Adaptive interactive expectations: dynamically modelling profit expectations

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Adaptive Interactive Expectations:
Dynamically Modelling Profit Expectations

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Declaration by author

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No jointly authored works.

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No contributions by others.

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None

Published Works by the Author Incorporated into the Thesis

Bell, WP 2009, *'Network Averaging: a technique for determining a proxy for the dynamics of networks'*, paper presented to Complex '09, the 9th Asia-Pacific Complex Systems Conference, Chuo University, Tokyo, Japan, 6 November 2009 – incorporated into Chapters 3 and 4.

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Additional Published Works by the Author Relevant to the Thesis but not Forming Part of it

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Abstract

This thesis aims to develop an alternative expectations model to the *Rational Expectations Hypothesis* (REH) and adaptive-expectations models, which provides more accurate temporal predictive performance and more closely reflects recent advances in behavioural economics, the *'science of complexity'* and network dynamics. The model the thesis develops is called *Adaptive Interactive Expectations* (AIE), a subjective dynamic model of the process of expectations formation. To REH, the AIE model provides both an alternative and a complement. AIE and REH complement one another in that they are diametrically opposite in the following five dimensions, agent intelligence, agent interaction, agent homogeneity, equilibrium assumptions and the rationalisation process. REH and AIE stress the importance of hyper-intelligent agents interacting only via a price signal and near zero-intelligent agents interacting via a network structure, respectively. The complementary nature of AIE and REH provide dual perspectives that enhance analysis.

The *Dun & Bradstreet* (D&B 2008) profit expectations survey is used in the thesis to calibrate AIE and make predictions. The predictive power of the AIE and REH models is compared. The thesis introduces the *'pressure to change profit expectations index', p^x*. This index provides the ability to model unknowns within an adaptive dynamic process and combine the beliefs from interactive-expectations, adaptive-expectations and biases that include pessimism, optimism and ambivalence.

AIE uses networks to model the flow of interactive-expectations between firms. To overcome the uncertainty over the structure of the interactive network, the thesis uses model-averaging over 121 network topologies. These networks are defined by three variables regardless of their complexity. Unfortunately, the Bayesian technique's use of the number of variables as a measure of complexity makes it unsuitable for model-averaging over the network topologies. To overcome this limitation in the Bayesian technique, the thesis introduces two model-averaging techniques, *'runtime-weighted'* and *'optimal-calibration'*. These model-averaging techniques are benchmarked against *'Bayes-factor model-averaging'* and *'equal-weighted model-averaging'*.

In addition to the aggregate called *all–firms*, the D&B (2008) survey has four divisions, manufacturing durables, manufacturing non–durables, wholesale and retail. To make use of the four divisions, the thesis introduces a *'link-intensity matrix'* based upon an *'input-output table'* to improve the calibration of the networks. The transpose of the table is also used in the thesis. The two *'link-intensity matrices'* are benchmarked against the default, a *'matrix of ones'*. The aggregated and disaggregated versions of AIE are benchmarked against adaptive-expectations to establish whether the interactive-expectations component of AIE add value to the model.

The thesis finds that AIE has more predictive power than REH. *'Optimal-calibration model-averaging'* improves the predictive performance of the better-fitting versions of AIE, which are those versions that use the *'input-output table'* and *'matrix of ones'* link-intensity matrices. The *'runtime-weighted model-averaging'* improves the predictive performance of only the *'input-output table'* version of AIE. The interactive component of the AIE model improves the predictive performance of all versions of the AIE over adaptive-expectations. There is an ambiguous effect on prediction performance from introducing the *'input-output table'*. However, there is a clear reduction in the predictive performance from introducing its transpose.

AIE can inform the debate on government intervention by providing an A*gent-Based Model* (ABM) perspective on the conflicting mathematical and narrative views proposed by the Greenwald–Stiglitz Theorem and Austrian school, respectively. Additionally, AIE can provide a complementary role to REH, which is descriptive/predictive and normative, respectively. The AIE network calibration uses an *'input-output table'* to determine the link-intensity; this method could provide *Computable General Equilibrium* (CGE) and *Dynamic Stochastic General Equilibrium* (DSGE) with a way to improve their transmission mechanism. Furthermore, the AIE network calibration and prediction methodology may help overcome the validation concerns of practitioners when they implement ABM.

Keywords

Expectations, profits, networks, adaptive, interactive, *model-averaging*, agent-based, Australia

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Contents

Figures

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Abbreviations

ABM	Agent-based Models
ABS	Australian Bureau of Statistics
ACCS	**A**ustralian Research Council **C**entre for **C**omplex **S**ystems
ADM	Arrow–Debreu–McKenzie model
AGE	Applied General Equilibrium
AIC	Akaike Information Criteria
AIE	Adaptive Interactive Profit Expectations
AMH	Adaptive Market Hypothesis
ANZSIC	Australian New Zealand Standard Industrial Codes
BIC	Bayesian Information Criteria
CAPM	Capital Asset Pricing Model
CGE	Computable General Equilibrium
D&B	Dun & Bradstreet
D&BSIC	Dun & Bradstreet Standard Industrial Classification
DVD	Digital Video Disc
DSGE	Dynamic Stochastic General Equilibrium
EMH	Efficient Market Hypothesis
fMRI	Functional Magnetic Resonance Images
GE	General Equilibrium
GET	General Equilibrium Theory
GTAP	Global Trade Analysis Project
p^x	Pressure to change profits expectations index
REH	Rational Expectations Hypothesis
RBC	Real Business Cycle
SMD	Sonnenschein–Mantel–Debreu Theorem
S&P	Standard & Poor’s
SOC	Self–Organized Criticality
TA	Threshold-accepting
VBM	Variable-based Models

1. Introduction

1.0 Introduction

This chapter provides the foundations for the thesis. Sufficient background for the research is discussed to introduce the research problem and justify the research. The methodology is briefly described and justified and each chapter of the thesis is outlined. The definitions and delimitations of the research are presented.

This thesis develops an *Agent-based Model* (ABM), called *Adaptive Interactive Expectations* (AIE), to model the interactive formation of profit expectations. It statistically compares the accuracy of the AIE model to the *Rational Expectations Hypothesis* (REH) and the standard non-interactive adaptive-expectations model. The thesis models profit expectations because profit expectations determine future investment and whether one business extends credit to another. Noting that, the interactive formation of profit expectations is readily extended to other forms of interactive-expectations.

This thesis also compares the epistemology of the neoclassical and *'science of complexity'* frameworks for three reasons. First, they are the frameworks that contain the REH and AIE models, respectively. REH is the main expectations model in neoclassical economics and forms a benchmark for the AIE. Second, the neoclassical framework is shown to be logically inconsistent, philosophically flawed and empirically questionable, thus it requires a replacement framework to model expectations. The *'science of complexity'* is discussed as a remedy to many of the neoclassical frameworks ailments. Similarly, the REH has come under increasing criticism, which opens the way for a replacement. Third, discussing the failures in the neoclassical framework and its expectations model, REH, informs the development of the AIE model.

The following references are provided to orientate the reader quickly. Table 2–3 provides an overview of the literature from which the component parts of the AIE model are drawn. Figure 2–2 provides context for REH and AIE with respect to agent intelligence and interaction. Section 3.2 provides a list of the ingredients of the formal AIE model. Equations (3-1), (3-3) and (3-4) are the core equations in the formal AIE model. Section 5.4.4 provides a list of the contributions of this thesis to the literature.

The structure of the chapter is as follows. Section 1.1 discusses the background to the research, which overviews the epistemology of economics. Section 1.2 presents the research problem. Section 1.3 justifies the research. Section 1.4 briefly justifies and outlines the methodology. Section 1.5 outlines the structure of the thesis and the contents of each chapter. Section 1.6 provides definitions. Section 1.7 presents the delimitations of scope of the thesis and key assumptions. Section 1.8 concludes the chapter.

1.1 Background to the research

This section discusses the background literature, which provides the motivation for the research problem, that is, to develop an alternative model for expectations formation to the REH and adaptive-expectations models. Not only does reviewing the failure of these models provide motivation to develop an alternative model but it informs also the development of an alternative model.

Section 1.1.1 discusses the failures of the REH and adaptive-expectations models. Section 1.1.2 discusses what caused the failure of REH and its neoclassical framework. Section 1.1.3 discusses what can be learned from the failure of the REH to inform the development of AIE.

1.1.1 Failures of the REH and adaptive-expectations models

The historical context for the REH and the adaptive-expectations models is discussed to show their failure to adequately model expectations.

Hick's (1939) adaptive-expectations model was the dominant expectations model in economics until Muth (1960; 1961), who was dissatisfied with the performance of the adaptive-expectations model, introduced REH that builds on rational choice (Von Neumann & Morgenstern 1944). Billari (2006, p. 2) describes the rational expectations paradigm as that which assumes homogenous economic agents who know their preferences and have unlimited computing power to calculate optimal solutions, and have perfect knowledge of all data relevant to calculate the optimal solution. Sargent (2008, p. 1) asserts in rational expectations that outcomes do not differ systematically (that is, regularly or predictably) from what people expect them to be. REH embodies the three neoclassical assumptions discussed in section 2.1.1. REH grew in importance as it became embedded in many neoclassical economic theories such as the *Efficient Market Hypothesis* (EMH), *General Equilibrium Theory* (GET), Computable General Equilibrium (CGE) and *Dynamic Stochastic General Equilibrium* (DSGE). Consistently, Simon (1984, p. 36) considers that REH is one of the three foundations for neoclassical economics. However, REH and the theories based on it are coming under increasing criticism because they have logical inconsistencies, poor predictive performance and contradict behavioural research but despite these anomalies, REH continues in extensive use and to inform policy. Section 2.1 further discusses this topic.

Lovell (1986, p. 122) states that there is sufficient empirical evidence to suspend belief in REH and calls for the empirical testing of REH against the alternatives. Prescott (1977, p. 30) claims, '*Like utility, expectations are not observed, and surveys cannot be used to test the rational expectations hypothesis. One can only test if some theory, whether it incorporates rational expectations or, for that matter, irrational expectations, is or is not consistent with observations.'* However, the EMH, GET and DSGE provide examples of theories that incorporate REH and are inconsistent with observation. They are discussed in turn.

Fama (1965; 1970) introduces the EMH that builds upon Bachelier's (1900) *'Theory of speculation: the origins of modern finance'* and extends REH. The EMH contends that markets use information efficiently in that markets reflect available information in the prices. Mandelbrot (1963) finds that Bachelier's (1900) random walk model of stock option prices based upon a Gaussian distribution fails to account for the clustered volatility of the price movement of cotton. Shiller (1981) observes that in contradiction to the EMH, the S&P stock prices move too much to be justified by the subsequent changes in the dividends. Furthermore, Farmer and Geanakoplos (2008) state that the market is essentially a dynamic process, hence the failure of EMH to model market dynamics is a serious shortcoming.

GET helps to prove that the neoclassical framework is logically inconsistent and degenerative. Walras (1874) introduces GET to find a price vector that would establish the balance between supply and demand across a number of markets. Arrow, Debreu and McKenzie (ADM) (Debreu 1959) extend Walras (1874) by incorporating elements of REH. The Arrow–Debreu Existence Theorem (Arrow & Debreu 1954) proves the existence of the price vector. However, the *Sonnenschein–Mantel–Debreu* (SMD) Theorem (Debreu 1959) proves that the ADM model of GET has a shapeless excess demand curve, which implies that there lacks a stable or unique price vector in contradiction to methodological equilibration that is one of the three fundamental assumptions in neoclassical economics, hence the lack of a stable price vector makes static analysis untenable. However, Smith (2007) uses experimental economics to show that interconnected markets do approximate market equilibrium and track a moving equilibrium even with few market participants and limited information. This suggests two ways to remedy the shapeless demand curve either use dynamics or introduce agents that use *'rule of thumb'* rather than utility curves. Furthermore, Farmer and Geanakoplos (2008, p. 14) note that there are problems with defining utility, which makes the use of alternatives desirable. However, neoclassical economics found an alternative solution to the shapeless excess demand curve by assuming all goods have a neutral Engel curve (Keen 2001, pp. 38-42). In practice there are few, if any, goods with neutral Engel curves. This solution protects the *hard-core* of neoclassical economics, but sacrificed realism, as part of the *'protective-belt'*. Lakatos (1976) would consider this falsification avoidance a sign of a degenerative scientific research program.

CGE embodies REH assumptions. An example of the prevalence, credibility and perceived importance of CGE is the Global Trade Analysis Project (GTAP 2009) coordinated by the Centre for Global Trade Analysis, Department of Agricultural Economics, Purdue University. GTAP (2009) provides figures on its use in global quantitative economic analysis to support its claim as a common language for global trade analysis. Mitra-Kahn (2008) notes that the *'general equilibrium'* in CGE models is an assumption and comes from balancing macro Keynesian simultaneous equations, where equilibrium is imposed from above, which makes CGE models *'top–down'* models. In comparison, the *'general equilibrium'* of GET and Applied General Equilibrium (AGE) models derive from finding a price vector that balances the supply and demand of the agents; equilibrium is calculated, with the simplex method in the AGE model, thus AGE and GET models are *'bottom–up'* models and seek to prove that *'general equilibrium'* exist. CGE and DSGE just assume that equilibrium exists even though the SMD Theorem proves the lack of general equilibrium in static models. Furthermore, Blatt (1983) discusses the dual (in)stability problem that proves that the imposition of equilibrium with these *'top–down'* models is also of questionable veracity. Altogether, this makes any policy derived from CGE or DSGE potentially misleading.

Additionally, the DSGE and CGE models use the word *'dynamic'*, but their claim to be dynamic is at the level that a number of pictures of motionless scenes can be combined to produce a moving film but fails to represent a dynamic process. However, each of these static pictures or GE is actually unstable. The CGE and DSGE produce dynamic instability, in contrast Smith's (2007) experimental economics produces *dynamic-stability* as an ongoing process. Keen (2001, pp. 175-6) quotes Jevons (1911), Clark (1898), Marshall (1920, p. xiv) and Keynes (1923) who recognise the economy as a dynamic process that is better modelled dynamically but they acknowledge also that static analysis provides a stop–gap measure until adequate technical ability arrives to do so. Section 5.3 further discusses *dynamic-stability* and *static-instability*.

DSGE are full multi-period dynamic models, which consider that the agents' expectations depend on the future states of the economy. This requires the model to be solved simultaneously over the full multi-period. The DSGE method directly uses REH. Kydland and Prescott (1982) introduce the first DSGE, called the Real Business Cycle (RBC). Summers (1986) describes the RBC as a floating Walrasian equilibrium buffeted by productivity shocks, which assumes no monetary policy effects on real activity; in which fiscal policy only works via incentives and economic fluctuations are purely the result of supply rather than demand. Stadler (1994) discusses five criticisms of the RBC. One, there is a lack of evidence for sufficient large real shocks to drive the model. Two, testing the RBC is purely subjective. Three, RBC fails to capture the business cycle because it lacks suitable transmission mechanisms. Four, the RBC does not explain recession well. Five, the representative agent makes the model unsuitable for welfare or policy development. Aoki (2007) suggests using an agent-based modelling (ABM) approach that would resolve two of the RBC problems, the poor transmission mechanism and the representative agent. In agreement, Kirman (1992, p. 131) suggests that it is insufficient to introduce heterogeneity into general equilibrium models without expanding the role of interactions between agents from anonymous price-takers to include the passage of information, the building of regulations, organising into groups for the purpose of trading, and more. Prescott (1988, p. 84) acknowledges that the RBC models are *'necessarily false and statistical hypothesis testing will reject them.'*

1.1.2 What caused the failure of REH and the neoclassical framework?

This section discusses three reasons for the failure of the neoclassical framework and its REH, which are chosen for their relevance to the thesis. First, instrumentalism, the philosophy underpinning neoclassical economics, is flawed. Second, neoclassical economics approximates the dynamic economy with static models. Lastly, neoclassical economics has blurred the distinction between subjective and objective probabilities by using rational choice theory beyond the domain intended by Von Neumann and Morgenstern (1944). The second and third reasons are interrelated, if one assumes that the economy is static, it is feasible to approximate subjective probabilities with frequentist probabilities. However, the economy is not static.

The philosophy underpinning neoclassical economics is instrumentalism. Friedman (1953, p. 15), a major proponent of instrumentalism, states that the assumptions need not be realistic but sufficient approximations to produce theories that predict accurately. This argument is used to justify the continued use of statics in economics. Musgrave (1981) discusses the flaws in instrumentalism, where he notes three types of assumption, negligibility, domain and heuristic. Musgrave (1981) notes that all theories make negligibility assumptions and these assumption are fine provided the theories can make falsifiable predictions. However, making domain assumptions means that theory is applied outside the scope of its assumptions and may well be misleading, such as, when static analysis is applied to a dynamic system. Musgrave (1981) notes that heuristic assumptions are fine too, provided that the theory can predict and the assumptions gradually become more realistic to allow more accurate prediction. However, neoclassical economics became less realistic after it introduces the neutral Engel curve assumption to maintain stability in GET. Section 5.3 further discusses the flaws in instrumentalism to establish the need for an alternative framework to the neoclassical theoretical framework for the AIE model.

Vercelli (2007, p. 21) discusses the two forms of decision theory, the objectivist theory introduced by Von Neumann and Morgenstern (1944) and the subjectivist theory, often called Bayesian, suggested by Savage (1954). Lucas (1986, p. S411) notes, '*the economic theory of choice is ... a description of a ... stationary "point" ... [in a] dynamic adaptive process.'* At such a point, the optimal adaptation has already happened and the decision–maker knows the complete list of its possible states and options, and is also aware of the consequences of each choice for each possible state. Vercelli (2007, p. 21) notes that the objective and subjective decision-making theories may appear different. However, their implications are almost identical axiomatically and ontologically because both theories refer to a world that is familiar to the decision–maker. The term '*subjective*' in the thesis refers to the much stronger form that Keynes (1937, pp. 213-4) uses when he discusses '*uncertain*' knowledge to claim that probabilities are unmeasurable, rather than the weaker form suggested by Savage (1954).

Von Neumann and Morgenstern (1944 p.19) developed rational choice theory and stipulate its domain of applicability to objective probabilities when they warn against rational choice theory use with subjective probabilities. However, both behavioural economists and economists who use REH continue to use rational choice theory with subjective probabilities. For instance, Van der Sal (2004, p. 432) notes that for nearly half a century the rational choice theories (Von Neumann & Morgenstern 1944) have been tested against individual behaviour but repeatedly the underlying assumptions and predictive value appear descriptively false. Tversky and Kahneman (1974, p. 1128) discuss anchoring and Kahneman and Tversky (1979) discuss prospect theory to model behaviour that is at odds with rational choice.

1.1.3 The failure of REH informing the development of AIE

The background establishes not only the need for an alternative expectations model to REH but establishes also the need for an alternative framework to the neoclassical and the need for an alternative to the utility curve concept. Keynes (1937, pp. 213-4) provides a suitable structure to develop an alternative expectations model and the *'science of complexity'* provides a suitable framework.

Keynes (1937, pp. 213-4) discusses '*uncertain*' knowledge and claims that probabilities relating to the relatively distant future are not measurable, where he suggests that people adopt the following three strategies in the face of uncertainty, which are further addressed in other literature.

1. Assume the present is a much more servable guide to the future than the past and largely ignore the unknowns in the future. This strategy could be modelled with the exponential smoothing in adaptive-expectations (Hicks 1939).
2. Assume the existing state of opinion is reflected in the prices and the characteristic of the existing output is a correct summing up for future prospects, unless something new and relevant comes into the picture. This strategy could be modelled by combining adaptive-expectations (Hicks 1939) and interactive-expectations (Flieth & Foster 2002).
3. Knowing our own judgement to be worthless; we fall back on the judgement of the rest of the world, in so doing, we conform to the behaviour of the majority or the average. This leads to a *conventional* judgement. This strategy could be modelled with interactive expectations (Flieth & Foster 2002).

The AIE model combines adaptive-expectations (Hicks 1939) and interactive-expectations (Flieth & Foster 2002). Both adaptive-expectations and interactive-expectations are dynamic and subjective models. Therefore, AIE is also a dynamic and subjective model. The adaptive-expectations model forms a benchmark for AIE to test the interactive component. By contrast, the other benchmark, REH (Muth 1960; 1961), is an objective and static model. The thesis compares the dynamic subjective model, AIE, and the static objective model, REH, within the *'science of complexity'* and neoclassical frameworks, respectively. Sections 2.1.6 and 3.1.4 further discuss Keynes' (1937, pp. 213-4) three strategies in relation to developing the AIE model.

1.2 Research problem

The research problem of this thesis is.

> ***Can a dynamic subjective expectations model be used to make more accurate temporal predictions than the REH and the adaptive-expectations models?***

To address the research problem, the thesis develops AIE as a dynamic subjective expectations model. Section 2.3 breaks the problem into seven testable smaller research questions. These questions involve empirically testing AIE against REH and adaptive-expectations models. These questions are made operational in section 3.8 by using the methodology in Chapter 3. Chapter 4 addresses the questions by analysing the results from running the AIE model outlined in Chapter 3. Sections 5.1 and 5.2 provide context within the literature for the questions addressed in Chapter 4.

1.3 Justification for the research

Section 1.1 provides a background to REH, which includes stressing the importance of REH to the neoclassical framework, where REH is a *hard-core* theory in the framework, which underpins the following major theories, EMH, GET, and DSGE. Section 1.1 also provides reason to develop a dynamic subjective expectations model within an alternative framework to neoclassical economics to replace REH for the following reasons. EMH, GET and DGE all show anomalies attributable to REH at their core. The neoclassical framework shows signs of degenerating. Instrumentalism, the philosophical underpinning to neoclassical economics, is flawed. The static analysis central to neoclassical economics and REH may misinform policy development. Static analysis was only ever intended as a stop–gap measure until the techniques for dynamic analysis were developed.

The thesis develops AIE as a potential replacement for REH. A profit expectations survey is used to calibrate and test AIE. Profit expectations are important because they determine whether a firm makes investments and whether one business will extend credit to another. Noting that, the concepts and techniques presented in the thesis and tested using profit expectations can be adapted to other forms of expectations.

1.4 Methodology

This section briefly justifies and outlines the methodology in section 1.4.1 and 1.4.2, respectively. Chapter 3 builds on this section to provide a fuller justification and description of the methodology.

1.4.1 Justifying the Methodology

The methodology chosen is ABM using falsifiable temporal prediction to compare the predictive power of the AIE model against the REH and adaptive-expectations models, hence there are two aspects to justify, which are using falsifiable temporal prediction and using an ABM. In addition, there is a need to justify introducing the *'pressure to change profit expectations index', p^x,* to replace probabilities and utility curves.

1.4.1.1 Justification for using falsifiable temporal prediction rather than stylised facts

Falsifiable temporal prediction is not commonly used in ABM that more often uses stylised facts to produce falsifiable predictions. However, falsifiable temporal prediction was chosen for two reasons. First, it allows AIE direct comparison with the benchmark models, REH and adaptive-expectations. Second, it provides credibility for the techniques developed to support AIE because practitioners appear reluctant to adopt ABMs (Dawid & Fagiolo 2008, p. 352). This reluctance is due in part to using stylised facts to verify and validate the models. Section 2.2.3 further discusses verifications and validation issues for ABMs. Section 5.4.3 further discusses the reluctance of the practitioners to adopt ABM.

1.4.1.2 Justification for using network ABM

The justification for using a network ABM is that it can model expectations dynamically. Section 1.1 discusses the problems with neoclassical economics modelling the economy statically and that the static methodology was only intended as a stop–gap measure until dynamic methodologies arrived. However, there are at least four methods for modelling dynamically, statistical mechanical ABM, network ABM, differential equations and evolutionary economics, among which network ABM was chosen because of the following reasons. The network ABM method was chosen over a statistical mechanical ABM method because the economy resembles a network lattice more than a gas; the network structure acts as a proxy for institution and rules. The network ABM was chosen over differential equations because the behaviour of individuals can be modelled and their interactions produce emergent macro level phenomena. Foster (2005, p. 5) and Amarala and Ottino (2004, p. 149) note that differential equations tend to be used in non-adaptive systems at the physio-chemical level. Section 2.2.1.1 further discusses differential equations. The Network ABM method was chosen over the evolutionary economic method because near–zero-intelligent agents appear to model economic situation well where the institutions are mature (Axtell & Epstein 1999, p. 177; Ormerod et al. 2007, pp. 208-9). Section 5.5.2 further discusses zero-intelligent agents.

1.4.1.3 Justification for introducing the 'pressure to change profit expectations index' p^x

The thesis introduces the p^x to replace probabilities. There is a need to justify replacing probabilities with an index, as probabilities are prevalent in economic decision theory. Section 1.1 discusses Keynes' (1937, pp. 213-4) view on uncertain knowledge where he claims that probabilities are unmeasurable. Lucas (1986, p. S411) notes, '*the economic theory of choice is ... a description of a ... stationary "point" ... [in a] dynamic adaptive process.'* AIE dynamically models uncertain knowledge to use the strong form of subjectivity as opposed to the weak form in Savage (1954) who suggested using a Bayesian approach, which is more suited to a stationary point. Section 3.1.4 further discusses probability in stationary decision theory and unknowables in dynamic adaptive processes. The index also provides a way to separate belief from outcome and probability. For example, Kahneman and Tversky (1979) introduce prospect theory that uses weights to model people's expectations. Additionally, Eichberger, Kelsey and Schipper (2009) discuss ambiguity, when they note the difficulty in adding together different beliefs and state '... *the separation of beliefs and outcome evaluation ... makes the theory easier to apply in economics and social sciences.'* The p^x provides a method to add together pressures from threes sources, interactive, adaptive and biases, including optimism, pessimism and ambivalence. Section 3.1.3 discusses the need for alternative measures of belief to outcome or probability. Yu and Cohen (2009) find that the Bayesian approach is a slightly less accurate model of learning than an exponential discounting model, which has many features in common with the leaky integration neuronal models. This suggests a more fundamental basis for modelling because the human decision-making process is essentially a biological process and the Bayesian approach is a mathematical approximation. Section 3.1.2 further discusses Yu and Cohen's (2009) findings.

1.4.2 Outlining the Methodology

Section 1.4.1 justifies using a network ABM and introducing p^x for AIE. This section outlines how AIE is developed to address the research problem in section 1.2 and research questions in section 2.3. Section 3.2 provides an overview of the ingredients to the formal AIE model; the core equations for the AIE model are equations (3-2), (3-3) and (3-4).

The D&B (2008) profit expectations survey provides index series for a change in actual profits and a change in profit expectations; the aggregate or *all–firms* series are shown in Figure 2–6. The firms completing the survey provide two responses what happened to their actual profits last quarter and what they expect their profits to be next quarter. There are three possible responses for both actual and expected profits, that is, either increasing, decreasing or *no–change*. These survey responses are aggregated to form the D&B (2008) profit expectations and actual profit indices.

The only exogenous input into AIE is the actual profits index series. The reason is to focus on endogenous processes and network structures. AIE simulates profit expectations by using the first two quarters from the D&B (2008) profit expectations index series to initialise the model and the D&B (2008) actual profit index series. AIE is calibrated using the D&B (2008) survey by minimising the model variance. Once calibrated, AIE is benchmarked against the following models, REH and adaptive-expectations. AIE is benchmarked against REH because REH is the main neoclassical expectations model, which shows many anomalies. AIE is benchmarked against adaptive-expectations to determine how effective the interactive component in AIE is in improving predictive performance.

In addition to the aggregate called *all–firms*, the D&B (2008) profit expectations survey comprises four divisions, non–durable manufacturing, durable manufacturing, wholesale and retail. Figure 2–7 shows the D&B (2008) profit expectations indices for the four divisions. The *all–firms* and four divisions provide an opportunity to test an aggregate and disaggregated version of AIE, respectively. The AIE uses an ABM that has a network whose nodes represent firms and the links represent the flow of expectations between the firms. In the aggregated AIE version, the link intensities between firms are set to one. In the disaggregated AIE version, the *'input-output table'* shown in Table 2–4 based on the four divisions allows calibration of the link-intensity between firms. The thesis introduces two '*link-intensity matrices'* based on the *'input-output table'* and its transpose, where a *'matrix of ones'* provides the default and benchmark *'link-intensity matrix'*, when testing these *'link-intensity matrices'* against the benchmark establishes whether the interactive-expectations network can be calibrated using an *'input-output table'*. This is a significant issue for practitioners who would like to validate ABM for use in policy development.

There exists uncertainty over how the interactive network should be structured. Thus, the approach adopted was to use 121 different network topologies and calibrate each one. Section 2.2.2 discusses the 121 network topologies. The 121 calibrated models based on the network topologies were model-averaged to represent the AIE model. Model-averaging across the 121 models was problematic because each network was based on three parameters regardless of how complex the network was. This fixed number of parameters and variable complexity made the use of the Bayesian Information Criterion (BIC) to form a weight in the model-averaging unsuitable because the BIC bases its measure of complexity on the number of parameters. The thesis introduces two model-averaging techniques to circumvent this problem, which are called *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'*. *'Bayes-factor model-averaging'* and *'equal-weighted model-averaging'* were used to benchmark *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'*.

The p^x for each firm for each period is the sum of the pressures from three sources, interactive, adaptive and bias, including optimism, pessimism or ambivalence. It is determined stochastically by using the p^x relative to fixed pressure levels that are determined experimentally as to whether a firm changes its profit expectations for the next period. A firm can be in one of three states, increase, decrease and *'no change.'* The interactive pressure on a firm is calculated using the number of firms it is linked to, which are in each of the three states. The adaptive pressure for each firm for each quarter is calculated from the difference between its actual profit state and its expected profit state for the current quarter and previous quarter. The bias pressure represents the general mood of the economy. The profit expectations state of each firm for each period is summed to calculate the profit expectations index of the model. This index is compared to the D&B profit expectations index to calculate the model variance.

Figure 3–2, Figure 3–3 and Figure 3–4 show the model variance for the 121 network topologies centred on model run *1* in Table 3–1.

1.5 Outline of the thesis

The thesis addresses the issues raised above in the following chapters.

The literature review in Chapter 2 justifies the need to find a replacement or supplement to REH, thus the thesis develops AIE as a potential candidate. REH is the standard neoclassical model of expectations and forms the core of many other neoclassical theories such as GET, EMH, CGE and DSGE. The literature reveals that many behavioural, logical and econometric discrepancies in these theories are related to their use of REH. Modelling expectations in an interactive and dynamic way may remedy many of the discrepancies found. A comparison of the *'science of complexity'* and neoclassical frameworks shows the former to be more suitable for the development of such a model. To supplement the behavioural literature already uncovered, the chapter surveys the literature in the interactive-expectations, network, ABM, input-output and adaptive-expectations fields to find components for AIE. The literature review finds that there is a gap in the literature for a dynamic subjective temporal predictive model of expectations and that constructing the model using an ABM methodology is the most appropriate. This combination of temporal prediction and ABM requires a discussion of multi-variable optimisation techniques. Furthermore, AIE uses a model-average across 121 different network topologies, where each network topology requires optimisation. The BIC proves unsuitable for model-averaging in this thesis because the network topologies in AIE have a fixed number of parameters regardless of complexity. Therefore, there is a requirement for the development of new model-averaging techniques. The research questions are developed from benchmarking different versions of the AIE model against REH and he adaptive-expectations model. Further questions are developed from benchmarking two new model-averaging techniques against existing techniques.

The methodology in Chapter 3 gives an overview of the AIE model. An ABM methodology is chosen to model expectations because it provides for dynamics and interactions between agents within a network structure. The neoclassical framework lacks these features, a lack that causes many discrepancies for REH, as discussed in Chapter 2. The D&B profit expectations survey is used to test the predictive power of AIE against REH adaptive-expectations; the survey was also discussed in Chapter 2. Chapter 3 justifies introducing the *'pressure to change profit expectations index'*, p^x, as a subjective measure of expectations to replace probabilities and separate belief from outcomes for an individual entity. The p^x combines the pressure to change profit expectations from three sources, interactive, adaptive and biases that are either optimistic, pessimistic or ambivalent. The interactive pressure for a firm is determined from the links in the network structure that represents the flow of expectations for the current quarter from other connected firms. The adaptive pressure for a firm is determined from the difference between actual profits and expected profits for the current and last quarters. The biases are an indication of the general mood of the economy. Stochastic equations are introduced to determine whether p^x is sufficient for a firm to change expectations next quarter. The techniques for calibrating the 121 network topologies are discussed. The model-averaging techniques for the 121 network topologies are *'optimal-calibration'*, *'runtime-weighted'*, *'Bayes-factor'* and *'equal-weighted'*. The thesis introduces the *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'* and benchmarks them against the *'Bayes-factor model-averaging'* and *'equal-weighted model-averaging'*. The thesis also introduces the *'link-intensity matrix'* based on the *'input-output table'* to better calibrate the network structure in the disaggregated AIE model. The default *'link-intensity matrix'* is a *'matrix of ones'*, which forms a benchmark. The *'transpose of the input-output table'* forms a *'link-intensity matrix'* and is also compared against the benchmark. Lastly, the research questions are made operational and refined to reflect the methodology.

Chapter 4 discusses the results from running the AIE model in Chapter 3 to answer the research questions. Different versions of the AIE model are calibrated using the D&B profit expectations survey and the predictive performances of the versions are compared against the benchmarks, REH and adaptive-expectations models. The aggregate AIE model is calibrated over a short and long period and their predictive performances are compared. The remainder of the results are derived from calibrating the AIE model over the short period only. Additionally, the predictive performance of the model-averaging techniques that the thesis introduces, called *'optimal-calibration'* and *'runtime-weighted'*, are compared with the benchmark model-averaging techniques called *'Bayes-factor'* and *'equal-weighted'*. Furthermore, the predictive performance of the aggregate AIE model that uses the *'link-intensity matrix'* based on the *'input-output table'* and its transpose, is compared with the predictive performance of the benchmark *'link-intensity matrix'* that is a *'matrix of ones'*.

The conclusion and implications in Chapter 5 provide context within the literature for the results from Chapter 4. The theoretical implications of the comparison between REH and AIE beget comparison between instrumentalism and scientific realism and between neoclassical and the *'science of complexity'* frameworks. The role of REH in the failure of GET and consequently the lack of foundation for the *'Fundamental Theorems of Welfare'* is discussed to highlight the need to find alternative theory to neoclassical economics to guide policy and practice. The policy implications are discussed, which includes using REH and AIE together in a complementary normative and descriptive/predictive role, respectively. Additionally, combining narrative, mathematics and ABM to inform policy and ameliorate each other's weaknesses is also explored. The practical implications are discussed, including the AIE network topology and model-averaging techniques to overcome the lack of validation credibility for ABMs. The contributions of the thesis to the literature are presented. Additionally, improvements to the AIE network calibration by using an *'input-output table'* and the number of firms to determine the *'link-intensity matrix'* are discussed, as is its possible application to CGE and DSGE to improve their transmission mechanism. The thesis concludes with further research ensuing from the research in the thesis.

The source code for the AIE model, model-averaging and optimisation techniques cited in Appendix A are provided on DVD.

1.6 Definitions

Definitions adopted by researchers are often not uniform, hence key and controversial terms are defined to establish positions taken in this thesis.

All–firms This term is for the aggregate of the four divisions of the D&B (2008) profit expectations survey, including manufacturing durable, manufacturing non–durable, wholesale and retail.

'input-output network' A network whose parameter values are constrained using the number of firms and the *'link-intensity matrix'* derived from an *'input-output table'*.

Input-output ratio *'Input-output tables'* are used to form ratios in an unconventional way in this thesis. Traditionally input-output ratios are based upon divisions of the economy. The thesis uses ratios derived from the *'input-output table'* for individual firms to form the interactive component of a *'pressure to change profit expectations index'* p^x. The *'input-output table'* in conjunction with the number of links to other firms within a network structure is used to calculate the index. Section 2.1.9.1 further discusses the interactive component of the p^x.

Network theory The thesis uses network theory rather than graph theory. Network theory is the study of network dynamics, which is more an experimental science

(Newman, Barabási & Watts 2006), whereas graph theory is the study of static networks, which is more a pursuit in pure mathematics.

Subjective — The thesis uses Keynes' (1937, pp. 213-4) '*uncertain*' knowledge as the basis for a non-probabilistic treatment of decision-making and introduces an index to replace probabilities. Additionally, the term subjective becomes synonymous with dynamic processes that uses Lucas' (1986, p. S411) observation that '*the economic theory of choice is ... a description of a ... stationary "point" ... [in a] dynamic adaptive process.*'

Objective — The thesis considers both probabilistic based decision theories as objective. These theories include Von Neumann and Morgenstern's (1944) rational choice and Savage's (1954) Bayesian approach. Additionally, the term objective becomes synonymous with static analysis that uses Lucas' (1986, p. S411) observation. The need for this approach to defining subjective and object stems from people using Von Neumann and Morgenstern's (1944) rational choice beyond its intended domain of frequentist probability.

Profit — Profit is simply income less expenditure, as used in the D&B (2008) profit expectations survey.

Parameter — See variable.

Run — The software simulating AIE has a combination of parameter settings, which produce a model variance. The combination of the parameter settings and model variance form a single run. Three of the parameter settings describe the network topology of AIE. The AIE model uses the model-averaging of 121 different network topologies to improve its predictive performance, which is the model-average of 121 runs.

Variable — The words *parameter* and *variable* are used interchangeably in the thesis.

1.7 Delimitations of scope and key assumptions

AIE is tested with the Australian D&B (2008) profit expectations survey, which makes the calibrations and predictions applicable to Australia. However, the AIE technique could be applied to any similar expectations surveys.

The AIE model has only one exogenous input, that is, the *'change in actual profits'*. The reason to restrict AIE to a single exogenous input was to focus on the interactive-expectations in the model and in particular the network. There is ample literature to suggest that the predictive ability of the AIE may improve by introducing exogenous inputs such as the change in credit and interest rates. However, time spent perfecting the calibration of the network structure to capture endogenous effects may well produce considerable gains and is a preferable first step before more exogenous factors are introduced.

1.8 Conclusion

This chapter has laid the foundations for the thesis. It has introduced the research problem and research questions. Then the research was justified, the methodology was briefly described and justified, each chapter of the thesis was outlined, and definitions were presented. Lastly, the delimitations of scope and assumptions were given. The thesis can proceed with a detailed description of the research outlined in this chapter.

2. Literature Review

2.0 Introduction

This literature review discusses how the neoclassical framework's three core axioms are logically inconsistent. The framework's chief expectations model is the *Rational Expectations Hypothesis* (REH), which is built upon the neoclassical axioms and rational choice. REH is important because many major neoclassical theories use REH such as the *Efficient Market Hypothesis* (EMH), *General Equilibrium Theory* (GET) and *Dynamic Stochastic General Equilibrium* (DSGE). However, there is an extensive empirically based literature that falsifies REH, rational choice and these theories. The literature finds that REH is more a normative model than a descriptive/predictive model. This presents a gap in the literature for a descriptive/predictive model of expectations that can complement the normative role of REH. This thesis develops the *Adaptive Interactive Expectations* (AIE) model to fill this gap in the literature. The literature that informs the development of AIE and that falsifies REH comes from numerous disciplines that include, neurology, psychology, physiology and the *'science of complexity'*.

Network theory is discussed to provide a proxy for institutional structure in AIE. *Agent-based Models* (ABM) are discussed because they can combine the behavioural rules within network structures used in AIE. Falsification and verification issues that relate to ABM are also discussed. AIE uses temporal prediction, thus it avoids many of the ABM verification issues. Optimisation techniques for functions of many variables are discussed because AIE has many variables and uses 121 network topologies to represent institutional structure, and consequently calibrating AIE is extremely time consuming. Model-averaging techniques are discussed because the 121 network topologies are structurally different and, therefore, are models in their own right. The thesis introduces two new model-averaging techniques called *'optimal-calibration'* and *'runtime-weighted'*.

There are three sections in this chapter. Section 2.1 discusses the parent disciplines and models relevant to the thesis. Section 2.2 examines the immediate discipline and analytical models relevant to the methodology. Section 2.3 outlines the research problem and questions that arose out of sections 2.1 and 2.2.

2.1 Parent disciplines, fields and models

This section of the literature review discusses the more conceptual literature to support the construction of AIE. The section compares the theoretical frameworks of neoclassical economics and *'science of complexity'* to provide context for REH and AIE as complements. REH and its criticisms from behavioural economics and econometrics are discussed. The section finds that REH is considered an assumption unamenable to falsification by some researchers, which requires that REH to be falsified as part of a larger theory such as the EMH, GET or DSGE. Therefore, falsification of the three theories is discussed in detail.

The EMH has a number of pricing anomalies, which can be explained by behavioural economics that also provides behavioural rules for AIE. DSGE fails to match a number of stylised facts about the business cycle. GET is logically falsified using the *Sonnenschein–Mantel–Debreu* (SMD) *Theorem* that proves that the three axioms for the neoclassical framework are inconsistent. GET and emergence form the microfoundations projects for neoclassical and complexity economics, respectively. Consequently, falsification of GET leads the thesis to adopt emergence for AIE to link together its micro level components. Profit expectations indices and phase changes are discussed because they are the macro level phenomenon that AIE is tested against. The adaptive-expectations model and interactive expectations model are discussed because they provide the micro behavioural rules for AIE, which are supported by findings from behavioural economics and whose findings are contrasted with REH, EMH, GET and DSGE. The limitations identified within REH, EMH, GET and DSGE provide justification for the AIE methodology.

The structure of this section is as follows. Section 2.1.1 discusses the theoretical frameworks. Section 2.1.2 discusses REH and behavioural economics. Section 2.1.3 discusses EMH. Section 2.1.4 examines the neoclassical and complexity microfoundations projections of GET and emergence, respectively. Section 2.1.5 discusses DSGE. Section 2.1.6 discusses emergence further, with a view to link together the behavioural rules in the AIE model. Section 2.1.7 discusses the profit expectations indices and phase changes. Section 2.1.8 discusses the adaptive-expectations model, which is a component and also a benchmark of AIE. Section 2.1.9 discusses phase changes and the interactive-expectations model, which is a component of AIE.

2.1.1 Theoretical Frameworks: Neoclassical, Complexity and Behavioural Economics

This section discusses the neoclassical and complexity economic frameworks to provide context for REH and AIE, respectively. REH and AIE are complements that provide advantages to analysing scenarios from two perspectives. The complexity economic framework uses a pattern recognition or inductive approach, which belongs to the philosophy of science. By contrast, the neoclassical framework uses a deductive or axiom-proof-theorem approach, which belongs to the philosophy of mathematics. However, neoclassical economics requires many simplifying assumptions in its axioms for the mathematics to remain tractable. The section introduces behavioural frameworks that aid the development of the AIE model, including ex-ante and ex-post rationalisation and the three systems cognitive framework.

The structure of this section is as follows. Section 2.1.1.1 defines the neoclassical framework. Section 2.1.1.2 defines the complexity framework. Section 2.1.1.3 compares the methodologies of the two frameworks and augments complexity with experimental and behavioural economics. Section 2.1.1.4 discusses the role of these frameworks in directing research. Section 2.1.1.5 discusses the role of AIE as a complement to REH, which enhances analysis by allowing a dual approach. Section 2.1.1.6 compares ex-ante and ex-post rationalisation to differentiate the rationalisation processes in AIE and REH at a neurological level. Section 2.1.1.7 discusses the three systems cognitive framework to provide context for AIE and REH at a psychological level. Section 2.1.1.8 compares objective and subjective expectations and their respective methodologies. Section 2.1.1.9 summarises the contents discussed in the previous sections.

2.1.1.1 Neoclassical

Table 2–1 compares the assumptions that Arnsperger and Varoufakis (2006) and Farmer and Geanakoplos (2008, p. 5) consider to define neoclassical and equilibrium economics, respectively. Arnsperger and Varoufakis (2006) note that other assumptions such as agents with complete knowledge are usually attributed to the neoclassical framework. However, Farmer and Geanakoplos (2008, p. 12) state that some neoclassical theory relaxes REH by introducing some form of bounded rationality. Therefore, rational expectations are excluded from the definition of neoclassical economics in this thesis. There are two points to note about neoclassical economics relaxing REH assumptions; the incremental move toward more realistic assumptions and the fact that the framework is blurring at the edges that makes it difficult to create a sharp definition. A further reason to exclude rational expectations from the definition is that this thesis uses REH as a benchmark for the AIE model, therefore, the definition of Arnsperger and Varoufakis (2006) provides a better structure to discuss REH within.

Table 2–1 Neoclassical Assumptions

	Arnsperger and Varoufakis (2006)	Farmer and Geanakoplos (2008, p. 5)
1	Methodological instrumentalism	Agent optimisation of utility
2	Methodological individualism	Perfect competition (price taking)
3	Methodological equilibration	Market Clearing
4		Rational Expectations

Instrumentalism

The philosophy underlying neoclassical economics is instrumentalism; '*a system of pragmatic philosophy that considers idea to be instruments that should guide our actions and their value is measured by their success*' (WordNet® 3.0 Princeton University 2009). Friedman (1953, p. 15), a major proponent of instrumentalism, states *'..., the relevant question to ask about the "assumptions" of a theory is not whether they are descriptively "realistic", for they never are, but whether they are sufficiently good approximations for the purpose in hand. And this question can be answered only by seeing whether the theory works, which means whether it yields sufficiently accurate predictions.'* Section 5.3 discusses the flaws in instrumentalism.

1. Methodological instrumentalism

Methodological instrumentalism explains all behaviour as a desire to maximise preference-satisfaction. There is no room for philosophical question as to whether a person will act in such a way. Traditionally in neoclassical economics preference-satisfaction is constant and determined exogenously, whereas in complexity economics preferences depend on the structure and history of interaction. Behavioural economics provides substantial experimental evidences against the utility maximising model of an individual. Sections 2.1.2, 2.1.3, 2.1.4 and 2.1.8 discuss this evidence. Based upon this evidence, AIE uses a set of rules to replace the utility maximising model.

2. Methodological individualism

Arnsperger and Varoufakis (2006) note that methodological individualism has two forms: explanation in terms of individuals alone; or explanation in terms of individuals plus relations between individuals. This thesis uses the first form to describe neoclassical methodological individualism, so that explanations for socio-economic processes are to be found by studying individuals interacting via a price signal only, where the individuals retain independent and constant preferences. This approach serves to isolate the individual from other non-price interactions and any influence that structure may have on interactions and on individuals and vice versa. However, this approach does allow modelling a complicated system with a simple system and a corresponding reduction in computational requirements but a cost to neoclassical economics for using a simple model of the economy is its failure to link microeconomic to macroeconomic phenomenon. Section 2.1.4 further discusses this linkage failure of GET.

