms across regions and time. The distribution is represented by CDF, in log form. Data source: Compustat - Capital IQ database (2018).

The results of Figure 36 present, contrary to financial theory, a broad distribution for the ROI of the firms, with 10% of firms reporting a return of less than 1% each year and a small component of firms generating a return over 15% – a very rough benchmark for an acceptable ROI. The observation of most significance is how the ROI was dispersed across regions at the time of the GFC in 2008, before becoming more homogeneous as the world recovered from the economic slowdown. In terms of validating an ABM, the relevance of this result is that the model must also produce a broad distribution of outcomes, which will incite a wide range of responses by investors and management. For future research, the distribution of ROI (and other profitability metrics) should be assessed over 2- or 3-year periods to determine whether returns become more normally distributed. This step would tend to remove any stochastic shock and reveal whether firms tend to generate sufficient returns to meet their WACC.

Figure 37 provides the growth in market capitalization of all globally listed firms across 1, 2, 3, 4, and 5 years. In contrast to the previous plots, which are grouped by region, the graphs are divided based on the percentile of the market capitalization of the firms. Based on the previously detailed characteristics of firm growth and their Laplacian distribution (see Section 1.2.5.2 and Section 3.2.1.1), the shorter time frames should exhibit a tent-like shape, before the distributions become more bell-shaped over extended periods. Also, the lower percentiles should present greater variability. In terms of growth expectations across the market capitalization there is no definitive direction from the financial literature, because as reported by Bogle (1998), the founder of index fund giant, Vanguard, stocks with a smaller capitalization are capable of outperforming (delivering superior growth) larger capitalization stocks, albeit with higher risk.

A result of note from Figure 37 is that the growth in market capitalization over the shorter periods matches the expectations; that is, larger firms exhibit less variability than their smaller counterparts and the median growth is close to 0. A minor observation is that across the shorter time periods the distribution of the lowest percentile stocks is not symmetrically distributed, with a heavier skew toward negative returns. Given the inclusion of all publicly listed global firms, this result is not overly surprising given the risks associated in emerging markets, which tend to have a higher proportion of lower percentile stocks.

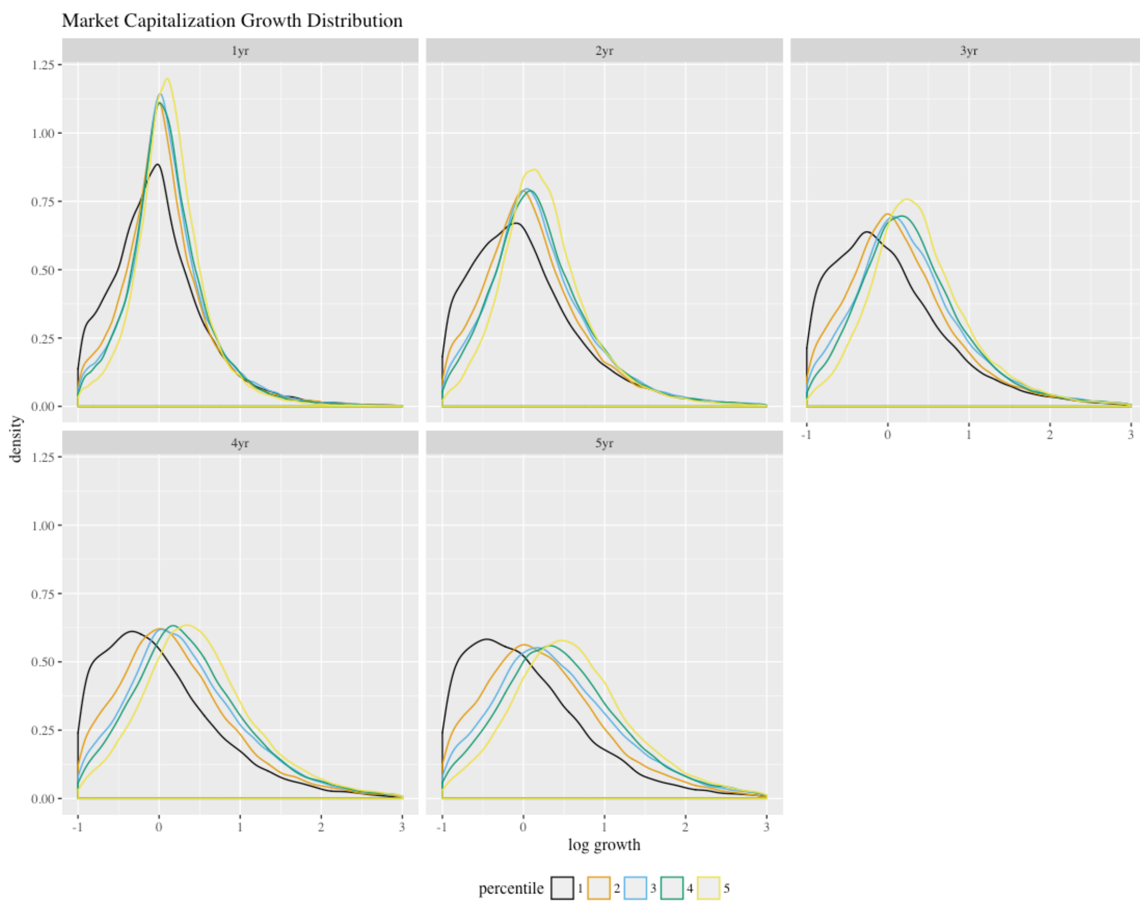

Figure 37: Growth in market capitalization of globally listed firms. Growth distributions are provided for 1,2,3,4, and 5 years of growth. A tent-shaped growth is representative of a Laplacian distribution. Data source: Compustat - Capital IQ database (2018).

The second major observation appears when growth is assessed over a longer period. Here it is seen that the higher percentile stocks, on average, record higher growth. The justification for this comment is that the peaks of the distributions move rightward as the percentile moves higher. Before interpreting this result, a cautionary note is that there are 10,000 firms in the uppermost percentile, which is a much larger sample than previous studies have considered when deciding the benefits or otherwise in investing in small vs. large cap stocks. Despite this, the observation opens a potential avenue of research that would involve the further dissection of the percentiles.

3.4.4 Section Summary

This section provided an exploration of empirical characteristics regarding the distribution of financial metrics of global publicly listed firms. Section 3.4.2 outlined the Compustat - Capital IQ database (2018) and the various modifications made to the data. Next, Section 3.4.3 detailed three relevant metrics and explained their implication for the model presented in Section 3.5. In general, the findings are supportive of the hypothesis that the distribution of firms is not normally distributed; instead it tends toward one matching a power-law, such that the mean or variance of the data is not well-defined.

3.5 Approach and Model Design

3.5.1 Introduction

This section provides the specification of the model implemented to answer the research questions identified in Section 3.2.3, with Section 3.5.2 specifying the background and justification for the model. Next, Section 3.5.3 details the purpose of the various agent classes, while Section 3.5.4 provides the detailed steps of the model. Within these sections characteristics of the model's behavior are also discussed. Finally, Sections 3.5.5 and 3.5.6 relate to the verifications steps and model output.

3.5.2 Model Background

The model implemented in this chapter fuses two frameworks with the intent to produce novel insights into the feedback mechanisms between investors, via an artificial stock market, and the decision-making processes within firms, with those firms traded on the artificial stock market. The first framework comes from the analytical model of Aghion & Stein (2008), while the second is in the vein of the model presented by Delli Gatti et al. (2005). With the model of Aghion & Stein (2008), which is analytical in nature, the challenge existed to “agentize” the model. Once this was achieved, as discussed throughout this section, the model was integrated into a market ecosystem, with the ecosystem’s foundations coming from Delli Gatti et al. (2005). The purpose of the model is for investors and firms to utilize various information metrics, which are all generated endogenously, to inform their decisions.

The essence, in terms of the implemented model, of Aghion & Stein (2008) is that a representative firm’s management possesses a utility function, with their behavior directed towards maximizing its value. The function, as seen in Equation 18, shows that the utility (U), is a function of the profits of the firm in the current period (π_1), and the price of the firm’s stock (P_1) multiplied by the management’s concern for the price (α).

Equation 18: The management utility function from Aghion & Stein (2008)

$$U = \pi_1 + \alpha P_1$$

Equation 19 explains how the firm's profits for the current period (π_1) are the sum of its sales (s_1) and margin (m_1). Aghion & Stein (2008) note that it would have been more realistic to have profits as the product of sales and margins but chose to use the sum on the basis that it allowed for easier manipulations and/or transformations without materially affecting the results.

Equation 19: The firm profit function per the Aghion & Stein (2008) model

$$\pi_1 = s_1 + m_1$$

In tpursuit of their highest possible utility, management apply their pre-determined level of ability to generate output. In doing so they divide their effort between growing sales and realizing higher margins. This distinction is vital, because as explained later, the implemented model divides firms into sub-classes based on their primary intention to grow sales or margins. For the following equations, the firm's ability is given by a, which is a normally distributed variable with a mean of A and variance of v^a (N(A, v^a)). In a step consistent with Holmstrom (1999), neither the market nor the management itself are aware of the firm's exact ability, with both parties left to infer it at each step. Regarding the effort employed by the representative firm, it is endowed with one unit of effort each period, with management allocating it between growing sales and margins as they attempt optimize profits. Equation 20 details how sales are determined in each period. By way of definitions: e is the effort applied by the firm into growing sales; q_1 is the size of the market; and ε^s is a normally distributed random variable – included to capture a sales shock. Note that this is consistent with the need to include a stochastic process in the growth equation of a firm, as mentioned in the theory of how firms grow (see Section 1.2.5.2).

Equation 20: The sales function from the Aghion & Stein (2008) model

$$s_1 = aeq_1 + \varepsilon^s$$

Equation 21 details how margins are determined at each step. The management's ability is applied to the residual effort of the firm $(1 - e)$, with ε^m, a normally distributed random variable, again included to represent a stochastic shock to margins.

Equation 21: The margin function for the Aghion & Stein (2008) model

$$m_1 = a(1 - e) + \varepsilon^m$$

Substituting Equation 20 and Equation 21 into Equation 19 provides Equation 22. In turn, firms are tasked with attempting to maximize the resulting function at each step. A vital component of the Aghion & Stein (2008) framework is that ability and effort are complementary in terms of increasing profits. From Aghion & Stein (2008) there are two vital components stemming from the complementary relationship. The first is that for investors to gauge the ability of a firm they should judge the performance of the firm based on its performance in respect to the variable to which they apply the highest effort. For example, for a firm applying greater effort into sales growth, sales growth should be the primary key performance indicator (KPI) for investors. The second is that if the market (q_1) is larger, growing sales has a higher marginal product, while margins are independent of market size.

Equation 22: The profit maximizing function from Aghion & Stein (2008)

$$\max\{E(\pi_1) = aeq_1 + a(1-e)\}$$

While the model of Aghion & Stein (2008) provided material insights, it was anticipated that further insights can be gained by agentizing the model, a step that involves a population of firms interacting with investors via a market ecosystem. The intention of the interaction is to see how firms and investors evolve, adapt, and behave in a dynamic environment. A key consideration in extending the model was to establish whether the stylized facts of firms' size and growth could be replicated. As mentioned previously, the framework established by Delli Gatti et al. (2005) was able to reproduce these stylized facts. However, the framework relied on a fully rationed equity market with credit markets being the main area of focus. The implemented model will reverse this by effectively closing credit markets, and for that matter not allowing additional capital raisings, thus making firms reliant on profits for additional capital, which is required to grow future profits.

The essence of the Delli Gatti et al. (2005) framework is that the supply side of the economy consists of 1 to N_t firms, with the number of firms (N) being dependent on *t* as there is an endogenous entry and exit process. The functionality of the model has firms determine their output based on the conditions of the economy and their desire to grow profits. Equation 23 specifies how firm *i* produces Y_{it} at time *t*. In turn, firms can sell this output without question. By way of definitions for Equation 23, K_{it} is the capital stock of firm *i* at time *t,* and ϕ is the capital productivity, which is assumed to be constant thru time and uniform across firms.

Equation 23: The Delli Gatti et al. (2005) production function

$$Y_{it} = \phi K_{it}$$

The price that firm *i* achieves at time *t* is given by P_{it}, per Equation 24. The price achieved by each firm is given by a random variable u_{it} which is the result of idiosyncratic shock (u_{it}) that each firm experiences. The shock to each firm is normally distributed with an expected value of 1 and a finite variance; therefore, price does not have a structural effect in the model. However, the process introduces a level of heterogeneity, as firms will not realize a persistent price across periods, nor will all firms receive an identical price within a period.

Equation 24: The price level as per Delli Gatti et al. (2005)

$$P_{it} = u_{it} P_t$$

Equation 25 is the profit (π_{it}) firm *i* generates at time *t*. The revenue for the firm is its output - Y_{it}, multiplied by the effective price the firm received for its products in time *t.* The variable cost for the firm is given by $g * r_{it} * K_{it}$, which is proportional to the firm's financing cost.

Equation 25: The Delli Gatti et al. (2005) profit function

$$\pi_{it} = u_{it}Y_{it} - g * r_{it} * K_{it} = (u_{it}\phi - g * r_{it})K_{it}$$

Within the variable cost term, the *g* variable is a constant which reflects the rate of global efficiency, r_{it} is the real interest rate, and K_{it} if the capital base of the firm. At the completion of each step the firm's profits are added to their capital base, with bankruptcy a possibility if profits erode the capital base of the firm.

To combine Delli Gatti et al. (2005) and Aghion & Stein (2008) several changes were made, as discussed in Section 3.5.4. The most significant change of the implemented model was to replace the debt markets of Delli Gatti et al. (2005) with an artificial stock market in the spirit of Oldham (2017a). The artificial stock market can have up to five participants who have the capability of considering varying amounts of history, with each participant utilizing different investment styles. As mentioned in Section 3.2.3 the implementation of only 5 investors, while novel, is a consequence of computational requirements of having multiple firms and investors. Section 3.5.3.3 provides a full explanation of these styles. In summary, the investors are either fundamental investors, who use the price to earnings (PE) ratio, price to growth (PEG) ratio, or price to book (PB) ratio, or chartists, who utilize the trends in either a firm's earnings or prices to inform their decision. The combination of fundamentalist and chartists has been a common approach in the artificial stock market literature, following its introduction by Lux (1997). This step achieves the objective of producing a market ecosystem where investors and firms interact.

3.5.3 Agent Classes

The implemented model consists of 4 components: the firms, the investors, the product market, and the share market. The agent classes for the model are the firms and investors. This section details the roles and functionality of these classes along with the model's global variables.

3.5.3.1 The Global Variables

Table 8 provides the definition for main global variables. In this instance, global variables refer to the variables the user sets, with the agents assigned identical values. Therefore, these variables do not provide a source of heterogeneity. Also, the model also allows the user to select the number of firms in the ecosystem, the proportion of sales growth firms, and the initial capital levels of the firms. Per Section 3.6.1, the settings for some of these variables remained fixed, while others were varied to test the dynamics of the model and test the various hypotheses related to the research questions. The reader should note that a later iteration of the model was varied such that the user could try and isolate the effects of certain procedures in the model. This results of this process is discussed in Section 3.6.3.

Table 8: Global variable definitions

Symbol	Name	Purpose
For firms		
g	Global Efficiency	The Delli Gatti et al. (2005) framework made use of a global efficiency variable g (see Equation 25). The implemented model utilizes the variable but in a modified fashion. Equation 37 shows that the variable indirectly, through the mr_{it} variable, combines with the interest rate to establish the return on the effort employed by a firm on achieving their margin goal.
ma	Management Ability	Firms possess a fixed level of ability – $ma_{i,}$ which differs from the ϕ variable defined in Equation 23 in that it is not uniform across firms. Instead, firms are initiated with a value taken from a Gaussian distribution, with the mean set by the users through the $ave\_ability$ parameter and a standard deviation of .05. This means the model has an additional level of heterogeneity Equation 33 and Equation 34 illustrate the relevance of a firm's ability, which is akin to the productivity of the firm; thereby, a firm with more (less) should generate greater (less) profits given the same amount of effort. A firm's ability, as per Aghion & Stein (2008), is unknown to both the firm and the market.
ir	Interest Rate	From the Delli Gatti et al. (2005) framework, an interest rate is utilized in determining the costs of the firm. In a deviation, the implemented model has fixed and variable cost components. The interest rate is utilized in Equation 37 and Equation 41.
pc	Price Concern	This variable controls the extent by which firms are concerned about their share price. It is akin to the a variable in Equation 18, with Equation 49 demonstrating its utilization in the implemented model. The influence of an increased concern for the share prices forms a significant component of the analysis of the model.
For the investors and the firms		
α	Memory Weight	In their decision-making processes, firms and investors consider, to varying degree, past results. The length of history considered is determined by the memory weight variable, as per Equation 48. The influence of past result lasts for $1/\lvert\ln(\alpha)\rvert$ periods. A higher (lower) memory weighting result means investors give more (less) consideration to the past performance of the firms.

For the market		
λ	Market Depth	This variable adjusts for the pricing effect of the implicit agents in the market; that is, it is a proxy for what other investors are doing in the market. Farmer (2002) justifies the use of this term and the general market pricing mechanism employed in this model. Section 3.5.4.3 details this process.

3.5.3.2 The Firms

The specifications for the firm class is derived from utilizing specific variables from the previously mentioned models. Table 9 details the vital firm characteristics and variables. While the firms share many common variables, they are divided into two classes: revenue growth and margin growth firms. The global *growth_pro* variable, which has a range of 0.0 to 1.0, is utilized by the user to set the proportion of each class. A setting of 1.0 means all firms will pursue revenue growth, while a setting of 0.0 means all firms will pursue margin growth. The principal purpose of a firm is to generate sufficient growth in the metric allocated per their sub-class. For instance, a revenue growth firm will allocate resources (effort) to meet their sales growth expectation. The ramifications of pursuing one growth aspect over another is central to the model.

Table 9: The definitions of the crictical firm variables

Symbol	Name	Purpose
ex_{it}	Growth Expectation	Firms hold a growth expectation, defined as the rate of growth above what is naturally achievable. The expectation guides the allocation of resources (Step 1 in Figure 38). Expectations are initially allocated to the firm in the range of 0.1 to 0.8; firms then adjust their expectation, as discussed in Section 3.5.4.5.

el_{it}	Additional Effort “evel	A vital decision for firms is to decide how much effort they must allocate to achieving their primary goal. The el_{it} variable represents the amount of additional effort the firm applies to achieve their growth objective. If a firm does not want to achieve additional growth in its primary objective, it will merely divide its effort equally between revenue and margin growth. Equation 28 provides further detail on how the level of effort is determined.
ra_{it}	Realized Ability	While firms have a base line of ability, they do not realize this ability with any certainty. They either under- or overachieve their ability in each period based on a deterministic stochastic process. Equation 31 shows how a firm’s realized ability is calculated at each step. Equation 32 provides the mechanism for calculating the stochastic factor. It should be noted that the variance of the stochastic factor increases as the firm’s growth expectations increase. The commentary for Equation 32 details the rationale for this assumption. The realized ability affects only the primary focus of the firms. That is, if the firm is a sales (margin) growth firm they will experience variable performance in their sales (margin) but will return a constant performance in their margin (sales) performance. The commentary for Step 1 and 2 of Equation 38 details this further.
c_{it}	Capital	Firms maintain and utilize a capital base to produce their output. This variable is akin to K_{it} in Equation 23. The capital base is added to if the firm makes a profit, with the rate of capital accumulation defined as per Equation 39.
u_{it}	Pricing Factor	This variable’s role is equivalent to u_{it} in Equation 24. Therefore, at each step firms realize a different price for their output. The pricing factor has the potential to either dilute or compound any over(under) realization of a firm’s productivity.
mr_{it}	Margin Realization	As per Equation 34 firms realize a given level of efficiency at each time step. For firms focused on sales growth this variable is constant and equal to the variable g (the global efficiency variable), with a detailed description of its purpose provided in Table 8. For firms focused on margin growth their realization of this variable is mixed. Equation 34 provides the mechanism by which this occurs.

π_{it}	Profit	Firms generate a profit or loss at each time step. Equation 38 provides the calculation, which is revenue minus the fixed and variable costs components. The sales and variable cost components vary based on the realization of each firm's ability and price level.
ri_{it}	Reinvest Rate	Firms must decide how much of their profits they will reinvest. Equation 40 and Equation 41 show how a firm's sub-class affects this process. There are two different equations because the model assumes that sales growth firms will be lower margin, and less inclined to re-invest, and margin growth firms are assumed to be less concerned with growing their capital base, and thereby will have a higher pay-out.
met_p_e_y	Meet Previous Expectations	This variable is updated to reflect whether the firm achieved its expectations in the prior period. It is used extensively in step 8 of the model as firms decide whether to adjust their expectations or effort.
pex_gap	Gap Between Expectations and Peformance	The over or underachievement of a firm's expectation is recorded through this variable. The gap is used in the process of firms updating their expectations.
	Miss Count	This variable records in how many consecutive periods firms miss their expectations. The variable is utilized by management to decide whether it is time for them to adjust expectations. The memory weight of the firms is a vital factor in this consideration.

3.5.3.3 The Investors

In contrast to the traditional artificial stock markets, the implemented model's investor population comprises single representative agents from different investing classes. The investing classes are fundamentalists, who use either a firm's PE ratio, PEG ratio, or PB ratio, or chartists, who utilize the trends in either a firm's earnings or prices to inform their decisions. The definitions and relevance for employing the various fundamentalist approaches are contained in Table 10. The rationale for providing three alternative metrics for the fundamentalists is that it provides the opportunity to introduce value and growth investors, thus providing a potentially more vibrant ecosystem of investors. Growth investors prefer companies that offer strong earnings growth, as reflected by higher PE and PEG ratios. Value investors, in contrast, prefer undervalued stocks, which tend to be identified by a low PB ratio.

Table 10: Financial variable definitions

Metric	Definition	Relevance
Price to Earnings (PE) Ratio	$\frac{share\ price}{earnings\ per\ share}$	The PE ratio is a widely used metric in financial markets due to the ease of interpretation. If the market has undervalued the earnings prospects of a firm, this will result in a low PE ratio, thereby highlighting an investment opportunity. Alternatively, a high PE is an indication that the stock may be over-priced. The rationale is that the stock price is higher than the growth potential of the firm. However, the “correct” PE for a stock depends on the market’s perception of the risk to the future growth prospects and earnings of the firm. Therefore, a firm may have a low PE ratio because the market perceives it as higher risk, or lower growth, or both.
Price to Growth (PEG) ratio	$\frac{PE\ ratio}{EPS\ Growth}$	The PEG ratio provides a metric capable of interpreting the interaction between a firm’s stock price, its EPS, and its growth. The advantage of the PEG ratio over the PE ratio is that the PE ratio tends to penalize high-growth companies by making them appear overvalued. Dividing the PE ratio by the earnings growth rate allows an improved comparison between firms with different growth rates. A lower PEG is preferable as the stock is comparatively cheaper than a higher ratio stock and should deliver superior returns. Both the PE and PEG ratio are favored by

		growth investors.
Price to Book (PB) Ratio	$\frac{share\ price}{book\ value\ per\ share}$	The PB ratio is the ratio of a firm's current market price to its book value per share. The book value per share comes from the firm's balance sheet and is the firm's total assets minus its total liabilities divided by the number of shares outstanding. The ratio reflects how the market values a firm's equity relative to its book value. The rationale for this approach is that a firm's market value reflects future profit potential generated from its capital, while the book value is just the historical cost of the capital. A higher PB ratio is an indication that the market expects a firm to generate higher profits from its capital base. The PB metric is a preferred tool of value investors, as it can easily identify those stocks with a market value well over the actual value of its capital.

In the model chartists compare the most recent metric, whether it be price or earnings, with an ensemble average of the respective metric. If the most recent realization of the metric is greater (less) than the ensemble average, then this is a positive (negative) information to be used in the decision-making process. Table 11 details the tolerances that define the investor's decision, while Section 3.5.4.2 details the specific decision-making process. Equation 26 provides the calculation for the ensemble average for the share price of firm *i* at time *t*. Also, it provides one of the mechanisms by which the short-term tendencies of investors are included.

Equation 26: The ensemble average for the share price of firm *i* at time *t*

$$\langle sp_{it} \rangle = \alpha * \langle sp_{it-1} \rangle + (1 - \alpha) * sp_{it}$$

By way of definition: α is the memory weight variable described in Table 8; $\langle sp_{it-1} \rangle$ is the ensemble average of the firm *i's* share price at time t-1, that is the prior period; and sp_{it} is the most recent share price for firm *i*. Substituting the share price with earnings for firm *i* returns the earnings ensemble average. Equation 27 provides the calculation for the decision metric for a share price chartist. A value of dsp_{it} greater (less) than one represents an increasing (decreasing) trend.

Equation 27: The decision metric for a share price chartist

$$dsp_{it} = sp_{it}/\langle sp_{it} \rangle$$

Table 11 provides a summary of the decision-making criteria for the various investor classes. Note that investors must decide to buy, hold or sell at each step of the model. Buying occurs when the investors assesses the stock as cheap, while selling occurs when the investors assess a firm as being expensive; that is a value higher their fundamental value. Holding is effectively a non-decision. In making their investment decisions, as detailed in Section 3.5.4.2, investors maintain different criteria for sales growth and margin growth firms. A single investor class, all classes, or any combination of investors can be selected when running the model. This functionality allows the user to specify a market ecosystem and assess how a changing investor population affects the behavior of firms and the market.

Table 11: Investor sub-class decision thresholds

Type	Firm Type	Thresholds	Action
Fundamentalists – PE	Sales Growth	> 25 < 20 25 - 20	Sell Buy Hold
	Margin Growth	> 18 < 14 18 - 14	Sell Buy Hold
Fundamentalists – PEG	Sales Growth	> 1.03 < 0.99 1.03 - 0.99	Sell Buy Hold
	Margin Growth	> 1.02 < 0.98 1.02 - 0.98	Sell Buy Hold
Fundamentalists – PB	Sales Growth	> 3 < 1 3 – 1	Sell Buy Hold
	Margin Growth	> 2 < 1 2 – 1 hold	Sell Buy Hold
Chartist – Moving average	Price	< 0.99 > 1.01 .99	Sell Buy Hold
	Revenue	< 0.99 > 1.01 .99	Sell Buy Hold
	Margin	< 0.99 > 1.01 .99	Sell Buy Hold

The role of the investor is to maintain a portfolio of *n* firms. The size of each holding will be a result of each investor's investment decisions, as explained in Section 3.5.4.2, based on the criteria in Table 11. Investors also maintain a holding of a risk-free asset, as explained in Table 12. To allow for this functionality, investors keep track of each of these variables. Table 12 provides the technical details of these characteristics.

Table 12: Definitions for the main investor variables

Symbol	Name	Purpose
rf_{jt}	Risk-free Asset	Consistent with the artificial stock market literature, investors maintain a holding in a risk-free asset, which is a proxy for cash. By buying (selling) stocks the investor's holding of the risk-free asset decreases (increases), as described in Section 3.5.4.4. For this model, investors receive dividend payments from the firms, which they can reinvest. In this iteration of the model, investors do not use any of the risk-free asset for consumption. Investors are initiated with 1 unit of the risk-free asset for each firm initiated in the population.
$holding_{ijt}$	Holding in Firm *i* at Time *t*	Investors keep track of their holding of each firm (*i*) at the end of each period (*t*). This fact ensures that they only sell a stock when they hold the stock, that is there is no short selling. Investors are initiated with 1 share of each firm

3.5.4 Model Design Overview

Figure 38 provides a flow diagram of how the model proceeds. The diagram is color-coded to reflect the distinct nature of the steps, with each step detailed in Section 3.5.4.1 through 3.5.4.6. Steps 1 and 2 (see Section 3.5.4.1) cover the product market and how firms allocate their effort and the return they generate from that effort. Steps 3 and 4, detailed in Section 3.5.4.2, relate to the decision-making process of the investors. Step 5 through 7 involve the mechanics of determining share prices for each firm and updating investor portfolios (see Sections 3.5.4.3 and 3.5.4.4). Step 8 (see Section 3.5.4.5) deals with how firms react to changes in their share price and missing their growth expectations. The final step (Section 3.5.4.6) relates to the firms updating their reinvestment plans and distributing any dividends. The previous section detailed the relevance of the initiation steps.

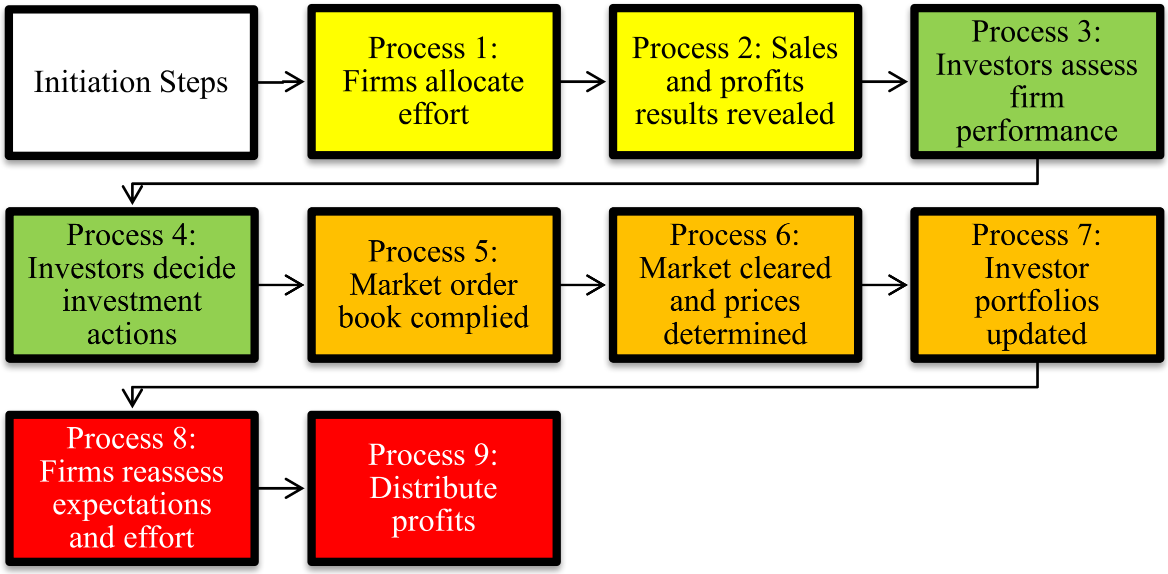

Figure 38: Representation of the model's processes

3.5.4.1 The Product Market

Following the initiation of the model, the first step involves the firms deciding how much additional effort to apply to achieve their primary growth expectation. Firms have their expectation initiated at a level between 0.1 and 0.8, with the distribution being uniform across the population. For sales growth firms their primary goal is to grow sales, while margin growth firms want to improve their margins. Firms are unaware of how much additional effort they must apply to achieve their expectations. Therefore, they apply a random search process to determine the optimal amount of effort to apply. The relevance of finding the optimal amount of additional effort is that a firm has a finite amount of effort to apply (1 unit), and a non-optimal allocation penalizes the firm. For a sales (margin) growth firm an over-allocation of effort to their primary objective will come at a cost of reduced margins (sales). The opposite holds for an under-allocation, with the additional issue that their primary expectation is unlikely to be met. Also, as discussed in Section 3.5.4.5, firms will adjust their expectations over time in response to either the over(under) achievement of them, or in response to the market.

Equation 28 expresses how firms decide their additional effort level, with el_{it} referring to the additional level of effort that firm *i* believes it needs to apply at time *t* to meet their expectations for period *t*, as given by ex_{it}. The function takes the form of a logistics function to, firstly, recognize the need to increase effort at an increasing rate if the firm wants to achieve higher growth and, secondly, bound the possible results between 0 and .5. The need for this bounding is seen in Equation 29.

Equation 28: The determination of additional effort

$$el_{it} = (1 + \left((1/ex_{it}) - 1\right) * \exp(-\ ex_{it})) *\ .5)$$

In Equation 29, $effort\_p_{it}$ refers to the level of effort firm *i* applies to their primary task (either growing sales or margins) at time *t*. The formula expresses that the level of effort a firm applies to its primary task is the addition of the previously determined level of additional effort and a constant, 0.499. This assumption reflects that a firm will apply at least 50% of their effort to their primary task but cannot apply all their effort to the primary task; that is, the upper bound for $effort\_p_{it}$ is 0.999.

In this iteration of the model the effort variable remains an abstract concept with no attempt to align it with a real-world variable. Given the concept borrowed from existing literature this approach is acceptable for now. However, in a topic discussed in more detail in Section 4.3.1, an attempt to quantify effort should be made. In summary, this could be achieved through the assessment of financial metrics (for example headcount or advertising costs). Alternatively, new CSS techniques such as natural language processing could be applied to conference call transcripts and strategy documents to quantify and then detect changes in effort.

Equation 29: The primary effort for a firm

$$effort\_p_{it} = 0.499 + el_{it}$$

The level of secondary effort is defined by Equation 30, where $effort\_s_{it}$ refers to the level of effort firm *i* applies to their secondary task at time *t.* The formula is consistent with Aghion & Stein (2008), in that firms have only 1 unit of effort to allocate between their primary and secondary objective. Increasing (decreasing) the effort allocated to the primary objective results in a decrease (increase) in the effort applied to the secondary objective of the firm.

Equation 30: The secondary effort for a firm

$$effort\_s_{it} = 1 - effort\_p_{it}$$

The second step of the model has firms realize their profit for the period. This step contains several sub-steps, which are the: realization of operating performance, as in Equation 31 through Equation 34; price realization, as in Equation 35; the accounting steps to determine a firm's profit, as defined in Equation 36 through Equation 38; and capital expenditure and dividend payments for the period. Consistent with Aghion & Stein (2008) and the models discussed in Section 3.3.2, stochastic processes are utilized throughout the model. One such process is the determination of the firms' returns on the effort they allocate to their primary objective. In a novel step this process is dependent on the previous decisions of the firm. The ability to include this factor, along with the heterogeneous expectations and abilities of the firms, demonstrate the utility of ABMs, as this sort of functionality is not readily available in traditional analytical frameworks. Axtell (2007) discusses the advantages of ABMs over standard economic frameworks.

Equation 31 defines the level of ability, ra_{it}, that firm *i* realizes at time *t* for their primary objective. Note that as discussed in Table 9, the level of realized performance in a firm's secondary objective is fixed. The realized ability of a firm is the combination of its initiated level of ability (ma_i), as detailed in Table 8, and the realization of the risk factor (as_{it}) for the period. The mean of the risk factor is 0, thus reflecting that on average a firm realizes their natural ability. However, firms are unaware of their natural level of ability so are incapable of attributing any under (over) performance to luck or superior management decisions.

Equation 31: The realized ability of a firm

$$ra_{it} = ma_i * (1 + as_{it})\text{where } as_{it}\ N(0, sd_{it})$$

The crucial component of Equation 31 is that the standard deviation of the risk factor is dependent on the level of additional effort a firm allocates to their primary objective. This assumption reflects the additional risk associated with pursuing a more aggressive strategy; that is, the model employs accepted concept of a risk-reward tradeoff. The assumption does not preclude the firm from attaining a higher expectation; rather, the outcome is a wider variance in the realization of higher expectations. The importance of this assumption will manifest itself in how investors reward (punish) firms for above (below) expectation results; that is, a high-risk strategy that is successful will be rewarded but firms run a higher risk of failure and disappointing the market.

Equation 32: The standard deviation used in determining a firm's realized ability

$$sd_{it} = 0.001 + \left(\left(1 - \left(effort_{p_{it}} * 2\right)\right) * \ -0.025\right)$$

Equation 33 is the production quantity (qty_{it}) of the given good for firm *i* at time *t.* As outlined in Section 3.5.2, firms provide a homogeneous good (or service) into a market which is subsequently cleared at each time period at a price explained by Equation 35. The (ra_{it}/ma_i) term is only relevant for sales growth firms because it is assumed that firms focused on margins will produce a quantity based on a fixed ratio of these two terms; that is, $ra_{it} = ma_i, so\ ra_{it}/ma_i = 1$. For the sales growth firms, depending on the result of Equation 31, the quantity produced becomes a function of their realized ability and is higher (lower) than their intrinsic rate if ra_{it}/ma_i is greater (less) than 1. The c_{it} term refers to the firm's capital level; therefore, there is a natural tendency for the output of firms to grow over time.

Equation 33: The quantity that a firm delivers in each period

$$qty_{it} = \left(effort_{sit} * \left(\frac{ra_{it}}{ma_i} \right) \right) * \ c_{it}$$

The relevance of a firm's margin performance is in the variable cost function, as defined by Equation 37. A critical component of the function is the realization of a firm's operational efficiency. For the margin growth firms, while they achieve a consistent production level, their margins are susceptible to variable performance via the realization of their operational efficiency. Conversely, sales growth firms realize a constant performance level of efficiency. Equation 34 defines the operational efficiency (mr_{it}) of firm *i* at time *t*. The g variable relates to the general productive capacity of a firm's capital, as per Delli Gatti et al. (2005), and is constant and fixed for all firms, per Table 8. For the margin growth firms, depending on the results of Equation 31, efficiency will be higher (lower) than the base rate g if ra_{it}/ma_i is greater (less) than 1.

Equation 34: The margin that a firm generates in each period

$$mr_{it} = g * \left(\frac{ra_{it}}{ma_i} \right)$$

Multiplying firm i*'s* output (qty_{it}) by the firm's price index (u_{it}) specifies the revenue (s_{it}) for the firm for period *t*. Per Delli Gatti et al. (2005), u_{it} is a random variable and represents the ratio of the current period's price (p_t) to the previous period's price (p_{t-1}) and is drawn from a Gaussian distribution with a mean of 1 and a finite variance. A value of u_{it} greater (less) than 1 reflects an increase (decrease) in the price level and will assist (impede) a firm's growth performance, noting that management cannot influence the pricing outcome.

Equation 35: The sales revenue that a firm genrates in each period

$$s_{it} = qty_{it} * u_{it} \text{ where } u_{it} \; is \; N(1, 0.05)$$

The firm incurs fixed and variable costs at each step. Equation 36 describes the fixed costs(fc_{it}) that firm *i* incurs in period *t.* The costs are the ratio of the firm's capital case and the interest rate ir. The ratio is homogeneous across firms.

Equation 36: The fixed costs for a firm

$$fc_{it} = c_{it} * \left(\frac{ir}{10}\right)$$

The interpretation of Equation 37 is that vc_{it} are the variable costs firm *i* incurs in period *t.* The calculation uses Equation 25 as a foundation with the addition of an efficiency factor. The costs are a function of the quantity of what is produced by the firm,

qty_{it}, per Equation 33; the interest rate *ir;* the realized productivity of the firm for the period mr_{it}, per Equation 34; and the effort the firm applied to realizing their margin growth expectation in time *t*, $effort_{it\_m}$.

Equation 37: The variable costs for a firm

$$vc_{it} = qty_{it} * (1 - ((mr_{it} * ir) * effort_{it_m})$$

The final sub-step in determining the performance of the firms is calculating their profits. Profits (π_{it}) for firm *i* at time *t* are given as sales revenue (s_{it}), as per Equation 35 minus fixed costs (fc_{it}), as per Equation 36, and variable costs (vc_{it}), as per Equation 37. Additionally, the margins for firm *i* for period *t* (m_{it}) are given by $= \pi_{it}/s_{it}$.

Equation 38: The profit function for a firm

$$\pi_{it} = s_{it} - fc_{it} - vc_{it}$$

Having realized their performance for a period firms will update a host of variables relating to their performance. The variables of highest relevance are sales and margin growth, which are simply the prior current period's performance divided by the last period's performance. In the instance that margins in the prior period were negative the denominator in the growth formula is set to .001 to avoid the obvious issue of calculating the percentage change from a negative margin to a positive margin. The firms then compare their growth to their expectation and update the *met_p_e_y* variable to reflect whether they met their expectations or not. The *pex_gap* variable is updated to reflect the gap in performance and expectation, noting this is bounded between -1 and 1. If the firm misses their expectation the *miss_count* variable is incremented by 1, or alternatively reset to 0 if the firm's growth expectation is met. The relevance of this will be seen in Step 8 of Equation 38.

If a firm generates a profit the firm will reinvest a certain proportion of that profit back into the business. This reinvestment is a proxy for growth capital expenditure (capex); that is, capital employed to grow the business. Therefore, the reinvestment rate is an integral part of the mechanism that determines the growth of the firm. Growth capex differs from maintenance capex in this model, in a similar manner to Delli Gatti et al. (2005), in that maintenance capex is implicitly captured in the cost base of the business, thus covering the depreciation of the existing capital base. Equation 39 defines the calculation for the change in the capital base on the condition that the firm makes a profit. If a firm records a loss, the capital base is reduced by the loss. This step implies that the capital base of a firm would remain constant if the firm breaks even or undertakes no reinvestment. In the case of bankruptcy – a negative capital balance – the capital base of the firm is reset to 1 and the firm "begins" life again.

Equation 39: The change in capital base for a firm

$$c_{it+1} = c_{it} + (\pi_{it} * ri_{it})$$

From Equation 39 it is seen that $c_{it+1}$is the level of capital employed by firm *i,* in the subsequent period *t+1*. The firm's capital increases by the firm's profits (π_{it}) for the period multiplied by its reinvestment rate (ri_{it}). The calculation is dependent on the objective of the firm, with Equation 40 providing the reinvestment rate (ri_{it_s}) for sales growth firms and Equation 41 specifying the rate (ri_{it_m}) for margin growth firms.

Equation 40: The reinvestment levels for a sales growth firm

$$ri_{it_s} = \exp\left(1 - \left(\frac{1}{effort_{it_s}^2}\right)\right)$$

A firm's reinvestment rate is assumed to be a function of its primary objective and the amount of effort it is applying to its primary task. The rationale for the difference was detailed in Table 9. Equation 40 shows that the reinvestment rate for a sales growth firm (ri_{it_s}). These firms will reinvest a higher proportion of their profits the greater effort they are allocating to growing sales.

Equation 41: The reinvestment level for a margin growth firm

$$ri_{it_m} = ir + (0.15 * \left(effort_{it_m}^{1.5}\right))$$

Equation 41 provides the re-investment calculation for margin growth firms. The rate ri_{it_m} reflects margin growth firms are less inclined to reinvest profits into future growth but must maintain a minimum reinvestment rate in line with the interest rate (ir). As the firm increases its allocation of effort into increasing margins, then the reinvestment rate also increases, albeit at a lower rate than the "growth" firms.

3.5.4.2 The Investor Decision-making Process

Investors perform a two-step process in making their investment decisions. The first step (Step 3 in Figure 38) involves the investors assessing the most recent results against their given benchmark. The next step comprises deciding upon an investment action and the conviction in that action. Table 11 detailed the variables that the five-different investor sub-classes consider in making their investment decisions. A vital component in the calculation of the variables is that they are not the most recent realization; for example, they reflect not only the last period's earnings, but are an ensemble average of the variable over previous periods (see Equation 42). The rationale for this specification is to allow investors to consider trends in a firm's performance and to have investors vary the amount of information they utilize in the assessment process, thereby allowing a comparison between short- and long-term investors. Ensemble averages for each firm are maintained for earnings, earnings growth, revenue growth, margin growth, and the capital base of the firms. The appropriate ensemble averages are utilized to establish the various ratios defined in Table 11.

Equation 42 provides the calculation for the ensemble average for the earnings (${es_{earning}}_{it}$) of firm *i* at time *t*. For the other variables, Table 8 defined the memory weight variable α, π_{it} is the profits of the firm for the current period, as defined by Equation 38, and $es_{earning_{it-1}}$ is the ensemble average from the previous period. The rationale for this specification is that a given period's earnings influences the ensemble average up to $\frac{1}{[\ln(\alpha)|}$ periods. Therefore, depending on the setting of the memory variable, its effect is two-fold: a high (low) α value moderates (amplifies) the effect of the current period's earnings, and a low (high) α value moderates (amplifies) the effect of past earnings. Short-termism on behalf of the investors manifests itself with a lower setting for $\alpha,$ resulting in investors being more reactionary to more recent results.

Equation 42: The ensemble average for a firm's earnings

$$es_{earning_{it}} = \alpha * es_{earning_{it-1}} + (1 - \alpha) * \pi_{it}$$

Having calculated the appropriate ratio for each of the firms, the investor(s) will decide whether they wish to buy, hold, or sell the stock and the size of their trades (Step 4 of Figure 38). Table 11 provided the criteria for determining the actions of the investors. In summary, if the ratio exceeds the upper threshold (did not meet the lower threshold) of the relevant ratio, the investor will want to sell (buy) the stock. An outcome between the two thresholds results in the investor taking no action, that is they will just hold.

After determining their preferred action, investors must first, check they have the required resources to undertake the action and then, based on their conviction, decide how much to trade. The need for the former comes from the model's assumption that investors cannot borrow new funds or raise funds by short-selling their current holdings.

Therefore, investors must have a positive balance of the risk-free asset at time t ($rf_j(t)$) to buy more stock and must hold a positive quantity of the relevant company ($holding_{ij}(t)$) if they intend to sell. If investors meet these requirements, then they establish their conviction in the trade. If an investor does not meet the trading requirements, the investor cannot participate in trading for the period.

Investor conviction is a function of the gap between the firm's actual result and the relevant investment threshold. The mechanism means that a large(small) gap results in a higher (lower) conviction. For example, Equation 43 provides the calculation for the buying conviction of investor *j* ($c_{ij}\_f_{pet}\_b$) – a fundamentalist who utilizes the PE ratio – for firm *i* at time *t*. By way of definitions, pe_{it} refers to the PE ratio of firm *i* at time *t* and bt_i is the buy threshold for firm *I* , with Table 11 providing the appropriate thresholds.

Equation 43: Buy conviction example for a fundamentalist using PE ratios

$$c_{ij}\_f_{pet}\_b = \frac{{}^{1}\!/_{pe_{it}} - {}^{1}\!/_{bt_i}}{1 - {}^{1}\!/_{bt_i}}$$

Equation 44 is the calculation for the selling conviction of investor *j*, a fundamentalist investor who utilizes the PB ratio at time *t* ($c\_f_{pbt}\_s$). The use of the value of 1 and 100 in Equation 43 and Equation 44 comes from bounding the possible values of the various ratios between 1 and 100. This assumption is made to remove the influence of obscure one-off results firstly and to bound the investors' conviction between 0 and 1, thereby ensuring they cannot sell more than they hold, nor purchase an excessive amount of the stock.

Equation 44: Sell conviction example for a fundamentalist using PE ratios

$$c_{ij\_}f_{pbt\_}s = \frac{pb_{it} - st_i}{100 - pb_{it}}$$

After investor *j* determines selling conviction, a decision can be made on the size (volume) of the trade for firm *i* at time *t*. Equation 45 provides the buying volume for firm i, for investor *j* at time *t*. The $\frac{1}{I}$ term is utilized to ration funds because unlike the standard artificial stock markets investors must allocate their holding of the risk-free asset (rf_{it}) across the populations of firms (*I* provides the number of firms in the population*).* Table 8 explains the transaction ratio variable (tr) and Equation 43 provides the conviction variable ($c_{ij\_}f_{pet\_}b$). The rationale of the equation is that the greater the conviction and the higher the investor's holding of the risk-free asset, the more the investor can allocate to attractive investments. The opposite holds where the investor has a low conviction in their trade.

Equation 45: Determining the buy volumes

$$v_{ijt} = \frac{1}{I} * tr * c_{ij\_}f_{pet\_}b * rf_{it}$$

Equation 46 illustrates how investor *j* determines how much of firm *i* to sell at time *t*. The essence of the equation is consistent with Equation 45, in that the greater the conviction and the higher the holding, the higher the volume of the trade. A higher volume will have a more detrimental effect on the price of the firm.

Equation 46: Determining the sell volumes

$$v_{ijt} = tr * c_{ij\_}f_{pbt\_}s * holding_{ijt}$$

3.5.4.3 The Market Mechanism

The next two steps (Step 5 and 6 of Figure 38) involve accumulating the trades of the investor(s) into an order book. The order book is then utilized to determine the new share prices of the firms following the clearing process. If orders for a given stock are positive (negative) this signals excess (insufficient) demand and the price of the stock will increase (decrease). Allowing various sub-classes of investors ensures diversity in the order book, which in turn allows for price discovery, with the investors with the higher conviction (and resources) dictating the direction of a firm's price, specifically, and of the market in general. This functionality addresses Shiller's (1984) concept of dumb or smart money dominating the market. After establishing the order book, the market is cleared, and new prices are struck. As discussed in Section 1.3.4.3 there are a variety of ways to clear the market through an ABM. The method employed in this model is consistent with the market maker model used in Chapter 2.

An additional step in this model is the calculation of an index at the completion of each period. The index is a price-weighted index, like the Dow Jones Index (DJI), where the value of the index is the mean of the share prices of all firms in the market. Therefore, as the share price of a given firm increases relative to the other firms, its weight in the index increases. The purpose of the index is to: 1) assess the volatility of the investors' behavior; and 2) provide an overall indication of the level of investment.

3.5.4.4 Updating Investor Portfolios

The next step in the process (Process 7 of Figure 38) involves updating the investors' holdings to reflect the outcome of the market clearing process. The step is straightforward bookkeeping; that is, updating the investors' balances of the risk-free asset and their stock holdings. The balance of the risk-free asset (rf_j) is increased by the proceeds of any sales and decreased by the cost of any purchases. The stock holding balances are updated similarly. A consequence of having multiple stocks and the market clearing process, which can result in substantial price movements, is that at times investors may incur a negative balance in their risk-free asset. While there is no explicit leverage allowed in the model, the issue of a negative balance is overlooked on the basis that investors do receive dividends (see Section 3.5.4.6) which will ultimately return the balance of the risk-free asset to a positive amount, and in the event of a negative balance investors are precluded from making any further investments.

3.5.4.5 Updating Growth Expectations

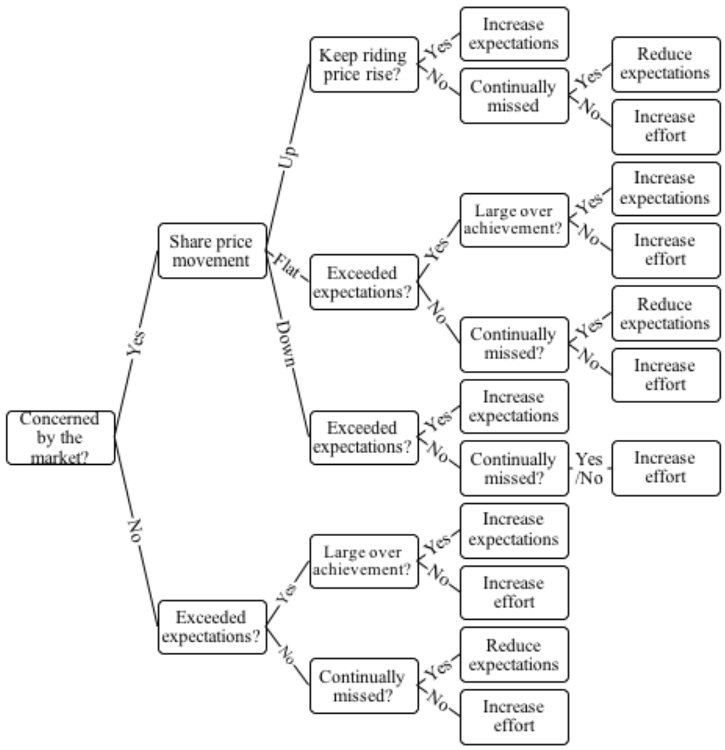

Figure 39: The decision tree that management considers

A defining feature of ABMs is the ability of agents to evolve as they react to other agents and their environment. Process 9 of Figure 38 involves the firms utilizing this capability to either adjust the level of effort applied to their primary goal or their growth expectations, noting these adjustments are both up and down. Factors that contribute to the adjustments include the memory of the firm, the size of the over(under) achievement of expectations, and the price reaction of investors. Figure 39 provides the decision tree that firms utilize in deciding their actions. Despite the daunting number of paths, a firm's decision effectively reduces to assessing whether they meet their internal expectations and from there adjusting their expectations or effort allocation. If they are concerned with their share price the chosen modification will undergo some additional adjustments.

3.5.4.5.1 Internal Expectations

Per Figure 39, outside of their concern for their share price the first concern that firms address is whether they have exceeded their internal expectations. To assess this, and commence the adjustment process, firms utilize the following variables: *pex_gap*, *met_p_e_y,* and *miss_count.* Within Section 3.5.4.1 it was explained how these variables are updated. Firms that have met expectations will have their *met_p_e_y* variable set to "true" and their *pex_gap* variable will be a positive value. In this scenario firms will decide to either increase their expectations, justified by overachievement of their existing target, or maintain their expectations and reduce the effort allocated to their primary goal. This functionality is justified because the firm's management disregards any "luck," thereby concluding that the overachievement resulted from an over-allocation of effort to the primary goal, which in turn meant that there was an under-allocation of effort to the secondary goal. This meant the firm generated a less than optimal level of profits. For example, a sales growth firm that exceeded their revenue growth expectations will have sacrificed some margin performance.

To decide whether to reduce effort or increase expectations firms will assess the size of the overachievement (the *pex_gap* variable provides this information). If the overachievement is large (minor) the firm will increase (maintain) expectations. The rationale for this assumption is that the firm's management attributes significant overachievements to their abilities and feel they can achieve greater growth in their primary objective by maintaining the same levels of effort. Alternatively, a narrow gain signals to management that extra effort allocated to the secondary objective will still allow them to achieve their primary objective yet improve their performance regarding their secondary objective.

Equation 47 defines how a firm adjusts their effort allocation to their primary objective. In the overachievement scenario, the pex_{it} variable is positive and with the $effort\_p_{it}$ being strictly less than 1, the amount of effort in the subsequent period will reduce. However, the level of primary effort cannot fall below .5; otherwise the firm would effectively switch classes.

Equation 47: How firms adjust their primary effort

$$effort\_p_{it+1} = effort\_p_{it}{}^{(1+pex_{it})}$$

Alternatively, having decided to increase expectations, Equation 48 defines how firm *i's* managements adjusts their expectations (ex_{it}) at time *t* for expectations in *t+1* (ex_{it+1}). Having exceeded their current expectations, the pex_{it} variable is positive, meaning expectations will increase. Despite having adjusted their expectations the firm will not reassess the levels of effort for their primary and secondary goals (see Equation 28) or their reinvestment policy.

Equation 48: How firms adjust their expectations

$$ex_{it+1} = ex_{it} * \left(1 + (pex_{it} * 0.25)\right)$$

The alternative scenario is that a firm has missed their growth expectation. In this instance the $met\_p\_e\_y$ variable is set to "false," the pex_gap variable will be a negative value, and the firm's $miss\_count$ variable will be greater than 0. Under this condition, the firm must decide how long they are prepared to tolerate the underachievement of their growth expectations. Unlike where firms overachieve, underf-achieving firms are less inclined to adjust their expectations. This assumption is based on the argument that having formed their expectations, firms hold a strong belief that they can achieve their targets given time to find the optimal resource allocation.

The memory weight variable (α) determines how patient firms are concerning the underachievement of their growth expectations. $\frac{1}{|\ln(\alpha)|}$ provides the number of consecutive periods that a firm will tolerate underachievement, noting that a higher value of α means that firms are more tolerant. The rationale for this approach is that if a firm has a long-term focus they will maintain a given target and adjust resources to meet that expectation. This may ultimately be a pointless task given either an unreasonably high expectation or low abilities. However, firms are given the opportunity to meet their initial expectations. Alternatively, a short-term firm may prematurely reduce their expectation, thus forgoing future growth.

In the instance that a firm has not missed expectations for $\frac{1}{|\ln(\alpha)|}$ periods, they adjust their efforts per Equation 47. However, as the pex_{it} variable is negative the effort applied to the primary task will increase. This change results in subsequent changes to the effort levels for the secondary task and the reinvestment rate. If a firm does miss their expectations in $\frac{1}{|\ln(\alpha)|}$ consecutive periods, they will reduce expectations, per Equation 48. Again, the firm will reduce expectations because the pex_{it} variable is negative.