In comparison, complexity economics studies the relationships among structure, interactions and individuals to explain macro socio-economic processes as an emergent process. AIE uses emergence to link the profit expectations of individual firms to the macro level profit expectations index. The network structure of AIE acts as a proxy for institutional structure and helps model emergence. Sections 2.1.4 and 2.2.1 further discuss emergence.

3. Methodological equilibration

Methodological equilibration is the imposition of equilibrium. Once the neoclassical agent's utility function and constraints are postulated, to develop predictions at the macro level the aggregate behaviour of the individuals has to be sufficiently regular. Arnsperger and Varoufakis (2006) reduce the equilibration process to three steps:

1. Discover an equilibrium
2. Assume that agents or their behaviour will find themselves at equilibrium
3. Demonstrate that any small perturbations are incapable of dislodging self-interested behaviour from the discovered equilibrium.

This simple approach provides for prediction. However, the neoclassical microfoundations project, as discussed in Section 2.1.4, has failed to find a price vector for which there is a stable unique equilibrium. Complexity economics does not impose equilibration and treats the economy as an evolutionary system. However, relaxing the equilibrium assumption creates modelling problems. The predictive problems associated with evolutionary systems are discussed in Section 2.2.3.

All three neoclassical economics assumptions have major problems. Salzano and Colander (2007, p. X) comment, '*The problem with [neoclassical] economics is twofold[:] the first is the simplicity of the model assumptions do not allow the complexity of the common sense interactions that one would expect; the second is the failure of the models to fit the data in an acceptable way.'* The next section discusses complexity economics that addresses these issues.

2.1.1.2 Complexity

Pryor (2000, p. 64) describes complexity economics as *'involving positive feedback, lack of determinable equilibrium, and the importance of adaptive process of interaction between many heterogeneous people, none of whom is completely aware of how such an interaction is turning out or what others are thinking.'* Pryor (2000, p. 63) notes that economists who use complexity theory are generally dissatisfied with neoclassical economics. These include, institutionalists, evolutionists, specialists in dynamic processes and nonlinear mathematics, experimentalists, specialists in comparative economic systems, Austrian economists, game theorists, anti-Walrasians, economic historians, etc. Delre and Parisi (2007, p. 212) note all these approaches differ to neoclassical economics which uses its static explanation of equilibrium to predict macro-variables and assumes that entities are REH rational and have full information. However, Pryor (2000, p. 65) notes within complexity economics that there exists a tension between the focus on process and structure. Delre and Parisi (2007, p. 212) discuss two of the alternative approaches to modelling complexity, evolutionary economics (Arthur, Durlauf & Lane 1997; Dosi & Nelson 1994; Nelson & Winter 1982) and agent-based computational economics (Epstein & Axtell 1996; Tesfation 2002). Bounded rationality features in both approaches. Evolutionary economics focuses on the fitness of agents' behaviours in the environment and how these behaviours adapt and evolve under the pressure of selection rules. Agent-based computational economics simulates the behaviours of economic agents by using computational models in order to show emergence. Emergence is the process whereby the interactions of economic agents that follow micro-level rules, leads to macroeconomic phenomenon. This is the modelling approach adopted by AIE and the micro-level rules of the agents are developed from behavioural economics discussed in Section 2.1.3. Other approaches to modelling complexity are discussed in Section 2.2.1. Sections 2.1.6 and 2.2.1 further discuss emergence.

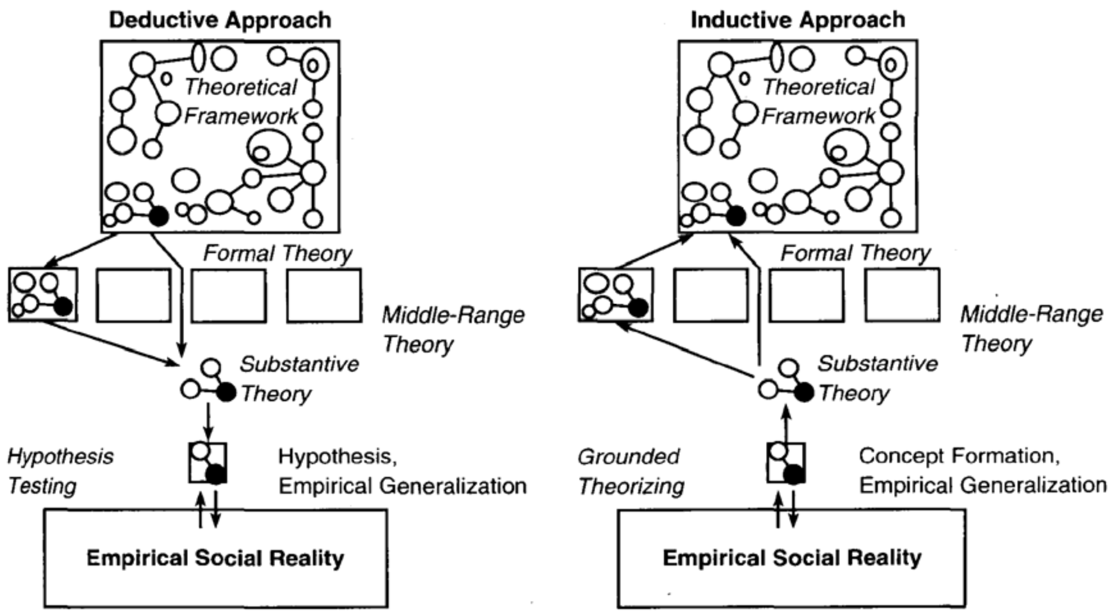
2.1.1.3 Complexity and Neoclassical Methodologies: Inductive and Deductive, respectively

'..., [neoclassical] theory is an elegant attempt to find a parsimonious model of human behaviour in economic settings. It can be criticized, though, as a quick and dirty method, a heroic attempt to simplify a complex problem. Now that we have begun to understand its limitations, we must begin the hard work of laying new foundations that can potentially go beyond it.'

(Farmer & Geanakoplos 2008, p. 54)

Neuman (2003, p. 51) discusses the two directions of theorising within social research methods as inductive and deductive see Figure 2–1.

Figure 2–1 Deductive and Inductive Theorising



(Source: Neuman 2003, p. 51)

Farmer and Geanakoplos (2008, p. 6) discuss the movement from qualitative narrative in political economy to highly mathematical *theorem-proof* format in neoclassical economics. However, both show continuity in that they are deductive approaches. In contrast, Brock (2000, p. 34) discusses the Santa Fe vision of complexity science as stressing pattern identification at macro levels and trying to reproduce these patterns by using micro rules, which is certainly an inductive approach. Blaug (1992, pp. 238-39) comments, '*[The] central weakness of modern economics is, indeed, the reluctance to produce theories that yield unambiguous refutable implications, followed by a general unwillingness to confront those implications with fact.'* Blaug (1992, p. 18) quotes the *Duhem–Quine Thesis*, '*no conclusive disproof of a scientific theory can ever be made.'* The *Duhem–Quine Thesis* or the *'under-determination problem'* can explain the '*general unwillingness to confront these implications with fact*' because any observation contradicting a theory can be explained by adding an auxiliary hypothesis. This technique makes the neoclassical framework impervious to empirical falsification. For example, Blaug (1992, p. 168) cites Weintraub (1985) arguing at length that GE must be appraised as research in mathematics and not as a theory that can be falsified. Additionally, Blaug (1992, p. 168) cites Hahn (1984, pp. 4-5) who claims that falsifiability for GE is unnecessary and argues that GE [science] provides understanding without prediction, justifying GE with the symmetry thesis.

The alternative to empirical falsification is logical falsification and more appropriate for a deductive approach to avoid the *Duhem–Quine Thesis*. For instance, the SMD theorem uses mathematical proof to show that the GET assumptions of methodological individualism and instrumentalism lead to a shapeless excess demand curve, which makes the equilibration assumption incongruent with the other GET assumptions. Therefore, one or more of the underpinning assumptions in the neoclassical framework is incorrect or the lack of dynamics is at fault. Section 2.1.4 discusses GET and SMD Theorem in more detail.

Experimental economics, an inductive approach, provides empirical falsification of the neoclassical framework and informs the results of the SMD Theorem. Smith (2007) discusses his motivation for developing experimental economics as his dissatisfaction with the gap between what market participants do and what is taught in the neoclassical theory of supply and demand. The explanation for market equilibrium in the neoclassical framework requires either that all market participants have perfect information or that there must be a large number of buyers and sellers who are all price takers. However, Smith (2007) uses experimental economics to show that interconnected markets do approximate market equilibrium dynamically and track a moving equilibrium even with few market participants and limited information. Smith's results are consistent with SMH, showing that one or more of the underpinning assumptions of neoclassical economics are faulty.

Behavioural economics, an inductive approach, provides empirical falsification of rational choice. Smith (1991) discusses the impasse between psychology and [neoclassical] economics over rational choice. He notes that psychology studies the behaviour of individuals and economics studies the behaviour of markets. This begs the question, does it make sense to study peoples' decision-making while isolated from interactive experiences in social and economic institutions? The psychologists expecting the market to be the sum of independent individual's choices share the same reductionist thinking as neoclassical economists that use a representative individual. Market rationality appears an emergent property where bounded rational agents make choices in an interactive environment governed by institutional rules and in double sided auctions produce near optimal outcomes, even if there are few agents and each agent has secret or limited information. This paradox of dual rationality between market and individual is modelled using near zero-intelligent agents to simulate markets that appear intelligent. Sutter, Kocher and Strauß (2009) conduct ascending sealed-bid English auction experiments to compare the bidding decisions of teams with individuals and find that the decisions between teams and individuals produced systematic differences. The teams are generally closer to the game theory prediction and are more likely to win bids paying higher prices but produce smaller profits. This supports Smith's call to study behaviour in an interactive environment. Section 2.1.3 further discusses the EMH and the impasse between psychology and economics.

Using a deductive approach, game theory models the strategic interactions between agents hence one would presume that it would inform the above impasse. However, Smith (1991, p. 879) notes that the axiomatic approach of game theory assumes individual rationality and complete information on payoffs (utilities) and other factors. Without this common knowledge, the models become insufficiently specified and the analysis incoherent. Thus it appears that game theory is incongruent with the findings of experimental economics and sheds little light on the above impasse. There appears a gap between strategic interactions and behavioural interactions required to model the double-sided auctions in Smith's experimental economics.

2.1.1.4 Frameworks Directing Research Programmes

Smith (1991) uses experimental economics to investigate specialisation and wealth creation within a free market. Beinhocker (2006) discusses complexity economics and evolutionary economics whose focus is also on wealth creation. This contrasts with the core focus of neoclassical economics on allocative efficiency, which can be attributed to its three underpinning assumptions. This focus on allocative efficiency is illustrated using CGE and neoclassical growth theory, as follows.

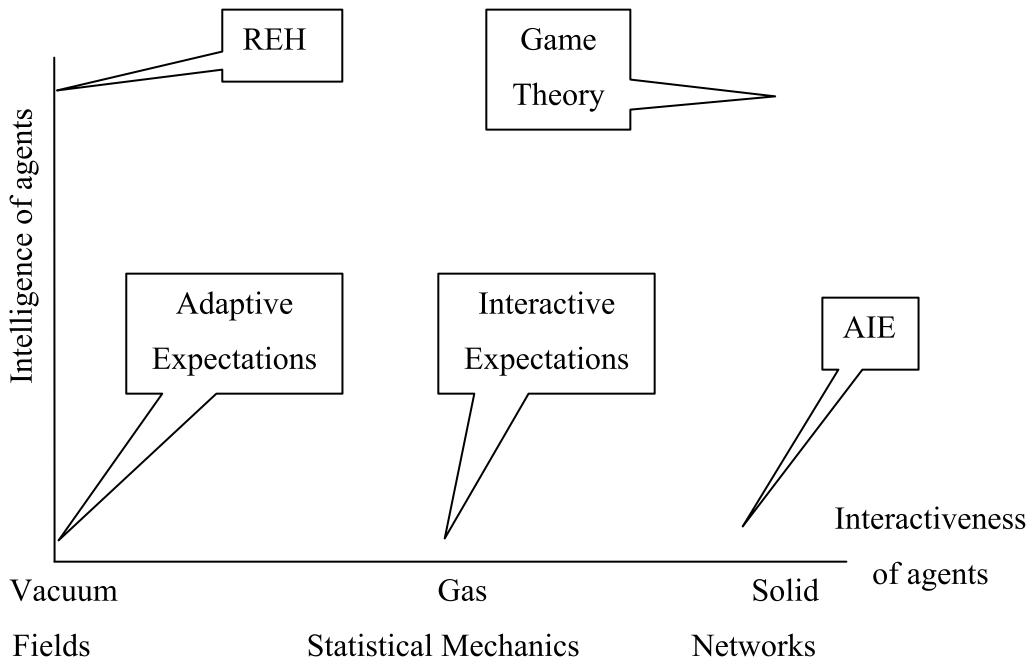
Blaug (1992, p. 168) notes that CGE is a highly prestigious area of economics and absorbs enormous intellectual resources. In a heuristic sense, CGE embodies rational choice and equilibrium economics, which puts equilibrium modelling and rational choice on the neoclassical *'do'* list and puts disequilibrium economics and alternatives to rational choice on the *'don't'* list. Blaug (1992, p. 168) concludes that there lacks a comparable and viable alternative to CGE and economist cannot easily switch to another scientific research program. Section 2.1.5 further discusses CGE.

Blaug (1992, pp. 238-39) cites the following problems with growth theory; its foundations use old–style stationary state analysis based on a GE model supplemented with factor–augmenting technical change to give the model some compound growth. Therefore, the model has difficulty handling anything but steady state growth. Blaug (1992, pp. 238-39) claims that no economy has ever been seen in steady state growth, because there are reasons why actual growth is always unsteady and always unbalanced, which severely limits usefulness of growth theory in policy application. There is a lack of correspondence between the unbalanced growth observed in the economy and the steady state models. Blaug (1992, pp. 238-39) admits that the more recent growth theory models, such as, DSGE that use stylised facts about the economy are an improvement but the models are still preoccupied with the perfectly competitive process. Blaug (1992, pp. 238-39) concludes that growth theory's contribution to a truly causal explanation of growth in industrialised economies is nil. Slightly less critical, Nelson and Winter (1982, p. 233) note that neoclassical growth theory has been fruitful in providing information about certain patterns of growth. However, it has been strikingly unsuccessful in handling technological change and stands as an obstacle to thinking about macroeconomics and microeconomics within the same intellectual framework. Section 2.1.5 further discusses CGE and its descendant DSGE.

2.1.1.5 REH and AIE are diametrically Opposed Complements Enhancing Analysis

This thesis introduces AIE as a complement to REH to allow complementary analysis. They complement one another in five dimensions, agent intelligence, agent interaction, agent homogeneity, equilibrium assumptions and rationalisation process. Figure 2–2 shows how the REH and AIE models map onto a two dimensional space, relating the intelligence of an agent and the level of interaction between agents.

Figure 2–2 Comparing Agent Interaction and Intelligence of REH and AIE



The other three dimensions are excluded to enhance clarity. An analogy between physical states and methodologies is used to provide a qualitative scale for the *'interactiveness of agents'* dimension. REH uses market prices to transfer information without the need for structure analogous to an electric field in a vacuum. The interactive-expectations model (Flieth & Foster 2002) uses a statistical approach to modelling portions of the population holding positive, negative and neutral expectations analogous to a statistical mechanical approach used to model gases. The interaction in AIE and game theory is via a network analogous to a network in a solid. However, the network structures generally differ; game theory tends to use *'compete graphs'* and AIE uses *'small-world networks'*. Section 2.2.2 further discusses networks. Additionally, the quality of interactions differs; AIE uses behavioural interactions, while game theory uses strategic interactions based on rational choice.

The neoclassical framework and REH is in the top left corner in Figure 2–2 and AIE, a near zero-intelligence ABM, is in the bottom right corner. Neoclassical economics and zero-intelligence ABM inhabit the diametrically opposite positions in both dimensions. Both positions are unrealistic but serve as benchmarks for other models and pragmatically one technique may be more suited to modelling certain phenomenon than the other. Section 5.5.2 should be consulted for the superannuation example. The neoclassical framework shows what can be attributed to super intelligent agents at equilibrium who only interact via a price signal, whereas the zero-intelligence ABM shows what can be attributed to a zero-intelligent agent who interacts via a structure while undergoing state changes or in disequilibrium. The zero-intelligence ABMs can model volatility better than neoclassical models. Sections 2.1.3 and 2.2.2 further discuss volatility. REH forms a benchmark for the AIE model and is in the top left corner in Figure 2–2. Section 2.1.2 further discusses REH. The bottom centre in Figure 2–2 shows the interactive-expectations, which forms a component of AIE. Section 2.1.9 further discusses interactive-expectations. The bottom left corner of Figure 2–2 shows adaptive-expectations, which is another component of AIE. Section 2.1.8 further discusses adaptive-expectations. The bottom right corner in Figure 2–2 shows AIE whose agents are near zero-intelligent but highly interactive.

2.1.1.6 Neoclassical Ex–post Rationalisation and Behavioural Ex-ante Rationalisation

This section discusses the concepts, ex-post and ex-ante rationalisation, to help frame REH or neoclassical and AIE or behavioural approaches to rationalisation at a neurological level. Libet's (1985) *'Unconscious cerebral initiative and the role of conscious will in voluntary action'* shows that initiation of action starts in the subconscious, before the conscious is aware of the action. Afterwards, the conscience rationalises the actions in the belief that it initiated the action. This ex–post rationalisation process is also known as confabulation. In behavioural economics Kahneman's (2003, p. 1451) three cognitive systems framework of perception, intuition and reasoning observes this distinction. In comparison, REH assumes perfect perception and reasoning systems, which makes any interaction with the intuition system irrelevant. REH is an extension of the ex-post rationalisation process that creates a story to explain why the expectations that agents form are purely rational and ignores any ex-ante rationalisation processes. REH has a preconceived idea of rationality that specifies how agents ought to behave in accordance with rational choice, which makes REH a normative theory. Behavioural economics endeavours to predict and explain the behaviour of agents as an ex-ante rationalisation process. For example, Kahneman's three cognitive systems of the perception, intuition and reasoning systems provide a framework to explain how the systems interact to produce predictable biases and sometimes outcomes consistent with rational choice.

2.1.1.7 Three Systems Cognitive Framework Justifying REH and AIE as Complements

This section discusses Kahneman's (2002) Three Systems Cognitive Framework to justify using REH and AIE as complements with the caveat that this framework is based on the psychology of an individual in isolation, rather than ideally on the psychology of individuals interacting in an institutional setting.

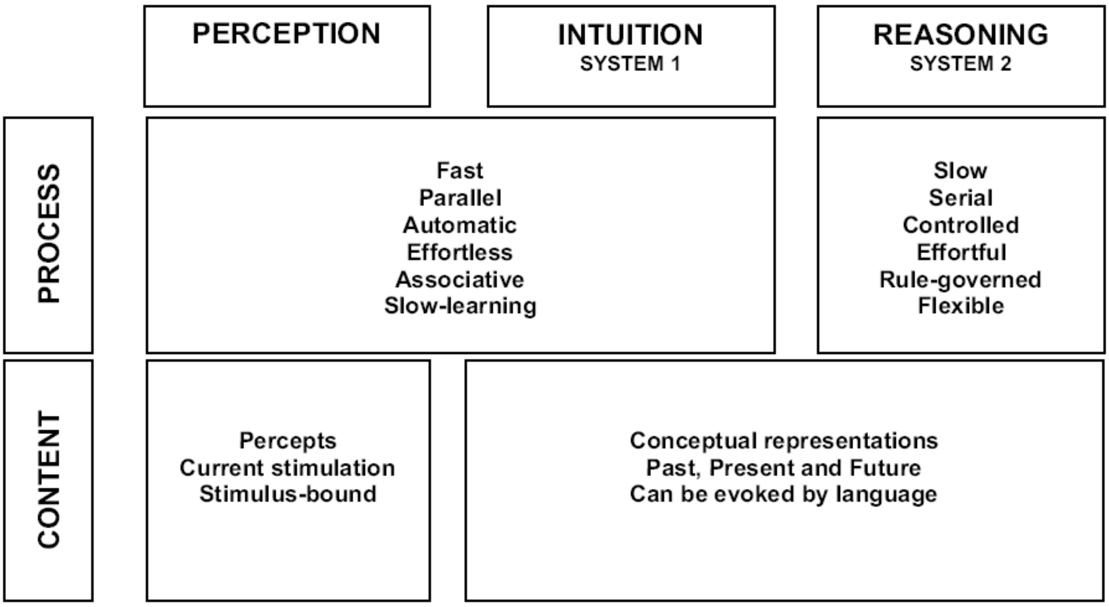
Kahneman (2002) notes that, unlike economics, psychology does not have a unified formal theory. However, a few general principles of perceptual and cognitive functions both predict and explain a wide array of phenomena of bounded rationality. Two rules of perception are provided that govern judgement and choice.

1. The perceptual primacy of changes over states
   => A myopic focus on change in decision-making
2. The representation of categories and sets by prototypes (averages) in perception and memory
   => A consistent pattern of error in task, which logically requires the evaluation of a sum

Both these general principles guide the development of AIE and are at odds with methodological instrumentalism. Kahneman (2002) provides substantive empirical support for the two rules and the framework in Figure 2–3.

Kahneman's (2002) framework in Figure 2–3 uses three modes of cognitive function, perception, intuition and reasoning. The judgment and decision processes of the intuition and reasoning systems differ in that the intuitive system is fast, parallel, automatic, effortless, associative and slow learning, whereas the reasoning system is slow, serial, controlled, effortful, rule–governed, and flexible. However, the content of both the reasoning and intuitive systems are concerned with past, present and future conceptual representations and can evoke language. This contrasts with the perception system whose content concerns current stimulation, stimulus-bound and precepts.
Kahneman (2002, p. 483) suggests four ways in which a judgment or choice may be made, see Table 2–2.

Figure 2–3 Three Cognitive Systems Framework



(Source: Kahneman 2002, p. 451)

Table 2–2 Intuition–Reasoning Judgement Selection Model

(i) no intuitive response comes to mind, and the judgment is produced by the reasoning system.

(ii) an intuitive judgment or intention is evoked, and

a. is endorsed by the reasoning system;
b. serves as an anchor for adjustments that respond to other features of the situation;
c. is identified as incompatible with a subjectively valid rule, and blocked from overt expression.

(Source: Kahneman 2002, p. 483)

Explicit judgments that people make (whether overt or not) are endorsed, at least passively, by the reasoning system. The monitoring by the reasoning system is normally quite lax, and allows many intuitive judgments to be expressed, including some that are erroneous. The intuitive system generates impressions of the attributes of objects of perception and thought. These impressions are not voluntary and need not be verbally explicit. In contrast, judgments are always explicit and intentional, whether or not they are overtly expressed. Thus, the reasoning system is involved in all judgments, whether they originate in impressions or in deliberate reasoning. The label *'intuitive'* is applied to judgments that directly reflect impressions.

The agents of AIE use simple rules and operate within the intuitive system. The agents of REH operate within the reasoning system, but contrary to the Three Cognitive Systems Framework their reasoning is fast and effortless. Neither REH nor AIE completely capture human behaviour. However, one may be more suitable than the other under different circumstances. Section 5.4 further discusses this suitability aspect.

2.1.1.8 Temporally Falsifiable Objective or Narrative Based Subjective Expectations

This thesis makes an original contribution by introducing a falsifiable subjective profit expectations model, the AIE model. This section discusses objective and subjective expectations models in relation to REH and AIE, respectively, and discusses their falsification to find a gap in the literature for a temporally falsifiable subjective expectations model.

Koppl (1999, p. 3) claims that economics has no satisfying theory of expectations and that the standard approaches are rational expectations, adaptive-expectations, and static expectations. Koppl (1999) classifies these approaches within objectivism because they fail to account for how economic expectations emerge from spontaneous mental activity. Temporal falsifiable mathematical models have been developed with all these approaches.

Conversely, Butos and Koppl (1997) discuss Hayek's and Keynes' views on expectations as two forms of subjectivism. Their views account for how economic expectations emerge from the mind but they use a narrative approach, which is difficult to falsify. Koppl (1999, pp. 8-9) notes if one lacks a falsifiable subjective models, one must decide a priori whether to represent expectations as *'rational'* and coordinative or as *'psychological'* and dis-equilibrating. Hence, the choice between faith and doubt in the coordinative prowess of the market becomes ideological rather than scientific. Butos and Koppl (1997, p. 333) note that there is a panorama of available subjectivist theory.

Butos and Koppl (1997, p. 354) notes that Keynes views expectations of the future as belief states. Similarly, AIE uses future belief states in profit expectations either increase, decrease or no-change. Butos and Koppl (1997, p. 333) quote Hayek (1973, p. 11) *'man is as much a rule-following animal as a purpose-seeking one'*. Similarly, the firms in AIE are rule following. Butos and Koppl (1997, p. 333) claim that Hayek rejected rationalism in favour of an evolutionary epistemology. Section 5.5.2 discusses why an evolutionary epistemology is unnecessary for AIE.

This thesis contributes to the literature by providing a falsifiable subjective expectations model. Section 3.1 further discusses objectivism and subjectivism to justify the use of an index in AIE rather than probabilities.

2.1.1.9 Framework Summary

Davis (2006) discusses whether the dominance of neoclassical economics as *'mainstream economics'* has been supplanted by a collection of competing research programmes such as behavioural economics, evolutionary economics, game theory, neuroeconomics and complexity theory, which share little in common. He states that an indicator of such a shift shows the need to discuss and compare frameworks and methodologies in PhD theses, as in this section. Moreover, the section highlights some issues where the competing research programmes share little in common, including approaches between inductive and deductive and levels of focus between market and individual. Additionally, Davis (2006, p. 5) notes that there is a lag between research and what is taught in universities. For instance, neoclassical economics continues to dominate the main course of instruction but no longer dominates mainstream economics.

Davis (2006) raises two questions *'Will the competing research programmes converge?'* and *'How will neoclassical economics fare in the plural state?'* Both questions are relevant to AIE. First, AIE integrates the elements from the various research programmes that form part of the convergence. Second, AIE treats REH as a complement to provide neoclassical economics a position as an extreme view of reality, thus enable a dual perspective with AIE and perhaps under limited circumstances REH may provide a preferable or satisfactory view.

There is conclusive deductive proof that the three underpinning assumptions of the neoclassical framework are incongruent, where REH is underpinned by all three neoclassical assumptions, methodological individualism, instrumentalism and equilibration. Therefore to seek alternatives to REH questions the core of neoclassical economics. The review of the failures of the neoclassical research programmes and the part that REH plays in its failure and the empirical evidence against REH has informed the construction of alternative expectations models.

2.1.2 Rational Expectations Hypothesis and Behavioural Economics

Simon (1984, p. 36) considers REH one of the three foundations for neoclassical economics. This section discusses REH for two reasons. One, it forms a benchmark for AIE. Two, REH is ubiquitous in neoclassical theory and underpins the EMH, GET, various CGE models, the *'permanent-income'* and *'life-cycle'* theories of consumption and *'policy ineffectiveness proposition'*. EMH, GET and CGE models are discussed in sections 2.1.3, 2.1.4 and 2.1.5, respectively, to provide motivation for the development of AIE. Additionally, this section discusses behavioural economics for two primary reasons. One, it shows that REH is derived using assumptions that are empirically inconsistent with the way individuals behave. Two, it provides support for the adaptive-expectations model, which forms a benchmark for AIE and also a component of AIE.

Muth (1960; 1961) introduces REH, which embodies all three neoclassical assumptions discussed in section 2.1.1. REH assumes that a homogenous or representative agent (methodological individualism) uses *'rational choice'* (Von Neumann & Morgenstern 1944) to maximise their utility (methodological instrumentalism) that assumes there is just one equilibrium (methodological equilibration). Billari (2006, p. 2) describes the rational expectations paradigm that assumes homogenous economic agents who know their preferences, have unlimited computing power to calculate the optimal solution, and have perfect knowledge of all data relevant to calculate the optimal solution. Sargent (2008, p. 1) asserts in rational expectations that outcomes do not differ systematically (i.e., regularly or predictably) from what people expect them to be. This assertion provides for empirical falsification and is used in section 3.7 to make REH operational. Lovell (1986, p. 112) observes that REH explicitly avoids modelling the process by which expectations are formed. This observation does present a gap for behavioural economics.

In the following sections, section 2.1.2.1 discusses criticism of REH from behavioural economics, while section 2.1.2.2 discusses falsification of REH using econometrics.

2.1.2.1 Criticisms of REH from Behavioural Economics

Van der Sal (2004, p. 432) notes that for nearly half a century rational choice theories have been tested against individual behaviour but repeatedly the underlying assumptions and predictive value appear descriptively false. Sargent (2008, p. 1) claims that believers in REH assume that people behave in a way to maximise their utility or profits. Thaler and Mullainathan (2008, p. 1) state that these maximisers in the neoclassical framework ignore virtually all the findings of cognitive and social psychologists. They highlight three assumptions of REH that are at odds with the findings, unbounded rationality, willpower and selfishness.

Addressing unbounded rationality, Simon (1972; 1979) criticises REH for its assumption that people have unlimited information processing ability. He introduces the term *'bounded rationality'* to describe a more realistic concept of human problems solving ability. It is perfectly rational for people to use *'rules of thumb'* to make decisions, thus make the best use of their limited cognitive abilities. He suggests that economic models that do not incorporate some form of bounded rationality are just bad economics. Sargent (2008, p. 1) claims that in rational expectations outcomes do not differ systematically (i.e., regularly or predictably) from what people expect. However, Tversky and Kahneman (1974) and Kahneman and Tversky (1979) provide extensive empirical evidence to show regular and predictable biases in people forming expectations. Importantly these biases do show that people developed expectations in a profoundly different way to that supposed by REH. Their empirical evidence supports Simon's *'rules of thumb'* concept. The AIE model uses bounded rationality and the agents use rules to form their expectations. The *'rules of thumb'* for AIE are developed from adaptive-expectations and interactive-expectations and are discussed in sections 2.1.8 and 2.1.9, respectively. Section 2.1.3.3 further discusses Kahneman and Tversky.

In addressing unbounded willpower, the representative agent in REH has perfect self-control; however it is evident that humans do lack self-control. Most at some time have eaten, drunk or spent too much and have exercised, saved or worked too little. The healthy eating and exercise initiatives and superannuation scheme show that governments recognise bounded willpower.

Addressing unbounded selfishness, REH does not specifically preclude altruistic acts. However, it does assume homogenous self-interested optimising agents. The free-rider problems in economics and game theory particularly would support this approach. However, at odds with unbounded selfishness there are instances where people do contribute to the public good, even if, their own private welfare is not improved. For instance, people give to charities and people refuse offers that they perceive as unfair in ultimatum games.

'Permanent-income' and 'Life-cycle' theories

These neoclassical theories have drawn criticism from two directions. First, O'Donoghue and Rabin (1999, p. 125) find that people procrastinate when they make investments for their retirement even though they know the importance of the decisions. People use a hyperbolic discounting function inconsistent with utility maximisation assumed in REH. Second, using the predictions of the life-cycle hypothesis Banks, Blundell and Tanner (1998) find that people fail to save sufficiently for their retirement.

However, Keen (2009) notes, '*von Neumann and Morgenstern specifically warned against having their model of consumer behaviour interpreted as it has in fact been interpreted in the economic literature, both by those who misapplied it--using it to model behaviour in one-off choices as in financial decisions--and those who criticised it.*' As Von Neumann and Morgenstern (1944 p.19) state, *'Probability has often been visualized as a subjective concept more or less in the nature of estimation. Since we propose to use it in constructing an individual, numerical estimation of utility, the above view of probability would not serve our purpose. The simplest procedure is, therefore, to insist upon the alternative, perfectly well founded interpretation of probability as frequency in long runs.'* Furthermore, Keen (2009) states if these test were applied as multiple repeats of the same choice, the tests that have 'contradicted' von Neumann & Morgenstern, would have instead confirmed von Neumann & Morgenstern. It is the misapplication of Neumann & Morgenstern's model in terms of subjective rather than objective probability by economists, which is at fault and not von Neumann & Morgenstern. This misapplication of Neumann & Morgenstern's model beyond the domain of its assumptions is a major flaw in REH.*'*

2.1.2.2 Falsification of REH using Econometrics

REH uses the assumption in equation (2–1) that $E(\varepsilon) = 0$, which is basically that a prediction is an unbiased estimate of an actual value.

$$\varepsilon = P - A \qquad (2\text{–}1)$$

Where P = predicted value

A = actual value

Muth (1961) implements the assumption in equation (2–1) and uses the assumptions in equation (2–2) that the forecast error is uncorrelated with the predicted value.

$$A = \beta_0 + \beta_1 P + \varepsilon \qquad (2\text{–}2)$$

Assuming $\beta_0 = 0$; $\beta_1 = 1$; $E(\varepsilon) = 0$

In equation (2–2), Lovell (1986, p. 115) notes that REH asserts that variance of actualisation will exceed the variance of predictions. Additionally, *'the prediction error must be uncorrelated with the entire set of information that is available to the forecaster at the time the prediction is made.'*

For instance, Lovell (1986, p. 120) notes that the prediction of some forecasters may be characterised as rational, in other examples the assumption of the rationality is clearly violated. In one example Lovell (1986, p. 115) finds that an alternative regression to that in equation (2–2) contains lagged actualisations and provides a much better fit to the data, thus implying firms are not REH rational because they do not make use of all the available data to make a prediction.

Lovell (1986, p. 115) notes that some firms are perennial optimists, generally overestimating the future, while others are perennial pessimists, usually underestimating sales volume. In aggregate the underestimates of the pessimists roughly cancel out the overestimates of the optimists. The offsetting of systematic error explains why the aggregates of prediction data are more accurate than the predictions of individual firms. This aggregation effect becomes apparent in the EMH, when comparing price movements in individual stock with market indices, see section 2.1.3.1.

Lovell (1986, p. 111) notes that there is disagreement over whether REH should be tested empirically because REH is an assumption, therefore not suitable for empirical analysis. The REH as an assumption argument avoids direct falsification. For instance, Prescott (1977, p. 30) claims, '*Like utility, expectations are not observed, and surveys cannot be used to test the rational expectations hypothesis. One can only test if some theory, whether it incorporates rational expectations or, for that matter, irrational expectations, is or is not consistent with observations.'* However, theories that incorporate REH have been falsified, for instance the EMH, GET and DSGE. Sections 2.1.3, 2.1.4 and 2.1.5 discuss these theories, finding that the EMH incorrectly models volatility in share market prices and fails to model the momentum effect. The SMD Theorem proves that the basic axioms for GET are logically incongruent; axioms REH also embodies. The stylised facts from the DSGE models fail to match those of the business cycle. Despite the presence of REH in all these conjoint failures, the *Duhem–Quine Thesis* can still be invoked to avoid falsification, as discussed in section 2.1.1.3. Using such a falsification avoidance construct, Popper (1972a; 1972b; 1972c) would label REH as unscientific. Additionally, Lakatos (1976) would consider REH part of the *'hard core'* of the neoclassical framework and components of the larger theories as part of a *'protective belt'*. Falsification avoidance is a sign of a degenerative scientific research program. Lovell (1986, p. 122) states that there is sufficient empirical evidence to suspend belief in REH and calls for the empirical testing of REH against alternatives. This thesis empirically tests REH against the adaptive-expectations and the AIE models.

2.1.2.3 Summary

REH and rational expectations appear to be normative assumptions and not explanatory or predictive theories. As explanatory or predictive theories, they are inadequate in the sense that people frequently fail to follow their prescription and as a normative theories they are indeterminate, as often prescriptions are ambiguous (Elster 1989). Lovell (1986, p. 120) concludes that expectations are a rich and varied phenomenon, which are not adequately captured in REH.

2.1.3 Efficient Market Hypothesis

This section discusses the *Efficient Market Hypothesis* (EMH). The EMH extends REH by using the assumption that markets use information efficiently. Section 2.1.2.2 discusses how Prescott (1977, p. 30) claims that REH cannot be falsified directly, as it is an assumption and can only be falsified as part of a larger theory. However, the EMH, like REH, also has a *'joint hypothesis problem'*.

Fama (1965; 1970) introduces the EMH, which builds upon Bachelier's (1900) *'Theory of speculation: the origins of modern finance'*. Bachelier (1900) argues that stock option prices follow a Brownian motion or random walk. EMH has criticisms from empirical economics and behavioural economics. Empirical economics shows that there are cases where stock prices do not follow a random walk. Behavioural economics explains why these stock price movements should be other than a random walk. EMH uses methodological instrumentalism or utility theory. However, Farmer and Geanakoplos (2008, p. 14) note that there are problems defining utility, which makes the use of alternative desirable. Consequently, this section also discusses aspects of behavioural economics that serve to replace utility maximisation for implementation in AIE.

The structure of the section is as follows. Subsection one describes the EMH. Subsection two discusses pricing anomalies that are at odds with the EMH. Section three discusses using behavioural finance to explain these pricing anomalies. Subsection four summarises section 2.1.3.

2.1.3.1 The Hypothesis

Fama (1965; 1970) introduces the EMH in three market efficiency levels: a strong level where all relevant information regarding a stock is fully reflected in its price; a semi-strong level where all publicly available information is reflected in its price; and a weak level where current prices reflex all past history of the prices. Equation (2–3) shows a formal presentation of the EMH using expected returns theory (Fama 1970, p. 384).

$$E(p_{j,t+1} \mid \Phi_t) = [1 + E(r_{j,t+1} \mid \Phi_t)] \; p_{j,t} \qquad (2\text{–}3)$$

Where $p_{j,t}$ = price of the security j at time t

$p_{j,t+1}$ = price of the security j at time t+1 with reinvestment of any cash income from the security during the interval

$r_{j,t+1}$ = one period return $(p_{j,t+1} - p_{j,t}) / p_{j,t}$

Φ_t = set of all information relevant to determining the expected value of $p_{j,t+1}$

If the market is efficient then the expected returns $E(r_{j,t+1} \mid \Phi_t) = 0$ because all the relevant information Φ_t is reflected in the price $p_{j,t}$ so that $E(p_{j,t+1} \mid \Phi_t) = p_{j,t}$. Barberis and Thaler (2002, p. 8) note that any test of the EMH jointly tests the discounted future cash flow model, making it difficult to provide evidence of market inefficiency. This is known as the '*joint hypothesis problem'*.

The EMH result that $E(p_{j,t+1} \mid \Phi_t) = p_{j,t}$ makes trading in securities a fair game because all the current information is reflected in the current price and the current price reflects the expected price. This result predicts that price movements are a random walk; so one test for the EMH is to test security prices for a random walk. Malkiel (1973) *'A random walk down Wall Street'* supports this prediction and Lo and MacKinlay (1999) *'A non-random walk down Wall Street'* discuss situations where the EMH fails. In sum, indices seem to follow a random walk but individual securities do not necessarily. These finding are consistent with Lovell's (1986) comment about REH, that is, working in highly aggregated situations but failing to describe the behaviour of individual firms. Other pricing anomalies and behavioural observations are discussed in sections 2.1.3.2 and 2.1.2.3, respectively.

2.1.3.2 Pricing Anomalies

The EMH has at least seven pricing anomalies, including excess volatility (Shiller 1981), lacking explanation for clustered volatility, serial correlation in stock-market returns (Fama 1970, p. 393), day-of-the-week effect, the January Effect, and momentum effect and over-reaction to news events (De Bondt & Thaler 1985). Shiller (1993, p. 84) notes that these anomalies call into question the basic underpinning of the EMH. Importantly for the thesis, the anomalies conjointly question the underpinnings of REH.

The structure of this section is as follows. Section one discusses EMH lacking dynamics. Section two discusses excess volatility. Section three discusses excess overreaction. Section four discusses clustered volatility. Section five discusses the *'no free lunch'* fallacy. Section six discusses failure of the *Capital Asset Pricing Model* (CAPM). Section seven summaries the discussions in this section.

1. EMH lacking Dynamics

Farmer and Geanakoplos (2008) consider the lack of dynamics in the EMH a serious shortcoming, considering that a market is essentially a dynamic process. For instance, Farmer and Geanakoplos (2008, pp. 32-3) discuss two proprietary trading signals in the US futures market, which allow profitable trading. Both these predictive trends are at odds with the EMH. The first signal has been in existence since 1975 at which time the signal was 14% and by 1998 this has declined to 4%. It has taken the market nearly 23 years to reflect the signal in the prices. The second signal they discuss is caused by a structural change in the market occurring in 1983 and has increased in predictive power over the following two and half decades. Farmer and Geanakoplos (2008, pp. 32-3) explain that the problem is that the EMH is an equilibrium model and the phenomenon being studied is essentially dynamic. The market might be efficient but EMH gives no indication to how long it takes a new signal to be fully reflected in the market prices, which highlights a limitation to neoclassical economics with its focus on equilibration. They claim that the need for a non-equilibrium theory is apparent, in such a theory, the EMH would be the special case when time tends to infinity.

Further to the EMH lacking dynamics, Schwert (2003, p. 970) surveys the literature of pricing anomalies and market efficiency and finds that many effects contradicting the EMH disappear or attenuate after the authors publish their findings. For example, the size effect and value effect have virtually disappeared; the weekend effect and the dividend yield effect have also lost their predictive power; and the small-firm turn-of-the-year effect has become much weaker. Similarly, the evidence that stock-market returns are predictable, using variables such as dividend yield or inflations, is much weaker. Schwert (2003, p. 970) concludes that the activities of practitioner to take advantage of the newly found patterns makes them disappear. These examples indicate that learning as a dynamic process is at work. This is consistent with Farmer and Geanakoplos (2008) observations about EMH lacking dynamic processes. AIE models expectations formation as a dynamic process but excludes learning; section 5.5.2 discusses the reason why.

2. Excess Volatility or Volatility without News

Shiller (1981) observes that, according to the EMH, the Standard & Poor's (S&P) stock prices move too much to be justified by subsequent changes in the dividends. He took the S&P stock price index and removed the long-run exponential growth trended p_t, similarly for the present discounted values of the actual subsequent dividends p^*_t. Equation (2–4) using the EMH shows that the expected returns $E(p^*_t)$ are reflected in the current price p_t. Equation (2–5) shows that any random error u from estimating p_t is uncorrelated with p_t as required by the EMH, as only unknown information could cause $E(p^*_t)$ to deviate from p_t. Schiller finds that the volatility of the stock-market prices $var(p_t)$ exceeded the volatility of the dividends $var(p^*_t)$ and since all variances are greater than or equal to zero the result is absurd, concluding the EMH is false.

$$E(p^*_t) = p_t \tag{2–4}$$

$$var(p^*_t) = var(p_t) + var(u) \tag{2–5}$$

However, ex-post rationalisation can be used to explain this absurd result and defend the EMH. Shiller (1981, p. 434) provides an example, *'Perhaps the market was rightfully fearful of much larger movements than actually materialized.'* He counters the argument stating that rational people should learn that this is not the case because they have over a century's worth of data showing otherwise.

The theory of rational bubbles is another ex-post rationalisation explanation used to defend the EMH. The theory uses volatility in the discount rates to explain the excess volatility in stock prices. However, Santos and Woodford (1997) and Diba and Grossman (1988) prove that the conditions, under which a rational bubbles could occur, are severely limited and that they would be inadequate to explain the excess volatility demonstrated by Shiller (1981).

3. Asymmetric Over-reaction/Under-reaction, January and Momentum Effects

De Bondt and Thaler (1985, p. 795) test the predictive ability of the overreaction hypothesis by using a time series of historical and publicly available Price/Earnings (P/E) ratios, thus testing all three forms of the EMH. De Bondt and Thaler (1985, p. 799) find that loser portfolios of 35 stock, those with low P/E ratios, outperform the market on average by 19.6% , thirty six months after formation. Winner portfolios under performed the market by 5%. They note that overreaction effect is asymmetric and that most of the excess returns are available in January. These effects could be explained by claiming that the loser portfolio had a higher risk or beta. However, De Bondt and Thaler (1985, p. 801) show that the loser portfolio has a significantly lower beta than the winner portfolio. They conclude that their results are consistent with psychological research that most people overreact to unexpected and dramatic news events. Barberis and Thaler (2003, p. 1113) claim that these results have been replicated by numerous authors. However, there is disagreement on how to interpret the results.

Jegadeesh and Titman (1993) extend De Bondt and Thaler (1985) to evaluate a trading strategy of buying winners and selling losers to take advantage of a momentum effect. They bought stocks based on their return over last six months, then held them for six months. The technique realised a compounded excess return of 12.01%. They ensured that the excess profits were unrelated to excess risk. They analysed the portfolio over 36 months following its formation and found that for the first 12 months excepting the first month the portfolio had positive returns. However, if the portfolio was held for 2 years, half the excess returns dissipated. They propose two alternative hypotheses to explain the momentum effect. Hypothesis one involves positive feedback traders. Hypothesis two involves temporal inconsistency to reacting to information, that is, under reaction to information in the short term and over reaction to information in the long term. They are unable to distinguish between the two hypotheses using the study in their paper.

Fama (1998) describes Jegadeesh and Titman's (1993) results a puzzle because they contradict EMH predictions, hence calls for more tests. Fama (1998) maintains that the EMH is still valid because over and under reaction to news cancel each other out in the long run. Additionally, he notes a missing explanation for the fact that the market seems to overreact in some cases and under react in others. The EMH explains these over and under reactions as chance. Fama (1998, p. 284) does concede that, however, '*if the long-term return anomalies are so large they cannot be attributed to chance, then an even split between over and under reaction is a pyrrhic victory for market efficiency*'. Fama (1998) claims that by using alternative methodologies many of the anomalies would cease to be significant and calls on behavioural finance to produce a contending model to replace the EHM, thus an empirical comparison can be made.

4. EMH unable to Explain Clustered Volatility

Mandelbrot (1963) finds that Bachelier's (1900) random walk model of stock option prices based upon a Gaussian distribution failed to account for the clustered volatility of the price movement of cotton. Mandelbrot (1963) finds that a Lévy flight distribution or fat tail distribution provides a better description of the data. Mandelbrot (1967, p. 394) discusses how Bachelier (1900) was aware of *'outliers'* or *'contaminators'* in his data, when he erroneously assumed and applied a Gaussian distribution. These outliers are consistent with a Lévy flight distribution. Bachelier's (1900) misspecification provides the foundation for the EMH.