3.5.4.5.2 The Market's Influence

Having assessed their performance against their internal expectations, firms will, if the price concern variable (pc from Table 8) is greater than 1, factor in the response from the market. The firm's management uses the price change in their stock to quantify the market's response. It should be noted that firms solely consider their most recent share price move rather than a string of price changes. Future iterations of the model could look to address this but given investors are already considering a string of past performance in their decision-making process. Therefore, the decision was made to avoid further complication and have firms consider a single price movement.

Figure 39 illustrates that there are three possibilities regarding how a firm views their share price movement: a material increase, an inconsequential change, or a material decrease. Each scenario elicits a different response from the firm. The most straightforward scenario is when there is an inconsequential price change. Under this condition, the firm assumes that the market is indifferent and they disregard the market and stick to their internal planning. In short, there are no changes from the steps undertaken in Section 3.5.4.5.1.

The next possibility is that the share price fell materially. The firm takes this signal as the market not being satisfied with their performance. This assumption assumes that managements makes no judgment as to whether the market has over- or undervalued at the time of the price decline. The basis of the assumption is that management accepts the market's valuation and does not attempt to value their company, thereby becoming solely reliant on the market to assess the value of the firm. If the firm ignores the market the only form of assessment for management is whether they have met their growth expectations.

If the firm's share price has fallen materially and the firm has achieved their internal expectation, the firm will increase their prior period's expectations. The rationale for this behavior is that the firm assesses the downward price as meaning that their growth expectations are too low. Therefore, in response, the firm increases their expectations. The expectation revision varies from Section 3.5.4.5.1, in that the expectation adjustment considers the share price change of the firm. Equation 49 is how firms update their expectations when considering the market's reaction.

Equation 49: How firms update expectations when considering the market

$$ex_{it+1} = \frac{1}{(1 + \left({}^{1}\!/_{ex_{it}} - 1\right) * \exp(pc * spm_{it}))}$$

The definitions for Equation 49 are, per Table 8: pc is the consideration that firms have for the movement in their share price; and spm_{it} is the most recent share price change and is the non-log return resulting from the market clearing process. The values of spm_{it} are capped between 1 and -1, so as to allow the formula to function with both positive and negative price movements. Figure 40 illustrates, for six different scenarios, how a prior expectation is revised based on the firm's concern for the market's reaction and their most recent share price movement. The main implication is that a more (less) severe price movement coupled with a higher (lower) concern for the market's reaction results in a greater (lesser) change in the expectations. Given the form of Equation 49, the relationships are not linear, with the function exhibiting diminishing returns.

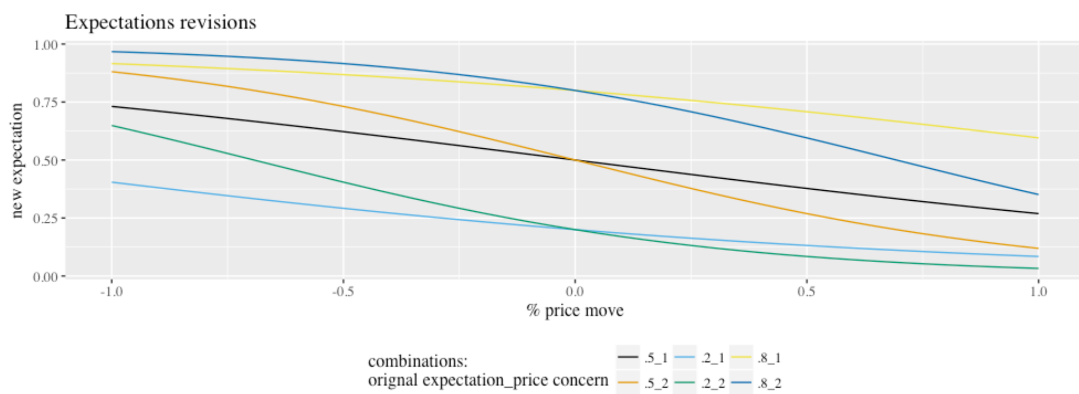

Figure 40: Examples of the functional form of expectations change formula.

If the firm has not exceeded internal expectations and its share price has fallen materially, they will undergo the process described in Section 3.5.4.5.1. The rationale for this behavior is that the firm agrees with the market about its performance and recognizes the need to meet its own internal expectations. The one exception to the process is that the firm will maintain expectations regardless of whether they have continually missed their objective, and rely on adjusting their allocation of effort to achieve their expectations.

If the firm's share price increases materially and the firm has exceeded internal expectations, the firm has an additional decision to make. The firm will perceive the positive price movement as a signal that the market is supportive of their performance and may look to capitalize on the positive sentiment, and follow the market's lead. The decision to follow the market is a random choice, with a 50:50 probability of selecting either option. If firms choose to capitalize on the positive sentiment, they will boost their current expectations via the formula used to produce Figure 40, with the exception that functional form is inversed.

The alternative option for firms is to ignore the temptation to ride the market higher. In this situation firms reduce their internal expectations. The rationale for this action is that the firm perceives that it has over-delivered and can therefore afford to reduce their expectations. The reduction in growth expectations of a firm's primary variable will lead to more balanced growth, because with the reduced expectations comes a reduction in the allocation of effort applied to the primary objective, noting that once the expectation is lower the firm will reallocate effort. Figure 49 defines how the revision to expectations occurs. The reduction occurs because spm_{it} is positive; therefore, ex_{it+1} is less than ex_{it}.

Firms face the possibility that their share price increased but they missed their internal expectations. Under this scenario the firm still undergoes the internal review because while they are pleased with the market's reaction, they are dissatisfied with continually missing expectations and will reduce them. Equation 49 is again used for this purpose because the firm is still conscious of the market, with both the concern and the share price change becoming factors in the expectation reduction. If the firm has not continually missed their expectations, then it will increase the allocation of effort to the primary objective.

Table 13: Summarizing what causes a change in expectations

Action	Scenarios
Increase in Expectations	No concern for the market and a large overachievement of expectations. Concern for the market, decide to ride momentuem higher. Concern for the market, and achieved internal expectations, but share price fell materially. Concern for the market, and a large overachievement of expectations, but muted share price response.
Reduction in Expectations	No concern for the market but continually miss expectations. Concern for the market, and continually miss expectations, but muted share price response. Concern for the market, share price materially increased, but decide not to ride the wave, and have continually missed expectations.

Table 13 summarizes the conditions in which firms increase or decrease expectations. The importance of the table is that the results section will look to assess whether changing expectations materially affects the growth profile of firms.

3.5.4.6 Dividend Distribution

Following the allocation of resources to capex, firms pay a fixed proportion of their excess capital out as a dividend to investors. Equation 50 defines this process. The fixed proportion is 60%, with the remaining 40% assumed to be absorbed by other expenses that are not explicitly modelled, such as taxes, interest charges, and other capitalized costs, for example research and development.

Equation 50: The calculation of the dividend payments

$$d_{it} = (((\pi_{it} * (1 - ri_{it})) * .6) * market\_depth$$

The last step is the distribution of the dividends to investors. This process required several assumptions, which stem from (and unlike the preceding artificial stocks markets literature), the market ecosystem experiencing an inflow of new funds via the firms' dividend payments. Without this mechanism, the model will not work because the investors' wealth would be effectively consistent, while the firm's earnings/capital would grow, causing the model to become imbalanced. This issue manifests itself in investors being unable to invest sufficient capital. Despite successfully infusing additional capital into the presented model, opportunities remain to enhance this process, a point discussed in Section 3.7.2.

The first assumption is that the dividend's available to the explicitly modeled investors is diluted by the market depth variable. The rationale is that the investors do not hold all the shares on offer and therefore do not receive all the dividends. The second assumption is that the number of shares owned by the investors is uncapped, which is a result of using the market maker model. The rationale of this assumption is that the investors are buying shares off other market participants, who are implicitly assumed to exist through the market depth variable. The important aspect is that the proportional ownership of each explicit investor is calculated, which is investor *j*'s holding in firm *i*, divided by an assumed number of shares on offer for firm *i*. The assumed number is the combined holdings of the explicit investors, with the rationale for this assumption being that market depth variable has already diluted the dividend stream through implying the existence of other investors.

3.5.5 Verification

While ABMs provide the researcher with great flexibility, there exists a considerable risk of the model not being implemented as intended. This risk predicates the need for the verification process. This step is utilized to ensure the design intentions of the model are met. This step does not involve an ex-ante assessment of the results, but rather several distinct review steps. The steps undertaken for the model and the analysis performed in this chapter were:

- an electronic journal, which recorded the output of various variables. In turn, this allowed manual calculations to be undertaken to ensure the calculations within the model were correct.
- visual inspection of various charts which plotted the behavior of variables; this included ensuring that the various investor classes invested per their relevant benchmarks and this was reflected in the relevant variables of the firms.
- a code walkthrough; this was undertaken to, ensure no coding errors were made and, to produce flow charts to ensure the code implemented the intended model.
- parameter sweeps of the extreme values.

3.5.6 Model Outputs

Given the object-oriented foundation of ABMs, the implemented model can collect extensive data at both the firm and market levels (Section 3.6 provides the analysis of the data generated by this model). At the market level, the focus is on understanding the behavior of the index, with the intent being to understand the conditions that generated more-or-less growth of index. From the index data, the distribution of price changes can also be determined. The intention of assessing this data is to identify the possible factors responsible for generating excessive volatility, and to see whether the model accurately reflects the volatility seen in the real-world.

At the firm level, to comprehend the effects of growth from management considering the market, a host of data is collected. The main variable of interest is the capital levels of firms, which is representative of how successful a firm is in growing. The median level of capital, and its growth, are collected at each step of the model, which is turn allows for the temporal evolution of the firms to be assessed. In addition, at the final step the capital levels of all firms in the population is collected. The data is then used to assess the firm size distributions. The other variables collected at the firm level include the number of expectation changes, whether expectations are met, and financial metrics such as the PE and PB ratios. This data is utilized to uncover the dynamics of the model and propose an explanation of how the feedback cycle between investors and firms affects capital growth.

3.5.7 Section Summary

This section provided the necessary details and justification for the implemented model. Section 3.5.2 provided the background to the model and explained how two other models served as the foundation for the executed model. Contained in Section 3.5.3 was a full explanation of the agent classes and the global variables. Next, Section 3.5.4 detailed the design of the model and explained how each process in the model operated. Provided in Section 3.5.5 were the verification steps undertaken to ensure the model served as intended. Finally, Section 3.5.6 itemized the output collected in the model, which was utilized to inform the results presented in Section 3.6.

3.6 Results and Findings

The purpose of this section is twofold, first to report on the initial characteristics of the model and second to investigate how the dynamics vary when the market ecosystem is expanded to include multiple investors. Common to both activities is management changing the concern they have for their share price, and the volume of history investors and firms considered. Section 3.6.1 provides the details of the various experiments undertaken to derive the results, along with a general explanation of their presentation. Next, Section 3.6.2.1 serves two purposes, first to provide a level of validation of the model and second to report on how the various investor classes, acting as the sole investor in the market, affect the market and the firms. Section 3.6.2.2 provides the results from having multiple combinations of investors co-exist in the market ecosystem. Next, Section 3.6.3 provides the results of simplifying several model processes and assumptions. The rationale of this step is to identify the primary drivers of the model. Finally, Section 3.6.4 summarizes the results and their importance.

3.6.1 Experimental Settings and Result Summary

This section introduces the various experiments undertaken and how they are reported. The intention of the experiments is to uncover how a positive feedback mechanism between firms and the stock market could operate and whether its effects were analogous to what is seen in the realworld. At this point no attempt is made to assess why some firms are more successful than others in growing or whether a certain class of investor is more successful. These are both fertile ground for future research. The charts presented in this section were created using the ggplot2 (Wickham, 2016) package, implemented in R (2017), and involve the use of facet grids. To aid readability, the horizontal facets have the prefixes a) through d), while the vertical facets are labeled 1) through 4); a given sub-plot will be referred to by its coordinates, such as facet a1.

The presentation of the results utilizes various methods. The first is to assess the temporal evolution, which is provided via a time-series plot of the median value of a given variable. The median is determined at each step from the value of the 60 runs of a specific combination, thereby allowing an analysis of how the behavior evolved. The next method is violin plots, which have the advantage of displaying both the density and distribution of a metric. The final presentation method is to provide, following a log transformation, the cumulative distribution charts of a given metric, thus ensuring the graphs are consistent with those presented in Section 3.4.3.

In developing the model, calibration was undertaken to ensure the model delivered intelligible results. Table 14 provides the settings that were decided upon. In addition, as discussed in Section 3.5.4, various assumptions regarding updating equations were made. Going forward, enhanced sensitivity analysis could be undertaken. Additionally, as reported in Section 3.6.3, certain processes are simplified to identify the primary dynamic producing the results.

Table 14: The baseline settings utilized in the experiments

Variable	Settings
Steps per run	1,000
Runs per setting	60
Number of firms (J)	500
Market depth (λ)	0.15
Transaction ratio (tr)	0.15
Interest rate (ir)	0.05
Global efficiency variables	10

Table 15 provides an overview of the main components of the two classes of experiments and a summary of the findings. In combination with Table 14, the reader should note that each model ran for 1,000 steps. The rationale for this decision is that the time-period implied per step is a year. Therefore, the growth experienced in the real variables becomes excessively large, yet this issue had to be balanced with allowing sufficient time for any underlying dynamics to appear and stabilize. Per the rationale provided in Section 2.5.2, 60 independent runs were adequate to gain a satisfactory level of stability in the price series.

Table 15: Experimental design and result summary

Model Setting	Key Components	Summary of Findings
Single Investor Classes	The following intervals were utilized for the note variables: Market concern [0,1,2] Memory [.80, .85, .90, .95] Investors [CE, PB, PE, PEG]	Where management disregarded the market's reaction it was found that the patience management showed, regarding achieving their expectations, affected capital growth. Once management considered the market, a more volatile market was more detrimental to capital growth. Once the market reduced in volatility, growth stabilized. Some agreement with the stylized facts of firm size and growth were found.
Combined Investor Classes	As above except the following investor combinations were used: Investors [All, CP + PB, PB + PE, PB + PE + PEG]	The introduction of a price-following investor had a material effect on the performance of the market and the firms. When all investors were engaged, this effect was moderated to a certain degree. The investor ecosystem that firms face was found to materially affect their decisions.

In ascertaining the results presented in Table 15 the analysis was undertaken in the order as presented in Section 3.6.2.1; that is, the analysis started at assessing the capital accumulation characteristics of the various environments, before assessing the behavior of the market, and then implying how that affected the conduct of the firms and the index. Through this process it became clear how and why the system behaved as it did. To ensure this point is not lost, Figure 41 is provided at this point to ensure the reader is aware of the dynamics as the results are explained.

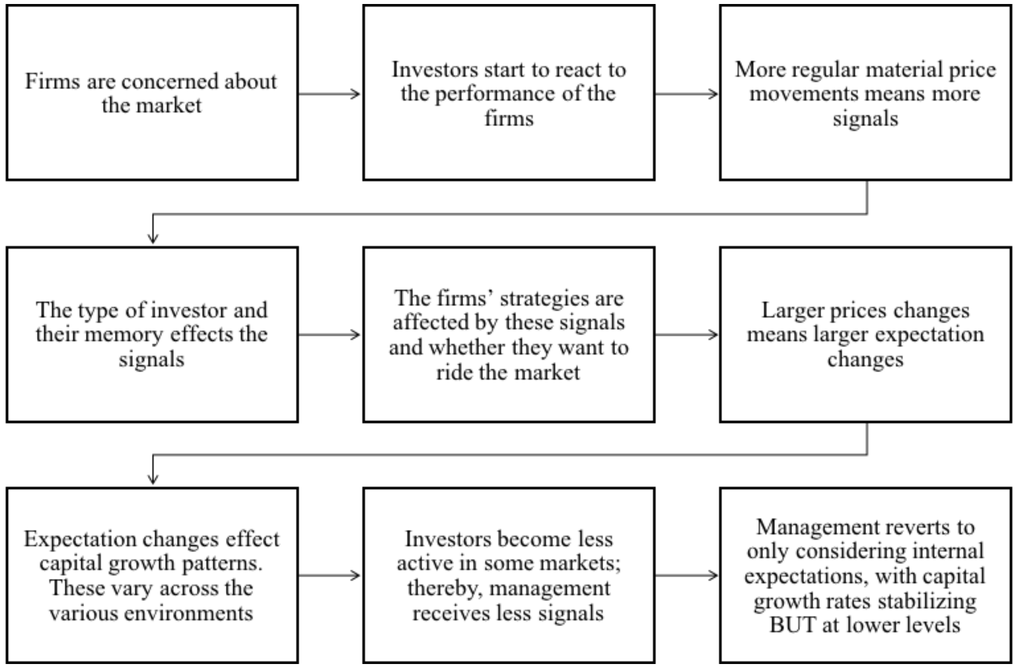

Figure 41: Summary representation of how the market ecosystem operates.

3.6.2 Detailed Results

3.6.2.1 Single Investor Classes

With the novelty of the implemented ABM it is necessary to establish reference behaviors and characteristics before introducing multiple investor classes within the environment. These behaviors relate to both the investors and the firms. The narrative concerning the reference behaviors is further divided into a baseline behavior where management does not react to the markets, and then an assessment of how an increasing concern for the market's reaction affects firm behavior. The first metric of interest is the rate and distribution of capital accumulation for the firms. Capital has been chosen as the variable that best represents the size of the firm. Figure 42 provides the median capital level of the firms across time.

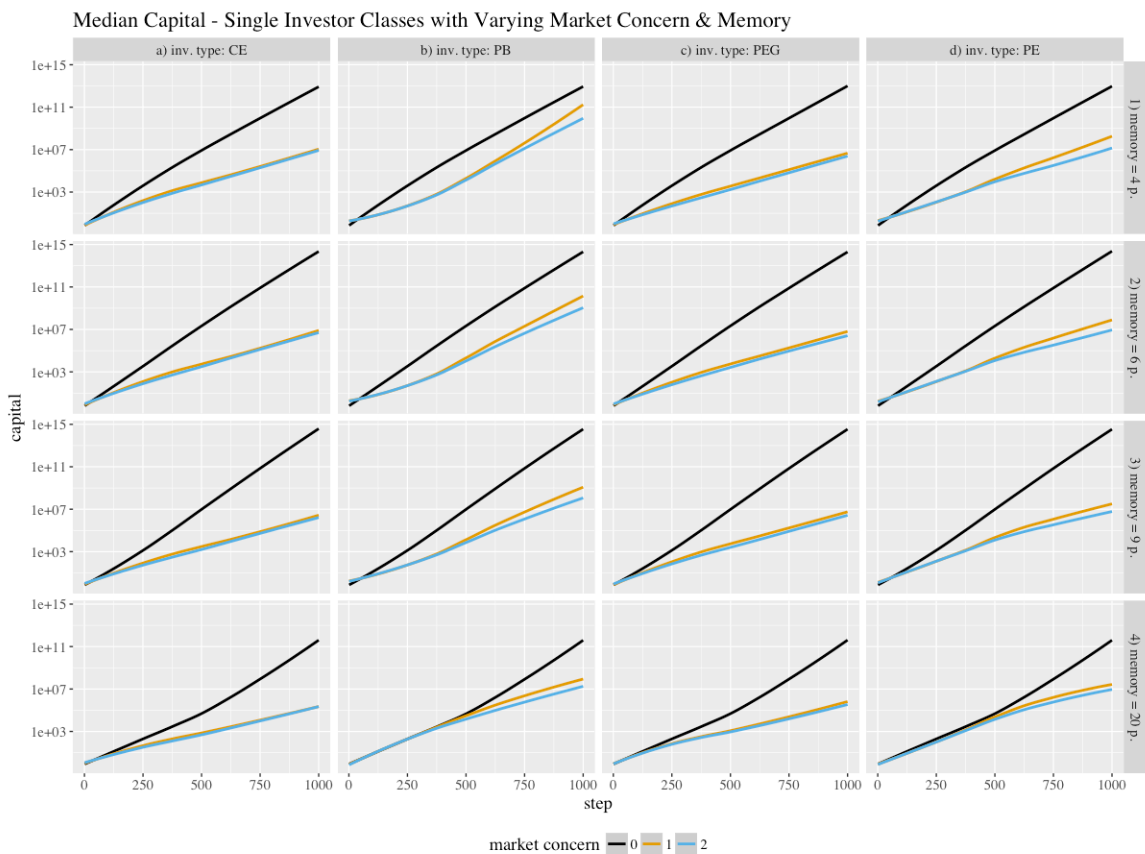

Figure 42: Temporal growth in the median capital levels of the firms. Facets differentiate the investors' classes and the memory utilization of the investors and firms. The lines represent the progression of the capital levels with management having different concerns for the market.

The first observation from Figure 42 is that when management becomes concerned with the market's reaction it has a detrimental effect on the rate of capital accumulation. The plots of capital accumulation where management has no concern for the market (the black lines) demonstrate this point. Once management becomes concerned with the market's reaction, a higher level of concern has an even more damaging effect on capital growth; that is, the orange lines sit above their blue counterparts. The various investor classes also appear to be influential on the level of capital growth, with higher levels achieved when management responds to investors who utilize a PB methodology (value investors). An environment with PE investors also appears more conducive to growth over an environment with PEG and CE investors. The memory of both agent classes appears to influence the dynamics of capital accumulation. To develop an initial hypothesis as to how and why the different investor classes affect capital growth, an analysis of the market return profiles (see Figure 45) is also required.

A second significant observation from Figure 42 is that the memory of management, even with no concern for the market, has a material effect. This result appears to exhibit a "Goldilocks" type outcome, where the optimal growth is achieved with the consideration of some history, but not too little or too much. This result is supported by facet rows 2 and 3 exhibiting the highest levels of accumulated capital. The initial hypothesis for this behavior, and one explored in depth later, is that the rate at which management update their expectations must have a meaningful effect on growth.

Having established that capital accumulation is influenced by management and investors, it is necessary to assess how that capital is distributed across firms. As discussed in Section 3.2.1.1 and confirmed in 3.4, the distribution of firm size should exhibit a power-law distribution. Figure 43 presents the capital distribution of firms for the various experimental settings in the same log (reversed) CDF as utilized in Section 3.4. The data was generated by collecting the capital levels of each firm at the completion of the simulation. Therefore, for each experimental combination there were 30,000 data points (500 firms x 60 runs per combination).

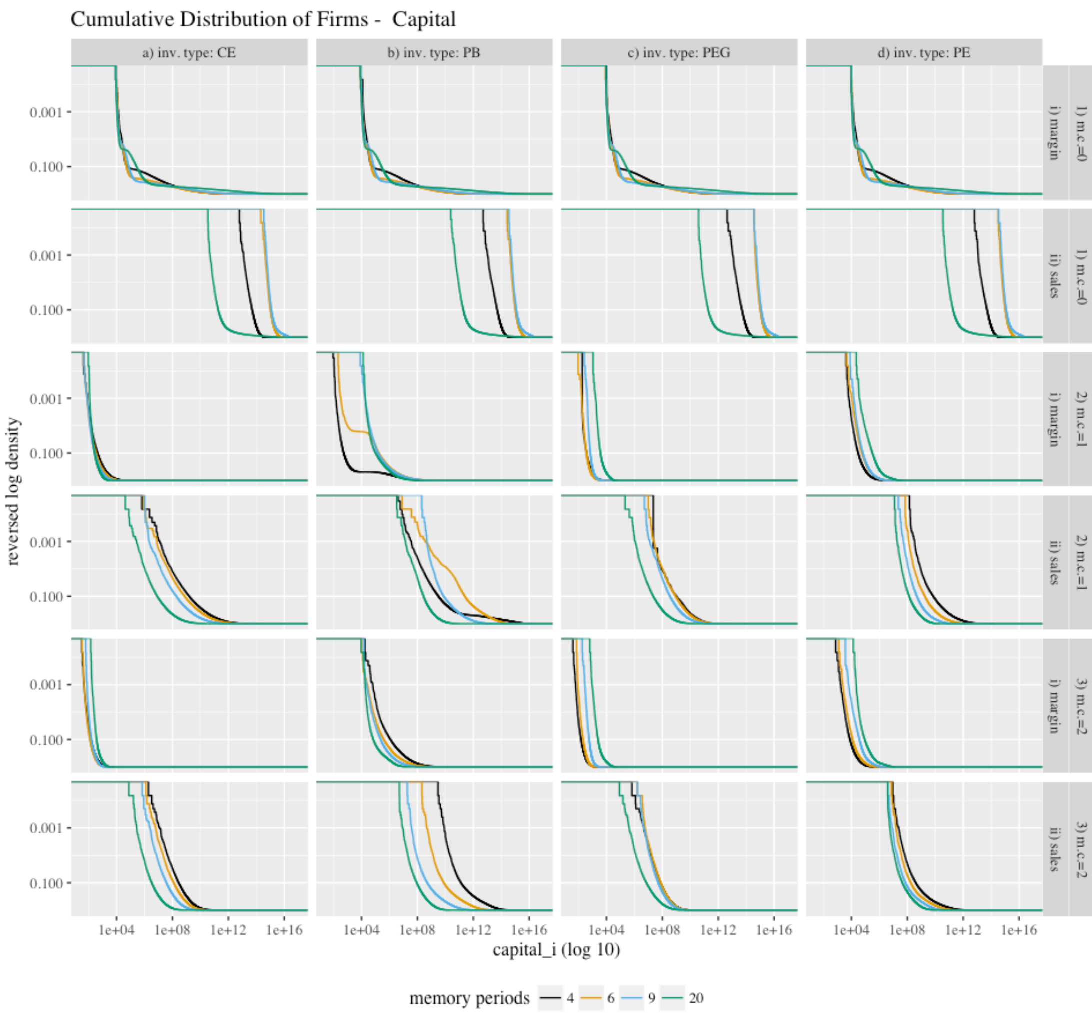

Figure 43: Firm size distribution at the completion of the simulation. Facets are differentiated further with the firm type recognized, via a secondary facet. The lines represent the CDF in log form and are separated by the memory utilized by the agents.

An additional facet was added to distinguish between the sales and margin growth firm classes. The rationale for this addition is to highlight the differential in capital levels between the two classes. It must be acknowledged that a factor in the division is the framework of the model, which had the margin growth firms tending to pay out a higher proportion of profits as a dividend. Regardless of this difference, Figure 43 highlights that the gap in capital between the two classes varies significantly, and margin growth firms are not precluded, under the right conditions, from growing to a size comparable with the sales growth firms. However, the shrinking of the gap is more a function of sales growth firms failing to grow.

In a similar manner to Section 3.4.3 the *fit_power_law* function (Csardi & Nepusz, 2006) was fitted to assess whether the distribution of capital matched the empirical evidence. Given the variations in capital accumulation the data was assessed with and without considering the primary objective of the firm. The results were somewhat inconclusive, with the power-law exponent ranging in value from 1.4 to over 5, with its significance also varying. Therefore, the model does not appear as successful as it predecessors in explaining firm size and growth distribution. The rationale for the variations across the samples is now discussed.

In a result consistent with what was seen in Figure 42, Figure 43 shows that once management becomes concerned with the market's reaction, it has a material effect on the dynamics of the system. In a significant finding, which helps explain the dynamics of Figure 42, it is the sales growth firms that appear more responsible for the reduction in capital levels once management reacts to the market. This is supported by the distribution curves in facets row 1i being located farther to the right than what is seen in rows 2i and

3i. In terms of the margin growth firms, they are also affected by management's concern for the market but not to same extent.

In an environment where management does not consider the market (facet row 1), the Goldilocks effect is clearly seen for the sales growth firms, with margin growth firms appearing not as affected. The likely reason is that sales are more volatile than margins because sales growth, as explained in Section 3.5.4.1, is a function of past profits and stochastic processes for a firm's realization of price and their ability, while margins are not reliant on past profits. Once management starts to reflect on the market's reaction, interesting dynamics develop where the distribution of capital for the sales growth is less influenced by the memory of management and investors. Alternatively, in general when compared to the base case, the capital distribution of margin growth firms is affected by memory length. It is apparent that is some situations the investor class influences capital accumulation. The PB investor environment is the most prominent example, which is a consistent theme of the results thus far.

At this point in the analysis it is pertinent to assess the return profile of the firms. The rationalization, despite the firms focusing on alternative strategies – that is, growing sales or margins – is that the ROI (given by *profits(t) / capital(t-1)*) of a firm provides a common base to judge how well a firm is employing its capital. As discussed in Section 3.4.3, firms are expected to cover their WACC, and the empirical evidence suggests that on average this does not occur, with the distribution of firm ROI's being highly skewed

Figure 44 illustrates the ROI generated under varying scenarios. The principal observation is that while sales growth firms can generate superior returns, these returns are erratic. This is best seen in facet row 1ii; where, while ignoring the market by management utilizing greater memory – implying a higher tolerance for missed expectations – is seen to have a disproportionate effect on the firm's ROI. This occurs because management continues to put resources into growing sales at the expense of margins. Once management considers the market, returns are generally more consistent, a point consistent with the EMF notion that the market acts as a disciplinary device. However, in unison with the results of Figure 42, considering the market leads to lower growth. Therefore, a crucial apex has been identified between growth and returns. Returns for the margin growth firms, while more consistent, also appear to be influenced by their investors. Noticeably, PEG and CE (see facet columns a and c) appear responsible for a wider dispersion in returns and lower growth, an outcome most likely caused by management failing to balance capital growth and returns.

The foundation of an acceptable hypothesis as to how management's reactions to their share price affects capital growth centers around the size and frequency of the share price movements. Namely, the more sizable the movement, the more immediate and larger the adjustment in expectations. Therefore, if a given investor class is responsible for a higher frequency of more significant price movements this will manifest itself in more frequent and larger changes in expectations, noting that no attempt is made at this stage to say whether the expectations are increased or decreased. The commentary regarding Figure 45 addresses the implications of this statement.

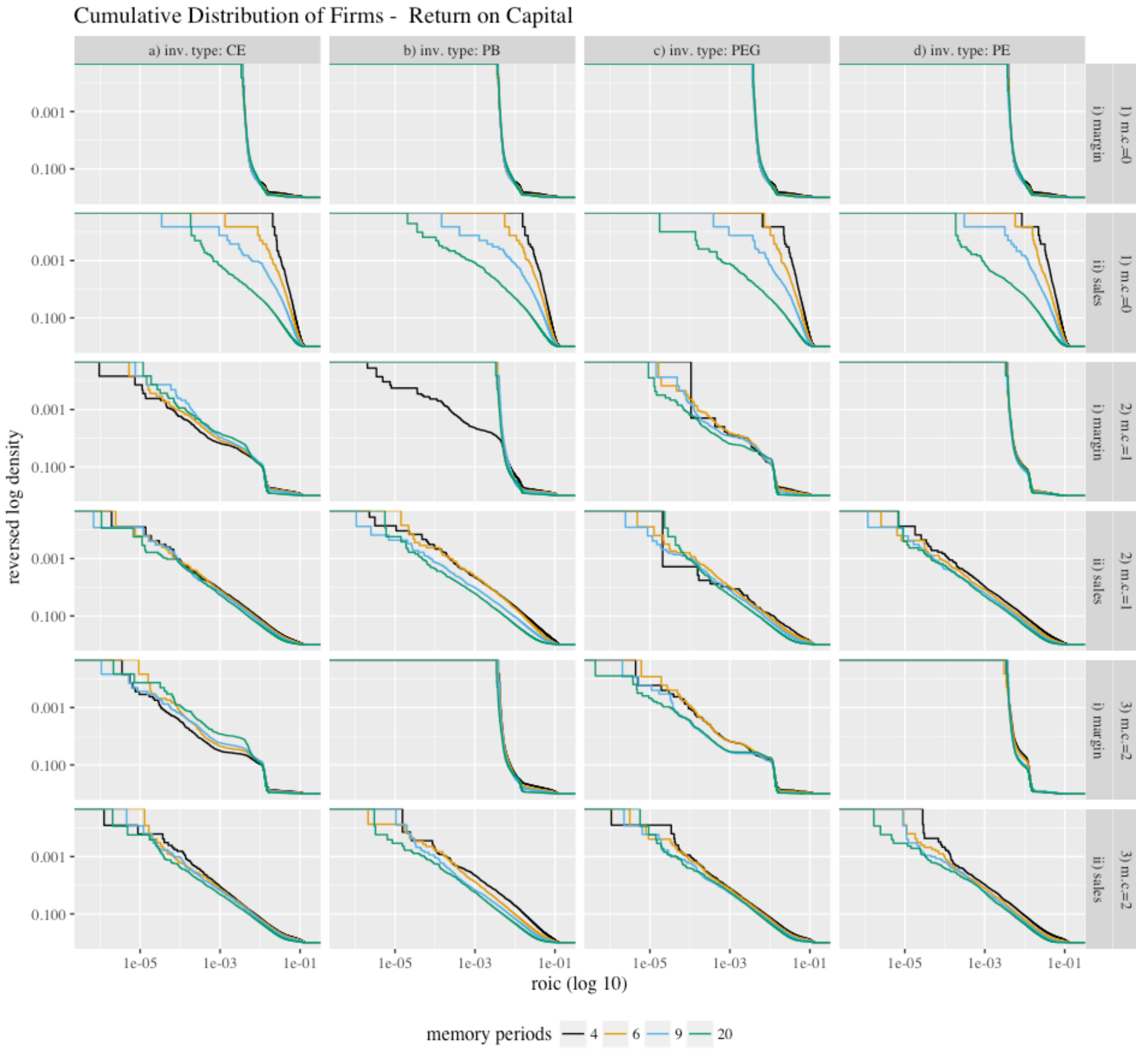

Figure 44: Firm ROI distribution at the completion of the simulation. Facets are differentiated further with the firm type recognized. The lines represent the CDF in log form and are separated by the memory utilized by the agents.

If management has no concern for the stock market, the rate of downward expectation adjustments simply becomes a function of how many consecutive periods management is prepared to under-deliver on their current expectations. Alternatively, expectations increase if the firm overachieves the current expectations by a large margin.

Figure 45 presents the distribution of the percentage change in the index of the artificial stock market. Violin plots are employed to illustrate the behavior because they have the advantage of showing both the distribution and density of the data. The immediate observation is that the CE and PEG investors are responsible for generating more extreme price movements, as witnessed by their respective plots; that is, they tend to be "taller," with higher density in the tails, with a bias toward larger downward movements. A factor in this characteristic is that early in the simulation firms provide investors with an overabundance of investment opportunities, such that the investors do not have sufficient funds to invest as they see fit, which results in muted upward price pressure. However, if the firm fails to meet the investor's requirements, the investor is unconstrained in their selling, which can lead to significant falls. The upshot of this is that there is an asymmetrical relationship, which sees firms tend to experience extreme price moves, with a bias for larger downward price movements. This dynamic will be seen to be crucial to understanding the dynamics of the model as it sends confusing messages to management, with the rate of expectation adjustment and growth affected.

Alternatively, the remaining classes exhibit a more condensed distribution, with PB investors responsible for the least volatility. An important element of the PB return profile is the lack of large negative movements. The upshot of this is that management will not need to increase expectations to satisfy the investors' appetite for growth. A more general repercussion of the distribution is that if there are large extreme movements management become more active in their reactions. The direct effect of higher volatility was seen in Figure 42, where the more volatile markets deliver lower capital growth, hence verifying the likely consequences of a positive feedback loop between management and investors; that is, reacting to a volatile market will lead to lower growth.

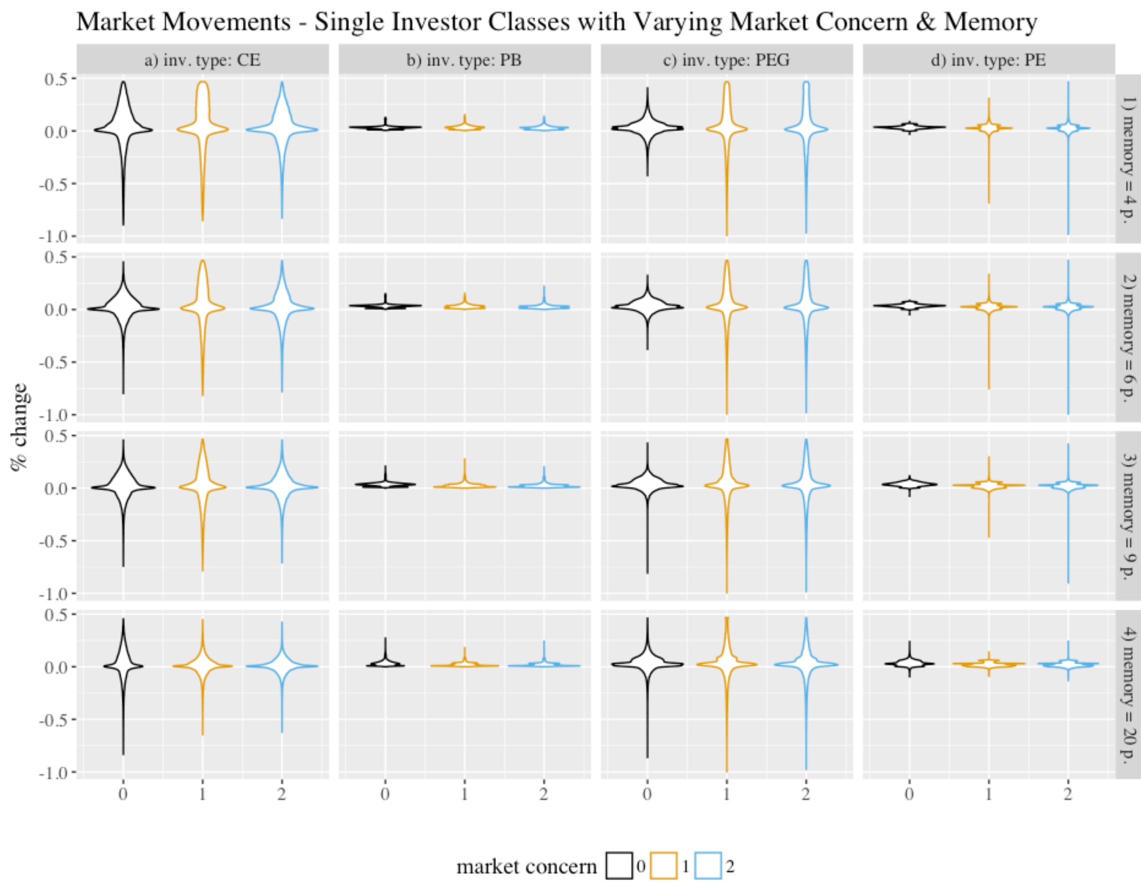

Figure 45: Distribution and density of the percentage change in the market index. Facets differentiate the investors' classes and the memory utilization of the investors and firms. The violin plots represent the returns with management having different concerns for the market.

Another observation from Figure 45 is that the plots vary when management is or is not concerned with the market. While the effect is not consistent across the investor classes – that is, in some instances when management becomes concerned, for example facet d2 and d3, the broadness of the distribution, per the plots height, increases, while in other cases, facets b2 and b3, the broadness of the distribution decreases. This outcome is supportive of the presence of Soros's (2009) principle of reflexivity; that is, investors' actions are affecting the objective structure of the market as management reacts to the market.

Having established the connection between the behavior of investors and management, the analysis returns solely to the dynamics of the firm. Figure 46 presents the temporal evolution of the median growth rate for firms. The first observation, which is consistent with Figure 42, is that, for a given memory length, the growth is unaffected when management is not concerned with the market. The more relevant observation, which explains the Goldilocks result of Figure 42, is that the amount of history management considers, while still ignoring the market, affects the growth profile of the firms. As mentioned previously, the amount of history relates to how long management is prepared to miss their expectations. An interim level of memory – facet rows 2 and 3 – produces a prolonged period of elevated growth, which eventually tapers off. In contrast, less memory – facet row 1 – sees growth decrease more rapidly, while extended patience – facet row 4 – sees an overall lower level of growth. Regardless of the length of the memory used, it appears that the median growth rate can approach some degree of a steady state, which signifies that firms can self-organize and find some optimal level of expectations and resource allocation.

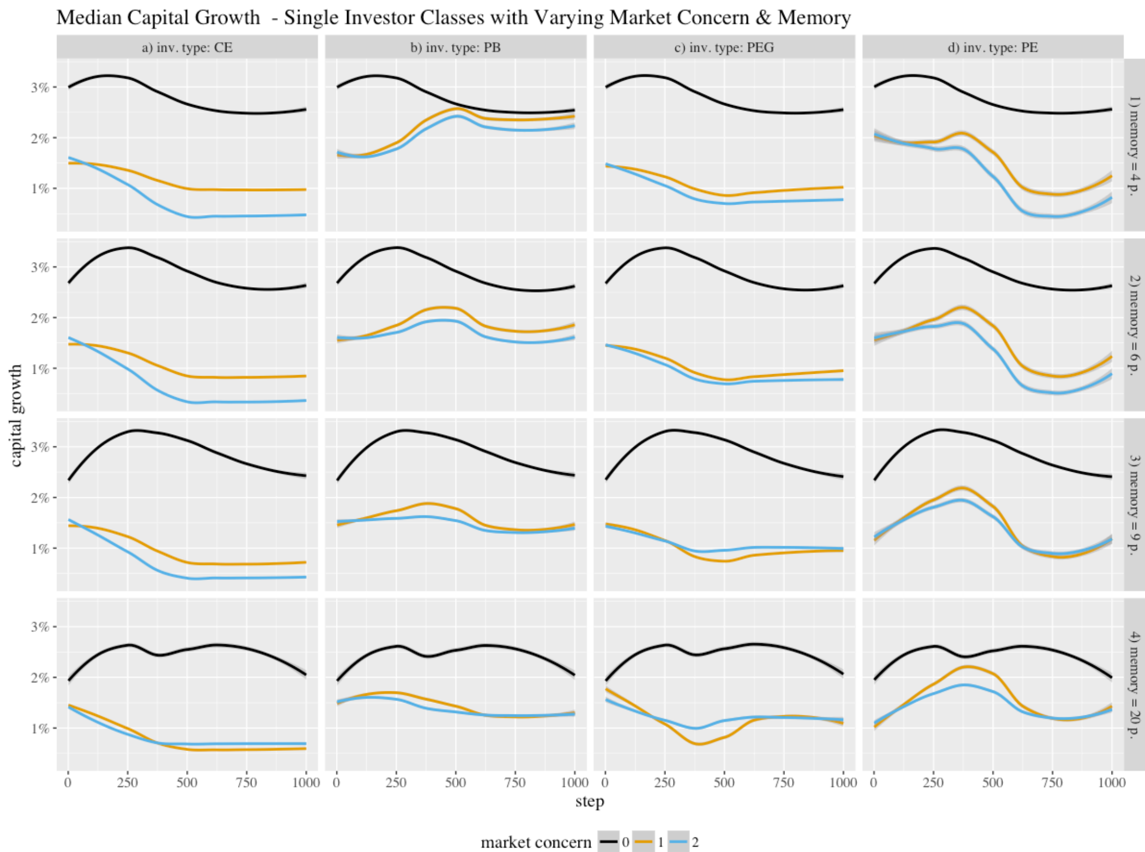

Figure 46: The temporal capital growth profile of the firms. Facets differentiate the investors classes and the memory utilization of the investors and firms. The lines represent the progression of the median capital growth with management having different concern for the market.

Once management becomes concerned with the market the effect of the various investor classes is evident. An environment with more volatile investors – columns a and c – exhibits lower growth, with growth declining from initiation, before eventually leveling out at an inferior level. A heightened concern for the market's reaction amplifies this behavior. Alternatively, the less volatile markets – columns b and d – see growth initially trend up, before declining later in the cycle. This result is suggestive of a structural shift occurring in the market, which in turn is responsible for the transition in growth. Having established an overview of the growth dynamics of the firms, it is now essential to explore the growth dynamics within the population of firms, and more specifically to assess whether the growth rates exhibit Laplacian distributions over the short-term before becoming Gaussian over the longer-term. Sections 1.2.5.2 and 3.2.1.1 provide details of this characteristic of firm growth.

To explore the capital growth distribution of the firms, separate charts are provided for sales growth (Figure 47) and margin growth firms (Figure 48). The reasoning for the separation is that the two firm classes demonstrate distinct behaviors and the overall distribution became disjointed; therefore, it was considered more relevant to discuss the two firm classes separately. The configuration of the figures differs from the previous charts. First the vertical facets reflect management's concern for the market. Next, the horizontal facets reflect the per annum (pa) log growth of the firms for the following periods 50, 25, 10 and 5. The growth was calculated as the annualized log difference of a firm's capital stock at the end of the simulation and its capital value – for example, 50 periods from the end of the simulation. The rationale for this approach is that the curves should, starting at the bottom of the figure, transition from Laplacian styled distributions to a Gaussian distribution.

There are multiple plots within each facet as firms were allocated to sub-groups based on the percentile rank of their capital levels. The distribution for the lower percentiles should exhibit a wider dispersion than the upper percentiles if the implemented model reflects the stylized facts of firm growth. The percentiles were allocated after subdividing the population data based on market concern and memory length. The final note is that Figure 47 and Figure 48 do not share the same x-axis scale, a fact that reflects the superior capital growth of sales growth firms.

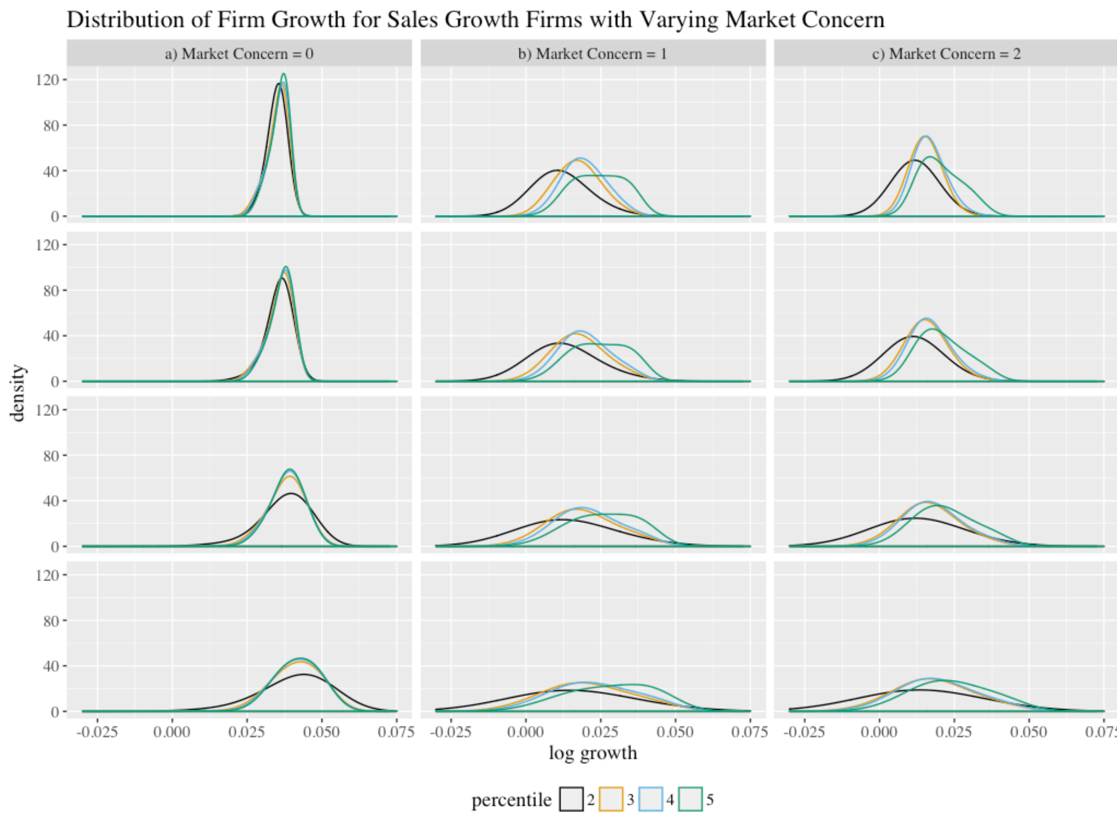

Figure 47: The capital growth distribution of sales growth firms. The vertical facets represent management concern for the market, with the horizontal facets denoting memory utilization. The distributions are split based on the percentile of the firm.

Of note from Figure 47 is the absence of any bottom percentile firms, thus confirming the superior capital growth of sales growth firms. Also, the characteristics of the distribution differ significantly when management does and does not consider the market. When the market is ignored, the plots exhibit a distribution, regardless of the percentile, tightly bunched around the mean. In a result counter to the expected dynamics, the distribution becomes less Gaussian as the analysis horizon expands. In terms of smaller firms exhibiting greater variance in growth, there is, at best, minor evidence of this in facet column a.

Once sales growth firms start considering the market the dynamics, as expected, change. The first observation relates to the overall lower growth in the system – a point previously identified, with the distribution exhibiting a much wider dispersion. This dispersion of growth does reduce overtime, and in a result more consistent with the empirical findings, the distribution does become more Gaussian. A result consistent with what was reported for Figure 37 in Section 3.4.3 is that larger firms have a tendency on average to exhibit higher growth as evidenced by the distribution of the 5th percentile being to the right of the remaining firms.

Figure 48 provides the growth distributions for the margin growth firms. Interestingly, the chart has plots for all five percentiles, indicating that under certain circumstances margin growth firms can achieve significant growth. However, this is very much the exception, so from this point forward the commentary will ignore the 5th percentile. The theme of these results supports the theory that once management becomes concerned with the market, outcomes change. When management does not consider the market, a contrasting result to the equivalent settings in Figure 47 appears. Namely, the distribution for the bottom two percentiles differs from the 3rd and 4th percentiles; that is, the lower two are tightly bunched, with the others more dispersed. This result may occur due to a lack of data in the upper percentiles and contradicts the empirical result, which simply highlights the fact that validating a model of firm growth is not an easy task.

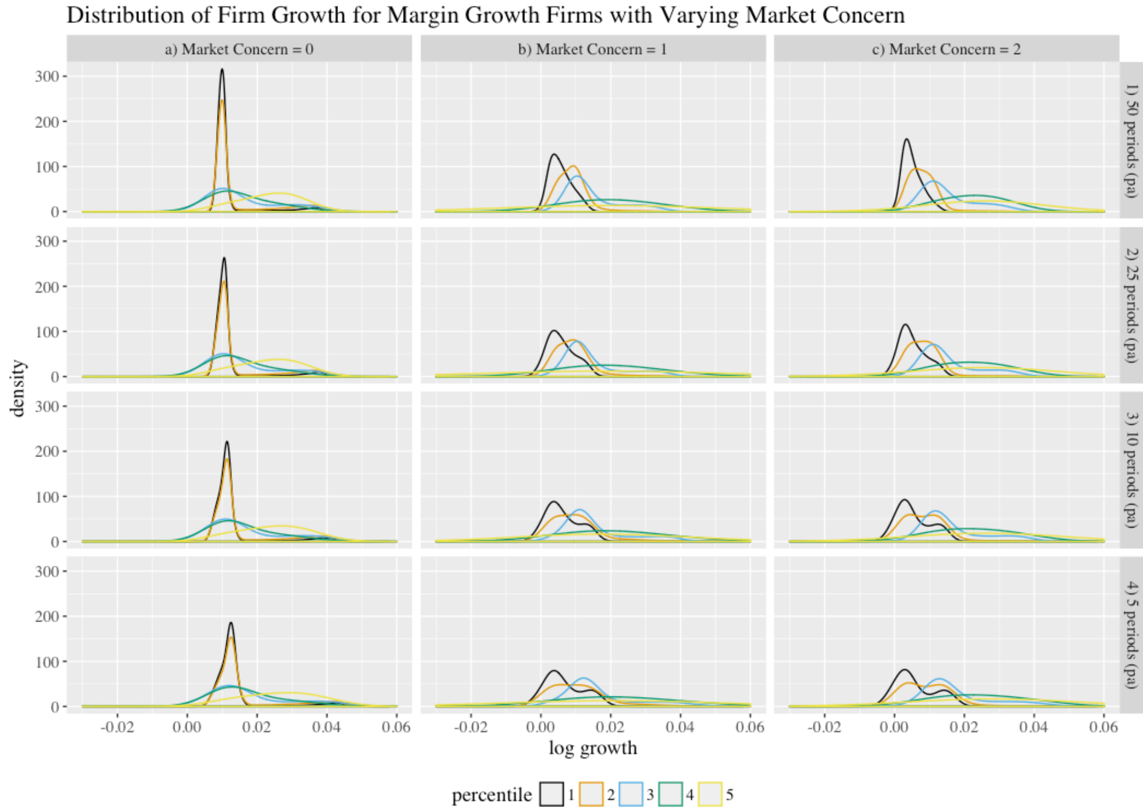

Figure 48: The capital growth distribution of margin growth firms. The vertical facets represent management concern for the market, with the horizontal facets denoting memory utilization. The distributions are split based on the percentile of the firm.

The features of facet columns b and c in Figure 48 – that is, firms responding to the market – are consistent with Figure 47. Specifically, larger firms tend to exhibit, on average, a higher propensity to grow. However, the distribution appears more consistent over time, with the only exception being that the lower percentile tends to exhibit a tighter band of lower growth – see facet c1.

The analysis of the results so far suggests the following: management's concern for the market's reaction is detrimental to capital accumulation; there is a Goldilocks effect where considering an interim level of past information appears optimal; the type of investor in the market has a material effect on the decisions of the firms; and the volatility of the market is dependent on the memory consideration of investors. These findings are all suggestive of a positive feedback loop between the decisions of management and the performance of their firm's share price. The first step in understanding the dynamics of the feedback loop is to look at the rate at which firms meet their expectations, remembering that firms will subsequently adjust these expectations under certain conditions. Figure 49 provides the median percentage of expectation achievement for the firms for the various parameter settings.

From Figure 49 the consequences of firms considering the market's response are clear. However, there are also crucial consequences when management ignores the market. The result of most interests for this circumstance, as illustrated by the black lines, is that the median level of achievement increases over time. This improved performance occurs because management is constantly adjusting both expectations and resources, yet at some points the improvement reaches a limit, implying there is a systematic level of underperformance in the environment. Critically, management's tolerance for missing expectations influences the rate of expectation achievement. When management has little patience – facet row 1 – there is a higher rate of performance; alternatively, when tolerance is too high – facet row 4 – there is a lower rate of achievement. Intermediate tolerance produces levels of achievement between the two extremes. There is a clear link between this dynamic and capital growth, per Figure 46. To address this issue further an understanding of how management adjust their expectations, (see Figure 50) is required.