Farmer and Geanakoplos (2008, pp. 29-30) discuss how the equilibrium models of the market, such as the EMH, have failed to explain clustered volatility. Additionally, they note that clustered volatility follows a power–law. Some REH proponents claim that there really is nothing to explain because volatility is just a random event. However, the clustered volatility could indicate that there lacks perfect rationality and the market is out of equilibrium where agents process information via decision-making rules using prices and other inputs. Prices are formed as a result of agents making decisions where the information processing is imperfect, producing feedback loops and amplifying noise. Farmer and Geanakoplos (2008, p. 30) note that there are many examples of non-equilibrium models, including ABMs, that generate clustered volatility and power–laws. Farmer and Geanakoplos (2008, p. 32) discuss how in physics power–laws are associated with non-equilibrium behaviour and are viewed as a possible signature of non-equilibrium dynamics. They also suggest that power–laws are an indication of non-equilibrium behaviour in economics. Consistent with their suggestion, Beinhocker (2006) uses power–laws in economics as a signature of non-equilibrium. Using power–laws in this way seems reasonable, given that non-equilibrium models generate power–laws and equilibrium models fail to generate power–laws. Section 2.2.1.2 further discusses power laws as a signature of non-equilibrium.

5. 'No free lunch' a Misguided Argument for the EMH

Barberis and Thaler (2003, p. 1057) discuss how many researchers still point to the inability of professional money managers to beat the market as strong evidence of market efficiency. They mistakenly treat statements 1 and 2 as an equivalence in a *'no free lunch'* argument.

1. *'prices are right'* => *'no free lunch'*
2. *'no free lunch'* => *'prices are right'*

Barberis and Thaler (2003, p. 1057) discuss the flawed reasoning. In an efficient market both statement 1 and 2 are correct. However, in an inefficient market there could be *'no free lunch'* and the *'prices are wrong'*, making statement 2 false. For instance, *'just because prices are away from fundamental value does not necessarily mean that there are any excess risk-adjusted average returns for the taking.'*

6. The failure of the Capital Asset Pricing Model

Fama and French (2004) evaluate the performance of the *Capital Asset Pricing Model* (CAPM) and conclude that empirical evidence invalidates the use of CAPM in applications, after finding that passive funds invested in low beta, small or value stocks tend to produce positive abnormal returns relative to CAPM predictions. This is relevant to EMH for two reasons; the criticisms come from the founder of EMH, Fama, and CAPM builds on the assumptions of EMH.

7. Pricing Anomalies Summary

The EMH ignores dynamics, hence bypasses the more important questions over *'How long does the market take before people cease to make profits from arbitrage from patterns in the market?'* or *'What contributes to these patterns, their persistence or attenuation?'* So, Fama's (1998) call for a contending EMH model, based on behavioural economics for empirical comparison, may be misguided, as the EMH is a static long run equilibrium model and the behavioural models are dynamic. Furthermore, the EMH is simply incorrectly specified and the *'joint hypothesis problem'* makes it exceedingly difficult to falsify. Therefore, from Popper's (1972a; 1972b; 1972c) perspective the EMH commands an exceedingly low level of scientific veracity. The EMH is at odds with the anomalies discussed, excess volatility, over-reaction/under-reaction, momentum effect and clustered volatility. These anomalies are consistent with non-equilibrium and positive feedback requiring dynamic market models. Behavioural economics explains these anomalies and informs the development of dynamic models.

2.1.3.3 Behavioural Economics

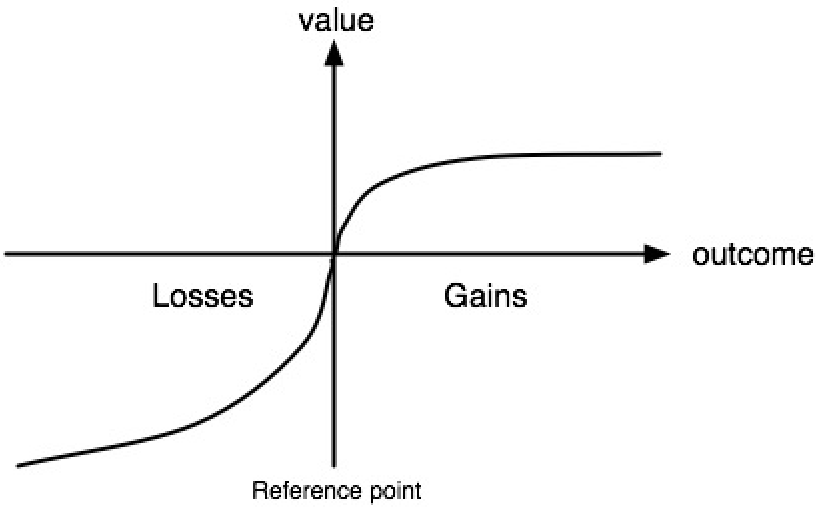
Van der Sa (2004, p. 432) notes that behavioural economics provides models to explain the observed behaviour at odds with expected utility. Van der Sa (2004, p. 426) uses five dimensions in discussing the difference between the behavioural approach and the standard financial or neoclassical approach that uses the EMH. First, behavioural studies have empirical components and have no normative significance. Second, behavioural choice models show high predictive value but are criticised for lacking robustness. Third, the behavioural methodology is inductive, working from observed individual behaviour to create higher-level aggregate rules. This approach is consistent with the *'science of complexity'* and AIE, but contrasts with standard finance and EMH methodology, which uses a deductive mathematical approach that starts with a set of axioms to prove a theorem. Fourth, decision-making is central to behavioural economics, whereas central to standard finance is the development of equilibrium theories and pricing risk. Fifth, behavioural economics focuses on process and outcome, whereas standard or neoclassical finance focuses on outcomes only. The process-orientated focus of behavioural economics interests this thesis for two reasons, it provides a solution to the lack of dynamics in the EMH and provides dynamics for the AIE model.

Glaser, Noth and Weber (2004) classified behavioural models as either belief based or preference based. Barberis and Thaler (2003, pp. 1066-9) discuss seven ways in which psychologists believe people form beliefs, overconfidence, optimism, representativeness, conservatism, belief perseverance, anchoring, and availability biases. The preference based models include prospect theory (Kahneman & Tversky 1979) and ambiguity aversion. This section discusses those belief-based and preference-based models, which are most relevant to AIE. Additionally, the section examines how the momentum effect and the departure from rational choice are evident in trading at a very basic physiological level. Section 3.1.3 discusses ambiguity.

1. Prospect Theory

Kahneman and Tversky (1979) introduce prospect theory as a more realistic alternative to expected utility theory (Von Neumann & Morgenstern 1944). Both theories provide models of decision-making under risk. Kahneman and Tversky (1979) note that people making choices under risk do so at odds with the basic tenants of utility theory. They introduce the *certainty* and *isolation effects*, which demonstrate the failure of utility theory. The *certainty effect* is under-weighting outcomes based on probabilities compared to certain outcomes. This effect contributes to asymmetric risk taking, that is, risk-aversion involving sure gains and risk-seeking involving sure losses. The *isolation effect* happens as people generally discard components that are common to all scenarios under consideration. This effect leads to people having inconsistent preferences when the same choice is presented in different forms. The two effects provide for an alternative theory of choice where '*value is assigned to gains and losses rather than to final assets and in which probabilities are replaced by decision weights.'* This alternative theory is used in AIE that abandons utility theory and probabilities for a *'pressure to change profit expectations index', p^x,* and percentage change in profits, respectively. Kahneman and Tversky (1979) note that decision weights are generally lower than the corresponding probabilities, except in the range of low probabilities. This overweighting of low probabilities may contribute to the attractiveness of both insurance and gambling and to the shape of the value function in Figure 2–4.

Figure 2–4 A Hypothetical Value Function



(Source: adapted from Kahneman & Tversky 1979)

2. Anchoring

This section discusses the anchoring heuristic for three reasons. First, it provides empirically based behavioural support for the momentum effect and adaptive-expectations. Second, the heuristic incorporated into adaptive expectations forms a component in AIE. Third, the heuristic provides falsification for the REH.

Tversky and Kahneman (1974, p. 1128) introduce the anchoring and adjustment heuristic to explain experimental results. They observe a consistent anchoring effect across many experiments in which people yield different estimates, given differing initial values, noting that the estimates are biased toward the initial values. This effect is present even if the starting value is determined randomly.

Contrary to the experimental results, the agents in REH recalculate estimates afresh each time in doing so they disregard previous estimates.

George and Hwang (2005) find that the heuristic helps to explain the stock price movements. They consider that traders use the 52-week high as a reference point or anchor against, which news is judged. If the stock price is near the 52-week high, there is resistance from traders to bid the price up or down according the news but eventually the news prevails. However, this predictable reluctance in prices to move disappears at prices that are neither near nor far from the 52-week high, where the news is more quickly reflected in the prices. The 52-week high is publicly and widely available information, hence the findings are contrary to the weak form of the EMH. This finding supports a chartists or technical analysis approach to shares trading.

Furthermore, the dynamics of the anchoring and adjustment heuristic can explain the exponential smoothing in adaptive-expectations where the model never reaches equilibrium but moves towards it asymptotically. Section 2.1.8 further discusses the adaptive-expectations model.

3. Availability

This section discusses the availability heuristic because it provides empirically based research to support the interactive-expectations used in the AIE model. In comparison, REH fails to account for this heuristic.

Tversky and Kahneman (1974, p. 1127) introduce the availability heuristic, that is, the ease with which occurrences or instances easily come to mind. They find that factors other than the probability or frequency of an occurrence contribute to an availability bias such as retrievability of instances, effectiveness of search and imaginability. Salience plays an important part in the retrievability of instances. For example, to see a house burn-down impacts people more than to read about it in the local newspaper. In interactive-expectations, this salience is reflected, in that, agents who are directly connected to an agent have more influence on that agent. Similarly, recent occurrences are relatively more available than earlier occurrences. In AIE, the recent occurrences are more heavily weighted, whereas REH fails to predict both salience and recency. This leads to a discussion of interactive-expectations in section 2.1.9.

4. Optimism

This section discusses optimism because the dataset used to test AIE exhibits persistent optimism, in that profit expectations are consistently above actual profits for the majority of the dataset. See Figure 2–6. Additionally, optimism also affects stock trading.

Puria and Robinson (2007) discuss optimism and economic choice. They find that optimism affects work and life choices, more optimistic people work harder, invest more in individual stocks and save more. Additionally, moderate optimists exhibit reasonable financial behaviour, whereas extreme optimists exhibit imprudent behaviour. They reason that moderate optimism creates overconfidence in one's ability to control future events, forgoing current expenditure for investment and giving the illusion of control when trading. Conversely, extreme optimists develop an attitude that the future will take care of itself, leading to a lack of planning.

5. Physiology and the Momentum Effect: Hormonal Male Traders

Coates and Herbert (2008) study the role of the endocrine system in financial risk taking in a group of male traders in London. They find a positive relationship between a trader's testosterone level and his daily Profit and Loss (P&L) and between his cortisol level and financial uncertainty, being measured by variance of economics returns and expected variance of the market. They note that the traders' hormone levels affect rational choice. The more profits the trader made relative to his daily average the higher his testosterone became. Heightened testosterone increases a trader's preference for risk. The process has a positive feedback, producing a financial variant of the *'winner effect'*. Additionally, short periods of high volatility increase a trader's cortisol levels, which increase his motivation and his ability to focus, producing a euphoric feeling. However, a prolonged period of elevated cortisol levels produces selective attention on mostly negative events and anxiety, reducing a trader's preference for risk. Even if the number of traders is small, these hormonal effects could reinforce the momentum effect and cause markets to deviate from rational choice.

2.1.3.4 Summary of EMH

Van der Sa (2004, p. 442) states that the evidence challenging the EMH is convincing and shows the importance of behavioural effects in financial markets. He notes, however, that there is a gap to be bridged between the individual investor and the market, and that the question of aggregation has not been settled yet. Smith (1991) makes a similar observation regarding auctions, see section 2.1.1.3 for discussion. This is a gap the *'science of complexity'* and emergence in particular could fill. Psychology informs behavioural economics about the individual but to develop behavioural economics into the sociological domain requires modelling interactions between individuals, using complexity science to produce emergence rather than using the methodological individualism of neoclassical economics. Van der Sa (2004, p. 442) also notes that the process-orientated research can help link the theories on individual choice behaviour and asset pricing.

Schwert (2003, p. 967) also discusses combining the findings in the anomalies literature with behavioural theories from the psychology literature to create new asset-pricing theories. He notes that models resulting from combining the literatures might explain some of the existing anomalies, but they fail to make predictions for observable behaviour that have not already been tested extensively, that is, behavioural models predict the behaviour they are designed to model but fail to make any novel predictions. He states that it will be a significant challenge to develop new behavioural theories that make refutable predictions to new tests to move beyond theories to explain the *'stylised facts'*. AIE moves on from explaining *'stylised facts'* by producing temporally falsifiable predictions.

Van der Sa (2004, p. 442) observes that the are many behavioural models with testable implications. However, each model sheds light on a particular pricing puzzle, handling each anomaly as an isolated problem and providing each with its own behavioural explanation(s). There lacks a coherent framework in behavioural economics that is comprehensive and surpasses individual cases. The coherent and comprehensive framework is the one clear advantage that the philosophy of mathematic approach adopted by neoclassical economics provides over the philosophy of scientific approach adopted by behavioural economics. However, the coherence of neoclassical economics comes at great cost to relevance, as Brock and Colander (2000, p. 76) note, when economists apply neoclassical economics to policy development that many modifications are made to allow for the unrealistic assumptions and that supplements are added, resulting in a pragmatic and eclectic approach. Section 5.4 further discusses policy implications.

Lo (2004) introduces the Adaptive Market Hypothesis (AMH) to reconcile the EMH and behavioural economics within an evolutionary framework. He provides a plausible narrative to describe how the behavioural rules are consistent with people adapting to a changing market environment. The behavioural rules in the guise of various strategies undergo selective pressure. The AMH differs from the EMH in several ways: arbitrage opportunities exist; risk and reward are unstable over time; the success of investment strategies wax and wan over time; adapting to changing market conditions and innovation is the key to success; and utility maximisation and profit are secondary to survival. According to the AMH, market efficiency is highly context dependent and dynamic and related to the number of competitors, the magnitude of profits available and the adaptability of the market participants.

Farmer and Geanakoplos (2008, p. 14) note that there are problems defining utility, therefore it makes the use of alternatives desirable. For example, the Black–Scholes (1973) model for pricing options are derived from only two assumptions, the price of the underlying asset is a random walk and that neither the person issuing the option nor the person buying it can make risk-free profits. This model only relies on information and arbitrage efficiency. They note that arbitrage efficiency may form a better basis for financial economics than equilibrium.

The EMH review has produced some useful findings for the AIE model. The AIE replaces the utility maximising agent of REH with the following behavioural rules and effects, prospect theory, anchor and adjustment heuristic, availability heuristic, and optimism bias. There is a need to supplement the behavioural rules with some form of aggregation technique. AIE has adopted a complex systems framework but uses an ABM methodology rather than evolutionary, as suggested by Lo (2004). Section 5.5.2 justifies AIE using a non-evolutionary approach.

2.1.4 Microfoundations Projects: from General Equilibrium Theory to Emergence

'The history of general equilibrium theory from Walras to Arrow–Debreu has been a journey down a blind alley ... because the most rigorous solution to the existence problem by Arrow and Debreu turns general equilibrium into a mathematical puzzle applied to a virtual economy that can be imagined but could not possibly exist, while the extremely relevant 'stability problem' has never been solved either rigorously or sloppily.'

(Blaug 2001, p. 160)

This section discusses the *General Equilibrium Theory* (GET) because it is a very important blind alley in economics and REH contributes to its failure. Understanding GET is necessary to appreciate the requirement for a replacement for the microfoundations project and to dispel the misconception that Computable General Equilibrium (CGE) models have microfoundations, but they just falsely assume microfoundations. The *'science of complexity'* approach provides a potential replacement for GET in the microfoundations project.

The microfoundations project in the neoclassical framework uses the Arrow–Debreu–McKenzie (ADM) model of GET, a reinterpretation of Walras' GET. The ADM model of GET was computerised, using Applied General Equilibrium (AGE) Models. Both the ADM model and the AGE are proven theoretical dead-ends that terminate the neoclassical microfoundations project. However, elements of the AGE model, such as, CES and terminology from the ADM model, survive as attachments to CGE and its descendent DSGE. Both CGE and DSGE are *'top–down'* macro-models. In contrast, GET and AGE are *'bottom–up'* macro-models. Section 2.1.5 discusses CGE and DSGE models and the distinction between *'top–down' and 'bottom–up'*.

The *'science of complexity'* microfoundations project uses emergence. The emergent concept is that the interaction of many parts produces macro phenomena that are absent in the individual parts. Emergence is modelled using ABMs or differential equations. Section 2.2.1 further discusses emergence. Gintis' (2007) *'dynamics of general equilibrium'* using an ABM embodies the *'science of complexity'* approach, providing a general equilibrium model with microfoundations, which uses assumptions that are more consistent with Vernon Smith's experimental economics. For instance, agents in Gintis (2007) have private information that he finds a prerequisite for a stable equilibrium. In contrast, agents in the ADM model have access to all the information they require, which results in unstable and multiple equilibria. Gintis' (2007, p. 1291) model produces variation in prices, which is more realistic than the single price vector in the ADM model. However, Gintis (2007) has been unable to find tractable alternatives to CES.

The structure of the section is as follows. Subsection one discusses the Lucas critique as the motivation for the microfoundations project. Subsection two discusses the early development of the GET and the Tâtonnement debate. Subsection three discusses the ADM model of GET. Subsection four discusses AGE. Subsection five discusses criticisms of GET and AGE. Subsection six summarises section 2.1.4.

2.1.4.1 The Lucas Critique: Motivation for the Microfoundations Framework

Lucas (1976) criticises the macroeconomic models used for policy formulation for lacking micro level foundations. He argues that such models should be based on fundamentals such as preference, technology and budget constraints to avoid making predictions based upon the economic structure containing previous policy formulation. This is because the structural parameters could change in response to policy initiatives and, if this were not part of the analysis, it would become impossible to predict the effects of policy (Gibson 2008, p. 3). The macroeconomic models Lucas criticises are empirical forecasting models that consist of econometric estimations of systems of equations of aggregate variables, similar to the simple IS–LM–BP and AS–AD models but at a much finer level of detail. Jan Tinbergen developed the first empirical forecasting model for national accounts and Lawrence Klein developed the first global empirical forecasting model. In part, the Lucas critique resulted in the move from the *'top–down'* approach using empirical forecasting models to a *'bottom–up'* approach. Rizvi (1994, pp. 360-1) states that the microfoundations project assumes that macro-phenomena must be reduced to micro-principles. The neoclassical microfoundations project uses GET and the *'science of complexity'* microfoundations project uses emergence.

2.1.4.2 Walras' General Equilibrium Theory

Walras (1874) developed GET because the supply and demand behaviour of a single market was understood but there lacked understanding of the supply and demand behaviour between markets. Walrasian GET creates a system of simultaneous equations to understand the interactions between markets. Walras (1954, p. 380) describes the Tâtonnement processes as groping toward but never reaching a constantly changing equilibrium price.

> *'Such is the continuous market, which is perpetually tending towards equilibrium without ever actually attaining it, because the market has no other way of approaching equilibrium except by groping, and, before the goal is reached, it has to renew its efforts and start all over again...'*

Walras' dynamic version of Tâtonnement gave way to a static simplification of the groping process to find the market clearing prices, that is, no transactions are made until the GE clearing price is met. Furthermore, GE requires the following simplifying assumptions, perfect information and no transaction costs. The GE equations were unsolvable for Walras because of the lack of economic data and the number of unknowns, thus he was unable to provide proof of the existence of the termination of the Tâtonnement process at GE. The Arrow–Debreu Existence Theorem (Arrow & Debreu 1954) provides proof of a GE solution. The existence theorem requires convex preferences as an additional simplifying assumption to Walras' GET. Convex preferences are utility curves or indifference curves that obey the law of diminishing marginal utility. However, the Arrow–Debreu Existence Theorem only proves that a GE solution exists, while the SMD Theorem proves that the solution lacks uniqueness, stability and computability. Section 2.1.4.5 further discusses criticisms of the convexity assumption and the SMD Theorem.

The first English translation of Walras' (1874; 1926, rev ed.) *'Eléments d'economique politique pure'* was Walras (1954) *'Elements of Pure Economics'* by Jervois, which allowed direct access to his theory to a wider audience of economists. However, an alternative neo-Walrasian GET in the English-speaking world had already developed prior to the translation. There is dispute in the literature over interpreting Walras. For instance, De Vroey's (1999, p. 427) book review of Walker (1996) *'Walras' Market Models'* shows disagreement over the Walrasian auctioneer. Walker claims that the auctioneer hypothesis is not explicitly made by Walras, arguing that the auctioneer is unnecessary. De Vroey argues that an auctioneer fits a hole in Walras' work perfectly.

Whether or not Walras intended an auctioneer is disputed. However, the neo-Walrasian GET literature does use the terms, Walrasian auction and auctioneer. A Walrasian auction is a process whereby every agent calculates their demand for a good at every possible price and submits bids to a Walrasian auctioneer. GE is reached when the prices are found so that the total demand across all agents meets the total amount of goods. The goods are transferred once the GE price vector is found.

Gintis (2007) notes that the progress in understanding the dynamics of the Tâtonnement process has been meagre. In a complexity approach, he uses an ABM to model the Tâtonnement process where agents are encoded with strategies governing their acquisition of information and their ability to imitate the strategies of other agents. The agents using higher payoff strategies over time increase in frequency at the expense of agents using lower payoff strategies. The model compares with a number of stylised facts.

2.1.4.3 Arrow–Debreu–McKenzie's General Equilibrium Theory

The collaborative effort between Kenneth Arrow, Gerard Debreu and Lionel W. McKenzie, called the Arrow–Debreu–McKenzie (ADM) model (Debreu 1959) and developed in the 1950s, is considered the first modern version of GET. The original Walrasian GET underwent additions and simplifications to cumulate in the ADM model. The Arrow–Debreu Existence Theorem (Arrow & Debreu 1954) provides proof of a GE solution, requiring that each utility curve displays diminishing marginal utility of consumption and each technology displays diminishing marginal product.

Farmer and Geanakoplos (2008, p. 6) note the profound effect of GET on the economics profession, causing a change from the narrative based *'political economy'* to the highly mathematical approach using *theorem-proof* format. However, neither approach is necessarily scientific (Milonakis & Fine 2008, p. 297).

In addition to the perfect spot market assumptions of the neo–Walrasian GET, the ADM model extends the notion of a commodity to include futures contracts, assuming that there are perfect futures markets for a finite number of commodities, which can be delivered at any fixed interval within a fixed time horizon to any destination in a specific condition. This assumption eliminates the need for probabilities, but ignores incomplete markets and the inherent uncertainty about the future. The criticism in section 2.1.4.5 further discusses the complete perfect futures market assumption. The ADM model uses a finite number of commodities, delivery periods and destinations as discrete approximations to the continuous ideal, required to find a GE. Section 2.1.4.5 discusses criticisms of the discrete approximation to the continuous. Additionally, the ADM model fails to capture the activities of government or monopolies. Section 2.1.4.5 also discusses these issues.

2.1.4.4 Applied General Equilibrium Model Implementing the ADM model

Scarf (1967a; 1967b) and Scarf and Hansen (1973) introduce the Applied General Equilibrium (AGE) model in an attempt to empirically estimate GE for the ADM model. Scarf (1967a) introduces a variant on the simplex method to estimate GE. Section 2.2.4 discusses the simplex method. Velupillai (2006, p. 360) states that the ADM model had remained in the realms of pure theory until Scarf's AGE model. Shoven and Whalley (1972; 1973) implement the Scarf's AGE model to study the distortion effects of taxation on a perfectly competitive economy. Velupillai (2006, p. 363) proves that AGE models cannot be solved precisely, finding that it is easy to show that the recursion used in the AGE model lacks computability. At this point, the neoclassical microfoundations research project has reached a theoretical and technical dead-end.

2.1.4.5 Criticisms of ADM model and AGE leading to Emergence as a Solution

This section discusses five criticisms of AGE and GET. Some consider the first criticism, the SMD Theorem, sufficient to call for an end to neoclassical microfoundations project using GET. However, discussing the remaining criticisms of GET serves three purposes. First, it informs the development of AIE. Second, it provides context for AIE. Third, it produces further evidence that the GET fails to provide microfoundations. This failure is even more marked after the GET assumptions have become increasingly unrealistic in an attempt to find a price vector that provides a unique and stable equilibrium. Lakatos (1976) would consider this reduction in scope of the GET the hallmark of a degenerative scientific research program.

The structure of this section is as follows. Subsection one discusses the SMD Theorem regarding the shapeless excess aggregate demand curve. Subsection two discusses the Greenwald–Stiglitz Theorem regarding information economics and complete markets. Subsection three discusses the non-computability of GE. Subsection four discusses the unrealistic fixed tastes, technology and resources assumptions of GET. Subsection five discusses the unrealistic convexity assumption. Subsection six discusses rational cooperation.

1. Multiple unstable equilibria and the Sonnenschein–Mantel–Debreu Theorem

This section outlines the proof of the SMD Theorem, and then discusses its implications. The Arrow–Debreu Existence Theorem (Arrow & Debreu 1954) proves the existence of GE, however the SMD Theorem (Debreu 1974; Mantel 1974; Sonnenschein 1972, 1973) proves that GE has multiple equilibria. Kirman (1992, p. 119) notes that the uniqueness of equilibrium in GET is required to justify comparative statics and its use in policy analysis. The multiple equilibria undermine methodological equilibration that is one of the three assumptions underpinning the neoclassical framework. Rizvi (1994, p. 358) considers this result the most significant *'negative'* result in mainstream economics, since the capital controversies and Arrow's impossibility theorem.

The SMD Theorem shows that if every agent has nicely shaped individual demand curves, one cannot also say that market demand has a nicely shaped curve. Such market demand curves provide for multiple equilibria using GET with the consequence that we cannot assure *dynamic-stability* or the stability of equilibrium. These stability issues are at odds with the neoclassical equilibration assumption because equilibrium lacking *dynamic-stability* makes the neoclassical technique of comparative statics meaningless. Moreover, the stability of equilibrium cannot be assumed as a small shock perhaps sufficient to move the system to an adjacent equilibrium also making comparative statics meaningless. Rizvi (1994, p. 363) concludes that the SMD Theorem brings the microfoundations project based on *General Equilibrium Theory* to an end. This suggests that the effort over the last one hundred years to find microfoundations for the demand curve as a result of utility-maximization is essentially wasted for the intended result.

Rizvi (1994, p. 370) and Ackerman (2002, p. 133) discuss two solutions to the SMD Theorem's result: (1) continue using GET for the microfoundations project but repair the shapeless market demand curve; or (2) use an alternative theoretical framework for the microfoundations project.

First solution, repairing the shapeless demand curve could take three approaches: (1) Modify the endowments or preferences of agents; (2) Introduce a continuum of agents, as the SMD *Theorem-proof* is for a discrete number of agents; and (3) Introduce decreasing density of wealth of agents. However, Rizvi (1994, p. 370) notes that none of these approaches have produced satisfactory results. Ackerman (2002, p. 127) considers the neoclassical aggregation process and the highly individual asocial nature of consumer preference, as sources of instability in GET that contribute to the shapeless aggregate demand curve. Ackerman (2002, p. 127) states that these sources of instability have been present in the neoclassical framework since its beginning. Ackerman (2002, p. 135) notes that GET fails to predict stable equilibrium in markets, however there are periods of stability in markets between bubbles and exogenous shocks. He claims that the cause of the markets stability is not endogenous, as GET would suggest, but exogenous from institutional structure and rules. This is consistent with the findings from Smith (2007) and from Gintis (2007).

Second solution is using another theoretical framework. McKenzie (2008) notes that GET fails to accommodate monopolies or government. Rizvi (1994, p. 372) discusses introducing macroeconomic structure similar to that in sociology. Ackerman (2002, p. 119) calls for the recognition of the central role of institutional and social constraint. Again, these factors are consistent with the finding from Smith (2007) and from Gintis (2007). Congruently, the AIE model uses a network structure as a proxy for institutional structure, see section 2.2.2.

McKenzie (2008) states that Walras and most GE models consider that people's tastes are constant. Rizvi (1994, p. 372) notes that introducing structure requires the abandonment of the constant individual preferences assumption and rational choice (Von Neumann & Morgenstern 1944). Consistently, Ackerman (2002, p. 119) calls for a new model of consumer choice. Rizvi (1994, p. 373) considers a complexity approach forsaking full optimisation and using agents that follow simple rules, as Simons (1972) describes. Consistently, the agents in the AIE model follow simple rules.

McKenzie (2008) also notes that each consumer in GET is an optimising unit who is uninfluenced by others. Similarly, the productive capabilities of firms are considered independent of others. GE lacks a good theory of when consumer sets or producer sets are affected by levels of production. Kirman (1992) considers that the microfoundations for economics will be found not from studying individuals in isolation, but in studying the aggregate activity resulting from the direct interaction between different individuals. Similarly, Ackerman (2002, p. 119) calls for the use of nonlinear analyses of social interactions.

Institutional or complexity economics using emergence would fit all the changes proposed by Kirman (1992), Rizvi (1994) and Ackerman (2002) and provide an alternative to the neoclassical framework using GET. Gibson (2007) and Gintis (2007) use ABM to simulate emergences as a replacement for the GET, however they use stylised facts as a form of falsifiable prediction rather than temporal prediction. Section 2.2.3 discusses issues over falsification and ABMs simulating emergence.

2. Imperfect information, Incomplete Markets and the Greenwald–Stiglitz Theorem

This section discusses the Greenwald–Stiglitz Theorem to show that GET makes impossible assumptions about information requirements, which provides further weight for a need to use bounded rationality.

Greenwald and Stiglitz (1986) make the point that in the comparison between economies with and without perfect information to state that the economy with perfect information will do better is irrelevant. The relevant question is *'How much does perfect information cost?'* For instance, the search costs for every consumer to optimise their utility across every possible product in the economy, perhaps millions of products, even if all the information were available, it would require agents with capabilities of imagination and calculation that exceed reality by many orders of magnitude. The are all requirements that must be met if the ADM model is taken literally (Majumdar & Radner 2008).

Arrow–Debreu Existence Theorem (Arrow & Debreu 1954) assumes that agents have perfect information to prove the existence of GE. The ADM model (Debreu 1959) assumes complete markets and perfect knowledge. The Greenwald–Stiglitz Theorem (Greenwald & Stiglitz 1986) relaxes these assumption and finds that tax interventions are almost always Pareto improving and that situations of imperfect information or incomplete markets are rarely constrained Pareto optimal. Greenwald and Stiglitz (1986) note that in virtually all economies that markets are incomplete and information is imperfect. They cite imperfect information dynamics such as adverse selection, moral hazard and signal screening where taxes and intervention are Pareto improving. Majumdar and Radner (2008) also cite the moral hazard problem. Addressing the ADM model's concept of complete markets, Greenwald and Stiglitz (1986) note that the quality of a commodity cannot be guaranteed, which produces an adverse selection dynamic, particularly in risk markets. They discuss improving the risk-transfer-risk-sharing function of the markets by using taxes to adjust the price signal for uninformed individuals.

Farmer and Geanakoplos (2008, p. 13) agree that financial markets are incomplete but ask *'does the government have the information to improve the situation?'* Furthermore, Koppl (2000, p. 109) notes that the costs of *'market failure'* need setting against *'government failure'* before contemplating intervention. Koppl (2000), giving an Austrian School perspective on a complex systems approach, argues that determining information requirements and the costs of government intervention is difficult, while the benefits appear more obvious. Section 5.4.2 further discusses the conflicting views on government intervention between the Austrian School and Greenwald and Stiglitz (1986), which provides a gap for ABMs, such as AIE, to inform the debate.

Given that economies operate with imperfect information, the more relevant question is *'How do agents use imperfect information?'*, rather than *'What is an agent's maximum utility given perfect information and unlimited computing power?'*

3. Computationally bounded agents and non-computability of competitive equilibrium

This section shows that attributing GET agents with the computational power of humans makes GE incomputable, adding weight to the need to consider bounded rationality, when developing models. Arrow–Debreu Existence Theorem (Arrow & Debreu 1954) proves the existence of GE, assuming that agents have unlimited cognitive power. Richter and Wong (1999) relax this assumption. They use a Turing computable function, which are those functions computable by human beings to formalise the computability of bounded rationality. Richter and Wong (1999) characterise all the agents with utility functions and endowment vectors to satisfy the assumptions of Arrow–Debreu Existence Theorem, where according to the theorem, there must exist a computable competitive price vector (GE). However, they are unable to compute a competitive equilibrium. This negative result adds weight to the argument that the current assumptions in Arrow–Debreu Existence Theorem are insufficient to ensure the existence of a GE, if the agents are bound.

4. GET assumptions: fixed tastes, technology and resources including population

McKenzie (2008) states that Walras and most GE models assume tastes, technology and resources, including population, are constants. These assumptions make GE a partial theory of economics, that of ceteris paribus, to focus on the variables that are easily modelled. Veblen's (1899) narrative, *'The theory of the leisure class : an economic study of institutions'*, discusses how changing tastes affect the economy. Schumpeter's (1939) narrative, *'Business cycles : a theoretical, historical, and statistical analysis of the capitalist process'*, discusses the role of technology in the business cycle, constantly disrupting equilibrium. Both these narratives describe the economy as a complex system and provide criticisms of the neoclassical approach, but neither author produced any testable models. At the time, it seemed reasonable for economists to describe the economy as a complex system and to criticise neoclassical economics using narrative, and for neoclassical economists to focus on the variables more easily modelled, given the mathematical techniques and computing power available. Currently, however, there is the computation power and techniques available to model the economy as a complex system.

GET is an allocative efficiency theory that ignores economic growth, which is essentially an out of equilibrium process. Section 2.1.1.4 discusses how GET provides direction for the neoclassical research programme and provides a poor foundation to model technological change in DSGE. Section 2.1.5 further discusses DSGE.

5. Convexity assumption

This section discusses utility curves and the convexity assumption to justify using an alternative in AIE. McKenzie (2008) acknowledges that the convexity assumption used in GET, since the work of Walras, is unrealistic.

Farmer and Geanakoplos (2008, p. 21) note that the suitability of utility as a foundation in economics has long been questioned. '*The concept of utility as it is normally used in economic theory is purely qualitative. The functional form of utility is generally chosen for convenience, without any empirical justification for choosing one form over another. No one takes the functional form and the parameters of utility functions literally. This creates vagueness in economic theory...'*

Sections 2.1.1.1, 2.1.2.1 and 2.1.3.3 discuss Kahneman and Tversky's investigation into psychology to provide a more realistic alternative to expected utility theory. Section 2.1.3.4 discusses Lo's

(2004) Adaptive Market Hypothesis, which provides alternatives to utility maximisation by using behavioural rules. Similarly, Gibson (2007) uses behavioural rules to replace the utility maximisation. Ormerod et al (2007, p. 202) discuss an ABM using zero-intelligent agents that operate under a continuous double auction for a single commodity. The agent chooses bids and asks totally at random from those that do not impose a loss on the agent, using no updating or any learning algorithm. Ormerod (2007, p. 202) notes that most of the social gain is achieved by the agents in a way consistent with Smith's experimental economics.

6. Rational Cooperation

Farmer and Geanakoplos (2008, p. 12) note that in GET Pareto Optimality is arrived at by everyone acting as selfish maximiser guided only by market prices. However, it is rational to cooperate, which introduces the whole field of game theory. From a game theory perspective, GET Pareto Optimal equilibrium is a form of Nash equilibrium. Game theory is a form of strategic interaction, but still ignores the influence of institutional structural on rational cooperation (Farmer & Geanakoplos 2008, p. 43).

2.1.4.6 Summary of General Equilibrium Theory

The SMD Theorem and Velupillai (2006) theoretically mark the end of the neoclassical microfoundations project. Popper (1999) considers a negative result as an essential part of learning, resulting in effort and energy being redirected into alternative microfoundations research projects. However, this does not appear to have happened in this case, despite there being ample and substantive criticism of the project. Lakatos (1976) provides a perspective to help explain the situation. There would normally be bridges available for scientists to move from one framework and research project to another, in this case from the neoclassical to complexity framework and from the GET to emergence microfoundations research project. However, the state of modelling in the emergence microfoundations project is still rudimentary and methodologies differ both philosophically and technically, making the transfer difficult from a deductive and mathematical approach to an inductive and ABM approach. So, the effort of the neoclassical microfoundations project has transferred to the CGE and DSGE projects that have well-developed models that superficially resemble the neoclassical microfoundations project. Section 2.1.5 further discusses CGE and DSGE.

The Greenwald–Stiglitz theorem proves that government intervention is always Pareto improving. However, this result relies on the *'Fundamental theorems of welfare economics'* that competitive equilibrium is Pareto efficient, which in turn relies on the failed GET. Furthermore, the Greenwald–Stiglitz theorem fails to address *'government failure'*. Incorporating *'government* *failure'* into the question over whether a government should intervene in a market means asking the question, *'Which is the least worse, the market failure or the government failure from the intervention?'*

Velupillai (2007, p. 275) discusses policy development underpinned by GET and game theory, noting that how many economics graduates see Nash equilibria and the *'Fundamental theorems of welfare economics'* as the processes that economies generate, but lack the ability to interpret actions, events and institutional pathologies and their frequent paralysis. Section 5.4 further discusses policy implication and the role of ABMs and AIE to provide an alternative perspective to inform debate.

2.1.5 Dynamic Stochastic General Equilibrium and Rational Expectations

'We need a new stochastic approach to study macroeconomy composed of a large number of stochastically interacting heterogeneous agents. We reject the standard approach to microfoundation of macroeconomics as misguided, mainly because the framework of intertemporal optimization formulation for representative agents is entirely inadequate to serve as microfoundations of macroeconomics of stochastically interacting microeconomic units.'

(Aoki 2007)

Section 2.1.4 discusses the failure of the neoclassical microfoundations project using *General Equilibrium Theory* (GET), which uses assumptions from REH. Despite the failure, many of the assumptions from GET and REH have found their way into Computable General Equilibrium (CGE) and from there into *Dynamic Stochastic General Equilibrium* (DSGE) that endeavours to model technological shocks with a collection of internally inconsistent assumptions that were originally designed to model an allocatively efficient price vector.

This section discusses the current problems with CGE and DSGE, finding that many of their problems relate to their GET and REH assumptions. The *'science of complexity'* approach does offer solutions; an approach the AIE model takes. The ancestors of DSGE are input-output and CGE models that are neoclassical *'top–down'* macro models that are not part of the microfoundations project. Two versions of DSGE are developed from 'dynamic' CGE, the Real Business Cycle (RBC) and the New-Keynesian DSGE.

The section structure is as follows. Subsection one discusses the development of CGE from its input-output model origins, the importance of CGE in policy development and CGE lacking microfoundations. Subsection two discusses the development of DSGE from CGE. Subsection three discusses the RBC and its criticisms. Subsection four discusses the development of New Keynesian DSGE from the RBC to rectify the deficiencies of the RBC, despite the fact that the Keynesian DSGE continues to have representative agent problems. Subsection five summarises section 2.1.5.

2.1.5.1 Computable General Equilibrium Modelling

Input-output models are the ancestors of CGE models. Leontief's (1966) input-output model provides the first empirically based model on a national scale. The *'input-output table'* shows the flow between different sectors or regions of the economy. The inputs are in the columns and the outputs are in the rows. The rows in the tables represent equations from the macro Keynesian model (Schaffer 1999). Walras' ambition to use simultaneous equations to relate markets together is solved empirically in the input-output model.

The CGE model consists of *'input-output tables'* or social accounting matrix plus elasticities to capture the behavioural response to change. There are basically two types of CGE, dynamic models that trace variables through time, and comparative static models that analyse the reaction of the economy to a change at a single point in time. The following three CGE models are examples of the dynamic variety. One, Johansen (1960) introduces a multi-sector growth model of Norway. Two, Stone (1960), as part of the Cambridge Growth Project, introduces the Cambridge Multi-sectoral Dynamic Model of the British economy. Three, Dixon and Rimmer's (2002) model of the Australian economy, which has been continuously developed at the Centre of Policy Studies (2009) at Monash University, Australia, since the late 1970s. The following CGE model is an example of the static variety. Taylor and Black (1974) analyse the effect of a percentage cut in tariffs on the percentage change in consumption, exchange rate and export volume in the Chilean economy.

An example of a global CGE model is the Global Trade Analysis Project (GTAP 2009) coordinated by the Centre for Global Trade Analysis, Department of Agricultural Economics, Purdue University. GTAP (2009) claims that their model provides a common language for global economic analysis; they cite the use of GTAP in three of the five quantitative studies at the 1995 conference of the WTO's Uruguay Round Agreement and in virtually all the quantitative work for the 1999 Millennium Round of Multilateral Trade. These examples do indicate the prevalence, credibility and perceived importance of CGE.

Mitra-Kahn (2008, pp. 20-6) discusses the confusion in the literature over the terms CGE and AGE, stating that CGE is not related to the ADM model of GET, whereas AGE is an application of the ADM model. Using the Lucas Critique helps make the distinction clear. The *'general equilibrium'* of CGE models comes from balancing macro Keynesian simultaneous equations, in which equilibrium is imposed from above that makes CGE models *'top–down'* models. In comparison, the *'general equilibrium'* of the AGE and ADM models derives from finding a prices vector that balances the supply and demand of the agents, where equilibrium is calculated, using the simplex method in the AGE model, thus AGE and ADM models are *'bottom–up'* models. Additionally, CGE models consider government within the model, whereas the AGE and ADM models only consider agents in pure competition and exclude the government.

However, there are similarities between the AGE and CGE models, including the use of elasticities, particularly the constant elasticity of substitution and factors such as technology and consumer tastes are considered exogenously given. Additionally, rational expectations behaviour assumed in the AGE and ADM models is also assumed in the CGE models but this behavioural assumption does not lead to the calculation of *'general equilibrium'* in CGE. An example from the literature of the confusion between terms, CGE and AGE, is provided by Kehoe and Kehoe (1994) who retain the title AGE for their model, when using *'input-output tables'* to find equilibrium.

In addition to CGE lacking microfoundations, the validity of imposing equilibrium as a *'top–down'* model is also questionable. Blatt (1983) discusses the dual (in)stability problem in an accelerator-multiplier model that is a version of the *'top–down'* models used in CGE, where the multiplier v can take the values $0 < v < 1$ or $v > 1$. If $v > 1$, there are endogenous trade cycles but the long-run equilibrium is unstable (explosive). If $0 < v < 1$, the long-run equilibrium is stable but there lacks endogenous trade cycles. A solution to this dilemma is to assume that all trade cycles are the result of exogenous shocks. However, this assumption contradicts empirical evidence. Blatt (1983) concludes that equilibrium analysis is unreliable and ineffective for understanding or developing policies to mitigate the severity of trade cycles. The following sections discuss how the basic CGE model is extended, while retaining the assumption that all trade cycles are the result of exogenous shocks.

2.1.5.2 Dynamic Stochastic General Equilibrium Modelling

In addition to the CGE model being split between comparative-static and dynamic models, the dynamic models are split between recursive-dynamic and full multi-period dynamic models. The recursive-dynamic CGE models assume that behaviour depends only on the current and past states of the economy. In contrast, the full multi-period dynamic models consider that the agents' expectations also depend on the future states of the economy. This requires the model to be solved simultaneously over the full multi-period. These models are known as *Dynamic Stochastic General Equilibrium* (DSGE) models and are of interest to this thesis because they introduce expectations into the CGE models. Importantly, DSGE relaxes the constant technology assumption of CGE to study its role as a driver for the business cycle. Consequently, DSGE uses shorter time intervals, typically quarterly, to capture the business cycle and study the effect of monetary and fiscal policy. In comparison, the comparative-static and recursive-dynamic CGE models focus on long run relationships, making them suitable for studying the long run impact of policies, such as openness of an economy to trade and tax regimes. For example, Kehoe and Kehoe (1994) and Shoven and Whalley (1972) present comparative-static and recursive-dynamic CGE models, respectively.

DSGE models are essentially explanatory models about the business cycle, as they do not make falsifiable temporal predictions. Troitzsch (2009) discusses the symmetry between explanation and prediction, defining three types of prediction.

1. Which kinds of behaviour can be expected under arbitrarily, given parameter combinations and initial conditions?
2. Which kind of behaviour will a given target system display in the near future?
3. Which state will the target system reach in the near future, again given that the parameters and previous states may or may not have been precisely measured?

Any good explanation will yield a type-1 and also possibly a type-2 prediction, but not every good explanation will yield a type-3 prediction, a falsifiable temporal prediction. For DSGE models, to maintain scientific credibility, stylised facts about the business cycle are used to create falsifiable predictions of type-1. Kaldor (1957) introduces six stylised facts about the business cycle in the US and UK.

1. The shares of national income received by labour and capital are roughly constant over long periods of time
2. The rate of growth of the capital stock is roughly constant over long periods of time
3. The rate of growth of output per worker is roughly constant over long periods of time
4. The capital/output ratio is roughly constant over long periods of time
5. The rate of return on investment is roughly constant over long periods of time
6. The real wage grows over time

Other stylised facts exist, such as Christiano and Eichenbaum (1990) citing Dunlop (1938) and Tarshis (1939) who observe that the correlation between hours worked and the *'return to working'* is close to zero. This fact is used to falsify a version of DSGE. Ormerod (2002) notes that the autoregressive AR(1) and AR(2) of output are positive and negative, respectively; a fact that also falsifies a version of DSGE. Canova (1998) discusses the business cycle facts serving two purposes, acting as a numerical benchmark and identifying important co-movements between variables. However, he notes that the de-trending process used to prepare the data for DGSE can determine the stylised facts and co-movements, which undermines the DGSE benchmarks and, consequently, the veracity of any DGSE results.

DSGE takes two forms, the real business cycle (RBC) (Kydland & Prescott 1982) and the New-Keynesian DSGE model (Rotemberg & Woodford 1997). Stadler (1994, p. 1751) notes that the RBC tries to account for the existence of business cycles in perfectly competitive economies with rational expectations. The New-Keynesian DSGE generally accepts rational expectations, but relaxes the perfect competition assumption, using costly price adjustments and externalities, and considers nominal shocks as the predominant impulse mechanism.

2.1.5.3 Real Business Cycle (RBC)

Summers (1986) notes the ascendency of the RBC in the economic profession. He describes the RBC as a floating Walrasian equilibrium buffeted by productivity shocks, based on the three assumptions: there are no monetary policy effects on real activity; fiscal policy only works via incentives; and economic fluctuations are purely the result of supply rather than demand. Stadler (1994, p. 1753) describes the RBC as an extension of the neoclassical growth theory from the late 1950s where the fluctuations in the Solow residual provide the technology shocks to explain the business cycle.

Stadler (1994, p. 1766) discusses five criticisms of the RBC. One, there is a lack of evidence for sufficiently large real shocks to drive the model. Two, testing the RBC is purely subjective. Three, RBC fails to capture the business cycle because it lacks suitable transmission mechanisms. Four, the RBC does not explain recession well. Five, the representative agent makes the model unsuitable for welfare or policy development. Each of the criticisms is discussed in turn.

1. *There is no independent evidence for the large, economy wide disturbances that drive these models*

Summers (1986, p. 2) states that Prescott fails to provide any independent evidence for the existence of the technological shocks, noting that these are rather important, as they are the only drivers in the RBC model. Some RBC theorists claim that real shocks account for all output fluctuations; Kydland and Prescott claim about 70 percent. However, Stadler (1994, p. 1779) notes that the empirical evidence supports the proposition that real shocks cause about one third of output fluctuations. Summers (1986, p. 4) claims that the ability to differentiate supply shocks from demand shocks disappears in the RBC because prices are not modelled, thus providing the RBC more latitude. However, Summers (1986, p. 5) explains how each of the major recession was caused by a credit crunch in an effort to control inflation, noting that the RBC is unable to model these causes of the business cycle. The New-Keynesian DSGE relaxes the RBC assumption that only real shocks are relevant to output fluctuations by introducing nominal shock.

2. *Testing is purely subjective.*

The models are not subject to formal econometric tests and there is no objective yardstick to measure how well RBC models account for the periodicity of cycles. Additionally, the RBC is not subjected to formal statistical tests against alternative models. Christiano and Eichenbaum (1990) find that the RBC fails to meet the stylised fact from Dunlop (1938) and Tarshis (1939) that the correlation between hours worked and the *'return to working'* is close to zero because existing RBC models predict the correlation in excess of 0.9.

3. The RBC cannot account for periodicity of cycles and the pattern of cycles generated by RBC models does not match reality well.

In the RBC, the cycle is driven by shocks to technology that affects the production functions by shifting it up or down. These shocks are amplified by the inter-temporal substitution of labour – a rise in productivity raises labour costs to increases the cost of leisure. Summers (1986, p. 2) finds no support, either at the micro or macro level, for the conjecture that inter-temporal substitution of labour are sufficiently large to cause fluctuations in the labour supply. Furthermore, Summers (1986, p. 4) notes the empirical evidence that consumption and leisure move in opposite directions is not resolved in Prescott's work. Additionally, Summers (1986, p. 2) calls into question Prescott's claim that the RBC parameters are empirically based.

Rotemberg and Woodford (1996, p. 87) find that RBC fails to model the movements in output, consumptions and hours – what they argue is the essence of the business cycle. They provide three possible reasons for the unrealistic performance of the RBC model. The business cycle is caused by shocks other than technological shocks. The RBC incorrectly models the shock transmission mechanism. Technology shocks are serially correlated and not a random-walk, as modelled by the RBC. Stadler (1994, p. 1778) considers that the RBC model cannot account for the output dynamics in the US GNP because the propagation mechanism is so weak.

Stadler (1994, p. 1777) notes that the RBC treats all real shocks as purely exogenous. He considers this a failing because it ignores endogenous factors, such as, firms innovating when they are expecting a boom, making the boom self-fulfilling. Additionally, he notes that the Solow residuals are Granger (1969) caused by money, interest rates and government spending, which is at odds with the RBC assumptions.

4. The RBC cannot account for recessions, for this would require an economy wide reduction in productivity.

Summers (1986, p. 3) asks what technological shock caused the 1982 recession?; What are the sources of technical regression? The proponents of the RBC, as far as the author is aware, have failed to answer these questions with anything more than oil shock.

5. *The use of the representative agent framework reduces the ability of the RBC models to address welfare or policy issues.*

Stadler (1994, p. 1779) notes that even if the RBC theory overcomes its numerous problems, the representative agent in the RBC makes it unsuitable for policy development because it is just too unrealistic. Every study of disaggregated micro level data, to the knowledge of the author, finds strong systematic evidence of individual difference in economic behaviour. This heterogeneity affects the overall impact in changes in interest rate on savings, or the impact of an investment tax credit. The RBC could relax the representative agent assumption (Stadler 1994, p. 1771). This last criticism is also relevant to the New-Keynesian DSGE.

2.1.5.4 New-Keynesian DSGE models

Rotemberg and Woodford (1997) introduce the New-Keynesian version of the DSGE model. This version relaxes the RBC assumption that only real shocks matter, allowing interest and money to play a part in the development of business cycles. Despite this increase in realism, Kirman (1992, p. 118) questions the validity of any model using the representative agent to analyse the effect of changes in government policy. This is because the reaction of a maximising representative individual may not be the same as the aggregate reactions of the individuals the representative agent represents. Kirman (1992, pp. 124-5) demonstrates this mismatch, using traditional utility curve maximisation with respect to a budget constraint for two individuals where each individual prefers more of good 1 than good 2, whereas the representative agent prefers the opposite. For example, different groups within the economy respond differently to interest rate changes, making the representative agent a limiting factor in developing a model to describe the business cycle. Kirman (1992, p. 119) suggests that introducing heterogeneous agents would provide the model with the ability to model distribution and coordination, which are fairly basic requirements in analysing changes in government policy.

Aoki's (2007, p. 141) heterogeneous stochastic model generates business cycles and fluctuation at the aggregate level from sectoral reallocation of resources, given a threshold for actions among agents that differ across firms and sectors. Aoki (2007, p. 123) claims that these heterogeneous acts cause the business cycle, rather than agents acting rationally or optimally. His threshold for action concept has similarities to the *'pressure to change profit expectations index', p^x,* introduced in AIE.

Kirman (1992, p. 129) notes that introducing heterogeneity in income or preferences of individuals may improve the smoothness of aggregate behaviour. However, Kirman (1992, p. 131) suggests that it is insufficient to introduce heterogeneity into general equilibrium models, without expanding the role of interactions between agents from anonymous price-takers to include the passage of information, the building of regulations, organising into groups for the purpose of trading, and more. This would require abandoning two of the neoclassical axioms, namely methodological individualism and instrumentalism.

2.1.5.5 DSGE Summary

The New Keynesian DSGE appears to resolve some of the shortcomings of the RBC. However, the representative agent problem provides limitations to the reliability and ability of DSGE to inform policy. The transmission mechanism in DSGE has substantive criticism. The benchmarks for DSGE are subjective and the benchmarks changes according to the de-trending filter used. The SMD Theorem shows that DSGE and CGE lack microfoundations. Despite all of the aforementioned considerations, DSGE and CGE remain active areas of research and policy development.

The ABM approach, as proposed by Aoki (2007), directly solves two of the DSGE problems, the poor transmission mechanism and the representative agent.

2.1.6 Using Emergence in an Economic System to Link the AIE Model Components

'Emergence refers to the arising of novel and coherent structures, patterns and properties during the process of self-organisation in complex systems. Emergent phenomena are conceptualised as occurring on the macro level, in contrast to the micro–level components and processes out of which they arise.'

(Goldstein 1999, p. 49)

This section provides an overview of how the component parts of the AIE model fit together within an emergence framework. In the AIE model, profit expectations at the macro level are an emergent property of the interaction among agents or firms at the micro level. The AIE model's component parts are adaptive-expectations (Hicks 1939), interactive-expectations (Flieth & Foster 2002) and small world networks (Watts & Strogatz 1998). Each component is discussed in more detail in sections 2.1.8, 2.1.9, and 2.2.2, respectively.

The *'Beer distribution game'* provides an example of business expectations and emergence in a simple supply chain, manufacturer, distributor, wholesaler and retailer. This emergence example is particularly relevant because this thesis' dataset (D&B 2008) covers the manufacturing, wholesale and retail divisions. Section 2.1.7 further discusses the D&B (2008) profit expectations survey.

Sterman's (2000, pp. 684-98) *'Beer distribution game'* provides an example of interactive and adaptive-expectations in the emergence of oscillation in a controlled environment. The game consists of an extremely simplified supply chain containing a manufacturer, a distributor, a wholesaler, a retailer and a customer. The game is played by a four–member team, where one member represents the manufacturer, a second member represents the distributor, a third member the wholesaler and the last member the retailer; a deck of cards represents the customer's weekly orders. Initially the supply chain is at equilibrium; then the customer's order undergoes a single one step increase and then remains constant. The aim of the game is to keep a constant minimal amount of stock because holding stock incurs a charge, as does a stock shortage. Sterman (2000, p. 686) notes oscillations in stock number arise as an endogenous consequence of the way the players manage their stock. He notes that the players' mental models, including their expectations, determine behaviour, which perpetuates the oscillations. The experiment has been trailed thousands of times; each time the oscillations continue with a 20–25 week period. Sterman calculates that the supply line can reach equilibrium in 4 weeks, if all players follow an optimal path; this fails to happen even though all the players have access to all the supply chain data. Sterman (2000, p. 708) notes that the results indicate a deeper defect in our understanding of complex systems. Sterman

(2000, p. 787) suggests that the *'Beer distribution game'* models one endogenous cause for the business cycle, where, because the economy is constantly subjected to exogenous shocks, it has no time to reach an equilibrium position and moves from one state to the next, a dynamic process. It is this dynamic process that the AIE model endeavours to emulate.

Beinhocker (2006, p. 185) observes three factors that affect emergent phenomena in an economic system, exogenous inputs, the behaviour of participants and the structure of institutions. Table 2–3 relates these three factors to the component parts of the AIE model and the AIE model itself.

Table 2–3 Factors affecting emergence in an economic system and correspondence to AIE

	Three factors affecting emergence (Beinhocker 2006)	Uncertain Knowledge (Keynes 1937, pp. 213-4)	Adaptive-expectations (Hicks 1939)	Interactive-expectations (Flieth & Foster 2002)	Social Interaction (Bowden & McDonald 2008)	Correspondence to AIE
1	Exogenous inputs help provide shocks and initiate changes in the complex system's dynamics	Narrative	Model	Narrative		The change in the actual profits index (D&B 2008) provides the exogenous shock to the model.
2	The behaviour of participants, including business expectations	Narrative	Model	Model	Model	Micro behavioural specifications combining adaptive and interactive-expectations to model an individual firm's profit expectations
3	The structure of institutions				Model	Using the network structure as a proxy to capture institutional structure. (Watts & Strogatz 1998)

Regarding factor one in Table 2–3, the exogenous inputs, Hick's (1939) adaptive-expectations model provides a link between actual profits and profit expectations for the AIE model. Bowden and McDonald's (2008) social interactions model lacks this link and Flieth and Foster's (2002) interactive-expectations model does provide a link, but in a narrative form only. Similarly Keynes' (1937) uncertain knowledge provides a narrative link to describe how rational economic men form expectations in the face of uncertain knowledge. Section 3.1.4 discusses modelling Keynes' (1937) uncertain knowledge by using an index as an alternative to *'Benthamite calculations'* and probabilities or methodological instrumentalism.

Regarding factor two in Table 2–3, the behaviour of the agents is modelled at the micro level by the four components of AIE or can be easily adapted to do so.

Regarding factor three in Table 2–3, the structure of institutions, Bowden and McDonald's (2008) social interactions model simulates the interaction of agents via a small world network (Watts & Strogatz 1998) and in this way captures institutional structure. In comparison, the Flieth and Foster's (2002) interactive-expectations model groups agents by the positive, negative or neutral expectations that they hold and treats the groups probabilistically. This method lacks any institutional structure. Similarly, Hick's (1939) adaptive-expectations model lacks structure. AIE models the three factors and endeavours to emulate the process of expectations formation using emergence. Section 3.3.2 discusses interactive-expectations further, comparing the probabilistic approach of Flieth and Foster's (2002) with the network approach of AIE.

Consistent with Beinhocker's economic emergent factors regarding behaviour and structure, Giddens (1990) states, '*Society only has form, and that form only has effects on people, insofar as structure is produced and reproduced in what people do'*. Giddens (1984) notes that society, an emergent phenomena, has both a structural and an agency component; The structural environment constrains individual behaviour, but also makes it possible. There is a duality to behaviour and structure, in that behaviour affects structure and structure affects behaviour. How structure, in the form of a network, affects behaviour is within the scope of the thesis. However, how behaviour affects structure is beyond the scope of this thesis.

Further to networks and emergence, Amarala and Ottino (2004, p. 149) note that the techniques for studying emergence in complex systems include nonlinear dynamics, statistical physics, and network theory. These techniques for modelling complex systems incorporate coherent explanatory mechanisms for the emergent phenomena. However, they claim that network theory does look the most promising of the three techniques, a path which this thesis follows. In comparison, Flieth and Foster's (2002) interactive-expectations model falls into the statistical physics category. Section 2.2.1 further discusses the alternative methods to model emergence.

Beinhocker (2006, p. 185) notes that traditional economics focuses on the first factor in Table 1, the exogenous causes for oscillations, while ignoring the latter two endogenous causes for oscillations. The following two examples illustrate the weakness in this approach and highlight the importance of factors two and three, the behaviour of the participants and institutional structure. Farmer, Patelli and Zovko (2005) capture features of the stock market, by modelling participants with zero-intelligence, where they find that institutional structure largely determines behaviour. Furthermore, that emulating REH produces unrealistic outcomes. REH predicts that agents form optimal predictions or expectations with all the available information and should behave accordingly. Any deviations from optimal behaviour are solely due to unforseen exogenous shocks. Counter to this, Bak, Paczuski and Shubik (1997) model *'noise–traders'* whose behaviour follows the behaviour of others and market dynamics, and *'rational–traders'* whose behaviour follows the fundamental value of the stock that includes dividends. They find that the model produces a Lévy–flight or fat–tailed distributions with a high number of noise–traders and a low number of rational–traders, indicating bubbles in the market, a realistic scenario. Conversely, with a relatively high number of rational–traders, the market prices become locked within a price range, which is an unrealistic scenario. The AIE model endeavours to incorporate the exogenous factors, while modelling these endogenous processes, which requires finding the appropriate level of sophistication for the agents.

Miller and Page (2007, p. 239) ask *'How sophisticated agents must be before they are interesting?'* and *'How to find the balance between a myopic simpleton and a hyper rational agent?'.* For this thesis, the hyper rational agent is represented by REH. For such an agent emergence is a nonexistent property because any difference between their profit expectations and actual profits is purely a product of unexpected exogenous inputs. Miller and Page (2007, p. 240) note that there is one way to be optimal or hyper rational, but there is a potential multitude of ways to be adaptive. You can incrementally make the myopic simpleton more intelligent by incorporating past periods remembered. Their observations are directly applicable to the AIE model because agents may require different memory for the two components of the AIE model, adaptive and interactive. This thesis uses the current period and last period for the adaptive-expectations and the current period for interactive-expectations. Sections 2.1.1.5 and 5.4.1 discuss the role of REH as the hyper rational benchmark and complement for AIE.

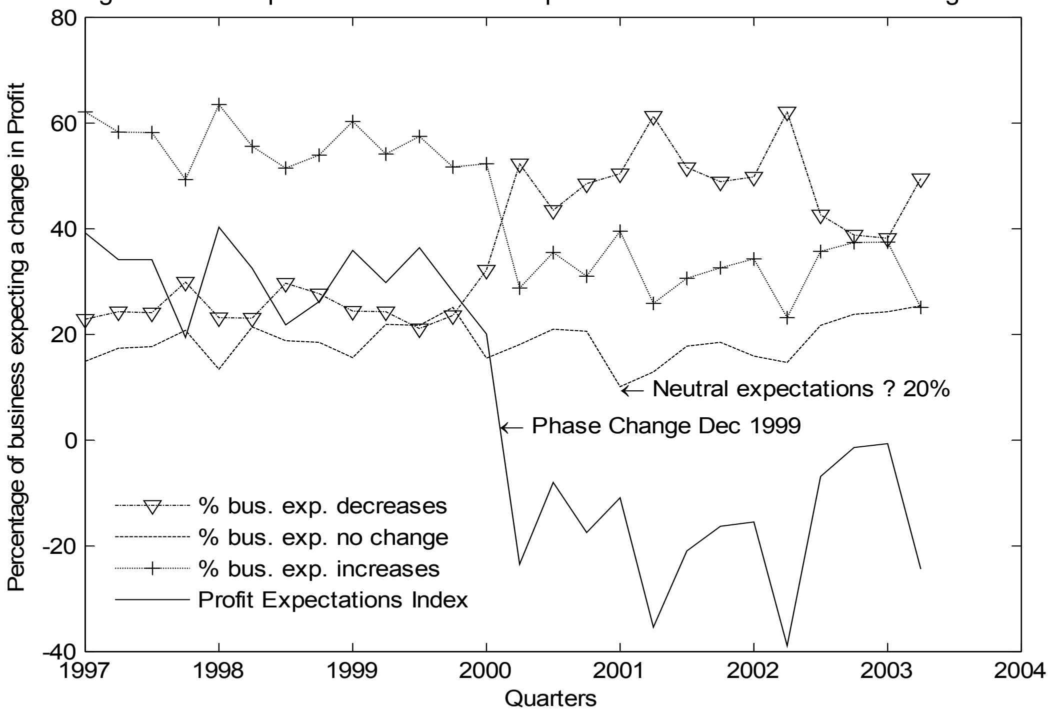
2.1.7 Profit Expectations Index and Expectations Phase Transitions

This section discusses the profit expectations indices used in the thesis and a phase transition in profit expectations investigated in the thesis. Figure 2–5 shows the percentage of businesses expecting profits to increase, decrease or remain unchanged each quarter. The Australian Bureau of Statistics (ABS 2002) surveys businesses the previous quarter for their expectations, and this is displayed in Figure 2–5. This discontinued survey ran quarterly from December 1996 to March 2003 and is an aggregate of ten economic divisions. The high level of aggregation and short duration make the survey unsuitable for this thesis. However, it does illustrate three important features. First, the components of a profit expectations index are formulated in equation (2–6).

$$\text{Profit Expectations Index} = \text{\% business expecting increases} - \text{\% business expecting decreases} \quad (2\text{–}6)$$

Second, forming the profit expectations index results in losing information; without knowing at least one of the components in addition to the profits index, it is impossible to accurately find the other two components. This thesis uses the percentage of business who expects *no–change* in profit in Figure 2–5 to decompose the *all–firms* profit expectations indices in Figure 2–6 into the number of firms holding positive, neutral and negative expectations where each firm is assigned a state of profit expectations with the value of 1, 0 or –1, respectively.

Figure 2–5 Components of the Profit Expectations Index and Phase Change



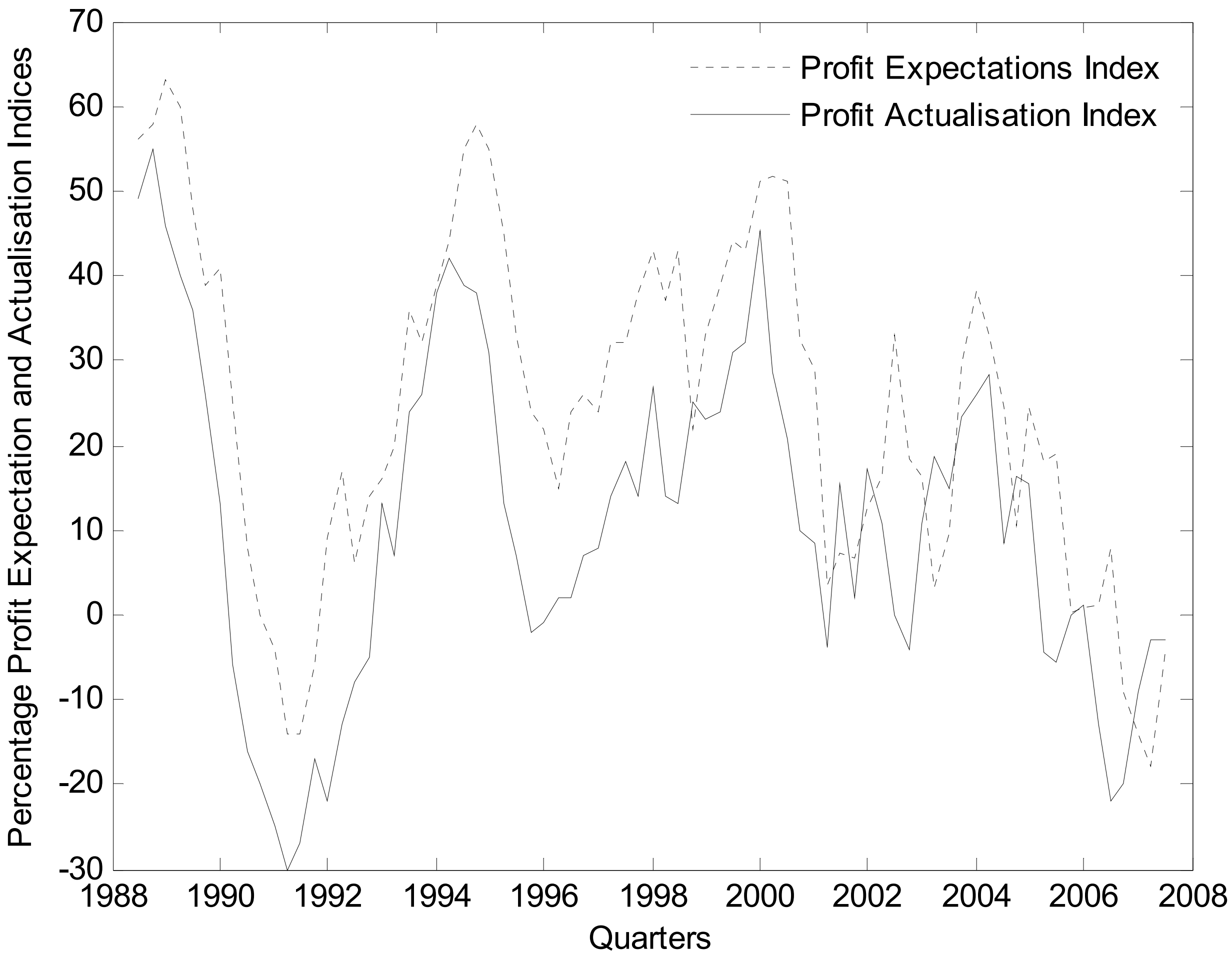
(Source: ABS 2002 Cat. No. 5250.0 tbl. 2)

Third, Figure 2–5 shows a phase change in profit expectations change starting about September 1999 and settling down in March – June 2000. This phase change is consistent with the *all–firms* profit expectations index in Figure 2–6. Additionally, such phase transitions are in agreement with the observations made by Flieth and Foster (2002) and Bowden and McDonald (2008). This thesis uses the June 2000 phase transition as a breakpoint to test a hypothesis about the phase transition. If the phase change concept is true, then calibrating a model over shorter time series will provide greater predictive power. Section 2.3 further discusses this hypothesis in research question 1.

2.1.8 Adaptive-expectations Model: an AIE Model Component and Benchmark

This section discusses the adaptive-expectations model (Hicks 1939) because it forms a benchmark for AIE and a component for AIE, by linking the actual profits and profit expectations. This link is important because another component of AIE, the interactive-expectations model (Flieth & Foster 2002), provides only narrative linking actualisation and expectations. Figure 2–6 compares the *all–firms* profit expectations and actual profits indices of the respondents to D&B (2008). These indices are used to test AIE. Figure 2–5 shows the ABS (2002 Cat. No. 5250.0 tbl. 2). The neutral expectations series from the ABS dataset supplements the D&B (2008).

Figure 2–6 All–firms Profit Expectations and Actual Profits Indices



(Source: D&B 2008)

In Figure 2–6, the *all–firms* is an aggregate of the respondents from the manufacturing, retail and wholesale divisions.

Equation (2–7) shows that the actualisation indices are calculated in a parallel manner to the expectations indices in equation (2–6).

$$\text{Actual profits Index} = \%\text{ business with actual increases} - \%\text{ business with actual decreases} \quad (2\text{–}7)$$

The respondents in the survey indicate whether they expect their profits will increase, decrease or remain unchanged in the next quarter and what actually happened in the previous quarter. D&B (2008) covers the following economic indicators, profits, sales, employees, capital investment, inventories, and selling prices. However, the focus of this thesis is on a single economic indicator for brevity and the indicator profits because profits embody most factors of production. Figure 2–6 matches the actualisation for the quarter with the expectations for that quarter. Noteworthy is the persistence of the profit expectations index above the actual profits index, indicating an optimism bias. This is in contradiction to REH, where profit expectations index curve ought to be centred randomly about the actual profits index curve. Section 2.1.3.3 further discusses optimism bias and its incorporation into AIE.

The thesis uses the model variance, the mean sum of the square of the errors *SSE/T* between the profit expectations indices of D&B (2008) and of the AIE model as a measure of fit; the lower the model variance the better the fit. The model variance for REH is simply that between the profit expectations and actual profits indices.

Lovell (1986, p. 112) cites Hicks' (1939) elasticity of expectations as the stem of the adaptive-expectations model and Nerlove (1964) and Holt et al (1960) with advocating the practical use of the model. Equation (2–8) shows the adaptive-expectations model in its simplest form.

$$P_t = A_{t-1} + \lambda\ (P_{t-1} - A_{t-1}) \qquad (2\text{–}8)$$

Where the prediction P this period is the same as last period's actual, if the previous period's prediction was perfectly accurate. Consider the extreme value for $\lambda = 0$, in this case a prediction is simply last period's actual. Now consider the other extreme value for $\lambda = 1$, in this case a prediction becomes static, without correction for error. For $0 < \lambda < 1$ the error is gradually adjusted for, giving exponential smoothing.

Section 2.1.3.3 discusses the anchoring and adjustment heuristic, which provide a psychological basis for using the adaptive-expectations model. Yu and Cohen (2009) provide a neurological basis for the use of adaptive-expectations, without the need for statistics. Yu and Cohen (2009) model people's pattern recognition in sequential binary data, using exact Bayesian inference and exponential discounting of the past. They find that exponential discounting may be a better model of sequential adaptation than exact Bayesian inference. Additionally, they note that the exponential discounting has the advantage of being similar to the standard models of neuronal dynamics. These standard models, called leaky integration neuronal models, have been used extensively to model perceptual decision-making and reinforcement learning. Furthermore, they show how the optimal tuning of the leaky integration process can be achieved without explicit representation of probabilities.

Section 3.1 discusses adaptive-expectations further as a component of AIE and the decision to introduce a pressure index as an alternative to using probabilities, which is common in the literature.

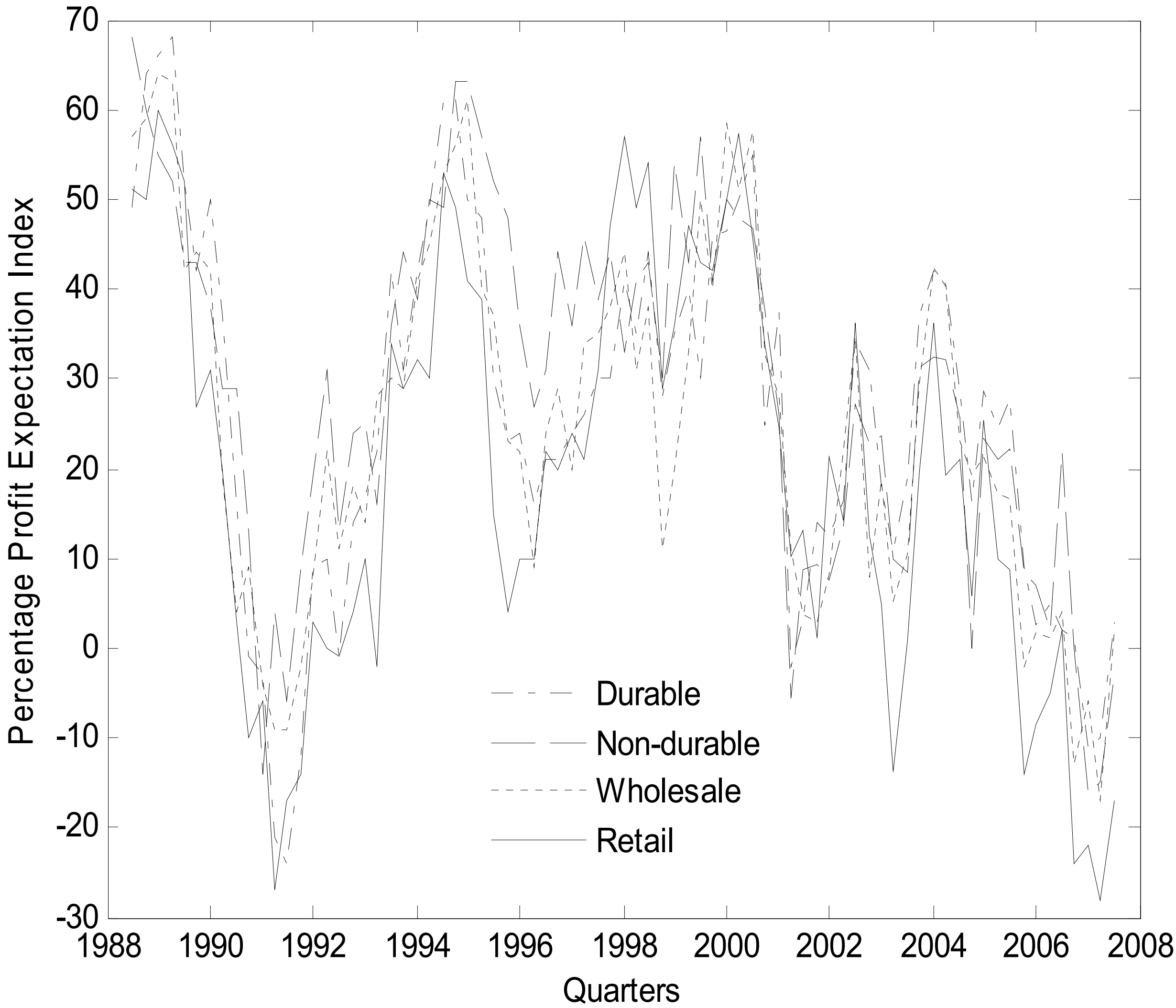
2.1.9 Interactive-expectations Model: an AIE Model Component

Flieth and Foster (2002) introduce interactive-expectations, where one person's opinion affects the opinions of others. Rather than using an expectations index, they use the interaction between positive, neutral and negative groups and the movement between the groups to simulate realistic jumps in opinion. The datasets include the German Federal Statistics Office economics indicators and German IFO Poll expectations. They note persistence in expectations and sudden phase changes, exhibiting herd type behaviour. Likewise, Bowden and McDonald (2008) find herd like behaviour in their simulation. Consistently, Shiller (2005) writes extensively about examples of *'irrational exuberance'* or herd behaviour within markets and in some instances between markets. Similarly, Ormerod (2005) notes the importance of two inter–sector connections on the business cycle. The first is technological connections, where one firm's output is another firm's input. The second is an information connection, where the opinions of one firm affect another firm's opinions. Hanneman and Riddle (2005) note that a network can represent informational flows and material flows, a point taken up in section 2.2.2 to extend interactive-expectations (Flieth & Foster 2002) with a small world network (Watts & Strogatz 1998). Section 2.1.6 discusses the *'Beer distribution game'*, which is an example of emergence from the interrelationship between material and information flows in a simple network or supply chain.

Figure 2–7 shows the profit expectations indices for the durable, non–durable, wholesale and retail divisions from the D&B (2008) profits expectations survey.

Figure 2–6 shows the profit expectations indices for the aggregate of these four divisions, called *all–firms*. Figure 2–7 shows the four divisions roughly moving in phase with one another. There is interaction between the firms in the divisions or interactive-expectations. Figure 2–7 could be said to represent a *'Beer distribution game'*, but, rather than occurring in a simple chain of four firms, there is a network of firms. The aim of the thesis is to model this interactive component as an emergent property.

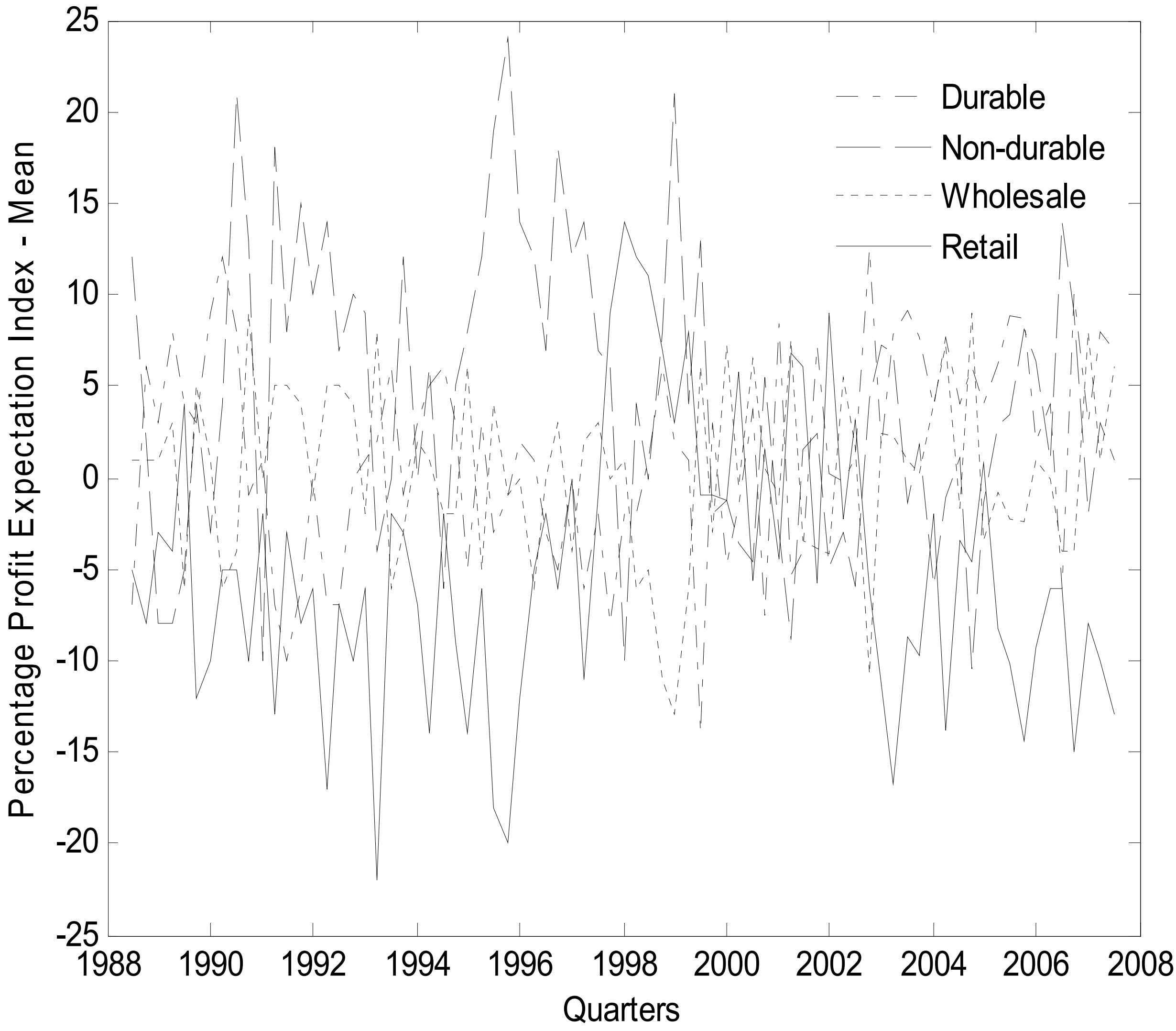
Figure 2–7 Wholesale, Retail, Durable and Non–durable Profit Expectations Indices



(Source: D&B 2008)

Figure 2–8 shows the profit expectations indices of each division in Figure 2–7 less the *all–firms* profit expectations index to more easily make comparisons between the divisions. Figure 2–8 also illustrates that the retail division most often holds the lowest profit expectations, while the non–durable most often holds the highest profit expectations.

Figure 2–8 Divisional Profit Expectations Indices less the *All–firms* Profit Expectations Indices



(Source: D&B 2008)

2.1.9.1 Using Input-output Tables to Represent Interactive Link-intensity

This section discusses using an *'input-output table'* to represent the magnitude of interactive-expectations between firms. The AIE model has an aggregated and disaggregated version; each has a different way to handle interactive profit expectations. The aggregated version uses the D&B (2008) *all–firms* dataset that is shown in Figure 2–6. In the aggregated version, the magnitude of interactive profit expectations or weight on the links between the firms is unity. In comparison, the disaggregated version uses the D&B (2008) durable, non–durable, wholesale and retail division datasets shown in Figure 2–7. These four divisions allow for the magnitude of interactive profit expectations among the firms of each division to be other than unity to better reflect the importance of expectations among the divisions. What follows is a description of how an *'input-output table'* is used to develop these magnitudes or weights.

Table 2–4 shows the collapsed intermediate *'input-output table'* for the four divisions, durable manufacturing, non–durable manufacturing, wholesale and retail.

Table 2–4 Input-Output Table for the Durable, Non–durable, Wholesale and Retail Divisions

($million)	Durable	Non–durable	Wholesale	Retail
Durable	38 684	8 314	25 578	7 436
Non–durable	6 665	30 759	10 791	17 460
Wholesale	7 656	7 342	39 707	5 448
Retail	1 177	3 423	3 644	4 104

(Source: ABS 2006b)

The output of intermediate goods from the durable division to the durable, non–durable, wholesale divisions are $38 683m, $8 314m, $25 578m and $7 436m, respectively. These outputs follow from orders that are met and orders would indicate expected sales. In an empirical study, Langlois (1989) finds that modelling firms, using a percentage mark–up over costs, fits the data better than firms maximising profits by producing until Marginal Revenue (MR) equals Marginal Cost (MC). Keen (2001) notes that the marginal approach to profit maximisation is true in static analysis, but in a dynamic environment the marginal approach does not hold. This thesis uses the mark–up approach because AIE is a dynamic model and the economy is dynamic. Therefore, expected sales are assumed proportional to the expected profits.

Furthermore, Keen and Standish (2006) and Keen (2004) show that profit maximisation at MR=MC is also untrue for static analysis, which provides further weight for AIE using the mark-up method and abandoning the MR=MC concept.

The thesis constructs ratios from the *'input-output table'* in an unconventional way because the ratios are calculated for each firm, rather than for each division of the economy. The ratio is based upon the number of links to other firms in the differing divisions within a network structure in conjunction with the figures in the *'input-output table*'. The ratio is used to form the interactive component of the *'pressure to change profit expectations index', p^x,* for each firm. The interactive pressure on a firm flows from other firms to which it is linked. For example, take a firm in the durable division whose profit expectations are *no–change* and the firm is linked to ten other firms. Of the ten linked firms, the durable, non–durable, wholesale and retail divisions have, respectively, one, two, three and four firms. Assume that the linked firms in the durable and non–durable divisions expect profits to increase and the linked firms in the wholesale and retail divisions expect profits to decrease. Additionally, assuming the firm uses the same mark–up for all its customers allows the output values in the *'input-out table'* to represent profits in the calculation of the index. So, the interactive component of p^x is [(1 x 38 684) + (2 x 8 314) + (–3 x 25 578) + (–4 x 7 436)] / [(1 x 38 684) + (2 x 8 314) + (3 x 25 578) + (4 x 7 436)]. Negative index values indicate pressure for a firm to decrease its profit expectations and positive index values indicate pressure for a firm to increases its profit expectations. Despite the mark–up assumption requiring a firm to have the same mark–up for all its customers, the assumption does allow for each firm to have a different percentage mark–up. Section 2.2.2 discusses using networks to represent interactive pressure between firms. Section 3.3 further discusses the aggregated version of the calculation of the interactive component of p^x. Section 3.6 discusses the disaggregated version of the calculation of the interactive component of p^x, which requires the *'input-output table'*. Section 5.6.3 in further research discusses alternative ways to calculate the interactive component of p^x, using the number of firms in each division and the network structures in conjunction with the *'input-output table'*.

The *'input-output table'* for the D&B divisions in Table 2–4 was compiled using the ABS (2006b) *'input-output tables'*. The ABS and D&B divisions do not match perfectly, hence some adjustments were required. The ABS (2006a) uses the Australian New Zealand Standard Industrial Codes (ANZSIC). D&B uses the D&B (2006) Standard Industrial Classification (D&BSIC). The retail, manufacturing and wholesale divisions of the ANZSIC and D&BSIC match perfectly. However, the durable and non–durable subdivisions of manufacturing do not match because the ANZSIC's

'Furniture and fixtures' are considered durables in the D&BSIC and ANZSIC's *'Rubber, plastics and leather'* are considered non–durables in the D&BSIC.

An unpublished experiment by the author to model profit expectations used an *'input-output table'* approach without a network structure, among the four divisions each containing 250 firms. The model was calibrated by minimising the model variance between the D&B profit expectations index and the model's index. The lowest calibration model variance found was 60. This approach was abandoned because the model variance was too high in comparison to the network approach of the AIE model. See Table 4–1. The poor result is attributed to the lack of network structure to model interactive-expectations. The disaggregated AIE model uses the *'input-output table'* and small world network together to provide information about flow intensity and economic structure. Sections 5.6.3 and 5.6.4 in further research discuss this technique of using an *'input-output tables'* as a *'link-intensity matrix'* to apply to networks as a replacement for neoclassical assumption in GET, CGE and DSGE.

2.2 Immediate discipline and analytical models

This section of the literature review discusses the more technical literature to support implementing AIE as an ABM.

Network theory and complex systems are discussed to provide a proxy for institutional structure in AIE. ABMs are discussed because AIE uses the techniques to combine behavioural rules from section 2.1 and network structures. ABMs have falsification and verification issues, which are discussed in section 2.2.3. To avoid many of the falsification and verification issues, AIE uses temporal prediction.

Optimisation techniques for functions of many variables are also discussed because AIE has many variables, which makes calibration time consuming. Compounding this problem, AIE uses 121 network topologies to represent institutional structure.

Model-averaging techniques are discussed to improve the predictive performance of AIE. The 121 network topologies are structurally different, hence they are models in their own right, and therefore they are amenable to model-averaging. The thesis introduces two new model-averaging techniques called *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'*.

The structure of this section is as follows. Section 2.2.1 discusses techniques for modelling complex systems and emergence to select a suitable modelling technique for AIE. Section 2.2.2 discusses network theory because AIE uses networks as a proxy for institutional structure. Section 2.2.3 discusses ABM falsification and verification issues. Section 2.2.4 discusses optimisation techniques for functions of many variables. Section 2.2.5 discusses model-selection and model-averaging techniques.

2.2.1 Modelling Complex Systems and Emergence

Section 2.1.3 defines emergence and discusses emergence in an economic system. However, this section discusses the modelling of complex systems or emergence in a broader context to justify the choice of methodology for the AIE model, that is, ABM using a network approach.

Amarala and Ottino (2004, p. 149) note three challenges to studying complex systems. First, their units are complex in structure, non–uniform, and lack strict definitional roles. Second, their nonlinear interactions take place within a complex network, including much background noise. Third, there are out–of–equilibrium changing forces from innovations and expectations. Techniques for studying emergence in complex systems include nonlinear dynamics, statistical physics, and network theory. All techniques incorporate coherent explanatory mechanisms for the emergent phenomena and meet the challenges listed above.

The structure of this section is as follows. Subsection one discusses nonlinear dynamics. Section two discusses statistical physics or mechanics. Section three discusses networks.

2.2.1.1 Non-linear dynamics

Beinhocker (2006) notes that the Lotka–Volterra model provides a simple example of nonlinear dynamic system exhibiting emergent endogenous cycles. Foster (2005, p. 5) notes that the nonlinear dynamic techniques feature more in non–adaptive systems existing in the physio–chemical setting, where energy is imposed. Examples include fractals, turbulence, Bénard cells, lasers, and cloud formations. Consistently, Amarala and Ottino (2004, p. 149) observe that nonlinear dynamics are well established in many branches of physics, physiology, and neurophysiology.

However, people do use nonlinear equations at higher levels of complex systems than the physio–chemical. For instance, Sterman (2000) provides many examples using nonlinear dynamic equations to describe business processes, but mainly microeconomic. Brock, Hommes and Wagener (2005) and Lux (1998), cited in Bowden and McDonald (2008, p. 291), model the process of expectations formation using nonlinear dynamics. Foster (2005, p. 877) notes that economic systems have additional layers of complexity to physio–chemical and bio–physical systems, such as acquired knowledge and interactive knowledge. But even at the physio–chemical level, there is criticism of the use of nonlinear equations. Grebogi (2007) argues, '*there exist levels of mathematical difficulty, brought from the theory of dynamical systems, which can limit our ability* *to represent chaotic processes in nature using deterministic models.'* Alternatives to deterministic equations are discussed in the next section.

2.2.1.2 Statistical Physics

This section discusses statistical physics, also known as statistical mechanics. Amarala and Ottino (2004, p. 148) note that scaling and universality are two emergent phenomena that statistical physics models well. Statistical mechanics is nondeterministic that has implications for forecasting and predictions. Section 2.2.3 discusses these implications.

The structure of this section follows. Section one discusses power-laws and scale invariance. Section two discusses universality; how there exists a commonality between emergent properties in different situations, which allows similar modelling techniques. Section three discusses ABM.

1. Power–laws and Scale Invariance of Criticality

Amarala and Ottino (2004, p. 150) note that the phenomena of power–laws and scale invariance of criticality are well documented. However, Bak, Tang and Wiesenfeld (BTW 1987; 1988), Newman (1996) and Barabási (2002, p. 88) express alternative views on the process leading to the power–law.

Bak, Tang and Wiesenfeld (1987; 1988) develop the concept of self–organized criticality (SOC). They note the lack of a characteristic scale, during a phase transition about critical points. The lack of characteristic scale exhibits both spatial and temporal power–laws. Additionally, they note that critical states occur naturally without external tuning.

In a contrarian view to SOC, Newman (1996) uses a simple stress model to show that it is sufficient condition to robustly produce extinctions following a power–law. He calls into question the concept of SOC, where there exists equivalence between SOC and the power law, because a power–law does not necessarily need SOC to occur, while he does aggress that a SOC necessarily leads to a power–law.

Consistently, Barabási (2002, p. 88) claims that computer simulation and calculations show that growth and preferential attachment within a network are sufficient condition for scale free networks or the power–law phenomenon. Section 2.2.1.3 further discusses scale free networks. Additionally, he observes that growing networks without preferential attachment have an exponential degree distribution.

2. Universality

Bak and Paczuski (1995, p. 6689) note that the statistics of large scale behaviour obey fundamental laws of nature, even though individual events are unique. The fundamental laws are *'universal'* and describe many types of systems. For example, Bak and Paczuski (1995, pp. 6692-3) observe that a Sand–pile SOC model can model earthquakes (Olami, Feder & Christensen 1992), star–quakes (Morley & García-Pelayo 1993) and production and inventory dynamics in a modified form (Bak et al. 1993). In a further example, Newman (1996) finds that his simple stress model can model both biological extinctions and earthquakes.