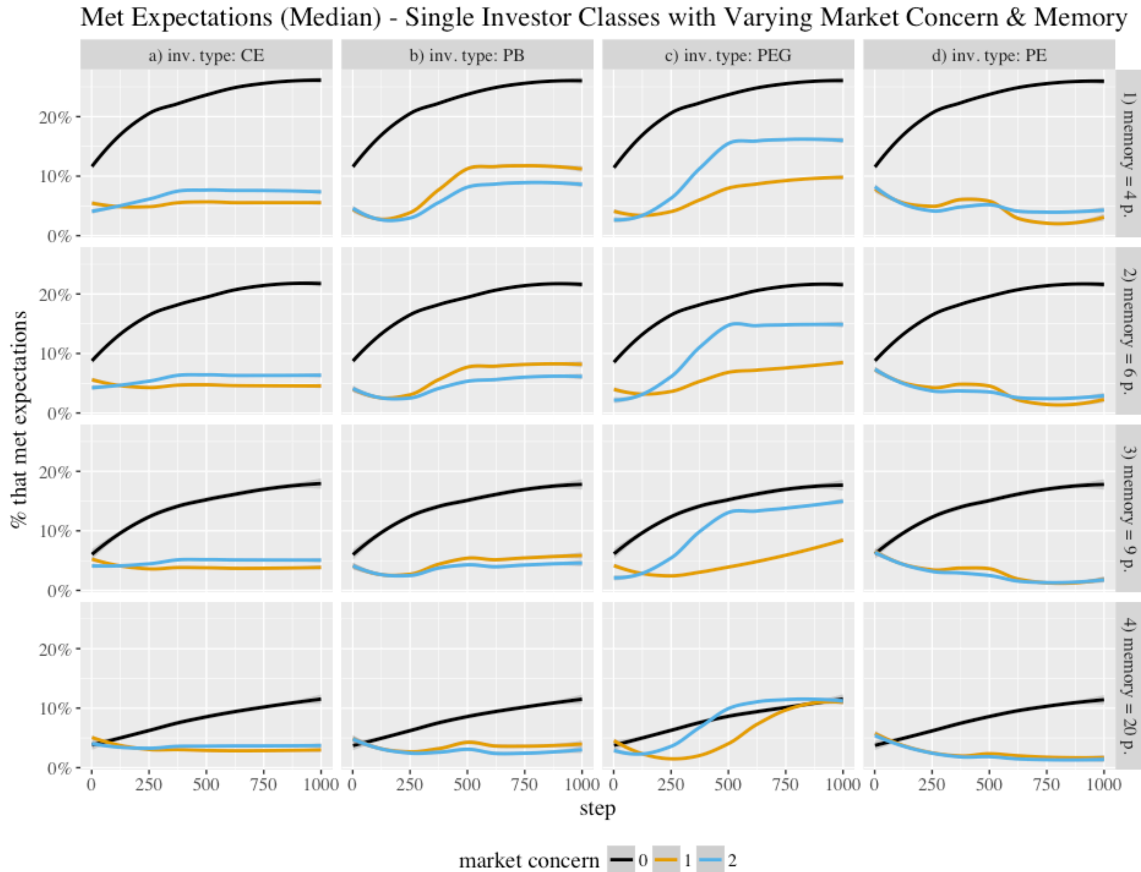

Figure 49: The progressive achievement of firms meeting their expectations. Facets differentiate the investors' classes and the memory utilization of the investors and firms. The lines represent the various percentage of firms achieving their expectations with management having different concern for the market.

Consistent with the previous analysis, once management considers the behavior of their share price the type of investor becomes material. In a market of CE investors – facet column a – firms never improve their rate of achievement. This environment also saw the lowest capital growth, yet the most volatile market behavior. For a market of PB investors – facet column b – there is an initial dip in achievement before the situation improves. The peak in expectation achievement parallels the characteristics of capital growth in this market (see Figure 46). Facet column c provides the results for an environment with PEG investors. Previously, this environment was identified as achieving the lowest levels of growth, yet had relatively high price volatility. This finding is suggestive of firms tending to, on average, reduce their expectations, which results in a rapid improvement in their performance, albeit at a lower growth rate. The benefit of lowering expectations is seen to eventually taper off. The adjustment is affected by the amount of history considered by the investors, as discussed concerning Figure 50. For PE investors, the rate of achievement declines monotonically, and may be related to the relatively poor capital growth performance of firms in this environment.

A fundamental element of the model is how firms adjust their expectations after assessing their performance in achieving those expectations and possibly the market's reaction. Figure 50 illustrates the median changes in expectations, both up and down. The interpretation of these charts provides meaningful insight into the previously discussed dynamics. From Figure 50 we gather insights into why the Goldilocks effect emerges when management ignores the market. For intermediate levels of memory, the net decline in expectations – seen by the solid black line lying <u>above</u> the bluish green dashed line – is reversed with the net change becoming positive around period 250, where the black solid line now sits <u>below</u> the bluish green dashed line. The significance of the reversal is that it occurs when the system had achieved peak growth (see Figure 46). Therefore, despite underachieving early expectations firms delivered higher growth. Vital to comprehending the previous dynamic is to recognize that firms increase expectation because of a substantial overachievement in a signal period, while they take varying lengths of time to reduce expectations that they do not achieve.

Figure 50: The evolution of firms changing their expectations, both up and down. Facets differentiate the investors' classes and the memory utilization of the investors and firms. The lines represent the various percentage of firms changing their expectations with management having different concern for the market.

Concerning the extremes, an alternate dynamic exists. For the impatient management – facet row 1 – there is a more pronounced early decline in expectations. The ramification of this finding is that management has not sufficiently explored alternative resource allocations before deciding to lower expectations; hence, there is a structural downward shift in expectations. This situation does not revert in later periods; therefore, the environment returns lower growth. For the most patient management – facet row 4 – while they ultimately experience a net increase in expectations, this occurs much later in the cycle. This dynamic is the result of management prolonging the decision to reduce their initial expectations, thereby striving to achieve unachievable objectives. The ramification of this delayed response is evident in Figure 46, where once adjustments occur and net expectations become positive, capital growth improves.

The above dynamic, combined with results of Figure 49, suggests that there is an optimal time to allow firms to evolve such that they have a higher tendency to overachieve lower expectations. An explanation for the existence of an optimal time period to allow firms to adjust their resources is that the model is initiated with firms endowed with a low(high) level of ability yet with high(low) initial expectations and it requires time for these firms to undertake the necessary adjustments – all of which occurs endogenously. If this time is too short, firms will reset their expectations too far below their potential, Alternatively, if firms take too long, they do not optimize their growth during the initial stages of the simulation.

Once management starts considering the response of investors it is seen that management are relatively more reactive when PB and PE investors exist. It is no coincidence this behavior matches the rate of capital accumulation seen in Figure 42, noting that all levels of growth are inferior to the scanerio where management does not consider the market. This result initially appears counter-intuitive because the CE and PEG investors generate more extreme index changes, meaning that firms would receive a higher volume of signals, thus, requiring more adjustments. In a result – which is a possible artifact of the model – what occurs is that in a market with PB investors, and to a lesser degree PE investors, there is consistently heavy trading early in the simulation.

This behavior results in firms having to react constantly but in this situation, the price changes are not as extreme, which mean crtically that the expectation revisions are more subdued. However, at a certain point, the investment decisions of these investors fade; therefore, price movements diminish in size and firms are not required to react as frequently and they return to their internal review process. This dynamic is responsible for the reduction in the rate of change in expectations and is explored again in Figure 51.

Regarding the CE and PEG investors, their behavior is more inconsistent but they are responsible for causing larger variations in returns and remain influential throughout the simulation. Therefore, in aggregate, firms are continually faced with deciding how to react to these investors. Crucially, the effect of a firm deciding not to ride the market higher manifests itself at this point. This is because firms are prone to receiving large positive price signals in a CE or PEG environment, and if they choose not to ride the market higher, and have missed their expectations continually, they will downgrade their expectations. Crucially, this downward adjustment is amplified by the large price signal; therefore, firms tend to overcompensate and reduce expectations too much, because of placing too much faith in the price signals from the market.

Figure 51 provides the evolution of the median firm PB and PE ratios. Regarding the verification of the model, the medians for the PB and PE ratios should settle within the bands assigned to the investors. For example, for facet column b, the median settles around 1.4 regardless of the other settings. Alternatively, the PEG investors exhibit a dynamic which highlights an interesting dilemma. In rough terms with the median growth rate of the firms being 3%, when firms ignore the market, the PEG ratio should see the

PE in the range of 3, which occurs, therefore again validating the model. However, once firms consider the market, the full extent of the feedback mechanism becomes evident. In this scenario, it was seen that growth rates are impaired as management erroneously interpret the price signals from the market and this leads to lower growth. This dynamic is what is responsible for the PE ratio in a PEG environment being so low.

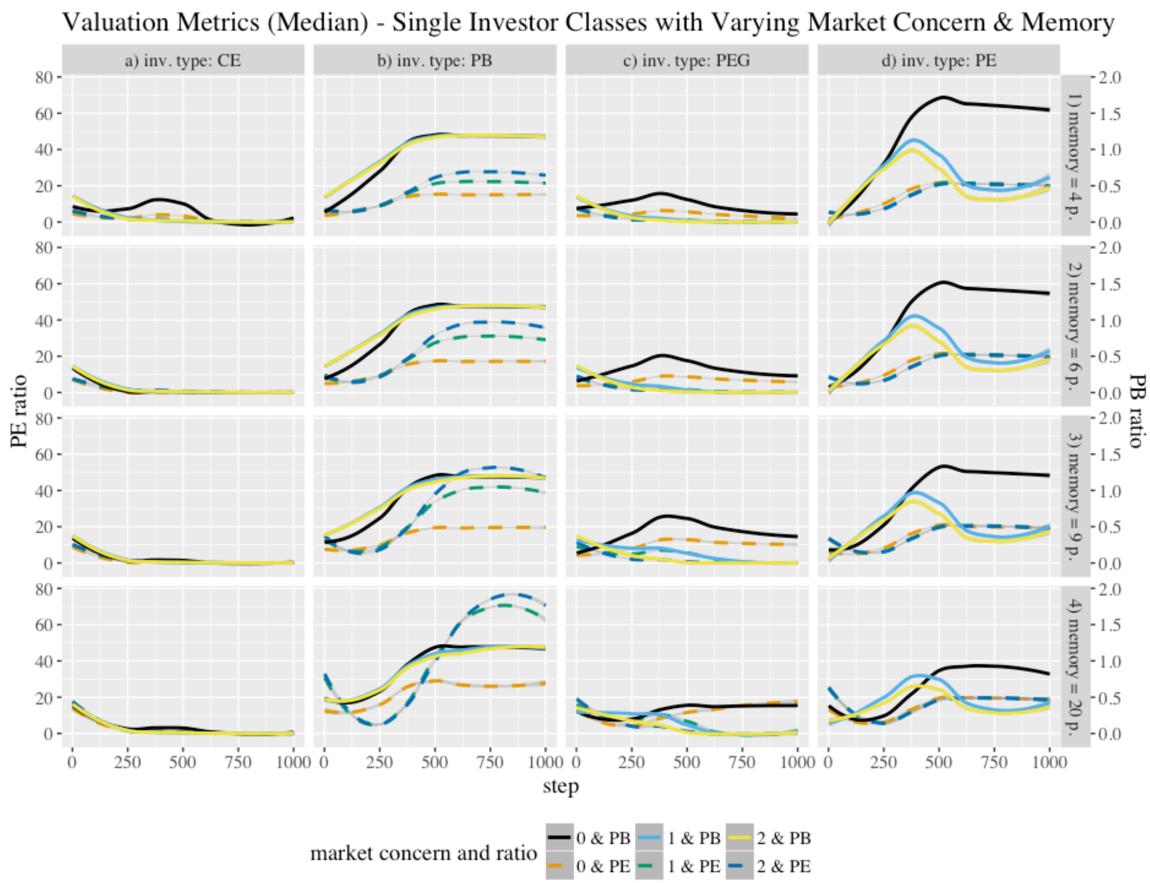

Figure 51: Evolution of the PE and PB ratios of firms.

For the PE and PB investors the steady state as investors become synchronized with the firms. This is situation they ultimately run out of high conviction investment opportunities. In isolation, this appears a shortcoming of the model. However, once multiple investors are introduced, it is anticipated that this outcome will diminish. Additionally, it is not entirely unreasonable that equity investors at some point become constrained. The more important consideration is how the restricted price signals affect decision-making within the firm.

The final piece of analysis regards how the stock market behaves under the four separate investor classes and whether there are any dislocations between the capital accumulation of firms and how much investors are willing to invest. Figure 52 provides this information, with the first point of note being that when firms do not react to the market the index, except for one scenario, achieves superior growth. However, there are some significant discrepancies. Firstly, facet column a, the CE investors appear to, on average, cease purchasing stocks despite the firms still growing, even when management ignores the market. The rationale for this outcome is that when firms eventually optimize their expectations and resource allocations their earnings growth no longer meets the requirement of the CE investors, who require a constant stream of growth. This fact is confirmed from facet column a in Figure 46, where it is seen that firms settle into stable growth. At this point the stochastic processes involved in determining growth would see the firms regularly switch from positive to negative growth, thus disrupting the trend. This moderation in investing also occurs with the other investor classes and corresponds to the investors finding a steady state in terms of their investment benchmark. Crucially, if firms ignore the market, this dynamic does not affect firm growth, with the effect seen in a higher terminal index level.

The dynamics of Figure 52 lead to a significant finding, one that captures the complete essence of the research questions posed for this chapter and completes the picture of how a feedback loop between the agents exhibits itself. Starting with the situation of firms referencing the market in their decision-making process, the amount of history that the investors consider is influential in determining the behavior of the index (a proxy for the share price of all firms), which in turn affects the capital growth of the firms, thus completing the loop. This result is seen by starting at facet row 1 and moving down to row 4 and observing the declining terminal index values as the amount of history utilization increases. A vital inflection dynamic also appears in the index, and occurs around the time when firms have moderated the changes in their expectations and their growth rates have stabilized. Therefore, dynamics of the index imply that if investors are too cautious in updating their ensemble averages – either the EPS or book value of their investments – it affects their willingness to stay invested in their stock or establish their conviction in adding to their existing holdings. This behavior then sends confusing signals to the firms, compromising their decision-making processes and capital accumulation. This result tends to contradict the concerns regarding investors exhibiting short-termism. However, as discussed in Section 3.7.2, a more dynamic investor decision-making framework may provide superior insights into this topic.

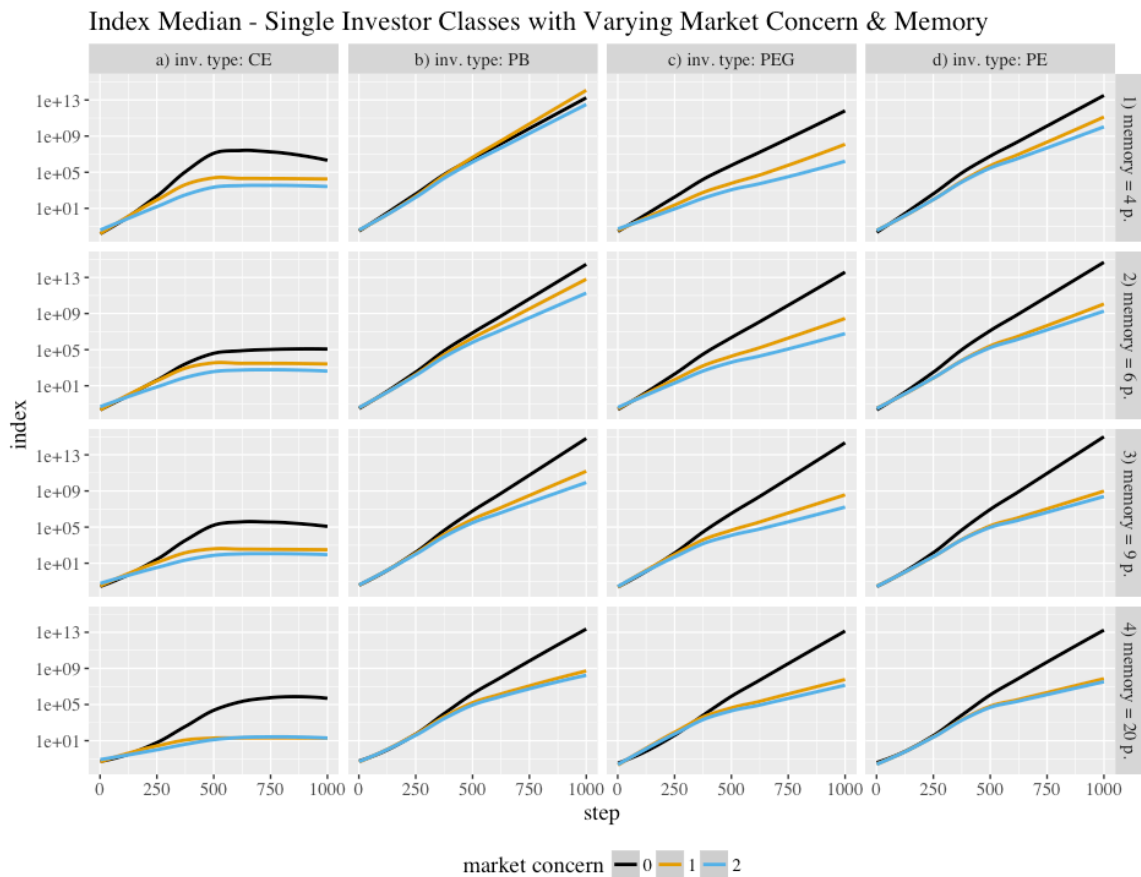

Figure 52: Temporal growth for the market index with single investor classes. Facets differentiate the investors' classes and the memory utilization of the investors and firms. The lines represent an index where management have differing concern for the market.

3.6.2.2 Multiple Investor Classes

Having established the baseline behavior of the model, this section reports on the outcome of introducing multiple investor classes into the ecosystem. The rationale for this step is to assess whether having multiple investors amplifies or restrains the behaviors reported for the single investor case. This scenario is more akin to the real-world markets and is consistent with the theories of Lo (2017) and Shiller et al. (1984)

that different investor classes exist in the market, with the dominant class switching with a possible consequence being a material market disruption.

Four investor combinations are assessed in this section. The first has all 5 investor classes operating. This situation and the second scenario of a PB investor mixed with a price chartist (CP investor) introduces the price chartist. The reason the CP class was excluded from the single investor class analysis will become evident. The other combinations see fundamental investors pitched against each other. No commentary will be provided regarding the results of management ignoring the market because the dynamics do not change from those of the single investor class.

The more pertinent point is what the return profile of the various investor combinations looks like. Figure 53 provides this for the multi-investor environments. The relevance of the return profile is that it is responsible for signaling to management the market's satisfaction with its performance. From Figure 45 it was seen that the return profiles of the various investor classes were divergent, with the main factors responsible for the higher volatility being PEG and CE investors, management's concern for the market, and the memory usage of all agents. Once investors are combined in the market an even greater variance in returns appears. At one end, where PB and PE investors, facet column c, are the sole participants, the return variation appears modest. At the other end, the inclusion of the CP investors – facet columns c and b results in the returns showing more extreme behavior. With the previously summarized dynamics of the model (see Figure 41), it is anticipated this finding will result in significant differences in the capital growth across the various settings.

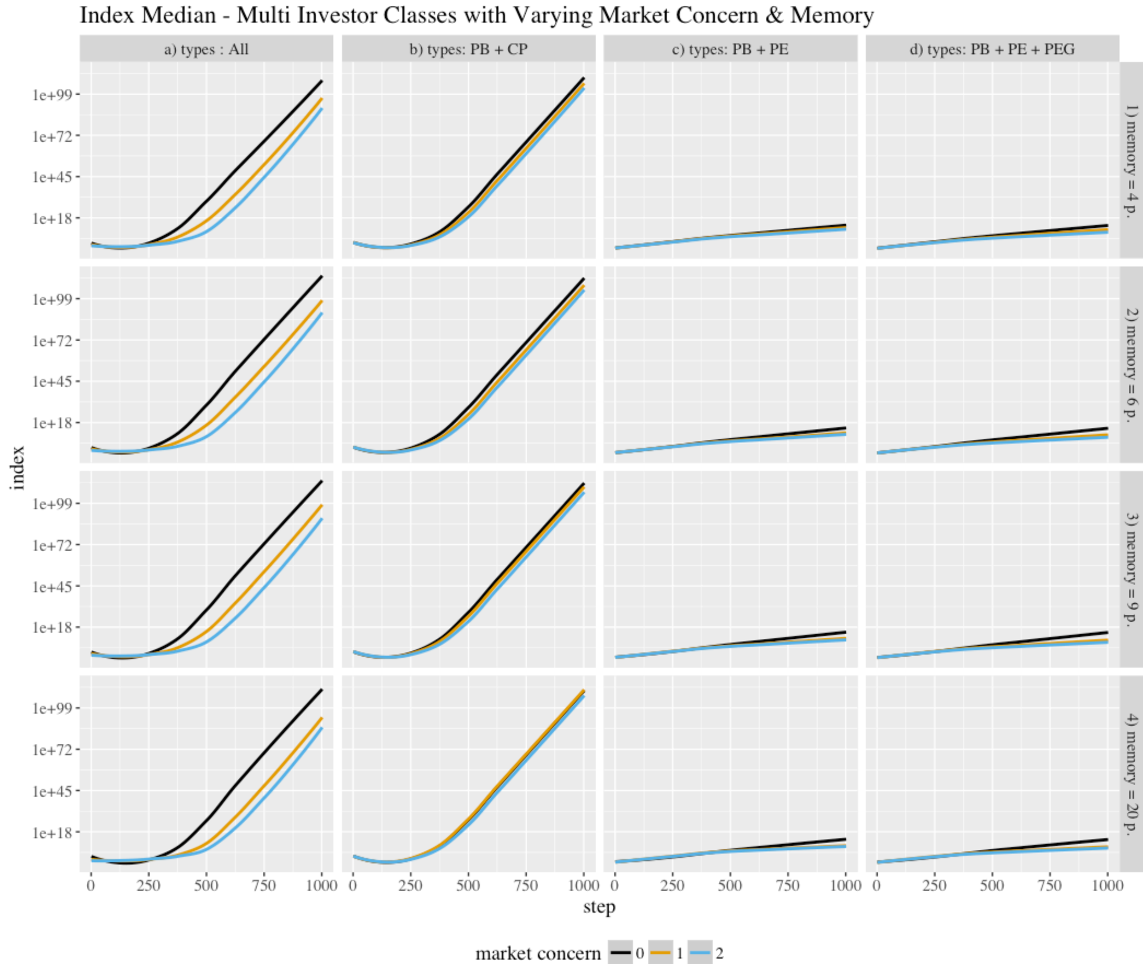

Figure 53: Temporal growth of the market index with multiple investor classes. Facets differentiate the investors'classes and the memory utilization of the investors and firms. The lines represent an index where management have differing concern for the market.

Returning to a market of PB and PE investors, the return profile is again affected by management becoming concerned with the market. In an important result, by combining these investors, the level of volatility – compared to a sole PE investor – reduces. This implies that value investors can balance out the more extreme behavior of growth investors, most likely because the book value of a company is more stable than its earnings. The ability of a PB investor to subdue growth investors diminishes once a PEG investor is introduced. This outcome would be partially due to the weight of money favoring growth investors but also that the PEG investors are more volatile than PE investors.

The ability of a CP investor to amplify any trend is seen by contrasting Figure 54, columns a and d. While the distribution shapes are somewhat similar – that is, there are some extreme moves but the bulk of the distribution is around 0 – the presence of a CP investor results in more extreme movements. The most extreme upward movements are no doubt the result of the CP investor sitting out of the market for several steps, therefore accumulating the risk-free asset via dividend payments before eventually returning and investing their enhanced cash balance. This effect is also seen in column b, where the distribution appears almost bimodal. Again, this implies that the CP investor must be sitting out of the market, and once the PB investor causes the price of a share to increase the CP investor follows.

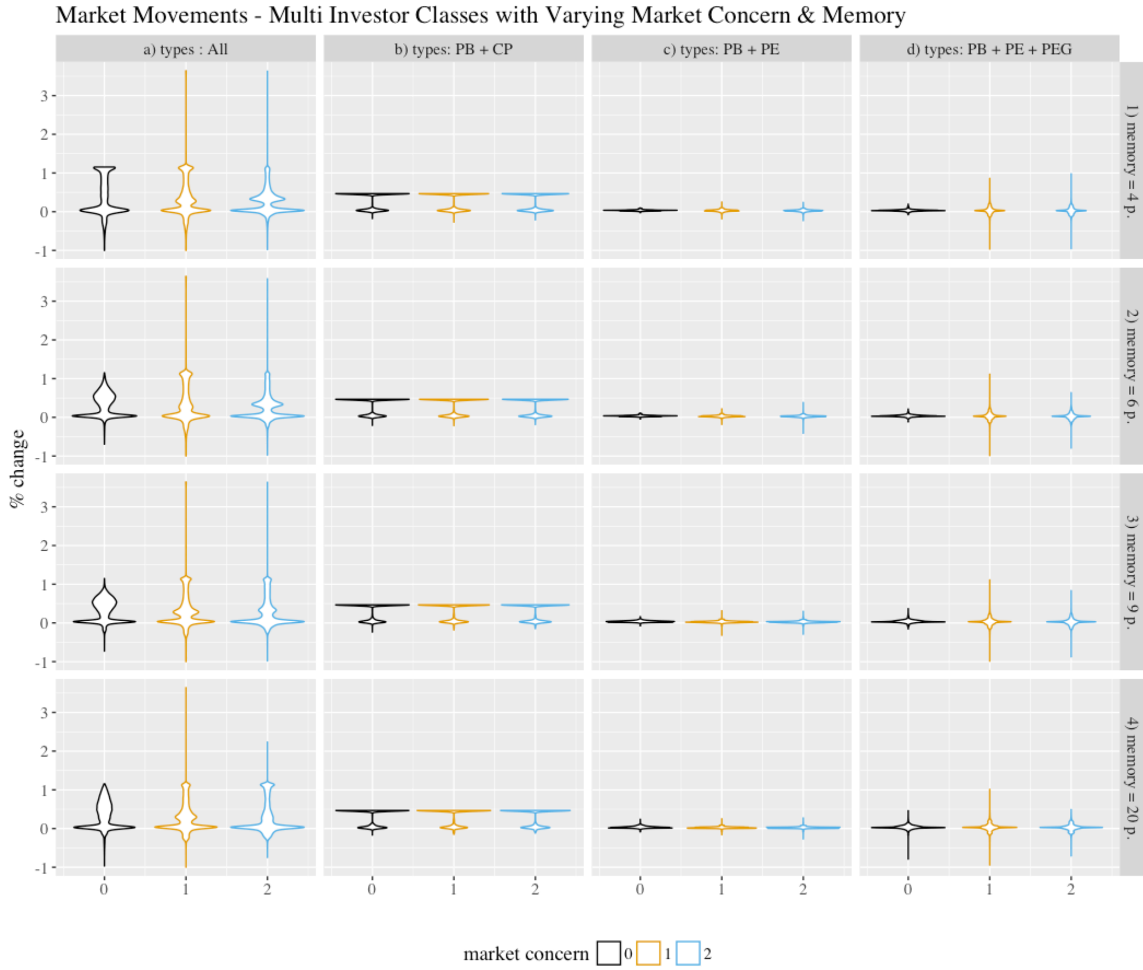

Figure 54: Distribution and density of the percentage changes in the index. Facets differentiate the investors' classes and the memory utilization of the investors and firms. The violin plots represent the returns with management having different concern for the market.

The relevance of the return profiles of the market relates to how it affects the behavior of the firms. Figure 55 presents this data. In the comments for the single investor environment and Section 3.6.1, it was noted that more extreme price movements lead to a greater number of expectation changes, and this delivered lower capital growth. For the less volatile environments the initial stages produced more changes, before settling down later in the simulation. Alternatively, the more volatile markets remain consistently unstable; thereby resulting in the rate of expectation changes remaining constant, resulting in more total changes. Therefore, from Figure 54 it is anticipated that the environments containing only fundamental investors will produce less changes in expectations across the simulation but more in the early stages.

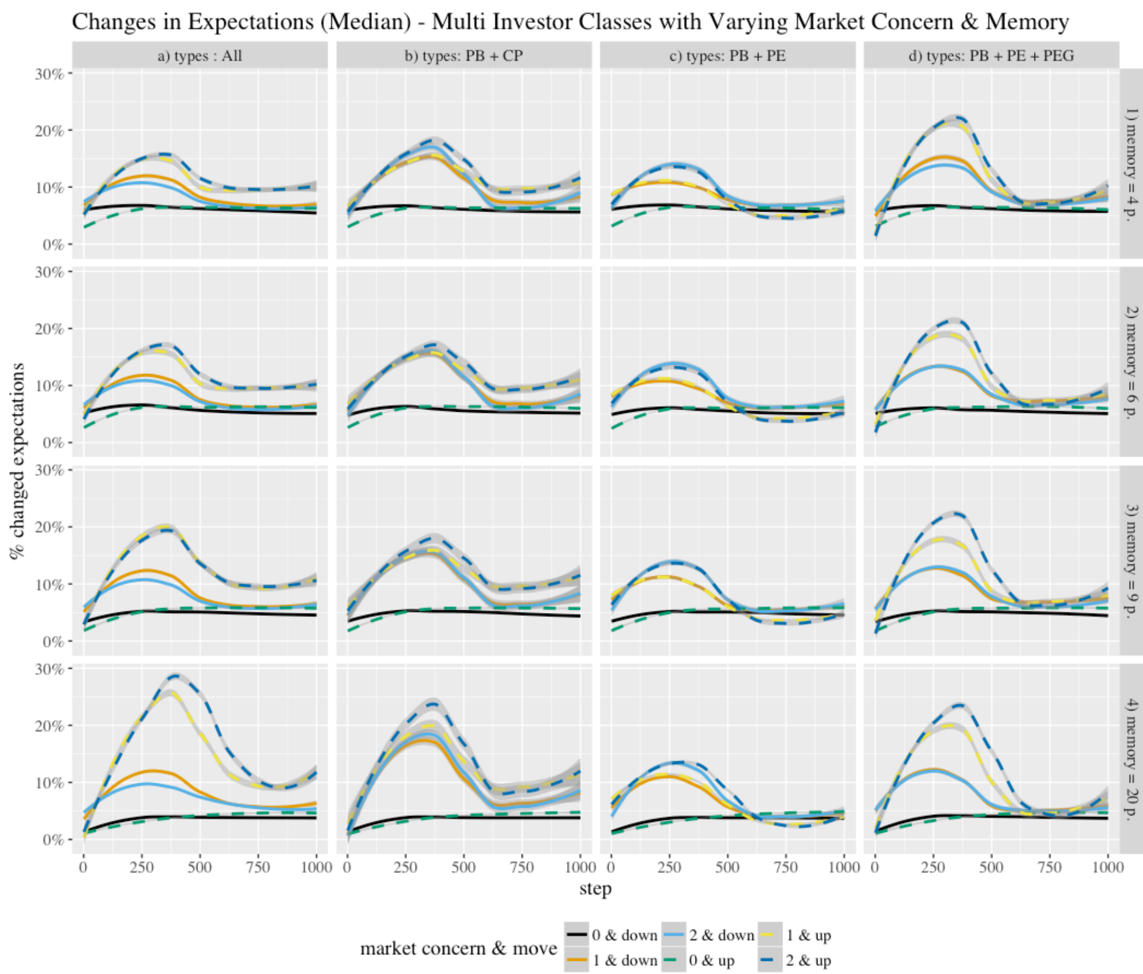

Figure 55: The evolution of firms changing their expectations, both up and down. Facets differentiate the investors classes and the memory utilization of the investors and firms. The lines represent the various percentage of firms changing their expectations with management having different concern for the market.

The other factor to consider is the memory level of the investors, with a higher level of memory meaning more changes. The findings from Figure 55 are consistent with these expectations. The anticipated behavior is seen in facets columns c and d, with there being a material net increase expectations in the first half of the simulation.

Regarding the environments with the CP investors (facet columns a and b), they also exhibit the initial bulge in expectation changes. However, the rate of change does not return to a level comparable to when management does not consider the market. Therefore, in general, firms remain in a reactive state and continue to alter expectations in response to the market. Having identified the behavioral characteristics of both the investors and the firms, the focus turns to how these behaviors have affected capital growth. Figure 56 presents the capital accumulation under the various conditions.

The destructive nature of the CP investor is the most notable observation from the results. This is most apparent in column b, where the PB and CP investor interact. In the single investor case the PB investor environment saw the highest levels of capital accumulation. However, with the introduction of the PB investors this reverses. The mechanism responsible for this result is that after experiencing a material share price gain, management decide not to boost expectations to ride the market higher (see the management decision tree in Figure 39); they misread the positive signal and reduce expectations too much, thereby delivering inferior growth. This result perfectly articulates the negative effect of the positive feedback loop between the market and firms by highlighting the dangers of management misinterpreting the market.

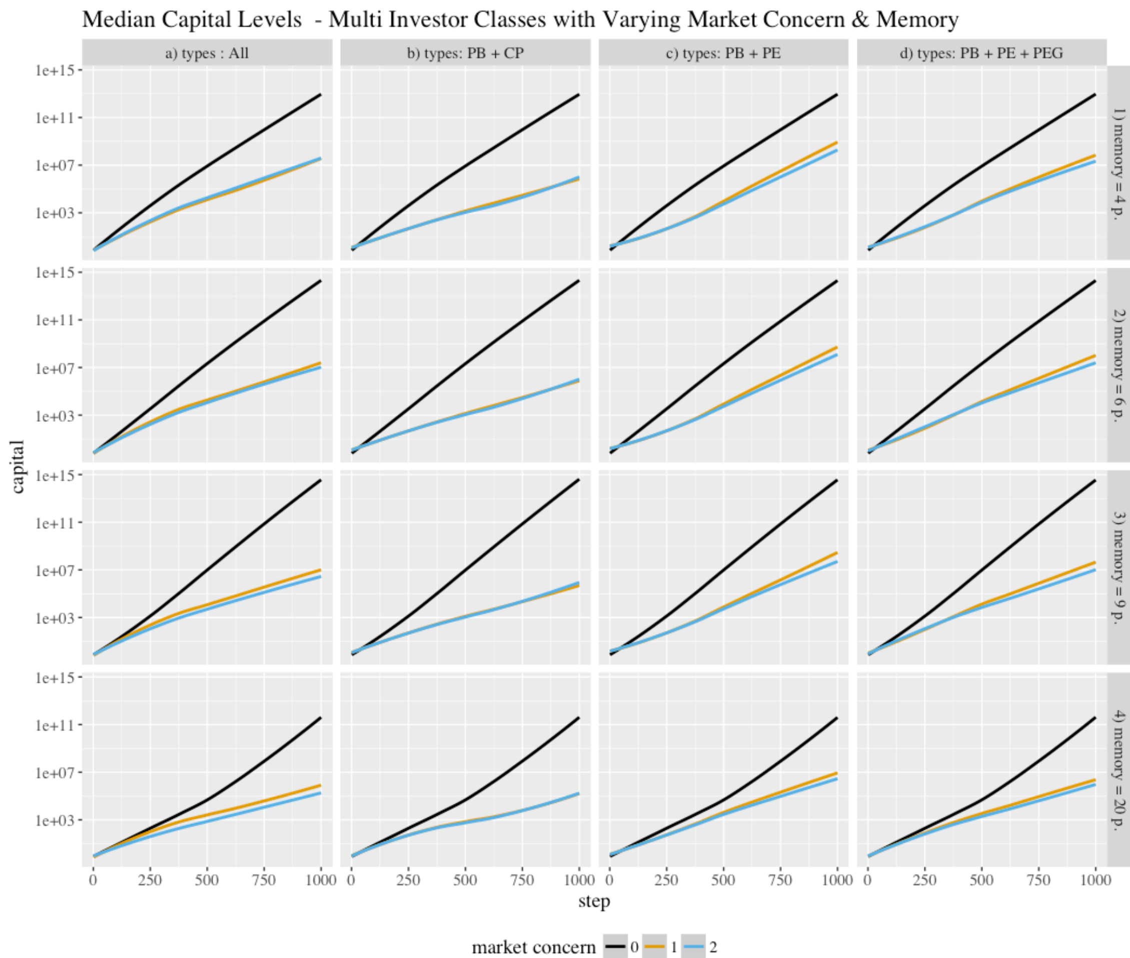

Figure 56: Temporal growth in the median capital levels of the firms. Facets differentiate the investors' classes and the memory utilization of the investors and firms. The lines represent the progression of the capital levels with management having different concern for the market.

Figure 57, for completeness, provides the distribution of capital amongst the firms. The results remain broadly consistent with those from Figure 43; namely, the number of past periods investors consider affects the width of the distribution and the gap between the sales growth and margin growth firms diminishes under certain conditions. The clearest example of the latter is facets c2 and c3. In these scenarios, it is a case of the margin growth firms achieving capital levels equivalent to when management ignores the market and the sales growth firms being penalized by the environment, thereby delivering a less than optimal level of growth. Given that no anomalies appeared in the evolution of the median capital level or the distribution of capital and the dynamics are now understood, the charts pertaining to the dynamics of firm growth are not provided.

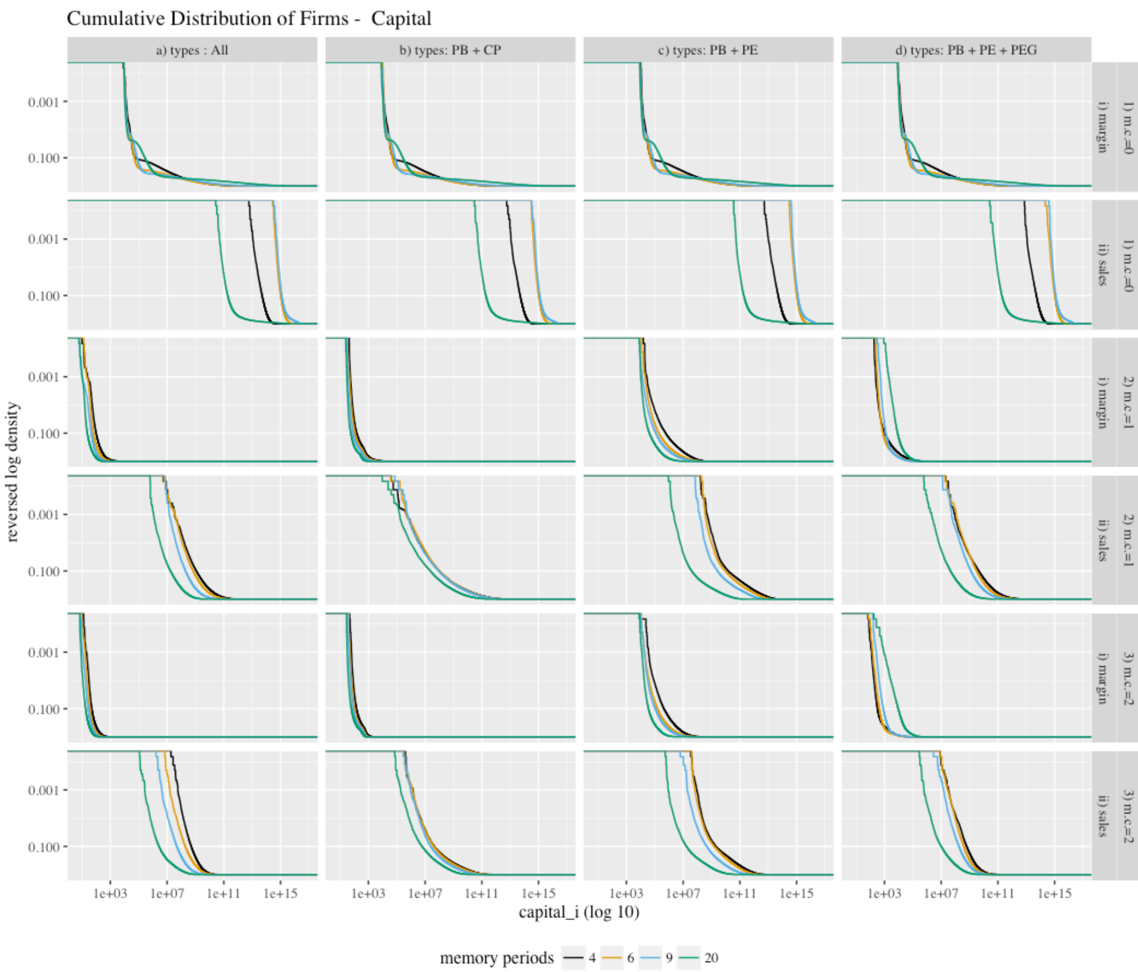

Figure 57: Firm size distribution at the completion of the simulation. Facets are differentiated further with the firm type recognized. The lines represent the CDF in log form and are separated by the memory utilized by the agents.

3.6.3 Reintroducing the Curse of Dimensionality

A topic not discussed thus far is to strike the right balance between developing a model that takes sufficient advantage of utilizing an ABM, while not overcomplicating the model such that dynamics responsible for creating the results are impenetrable. Eberlen, Scholz, & Gagliolo (2017) highlight this point when they suggest that "a model with many parameters will be of limited theoretical value." This issue is captured via the "curse of dimensionality," with the proposed solution provided via Occam's razor (or the law of parsimony). The prescribed approach is to restrict the model's parameters to only those that are strictly necessary to test the hypothesis. To achieve this in the model detailed in Section 3.5 the decision was made to implement the model with various equations that did not directly require a specific exogenous parameter. Examples of these equations are the ones related to the realization of the firms' effort (see Equation 32), reinvestment rates (see Equation 40 and Equation 41), and changes to expectations (see Equation 48). The downside to the implemented approach is that it requires an accurate specification for each of the equations. In turn, the dynamics of the model may be a function of the model's design (or artifact), rather than coming from a genuinely emergent bottom-up process. To address this issue. Sections 3.6.3.1 through 3.6.3.2 implement a "simplified" model and report on some preliminary results.

3.6.3.1 The Modified Approach

The implementation of a simplified framework required multiple steps. The first step was to identify the processes deemed as possibly overcomplicated. Next was to design and implement an alternate framework, before finally testing the changes. The modified processes and the specific changes are summarized in Table 16, noting the processes related to those illustrated in Figure 38. A common component among the changes was to introduce new variables (such as the *expectation_adjuster*), thereby complicating the parameter space. However, this was a necessary evil because each of the three components was vital to testing the dynamics of the expanded market ecosystem.

Table 16: A summary of the revised processes

Process	Change
Process 1: Reinvestment Rate	As part of deciding how much effort to apply to achieve their primary effort, firms set their reinvestment rates, and by default their dividend payout ratio (see Equation 40 and Equation 41). A new global variable (*reinv_ratio*) is introduced to achieve the simplification of the reinvestment process. The change means that there is a homogeneous reinvestment rate, and payout ratio (*1 - reinv_ratio*), across the firms.
Process 2: Realization of ability	Per Equation 32, the realization of each firm's ability was dependent on a stochastic process where the standard deviation of the function was in turn dependent on the amount of effort the firm applied. This change replaced Equation 32 with a global variable named *effort_std_dev*. Therefore, each firm's effort realization comes from an equal Gaussian distribution.
Process 8: Updating expectations	The area of greatest possible contention is the process by which firms adjust their expectation. While the process is justified (see Section 3.5.4.5), the functional form (see Equation 48) by which firms adjust expectations is an area of further refinement. Specifically, efforts should be made to inform the function with the use of real-world data; Section 4.3.1 discusses this issue. With the expectation process a vital component there was no possibility of removing the process. Instead, the model utilizes a new global variable, *expectation_adjuster*, which is bounded between 0 and 1. The purpose of the variable is that when firms are required to adjust expectation, a process which remains consistent with Section 3.5.4.5, firms increase expectation by dividing their current expectations by the value of the *expectation_adjuster* variable. Alternatively, expectations reduce by multiplying a firm's current expectation by the *expectation_adjuster* variable.

A possible objection to the implemented approach is that by introducing three new global variables the model, and its associated parameter space, has become more complicated, therefore, making a comparative analysis unfeasible. To overcome this objection the BehaviorSearch functionality in NetLogo was utilized to find the optimal settings for each of the newly introduced global variables. By way of a brief background, BehaviorSearch allows the use of genetic algorithms and other heuristic techniques to examine the parameter space to find the parameter settings that produce the highest fitness for a predetermined output variable. For assessing the changes to the model, the index value was chosen as the variable of interest because it is a function of both the behavior of the investors and the firms.

Table 17: The parameter settings for the simplified parameter sweep

Variable	Setting	Interpretation
reinv_ratio	0.90	One of the greatest challenges of the model was the distribution of dividends to investors and allowing investors to reinvest those funds. Too much reinvestment would see the investors starved of capital, and a too-high payout would see the firms starved of capital. The indentified setting indicates that the model's environment is better served by firms reinvesting a majority of their profits.
effort_std_dev	0.001	An unsurprising result as it means that firms will experience minimal variation in the realization of their effort.
expectation_adjuster	0.85	Given the utilization of this variable the discounting/growth of current expectations is not excessive.

3.6.3.2 The Results of Simplifying the Model

Having established the settings for the new global variables a parameter sweep consistent with Section 3.6.1 was run with the simplifications turned on and off. As seen from Figure 58 and Figure 59 this process involved testing each component individually, before testing the combined effect of using a fully simplified model against the original model. A further point regarding the comparative analysis was that it was done using a PB investor and then a PEG investor. By way of explanation for Figure 58 and Figure 59, the vertical facets now reflect the process that has been simplified: that, is facet a relates to the use or otherwise of the *effort_std_dev* variable; facet b relates to the use or otherwise of the *expectation_adjuster* variable; facet c relates to the use or otherwise of the *reinv_ratio* variable; and facet d relates to using, or none of the simplified variables. The vertical axis is the measure of the capital, with the facets representative of the length of history the firms and investors utilize.

There is one glaring outcome from the comparative analysis, which is the substantial difference in the median capital level of the firms once all simplifications are utilized (see facet d1). This outcome appears to be an emergent outcome because compared to utilizing the simplified expectation adjustment process (facet b) the accumulation of capital is inferior. Alternatively, when the simplified dividend process is utilized (facet c), the capital accumulation is superior but not to the extent of the results in facet d. Therefore, what process can produce such a result?

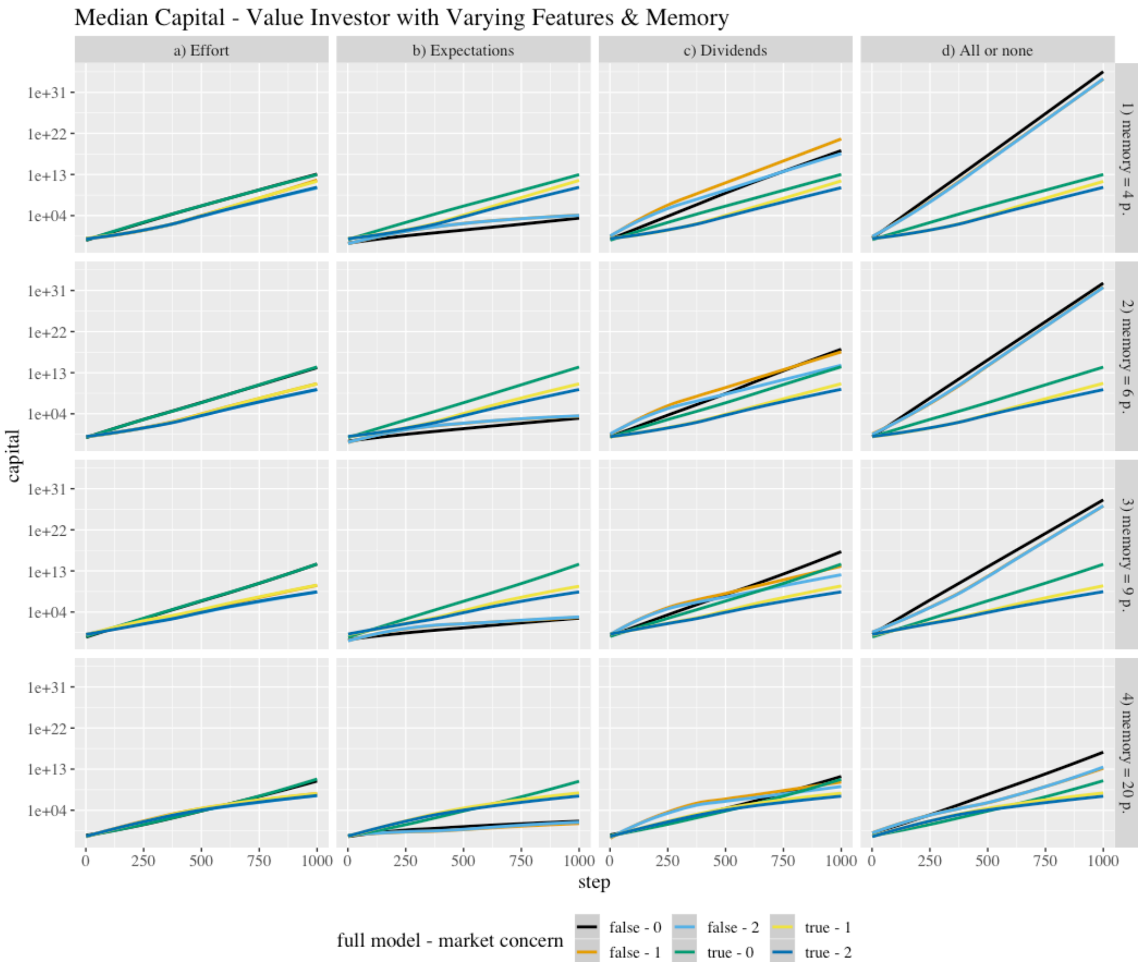

Figure 58: Growth in the median capital levels of the firms with a PB investor. Facets differentiate the specifications of the model and the memory utilization of the investors and firms. The lines represent the progression of the capital levels with management having different concern for the market and whether the full model is utilized (true) or not (false).

The following is an explanation of the dynamics responsible for producing the results in facet d. By having a fixed amount by which they adjust their expectations, and not considering the market, the firms take less time to find a level of growth that they can consistently achieve. Within this process, the firms are also crucially rebalancing their allocation of effort between their primary and secondary objective as their growth expectations fall. This process results in the firms growing its profitability, which is a combination of both sales and margins, because they will not be as extreme in their expectation. The vital component in this process is that the firms retain and reinvest a fixed, and very high, proportion of their profits in the fully simplified model. However, despite the high reinvestment rate, there is sufficient capital released to the investors, which they, in turn, reinvest, thus pushing the index higher. Ultimately, the scenario just described is unrealistic for several reasons, with the most significant issue being, per Section 3.3.2, that as a firm reaches a certain size its growth will slow. Therefore, at some point, it becomes more efficient for a firm to increase dividends or return capital to shareholders.

Regarding the dynamics associated with facet d in both Figure 58 and Figure 59, as the length of history utilization grows the extreme behavior diminishes. The mechanism responsible was partially explained with the commentary related to Figure 55, which is that it is not optimal for firms to wait too long in reducing their expectation. A point of difference with this outcome is the lack of the Goldilocks effect, which penalized firms for being too impatient in reducing their expectations. The likely reason for this is that the fixed decrease means that firms do not overreact if they miss their expectations. Next, Figure 59 presents the results for an ecosystem containing a PEG investor.

The rationale for providing Figure 59 was that an environment containing a PEG investor produced results that differed sufficiently from a PB investor. In this instance, it appears that simplifying the model produces results in line with the observations regarding the PB investor. This outcome is not surprising given the most significant result was seen when firms ignored the market's response.

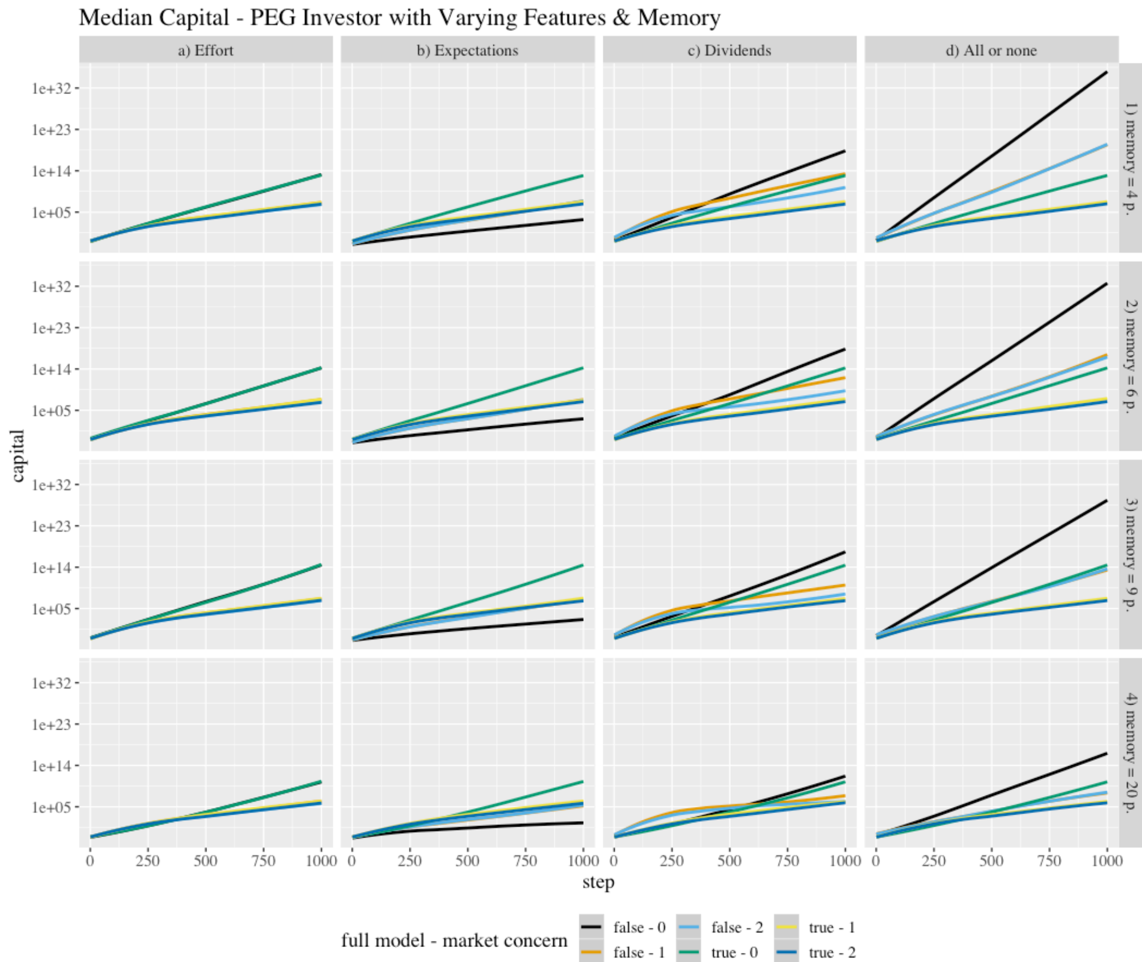

Figure 59: Growth in the median capital levels of the firms with a PEG investor. Facets differentiate the specifications of the model and the memory utilization of the investors and firms. The lines represent the progression of the capital levels with management having different concern for the market and whether the full model is utilized (true) or not (false).

3.6.3.3 Conclusion

The results in Section 3.6.3.2 highlight both the benefits and hazards of ABMs. In terms of hazards, when given a "blank canvas" a modeler must provide the grounds that fully support and justify the model and remain focused on developing an acceptable model. Also, the modeler must fully comprehend the mechanisms responsible for the results. Alternatively, ABM allows a modeler to investigate multiple processes to uncover the most vital components, and in some instances, emergent outcomes arise. This characteristic (that is, the ability to investigate a broad range of mechanisms and variables) is the greatest strength of ABM, but one that requires a logical utilization.

Given the novel nature of the model presented in this chapter the opportunity remains to refine the model. Section 3.6.3.2 provided sufficient evidence that the process by which firms update their expectations will be a crucial area of investigation, as will be how the firms adjust their reinvestment. In making these refinements all efforts must be made to support the changes with evidence from the real world, a topic discussed in Section 4.3.1. Despite this the utilized of logical heuristics proved a worthwhile exercise, with many novel insights appearing throughout Section 3.6.

3.6.4 Section Summary

This section provided the rationale for and the results of the experiments deployed to uncover how the existence of a meaningful feedback loop between financial markets and investors manifests itself in the behavior of a financial market ecosystem. Before delving into the details, Section 3.6.1 provided an overview of the approached employed, the various experimental settings, and an early assessment of the general results. Section 3.6.2.1 then delivered a detailed appraisal of the dynamics of the model, where a single investor class was engaged. In general, the model was capable of producing results in broad agreement with the stylized facts of firm size and growth. The section revealed that when management has no concern for the market the speed at which firms adjust to their environment has significant sway over their growth. Once management considered the price signals from the stock market, it resulted in the development of a complex set of dynamics. In the next section, Section 3.6.2.2, the market ecosystem was expanded to explore how the interaction of various investor classes affected the system. While the dynamics remained consistent with the single investor class execution, the introduction of a trend follower was responsible for some extreme behavior, all of which management were required to act upon. Finally, Section 3.6.3 explored the sensitivities of the model by simplifying several assumptions.