3. Agent-based Models

This form of modelling traces it origins to Von Neumann and Burks (1966). Amarala and Ottino (2004, p. 151) note that some phenomenon can and should be modelled with algorithms, rather than with equations. Wilensky (2001) agrees, adding that an understanding of patterns as emergent phenomena, rather than as results of equations, is both a more accurate picture of nature and easier for most people to understand. Amarala and Ottino (2004, p. 148) observe that ABM has supplanted the equation–based approaches in behavioural based economics.

Amarala and Ottino (2004, p. 148) note that using discrete or ABM with Monte Carlo simulation leads away from forecasts with unique solutions. This approach is consistent with Gould's (1989) observation, cited in Bak and Paczuski (1995, p. 6689),, '*If the tape of biological evolution were replayed a million times, not once would we see life forms similar to our own.'* He notes that the concept of detailed prediction is utterly irrelevant. However, Farmer (2001, p. 70) notes that ABMs of stock markets are *'so far'* unsuitable for prediction, but are useful for understanding market mechanisms. He leaves open the possibility of forecasts with ABM in the future; a possibility this thesis tests with AIE.

Beinhocker (2006, p. 134) notes that Arthur et al. (1996) built the *'Santa Fe Artificial Stock Market'*, an ABM of the stock-market at the Santa Fe Institute, starting in 1987. They tried to model the real decision-making processes of agents, which are a departure from the rational–expectations model, where agents assume perfect knowledge and infinite computational power to make the optimal decision. Farmer, Shubik and Smith (2005, p. 40) note that the *Santa Fe Artificial Stock Market* captures qualitative features of markets, but fails to capture quantitative features. Additionally, ABMs tend to require ad hoc assumptions that are difficult to validate. To reduce the number of ad hoc assumptions, they take a zero-intelligence approach to ABM, an approach diametrically opposite to REH. They attributed the zero-intelligence approach to Herbert Simon. A further advantage of zero-intelligence is that any observation can be attributed to institutional structure. Farmer, Patelli and Zovko (2005, p. 2259) show that the institutional configuration plays an important role in determining the power–law distribution of volatility on the stock-market temporal structure. This result is consistent with Bak, Paczuski and Shubik (1997), discussed in section 2.1.6, who model *'noise–traders'* and *'rational–traders'*, finding that their model produces a Lévy–flight or fat–tailed distributions with high numbers of *'noise–traders'* and low numbers of *'rational–traders'*, indicating bubbles in the market, making it a realistic scenario. Conversely, with relatively high number of rational–traders, the market prices become locked within a price range, an unrealistic scenario. Zero-intelligence ABMs can be made more realistic by adding a little intelligence.

These results highlight the importance of institutional structure and noise–traders or interactive-expectations over rational expectations. This thesis will use an ABM approach and endeavours to verify its findings by benchmarking the AIE model against REH and adaptive-expectations models.

2.2.1.3 Networks

Amarala and Ottino (2004, p. 151) note that networks consist of nodes and connecting links. Examples within the biological sciences include food chains, autonomous nervous system of complex organisms, gene regulation networks, protein networks and metabolic networks. Examples of networks are the World Wide Web – a network of web pages connected by hyperlinks, the Internet – a network of server. Examples of social networks are ubiquitous; Twitter, Facebook, and emails – if individual A emails B and B replies, they are connected.

They note two limiting network topologies.

(i) A d–dimensional graph where every node connects with a well defined set of close neighbours.

(ii) A random graph where every node has an equal probability of being connected to some other node.

Amarala and Ottino (2004, p. 151) claim that neither limit describes real networks, which are both clustered and small–world; clustered meaning a high degree of local connectivity and small–world meaning it only takes a small number of steps to connect any two nodes. Amarala and Ottino (2004, p. 155) note that empirical data suggests that there are three types of real networks, scale–free, single–scale, and broad–scale (or truncated scale free networks). This section discusses the three types of networks in turn, followed by their application in economics.

1. Scale–Free Networks

Amarala and Ottino (2004, p. 153) note that a subset of real–world networks, called scale free networks, provides extremely efficient communication and navigability. Scale free networks observe the power–law, a log–log relationship, where a linear relationship forms between the log of the frequency of '*the number of connections of a node*' and the log of '*the number of connections of a node*'. Albert and Barabási (2002, pp. 71-8) show that scale–free networks can emerge as a consequence of simultaneous growth and preferential attachment (Barabási 2002, p. 88). The Internet exemplifies this, as new nodes are added. The efficiency and the simple mechanism for the growth of the network brought many researchers to believe in the complete ubiquity of the scale free networks. Barabási (2002) provides the following examples, the distribution of collaboration of movie actors, World Wide Web distribution of links, and distribution of sexual partners amongst Swedish people.

2. Single–Scale Networks

Amarala and Ottino (2004, p. 154) note that an additional subset of real–world networks, called single scale networks, provides an alternative to the extremely efficient scale–free networks. Single scale networks distributions are characterised by a rapidly decaying tail, such as exponential or Gaussian in a semi–log relationship, where a linear relationship forms between the log of the frequency of *'the number of connections of a node'* and *'the number of connections of a node'*. Examples of single–scale networks include the distribution of neurons in a nematode, and the Southern California power grid. They suggest that single–scale, rather than scale–free networks, emerge for three reasons, ageing, cost of adding links and limited capacity, and limits on information and access. First, an example of ageing is that older actors reduce or stop forming new links, which limits the growth process, which leads to the power–law distribution. Second, an example of the cost of adding links and limited capacity is airport hubs, where there is a limited capacity to the number of additional landing spots, beyond which it becomes necessary to add a new runways to accommodate growth in arrivals, and thus adding an extra runway may not be an option. Third, an example of the limits on information and access is that there exists little in cost to adding a link to a web page, but distinct interest areas may preclude the addition of a link to a page no matter how popular it is. Barabási (2002, p. 88) claims an alternative view that computer simulation and calculations show that growing networks without preferential attachment have an exponential degree distribution.

3. Broad–Scale Networks (or truncated scale–free networks)

Amarala and Ottino (2004, p. 155) note that broad–scale networks are characterised by a power–law regime, but have a sharp cut off unrelated to the finite size of the network.

4. Networks and Economics

Foster (2006, p. 1078) notes that in complex systems value derives from the network of connections between entities. This contrasts sharply with traditional economics, where value emanates from the elements themselves. The traditional economics framework and REH implicitly assumes complete connectivity between all entities, where all knowledge permeates all the elements instantly (Foster 2005, p. 23). This situation is analogous to a magnetic or electric field where a force acts on every element instantaneously. The advantage to using this field approach is that it allows for use of integral mathematics. However, this approach has difficulty with information asymmetry and bounded rationality. Contrastingly, information asymmetry and bounded rationality are implicit to real–world networks that lack total connectivity, hence provide a more realistic model of the economy. Consistently, Potts (2000) notes that economic systems do not exist in integral space. Section 2.1.1.5 further discusses the field approach of neoclassical economics and REH in relation to the network approach of AIE shown in Figure 2–2.

Bowden and McDonald (2008) use various network structures to study their effect on interactive-expectations. This thesis uses a similar network approach, as discussed in section 2.2.2.

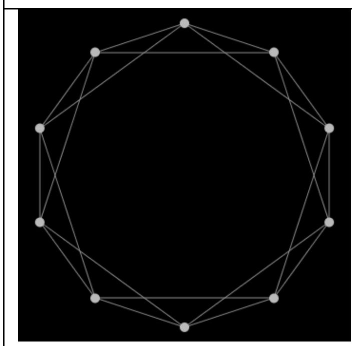
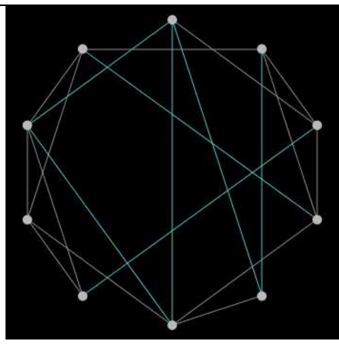
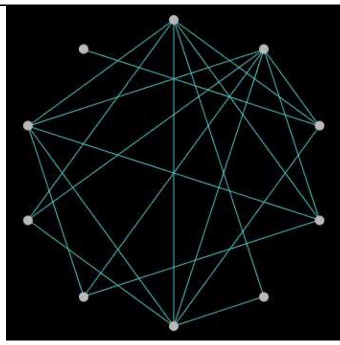
2.2.2 Applying Network Theory to the AIE Model: A Proxy for Institutional Structure

This section discusses small world networks (Watts & Strogatz 1998) that form a component of the AIE model to provide a proxy for instructional structure. Specifically, they extend Flieth and Foster's (2002) interactive-expectations model to allow a network, rather than a statistical mechanical approach, to model information flow, as section 3.3.2 discusses.

Ormerod et al. (2007, pp. 208-9) discuss institutions as topology and protocols governing agent interaction. They note that, as a system matures, the importance of the network or institutional structure increases and the degree of cognition required to assign to an agent in a social network decreases, which implies that successful institutional structures allow even low cognitive agents to arrive at *'good'* outcomes. This observation of Ormerod et al. (2007, pp. 208-9) suggests the need to focus resources on determining the correct network structure, rather than on modelling the cognitive ability of the agent. Section 2.1.1.5 further discusses this diametrically opposed focus of AIE and REH on networks structure and cognitive ability, respectively. Additionally, Section 5.6.10, in further research, further discusses the focus on network structure rather than exogenous inputs.

Figure 2–9 illustrates networks that are defined by three parameters: the number of nodes n, the number of links per node L, and the probability that a link has been rewired ρ from the lattice arrangement in a regular network.

Figure 2–9 Regular, Small World and Random Networks.

Regular	Small–world	Random
		
$\rho = 0$	$\rho = 0.3$	$\rho = 1$

(Source: adapted from Watts & Strogatz 1998; Wilensky 2005)

Figure 2–9 shows ρ = *0, 0.3* and *1* representing a regular, small world and random network, respectively, and sets n = *10* to allow for easier viewing. Hanneman and Riddle (2005 Chp. 8, Clustering) describe small world networks as networks with a short path between any two nodes and a high degree of clustering. Nodes that are highly interconnected within a neighbourhood are considered highly clustered. Regular networks are highly clustered but have long paths between some of their nodes. In comparison, random networks lack clustering but have short paths between any two nodes. Hanneman and Riddle (2005 Chp. 8, Clustering) note a paradoxical property of networks: as ρ increases from zero to one, the average path-length drops quickly, but relatively clustering remains high, until ρ approaches 1. These intervening networks with high clustering and short average path lengths are small world networks.

In the AIE model, the nodes in Figure 2–9 represent the firms and the links represent the flow of profit expectations between the firms; the links are undirected, that is, information can flow both ways. The AIE model uses similar network topologies to Bowden and McDonald (2008), as they also study how differing network topologies affect interactive-expectations formation. The AIE model sets $n = 200$ and has 121 possible network topologies by ranging $\rho = 0, 0.1, 0.2, \ldots, 1$ and $L = 2, 4, 6, \ldots, 22$. There is a lack of data describing the topology of an interactive-expectations network, hence a suitable proxy is selected by calibrating all 121 network topologies and model-averaging them, which is acceptable because each network topology is a model in its own right. Section 2.2.4 discusses techniques to minimise the model variance or optimising each model to address calibrating the AIE model. Section 2.2.5 discusses model-averaging. Section 3.4.1 presents a visualisation of the network topology and model variance. Section 5.6.3, in the further research, discusses ways to use an '*input-output table*' to better define the 121 network topologies.

2.2.3 Model Falsification and Verification Issues

'[The] central weakness of modern economics is, indeed, the reluctance to produce theories that yield unambiguous refutable implications, followed by a general unwillingness to confront those implications with fact.'

Blaug (1992, pp. 238-39)

This section builds on the framework discussion in section 2.1.1 to discuss how the approach to falsificationism differs among ABM, narrative and *Variable-based Models* (VBM) that are sometimes referred to as *Equation-based Models*. These differences in approach are important in considering what can be deemed scientific. This section compares traditional falsifiable temporal prediction as a demarcation of science with alternatives, such as stylised facts. The discussion finds the approaches of ABM, VBM and narrative all have strengths and weaknesses. Additionally, stylised facts have credibility issues, hence the traditional scientific method of comparing the temporal predictive power of the AIE against REH and adaptive-expectations model is adopted. Section 5.4 builds upon this section to discuss implication for policy and practice. Furthermore, this section provides justification for further research in section 5.6.6 that discusses multiple level patterns.

Blaug (1992, p. 13) cites Popper (1972b) proposing falsification as an essential element in the criteria of demarcation between science and non–science and as a solution to the *problem of induction*. He notes a logical asymmetry that there is a '*logic of disproof*' to justify falsificationism, but there lacks a '*logic of proof*' to justify verificationism. Amarala and Ottino (2004, p. 159) note that most scientists still operate under the *'Newtonian'* concept of prediction. If the location and velocity of a number of particles are given, an exact trajectory can be calculated. Smith and Coney (2007, p. 91) call this form of prediction *Variable-based Modelling* (VBM). They note two main forms: modelling causal flow through variables using multiple regression, and differential equations or nonlinear equations, discussed in section 2.2.1.1. They claim that in VBM the focus is on the relations between variable, whereas in ABM the focus is on the interactions between agents. VBM offers concise quantitative descriptions of phenomena, allowing quantitative prediction, whereas ABM offers insight into generative processes. Consistently, Foster (2006, p. 1080) observes that trajectories of data are manifestations of historical process and fail to capture the process itself. Additionally, knowing the exact trajectories of individual particles would tell us nothing useful about emergent properties.

With regards to VBM predictions in emergent phenomenon, Loungani (2000), in an IMF study, notes, '*The record of failure to predict recessions is virtually unblemished.*' This is consistent with Grebogi's (2007) observation, when modelling complex systems with VBM, that the predicted and actual values soon diverge, an inherent problem. This observation is discussed further in section 2.2.1.1.

Instead of temporal prediction, Amarala and Ottino (2004, p. 159) note that more useful allometric relationships could be determined. For example, the functional relationship between an organism's mass and its metabolic rate holds over 27 orders of magnitude of mass. In another example, Foster (2005, p. 21) notes the income and wealth distribution power–law ascribed to Vilfredo Pareto, and its relationship to economic growth ascribed to the Cambridge School. This section discusses alternatives to temporal falsificationism, such as stylised facts, calibration, and appreciative theory, and debugging problems unique to ABM programming.

Epstein (1999, p. 46) calls for ABM to match stylised facts that based upon generic empirical regularities provide falsifiable predictions. For instance, Gould (1980, p. 184) notes, '*the fossil record is a faithful rendering of what evolutionary theory predicts*'.

The macro–meso–micro methodology (Foster & Potts 2009) provides a micro–meso–macro perspective on the methodology of evolutionary economics that integrates history, simulation and econometrics. Foster and Potts (2009) call for research to begin with appreciative theory, from which to develop formal theory, because evolutionary economic modelling requires an appreciation of an economy's history. Consistent with this approach, Lipsey et al (2005) devote the first 439 pages of their 595 page book to the history of technology and appreciative theory, before starting on formal theory. The appreciative theory followed by formal theory process provides for falsificationism because formal theory developed in this way can be falsified, if it proves inconsistent with the appreciative theory.

Foster and Potts (2009) suggest a falsification method at the micro level, that is calibrating simulations against econometrically estimated parameters on time series variables. This restricts the permissible values for the model, which makes the model more falsifiable. They note that calibrating models in structurally changing states further restricts parameter values, thereby making the model even more falsifiable.

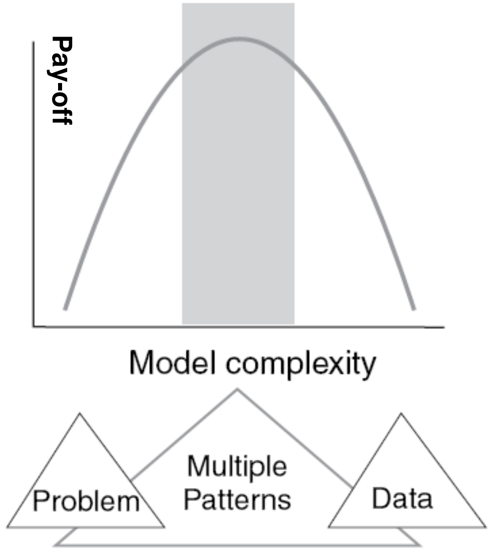
Combining calibration and appreciative theory, Foster and Potts (2009) compare ABM and the RBC, noting that both can be calibrated to fit any time series. However, ABM calibration requires historical analysis of the institutional settings, that is, the development of appreciative theory before the development of formal theory. This additional structural constraint acts to increase the falsifiability of ABMs. In contrast with RBC modelling where calibration is institutionally unconstrained.

The ACCS (2007) notes that a universal problem for complex system research, which includes ABM, is the challenge of developing cost– and effort–effective means for providing convincing evidence that the model is valid and that the insights it generates are properties of the application being studied and not simply artefacts of the model. Using calibration constraints, appreciative theory and stylised business facts go some way to addressing these concerns, but debugging ABM programs presents a unique difficulty.

Gilbert and Troitzsch (2005, p. 213), Gilbert (2008) and Galán et al. (2009) discuss the difficultly in debugging ABM programs, compared with other programming methods. Gilbert and Troitzsch (2005, p. 213) note that methodologically ABM has more in common with natural sciences and engineering than with deductive logic or mathematics, which makes debugging ABM different to most programming methods, where the results can be checked arithmetically or logically. In comparison, ABM results need replicating, as in experimental science. Consequently, the ability to implement the model in another ABM language to reproduce the results would improve confidence in the veracity of the results, but can never prove the results.

A quote from Epstein (1999, pp. 45-6) nicely summarises the ABM falsification issue. *'Does the hypothesized micro specification suffice to generate the observed phenomenon . . .? The answer may be yes and, crucially, it may be no. Indeed, it is precisely the latter possibility — empirical falsifiability — that qualifies the agent-based computational model as a scientific instrument.'*

Figure 2–10 Medwar Zone



(Source: Grimm et al. 2005, p. 988)

Consistently, Grimm et al. (2005) and d'Aqunio et al. (2001, pp. 42-7) note that there lacks a unifying framework for designing, testing, and analysing bottom–up models (*agent-based* or network models). Furthermore, d'Aqunio et al. (2001, pp. 42-7) suggest using numerous methods to verify or validate bottom–up models, adopting triangulation techniques from qualitative research.

In one such method, Grimm et al. (2005) suggest adapting the Medawar Zone from science to bottom–up models. The Medawar Zone finds the optimal pay–off to model complexity. Figure 2–10 shows that their proposed adaptation of the Medawar Zone relies on multiple patterns at differing scales to test the model and achieve the optimal pay–off to model complexity. This comparison of differing scales could be achieved in the AIE model by concurrently modelling and comparing simulations of the profit expectations for the individual divisions of manufacturing, retail and wholesale with their aggregate. Section 5.6.6, in further research, further discusses multiple patterns as a form of falsification, as suggested by Grimm et al. (2005). Additionally, d'Aqunio et al. (2001, pp. 42-7) suggest using statistical techniques to compare the model's multiple output with the data.

Given all the validation and verification problems of ABM using stylised facts, this thesis adopts the traditional scientific approach of comparing models using temporal predictions, where the AIE and its benchmark models are calibrated using the D&B (2008) profit expectations data, then the predictions of the calibrated models are compared. If the AIE model has less predictive power than REH, the agents require more intelligence or memory. If the AIE model has less predictive power than the adaptive-expectations model, the agent's interactive component requires adjustment. Table 4–1 compares the predictions of the AIE, REH and adaptive-expectations models. In comparison to ABM, a narrative approach to describing the process of profit expectations formation is unfettered by the practical considerations, such as, data availability and limited computing power and time, hence may well find itself to the right of the Medawar zone, describing nonexistent data. The AIE model is parsimonious and approaches the Medawar zone from the left. The only exogenous input into AIE is the D&B (2008) change in actual profits index. This is to focus on the network structure to capture endogenous effects as suggested by Ormerod (2007, pp. 208-9) in section 2.2.2. Section 5.6.10, in further research, further discusses adding more exogenous inputs.

Considering the relationships among ABM, narrative and traditional mathematical approaches to economics, Miller and Page (2007, pp. 78-9) note that ABMs are an interesting trade off between the precision of traditional mathematical tools used in economics and the flexibility of narrative. ABMs have the following flexibility advantages over traditional mathematical tools, heterogeneous agents, process oriented, adaptive, and spatial or networked. They note that models developed without incorporating these factors can lack applicability. This is congruent with Tukey's (1962, p. 13) maxim for data analysis: *'Far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question, which can always be made precise.'* The precision advantage of ABMs over narrative is the ability to make falsifiable predictions. In comparison, narrative theorising, often unverifiable, may appear logical and coherent but may contain serious flaws.

Gonzalez et al.'s (2004) study helps to understand why people favour precise answers to the wrong questions over vague answers to the right questions. They examine the response of the brain to various framing effects, using functional Magnetic Resonance Images (fMRI). The framing involves four possibilities: two economically equivalent in terms of gain and two economically equivalent in terms of loss and both having one certain and one risky alternative. The fMRI of the brain in the risky gain and the certain loss frames displays similar and more active patterns, denoting more cognitive effort, than the fMRI of the certain gain. They postulate that the preference for certainty [or precision] over risk [or vagueness] is a matter of minimising cognitive effort.

2.2.4 Optimisation Techniques for Functions of Many Variables

This section discusses methods to search for the global minimum of functions with many parameters. The model variance of the AIE model is the function being minimised, whose many parameters are listed in equation (3–1). Additionally, section 3.4.1 provides a visualisation of the topology of the model variance space of the AIE model, which shows multiple equilibria indicating nonlinearity. This rugged landscape makes the use of a simple gradient method unsuitable because the method becomes stuck on local minima, which requires the use of a more sophisticated search method. The search methods being compared are the *grid-search*, *simulated-annealing*, *threshold-accepting*, and *unconstrained-nonlinear-optimisation*. They are addressed in the order from most expensive to least expensive in terms of time.

Subsections one, two, three and four discuss the *grid-search*, *simulated-annealing*, *threshold-accepting*, and *unconstrained-nonlinear-optimisation* methods, respectively. Subsection five summaries the findings. Section 3.4 discusses how the four methods are combined and related to the research questions.

2.2.4.1 Grid-search

The *grid-search* method calculates the objective function for every permutation of the discrete values of the parameter ranges. The advantage is that the method is very thorough in comparison to the other techniques. In particular, this method allows the discovery of multiple equilibria. Its disadvantage is that the time taken to make a *grid-search* grows exponentially, as the number of parameters increases. In the case of the AIE model it takes about 75 years to complete a *grid-search* with 9 parameters being investigated, each parameter having a set of 11 values and the time to calculate the model variance about 1 second.

The *simulated-annealing*, *threshold-accepting* and *unconstrained-nonlinear-optimisation* searches all take much less time than a *grid-search*. However, they all search for a single minimum, rather than multiple equilibria. Hence, for this research the search for multiple equilibria is practically precluded. The test for multiple equilibria is performed indirectly in the research question one of this thesis. However, the following discussion shows that *simulated-annealing*, *threshold-accepting* and *unconstrained-nonlinear-optimisation* searches all have problems of their own.

2.2.4.2 Simulated-annealing

Kirkpatrick, Gelatt and Vecchi (1983) introduce optimisation by *simulated-annealing*. They use the analogy between statistical mechanics and annealing solids to find the minimum of a given function depending on many parameters. Kirkpatrick, Gelatt and Vecchi (1983) use the *simulated-annealing* method to provide solutions to the travelling salesman problem, which belongs to the large class of NP-complete (nondeterministic polynomial time complete) problems. Independently, Cerný (1985) provides a method and an example similar to Kirkpatrick, Gelatt and Vecchi (1983), using the analogy to statistical thermodynamics and solution to the travelling salesman problem. Kirkpatrick, Gelatt and Vecchi (1983, p. 672) note that, as the size of the problem increases, a worst case-scenario for many algorithms, the problem increasingly falls into the domain of statistical mechanics.

Kirkpatrick, Gelatt and Vecchi (1983) and Cerný (1985) build upon Metropolis et al. (1953). Metropolis et al. (1953) model the interaction of particles in two dimensions, using Boltzmann Probability Factor in equation (2–9), which defines the probability of state *i* of the particles. They note that within statistical error their model is consistent with experimental results. Metropolis et al. (1953, p. 1088) introduce a new way to use the Boltzmann Probability Factor, selecting configurations with a probability $exp(-E/kT)$ and weighting them evenly. Previously, configurations were chosen randomly and weighted with probability $exp(-E/kT)$.

$$\exp(\, -E_i \,/\, (k_B\, T)\,) \qquad (2\text{–}9)$$

Where

E_i = the energy of state or configuration *i*

T = the temperature

k_B = Boltzmann's constant

Kirkpatrick, Gelatt and Vecchi (1983) and Cerný (1985) use Metropolis et al.'s (1953) model because it provides an efficient simulation of a collection of atoms in equilibrium at a given temperature. Additionally, they identify two analogies that allow Metropolis et al.'s (1953) model to solve the travelling salesman problem: (1) between finding the lowest energy state of a system of particles and minimising an objective function and (2) between a random movement of a particle within its neighbourhood and a random selection of a parameter set x_i' within the neighbourhood of an initial parameter set x_i. Equation (2–10) shows Kirkpatrick, Gelatt and Vecchi (1983) adaptation of equation (2–9).

$$P(\Delta E) = \exp(-\Delta E/k_B T) \qquad (2\text{–}10)$$

Where

$P(\Delta E)$ = probability that the new configuration is accepted

ΔE = the change in energy of the system from the change in configuration

Their *simulated-annealing* method allows for a gradual lowering of the temperature to allow their algorithm to find the system's lowest energy state, which is equivalent to finding the lowest model variance in the AIE model. A physical example is very slow cooling that allows the formation of a perfect crystal with regular global and local structure, leading to the system's lowest energy state. Alternatively, faster cooling causes imperfections in the crystal, disrupting the global structure and leaving the crystal in a higher energy state. Even faster cooling can cause a glass to form with local structure, but a random global structure, which leaves the system in even higher energy state. The imperfect crystal and glass are analogous to the search algorithm becoming stuck on a local minimum. Figure 2–11 shows the *simulated-annealing* algorithm.

Figure 2–11 Simulated-annealing Algorithm

1. Choose an initial configuration (x_i)
2. Choose an initial temperature $T_s > 0$
3. Opt: choose a new configuration (x_i') which is a stochastic small
4.   perturbation of the old configuration (x_i)
5.   compute $\Delta E = E(x_i') - E(x_i)$
6.   if $\Delta E > 0$
7.   then $(x_i) = (x_i')$
8.   else if $P(\Delta E) >$ Random(0,1)
9.   then $(x_i) = (x_i')$
10.   if cooling (annealing) schedule met or number of iterations I to great
11.   then lower temperature T
12.   if $\Delta E = 0$ for some time
13.   then stop
14. GOTO Opt

Where

Random(0,1) is a random uniform distribution over the interval 0 to 1.

$E(x_i)$ = the energy of the system at configuration *i*

(Source: Adapted from Dueck & Scheuer 1990, p. 162)

The stopping condition is determined by how much time is available or whatever energy level is considered sufficiently low for the needs at hand. Lines 8 and 9 allow the energy of the system to increase on a random basis. This uphill movement prevents the algorithm becoming stuck on a local minimum. There are four considerations in using the algorithm, the initial starting parameter set, the stopping condition, the neighbourhood function, and the cooling schedule. First, the initial starting parameter set can affect the final solution, however conducting *simulated-annealing* searches from different start locations can address this issue. Second, the time or resources available determine the stopping function that could be a set number of iterations or a sufficing condition that finds a low enough energy level to meet the requirements at hand. Third, the neighbourhood function requires decisions on its diameter and distribution that can be normal, uniform or so forth. Fourth, the cooling schedule requires decisions on the cooling increments and how long to stay at each temperature. Usually, the algorithm stays at one temperature until a new equilibrium is reached. This new equilibrium is typically determined by constant variation in the energy level. Additionally, as the temperature comes closer to zero, the increments may be decreased to prevent a premature freeze of the system.

de Vicente, Lanchares and Hermidab (2003) note that to find the most suitable annealing schedule requires costly finetuning studies. These finetuning considerations are addressed by Ingber (1993), Weinberger (1990), Dodd (1990), de Vicente, Lanchares and Hermidab (2003) and Dueck and Scheuer (1990) who are discussed in the following three paragraphs and section 2.2.4.3, respectively.

Ingber (1993) introduces *adaptive simulated-annealing*. His algorithm uses an annealing schedule for *'temperature' T* decreasing exponentially $T = T_0 \exp(-ck^{1/D})$, where k is the annealing-time and D is the dimension of the parameter space. He states that this annealing schedule is faster than fast Cauchy annealing, where $T = T_0/k$, and much faster than Boltzmann annealing, where $T = T_0/ \ln k$. Ingber's (2008) *adaptive simulated-annealing* provides 100 options that allow for finetuning the annealing process. Ingber (2008) states that these 100 options are required because there are many classes of nonlinear stochastic systems, each requiring specific tuning. This is consistent with Weinberger's (1990) correlated and uncorrelated fitness landscapes.

Dodd (1990) identifies an additional consideration, that is, the considerable time to run a *simulated-annealing* process, which has two reasons. First, *simulated-annealing* is an evolutionary serial process, where each step depends on the preceding step. Second, the annealing schedule that is the time taken to reach equilibrium at each temperature. Dodd (1990) finds that using multiple fast annealing can provide comparable results to a slow annealing run. Dodd (1990) uses N parallel processors and compares the results of the slow annealing run taking I iterations with 2 runs of $I/2$ iterations, 4 runs of $I/4$ iterations, N runs of I/N, where N is some power of 2. The starting parameter set x_i in each run differs. He uses a geometric annealing schedule, $T_s g^0$, $T_s g^1$, $T_s g^2$, $T_s g^3$, ..., T_f *where* $g \in (0,1)$. This schedule avoids waiting at each temperature for equilibrium.

de Vicente, Lanchares and Hermidab (2003) introduce thermodynamic *simulated-annealing*, which uses an annealing schedule derived from thermodynamic laws. Its advantage over the *simulated-annealing* algorithm is that the temperature is adjusted continuously using the variation of the state functions that consists of the internal energy and entropy.

2.2.4.3 Threshold-accepting

Dueck and Scheuer (1990) introduce another general purpose optimisation algorithm, called *threshold-accepting* that they find superior to *simulated-annealing*. Figure 2–12 shows the *threshold-accepting* algorithm, where the line numbering allows for easy comparison with the *simulated-annealing* algorithm in Figure 2–11. The two main differences are. First, the temperature *T* in *simulated-annealing* is replaced with a threshold *T*. Second, the stochastic mechanism in *simulated-annealing* in lines 6 to 9 is replaced with a much simpler deterministic process. Despite these simplifications and like *simulated-annealing*, the *threshold-accepting* algorithm still has to consider the cooling or annealing schedule.

Figure 2–12 Threshold-accepting Algorithm

```
1.     Choose an initial configuration (xi)
2.     Choose an initial THRESHOLD Ts > 0
3.     Opt: choose a new configuration (xi’) which is a stochastic small
4.             perturbation of the old configuration (xi)
5.             compute ΔE = E(xi’) – E(xi)
6.             if ΔE > –T
7.                     then (xi) = (xi’)
8.
9.
10.            if cooling (annealing) schedule met or number of iterations I to great
11.                    then lower THRESHOLD T
12.            if ΔE = 0 for some time
13.                    then stop
14.    GOTO Opt
```

(Source: Adapted from Dueck & Scheuer 1990, p. 162)

2.2.4.4 Unconstrained-nonlinear-optimisation

Unconstrained optimisation is an alternative to *threshold-accepting* or *simulated-annealing*, where there are a number of methods available that fall into two broad categories, those that use gradients and those that use function evaluations only (MathWorks 2007). The latter category is suitable for problems that are very nonlinear and or have a number of discontinuities, which describes AIE’s optimisation problem. The generic term, given to techniques to solve such problems, is *unconstrained-nonlinear-optimisation*. Lagarias et al. (1998) note that the Nelder–Mead (1965) simplex method is popular for *unconstrained-nonlinear-optimisation*. However, they observe that there lacks a formal proof for minimisation for dimensions greater than one. Additionally, McKinnon (1998) shows that the Nelder–Mead simplex method fails to find a minimum for some strictly convex functions of two dimensions. Lagarias et al. (1998) provide three reasons why the method is popular despite its shortcomings. Firstly, in many instances in industry users only want an improvement in some performance measure, which the Nelder–Mead method usually provides within the first few iterations. Secondly, there are many applications, where function evaluation is enormously expensive or time consuming, when methods such as *threshold-accepting* or *simulated-annealing* become prohibitively expensive with their numerous evaluations, whence the efficiency of the Nelder–Mead method outweighs the lack of convergence theory. Thirdly, the steps of the Nelder–Mead method are relatively easy to explain to people.

What follows is a short description of the Nelder–Mead method. For a function y of n dimensions, $(n + 1)$ points are taken to form a simplex; a regular simplex is unnecessary. The point P_l has the lowest y value y_l and point P_h with highest y value y_h. Calculate the centroid P_c of all the points excepting P_h. A new point with a lower y value replaces point P_h, after using three operations, reflection, expansion and contraction.

The reflection takes point P^* on the vector through P_c and P_h on the far side of P_c furthest from P_h. If $y_l < y^* < y_h$, replace P_h with P^* and start the process again. If $y_l > y^*$, that is, a new minimum is produced, start the expansion phase.

The expansion takes a new point P^{**} along the vector through P_c and P_h further away from P_h than P^*. If $y^{**} < y_l$, replace P_h with P^{**} and start the process again. If $y^{**} > y_l$, the expansion has failed, replace P_h with P^* and start the process again.

The contraction phase follows, if on reflecting $y^* > y_i$ for all $i \neq h$, first define a new P_h. If $y^* < y_h$, let the new $P_h = P^*$, otherwise the new P_h = old P_h. Take a point P** on the vector through P_c and new P_h and between P_c and new P_h. If y** < min(y^*, y_h), replace P_h with P^{**} and start the process again. If y** > min(y^*, y_h), the contraction has failed, thus replace all points P_i with $(P_i + P_l)/2$ and restart the process.

2.2.4.5 Search Summary

The *grid-search* method is impractical for large dimensional parameter spaces. The various *simulated-annealing* and *threshold-accepting* algorithms provide a solution to finding global minima in large dimensional parameter spaces. However, the annealing process is time consuming for three reasons. First, it requires configuring and finetuning. Second, the annealing process itself is time consuming. Third, there lacks a standard annealing algorithm, hence selecting the best algorithm among those available or developing a hybrid would also be time consuming. Levin (1973, p. 265) proves, '*several well-known large-scale problems of the "sequential search" type can only be solved in the time it takes to solve any problem of the indicated type, in general.*' This proof is consistent with the trade-off, found in this section, between increased time in calibrating a search algorithm and decreased search time for the algorithm. Likewise, the *unconstrained-nonlinear-optimisation* requires no calibration, but it can becomes stuck on local minimum, which makes the results uncertain but easily remedied by starting the *unconstrained-nonlinear-optimisation* process from a number of locations, however this remedy increases the search time.

This thesis uses a combination of a *limited-grid-search*, *threshold-accepting* and *unconstrained-nonlinear-optimisation* methods to find global minimum for each of the 121 network topologies. Section 3.4 discusses the methodology of combining the search methods in detail. Section 2.2.5 discusses how to model-average the 121 network topologies to improve the predictive performance of the AIE model.

2.2.5 Model-selection & Model-averaging: Optimal-calibration & Runtime-weighted

This section discusses model-selection and model-averaging to support the development of *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'* methods because the existing model-selection criteria are unsuitable for creating model weights for the AIE model. The discussion examines why the existing model-selection criteria are unsuitable, leading to the *'runtime-weighted model-averaging'* formula in equation (2–16) and the '*optimal-calibration model-averaging'* method in section 2.2.5.2. These methods are developed further in section 3.5. To that end, this section discusses the link between the Bayesian Information Criteria (BIC), a model-selection method, and Universal Intelligence (Legg & Hutter 2007, p. 23), a model-averaging method. They are linked because both methods seek to balance a model's goodness of fit with a model's complexity by rewarding the former and penalising the latter. Components from the BIC and Universal Intelligence are used to develop the weighting formula in equation (2–16).

The structure of the section is as follows. Section one discusses model-selection and the problems with applying the BIC to form weights for the AIE model. Section two introduces the *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'* methods.

2.2.5.1 Model-selection

The BIC is used in model-selection, where the model with the lowest BIC is the preferred model. The thesis uses Green's (2003, p. 160) version of BIC shown in Equation (2–11). The BIC is also know as the Schwarz information criterion (SIC) after its originator Schwarz (1978).

$$\mathrm{BIC}(k) = \log \sigma^2 + (k \log n) / n \qquad (2\text{–}11)$$

Where

k = the number of parameters in the model

n = sample size

σ^2 = model variance

Note that the form of equation (2–11) differs to the original version. Equation (2–11) has a trade off between goodness of fit and parsimonious specification. A decrease in the BIC results from a decrease in model variance, which means that the model has a higher goodness of fit. A way to increase goodness of fit is to increase the number of parameters. However, increasing the number of parameters increases the BIC. This outline demonstrates the trade off between goodness of fit and parsimony, a search for an explanation in the simplest possible terms. The BIC is a method to implement Occam's razor that states *'entities should not be multiplied beyond necessity – or – keep the simplest theory consistent with the observations.'* The other main model-selection criteria is the Akaike Information Criteria (AIC) (Akaike 1974). This thesis uses the BIC in preference to the AIC because Schwarz (1978) proves that his information criteria optimally penalises models for complexity.

However, there are two reasons why the BIC is inappropriate for selecting among the AIE models. Firstly, each network structure in the AIE model has multiple equilibria. Secondly, the definition of complexity of the BIC is inapplicable to the network topologies of the AIE model.

The first reason for BIC unsuitability is the multiple equilibria in the AIE model. In a strict application of BIC, the multiple equilibria would be ignored to select the global minimum but all equilibria are a plausible solution. However, it was considered too impractical to determine the multiple equilibria in the AIE model, given the computational time required and the limitations of the mathematical techniques available. Section 5.6.7, in further research, further discusses multiple equilibria and phase changes.

The second reason for BIC unsuitability is that BIC calculates complexity as a function of the number of variables in the model but the AIE model has a fixed number of variables and the complexity of the model varies greatly by altering two variables, '*the probability of a link being rewired'*, and *'the number of links in a network'*. An approximation to the level of complexity could be made by equating *'the number of links in a network'* to the level of complexity, which could be used in a modified BIC. However, the level of complexity is two dimensional and not easily ranked, where *'the probability of a link being rewired'* is the other dimension.

The thesis uses model-averaging to solve the ranking problem because each network topology in AIE has a unique structure and is a model in its own right, therefore amenable to model averaging. The network topology in AIE is determined by the following three variables *'the number of firms',* '*the probability of a link being rewired'* and *'the number of links in a network'*. The *'number of firms'* is fixed at *200*, hence the latter two variables determine the network topology. Section 2.2.2 discuses the 121 structures used in AIE as the product of the 11 settings for *'the number of links in the network*' and 11 settings for the *'probability of a link being rewired*'. The thesis uses the term *network-averaging* to describe the above process of model-averaging across network topologies.

The *network-averaging* uses *'equal-weighted model-averaging'* in the first instance to solve the ranking problem, which also improves predictive performance. Furthermore, the thesis develops two model-averaging techniques that address the ranking problem and are tested for their ability to improve predictive performance, *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'*. *'Runtime-weighted model-averaging'* addresses the ranking problem directly by creating an alternative measure of complexity that builds on Hutter (2005) and Legg and Hutter (2007). In comparison, *'optimal-calibration model-averaging'* finds an indirect solution to the ranking problem. Section 2.2.5.2 further discusses the model-averaging solutions to the ranking problem.

2.2.5.2 Model-averaging

Bates and Granger (1969) introduce *'model-averaging'* to improve forecasting accuracy. Clemen (1989) reviews the combining forecasts literature and concludes that (1) forecast accuracy is substantially improved by combining multiple individual forecasts, and (2) simple combinations of models often work reasonably well, compared to more complex methods. His review discusses combining differing models to improve forecast accuracy or *'model-averaging'* (Bates & Granger 1969). Model-averaging has an extensive literature; see Garratt et al. (2007), Fernandez, Ley and Steel (2001), O'Hagan (1995) and Garratt et al. (2003).

The structure of this section is as follows. Section one discusses the development of *'runtime-weighted model-averaging'* that builds on Hutter's (2005) *'Universal Intelligence'* and section two discusses the development '*optimal-calibration model-averaging'*.

1. Runtime-weighted Model-averaging

Hutter (2005) introduces *'Universal Intelligence'* and Legg and Hutter (2007) introduce *'Universal Artificial Intelligence'*. They provide a model-weighing framework that is able to accommodate any combination of environment and agent. However, this framework is practically incomputable, which requires that suitable proxies for the framework's components be developed.

Hutter (2005, p. 30) discusses the weighting method as combining Epicurus' principle of multiple explanations and Occam's razor. Epicurus' principle of multiple explanations is, *'if more than one theory is consistent with the observations, keep all the theories.'* Equation (2–12) defines the universal intelligence of an agent π, which combines both Occam's razor and Epicurus' principle (Legg & Hutter 2007, p. 23).

$$\Upsilon(\pi) := \sum_{\mu \in E} 2^{-K(\mu)} V_{\mu}^{\pi} \qquad (2\text{–}12)$$

Where

π = an agent

μ = an environment

E = a wide range of environments that have well defined rewards

K = Kolmogorov complexity function

V = value function

Legg and Hutter (2007, p. 24) state that the ability of the agent π to achieve in environment μ is represented by V_{μ}^{π}. This ability of the agent would correspond to some inverse function of the model variance of the AIE model. The environments E in the *'universal intelligence'* framework would correspond to 121 network topologies in the AIE model. They use the term $2^{-K(\mu)}$ to represent Occam's razor. This term weights the agent's performance in each environment inversely proportional to its complexity. The Kolmogorov function represents any environment by the shortest non–repeating binary string. This function is not computable, therefore requires a proxy. Levin's (1973, p. 266) *Kt* complexity provides such a proxy, which considers that the complexity of an algorithm is determined by both its minimal description length and running time. Levin complexity makes the assumption that Universal Turing machines are able to simulate each other in linear time to retain invariance with Kolmogorov complexity (Legg & Hutter 2007, pp. 36, 9). The time t for each network structure of the AIE model to run becomes a proxy for complexity. Each of the 121 network topologies has different running times; generally the more links L in the network the longer the running time, and intuitively more complex. The probability of a link being rewired ρ has the general effect of making the running time longer; again intuitively more complex.

Equation (2–13) shows the complexity component of the BIC formula in equation (2–11) replaced with Levin's complexity *Kt*, where t is the model runtime and K is the *'runtime-weighted constant'* denoted by c and determined experimentally. The *'runtime-weighted constant'* will vary according to the speed of the computer running the AIE model, but using the same computer to measure the runtime for all the versions of the AIE model would prevent this problem. Alternatively, each computer could be benchmarked by using the runtime of a standard AIE model that becomes the unit-time for each computer. This allows for a quasi universal '*runtime-weighted constant' c* after normalising the times.

$$\mathrm{BIC}^* = \log \sigma^2 \ + (\ ct \log n\ ) / n \qquad (2\text{–}13)$$

Where

* denotes a modification to representing complexity that is using Levin's complexity *Kt* denoted *ct* to replace the BIC complexity measure *k* in equation (2-11)

t = the time for the model to run

c = *runtime-weighted constant* determined experimentally

Now to address the 121 network topologies using model-averaging, Kass and Raftery's (1995, p. 773) note that *Bayes-factors* may be converted to weights for the various models to make composite estimates. Equation (2–14) shows Kass and Raftery's (1995, p. 791) observation that the BIC gives a rough approximation to the logarithm of the *'Bayes-factor'* (K), which is easy to use and does not require evaluation of the prior distribution.

$$\log K \approx -(n/2)\ \mathrm{BIC} \qquad (2\text{–}14)$$

Where $\approx$ denotes approximately

From equation (2–13) and equation (2–14)

$$\log K^* \approx -(n/2)\ (\log \sigma^2 \ + (\ ct \log n\ ) / n\ )$$

$$\log K^* \approx -(n/2) \log \sigma^2 \ + \ -(1/2)\ (\ ct \log n\ )$$

$$K^* \approx \sigma^{-n}\ n^{-ct/2} \qquad (2\text{–}15)$$

Does equation (2–15) make sense? Equation (2–15) conforms to the three observations about equation (2–12). The first observation is a fit measure inversely proportional to some function of the model variance. The second observation is a complexity penalty. The third observation is that the weight is a product of fit measure and complexity penalty measure. Equation (2–15) has the following two additional benefits related to *n,* the number of observations. The first benefit is that between two models with the same variance the model that has a larger number of observations has a higher weight. This observation makes sense because we can be more confident that the model with the larger number of observations has a more accurately determined model variance, therefore, more confidence that the model fails to fit the data. The second benefit is that between two models with the same runtime or complexity the model with the larger number of observations is more heavily weighted. This observation also makes sense because it rewards a model for fitting more data points. However, a drawback to equation (2–15) is the requirement to determine the *'runtime-weighted constant' c* experimentally. Section 3.5.1 discusses the method to find the *'runtime-weighted constant' c*.

Equation (2–16) shows the *'Bayes-factor'* from equation (2–15) used to form a weight for each model.

$$w_m = \frac{\sigma^{-n}_m \; n\text{\^{}}(-ct_m/2)}{\Sigma^M_i \, \sigma^{-n}_i \; n\text{\^{}}(-ct_i/2)} \qquad (2\text{–}16)$$

Where

w_m = weight for each model m

M = the number of models

The derivation of the weight in equation (2–16) assumes that theorem 2 of Levin's (1973, p. 266) complexity is *Kt* when it is in fact *Kt + c*. However, equation (2–16) can be derived from either form of Levin's complexity and the derivation from the simpler form aids clarity.

Fernandez, Ley and Steel (2001, p. 387) note that *Bayes-factors* are known to be rather sensitive to the choice of the prior distribution for the parameters within each model. The AIE model has no such problem because the parameters are exact values chosen for each simulation. The priors are point mass at the chosen values of the parameters. Thus, there is little need to consider complex priors in model-averaging.