3.7 Discussion and Conclusion

Section 3.6.4 provided a concise summary of the findings related to the model and the various experiments. These findings illustrated the benefits of employing an ABM to investigate an otherwise intractable analytical problem. More so, the approach produced meaningful insights by agentizing a previously defined analytical model. Through implementing the tailored model, and collecting data at the micro- and macro-level, the dynamics underlying the possible feedback mechanism between firms and the stock market became obvious. Given the novelty of the results, they provide crucial insights into quantifying the effect of short-termism and management becoming predisposed to listening to the market. Section 3.7.1 discusses in more specific detail the implications of Section 3.6.4, with Section 3.7.2 outlining possible avenues for future extensions. Finally, Section 3.7.3 provides concluding remarks.

3.7.1 Implications of the Findings

While other models, such as Delli Gatti et al. (2005), have been successful in replicating the stylized facts of firm growth and size with the increasing prevalence of short-termism among decision-makers in financial markets, it was deemed worthwhile to develop a framework capable of considering both issues. The initial findings suggest this research topic remains relevant and has scope to expand. The first finding that supports ongoing research is how the speed at which management update their expectations affects capital growth. The relevance of this avenue is that traditional economic theory remains mute on how firms adjust their resource allocation in the face of a variety of inputs. This is because neoclassical economics assumes that firms will set production levels such that their marginal costs equal their marginal revenue, with the firms presumed to know their cost curve and the demand equation for their output.

Another insight from the model relates to how management interprets the price signals from the market. Though the recognition of these signals is not new, the model provided insight into how these signals may affect real economic variables, such as the capital accumulation of the firm. The finding of most significance is that if firms receive large signals, they overact, mainly by reducing expectations following a sizable upward price movement, and this has a detrimental effect on capital growth. In contrast, the model showed that if firms were left uninterrupted by the market, their ability to optimize their resource allocation improved. This result is meaningful and supports the hypothesis that by having to interact with the market continuously impairs firm performance, with the greater economy affected.

Coupled with this finding is the result that certain investor classes were responsible for more extreme market behavior. It was also found that certain combinations created more divergent dynamics. These results are supportive of the need to address financial markets as an ecosystem and understand the dynamics between the growth and decline of certain investor classes. The ramification of this is that if management considers the market's reaction they need to be extremely mindful of who their investors are. This finding essentially fuses the decision-making process of firms with that of investors. The consequence of this relationship takes on greater meaning when one considers that the actions of management will influence the behavior of the investors, thereby highlighting the dangers of allowing positive feedback loops to operate – a hazard that escalates if investors are more reactive.

Of course, the implications presented in this chapter remain speculative unless they are supported by empirical evidence or they make accurate predictions of how the market and firms will perform. The empirical facts of greatest relevance to this paper were the distributions relating to firm size and growth. An extensive dataset was analyzed with the results suggesting that certain discrepancies across regions exist, possibly due to structural issues of regional capital markets or the maturity of those markets. Additionally, widely recognized financial metrics (for example, PE and PB ratios), were also found to exhibit skewed distributions. This finding provides another layer of validation requirement for future theories. As for the executed model, the level of validation was mixed, mainly due to an inability to decompose the empirical data to the same level of the model's data; that is, it is hard to establish what the primary objective of a real-world firm may be.

3.7.2 Further Extensions

Given the originality of the model there exists a numerous avenue for future work. One such avenue is to expand the analysis of the ecosystem to identify the attributes responsible for the variations in firm growth. This extension would seem to be a simple matter of ratifying that firms endowed with higher ability accumulate more capital. However, it was clear that the rate of capital accumulation can be affected by many factors. Also, the ROI of firms should not be ignored, as this is ultimately a more important metric for investors. An assessment of the investment performance of the various investor classes is also warranted. This analysis would be used to identify the conditions under which certain investors outperform and how the interaction of different investor classes influences performance. A crucial component of this analysis would be to assess the effect of myopic updating compared to a longer-term updating process.

Opportunities exist to make various modifications to the model. A potential change relates to the decision tree employed by management. While the implemented tree was justified, future iterations may look to change certain behaviors; for example, what firms consider as a significant price move and how much they vary those expectations. The investor decision-making process could be adjusted to become forward-looking; that is, expectations are formed regarding the future performance of their investments and firms are rewarded or punished based on the achievement of those expectations. Vitally both changes maintain the spirit of the existing model, which is to have management receive signals from the market, which they use to inform their resource allocation.

An innovative feature of the model was the ability of investors to access new funds. This feature was an advance over traditional bespoke agent-based artificial stock markets, as discussed in Le Baron (2006), Sornette (2014), and Dieci & Xue-Zhong (2018), where investors cannot obtain additional funds. While the functionality was acceptable for this paper, it may be possible to refine it in future iterations. However, the issue will remain considering that if one compounds the growth of the dividend paymenyts – starting at $1 at 2% pa and with 500 companies – the numbers become very large very quickly.

Despite this paper adding to research regarding the existence of power-law distributions in finance and economics, much remains to be discovered as to why these distributions appear with such consistency. A focus should be to establish if any parameters are capable of "bounding" the market and assessing whether financial markets become more volatile as the market approaches these bounds. Also, a more definitive answer relating to whether the distribution of firm size and growth are consistent for public and private firms. The final avenue of future research would involve the continual attempt to validate the model against real-world data. While several models, as noted in Section 1.2.5.2, have been successful in explaining firm growth, they have not explicitly considered the role of the stock market in that growth. It may ultimately prove to be a spurious relationship, but given the comments of Dimon & Buffett (2018), this seems unlikely; hence the motivation for future research exists.

3.7.3 A Final Word

An ambitious research agenda was undertaken in this chapter with a novel ABM implemented to address a vital concern relating to how secondary equity markets operate. An important, and novel, element of the research was to integrate the characteristics of empirical facts relating to multiple facts pertaining to investment market and firms, with all of them exhibiting the statistical imprint of a CAS. While many of these facts had been previously recognized, the novelty was to expand and combine the data. Ultimately, the research highlighted the benefits of ABM and the need to consider financial markets, and the economy in general, as a system of heterogamous interacting agents.

4 CONCLUDING REMARKS AND ROADMAP FOR THE FUTURE

4.1 Introduction and Summary of Results

This dissertation set out to justify the continued utilization of CSS methods to assess the inner workings of financial markets by providing a thorough review of why the approach is required and presenting two models that demonstrated the utility of ABM. Chapter 1 provided the history behind the entrenched EMF approach, before highlighting several concerns relating to the central concepts of the EMF: market efficiency and the rational representative agent. The chapter then justified why an interdisciplinary approach centered around considering any system as a CAS and why the implementation of CSS tools was a feasible alternative. Finally, the chapter provided an outline of how a CSS approach could be employed to better understand the mechanisms and dynamics of financial markets. Chapter 2 examined the ramifications of having investors connected in a dynamic information network, with those investors being either short- or long-term investors and having differing inclinations for following specific information sources. The result highlighted that short-term investors tend to increase market volatility, and gain at the expense of long-term investors. However, if long-term investors can regularly switch advisers, they too can produce increased volatility. The model in Chapter 3 significantly expanded the agent-based artificial stock market framework by having multiple firms traded on the market, with the management of those firms adjusting growth expectations and resource allocations after factoring in the market's response to their performance. This approach produced numerous novel insights including quantifying the lost capital growth due to management considering the markets, thereby validating the approach and opening a new avenue of research for the ABM community. Chapter 3 also provided an extensive set of empirical facts related to firm size, growth, performance, and valuations. This data was used to inform the model and assess the model's validity. The remainder of this chapter will discuss the main ramifications of the various findings and outline feasible extensions to the research presented in this dissertation and to the CSS paradigm in general.

4.2 A Discussion Regarding the Relevance of this Disertation

Given that financial markets are an integral part of the modern economy it is essential that the mechanisms and processes driving them are (to the best of anyone's ability), fully understood. This goal is imperative to avoid the loss of wealth through erroneous investment strategies and to ensure that financial markets contribute to the efficient allocation of resources throughout the global economy. While the initial theories, such as the EMF, were relatively successful in explaining the performance of financial markets, their status faces a multi-prolonged attack. The main attack comes from the failure of the EMF to anticipate periods of extreme market volatility, with a secondary threat coming from the increasing prevalence of data supporting various arguments that investors do not act in a rational manner.

Although arguments for considering alternatives, such as the CAS approach, has been forcibly made (see for example Farmer & Foley (2009)) they have made little progress in becoming the primary framework by which policy-makers and market participants assess financial markets. Therefore, it is essential that the research effort continues in a vigorous and innovative manner. Section 4.3 provides possible avenues for future research that meet this requirement. In summary, the research tasks involve leveraging the strengths of the CAS approach and integrating data from both traditional and non-traditional sources – noting that in today's world the non-traditional quickly transitions to the traditional. An example of this transition is how satellite images have now become an input into forecasting economic activity (Nie & Oksol, 2018). Section 4.4 provides a cautionary note regarding the utilization of new data sources without proper grounds.

The confidence in the continued utilization of the CAS approach comes from its ability to address the shortfalls of the rational representative agent approach. The factor of greatest importance is the ability of the CAS to consider HIAs who utilize an inductive approach in their decision-making and can evolve and adapt to their ever-changing environment. Thus, the CAS approach better reflects how humans operate, not only in financial markets but, in their role as economic agents in general. The utilization of CSS tools and particularly ABM will play a critical role in evolving the CAS approach as they remain the optimal approach for uncovering the solution structure, testing the dynamics of the system, and examining the sensitivity of the model's output against its assumption (Axtell, 2000). Also, while recognizing that it cannot answer all the questions, network science will play an increasing role in understanding the economy as improvements in data collection and analysis techniques will uncover more and significant interconnections between agents and institutions. Whether the CAS research efforts can entirely uncover the dynamics of financial markets, thus helping investors avoid catastrophic losses, only time will tell, but at this point, there remains a vibrant research agenda.

4.3 Future Work

There are plentiful opportunities to extend not only the frameworks presented in this dissertation but also the CAS paradigm within the finance and economics discipline. The opportunities proposed in this section center around the enhanced utilization of data (see Section 4.3.1) to inform, calibrate, validate, and verify models, and to expand the frameworks applied to answer how and why financial markets perform as a CAS (see Section 4.3.2). Both pursuits serve the goal of better interpreting the behavior of market participants through computation and data.

4.3.1 Making More Extensive Use of Data

The purpose of this section is not to expose the benefits of data science/machine learning paradigm (Section 4.4 contains my views on this). Rather this section will discuss how data can be utilized to enhance the models presented in Chapter 2 and 3, which were, to varying degrees, informed by the stylized facts of financial markets. The scope of the discussion is restricted to the potential of capturing and interpreting data from existing sources, as opposed to speculating on new sources such as extensive investor surveys and increased monitoring. Another characteristic of the data is that it should be relatively easy and timely to capture. This data would be used to inform future modeling attempts, and possibly serve as an input into a model.

Regarding investors networks, as discussed in Section 1.4.2 and 1.4.7, there has already been extensive work undertaken in the area. However, the work regarding empirical networks suffers from a lack of timely data. One of the main issues surrounding this is the confidentiality requirements of investors. Therefore, advances in this area of research will only come from specific companies undertaking assessments of their share registry or making that data available (for example, Musciotto et al. (2018)). The benefit of undertaking this analysis is that firms would gain a greater appreciation of who their owners (especially short-term versus long-term investors) are thereby improving their ability to interpret signals from the market. Share registry services and custodians maintain the required data shareholder data for numerous firms but accessing this data will prove a difficult task. The opportunity exists for brokers to use their trading data to form a clear picture, as far as their client base will allow, of their client ecosystem.

Regarding quantifying investor trust, research exists that can be utilized to achieve this goal. Starting with the work of Gruber (1996) and Sirri & Tufano (1998) it has been established that the flows into and out of mutual funds is highly dependent on manager performance, thus flows provide an ex-post proxy of trust. Additionally, the recommendations of stock analysts have been found to positively influence stock prices (Barber et al., 2001), thereby providing possible insight into what is required for investors to build (and lose) trust in their Oracles. Finally, the existing literature on herding (see Section 1.4.6) covers investors "blindly" following other investors after establishing some level of trust. The missing link in this process is how to assess the level of trust investors maintain at any point in time. Market participants would benefit from establishing such a metric because if investors are "trusting," it is likely that the market will tend to follow the whim of whoever the established Oracles are at a particular point in time. The danger in such a situation is that one investor is unlikely to hold the right answers all the time and compounding this concern, poor (or non-optimal) investment strategies may hold sway for an extended period, with their inevitable demise likely to lead to investment losses and poor resource allocation during their reign.

Moving forward to assessing the intention of management, two feasible alternatives exist. The first is to make better use of the financial reports of firms, which provide a wealth of information regarding their performance. Data service providers such as Bloomberg, FactSet, and Compustat provide electronic access to this data, with the data already utilized extensively by the commercial and academic worlds. Changes in a metric such as expenses (for example, R&D and sales & marketing) and capital expenditure are all capable of contributing to a definition of effort and establishing the intentions of management. Profitability margins are easily attainable from financial accounts – mainly profit & loss statements – and are the obvious candidate for assessing performance, with the earnings guidance provided by management a clear proxy for their intentions. The one downside to relying on financial data comes from the ability of management to manipulate their results by exploiting accounting rules.

An alternative approach is to utilize natural language processing (NLP) to assess the intentions and expectations of firms by analyzing a variety of documents. Thorsrud

(2018) articulates the rationale for such an approach by considering words as the new numbers. The documents likely to yield the most significant returns are financial filings, the transcripts of management conference calls, and other company commentary related to their earnings performance. A critical component in retrieving this data is being able to reduce it to a single metric, which can then be used to categorize each firm. However, such an ambiguous task is feasible with recent advances in machine learning. An example of this approach is Hoberg & Phillips (2017), who successfully extracted vital financial metrics from over 50,000 10-K forms of USA companies.

The final consideration is whether data can be used to assess the time-horizon of market participants. Trading volumes are an apparent candidate for helping assess the behavior of investors. However, this is an interpretation of the behavior of the entire population and does not consider the heterogeneous nature of investors. Therefore, the need exists to explore alternatives. As discussed above, without client level trading data this may be a complicated issue to resolve. A minimum step may be to assess the stated portfolio turnover target of all mutual funds, which is found in a fund’s public disclosure statements (PDS). Regarding the long-term intention of firms, the same data sources highlighted above are likely to provide the foundation for assessing whether firms are committed, or otherwise, to their stated goals, noting that in today’s world there is the need to retain a flexible approach to meet a more dynamic business environment.

4.3.2 Reflexivity Revisited

While Section 1.3.4.2 discussed the concept of reflexivity, and its relevance to ABM, the models presented in Chapters 2 and 3 did not fully exploit the concept. The missing ingredient was that the agents did not adapt to reflect the dynamics of their environment. For example, the investors in Chapter 2 were initiated with a static set of rules in which they assessed their environment. While this approach was sufficient to create meaningful results if the agents were truly reflective, each agent would be free to adjust their mental model in response to the market. Additionally, per Beinhocker (2013) the model's structure could potentially adjust. A speculative result of such a process would see some investors anticipate periods of excessive volatility and divest ahead of time, while others may anticipate the inflation of a bubble and invest ahead of time.

The integration of the theory of reflexivity is technically feasible given the utilization of learning algorithms (see Section 1.3.2.3) within the ABM literature. An early example of such an approach is the El Farol model (see Section 1.2.5.3), where agents are provided with numerous strategies, which they assess before selecting the one that provides the best outcome. The issue that is likely to cause the most concern is incorporating the fallibility of the agents in the updating process; that is, where would a modeler draw the line been a feasible error and an unrealistic error? A quick review of the history of financial markets suggests that investors continually make decisions which ex-post look unrealistic, but ex-ante seemed reasonable – think tulips and cryptocurrency. Another issue is how the model's structure would change, and more specifically how it would change to reflect the actions of the agents. Having identified some considerations in implementing reflexivity in a model, it is left to others to consider solutions.

4.4 Concluding Remarks

This dissertation's objective was to vindicate the continued use and extension of CSS methods to assess the behavior of financial markets. In summary, the CSS approach is justifiable because it is capable of not only addressing the shortfalls of the neoclassical approach but avoids placing excessive reliance on the latest artificial intelligence and machine-learning approaches to resolve the critical how and why questions regarding the behavior of financial markets. The basis of this statement is that the CSS approach, and especially ABMs, are focused on (or if not, should be) identifying the dynamics responsible for producing the macro-emergent outcomes in the economy, some of which have resulted in excessive financial losses in the past – for example, the 2008 sub-prime crisis. A pure data science approach is unlikely to succeed in such a task because the algorithms are designed to recognize patterns and extrapolate a prediction, thereby these approaches are reliant on the data "forming" in a certain manner without understanding why the data has formed in the given manner. This issue is an even greater concern when a structural change occurs in the markets (for example, interest payments are no longer tax deductible), or a new object enters the system (for example, credit default swaps), because the algorithms are incapable of instantaneously adjusting for such step-changes. In contrast, the CSS approach sets out to identify why the data forms in a given way, which allows practitioners to identify if, and why, a step-change will occur and what effects it may produce, and assess whether the economy is moving towards a dangerous state.

A significant problem that CSS, and for that matter the data science and behavioral economic approaches, faces is delivering transparent and easily interruptible results for policymakers and practitioners. This factor is traceable back to Keynes's (1936) concept of aggregate demand, a theory that created macroeconomics and propelled economics into the political mainstream (Marglin, 2018), with other examples including the beta coefficient from the CAPM, the Phillips curve, and Markowitz's efficient frontier. The defining feature of these concepts is how they provide "rules of thumb" that are easily deployable, well-accepted, and comprehensible for experts and lay people, therefore making it difficult to displace these theories despite their shortcomings.

Per Manzo (2014), ABMs have faced extensive criticism because of their reliance on initial conditions, being only moderately comparable and reproducible, lacking transparency, and the uncertainty of their outcomes. Therefore, CSS must avoid at all cost being consigned to a "black-box" art as any recommendations and findings will be automatically met with suspicion. In turn, ABM researchers must continue to balance the need to demonstrate their primary advantage of being capable of considering a richer set of specifications, thus allowing for the assessment of complex phenomena (Leombruni & Richiardi, 2005). The proposed solution is that those using ABMs must continue the quest to incorporate data into their models and provide outputs that are verifiable against stylized facts extracted from numerous sources, thereby providing more holistic insights. While this approach may not produce precise economic forecasts, it will provide deep insights into how the economy operates as a CAS, thereby providing the necessary insights to avoid the inefficient allocation of resources in the economy. While there is no shortage of avenues to explore, this dissertation has provided not only rich sources of potential research but also the rhyme and reason for doing so. The latter is especially important because to replace the embedded theories of neoclassical economics will required sustained, focused, and concentrated effort and time.

APPENDIX

Table 18: Power-law coefficients for market capitalization of global firms

Year	Region	Power-law comp.	X Min	p-value of the Kolmogorov-Smirnov test	Region	Power-law comp.	X Min	p-value of the Kolmogorov-Smirnov test
2007	Northern America	1.76	1,404.45	0.01	Middle East	1.64	238.93	0.02
2008	Northern America	1.83	1,348.70	0.28	Middle East	1.65	120.95	0.05
2009	Northern America	1.84	1,902.79	0.05	Middle East	1.71	205.53	0.06
2010	Northern America	1.83	1,746.02	0.02	Middle East	1.65	182.86	0.02
2011	Northern America	1.82	1,787.91	0.01	Middle East	1.72	170.60	0.19
2012	Northern America	1.80	1,703.62	0.01	Middle East	1.70	156.13	0.14
2013	Northern America	1.83	2,369.78	0.01	Middle East	1.71	209.80	0.14
2014	Northern America	1.83	2,731.00	0.00	Middle East	1.71	298.47	0.12
2015	Northern America	1.72	1,338.04	0.00	Middle East	1.64	119.13	0.01
2016	Northern America	1.77	2,159.35	0.00	Middle East	1.65	135.77	0.01
2017	Northern America	1.80	2,946.55	0.00	Middle East	1.65	135.49	0.01
2007	Africa	1.56	134.40	0.00	Oceania	1.79	208.32	0.07
2008	Africa	1.62	89.22	0.00	Oceania	1.71	61.50	0.64
2009	Africa	1.58	79.75	0.00	Oceania	1.50	11.25	0.00
2010	Africa	1.94	617.60	0.67	Oceania	1.53	24.29	0.00
2011	Africa	1.74	167.53	0.10	Oceania	1.73	128.17	0.12
2012	Africa	1.90	645.66	0.41	Oceania	1.59	55.92	0.01
2013	Africa	1.96	534.04	0.58	Oceania	1.58	50.55	0.01
2014	Africa	1.72	161.55	0.01	Oceania	1.59	61.44	0.01
2015	Africa	2.03	421.03	0.73	Oceania	1.42	7.80	0.00
2016	Africa	1.85	253.52	0.73	Oceania	1.49	17.05	0.00
2017	Africa	1.90	469.96	0.67	Oceania	1.44	10.61	0.00
2007	Eastern Europe	1.95	668.70	0.71	Southern and Eastern Asia	1.88	518.76	0.00
2008	Eastern Europe	1.57	19.27	0.08	Southern and Eastern Asia	1.85	209.21	0.00
2009	Eastern Europe	1.51	18.16	0.00	Southern and Eastern Asia	1.97	585.59	0.12
2010	Eastern Europe	1.52	37.82	0.00	Southern and Eastern Asia	1.99	753.43	0.02
2011	Eastern Europe	1.55	42.41	0.04	Southern and Eastern Asia	1.89	319.05	0.00
2012	Eastern Europe	1.59	71.12	0.11	Southern and Eastern Asia	1.88	361.87	0.00
2013	Eastern Europe	1.68	138.16	0.40	Southern and Eastern Asia	1.92	450.69	0.00
2014	Eastern Europe	1.74	155.06	0.65	Southern and Eastern Asia	2.03	835.18	0.01
2015	Eastern Europe	1.73	152.54	0.45	Southern and Eastern Asia	1.42	30.43	-
2016	Eastern Europe	1.67	106.47	0.15	Southern and Eastern Asia	1.42	30.99	-
2017	Eastern Europe	1.57	50.95	0.03	Southern and Eastern Asia	2.11	1,434.23	0.03
2007	Latin America and Car.	1.80	615.53	0.21	Western Europe	1.91	1,535.05	0.98
2008	Latin America and Car.	1.70	170.74	0.15	Western Europe	1.76	312.46	0.05
2009	Latin America and Car.	1.85	677.58	0.25	Western Europe	1.94	1,392.21	0.73
2010	Latin America and Car.	2.00	1,296.80	0.47	Western Europe	1.93	1,247.73	0.54
2011	Latin America and Car.	2.02	1,173.73	0.63	Western Europe	1.91	1,042.49	0.44
2012	Latin America and Car.	1.71	377.78	0.00	Western Europe	1.96	1,586.40	0.83
2013	Latin America and Car.	2.07	1,766.04	0.80	Western Europe	1.62	232.42	0.00
2014	Latin America and Car.	1.81	458.81	0.00	Western Europe	1.65	250.82	0.00
2015	Latin America and Car.	1.98	744.77	0.36	Western Europe	1.98	1,839.51	0.49
2016	Latin America and Car.	1.57	80.00	0.00	Western Europe	2.00	1,827.74	0.59
2017	Latin America and Car.	1.52	92.48	0.00	Western Europe	2.02	2,606.13	0.89

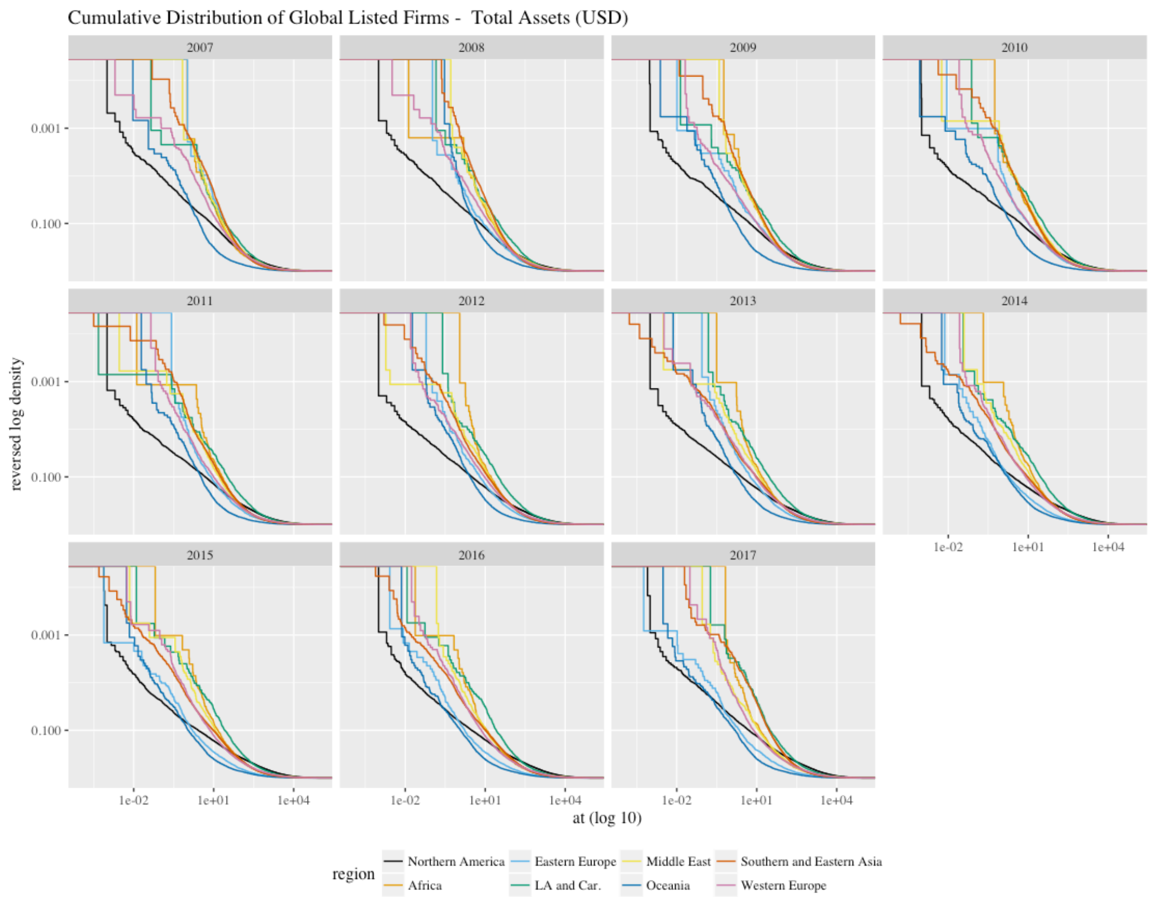

Figure 60: The distribution of the total assets of firms across regions and time. The distribution is represented by CDF, in log form. A "straight" line is indicative of a power-law distribution. Data source: Data source: Compustat – Capital IQ database (2018).