2. Optimal-calibration Model-averaging

This thesis introduces *'optimal-calibration model-averaging'* as an alternative approach to *'runtime-weighted model-averaging'*. As discussed, *'runtime-weighted model-averaging'* directly addresses the inadequacy of the BIC to select among models with varying degrees of complexity, but with a fixed number of variables, by using the *'runtime'* as a proxy for complexity. In contrast, *'optimal-calibration model-averaging'* avoids the complexity issue by simply ranking the 121 models in the order of model variance, which uses equal weights and simply model-averages the first two models, the first three models, the first four models and so on, until the 120 model-averaged combinations are calculated. The combination of models averaged with the lowest model variance becomes the optimal number of models to average. The predictions from this optimal number of models are averaged to form the *optimal-calibration* prediction. Section 3.4.2 further discusses the method to find the optimal number of models. The *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'* techniques are benchmarked against the *'equal-weighted model-averaging'* and '*Bayes-factor model-averaging*' techniques.

The literature supporting the component parts of the AIE model is now in place ready to discuss the arising research questions.

2.3 Research Questions

The overarching research question or problem arising from the literature review is.

> ***Can a dynamic subjective expectations model be used to make more accurate temporal predictions than the REH and the adaptive-expectations models?***

Pertinent issues arising from the research problem are whether the subjective model, the AIE model, is an improvement on existing objective models and what techniques can improve the predictive performance of the AIE model. The research problem is addressed via seven more specific research questions.

1. Do the profit expectations undergo a significant structural change or phase shift during the quarter ending March 2000?

This question determines whether to calibrate the model with all the data available, or just use the data after the March 2000 quarter. The issue over whether the March 2000 quarter signifies a change in profit expectations, due to a change in structure or a phase shift, is left for further research. Section 5.6.7 further discusses the issue.

2. Does 'optimal-calibration model-averaging' improve predictive performance over '*equal-weighted *model-averaging' and '*Bayes-factor *model-averaging' for the AIE model?

To improve predictive performance and overcome the complexity ranking problem AIE uses model-averaging across 121 network topologies that are structurally different hence models in own right. This thesis introduces *'optimal-calibration model-averaging'* and uses *'equal-weighted model-averaging'* and *'Bayes-factor model-averaging'* as benchmarks.

3. Does 'runtime-weighted model-averaging' improve predictive performance over 'equal-weighted model-averaging' and 'Bayes-factor model-averaging' for the AIE model?

This thesis introduces *'runtime-weighted model-averaging'* and uses *'equal-weighted model-averaging'* and *'Bayes-factor model-averaging'* as benchmarks.

4. Does the interactive-expectations network improve the predictive power of the AIE model?

This question tests whether the subjective part of the AIE model, that is, the interactive network improves the predictive power of the model. To answer this question the AIE model is benchmarked against the adaptive-expectations model that is the AIE model with the interactive component set to zero. Section 3.4.2 details these settings.

5. Does the subjective approach of the aggregated AIE model improve predictive performance over the objective approach of REH?

To answer this question the AIE model is benchmarked against REH. This question helps determine the appropriate level of intelligence of the agents.

6. Does introducing an input-output table link-intensity matrix improve the predictive performance of the disaggregated AIE model?

Based upon an *'input-output table'*, the *'link-intensity matrix'*, introduced in section 2.1.9.1, provides a way to weight the intensity of the interactive links between the firms.

7. Does disaggregating the AIE model improve predictive performance?

To test this question the aggregated version of the AIE model is compared with the disaggregated version of the AIE model with the interactive link matrix that provides the best predictive performance.

2.4 Conclusion

The literature review finds that the neoclassical framework is unsound. Additionally, REH, the main expectations theory of the neoclassical framework, is a normative, rather than a predictive or descriptive theory of expectations. This presents a gap for a predictive and descriptive theory of expectations that uses an alternative framework. This thesis introduces AIE as a predictive and descriptive complement to the normative REH. The review finds that the *'science of complexity'* framework provides a suitable alternative framework for AIE for four reasons. Firstly, it provides emergence as a replacement for the failed neoclassical microfoundations project, based upon GET. Secondly, it can incorporate behavioural economics to replace the utility curve concepts from neoclassical economics, which are responsible for the shapeless excess demand curve and GET failure. Thirdly, it provides for a dynamic treatment of expectations formation, which is lacking in the comparative statics of neoclassical economics. Lastly, it allows for structure and concepts from institutional economics in the form of network theory that are lacking in neoclassical economics.

The literature supporting the component parts of the AIE model is now in place permitting the discussion of the methodology to address the research questions.

3. Methodology

3.0 Introduction

Building on the methodology outlined in section 1.4, this chapter describes the methodology to assure appropriate procedures are followed to produce the results to answer the research questions. The chapter addresses four major areas. Building on section 2.1, the first area is justifying the use of a *'pressure to change profit expectations index'*, p^x, rather than a utility curve or probabilities that are commonplace in the literature. Second, the mechanics of building the AIE model are detailed, which includes decomposing the D&B profit expectations and actual profits indices into profit states for individual firms, calculating p^x for the aggregate AIE model and calculating p^x using a *'link-intensity matrix'* for the disaggregated AIE models. Third, methods to calibrate the AIE models are detailed, building on section 2.2.4. Fourth, the four model-averaging techniques for the 121 network topologies within the AIE models are detailed, building on section 2.2.5.

Addressing the research questions requires benchmarking the AIE model against the adaptive-expectations model and REH. This is done for the aggregate and disaggregated version of the AIE model. Benchmarking the AIE against the adaptive-expectations model answers the question, whether the introduction of the interactive network improves predictive performance. Furthermore, model-averaging is introduced to overcome the model complexity ranking issue and improve predictive performance. To further improve the predictive performance, the thesis introduces *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'* techniques, which are tested against the benchmarks *'equal-weighted'* and *'Bayes-factor model-averaging'*. Finally, addressing the research questions requires benchmarking the *'link-intensity matrix'* based on an *'input-output table'* and its transpose against a *'matrix of ones'*.

The structure of the chapter is as follows. Section 3.1 discusses the justifications for the framework and methodology, in particular the use of p^x. Section 3.2 discusses the ingredients of the formal AIE model and the decomposition of the D&B profit expectations and actual profit indices into the actual and expectations profit states of individual firms. Section 3.3 discusses the calculation of p^x for the aggregate AIE model. Section 3.4 discusses the search techniques used to calibrate the parameters for the AIE model. Section 3.5 discusses model-averaging over the 121 network topologies to improve the predictive performance of the AIE model. Section 3.6 discusses the changes to the p^x calculation for the *'link-intensity matrix'* in the disaggregated AIE model. Section

3.7 discusses ways to make REH operational. Section 3.8 refines the research questions to make them operational. Section 3.9 concludes the chapter.

3.1 Justification for the Framework and Methodology

The literature review in chapter 2 justifies the use of the *'science of complexity'*, rather than neoclassical economics, for the framework of the thesis. The chapter finds that the neoclassical framework is unsound and the *'science of complexity'* framework provides a suitable framework for AIE for four reasons. One, it provides emergence as a replacement for the failed neoclassical microfoundations project based upon GET. Two, it can incorporate behavioural economics to replace the utility curve concepts from neoclassical economics, which are responsible for the shapeless excess demand curve and GET failure. Three, it provides for a dynamic treatment of expectations formation, which is lacking in the comparative statics of neoclassical economics. Four, it allows for structure and concepts from institutional economics in the form of network theory, which are lacking in neoclassical economics.

This section justifies the introduction of the subjective *'pressure to change profit expectations index'*, p^x, to replace the utility curve concepts from neoclassical economics and probabilities of the standard decision theories. The need to find a replacement for the utility curve concept has already been discussed in chapter 2. However, there is a need to justify the use of an index rather than probabilities, given their extensive use in the decision theory literature and common use in the expectations literature, see Flieth and Foster (2002) and Bowden and McDonald (2008).

The structure of this section is as follows. Section 3.1.1 discusses the basic concepts. Section 3.1.2 argues that biologically and psychologically people are not probability calculators. Section 3.1.3 argues the need for an alternative measure of belief to probability or outcomes. Section 3.1.4 argues that there is a pure form of uncertainty, the unknown, unamenable to probability theory, which requires people use a dynamic adaptive approach.

3.1.1 Probability and Decision Theory: Objective and Subjective

Hutter (2005, pp. 40-5) notes that there are at least three interpretations of probabilities, the frequentist, the objectivist and subjectivist. Each describes uncertainty from differing sources and schools of thought. Hutter (2005, p. 56) notes that there is an ongoing debate between the various schools.

- The frequentist interpretation sees that probabilities are the relative frequencies, for example, the relative frequency of tossing heads.

- The objectivist interpretation sees that probabilities are real aspects of the world, for example, the probability that some atom decays in the next hour.
- The subjectivist interpretation sees that probabilities describe an agent's degree of belief in something, for example, it is plausible that extraterrestrials exist.

Vercelli (2007, p. 21) discusses the two forms of decision theory, the objectivist theory introduced by Von Neumann and Morgenstern (1944) and the subjectivist theory, often called Bayesian, suggested by Savage (1954). The following examples help to illustrate the differences between the concepts. The objectivist theory uses the frequentist interpretation of probability and is valid when the probabilities are known, for example, a roulette wheel. The subjectivist theory uses subjectivist or personal interpretation of probability and is more appropriate when the probabilities are unknown, for example, horse racing.

3.1.2 Modelling Biological Cognitive Systems as Probability Calculators

This section makes the first argument for using an index. The probability in AIE is of the subjectivist kind, hence it could be argued that it is amenable to Bayesian analysis. Hutter (2005, p. 57) claims that, given the success story of Bayesian probability theory, it is surprising that so many alternative approaches have been considered in artificial intelligence. However, Hutter (2005, p. 58) concedes that other approaches may survive as useful (efficient) approximations to a full Bayesian treatment. Conversely, Yu and Cohen (2009) find that the Bayesian approach is a slightly less accurate model of learning than an exponential discounting model that has many features in common with the leaky integration neuronal models. Furthermore, it provides a more fundamental basis for modelling because the human decision-making process is essentially a biological process and the Bayesian approach is a mathematical approximation. Additionally, Yu and Cohen's exponential discounting approach is consistent with Tversky and Kahneman's (1974, p. 1128) anchoring and adjustment heuristic and Hicks' (1939) adaptive-expectations, which provide a psychological and economic basis for using a discount rate, rather than probabilities. Section 2.1.3.3 discusses Kahneman and Tversky and section 2.1.8 discusses Hicks (1939) and Yu and Cohen (2009).

3.1.3 The need for an Alternative Measure of Belief to Outcome or Probability

The section makes the second argument for an index by discussing three aspects to why there is a need for an alternative measure of belief to outcome or probability. First, how people have an asymmetry in their attitude toward *'risk'*, is at odds with probability theory and requires modelling with weights. Second, how people are *'ambiguity'* adverse, is at odds with the Bayesian approach and requires techniques to weight non-additive multiple probability distributions representing differing beliefs. Third, how there is a substantial gap between the D&B profit expectations and actual profits indices indicates an optimism bias. These three aspects are addressed in turn.

Kahneman and Tversky (1979) introduce prospect theory as an alternative decision-making theory to Von Neumann and Morgenstern's (1944) rational choice. Kahneman and Tversky (1979) find that replacing probabilities with weights provides a more accurate description and prediction of people's decision–making; people are *'risk'* adverse in gains but *'risk'* seeking in losses. Section 2.1.3.3 further discusses prospect theory.

Ellsberg (1961) provides evidence that peoples' beliefs cause people to act at odds with the Bayesian approach and call into question the applicability of conventional probabilities to beliefs. Camerer and Weber (1992) discuss the ambiguity or uncertainty about probabilities and find that people are *'ambiguity averse'*. They observe this in a dozen or so experiments, thus confirming Ellsberg's (1961) findings. Eichberger, Kelsey and Schipper (2009) discuss ambiguity in social interaction and state '*A decision–maker is said to have an ambiguous belief if it is not precise enough to be represented by a single probability distribution.*' Eichberger, Kelsey and Schipper (2009) cite Knight (1921) contrasting risk with ambiguity. In risk, probabilities are known, whereas with ambiguity, probability cannot be assigned. They claim ambiguity is commonplace; for example, the probability of the success of a peace negotiation or the likely impact of a new technology. However, they note that Savage's (1954) subjective decision-making theory has made the distinction between ambiguity and risk from an analytical point of view obsolete because beliefs are represented by a probability distribution. This view on the demise of the distinction is consistent with Vercelli (2007, p. 21), as discussed in section 3.1.4. Eichberger, Kelsey and Schipper (2009) use Choquet's (1954) expected utility framework to generalise the subjective expected utility because '*it maintains the separation of beliefs and outcome evaluation, which makes the theory easier to apply in economics and social sciences.'* Section 5.4.2 in further research discusses investigating links between Leaky Integration Neuronal Models (Yu & Cohen 2009) and Ambiguity Models (Eichberger, Kelsey & Schipper 2009) to provide a more fundamental basis for behavioural economics.

Further to the need to separate belief from probability and outcome, Figure 2–6 shows a persistent optimism bias, as the profit expectations exceed the actual profits for almost the entire history of the D&B survey. In contrast to the D&B survey, Bowden and McDonald (2008), who use a Bayesian approach to model the price movements of shares, assume that agents find the true state of the world and simulate the time lag for agents to find the true state of the world. Figure 2–6 shows that the firms never seem to learn the true state of the world. This is a form of optimism bias and is reflected in the calculation of p^x, see section 3.3.1.3.

3.1.4 Probability in Stationary Decision Theory –v– Unknowables in Adaptive Processes

The third argument for using an index, rather than probabilities, hinges on the more pure form of uncertainty, the unknowable. Vercelli (2007, p. 21) and Keynes (1937) make the unknowable argument using different approaches that are axiomatically and the inability to measure the value of current additions to investments, respectively. Vercelli (2007, p. 21) notes that the objective and subjective decision-making theories may appear very different. However, their implications are almost identical axiomatically and ontologically because both theories refer to a world that is familiar to the decision-maker. As Lucas (1986, p. S411) notes '*the economic theory of choice is ... a description of a ... stationary "point" ... [in a] dynamic adaptive process.'* At such point, the optimal adaptation has already happened and the decision-maker knows the complete list of its possible states and options, and knows the consequences of each choice for each possible state. However, in an environment, where there are innovations, which provide novel states and outcomes that were formerly unknown, which requires true learning and makes it not possible to attribute probabilities. Such a situation requires a dynamic adaptive approach.

Keynes (1937, pp. 213-4) discusses '*uncertain*' knowledge claiming that probabilities relating to the relatively distant future are not measurable because *'the prospect of a European war*' or *'the rate of interest twenty years hence*' are so uncertain that *'there is no scientific basis on which to form any calculable probability whatever. We simply do not know'*. The probabilities of events affecting the value of current additions to capital are not measurable. Therefore, the present value of current investment cannot be calculated. He suggests that people adopt the following three strategies in the face of uncertainty.

1. Assume that the present is a much more servable guide to the future than the past and largely ignore the unknowns in the future. This is a form of exponential discounting and is reflected in the calculation of p^x, see section 3.3.1.3.
2. Assume that the existing state of opinion is reflected in the prices and the characteristic of existing output is a correct summing up of future prospects, unless something new and relevant comes into the picture. This is a dynamic adaptive-expectations approach and is reflected in the calculation of p^x, see section 3.3.1.3.
3. Knowing that our own judgement is to be worthless, fall back on the judgement of the rest of the world, by doing so conform to the behaviour of the majority or the average,

leading to a *'conventional'* judgement. This is an interactive-expectations approach and is reflected in the calculation of p^x, see section 3.3.1.2.

3.2 Ingredients of the formal AIE model

The ingredients for the AIE model are discussed throughout the literature review in chapter 2. This section provides consolidation and before developing the formal AIE model.

The model uses one source of exogenous input, the D&B (2008) *'all–firms actual profits index',* to model the D&B (2008) *'all–firms profit expectations index'*. The use of a single exogenous input is not to say that other inputs are unimportant, but that a single exogenous input and the endogenous effects are sufficient to model the profit expectations index more closely than the REH and adaptive-expectations models. Benchmarking AIE against the adaptive-expectations model allows the value added by the endogenous component to be evaluated.

Table 2–3 shows the component parts of the AIE model. Adaptive-expectations are used to model how a business adapts to exogenous changes. Interactive-expectations are used to model how the expectations of one business affect that of others. The interactive-expectations act through a small world network to create endogenous effects. These components are interrelated via Keynes' *'uncertain knowledge'*, as discussed in section 3.1. Additionally, the adaptive-expectations model embodies Tversky and Kahneman's (1974, p. 1128) anchoring and adjustment heuristic. The literature review in chapter 2 discusses the inadequacies of the REH and adaptive-expectations models to justify the development of the AIE as a replacement.

The data for the interactive network is unavailable. Therefore, the thesis develops a new technique, called *network-averaging*, to provide a proxy for the network. *Network-averaging* involves calibrating the AIE model over a 121 different network topologies and then model-averaging over these topologies. The thesis also develops two new model-averaging techniques, *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'*, to improve the predictive power of the *network-averaging*.

The data for the D&B (2008) survey was only available in index form to ensure the anonymity of the respondents. However, the AIE simulation requires data for individual businesses, therefore, the indices are decomposed to create datasets for individual business. The results from the AIE model are aggregated to form a profit expectations index for comparison with the index from the D&B survey.

3.2.1 Decomposing the D&B Indices into the States of Firms and Initialising AIE

This section discusses how the D&B (2008) *'all–firms profit expectations and actual profits indices'* are decomposed into the profit expectations and actual profit states for each firm. Because, the state of the individual firms is unavailable, requiring the D&B (2008) index to be decomposed into states for each firm. This decomposition is required for the whole of the D&B (2008) actual profit index because the actual profit state of each firm acts as the sole exogenous input into the AIE model. The decomposition is required for the first two quarters of the D&B (2008) profit expectations index to initialise the AIE model.

The structure of the section is as follows. First, the section discusses how the individual firm's profit expectations and actual profits states are calculated from the indices. Second, the section discusses the initialisation of AIE and the general process used to calibrate AIE.

The state of each firms' profit expectations and actualisation levels are calculated from the D&B (2008) indices. To do this, equation (2–6) is used to decompose the profit expectations index into the percentage of firms who expect profits to increase, decrease and undergo *no–change*. Similarly, equation (2–7) is used to decompose the actual profits index into the percentage of firms whose profits actually increase, decrease and undergo no change. The decomposition requires the ABS (2002 Cat. No. 5250.0 tbl. 2) aggregate of the percentage of firms that expect *no–change* in profits, which acts as a proxy for the unavailable D&B (2008) *no–change* data for both the profit expectations and actual profits. This *no–change* dataset is the best that could be found. From the percentage breakdowns, each firm i at time t is assigned a level of expectations $e_{i,t}$ of *1, 0 or –1* to represent whether they expect profits to increase, undergo *no–change* or decrease. The actualisations $a_{i,t}$ are assigned similarly. So far these assignments reflect the D&B (2008) indices.

The first two quarters from the D&B (2008) indices are used to calibrate the AIE model. Section 3.3 discusses how firms change their expectations for the next quarter based upon the p^x. Once the AIE model calculates the expectations of each firm for each period, the AIE model's *'profit expectations index'* is calculated with equation (2–6).

Section 3.4 discusses the techniques used to find the parameter settings in the AIE model, which minimise the model variance between the *'profit expectations index'* of the AIE model and of the D&B (2008) survey.

3.3 The Pressure to Change Profit Expectations Index p^x

The p^x index provides a non-probabilistic method to enable the summing of pressures that can change the profit expectations of an individual firm from three sources, interactive pressure, adaptive pressure, and biases, including optimism, pessimism or ambivalence. The p^x index is used to determine stochastically whether a firm changes its profit expectations.

The structure of the section is as follows. Section 3.3.1 discusses the calculation of p^x. Section 3.3.2 compares two approaches to interactive-expectations, statistical and network. Section 3.3.3 discusses how p^x is used stochastically to determine whether a firm changes expectations. Section 3.3.4 discusses how the maximum and minimum p^x is restricted to be 100 and –100, respectively.

3.3.1 Calculating the Pressure to Change Profit Expectations Index

This section discusses how the $p^x_{i,t}$ is calculated for each firm i each quarter t. Equation (3–1) shows the calculation of the p^x for (a) firms who currently expect profits to decrease, (b) firms who currently expect no change in profits, and (c) firms who currently expect profits to increase. The p^x in each equation has three main components, the interactive and adaptive influences and the biases. The biases include optimism, pessimism and ambivalence. The interactive influence uses the difference between profit expectations of the firm and those firms linked to it; furthermore, this difference is normalised and put to a power ranging between *1* and *3* by increments of 0.2. The adaptive influence uses the error between the expected profits and actual profits for the current and the previous period. This section discusses these components and compares them to the interactive-expectations and adaptive-expectations from which the AIE model is developed.

The structure of the section is as follows. Section one discusses the three biases, optimism, ambivalence and pessimism. Section two discusses the interactive influence and interactive power. Section three discusses the adaptive influences. Section four compares the network and statistical approaches to modelling interactive-expectations.

3.3.1.1 Biases: Optimism, Ambivalence or Pessimism

The basic tendencies β in equation (3–1) are, as the name suggests, the tendency for a firm to feel pressure to change to another level of expectations. The basic tendency to increase β^+, to decrease β^- and to be neutral β^0 could be interpreted, respectively, as optimism, pessimism, or ambivalent feelings that permeate the economy. Looking at Figure 2–6, it appears that there are overly optimistic expectations because profit expectations exceed actual profit for most of the time, thus one would predict that the basic tendency to increase is greater than the basic tendency to decrease. The AIE model does find this to be the case.

3.3.1.2 Interactive Influence and Interactive Power

The interactive influence I in equation (3–1) indicates the influence of other firms, holding differing levels of profit expectations, has on the firm. Each firm is linked to other firms via a network. The total number of links to a firm $L = L_{i,t}^{+} + L_{i,t}^{0} + L_{i,t}^{-}$ is the sum of the links to firms that hold optimistic, ambivalent and pessimistic expectations, respectively. Section 2.2.2 discusses the 121 network topologies (L and ρ) and parameters ranges that AIE uses. The AIE model borrows the network naming conventions and topology parameters from Watts and Strogatz's (1998) small world networks, the code from Wilensky (2005), and parameter increments from Bowden and McDonald (2008). This ensures that the design of the AIE model's network builds on the existing literature.

The interactive power δ in equation (3–1) varies from 1 to 3 by increments of 0.2. These increments are chosen to test Flieth and Foster's (2002) assumption that $\delta = 2$. See equation (3–2). The interactive components are adapted from Flieth and Foster (2002) and Bowden and McDonald (2008).

3.3.1.3 Adaptive Influence

The adaptive influences A and A_{-1} in equation (3–1a) indicate the influence that the firm's own expectations are met. The adaptive influences' weights are the parameters, $(a_{i,t} - e_{i,t})$ and $(a_{i,t-1} - e_{i,t-1})$, which form a link between the actual profits and profit expectations. For example, if the firm's expectations are met, that is, $(a_{i,t} = e_{i,t})$ and $(a_{i,t-1} = e_{i,t-1})$, the firm has zero pressure from adaptive influences to change profit expectations. If the firm's expectations are exceeded, that is, $(a_{i,t} > e_{i,t})$ or $(a_{i,t-1} > e_{i,t-1})$, the adaptive influence increases pressure on the firm to increase its expectations. The AIE model uses the current and last quarter only, in accordance with the discounting, as discussed in sections 3.1. Additionally, AIE reflects the fact that a firm lacks full information about the actual profits for the current quarter until the following quarter, thus a firm behaving adaptively would use the full information available from last quarter and the partial information available about this quarter.

The adaptive-expectations influence A is adapted from Hicks' (1939) adaptive-expectations. This influence allows a connection between actual profits and profit expectations, which Flieth and Foster's (2002) Interactive-expectations lacks. See equation (3–2).

Equation (3–1) – Pressure to change profit expectations index

(a) For firm *i* who currently expects profits to decrease ($e_{i,t} = -1$)

The pressure to increase expectations

$$p^x_{i,t} = \beta^+ + \beta^0 + A\,[\,a_{i,t} - e_{i,t}\,] + A_{-1}\,[\,a_{i,t-1} - e_{i,t-1}\,] + I\,[\,(L_{i,t}^+ + L_{i,t}^0) / L\,]\hat{}\delta$$

(b) For firm *i* who currently expects no change in profits ($e_{i,t} = 0$)

positive pressure to increase expectations and

negative pressure to decrease expectations

$$p^x_{i,t} = \beta^+ - \beta^- + A\,[\,a_{i,t} - e_{i,t}\,] + A_{-1}\,[\,a_{i,t-1} - e_{i,t-1}\,] + I\,[(\,L_{i,t}^+ / L\,)\hat{}\delta - (\,L_{i,t}^- / L\,)\hat{}\delta]$$

(c) For firm *i* who currently expects profits to increase ($e_{i,t} = 1$)

The pressure to decrease expectations

$$p^x_{i,t} = \beta^- + \beta^0 + A\,[\,e_{i,t} - a_{i,t}\,] + A_{-1}\,[\,e_{i,t-1} - a_{i,t-1}\,] + I\,[\,(L_{i,t}^- + L_{i,t}^0) / L\,]\hat{}\delta$$

Where

$p^x_{i,t}$ = pressure to change profit expectations index for firm *i* at time *t*

$p^x_{i,t} \in [-100, 100\,]$

β^+ = basic tendency to increase expectations – optimism bias

β^0 = basic tendency to neutral expectations – ambivalence bias

β^- = basic tendency to decrease expectations – pessimism bias

A = adaptive influence this quarter

A_{-1} = adaptive influence last quarter

$a_{i,t}$ = profit actualisation of firm *i* at time *t*

where a decrease, no change or increase is –1, 0 or 1, respectively

$e_{i,t}$ = profit expectations of firm *i* at time *t*

where a decrease, no change or increase is –1, 0 or 1, respectively

I = interactive influence

L = total number of links to a node or firm (2, 4, 6, …, 22)

L^+ = the number of linked firms who expect profits to increase (e = 1)

L^0 = the number of linked firms who expect no change in profits (e = 0)

L^- = the number of linked firms who expect profits to decrease (e = –1)

δ = interactive power (1.0, 1.2, 1.4, …, 3.0)

3.3.2 Comparing Interactive-expectations Approaches: Network versus Statistical

This section compares two different approaches to modelling interactive-expectations, the network and statistical approaches, as shown in equation (3–1) and equation (3–2), respectively. Equation (3–2) results in a probabilistic treatment of the whole population's expectations, whereas equation (3–1) considers each firm within a network of interactive influence. These two differing approaches are appropriate to the situation being studied. Flieth and Foster (2002) model interactive-expectations in an electoral opinion poll, whereas, this thesis models interactive profit expectations among the manufacturing, wholesale and retail divisions. Flieth and Foster's (2002) approach more closely approximates a complete graph, as individuals discuss political events and are exposed to regular national media coverage of political events, which includes regular surveys of the voting population, thus providing feedback to all individuals. In comparison, the AIE model's approach more closely resembles a network of interconnected supply chains, as firms are linked to one another via orders in expectations of sales, as discussed in the *'Beer distribution game'*. Admittedly, the two situations are not as black and white as portrayed, but more different shades of grey.

Equation (3–2) – Interactive Influence using a Statistical Approach

For firms who currently expect profits to decrease – the interactive pressure to increase expectations

$$I\ [\ (N^{+} + N^{0})\ /\ N\ ]^{\wedge}2$$

Where

I = interactive influence

N = total number of firms

N^{+} = the total number of firms who expect profits to increase

N^{0} = the total number of firms who expect no change in profits

δ = interactive power = 2

(Source: Adapted from Flieth & Foster 2002)

Section 3.1 discusses why an index is more suitable than probabilities for the task at hand. In addition, the index more easily handles double jumps in expectations. A double jump in expectations is when a respondent changes from expecting profits to decrease in one quarter to expecting profits to increase in the next quarter, or vice versa, which bypasses the intervening *no–change* in expectations. This relaxes Flieth and Foster's (2002) simplifying assumption that no such double jumps would occur over a quarter.

3.3.3 Stochastically Determining the Pressure Level at which to Change Expectations

Equation (3–3) shows how the p^{x}, in conjunction with a random number generator and the *'pressure levels to change expectations'* p^{+}, p^{++}, p^{-} *and* p^{--}, determines the level of expectations a firm holds for the next quarter $e_{i,t+1}$.

Equation (3–3) – Determining the pressure level at which to change expectations

(a) For firms who currently expect profits to decrease, determining the pressure level to increase expectations

if random (p^{+}) < $p^{x}_{i,t}$ then $e_{i,t+1} = 0$

the firm increases expectations one level

if random ($p^{++} - p^{+}$) < ($p^{x}_{i,t} - p^{+}$) then $e_{i,t+1} = 1$

the firm increases expectations two levels

(b) For firms who currently expect no change in profits determining the pressure level to increase or decrease profit expectations

if $p^{x}_{i,t} > 0$ and if random(p^{+}) < abs($p^{x}_{i,t}$) then $e_{i,t+1} = 1$

the firm increases expectations one level

if $p^{x}_{i,t} < 0$ and if random(p^{-}) < abs($p^{x}_{i,t}$) then $e_{i,t+1} = -1$

the firm decreases expectations one level

(c) For firms who currently expect profits to increase

The pressure to decrease expectations

if random (p^{-}) < $p^{x}_{i,t}$ then $e_{i,t+1} = 0$

the firm decreases expectations one level

if random ($p^{--} - p^{-}$) < ($p^{x}_{i,t} - p^{-}$) then $e_{i,t+1} = -1$

the firm decreases expectations two levels

Where

p^{+} = the pressure level at which a firm increases profit expectations by 1 level

p^{++} = the pressure level at which a firm increases profit expectations by 2 levels

p^{-} = the pressure level at which a firm decreases profit expectations by 1 level

p^{--} = the pressure level at which a firm decreases profit expectations by 2 levels

$e_{i,t+1}$ = profit expectations the firm holds next quarter

The random function in equation (3–3) reports a random integer greater than or equal to 0, but strictly less than the pressure to change level (Wilensky 1999). The random function uses a flat distribution. The profit expectations index for the next quarter is calculated from the number of firms holding positive and negative expectations for the next quarter, as per equation (2–6). These values are aged and the process is repeated for each quarter to form a single run.

At the end of the run, the model variance between the *all–firms* profit expectations of D&B (2008) and of the AIE model is calculated. What has been described so far in this section is the process for a single run to find the model variance for a single set of parameter values. Section 3.4 discusses the process used to search the parameter space for the local minima of model variance.

3.3.4 Ensuring the Pressure to Change Index does not exceed 100

Line 1 in equation (3–4) shows how the p^x is constrained to a maximum of *100* by setting p^x in equation (3–1a) to *100*. The parameters $a_{i,t}$, $e_{i,t}$, $a_{i,t-1}$ and $e_{i,t-1}$ all can take the values *1, 0* or *–1*, hence the maximum values for $[\ a_{i,t} - e_{i,t}\ ]$ or $[\ a_{i,t-1} - e_{i,t-1}\ ]$ is *2*. This could result in doubling the weight of A or A_{-1} on the p^x, thus the factor of *2* is introduced in line 2 of equation (3–4). The maximum value for $(L_{i,t}^{+} + L_{i,t}^{0}) / L$ is *1*, hence a factor of *1* is introduced in line 2 of equation (3–4) for *I*. The constraint in line 2 allows β^0 to be determined in line 3 with the condition that β^0 is not less than zero. This constraint allows the elimination of β^0 from the parameter sweeping.

Equation (3–4) – Fixing the maximum p^x to 100

1. $100 >= \beta^+ + \beta^0 + A\ [\ a_{i,t} - e_{i,t}\ ] + A_{-1}\ [\ a_{i,t-1} - e_{i,t-1}\ ] + I\ [\ (L_{i,t}^{+} + L_{i,t}^{0}) / L\ ]\hat{}\delta$
2. $100 >= \beta^+ + \beta^0 + I + 2 * [\ A + A_{-1}\ ]$
3. $\beta^0 = 100 - (\ \beta^+ + I + 2 * [\ A + A_{-1}\ ]\ )$

   Where $\beta^0 >= 0$

Additionally, the parameter β^- proved to be redundant and eliminated by setting it to zero.

3.4 Calibrating the AIE model's 121 network topologies

This section discusses the calibration of the AIE model, which is performed by minimising the model variance. Section 2.2.4 discusses four optimisation techniques for functions of many variables, *grid-search*, *simulated-annealing*, *threshold-accepting* and *unconstrained-nonlinear-optimisation*, where its is found that each technique has problems. This section discusses how three of the four techniques are integrated to overcome these problems to find the 121 global minima of the model variance for each of the network topologies in the AIE model. The section presents a visualisation to illustrate the problem of finding minimums in the AIE model.

The structure of the section is as follows. Section 3.4.1 presents a visualisation of the minimisation showing the model variance and network topologies. Section 3.4.2 discusses the minimisation process.

3.4.1 Visualisation of the Model Variance of the Network Topologies

Figure 3–1 shows 200 runs ranked in the ascending order of model variance for the short period calibration of the AIE model. Table 3–1 shows the parameters settings and associated model variance for the first 5 runs in Figure 3–1.

Figure 3–1 The 200 runs with the lowest model variance from the limited gradient method

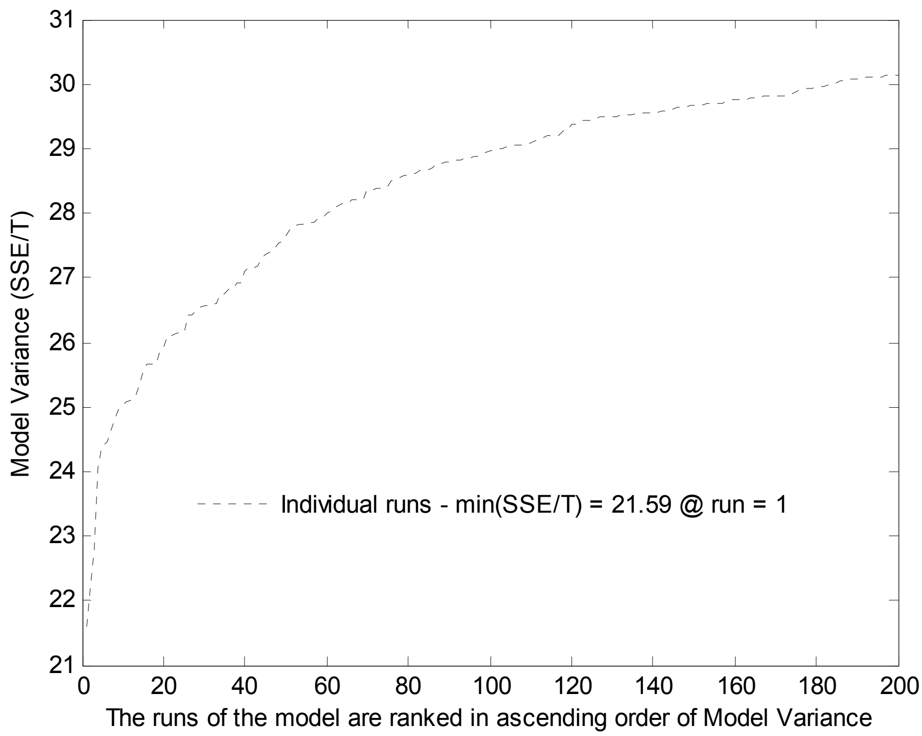


Table 3–1 Parameter values for the five runs with the lowest model variance (*SSE/T*)

Run	*SSE/T*	δ	ρ	L	β^{+}	I	A	A_{-1}	p^{+}	p^{++}	p^{-}	p^{--}
1	21.59	1.2	0.6	16	3	27	13	18	45	117	48	122
2	22.20	1.8	0.9	22	5	24	10	19	45	117	48	122
3	22.80	2.8	1	12	4	30	9	18	45	117	48	122
4	24.07	1.4	0.3	22	4	28	12	22	45	117	48	122
5	24.37	1.8	0.8	8	4	30	9	19	45	117	48	122

Figure 3–2, Figure 3–3 and Figure 3–4 provide a visualisation of the model variance topology. The model variance of run 1 from Table 3–1 is the black diamond shape in Figure 3–3. The three figures show the topology of the model variance by altering the network parameter values of (*L, ρ, δ*); the other parameter values are kept constant and are those shown shaded light grey in run 1 from Table 3–1. Of note from inspection of the Figure 3–2, Figure 3–3 and Figure 3–4 is the ruggedness of the landscape or sensitivity of model variance to changes in parameter values.

Figure 3–2 SSE/T for various L and ρ for δ = 1.0

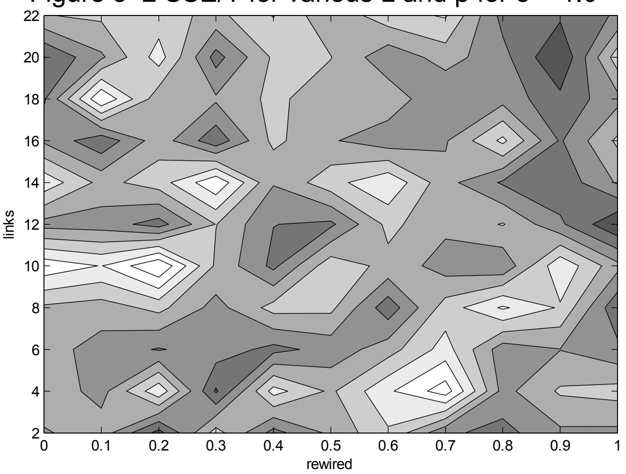
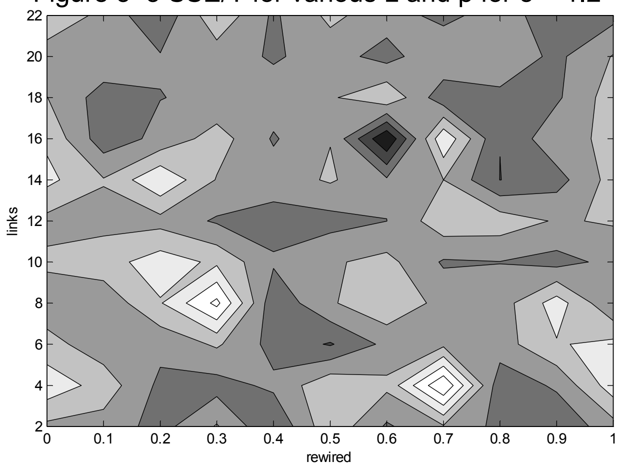


Figure 3–3 SSE/T for various L and ρ for δ = 1.2



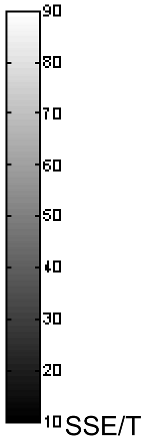
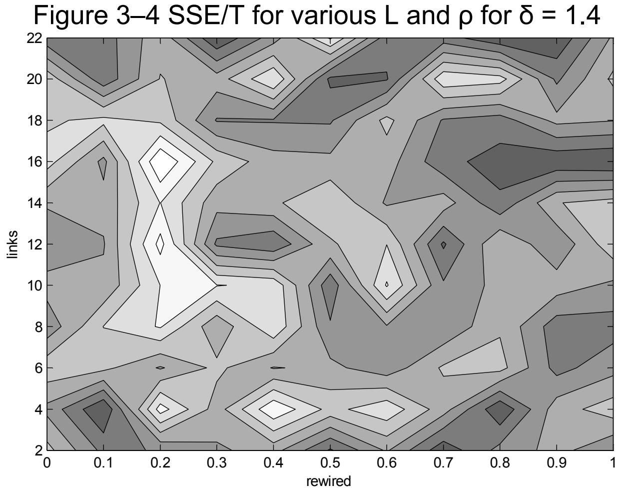


Figure 3–4 SSE/T for various L and ρ for δ = 1.4



3.4.2 Combining the Search Techniques to Find the Global Minimum

Combining the *limited-grid-search*, *unconstrained-nonlinear-optimisation* and *threshold-accepting* search techniques reduces the chance of becoming stuck on local minima, without incurring the time cost for an exhaustive *grid-search* or the calibration problems with *threshold-accepting* or *simulated-annealing*. The combined search technique starts with a *limited-grid-search*. The minima results from the *limited-grid-search* are fed into an *unconstrained-nonlinear-optimisation*, which inturn feeds minima into a *threshold-accepting* method, until a stable minimum is found for each of the 121 network topologies. Table 3–2 shows the percentage decrease in average model variance of the 121 network topologies for the five versions of the AIE model. In total, 605 (5x121) models were optimised.

Table 3–2 Percentage Decrease in Model Variance using the Differing Optimisation Techniques

Version of AIE Model			Search Technique	The average of the minimum model variance for the 121 network topologies	Percent Decrease	
Aggregated	Long Calibration		Limited-grid-search	49.93	0.09	Grid to Nonlinear Opt.
			Nonlinear-optimisation	49.88	3.42	Nonlinear Opt. to TA
			Threshold-accepting	48.18	3.50	Total Decrease
	Short Calibration		Limited-grid-search	27.54	7.40	Grid to Nonlinear Opt.
			Nonlinear-optimisation	25.51	4.56	Nonlinear Opt. to TA
			Threshold-accepting	24.34	11.62	Total Decrease
Disaggregated	Link-intensity Matrix	Input-Output	Limited-grid-search	26.97	0.13	Grid to Nonlinear Opt.
			Nonlinear-optimisation	26.83	0.32	Nonlinear Opt. to TA
			Threshold-accepting	26.51	0.45	Total Decrease
		Transpose	Limited-grid-search	27.73	0.65	Grid to Nonlinear Opt.
			Nonlinear-optimisation	27.55	3.15	Nonlinear Opt. to TA
			Threshold-accepting	26.69	3.78	Total Decrease
		Matrix of ones	Limited-grid-search	25.82	0.19	Grid to Nonlinear Opt.
			Nonlinear-optimisation	25.62	0.21	Nonlinear Opt. to TA
			Threshold-accepting	25.41	0.41	Total Decrease

In addition to optimising the 605 models in Table 3–2, the benchmarks for AIE, the aggregated and disaggregated adaptive-expectations models, were also optimised. The adaptive-expectations models lack network topologies, thus are excluded from Table 3–2. The adaptive-expectations model is the AIE model with the network topology values set to $L = 1$ and $\rho = 0$ and $I = 0$. The lack of a *'121 networks'* for the adaptive-expectations model means that the selection of the 121 parameter sets for *model-averaging* is arbitrary. It was found that, as the 121 parameter sets converged on a global minimum, the model-averaging result deteriorated considerably. To solve this problem the disaggregated adaptive-expectations model had a complete *grid-search*, as the high performance computing centre wanted to test a new computer for a month. The 121 parameter sets with the lowest model variance are used. The increments in the *grid-search* are large enough to make model-averaging meaningful, thus providing the disaggregated AIE model with a more rigorous benchmark.

For the aggregated adaptive-expectations model a slightly lower model variance for the model-averaging was found by setting the network topology to values other than $L = 1$ and $\rho = 0$. Since $I = 0$, these alternate network topology settings only indirectly affect the model variance calculation because the random functions in the model are affected by using different parameters. This use of the randomness function allowed a more meaningful use of model-averaging, thus providing the aggregated AIE model with a more rigorous benchmark. Section 5.6.11 in further research discusses using the random seed function built into NetLogo to provide a more elegant solution.

Section 3.5 discusses the three *'link-intensity matrices'* used in the disaggregated AIE model, which are the *'matrix of ones'*, the *'input-output table'* and the transpose of the *'input-output table'*, where the *'matrix of ones'* is a default to benchmark the other two *'link-intensity matrices'*. Section 2.1.9.1 discusses the derivation and justification of the *'input-output table'*. The transpose of the *'input-output table'* that reverses the intensity of interactive profit expectations in the network is used to investigate its effect on the predictive performance.

The *limited-grid-search* treats the network topology parameters as any other parameter to find a single global minimum for all 121 models. Each run in the AIE model is defined by the eleven parameters: β^+, I, L, δ, A, A_{-1}, ρ, p^+, p^{++}, p^- and p^{--}. Initialising the limited grid method involves setting values for the 11 parameters based upon reason and assumption. The limited gradient search has two phases, a gradient search and limited broad sweep.

1. To make a gradient search, each parameter value is allowed to vary plus or minus one increment: $\beta^+ \pm 1$, $I\pm 1$, $L\pm 2$, $\rho\pm 0.1$, $\delta\pm 0.2$, $A\pm 1$, $A_{-1}\pm 1$, $\rho\pm 1$, $p^+\pm 1$, $p^{++}\pm 1$, $p^-\pm 1$ and $p^{--}\pm 1$. This gives 3^{11} parameter combinations or runs at 1 to 2 seconds per run; it takes 2 to 4 days of CPU time. The minimum parameter values are $L = 2$, $\delta = 1$ and $\beta^+ = \beta^0 = I = A = A_{-1} = \rho = p^+ = p^{++}$

$= p^{-} = p^{--} = 0$. The condition in equation (3–4) determines β^{0}. The gradient method is repeated until a local minimum is found. The parameter values from the local minimum are used in a limited broad sweep.

2. To make a limited broad sweep, the pressure levels to change expectations (p^{+}, p^{++}, p^{-} *and* p^{--}) are held constant. The ranges for other parameters are $\beta^{+} \pm 5$, $I \pm 5$, $L = (2, 4, 6, \ldots, 22)$, $\delta = (1.0, 1.2, 1.4, \ldots, 3.0)$, $\rho = (0, 0.1, 0.2, \ldots, 1)$, $A \pm 5$, $A_{-1} \pm 5$. This gives 11^{6} parameter combinations or runs at *1* to *2* seconds per run; this takes *20* to *40* days of CPU time. The parameters from the run with the minimum model variance in the limited broad sweep are used to initialise the next gradient method search. The gradient method and limited broad sweep are repeated, until a global minimum is found. The visualisation in Figure 3–2, Figure 3–3 and Figure 3–4 are produced from a limited broad sweep.

Once the *limited-grid-search* has found its global minimum, the parameter settings that give the lowest model variance for each of the 121 network topologies are collected from the *grid-search*. These 121 parameter settings are used to initialise an *unconstrained-nonlinear-optimisation*. The 121 parameter settings from the *unconstrained-nonlinear-optimisation* are used to initialise the *threshold-accepting* search. Once a stable minimum for each network topology is found, the process is completed.

Table 3–2 shows that combining three optimisation techniques can decrease the model variance by up to further 11%. Without the *unconstrained-nonlinear-optimisation* and *threshold-accepting* techniques, this 11% improvement would have been missed by the gradient and *limited-grid-search*, as discussed in points 1 and 2 above.

Section 5.6.1 in further research discusses combining the *unconstrained-nonlinear-optimisation* and *simulated-annealing* techniques to reduce the search time. Section 5.6.13 also in further research discusses using the parallel processing power in computer graphics adaptors to further reduce the search time.

3.5 Model-averaging

This section discusses the model-averaging of the results from the optimisation in section 3.4. Model-averaging combines forecasts to enhance predictions (Bates & Granger 1969). The models being averaged are the 121 network topologies; each network topology is a model in its own right, as they differ structurally. There is a requirement for model-averaging because of the following two reasons. First, there lacks information on the topology of the interactive-expectations network for the AIE model and a single simple network topology would be insufficient to capture the complexity of the economic structure. Second, there an issue over ranking the complexity of the network topologies, which model-averaging can circumvent as discussed in section 2.2.5.

This section builds on the model-selection and model-averaging literature in section 2.2.5 to detail two model-averaging methods that this thesis introduces, *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'*. These methods both involve a calibration and prediction phase. The *'equal-weighted'* and *'Bayes-factor model-averaging'* act as benchmarks for the *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'*.

The predictive performance of the AIE model is enhanced using a model-average of the 121 different network topologies that is the model-average of 121 runs. The runtime is the length of time it takes for one simulation to run.

The graphs illustrating the discussions in this section are those from the disaggregated version of the AIE model using an *'input-output table'* for the *'link-intensity matrix'*. These results are presented into Table 4–1.

The structure of the section is as follows. Section 3.5.1 discusses *'runtime-weighted model-averaging'*. Section 3.5.2 discusses *'optimal-calibration model-averaging'*. Section 3.5.3 discusses *'equal-weighted model-averaging'*. Section 3.5.4 discusses *'Bayes-factor model-averaging'*.

3.5.1 Runtime-weighted Model-averaging

This section reviews the equations for *'runtime-weighted model-averaging'* and presents the graphs from the calibration, prediction and evaluation phases.

The structure of the section is as follows. Section one reviews the weighting equations derived in section 2.2.5.2. Section two discusses the calibration phase. Section three discusses the prediction phase. Section four discusses the evaluation phase.

3.5.1.1 Runtime-weighted Model-averaging Formula

The *'runtime-weighted model-averaging'* uses equation (2–16) derived from equation (2–15). These equations are derived in sections 2.2.5.2 and are replicated below for easy reference.

$$K^* \approx \sigma^{-n}\, n^{-ct/2} \qquad (2–15)$$

Where

K = *'Bayes-factor'*

* denotes a modification to representing complexity that is using Levin's complexity *Kt* denoted *ct* to replace the BIC complexity measure *k* in equation (2-11)

n = sample size

σ^2 = model variance

t = the time for the model to run

c = *'runtime-weighted constant'* determined experimentally

≈ denotes approximately

Equation (2–16) shows the *'Bayes-factor'* from equation (2–15) used to form a weight for each model.

$$w_m = \frac{\sigma^{-n}_m \;\; n\text{\^{}}(-ct_m/2)}{\Sigma^M_i\, \sigma^{-n}_i \;\; n\text{\^{}}(-ct_i/2)} \qquad (2–16)$$

Where

w_m = weight for each model m

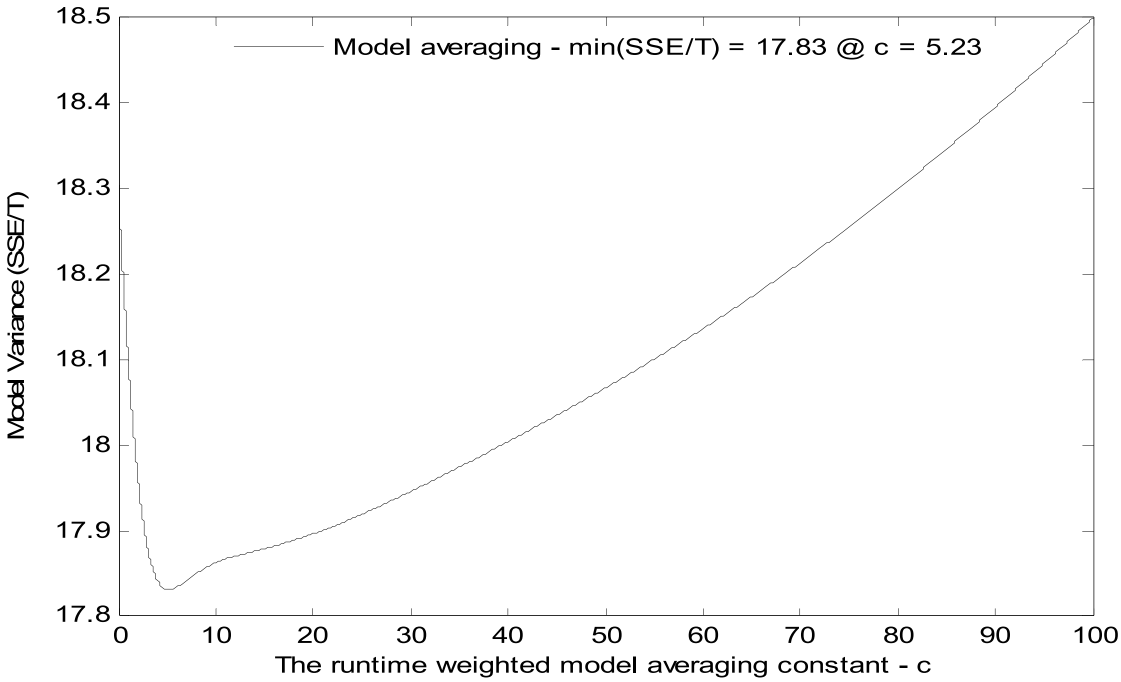
t_m = runtime for model m

M = the number of models

3.5.1.2 Calibration

The *'runtime-weighted model-averaging'* requires the runtime t_m for each model, which is the time to run for each of the 121 network topologies with the lowest model variance, as found in section 3.4. The runtime t_m is determined by taking the average of ten runs, after allowing an initial 10 runs for a burn-in to remove any initial transient effects. These 121 runtimes t_m are used in equation (2–16) to determine the *'runtime-weighted constant' c*, so that its values minimise the model variance for the model-average of the minimums of the 121 network topologies. Figure 3–5 shows the *'runtime-weighted constant' c* ranging from *0* to *100* by *0.01* increments and that the optimal value for the *'runtime-weighted constant' c* is 5.23, giving a model variance of 17.83.

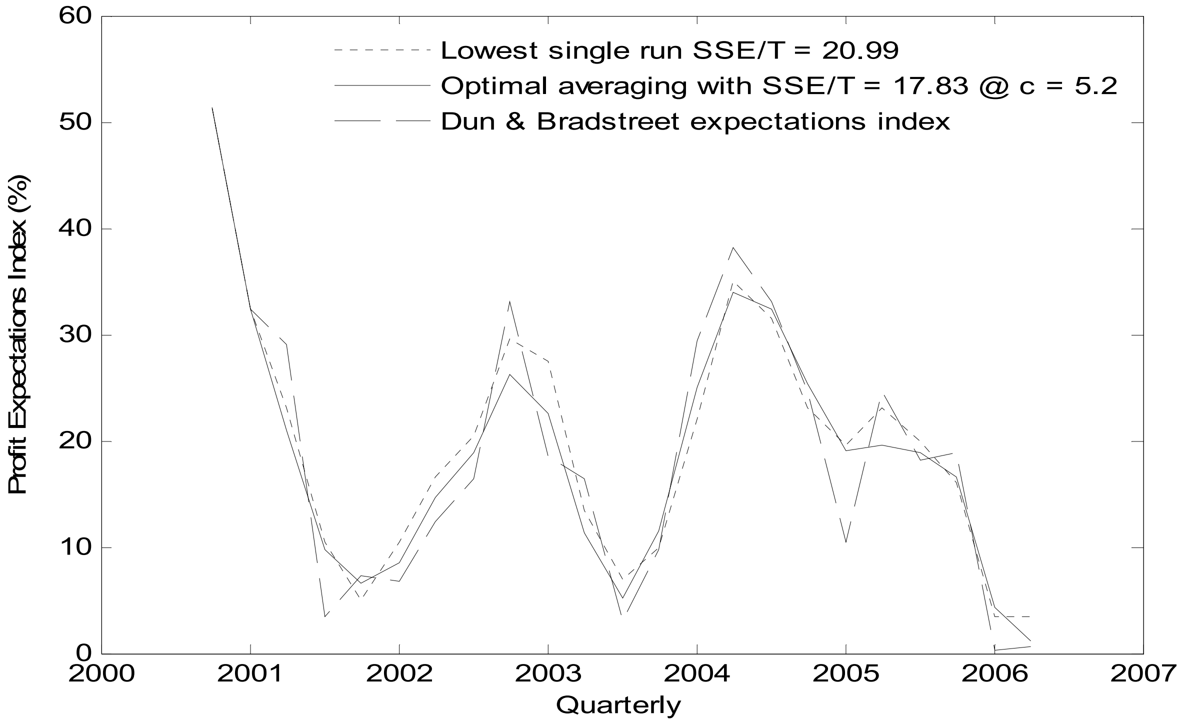
Figure 3–5 Finding the optimal *'runtime-weighted constant' c*



The *'runtime-weighted constant' c* determines the trade-off between simplicity and complexity of the model, usually associated with the low and high goodness of model fit, respectively. A smaller *'runtime-weighted constant' c* provides more complex models with a larger weight. This is easily seen by setting the *'runtime-weighted constant' c* in equation (2-16) to *zero*, in which case both simple and complex models are weighted only according to their model variance, thus favouring complex models.

Figure 3–6 shows the profit expectations index for each quarter of the model-average with the optimal value for the *'runtime-weighted constant'* $c = 5.23$. The model-average is compared against the D&B profit expectations index and the index of the model of the network with the lowest model variance.

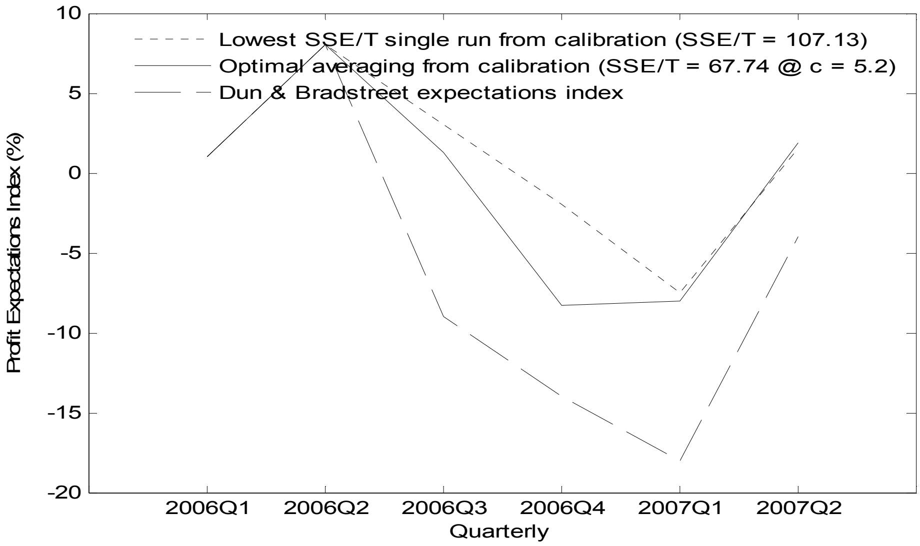
Figure 3–6 Comparing the Calibration of the AIE model against the D&B Index



3.5.1.2 Prediction

Figure 3–7 shows a prediction model variance of 67.74, using the *'runtime-weighted model-average'* for *'runtime-weighted constant' c = 5.2*. The model-average is compared against the D&B profit expectations index and the index of the model of the network with the lowest model variance.

Figure 3–7 Prediction based upon the calibration *'runtime-weighted constant' c* = 5.2



3.5.1.2 Evaluation

Figure 3–8 evaluates the prediction in Figure 3–7, finding that the *'runtime-weighted constant' c = 121.7* gives a lower model variance of 64.49, compared to the prediction model variance of 67.74.

Figure 3–8 Evaluating the prediction using *'runtime-weighted model-averaging'*

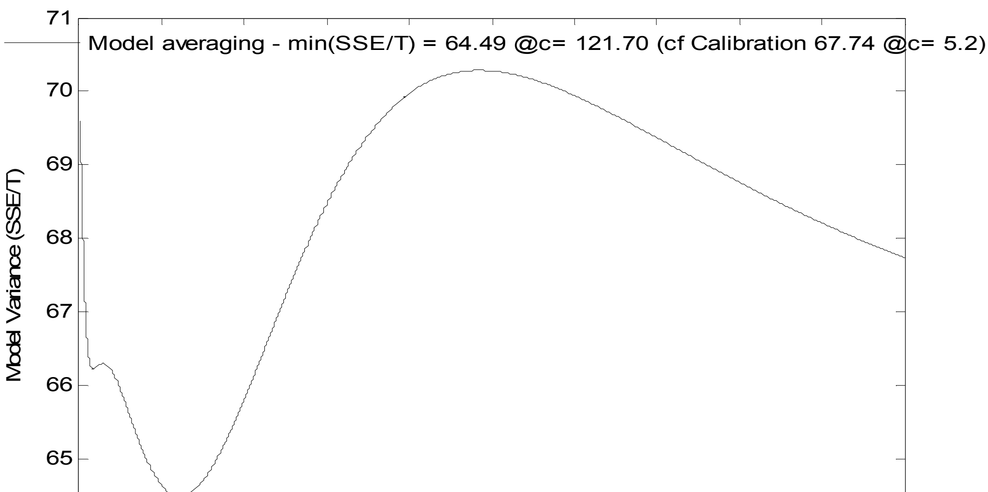


Table 4–1 presents these results.

3.5.2 Optimal-calibration Model-averaging

This section discusses *'optimal-calibration model-averaging'*. Rather than using a formula, *optimal-calibration* simply ranks the 121 network topologies in an ascending order of model variance and selects the number of models to an average that produces the lowest model variance.

The structure of this section is as follows. Section one discusses the calibration process. Section two discusses the prediction. Section three evaluates the prediction.

3.5.2.1 Calibration

The upper dashed line in Figure 3–9 shows the runs arranged in an ascending order of model variance. A model-average is produced from the first two models of networks with the lowest model variance by averaging their profit expectations indices for each quarter. The model-averaging process is repeated for the first three models of networks, first four models of networks, and so on. The lower solid line in Figure 3–9 shows the model variance of the model-average of the respective number of models. The *optimal-calibration* is found by minimising the model variance, shown in the solid line. Figure 3–9 shows that averaging the first 2 runs minimises the model variance at 16.46.

Figure 3–9 Minimising the model variance using *'optimal-calibration'*

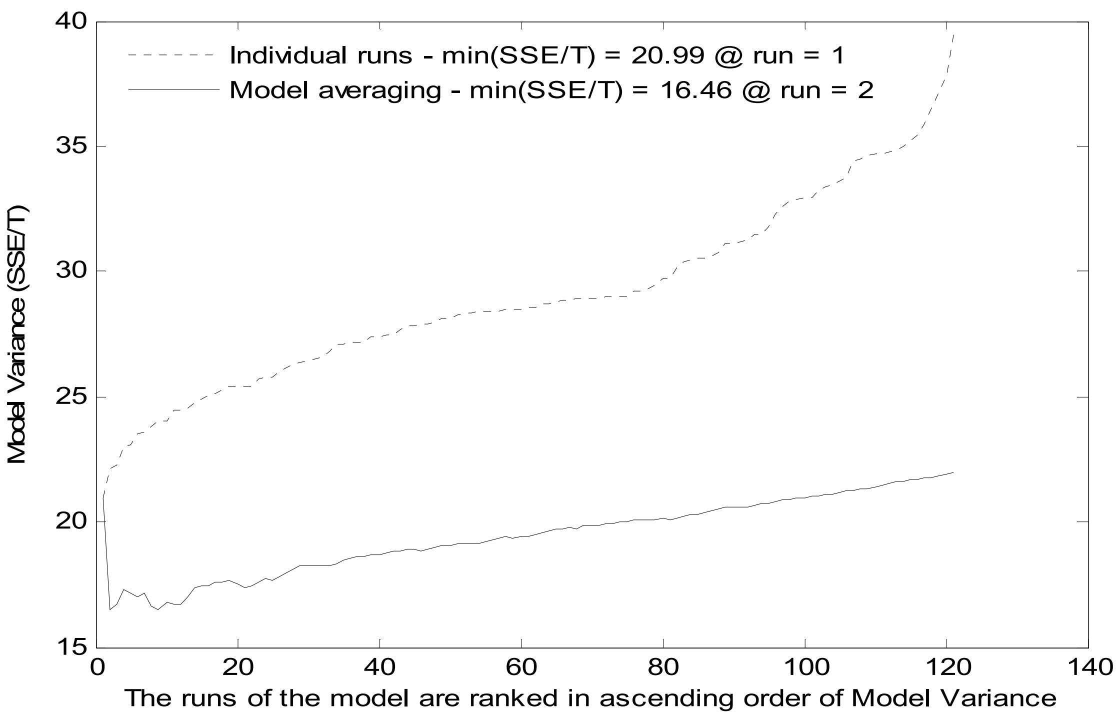
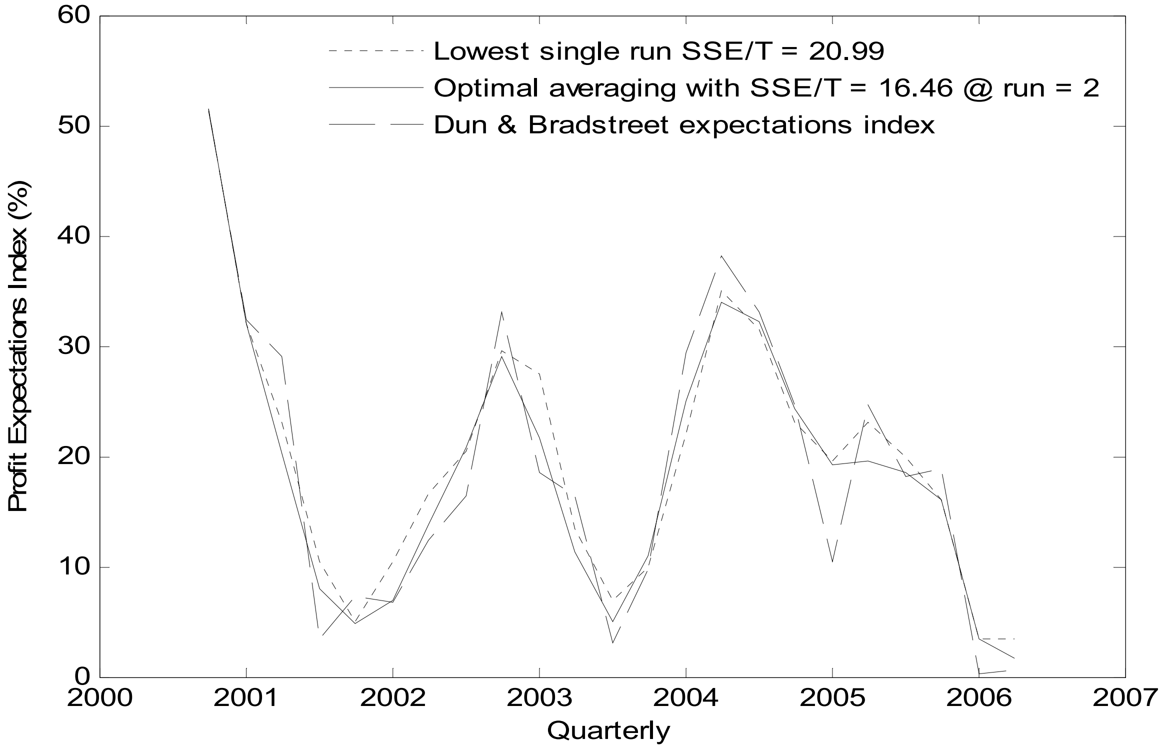


Figure 3–10 shows the profit expectations index for each quarter of the *'optimal-calibration'* model-average with the optimal number of models of networks being two. The model-average is compared against the D&B profit expectations index and the index of the model with the lowest model variance = 20.99.

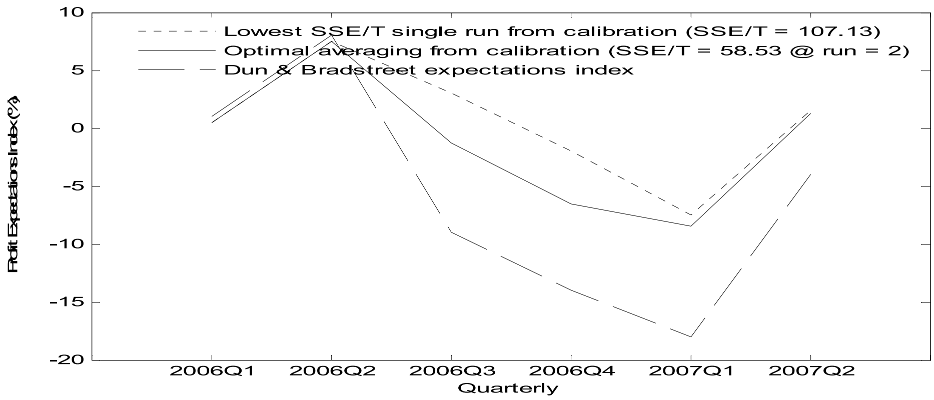
Figure 3–10 Minimising the model variance using *'optimal-calibration'*



3.5.2.2 Prediction

In the forecasting phase, the parameter sets from the runs from the calibration are used to make predictions. The calibration order of the parameter sets is maintained. The dotted line in Figure 3–11 shows the predicted profit expectations index, using the parameters from the single run with the lowest model variance from the calibration phase. The solid line in Figure 3–11 shows the predicted profit expectations index, using the model-average of the first two from the calibration phase. The dashed line in Figure 3–11 shows the D&B profit expectations survey index; the index set being modelled.

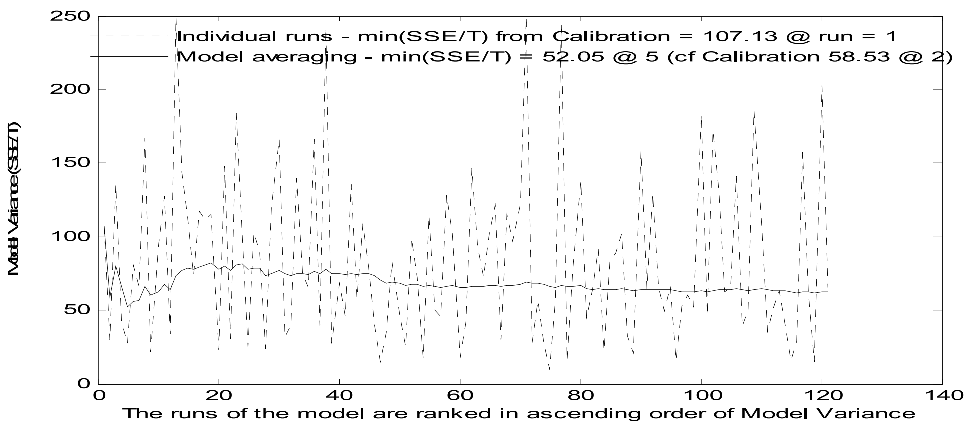
Figure 3–11 Prediction using *'optimal-calibration model-averaging'*



3.5.2.3 Evaluation

Figure 3–12 evaluates the performance of the *'optimal-calibration model-averaging'*. The calibration phase finds that two runs are the optimal number of runs to average, which produces a model variance of 58.53. However, the evaluation finds that five runs are the optimal number of runs to average, which produces a model variance of 52.05.

Figure 3–12 Prediction performance using *'optimal-calibration model-averaging'*



3.5.3 Equal-weighted Model-averaging

'Equal-weighted model-averaging' simple involves averaging each of the models based on the 121 network topologies with equal weight, which makes specialised calibration optimisation techniques unnecessary. *'Equal-weighted model-averaging'* provides a benchmark for the *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'*. Both Figure 3–13 and Figure 3–14 compares *'equal-weighted model-averaging'*, *'Bayes-factor model-averaging'*, the single run with the lowest model variance and the D&B profit expectations index. Table 4–1 presents these results.

Figure 3–13 Calibration Period: Comparing Equal-weighted & Bayes-factor Model-averaging

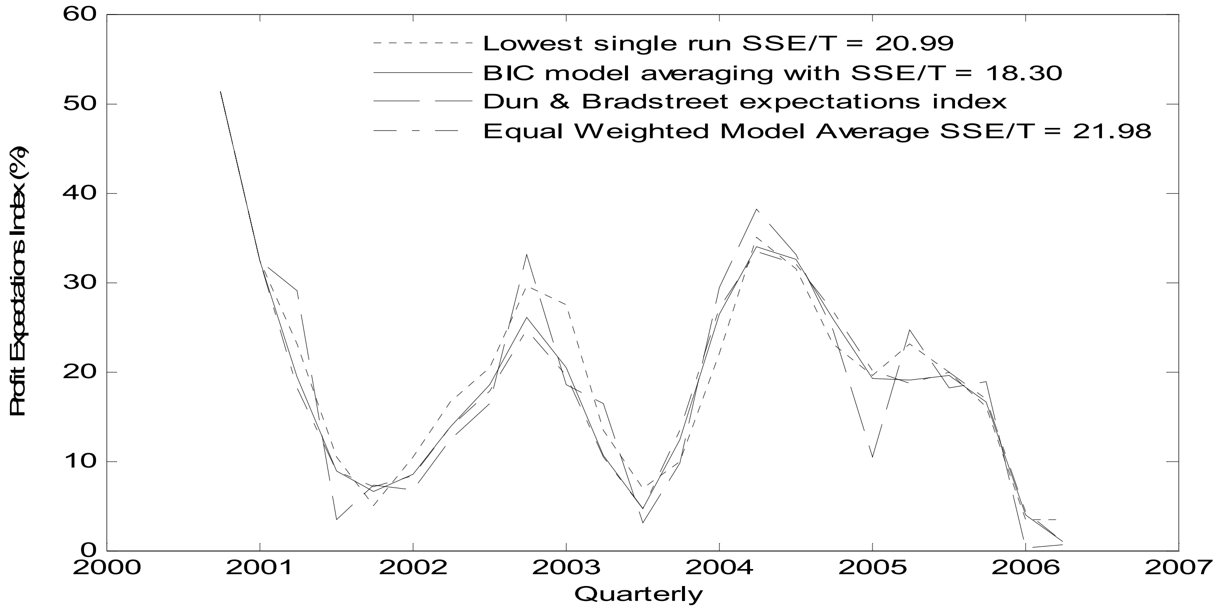
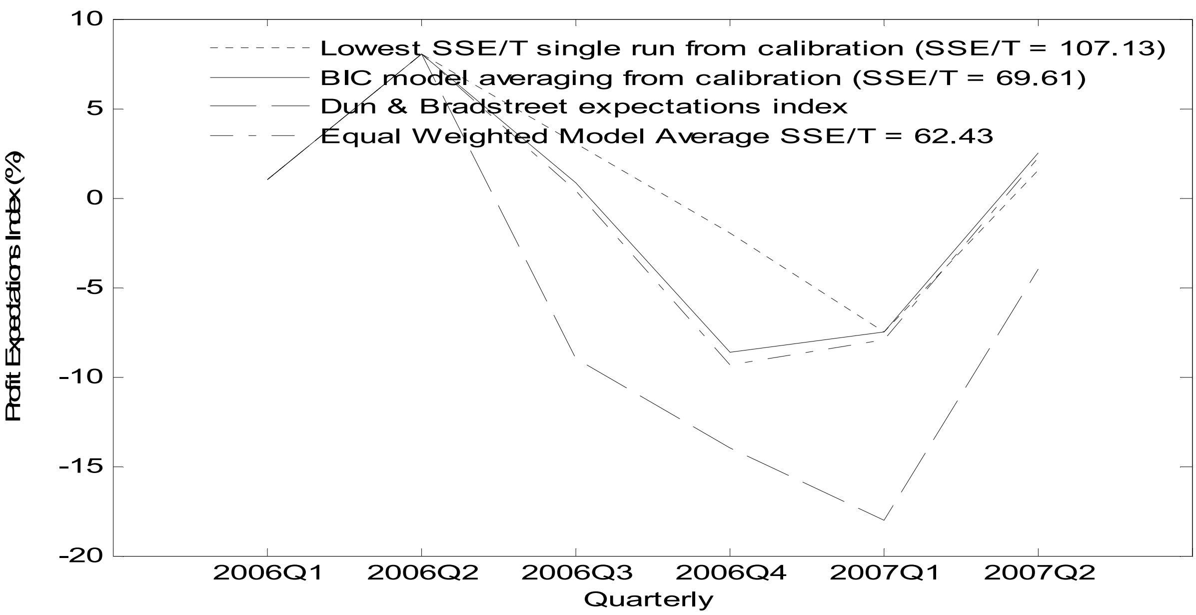


Figure 3–14 Prediction Period: Comparing Equal-weighted & Bayes-factor Model-averaging



3.5.4 Bayes-factor Model-averaging

'Bayes-factor model-averaging' provides a benchmark for the *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'*. Like *'equal-weighted model-averaging', 'Bayes-factor model-averaging*' does not require any specialised calibration optimisation techniques. Equation (3–5) shows the *Bayes-factor* for the AIE model, which is equation (2–15) with the *'runtime-weighted constant' c = 0*.

$$K^* \approx \sigma^{-n} \qquad (3\text{–}5)$$

Where

K = *Bayes-factor*

* denotes that there is no adjustment for complexity

n = sample size

σ^2 = model variance

≈ denotes approximately

Equation (3–6) shows the *Bayes-factor* from equation (2–15), used to form a weight for each model.

$$w_m = \frac{\sigma^{-n}{}_m}{\Sigma^M{}_i\, \sigma^{-n}{}_i} \qquad (3\text{–}6)$$

Where

w_m = weight for each model m

M = the number of models

Figure 3–13 and Figure 3–14 show the calibration and prediction phases, respectively, for the *'Bayes-factor model-averaging'*. Table 4–1 presents the results.

3.6 The disaggregated AIE model

This section discusses the disaggregated AIE model because the introduction of three *'link-intensity matrices'* adds an extra layer of complexity to calculating p^x.

Figure 2–6 shows the D&B *all–firms* profit expectations and actual profit indices used in the aggregated AIE model. Figure 2–7 shows the four divisions of the D&B *all–firms* profit expectations indices, durable manufacturing and non–durable manufacturing, wholesale and retail, used in the disaggregated AIE mode. Sections 2.1.8 and 2.1.9 discuss the *all–firms* and its four divisions, respectively.

Section 3.2 discusses the ingredients of the formal AIE model and the decomposition of the D&B *all–firms* profit indices to provide the states of each firm for the aggregate AIE model. The ingredients and decomposition process for the disaggregate AIE model are essentially the same as for the aggregate AIE model. However, there are 50 firms allocated to each division in the disaggregated AIE model. Section 2.2.2 discusses the network structure for the aggregate AIE model. In the disaggregated model, the firms are arranged, alternating by division around the network in the following order, durable, non–durable, wholesale, retail. This is to represent small supply chains similar to the *'Beer distribution game'*, as discussed in section 2.1.6. The 50 firms in each of the four divisions is chosen for the simplicity of designing the network structure and following Bowden and McDonald's (2008) lead who use 200 firms in their model because they find that their results are similar, whether using 200 or 400 firms and using 200 firms saves considerable computing time. Section 5.6.3 in further research discusses how to improve the network structure, using the number of firms in each division and *'input-output tables'*.

The disaggregate AIE model uses three types of *'link-intensity matrix'*, the *'matrix of ones'*, the *'input-output table'* and the transpose of the *'input-output table'* to investigate which approach provides the best predictive performance, where the *'matrix of ones'* is a default to benchmark the other two *'link-intensity matrix'*. Section 2.1.9.1 discusses the rows of the *'input-output table'* that represent output, which is equivalent to sales. Furthermore, if one assumes that each firm uses the same percentage mark–up for all its customers, output is proportional to the profits. Section 2.1.9.1 discusses and justifies the derivation in more detail and notes that the mark-up between firms can differ. The transpose of the *'input-output table'* investigates what effect that reversing the intensity of profit expectations in the network has on the predictive performance. One would predict that the order of best predictive performance for the *'link-intensity matrix'* from best to least is *'input-output table'*, *'matrix of ones'*, then and the transpose of the *'input-output table'*. The results in Table 4–1 confirm this prediction. This prediction is made because the *'input-output table'* provides an indication of the expected profits, as discussed in section 2.1.9.1. The transpose of the *'input-output table'* is expected to provide a worse indication of expected profits than the *'matrix of ones'*.

Equation (3–7) shows the calculation of p^x for the disaggregated AIE model, based upon equation (3–3) for the aggregated AIE model. Note that the parameters are common for all four divisions because using four set of parameters, one for each division, would have made it too difficult to minimise the model variance. The optimism, pessimism and ambivalence biases and adaptive influence all function in the same way as in the aggregate AIE model. However, the *'link-intensity matrix'* $io_{d,c}$ does affect the interactive influence because the link calculation is no longer a simple count of the links to firms of differing expectations states. Instead, each of these links is now weighted with an element from $io_{d,c}$, row d column c, signifying the flow of profit expectations from firms in division c to firms in division d. For instance, the link-intensity on firm i in division d at time t from other firms who expect profits to increase is $L^+_{i,d,t} = \Sigma_c \, n^+_{i,d,c} \, io_{d,c}$ where $n^+_{i,d,c}$ is the number of links to firm i in division d from firms in division c who expect profits to increase. Note that $L = L^+ + L^0 + L^-$, thus I is always multiplied by factor less than or equal to unity.

Additionally, the use of the *'input-output tables'* in this thesis is unconventional because the tables are applied to individual firms, rather than divisions. Firms within the same division can supply one another, which implies that d can equal c in matrix $io_{d,c}$. This treatment of the diagonals in matrix $io_{d,c}$ contrasts with the traditional input-output analysis, where the diagonals are sometimes ignored.

Equation (3–7) – Pressure to change profit expectations index

(a) For firm i who currently expects profits to decrease ($e_{i,d,t} = -1$)

The pressure to increase expectations

$$p^x_{i,d,t} = \beta^+ + \beta^0 + A\,[\,a_{i,d,t} - e_{i,d,t}\,] + A_{-1}\,[\,a_{i,d,t-1} - e_{i,d,t-1}\,] + I\,[\,(L_{i,d,t}^+ + L_{i,d,t}^0)\,/\,L\,]^\wedge\delta$$

(b) For firm i who currently expects no change in profits ($e_{i,d,t} = 0$)

positive pressure to increase expectations and

negative pressure to decrease expectations

$$p^x_{i,d,t} = \beta^+ - \beta^- + A\,[\,a_{i,d,t} - e_{i,d,t}\,] + A_{-1}\,[\,a_{i,d,t-1} - e_{i,d,t-1}\,]$$
$$+ I\,[(\,L_{i,d,t}^+ / L\,)^\wedge\delta - (\,L_{i,d,t}^- / L\,)^\wedge\delta]$$

(c) For firm *i* who currently expects profits to increase ($e_{i,d,t} = 1$)

The pressure to decrease expectations

$$p^{x}_{i,d,t} = \beta^{-} + \beta^{0} + A\,[\,e_{i,d,t} - a_{i,d,t}\,] + A_{-1}\,[\,e_{i,d,t-1} - a_{i,d,t-1}\,] + I\,[\,(L_{i,d,t}^{-} + L_{i,d,t}^{0}) / L\,]^\wedge\delta$$

Where

$p^{x}_{i,d,t}$ = pressure to change profit expectations index for firm *i* in division *d* time *t*

$p^{x}_{i,d,t} \in [-100, 100]$

β^{+} = basic tendency to increase expectations

β^{0} = basic tendency to neutral expectations

β^{-} = basic tendency to decrease expectations

A = adaptive influence this quarter

A_{-1} = adaptive influence last quarter

$a_{i,d,t}$ = profit actualisation of firm *i* of divisions *d* at time *t*

where a decrease, no change or increase is –1, 0 or 1, respectively

$e_{i,d,t}$ = profit expectations of firm *i* of divisions *d* at time *t*

where a decrease, no change or increase is –1, 0 or 1, respectively

I = interactive influence

$L = L^{+} + L^{0} + L^{-}$ Total interactive intensity via links to other firms

$L^{+}_{i,d,t} = \Sigma_c\, n^{+}_{i,d,c}\, io_{d,c}$ where c = (durable, non–durable, wholesale, retail)

$L^{+}_{i,d,t}$ = The interactive pressure on firm *i* in division *d* to increase its expectations from other firms in division *c* who expect profits to increase (e = 1)

$n^{+}_{i,d,c}$ = the number firms in division *c* who are linked to firm *i* in division *d* and expect profits to increase

$io_{d,c}$ = an element from the input-output table, row *d* column *c* in Table 2–4, signifying the flow of profit expectations from firms in division *c* to firms in division *d*

$L^{0}_{i,d,t} = \Sigma_c\, n^{0}_{i,d,c}\, io_{d,c}$

$n^{0}_{i,d,c}$ = the number firms in division *c* who are linked to firm *i* in division *d* and expect *no–change* in profits

$L^{-}_{i,d,t} = \Sigma_c\, n^{-}_{i,d,c}\, io_{d,c}$

$n^{-}_{i,d,c}$ = the number firms in division *c* who are linked to firm *i* in division *d* and expect profits to decrease

δ = interactive power (1.0, 1.2, 1.4, …, 3.0)

Section 2.2.3 discusses using multiple levels of emergence to evaluate *Agent-based Models* (ABM). This would require minimising the model covariance for the four divisions in the disaggregated AIE model. However, to ease comparison among the results from the various aggregate and disaggregated AIE models, it was decided to minimise the model variance of the *all–firms* level in all cases. See Table 4–1. Section 5.6.6 in further research further discusses the covariance search and emergence at multiple levels.

3.7 Rational Expectations Hypothesis Made Operational

Section 2.1.2 discusses REH in detail. This section discusses REH because it provides a benchmark for AIE and needs to be made operational. Sargent (2008, p. 1) asserts in rational expectations that outcomes do not differ systematically (i.e., regularly or predictably) from what people expect them to be. To make this assertion operational and provide a benchmark for AIE requires finding the model variance for REH, which is simply calculated as the SSE/T between the D&B actual profit index and the profit expectations index.

3.8 Research Questions Refined and Made Operational

This section uses the information from the methodology to refined and make operational the research problem and questions from the literature review in chapter 2. They are listed for review. The research problem is.

> ***Can a dynamic subjective expectations model be used to make more accurate temporal predictions than the REH and the adaptive-expectations models?***

Pertinent issues arising from the research problem are whether the subjective model, the AIE model, is an improvement on existing objective models and what techniques can improve the predictive performance of the AIE model. The research problem is addressed via seven more specific research questions.

1. Do the profit expectations undergo a significant structural change or phase shift during the quarter ending March 2000?

This question determines whether calibrate the model with all data series available or just use the data after the March 2000 quarter. The issue over whether the March 2000 quarter signifies a structural change in profit expectations or a phase shift is left for further research; see section 5.6.7. The method involves using prediction to test for a significant structural change or phase shift in profit expectations. This requires calibrating the AIE model over a long and a short period and using their respective predictions over the same prediction period to test this research question. The long calibration period is June 1988 to December 2006 and the short calibration period is March 2000 to December 2006. The prediction period for both is March 2006 to June 2007.

2. Does 'optimal-calibration model-averaging' improve predictive performance over 'equal-weighted model-averaging' and 'Bayes-factor model-averaging' for the AIE model?

To improve predictive performance and overcome the complexity ranking problem AIE uses model-averaging across 121 network topologies that are structurally different hence models in own right. This thesis introduces *'optimal-calibration model-averaging'* and uses *'equal-weighted model-averaging'* and *'Bayes-factor model-averaging'* as benchmarks. The model-averaging technique is applied to all versions of the AIE model and the enhancement to predictive power is discussed.

3. Does 'runtime-weighted model-averaging' improve predictive performance over 'equal-weighted model-averaging' and 'Bayes-factor model-averaging' for the AIE model?

This thesis introduces *'runtime-weighted model-averaging'* and uses *'equal-weighted model-averaging'* and *'Bayes-factor model-averaging'* as benchmarks. The model-averaging technique is applied to all versions of the AIE model and the enhancement to predictive power is discussed.

4. Does the interactive-expectations network improve the predictive power of the AIE model?

This question tests whether the subjective part of the AIE model, that is, the interactive network improves the predictive power of the model. To answer this question the AIE model is benchmarked against the adaptive-expectations model, that is the AIE model with the interactive component set to zero; the interactive intensity $I = 0$, interactive power $\delta = 0$, the probability rewired $\rho = 0$ and number of links $L = 1$ to prevent a divide by zero error. The comparison is performed for the aggregated and disaggregated versions of the AIE model.

5. Does the subjective approach of the aggregated AIE model improve predictive performance over the objective approach of REH?

To answer this question the AIE model is benchmarked against REH.

6. Does introducing an input-output table link-intensity matrix improve the predictive performance of the disaggregated AIE model?

The *'link-intensity matrix'* introduced in section 2.1.9.1 is based upon an *'input-output table'* to provide a way to weight the intensity of the interactive links between the firms. The disaggregated AIE model comes in three forms dependent on the *'link-intensity matrix'* used, the *'input-output table'* in Table 2–4, its transpose and a *'matrix of ones'*. The *'input-output table'* and its transpose are compared against the *'matrix of ones'*, using calibration and prediction. The prediction made is that the predictive performance of the three models ranked from best to worst is *'input-output table'* , *'matrix of one'*, and the transpose.

7. Does disaggregating the AIE model improve predictive performance?

The version of the interactive link matrix disaggregated AIE model with the best predictive performance is compared with the aggregated AIE model. This requires calibrating the aggregated and disaggregated AIE models over the period March 2000 to December 2005 and predicting over the period March 2006 to June 2007 to compare their predictions.

3.9 Conclusion

This chapter has detailed and justified the methodology to address the research questions developed in chapter 2. These questions are refined to reflect their context within the methodology in this chapter. Chapter 4 discusses the results presented in Table 4–1 to answer the research questions.

4. Results

4.0 Introduction

This chapter analyses the results from the AIE model to answer the research questions listed in section 3.8. Chapter 5 discusses the findings of this chapter within the context of the literature. Hence this chapter refrains from discussing the literature to provide an uncluttered presentation of the results.

4.1 Research Questions

This section consists of seven subsections that correspond to a research question of the same number. Table 4–1 shows the results from running the AIE model. Portions of Table 4–1 are analysed under each of the research questions.

Table 4–1 shows the model variance of the various AIE models and their benchmarks. The table shows three phases, the calibration, prediction and evaluation. The calibration phase for the *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'* require some form of optimisation to produce an optimal *'runtime-weighted constant' c* value or *'number of runs'*, respectively. These optimal values are used in the prediction phase. The evaluation phase tests the efficacy of the model-averaging technique. The evaluation phase compares the prediction model variance, using the optimal values found in the calibration phase with optimising the model within the prediction period.

The two major divisions of the AIE models are aggregated and disaggregated. All the models in the Table 4–1 use the short calibration period, except for the aggregated version of the AIE model labelled 'long calibration'. This 'long calibration' period result is compared with the 'short calibration' period results to answer research question one.

The adaptive-expectations model forms a benchmark for the AIE model and also has both an aggregated and disaggregated version. The adaptive-expectations model is the AIE model with the interactive-expectations component set to zero. REH provides another benchmark for the AIE model, where a single REH benchmark provides for both aggregated and disaggregated versions. The disaggregated AIE model uses a *'link-intensity matrix'* that represents the intensity of interactions among firms of differing divisions. There are three types of *'link-intensity matrix'*, based on an *'input-output table'*, its transpose, and a *'matrix of ones'* that represents the default.

Table 4–1 The results of the AIE simulation for the aggregated and disaggregated versions

Version of AIE Model			Model-averaging Method	Calibration		Prediction	Evaluation	
				SSE/T	Runs or c	*SSE/T*	*SSE/T*	Runs or c
Aggregated	Long Calibration		Optimal-calibration	37	6 runs	248	190	1 run
			Runtime-weighted	37	0	229	208	c = 2.04
			Bayes-factor	37		229		
			Equal-weighted	41		252		
			Single run	42		190		
	Short Calibration		Optimal-calibration	17	9 runs	67	49	17 runs
			Runtime-weighted	18	c = 0	67	66	c = 2.01
			Bayes-factor	18		67		
			Equal-weighted	21		62		
			Single run	19		78		
	Adaptive-expectations		Optimal-calibration	30	8 runs	114	87	29
			Runtime-weighted	32	c = 6.4	99	98	c = 0
			Bayes-factor	32		98		
			Equal-weighted	41		102		
			Single run	32		93		
Disaggregated	Link-intensity Matrix	Input-Output	Optimal-calibration	16	2 runs	59	52	5 runs
			Runtime-weighted	18	c = 5.2	68	65	c = 122
			Bayes-factor	18		70		
			Equal-weighted	22		62		
			Single run	21		107		
		Transpose	Optimal-calibration	17	5 runs	80	65	46 runs
			Runtime-weighted	18	c = 0	79	60	18
			Bayes-factor	18		79		
			Equal-weighted	22		68		
			Single run	20		83		
		Matrix of ones	Optimal-calibration	17	7 runs	54	36	2 runs
			Runtime-weighted	17	c = 7.02	72	62	c = 0
			Bayes-factor	18		62		
			Equal-weighted	21		65		
			Single run	19		96		
	Adaptive-expectations		Optimal-calibration	27	8 runs	99	96	2 runs
			Runtime-weighted	28	c = 0	103	103	c = 0
			Bayes-factor	28		103		
			Equal-weighted	28		101		
			Single run	30		126		
REH			Short period	201		93		
			Long period	326		93		

4.1.1 Do the profit expectations undergo a significant structural change or phase shift during the quarter ending March 2000?

This question compares the predictive performance of the aggregated AIE model calibrated over a short and a long period. Table 4–1 shows that the model variances for prediction, calibrated over the short period, is about a third of that calibrated over the long period. This shows that profit expectations have undergone a significant structural change or phase shift during the quarter ending March 2000. The cause of change in profit expectations during the March 200 quarter cannot be ascertain from the results, whether it is due to structural change or a phase shift. Because calibrating over the short period provides much better predictive performance, the remaining questions only address models calibrated over the short period, unless otherwise noted. Sections 5.6.5 and 5.6.7, in further research, further discuss the structural change and phase shift issue, in particular, calibrating AIE in the pre March 2000 period to compare with a post March 2000 calibration.

4.1.2 Does 'optimal-calibration model-averaging' improve predictive performance over 'equal-weighted model-averaging' and 'Bayes-factor model-averaging' for the AIE model?