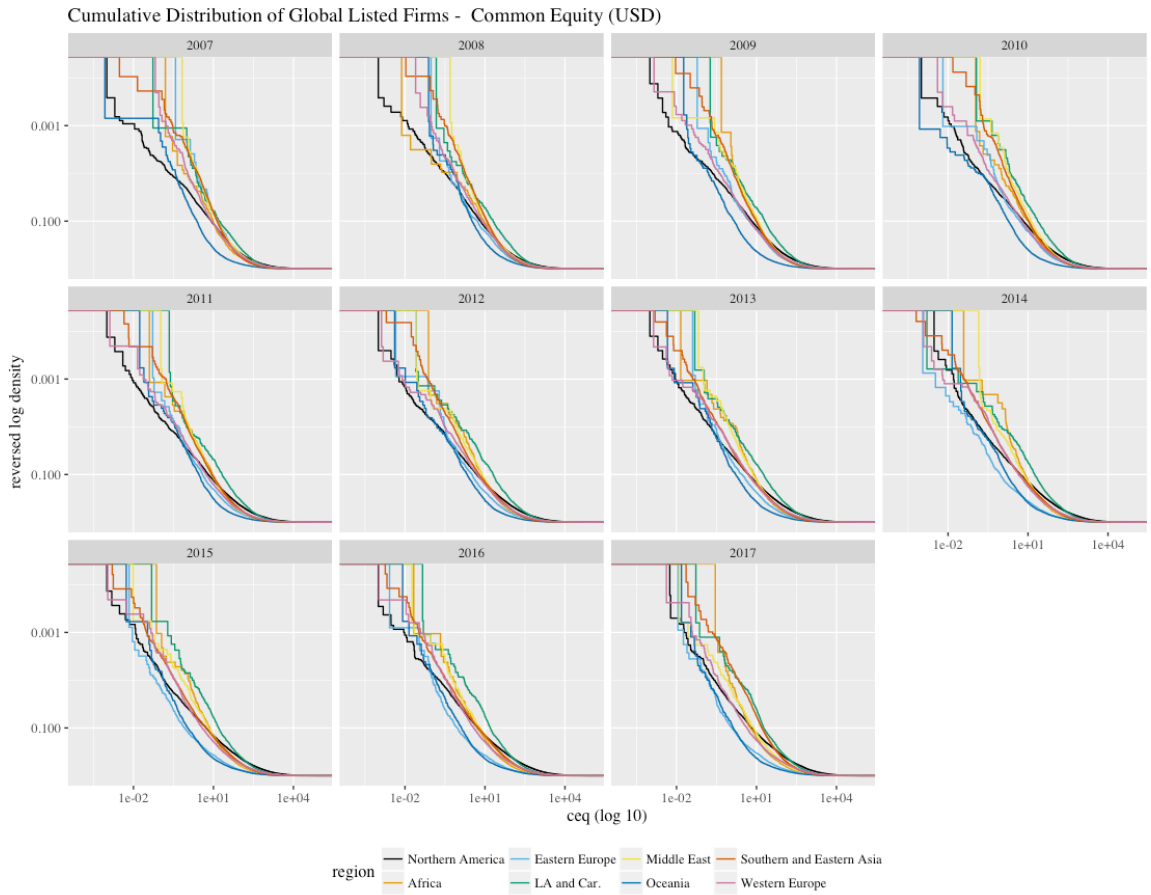

Figure 61: The distribution of the common equity of firms across regions and time. The distribution is represented by CDF, in log form. A "straight" line is indicative of a power-law distribution. Data source: Compustat – Capital IQ database (2018).

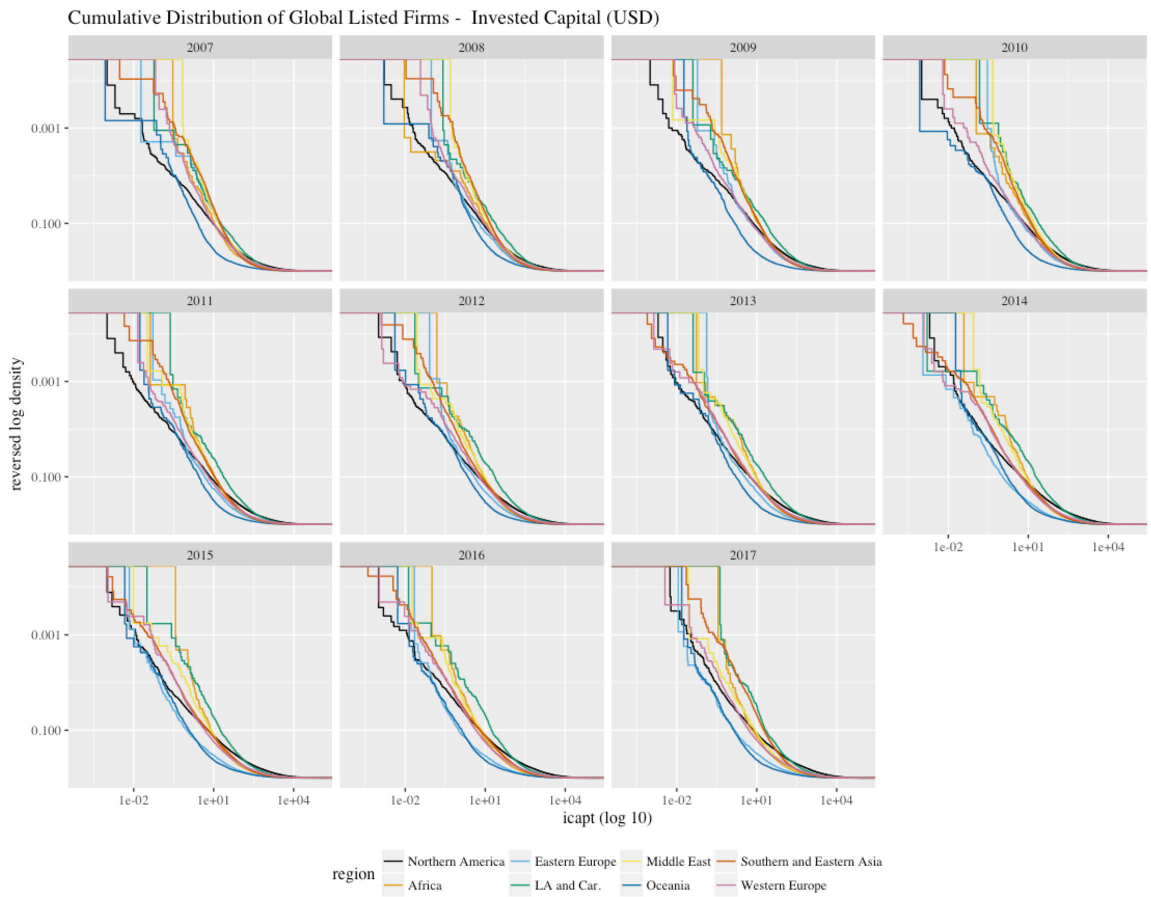

Figure 62: The distribution of the invested capital of firms across regions and time. The distribution is represented by CDF, in log form. A "straight" line is indicative of a power-law distribution. Data source: Compustat – Capital IQ database (2018).

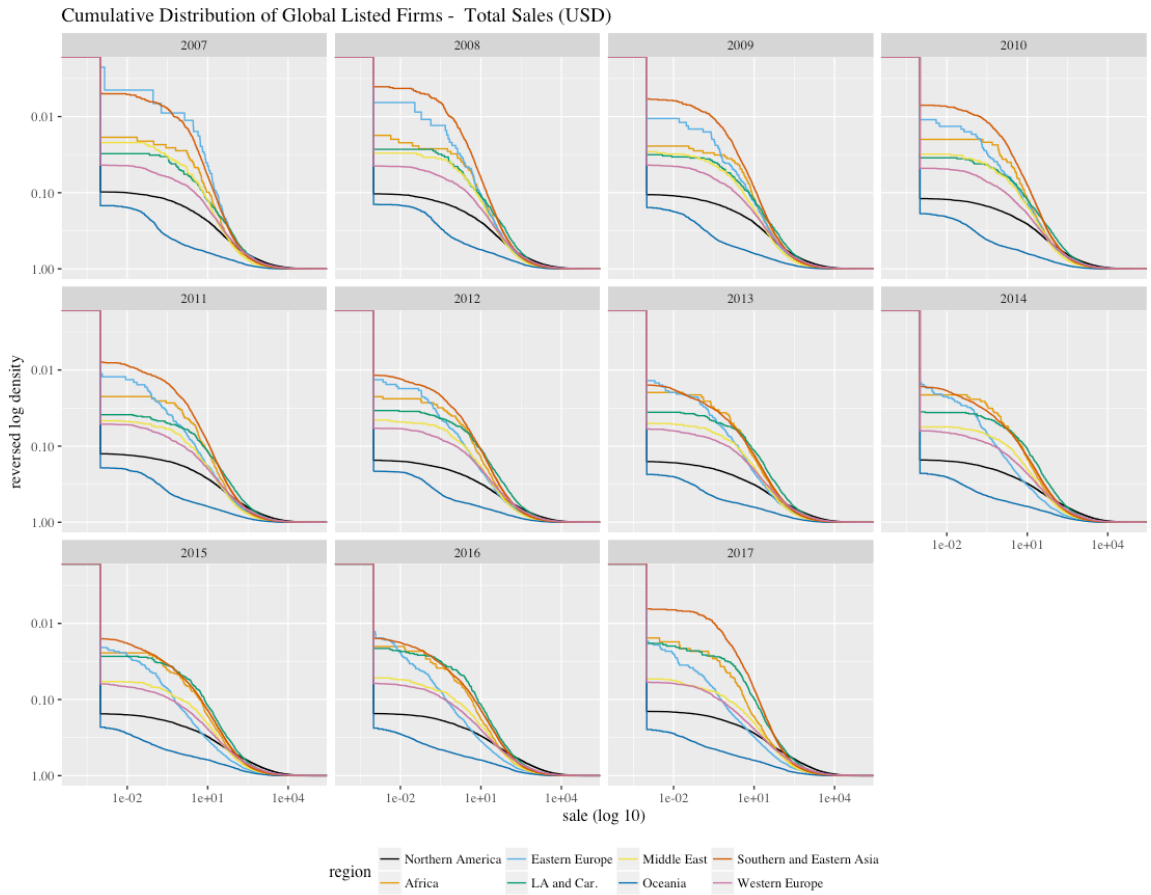

Figure 63: The distribution of the sales revenue of firms across regions and time. The distribution is represented by CDF, in log form. The lack "straight" lines is indicative that a power-law distribution is not present. Data source: Compustat – Capital IQ database (2018).

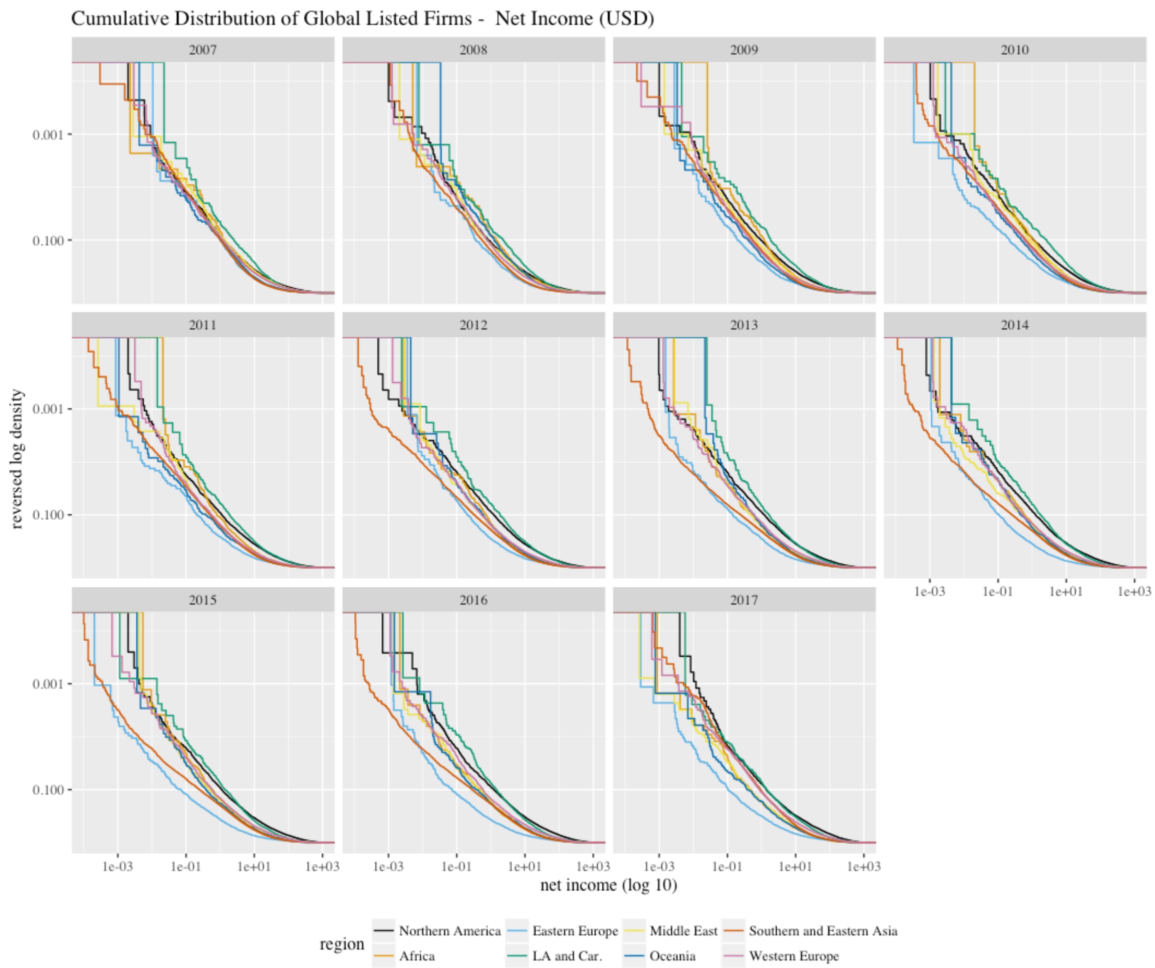

Figure 64: The distribution of the net income of firms across regions and time. The distribution is represented by CDF, in log form. A "straight" line is indicative of a power-law distribution. Data source: Compustat – Capital IQ database (2018).

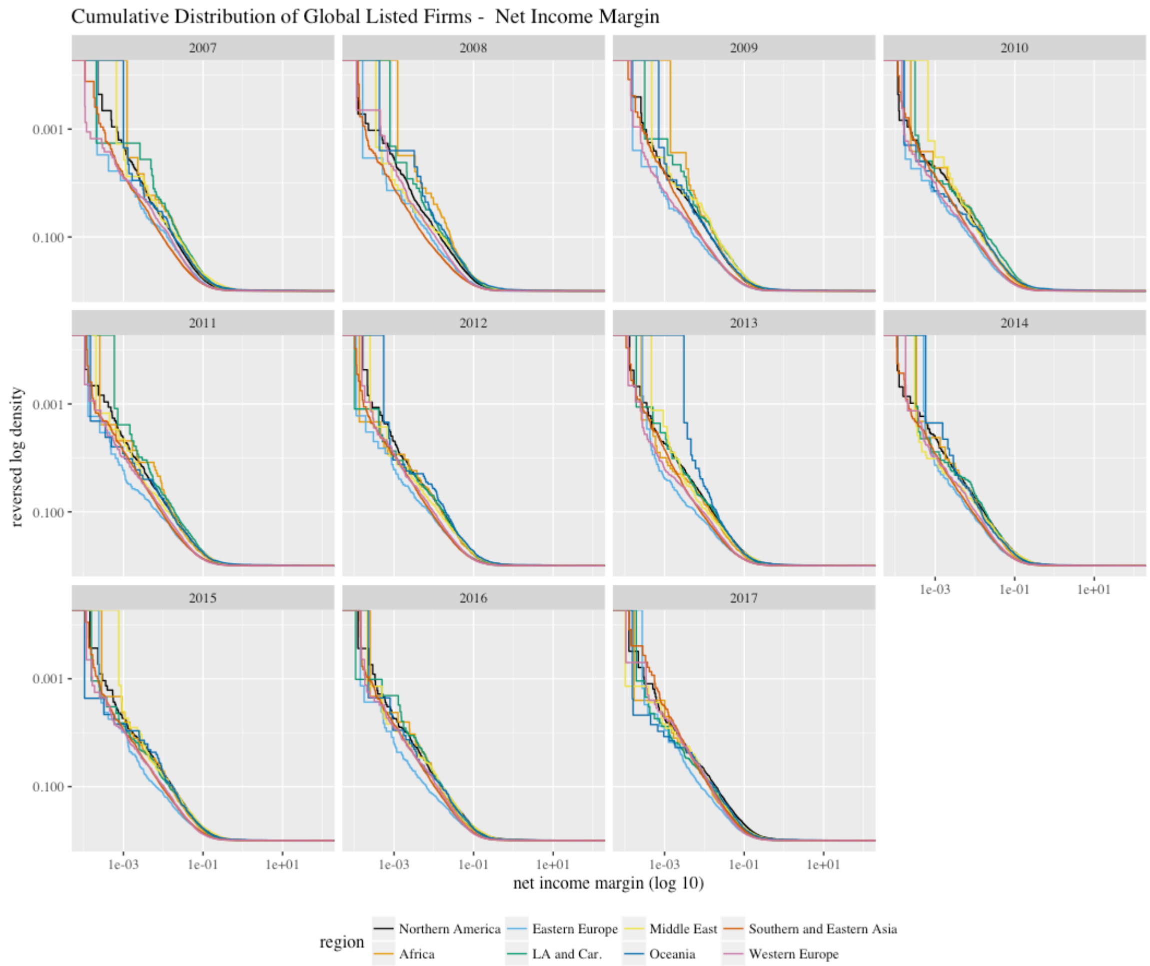

Figure 65: The distribution of net income margins of firms across regions and time. The distribution is represented by CDF, in log form. A "straight" line is indicative of a power-law distribution. Data source: Compustat – Capital IQ database (2018).

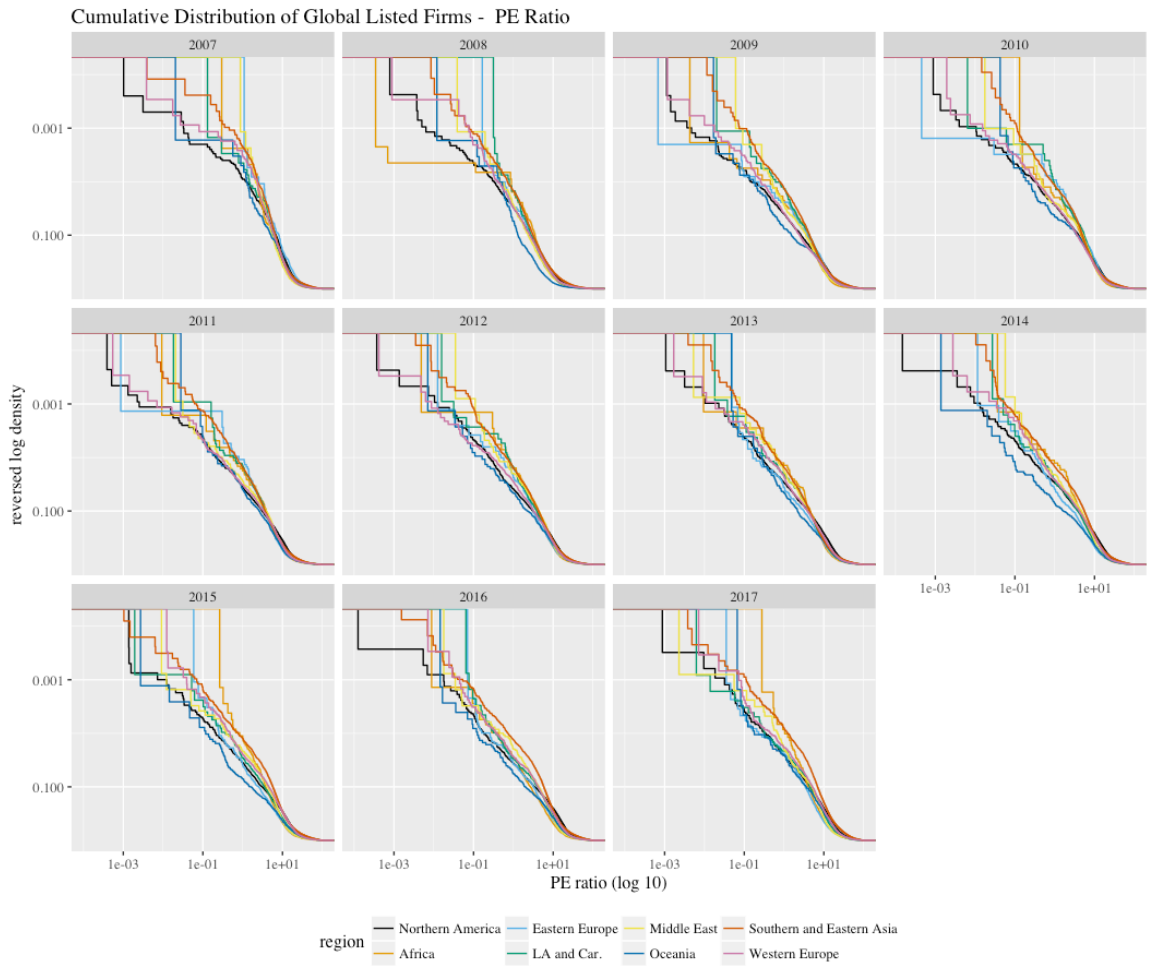

Figure 66: The distribution of the PE rations of firms across regions and time. The distribution is represented by CDF, in log form. A "straight" line is indicative of a power-law distribution. Data source: Compustat – Capital IQ database (2018).

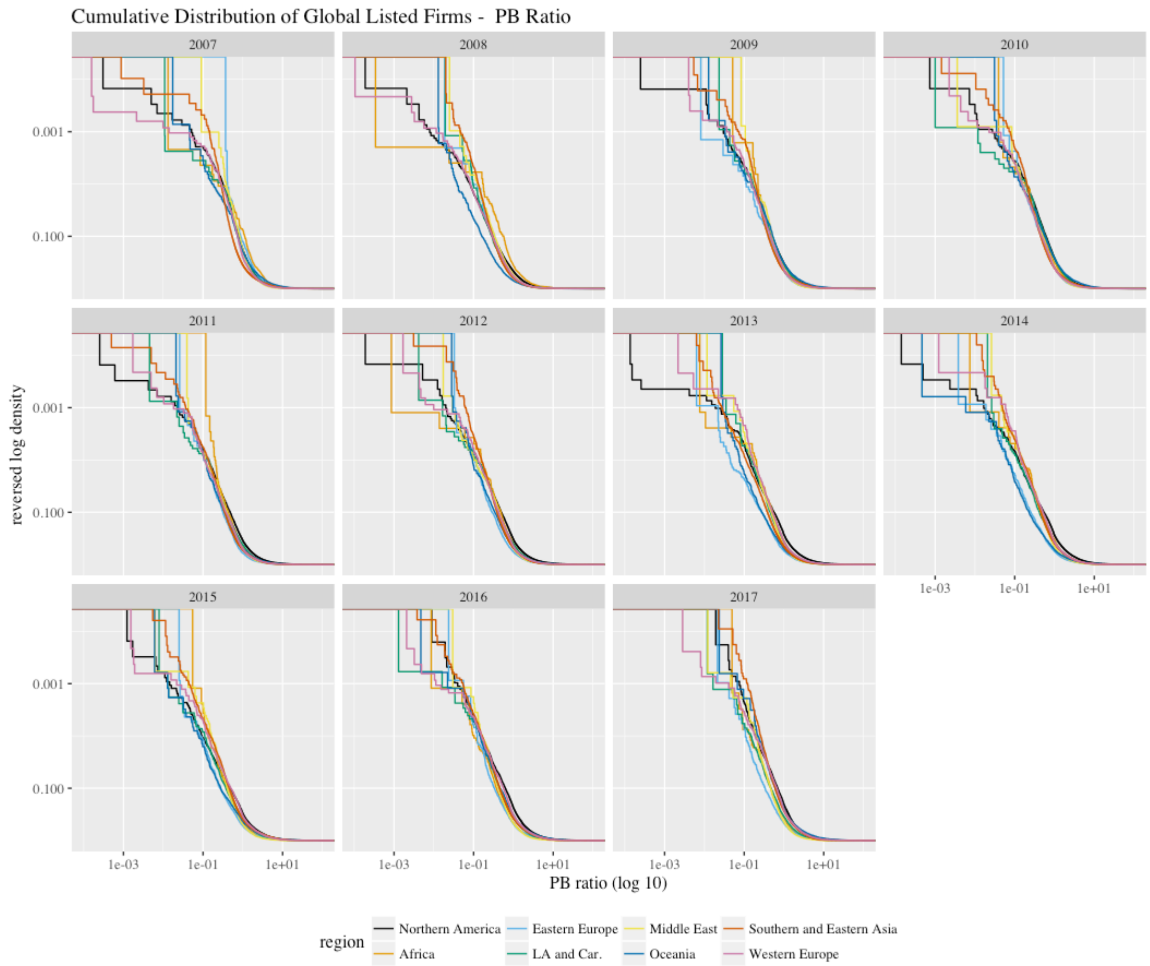

Figure 67: The distribution of the PB ratios of firms across regions and time. The distribution is represented by CDF, in log form. A "straight" line is indicative of a power-law distribution. Data source: Compustat – Capital IQ database (2018).

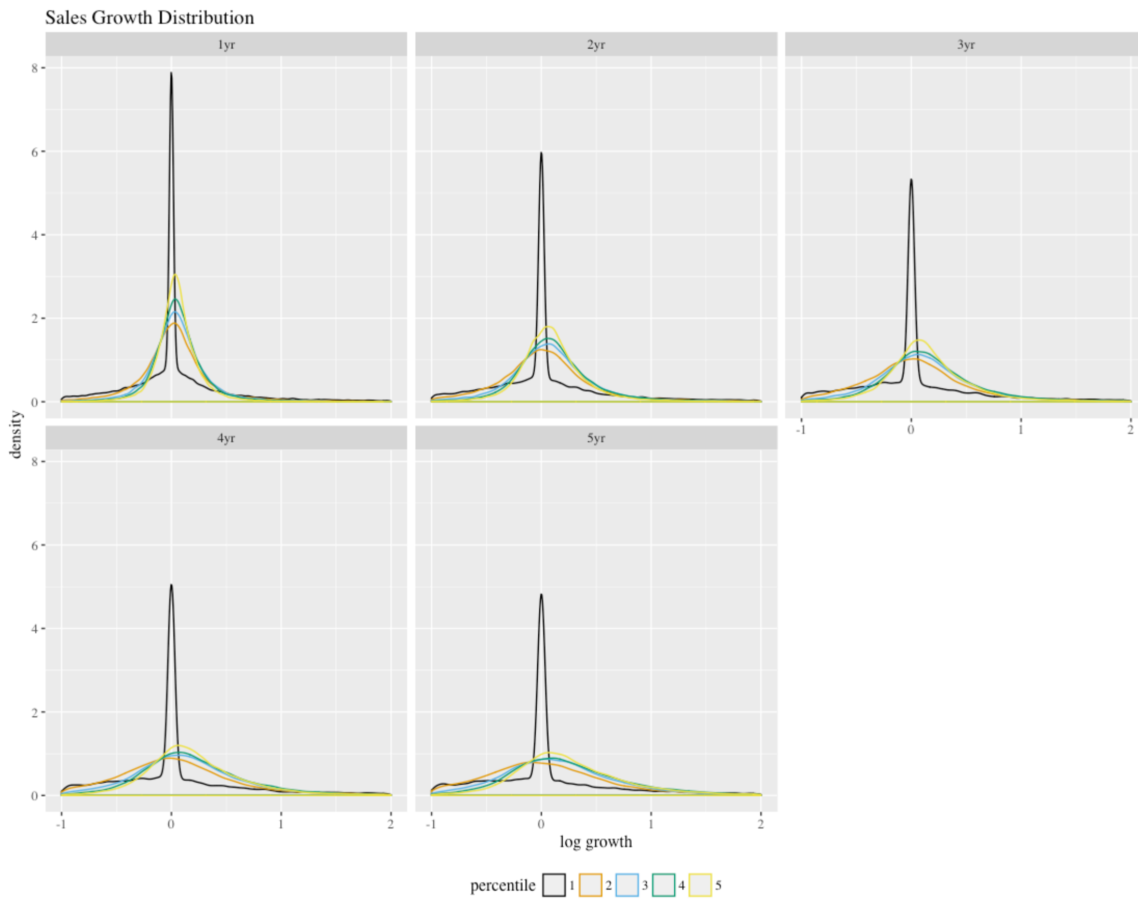

Figure 68: The distribution of the sales growth of firms across regions and time. The distribution is represented by CDF, in log form. The distributions should be tent-like, with the lower percentiles exhibiting greater variance. Data source: Compustat – Capital IQ database (2018).

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