This question compares the model variance of the predictions of the *'optimal-calibration model-averaging'* against two benchmarks, *'Bayes-factor model-averaging'* and *'equal-weighted model-averaging'*. Table 4–2 provides the information from Table 4–1 in a form that more readily addresses this question.

Table 4–2 Comparing the model variance of the prediction of model-averaging techniques

<table>
<tr><th colspan="2" rowspan="4">Model Variance
(*SSE/T*)</th><th colspan="7">Version of AIE model</th></tr>
<tr><th colspan="3">Aggregated</th><th colspan="4">Disaggregated</th></tr>
<tr><th rowspan="2">Long Calibration</th><th rowspan="2">Short Calibration</th><th rowspan="2">Adaptive-expectations</th><th colspan="3">Link-intensity</th><th rowspan="2">Adaptive-expectations</th></tr>
<tr><th>Input-Output</th><th>Transpose</th><th>Matrix of Ones</th></tr>
<tr><td rowspan="4">Model-averaging Techniques</td><td>Optimal-calibration</td><td>248</td><td>67</td><td>114</td><td>59</td><td>80</td><td>54</td><td>99</td></tr>
<tr><td>Runtime-weighted</td><td>229</td><td>67</td><td>99</td><td>68</td><td>79</td><td>72</td><td>103</td></tr>
<tr><td>Bayes-factor</td><td>229</td><td>67</td><td>98</td><td>70</td><td>79</td><td>62</td><td>103</td></tr>
<tr><td>Equal-weighted</td><td>252</td><td>62</td><td>102</td><td>62</td><td>68</td><td>65</td><td>101</td></tr>
</table>

Table 4–2 shows that the model variance of the *'optimal-calibration model-averaging'* is less than the ***'Bayes-factor model-averaging'*** for the disaggregated AIE versions with a *'matrix of ones'* and *'input-output table'* and to a lesser extent the disaggregated adaptive-expectations model.

Additionally, the model variance of the *'optimal-calibration model-averaging'* is less than the ***'equal-weighted model-averaging'*** for the disaggregated AIE versions with a *'matrix of ones'* and *'input-output table'* and to a lesser extent the following two adaptive-expectations versions, aggregated with a long calibration and disaggregated with short calibration.

Conclusion

'Optimal-calibration' provides better predictive performance than '*equal-weighted' or 'Bayes-factor model-averaging'* for the disaggregated AIE versions with a *'matrix of ones'* and *'input-output table'*. Noting that, these two AIE versions provide the best predictions, which indicates that, the *'optimal-calibration'* technique is more usefully applied to models that have a history of good predictive performance, which require recalibrating, rather than use the technique on unproven or newly developed models.

4.1.3 Does 'runtime-weighted model-averaging' improve predictive performance over 'equal-weighted model-averaging' and 'Bayes-factor model-averaging' for the AIE model?

This question compares the predictive performance of the *'runtime-weighted model-averaging'* against two benchmarks, '*Bayes-factor model-averaging'* and *'equal-weighted model-averaging'*. Note that the *'Bayes-factor model-averaging'* is the *'runtime-weighted model-averaging'* less the runtime-weighted component. Table 4–2 shows that variance of the *'runtime-weighted model-averaging'* is less than the *'Bayes-factor model-averaging'* for the AIE version with an *'input-output table'* only and by a margin of 2 only. Additionally, the model variance of the *'runtime-weighted model-averaging'* is less than the *'equal-weighted model-averaging'* for the long calibration AIE version and aggregated adaptive-expectations model only. Noting that, these two models are the worst and second or third worst predicting models.

Conclusion

Except for the AIE version with an *'input-output table'*, the *'runtime-weighted model-averaging'* fails to improve the prediction performance over the *'Bayes-factor model-averaging'* and makes the prediction performance worse for the AIE version with a *'matrix of ones'* and the aggregated adaptive-expectations model.

4.1.4 Does the interactive-expectations network improve the predictive power of the AIE model?

This question benchmarks the AIE model against the adaptive-expectations model that is the AIE model less the interactive network. Table 4–1 shows that the model variance for all AIE versions for both calibration and prediction phases is less than that for all adaptive-expectations models. Section 5.6.11, in further research, discusses using the random seed function in NetLogo to improve the adaptive-expectations model as benchmark.

Note that a slightly lower model variance for the aggregated adaptive-expectations model was found by setting the network topology to values other than $L = 1$ and $\rho = 0$, as stipulated in the methodology. Since $I = 0$, these alternate network topology settings only indirectly affect the model variance calculations because the random functions in the model are affected by using different parameters. Table 4–1 shows these lower model variances to provide a tougher benchmark for the AIE model.

Conclusion

The interactive network improves predictive performance.

4.1.5 Does the subjective approach of the aggregated AIE model improve predictive performance over the objective approach of REH?

This question benchmarks the AIE against REH. Table 4–1 shows that the model variances for both calibration and prediction of all AIE versions are lower than the model variances of REH, except for the prediction of the aggregated AIE model calibrated over the long period, which was rejected in research question one. An interesting point is that the predictive performance of REH is better than the adaptive-expectations models.

Conclusion

The AIE model provides better predictive performance than REH that in turn provides better predictive performance than the adaptive-expectations model.

4.1.6 Does introducing an input-output table link-intensity matrix improve the predictive performance of the disaggregated AIE model?

This question compares the predictive performance of introducing the *'link-intensity matrix'* into the disaggregated AIE model, based on an *'input-output table'* and its transpose against the benchmark a *'matrix of ones'*. Table 4–2 clearly shows that the predictive performance of the transpose *'link-intensity matrix'* is less than that of the *'matrix of ones'*. However, it is difficult to decide which *'link-intensity matrix'* has the better predictive performance between the *'input-output table'* and *'matrix of ones'*.

Conclusion

There is an ambiguous effect on prediction performance from introducing the *'input-output table'*. However, there is a clear reduction in predictive performance from introducing the transpose.

4.1.7 Does disaggregating the AIE model improve predictive performance?

This question compares the predictive performance of the aggregated and disaggregated AIE versions. Table 4–2 clearly shows that the disaggregate AIE version with a transposed *'input-output table'* is unsuitable. However, Table 4–2 shows also the disaggregated AIE versions with an *'input-output table'* and *'matrix of ones'* provide better predictive performance than the aggregated AIE version for '*optimal-calibration model-averaging'*. *'Runtime-weighted model-averaging'* is exclude form discussion because it has proven ineffective. However, the *'Bayes-factor model-averaging'* and *'equal-weighted model-averaging'* results are ambiguous, that the disaggregated AIE version combines data from both *'input-output tables'* and the D&B (2008) expectations survey, which introduces more error into the disaggregated model and makes uncertain whether the ambiguous results are due to a poor model fit or compounding error.

Conclusion

The results are ambiguous but *'optimal-calibration'* favours the predictive power of the disaggregated version over the aggregated version, which suggests that alternative ways to model disaggregated AIE be tried. Section 5.6.3, in further research, discusses an alternative way to develop the *'link-intensity matrix'*.

4.2 Conclusion

This chapter analyses the results from running the AIE model to address the research questions without reference to the literature, where Chapter 5 relates the findings to the literature.

5. Conclusion and Implications

5.0 Introduction

This chapter links the results from chapter 4 to the literature in chapter 2 by discussing the links in the following three contexts, theoretical and policy implications, the limitations of *Adaptive Interactive Expectations* (AIE) and further research ensuing from the research in the thesis.

The chapter discusses the theoretical implications of the results as a comparison between the dynamic scientific realism of the *'science of complexity'* and static instrumentalism of neoclassical economics. The chapter compares differing views on government intervention and how Agent-based Modelling (ABM) can complement the mathematical and the narrative methodologies to inform the debate, where a complementary approach for AIE and *Rational Expectations Hypothesis* (REH) in a descriptive/predictive and in a normative role, respectively, for policy is also discussed. Furthermore, AIE has practical implications for economic practitioners who are reluctant to supplement their analysis with *Agent-based Models* (ABM). Finally, comments are made on how the AIE network could be improved and adapted for use in *Computable General Equilibrium* (CGE) and *Dynamic Stochastic General Equilibrium* (DSGE) models to overcome their unrealistic transmission mechanism.

The structure of the chapter is as follows. Section 5.1 relates the research questions to the literature. Section 5.2 discusses the research problem or overarching research question. Section 5.3 discusses the implications for theory. Section 5.4 discusses the implications for policy and practice. Section 5.5 discusses the limitations of AIE. Section 5.6 discusses further research.

5.1 Conclusions about each research question

This section connects the conclusion about each research question found in chapter 4 with the literature because chapter 4 refrains from making references to the literature to unambiguously present the results. The questions as section headings are repeated for easy reference.

5.1.1 Do the profit expectations undergo a significant structural change or phase shift during the quarter ending March 2000?

Section 4.1 shows that the profit expectations undergo a significant structural change or phase shift during the quarter. This observation fails to falsify Flieth and Foster's (2002) adaptive expectations model, which adds to its verisimilitude. Section 5.6.7, in further research, further discusses identifying structural and phase change.

5.1.2 Does 'optimal-calibration model-averaging' improve predictive performance over 'equal-weighted model-averaging' and 'Bayes-factor model-averaging' for the AIE model?

The *'optimal-calibration model-averaging'* does improve the predictive performance over *'Bayes-factor model-averaging'* and *'equal-weighted model-averaging'* for the better predicting AIE models. This makes *'optimal-calibration'* useful for recalibrating models with a proven track record of good predictive performance, rather than using *'optimal-calibration'* on unproven model.

5.1.3 Does 'runtime-weighted model-averaging' improve predictive performance over 'equal-weighted model-averaging' and 'Bayes-factor model-averaging' for the AIE model?

This technique proved ineffective for all but the disaggregated AIE with the *'input-output table' 'link-intensity matrix'*. Section 5.6.8, in further research, further discusses the technique.

5.1.4 Does the interactive-expectations network improve the predictive power of the AIE model?

The interactive-expectations network does improve the predictive power of all versions of the AIE model over the adaptive-expectations models. Flieth and Foster's (2002) interactive-expectations model lacks temporal prediction, but the improvement in predictive power is consistent with their modelling of endogenous shifts in expectations.

5.1.5 Does the subjective approach of the aggregated AIE model improve predictive performance over the objective approach of REH?

The subjective approach of the AIE model improves predictive performance over REH. The AIE model developed within the *'science of complexity'* framework provides better predictive performance than REH developed within the neoclassical framework. Thus the results favour the *'science of complexity'* over the neoclassical framework.

An interesting point is that REH has better predictive performance than the adaptive-expectations model. It was Muth's dissatisfaction with the adaptive-expectations model that spurred the development of REH. For comparison, Figure 2–2 shows adaptive-expectations at the origin with agents of low intelligence and low interactiveness. Muth's solution was to increase the intelligence of the agents. The AIE solution is to increase the interactiveness of agents. The results favour the focus on interaction rather than intelligence, which is consistent with Ormerod et al. (2007, pp. 208-9) who call to focus on the structure of interaction discussed in section 2.2.2.

5.1.6 Does introducing an input-output-table link-intensity matrix improve the predictive performance of the disaggregated AIE model?

It is difficult to determine, if there is any predictive performance improvement from introducing the *'input-output table'* as a *'link-intensity matrix'*, compared to the benchmark, the *'matrix of ones'*. However, the predictive performance of the transpose of the *'input-output table'* is clearly worse than the *'matrix of ones'*. This last result indicates that pursuing the link-intensity concept further may be advantageous. Section 5.6.3 in further research discusses an alternative way to use *'input-output tables'* to calibrate the *'link-intensity matrix'*.

5.1.7 Does disaggregating the AIE model improve predictive performance?

The results slightly favour a disaggregated approach. Improving the *'link-intensity matrix'* would improve the predictive performance of the disaggregate AIE models over the aggregated AIE model, see section 5.6.3. Another consideration is the levels of patterns in the emergence in disaggregated models as discussed by Grimm et al. (2005) in section 2.2.3. Section 5.6.6 in further research discusses Grimm et al. (2005) and using a covariance search. .

5.2 Conclusions about the research problem

The overarching research question or research problem of this thesis is.

> ***Can a dynamic subjective expectations model be used to make more accurate temporal predictions than the REH and the adaptive-expectations models?***

The findings show that a subjective expectations model such as AIE can make falsifiable temporal predictions and outperform objective models such as REH and the adaptive-expectations model. The other advantage of AIE over REH is that it is founded upon empirically verified behavioural research. Muth introduced REH prior to much of the behavioural research that contradicts his simplifying assumptions of the homogenous rational agent with perfect knowledge and unlimited computing power. Section 5.3 further compares the realistic assumptions of AIE with the unrealistic assumptions of REH.

5.3 Implications for theory

This section discusses the implications for theory. The thesis is an experiment comparing AIE with REH, but more importantly the experiment allows a comparison between the neoclassical and *'science of complexity'* frameworks.

The results of the thesis show that AIE provides better predictive performance and describes reality far more accurately. Additionally, it was found that REH assumptions relegate its applicability to an extremely narrow domain but despite this, REH may retain a useful function as a normative or heuristic theory used with the caution that the assumptions of the neoclassical framework and of REH are logically inconsistent, see section 2.1.4.5. Section 5.4 discusses REH and AIE taking on complementary roles where REH takes on a normative role while AIE takes on a descriptive/predictive role.

In the bigger picture, the comparison between AIE and REH is also a comparison between the complexity and neoclassical frameworks, respectively. The predictive performance of a theory is more important than the ability of a theory to describe reality in the view of neoclassical economics whose underlying philosophy is instrumentalism, where ideas are instruments and realism is unnecessary and the only measure of the success of an idea is its ability to predict. Therefore from a neoclassical perspective the ideas and assumptions in the complexity framework are more valuable than those in the neoclassical framework because AIE makes more accurate predictions than REH.

Furthermore, Friedman (1953, p. 15), a major proponent of instrumentalism, states that assumptions only need to be judged by their ability to provide sufficiently accurate predictions, not whether the assumptions are realistic. However, Musgrave (1981) discusses the flaws in instrumentalism, when he notes three types of assumption, negligibility, domain and heuristic. Musgrave (1981) discusses Friedman's example of assuming no air resistance when he applies Newton's Universal Law of Gravity in the earth's atmosphere, which is a negligibility assumption when applied within the domain of objects of high mass and low air resistance, but outside this domain the theory of gravity fails to provide an adequate model for, by way of example, the terminal velocity of a skydiver. Musgrave (1981) notes that Friedman and neoclassical economics fail to acknowledge or to clearly specify their domain assumptions and when operating outside of this domain theory may well be misleading or incorrect. Colander (2000, p. 3) equates neoclassical economics '*to the celestial mechanics of a nonexistent universe*' for using theory outside its domain assumptions. The gap between the real economy and the domain assumptions of neoclassical economics makes it inappropriate for policy development unless used with great caution, see section 5.3.2.

Friedman (1953, p. 14) continues his advocacy of instrumentalism *'Truly important and significant hypotheses will be found to have "assumptions" that are wildly inaccurate descriptive representations of reality, and, in general, the more significant the theory, the more unrealistic the assumptions (in this sense)'*. Musgrave (1981) notes that this approach may be suitable for heuristic assumptions, for example he cites Newton's solar system consisting of just the sun and the earth, an unrealistic assumption, but the model made reasonably accurate predictions and introducing more realistic assumptions lead to an increase in predictive performance, which eventually lead to the many bodies' problem and Poincare's solution, with this inturn ushering in chaos theory and complexity theory. Keen (2001, p. 153) summarises, in contradiction to Friedman (1953, p. 14), that abandoning the factually false heuristic assumptions normally leads to better theory – not worse theory. The parallel in neoclassical economics is its three underlying assumptions discussed in section 2.1.1.1, methodological instrumentalism, methodological individualism, and methodological equilibration. Abandoning these three unrealistic assumptions for more realistic ones includes. First, agents are rule following. Second, agents interact directly not just via uniformly known market prices. Third, assume the economy is dynamic. These realistic assumptions describe the *'science of complexity'* framework and AIE, which describes and predicts more accurately than REH.

Section 2.1.4.5(5) discusses the need for neoclassical economists to focus on the variables more easily modelled, given the mathematical techniques and computing power available in the 1950s. Additionally, Musgrave (1981) notes Newton simplifying the many body problem with a two body problem as a heuristic assumption to allow calculation. All the neoclassical assumptions can be seen in this light, which allows simple, mostly linear, theory to approximate the economy that is in fact a complex system. For instance, Keen (2001, pp. 175-6) quotes Jevons (1911), Clark (1898), Marshall (1920, p. xiv) and Keynes (1923) who recognise the economy as a dynamic process that is better modelled dynamically but static analysis provides a stop–gap measure until adequate technical ability arrives to model the economy dynamically.

The static and dynamic divide between REH and AIE and between neoclassical and complexity economics is an important dimension to discuss for two reasons. First, there is a need to reconcile the inconsistency between the SMD Theorem and Smith's experimental economics. Second, there is a need to explain why DSGE and CGE, even though using the word '*dynamic'*, are still part of the *'static'* stop–gap measure.

There is an inconsistency between the SMD Theorem that finds GE unstable, and Smith's (2007) experimental economics that finds stability in market prices. The static/dynamic divide provides a simple explanation for the inconsistency. The SMD Theorem is a static theory by assuming that all the buyers and sellers agree on a price at one point in time and then swap the goods. Smith's (2007) markets are dynamic in that buyers and sellers continually trade. In summary, the examples show *static-instability* and *dynamic-stability*. Keen (2001) illustrates the difference between dynamic and static economic analysis with the analogy of learning to ride a bike, where learning how to balance on a stationary bike tell us very little about riding a moving bike. Furthermore, it is easy to balance on a moving bike but nearly impossible on a stationary bike, hence why waste time learning to balance on a stationary bike when you want the bike to move. Static economics has failed to find a stable GE and modelling the dynamic economy as a static entity may well be misleading and time–wasting.

The DSGE and CGE models use the word *'dynamic'* but they are still part of the stop–gap static regime because their claim to being dynamic is at the level that a number of pictures of a stationary bike can be combined to produce a moving film, however, each of these still pictures or GE is actually unstable. In contrast to the CGE and DSGE models that produce dynamic instability, Smith's experimental economics produces *dynamic-stability*. Making the CGE and DSGE dynamically stable requires relaxing the methodological equilibration assumption. Section 5.6.3 and 5.6.4, in further research, further discuss this relaxation.

Farmer and Geanakoplos (2008, p. 54) discusses neoclassical theory as *'an elegant attempt to find a parsimonious model of human behaviour in economic settings. It can be criticized, though, as a quick and dirty method, a heroic attempt to simplify a complex problem. Now that we have begun to understand its limitations, we must begin the hard work of laying new foundations that can potentially go beyond it.'* The computing power is available and the *'science of complexity'* provides a suitable framework. Additionally, the *'science of complexity'* uses scientific realism that provides a much sounder philosophical basis than the instrumentalism of neoclassical economics.

While Farmer and Geanakoplos (2008, p. 54) call neoclassical economics *'an heroic attempt to simplify a complex system'*, Blaug (1992, pp. 238-39) criticises neoclassical economics for its '*reluctance to produce theories that yield unambiguous refutable implications, followed by a* *general unwillingness to confront those implications with fact.'* Given that neoclassical economics is based upon instrumentalism whose only claim to the validity of a theory is its ability to predict, this begs the question what is neoclassical theory? Neuman (2003, p. 43) discusses the difference between social theory and ideology, noting that ideologies avoid tests and discrepant findings.

Blaug's criticisms are confirmed in the discussion of REH, the *Efficient Market Hypothesis* (EMH), *General Equilibrium Theory* (GET) and *Dynamic Stochastic General Equilibrium* (DSGE) in sections 2.1.2, 2.1.3, 2.1.4 and 2.1.5 respectively. On REH, Prescott (1977, p. 30) claims, '*Like utility, expectations are not observed, and surveys cannot be used to test the rational expectations hypothesis. One can only test if some theory, whether it incorporates rational expectations or, for that matter, irrational expectations, is or is not consistent with observations.'* Following his advice, REH is examined within the larger theories of DSGE, EMH and GET. Regarding DSGE, Mäki (2002, p. 42) discusses how Kydland and Prescott (1982) create a new method for testing their model rather than use standard econometric testing, where parameters of their model are quantified from calibration and they claim that these calibrated parameters yield empirical content for testing. However, Prescott (1988, p. 84) acknowledges that their models are *'necessarily false and statistical hypothesis testing will reject them.'* Regarding EMH, Barberis and Thaler (2002, p. 8) note that any test of the EMH jointly tests the discounted future cash flow model that makes it difficult to provide evidence of market inefficiency, which is known as the *'joint hypothesis problem'*. Regarding GET, the *Sonnenschein–Mantel–Debreu* (SMD) Theorem finds that the aggregate excess demand curve is shapeless, that proves the neoclassical assumptions are inconsistent, when an attempt is made to fix the shapeless curve by specifying that all goods have neutral Engel curve, which results in the domain assumptions of GET becoming even more unrealistic because in practice there are few, if any, goods with neutral Engel curves (Keen 2001, pp. 38-42).

The *'science of complexity'* offers a number of approaches that can allow economics to become a science and resolve many of the current impasses. Section 2.1.3.4 discusses Lo's (2004) *Adaptive Market Hypothesis* (AMH) to reconcile the EMH and behavioural economics within an evolutionary framework. Sections 5.6.3 and 5.6.4 discuss how agents within a network structure based on an *'input-output table'* be implemented in CGE, GET and DSGE to improve shock transmission and the realism of the models to make them more suitable for policy development, which in effect makes CGE, GET and DSGE into ABMs.

In summary, the neoclassical framework was a computationally expedient stop-gap. However, logically, philosophically and empirically the AIE and *'science of complexity'* are an improvement over REH and neoclassical framework, respectively.

5.4 Implications for policy and practice

This section discusses the implication for policy and practice by addressing the following three questions. How can REH and AIE be used in a complementary approach to better inform policy? How can ABMs using networks based on the *'input-output table'* better inform policy? What are the implications for practice from using a complementary approach and *'input-output networks'*? This section is structured in the way that the three questions are addressed in their own subsection.

5.4.1 Using REH and AIE in a Complementary Approach to better inform Policy

A complementary REH/AIE approach provides for more robust policy formation, where REH is more appropriate when all the relevant data about prices is easily accessed and presented as easily digestible information and the computing power required to make decisions based on the information is small. In comparison, the AIE model is more suitable in the following five situations, first, whenever the links between entities are important due to social structure and institutions; second, there is an excessive amount of information to process; third, the time available is too short for an entity to calculate optimal answers; fourth, the agent lacks the necessary information; and fifth, the agent resorts to *'rule of thumb'*.

The following example from the superannuation industry illustrates the usefulness of using REH and AIE as complements for policy analysis. There is reform underway for the superannuation industry in Australia to provide customers with consistently presented information, so that customers can make easier comparisons between superannuation funds to make optimal investment decisions. The superannuation industry has created a representative agent who has $50,000 in superannuation savings, where the fees for the representative agent are calculated and presented to the potential customer to make it easier to compare superannuation fund fees. If one makes three assumptions, that the whole population understands the EMH, that the EMH is true and that the whole population has the patience to check all the relevant websites for the fee details, then all the consumers would pick the fund with the lowest fees. However, this decision based on the representative agent's fees is suboptimal for most Australians, because there are few in Australia with exactly $50,000 in super savings. This example, therefore, serves to illustrate a problem with the representative agent in REH.

Conversely, if all the information to calculate fees with formulas is available for superannuation funds and posted on the websites of fund providers, this calculation may be beyond the cognitive ability or patience of portions of the population, hence this portion resorts to some *'rule of thumb'* to select a subset of the superannuation funds to check out, where this situation more closely resembles AIE. This superannuation scenario provides a simple example but it does illustrate the benefit of analysing a situation with both approaches to help government avoid failure in mandating inappropriate reform, where AIE models what consumers actually are, humans with their shortcomings, and REH models what consumers ought to be, humans as optimisers to meet policy objectives. In this scenario, REH plays a normative role and AIE plays a positive role being both a descriptive and predictive theory.

REH is part of the neoclassical framework that assumes a normative role in that the world is best structured to reflect the neoclassical framework, where the role of government is to adjust those parts of the economy that fall short of framework's ideal (see sections 2.1.4.5(2), 2.1.4.6 and 5.4.2). However, to use neoclassical economics in this normative role requires considerable caution because the economy lies outside the domain assumptions of neoclassical economics and the assumptions of neoclassical economics are internally inconsistent. Furthermore, the justification of neoclassical economics for government intervention is based on the *'Fundamental theorems of welfare economics'*, which in turn rely on the neoclassical assumptions. However, the SMD Theorem shows that the neoclassical assumptions lead to a shapeless aggregate demand curve, which implies an unstable price vector and economy that in effect invalidates the proof for the neoclassical *'Fundamental theorems of welfare economics'*. A corollary to SMD Theorem is that the closer the world is made in the image of neoclassical economics the more unstable it becomes. This theorem leaves the question over the role of government in economic intervention open for debate --a debate that components of the AIE could help inform.

5.4.2 Narrative, Mathematical and ABM Methodologies Together Informing Policy

This section discusses the narrative, mathematical and ABM approaches to inform the policy debate and argues for the inclusion of ABM, such as AIE, in policy development and builds upon the discussion of model falsification and verification issues in section 2.2.3. Given that both mathematical and narrative approaches are deductive, ABM does offer a unique inductive perspective. Section 5.4.1 discusses how the neoclassical role for government in the economy lacks theoretical foundations, which leaves a theoretical void in the argument for government intervention. Two competing alternatives and extreme views on intervention are Greenwald and Stiglitz (1986) and the Austrian School, where Greenwald and Stiglitz (1986) mathematically prove that every market would benefit from government intervention and the followers of the Austrian School who use narrative to prove that economic volatility and instability are the product of the normal dynamic processes in the economy and that government either causes or exacerbates the problems in the economy. Modelling government intervention with ABM would help inform this impasse.

Greenwald and Stiglitz (1986) also prove that every market lacks the information to function efficiently and only the government could provide this information in a cost effective way. However, the government providing near costless information moves the economy closer to the neoclassical framework whose price vectors are unstable, which makes the economy unstable. This conclusion comes with the caveat that the economy, which is dynamic, lies outside the domain assumptions of neoclassical economics, which is static. Both Gintis (2007) and Smith (2007) find that price stability comes from agents or people holding private and incomplete information. They use ABM and experimental economics, respectively, arriving at similar conclusions. These inconsistencies highlight the need to move toward models that consider both completeness of information and interaction as variables to avoid making incorrect policy prescriptions.

Keen (2001, pp. 304-5) notes that the Austrian School shares many features in common with the neoclassical school but differ by lacking the methodological equilibration and adding explanations of the causes of disequilibria. The Austrian School believes that the economy is in disequilibrium but not too far from equilibrium for too long because this would require acknowledging a possible role for government. In effect, the Austrian disequilibrium is not too different from neoclassical methodological equilibration. However, a major distinction between the Austrian and neoclassical schools is the focus on narrative and mathematics, respectively. The Austrian school uses a narrative argument for non-intervention by the government, which is subject to a narrative counter argument and so on, where if parties fail to agree, the situations usually degenerate into the parties falling back on ideological positions.

In summary, neoclassical mathematics is based on internally inconsistent and non-domain assumptions, whereas Austrian narrative provides a detailed and possibly accurate but unfalsifiable description. In comparison, ABM offer the ability to model the economy dynamically and realistically, as a complex system, and provide falsifiable experiments, hence ABM can inform the intervention debate by running experiments to compare market failure with government intervention failure to find the better option. Section 2.2.3 further discusses ABM as third option and the methodological problems with narrative and mathematics.

5.4.3 Theory in Practice

This section discusses putting ABM and, in particular, components of the AIE model into practice. Brock and Colander (2000, p. 76) note that when economists apply neoclassical economics to policy development many modifications are made to allow for the unrealistic assumptions and many supplements are added, which results in a pragmatic and eclectic approach. Consequently, practitioners adjust for domain assumption problems even if they are unrecognised as such. This eclectic approach could easily accommodate ABM, which would introduce dynamic modelling into the practitioner's toolbox. However, despite encouraging signs, Dawid and Fagiolo (2008, p. 352) note that ABM are not considered standard tools. They consider factors other than inertia in the profession to learning new tools are impeding the uptake of ABM, such as concerns over empirical model validation and robustness checks and the unrestricted number of potential model parameters. See Gilbert and Troitzsch (2005), Gilbert (2008) and Galán et al. (2009) for a discussion of validation and robustness checks in ABMs that use predictions against stylised facts.

In contrast, the AIE model addresses empirical validation and robustness checks directly by calibrating against empirical data and using temporal prediction for validation, rather than stylised facts. This avoids the issue over what is considered scientific, when stylised facts are used. Sections 2.1.5.2 and 2.2.3 further discuss stylised facts and temporal prediction. In addition, AIE is benchmarked against REH and adaptive-expectations models, which ensures that the dynamic modelling is worth the extra calibration and predictions costs.

Furthermore, the thesis introduces *network-averaging* that is the model-averaging of AIE with different network topologies, to partially address the unrestricted number of parameters issue, which is an important issue for ABM models because generally there lacks information on how to structure and design the network. In conjunction with *network-averaging*, the thesis introduces *'runtime-weighted model-averaging'* and *'optimal-calibration model-averaging'* to improve predictive performance. Additionally, the thesis introduces an *'input-output network'*, which uses a *'link-intensity matrix'* based on an *'input-output table'* and number of firms to further restrict the parameters in networks of AIE, where there may be an input-out table equivalent for other ABM projects, which would allow transfer of the concept.

Implementing the *'input-output network'* in CGE and DSGE could improve policy applicability and accuracy by making the underlying assumptions more realistic. Governments routinely use CGE even though it lacks microfoundations, as discussed in section 2.1.4.5. DSGE is criticised for its poor modelling of transmission of shocks, as discussed in section 2.1.5. CGE and DSGE fail to capture the network dynamics of the economy, for example, take two sectors of equal input-output size that have few and many firms, respectively, where the linkages and number of firms determine the speed of transmission of any shock and potentially setting up endogenous effects. Using an AIE variant to replace the REH assumptions will provide an alternative mechanism to model shocks and help address the lack of microfoundations. Sections 5.6.3 and 5.6.4 further discuss implementing the *'input-output network'*.

The AIE model also introduces the *'pressure to change profit expectations index'*. This index allows the modelling of belief and of outcome separately and the modelling of uncertainty without probabilities that are better suited to modelling risk, which section 3.1 further discusses. This pressure to change belief index could be adapted for use in other ABM.

The AIE is a **profit** expectations model. However, AIE could easily be extended to model the expectations of inflation, employment, inventory, sales, etc.

Brock and Colander (2000, p. 79) discuss how the complexity approach lacks a complete formal model of the economy but can be used to develop policy with informal models that describe the current economy and the effect of policy upon it. To that end, the AIE has made the following contributions to the literature.

5.4.4 Contributions of the thesis to the literature

The thesis contributes to the literature in three ways, AIE as a formal model and a general theory and its supporting techniques. As a formal model of expectations formation, AIE is descriptively more accurate than the REH and adaptive-expectations models and predicatively more accurate, as tested against D&B (2008) dataset. As a general theory, AIE provides a complementary role to the REH for policy analysis, being positive and normative, respectively. As part of the methodology to support the formal AIE model, the following five techniques were developed:

- *'Pressure to change profit expectations index', p^x,*
- *Network-averaging,*
- *'Runtime-weighted model-averaging'*,
- *'Optimal-calibration model-averaging'* and
- *'Input-output networks'*.

5.4.4.1 Pressure to change profit expectations index

The *'pressure to change profit expectations index'*, p^x, provides the ability to model unknowns within an adaptive dynamic process and combines beliefs from interactive expectation, adaptive-expectations and biases, including, pessimism, optimism and ambivalence.

5.4.4.2 Network-averaging

AIE uses networks to model the flow of interactive expectations between firms, however, there lacks data on these network structures, hence the thesis introduces *network-averaging,* that is the model-averaging of AIE with 121 different network topologies, to simultaneously address two issues, the lack of data on the interactive network structure and the complexity ranking problem of different network topologies as discussed in section 2.2.5.1.

5.4.4.3 'Runtime-weighted model-averaging' and 'optimal-calibration model-averaging'

Further to the complexity ranking problem, these 121 networks are defined by three parameters regardless of their complexity, which makes the use of the Bayesian technique unsuitable for model-averaging over the network topologies because the Bayesian technique uses the number of parameters as a measure of complexity. Hence, the thesis develops two model-averaging techniques to overcome this limitation to the Bayesian technique and improve predictive performance.

5.4.4.4 Input-output Network

The aggregate AIE model uses the *all–firms* dataset from the D&B (2008) survey. This all–firms dataset has four divisions, manufacturing durables, manufacturing non–durables, wholesale and retail. The disaggregated AIE model uses these four divisions. The thesis introduces a *'link-intensity matrix'* to improve the calibration of the networks, which is calculated using an *'input-output table'* and the observation that profits are determined by mark-ups. The transpose of the table is also used. The two *'link-intensity matrices'* are benchmarked against the default, a *'matrix of ones'*. Section 2.1.9.1 discusses the calculation of the *'link-intensity matrix'* in more detail.

5.5 Limitations

This section discusses two limitations to the AIE model, the computing requirements and the lack of evolutionary processes such as learning. Section 5.5.1 discusses the computing requirements issue and section 5.5.2 discusses the evolutionary and learning issues.

5.5.1 Computing Power

Ten years of computer processor time were used in developing the AIE model for this thesis, which includes time for numerous detours and incomplete jobs. However, it does serve to indicate the serious amount of computing power required to calibrate the AIE model. This limitation could be address in several ways.

Since the timeliness of predictions is usually an issue, a highly concurrent system of 121 processors to calibrate the 121 network topology models would be advantageous. Currently this amount of computing power is available only to larger institutions; however this may not be the case in 10 years from now. If Moore's Law holds true that the number of transistors to be placed onto an integrated circuit cheaply doubles every two years, the current quad processor desktop computers will be replaced with a 128 processor desktop computer in ten years.

An alternative approach is programming graphic adaptors of computers, which are massively parallel, to provide the potential to run all 128 network topologies simultaneously on one computer. This parallel programming approach is gaining ground and looks promising, as the amount of RAM in graphics cards increases and concurrent programming languages becomes more 'user-friendly'. Currently, the most prominent instance of this is NVidea's CUDA system (http://www.nvidia.com/object/cuda_home.html#), which enables up to 512 cores to run simultaneously on a single PC. Distributed processing is also supported in Mathematica and many other numeric programs these days. Section 5.6.13 discusses further research into using graphic adaptors to decrease the time to calibrate the AIE model.

People donate CPU time on their home PCs for projects such as the Search for Extra-Terrestrial Intelligence (SETI) or prime number work. AIE could be run in a similar way by distributing the processes over a number of CPUs. However, establishing such a regime requires considerable coding effort.

AIE is coded in NetLogo a fourth generation language, which is itself written in Java. Java is a flexible interpreted language, which will run on almost combination of hardware and operating system. Writing the code in a third generation language such as C or C++ would provide a significant decrease in the time to calibrate the AIE model. Unfortunately development time is far greater, when using a third generation language than NetLogo, and requires more technical expertise.

Additionally, the calibration from the previous prediction can be used as the starting point for the search to calibrate the model for the next prediction, which saves considerable time. Another option is improvements in search techniques to calibrate the model, which could further reduce the search time and section 5.6.1 discusses this point in further research.

5.5.2 Learning and other evolutionary processes

AIE is limited with regard to model learning unlike evolutionary economics. This is a concern because firms or people do learn from experience and change the rules under which they operate. However, there are three considerations that ameliorate this concern. First, the AIE model has a short calibration and prediction period. Second, existing near-zero-intelligent ABMs capture the most salient feature of mature systems. Third, the firms in the D&B survey exhibit impediments to learning the true state of the world. This section discusses the three considerations.

First, the AIE model is calibrated over a short period, after the profit expectations undergoes a structural change or phase transition. If the phase change or structural change in expectations is considered a period of rapid learning or changing of rules, the period outside the phase change is seen a time of stable rules and slow learning where learning serves to reinforce the existing rules or provides insufficient impetus for entities to change their own rules. Then the calibration and prediction of the AIE model during a period of stable rules makes the modelling of learning of minor importance. Given the computing requirements of the AIE model, the scope of the thesis is limited to one relative stable period to avoid the overly onerous computing requirements to calibrate and predict over numerous periods and the additional requirement to model phase changes between the stable periods and their relation to changes in rules or learning. This rather major extension to the AIE model is left for further research, and will prove to be more practical in the future when the computing power has improved. Section 5.6.5, in further research, further discusses the phase change concept.

Second, AIE models a mature system, hence individual learning may have little relevance as section 2.2.2 discusses Ormerod et al.'s (2007, pp. 208-9) observation about how the more mature a system is, the more important the structure of the network is in determining the emergent behaviour than the intelligence of the individual agent. Consistently, Axtell and Epstein (1999, p. 177) note, '*very little individual rationality may be needed for society as a whole ultimately to exhibit optimal behaviour.'* There is a large theoretical and experimental literature investigating how rational humans are, but from a network dynamic perspective this may be immaterial. This observation changes the focus from individual learning and raises the question *'How does a network structure reflect learning?'* This is an interesting question, but it is beyond the scope of the thesis. The thesis makes the assumption that the profit expectations network is mature in between the structural breaks because the players have had chance to learn the rules.

Third, Figure 2–6 shows a persistent gap between the actual profits and expected profits, reflecting an optimism bias. This gap suggests that agents fail to accurately learn the true state of the world. The gap was one reason for abandoning the Bayesian learning approached, as discussed in section 3.1.

5.6 Further research

This section discusses thirteen areas for further research ensuing from the AIE model development.

5.6.1 Integrating *Unconstrained-nonlinear-optimisation* and Simulated-annealing

This section discusses integrating *unconstrained-nonlinear-optimisation* and *simulated-annealing* to reduce the time required to calibrate the AIE model. Sections 2.2.4.3 and 2.2.4.4 discuss *simulated-annealing* and *unconstrained-nonlinear-optimisation*, respectively. The concept is to initialise the combined method with a best guess starting point, and then run the *unconstrained-nonlinear-optimisation* to find a minimum. From this minimum use a *simulated-annealing* type hop to reach another state or point. Again the *unconstrained-nonlinear-optimisation* is performed until a new minimum is found. If the new minimum is less than the old minimum, the approach is to decrease the *simulated-annealing* temperature/threshold. Regardless of whether the temperature/threshold was decreased or unchanged, a *simulated-annealing* type hop is used to move to another state. The process becomes iterative until the temperature/threshold minimum value is reached or the maximum number of iterations exceeded.

5.6.2 Linking Leaky Integration Neuronal Models and Ambiguity Belief Models

This section discusses linking leaky integration neuronal models and ambiguity belief models because the AIE model combines three sources of pressure to change expectations, adaptive, interactive and bias whether pessimistic, optimistic or ambivalence, as shown in equation (3–1). Section 3–1 discusses the requirement for an alternative to probability and separating belief from outcome.

Further research into a possible commonality between leaky integration neuronal models and ambiguity belief models may provide a fundamental basis for how people combine ambiguous beliefs. This could improve modelling techniques for behavioural economics generally. Specifically, it could improve the procedure to combine the three sources of pressure to change profit expectations in the AIE model. Leaky integration neuronal models are examined in Yu and Cohen (2009) and ambiguity belief models in Eichberger, Kelsey and Schipper (2009).

5.6.3 Improving AIE Networks using Input-Output tables and the Number of Firms

The findings of the thesis show that the predictive power of the AIE model may improve using a *'link-intensity matrix'* based upon an *'input-output table'*. This concept can be further extended by placing into the AIE network the number of firms in each division in the same ratio, as that in the D&B Survey. The randomisation of the links could be produced in a similar fashion to the existing

AIE network. However, the sum of the link intensities between each division is calibrated according to the *'input-output table'*. This does provide more realism in the AIE network because the network dynamics will differ both endogenously and to exogenous factors according to the number of firms in each division. The number of firms in each division is an important attribute, which is missed from the current input-output analysis and its descendants CGE and DSGE that lack the network dynamics that contributes to their poor ability to model shock transmission.

5.6.4 Introducing Networks based on Input-Output tables into CGE and DSGE

Implementing a network structure, as outlined in section 5.6.3, could be the first step in replacing the neoclassical assumptions in GET, input-output modelling, CGE and DSGE. This provides a transition to a *'science of complexity'* framework, to await a more comprehensive and coherent list of behavioural rules that still appears to be work under progress. However, Ormerod et al. (2007, pp. 208-9) and Axtell and Epstein (1999, p. 177) discuss that the major gains in modelling may well come from focusing on the structure of interaction, rather than on behavioural rule.

5.6.5 Relationship between Structural Change in a Network and Volatility

Section 2.1.3.2 discusses the EMH and pricing anomalies, such as excess volatility and clustered volatility, where there appear at least two types of volatility, cluster volatility and general background volatility or noise. The general background volatility or noise is modelled in Bowden and McDonald (2008) and Duan and Abbott (2008), respectively, who use small world networks with fixed structures. It would be useful to investigate the relationships among clustered volatility, power–laws, non-equilibrium dynamics and changes in network structures, as discussed in sections 2.1.3.2 and 2.2.1.2. This research could inform the further research suggested in section 5.6.7.

5.6.6 Multiple Levels of Patterns in Emergence

The AIE model presented in the thesis uses temporal prediction for falsification. Alternatively, stylised facts as predictions could be used for falsification. Section 2.2.3 discusses the use of multiple levels of emergence as stylised facts to evaluate ABMs. This would require minimising the model covariance for the four divisions in the disaggregated AIE model. However, to ease comparison among the results from the various aggregate and disaggregated AIE models it was decided to minimise the model variance of the *all–firms* level in all cases, see Table 4–1.

5.6.7 A Phase Change or Structural Change Causing a Change in Profit Expectations

Research question one in the thesis finds that there is a phase change or structural change that causes a change in profit expectations in the quarter ending March 2000 but is unable to determine whether the change is due to structure or phase. A possible way to differentiate the two is to calibrate the AIE on either side of the quarter ending March 2000 and compare the network structures. Similar network structure would indicate a phase change rather than a structural change causing the change in profit expectations.

5.6.8 Benchmark Runtime-weighted Model-averaging in a Controlled Experiment

Research question three in the thesis investigates the efficacy of *'runtime-weighted model-averaging'* and found that the technique was ineffective for all version of the AIE, except the *' input-output table' 'link-intensity matrix'*. The technique was developed because the AIE networks could vary in complexity but always retain the same number of parameters. This made the application of the Bayesian Information Criterion (BIC) as a model weight in model-averaging unsuitable because the BIC relies on the number of parameters to measure complexity. The suggested research is to use datasets where the complexity does vary with the number of parameters to allow the *'runtime-weighted model-averaging'* to be benchmarked against a model-averaging technique based on the BIC, which could determine if the *'runtime-weighted model-averaging'* is a valid technique for use in other situations, where there is a fixed number of parameters but variable complexity.

5.6.9 Impulse Propagation in Dynamics models for Policy Analysis

It is traditional that policy analysis or shock analysis uses some form of impulse applied to a model in equilibrium or at rest, and then study the propagation of the impulse. However, AIE is a dynamic model moving from state to state and the initial conditions very much determine the reaction of the system to the impulse. It would be useful to investigate how long it would take after no further changes in actual profits, before profit expectations became constant. This would measure the interactive lag in the system or endogenous lag time. A prediction is that the lag would be greater than that in the *'Beer Distribution Game'* of 26 weeks because the AIE is a complex network of supply chains whereas the *'Beer Distribution Game'* is a single simple linear supply chain. Section 2.1.6 discusses the *'Beer Distribution Game'*.

The impulse propagation analysis becomes more a policy tool, if AIE were adapted to model changes in prices to determine inflation expectations.

5.6.10 Adding Exogenous Inputs to AIE to supplement the Change in Actual Profits

The AIE model has only one exogenous input - the change in actual profits. The reason to restrict AIE to a single exogenous input in the thesis was to focus on the interactive component in the model and in particular the network. There is ample literature to suggest that introducing exogenous inputs, such as, the change in credit and interest rates may improve the predictive ability of the AIE. However, time spent perfecting the calibration of the network structure to capture endogenous effects may well produce considerable gains and is a preferable first step before introducing more exogenous factors.

5.6.11 Using Random Seeds to Improve Adaptive-expectations as a Benchmark

The adaptive-expectations model without a network structure provides a benchmark for the AIE model with its 121 network topologies. The adaptive-expectations model requires 121 parameter sets to provide a model-averaging benchmark for the AIE. Optimising the 121 network topologies of the AIE model, and then model-averaging the 121 minima is meaningful because each network topology is a model in its own right. However, model-averaging the 121 parameter sets from the adaptive-expectations model is problematic because they are parameter sets from a single model. Consistently, the model-averaging becomes meaningless as the parameter sets converge on a global minimum. Section 3.4.2 discusses the actions taken to remedy the problem of minimising the model variance of the adaptive-expectations model and model-averaging the 121 parameter sets. Separate solutions were found in the thesis for the aggregated and disaggregated adaptive-expectations models.

The disaggregated adaptive-expectations model had a complete *grid-search* in the thesis. The units of the *grid-search* are far enough apart to allow for meaningful model-averaging. This technique while effective was only possible because the high performance computing centre wanted a job to test their computer for a few weeks.

For the aggregated adaptive-expectations model a slightly lower model variance for the model-averaging was found by setting the network topology to values other than $L = 1$ and $\rho = 0$. Since $I = 0$, these alternate network topology settings only indirectly affect the model variance calculation because the random functions in the model are affected by using different parameters.

Using the random seed function built into NetLogo would provide a more elegant solution. The same 121 random seeds used in the adaptive-expectations models could be used for the 121 network topologies in the AIE model to allow the model-averaging of the adaptive-expectations model to become a more rigorous benchmark.

5.6.12 Using the Levenberg-Marquardt system for nonlinear parameter estimation

Investigating how other techniques, such as the Levenberg-Marquardt system for nonlinear parameter estimation could be applied to the AIE model optimisation. The Levenberg-Marquardt system is applied widely in hydraulic and biological modelling (the once commercial and now freeware program PEST implements nonlinear parameter estimation in a model-independent way: see http://www.pesthomepage.org/Home.php).

5.6.13 Testing parallel processing on a graphics adaptor

A worthwhile future research project would be posting the AIE and ABM generally to an NVidea's CUDA system (http://www.nvidia.com/object/cuda_home.html#) to see how much faster the calibrations could be performed. This could be feasible via the NetLogo-Mathematica interface, combined with the capability to produce C code from within Mathematica.

A Source code for the AIE Model, Model-averaging and Optimisation

The source code for the AIE model, model-averaging and the optimisation are provided on the attached DVD. Consult the readme file for a description of the DVD contents.

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