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Adaptive Interactive Profit Expectations and Small World Networks

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Abstract The aim of this paper is to simulate profit expectations as an emergent property using an agent based model. The paper builds upon adaptive expectations, interactive expectations and small world networks, combining them into a single adaptive interactive profit expectations model (AIE). Understanding the diffusion of interactive expectations is aided by using a network to simulate the flow of information between firms. The AIE model is tested against a profit expectations survey.

The paper introduces "optimal calibration model averaging" and the "pressure to change profit expectations index" (p^x). Optimal calibration model averaging is an adaptation of "model averaging" to enhance the prediction performance of multiple equilibria models. The p^x is a subjective measure representing decision making in the face of uncertainty.

The paper benchmarks the AIE model against the adaptive expectations model and the rational expectations hypothesis, finding the firms may have adequate memory although the interactive component of AIE model needs improvement. Additionally the paper investigates the efficacy of a tuneable network and equilibrium averaging. Finding the tuneable network produces widely spaced multiple equilibria and the optimal calibration model averaging enhances calibration but not prediction. Further research includes disaggregating the AIE model, using an input–output table to reflect the intensity of interaction between firms of different divisions, and supplementing optimal calibration model averaging with runtime weighted model averaging.

Key words Expectations – Interactive – Adaptive – Business cycle – Profit – Networks – Agent based model – Australia – Surveys – Equilibria Averaging

1 Introduction

Profit expectations are important because they influence future investment and credit decisions as such they contribute to the business cycle and economic growth.

This paper builds upon adaptive expectations (Hicks 1939), interactive expectations (Flieth & Foster 2002), small world networks (Watts & Strogatz 1998) and the findings of the 'Beer Distribution Game' to simulate the process of profit expectations formation using an agent based model. Adaptive expectations form when a firm changes its future expectations based upon the difference between actualisations and expectations for the current or previous periods. Interactive expectations form when a firm's expectations are affected by the expectations of other firms for the current or previous periods. Understanding the diffusion of interactive expectations is aided by using a network to simulate the flow of information between firms. The paper combines all three components into the adaptive interactive profit expectations (AIE) model.

This is an empirically based study using profit expectations and actualisation indices from the Dun and Bradstreet (D&B 2008) National Business Expectations Survey. These indices are based upon the change in profit expectations and actualisation rather than the level of expected or actual profit. This approach is consistent with Kahneman's (2002) empirically supported observation "the primacy of change over state" but at odds with utility curve theory.

The paper compares predictions based upon short and long calibrations of the AIE model to test the concept of phase changes in expectations first proposed by Flieth and Foster (2002) and subsequently simulated by Bowden & McDonald (2006). The AIE model is benchmarked against the rational expectations hypothesis (Muth 1960, 1961) to gauge how rationally or myopically firms form expectations. Additionally, the AIE model is benchmarked against the adaptive expectations model to test the interactive component of the AIE model. In effect the adaptive expectations model is the AIE model without the interactive components, such as the network.

Tesfation (2008) lists four objectives of agent–based computation economics: (1) empirical understanding, (2) normative understanding, (3) qualitative insight and theory generation and (4) methodological advancement. How does this paper contribute to these objectives? The AIE model contributes to empirical understanding by generating a bottom up model of profit expectations. The methodological advancements include: (1) introducing a '*pressure to change profit expectations index*', (2) adapting model averaging (Bates & Granger 1969) to handle calibration and predictions in multiple equilibria models, and (3) using calibration and prediction of benchmark models to evaluate the AIE model.

The structure of the paper is as follows. Section two discusses the literature supporting the AIE model and develops the research questions. Section three covers the methodology for the AIE model and refines the research questions. Section four presents the results. Section five discusses the results. Section six concludes the paper.

2 Literature Review

The literature review consists of the following sections. Section one provides an overview of the components of the AIE model and discusses their relationship to emergence. Experimental support for the AIE model and emergence in business expectations is exemplified using the 'Beer distribution game' (Sterman 2000). Additionally the section provides justification for using the agent based model approach by showing how the agent based model fits between the traditional mathematical and narrative approaches to economics. Verification issues regarding agent–based models are also addressed. Section two discusses the profit indices (ABS 2002; D&B 2008) used in the paper's AIE model and identifies a phase change in profit expectations. Testing for this phase change forms the basis of a research question. Section three discusses using the adaptive expectations model (Hicks 1939) and the rational expectations hypothesis (Muth 1960, 1961) as benchmarks to the AIE model. The adaptive expectations model (Hicks 1939) is also a component of the AIE model. Section four discusses interactive expectations (Flieth & Foster 2002), a further component of the AIE model. Section five discusses small world networks (Watts & Strogatz 1998) used to extend interactive expectations (Flieth & Foster 2002).

2.1 Relating Emergence to the Components of the AIE Model

"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 2.3, 2.4, and 2.5 respectively.

The 'Beer distribution game' provides an example of business expectations and emergence in a simple supply chain: manufacturer, distributer, wholesaler and retailer. This emergence example is particularly relevant because this study's dataset (D&B 2008) covers the manufacturing, wholesale and retail divisions.

Sterman's (2000, pp. 684-98) 'Beer distribution game' provides an example of interactive/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. Table 1 shows the three factors and their correspondence to the component parts of the AIE model and the AIE model itself. Regarding factor one in Table 1, the adaptive expectations model provides a link between profit actualisation and profit expectations for the AIE model. The social interactions model (Bowden & McDonald 2006) lacks this link. The interactive expectations model (Flieth & Foster 2002) does provide a link but in a narrative form only. Regarding factor two in Table 1, the behaviour of the agents, participants or firms is modelled at the micro level by all three component models of the AIE model or can be easily adapted to do so. Regarding factor three in Table 1, the social interaction model (Bowden & McDonald 2006) studies the interaction of agents via a small world network (Watts & Strogatz 1998) and in this way captures institutional structure. In comparison, the interactive expectations model (Flieth & Foster 2002) groups agents by the positive, negative or neutral expectations they hold and treats the groups probabilistically, so lacking any institutional structure. Similarly, the adaptive expectations model (Hicks 1939) lacks structure. The AIE model covering all three factors endeavours to emulate the process of expectations formation using emergence.

Table 1 Factors affecting emergence in an economic system and correspondence to the AIE model and its components

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

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 this study follows. In comparison, Flieth and Foster's (2002) interactive expectations model falls into the statistical physics category.

Beinhocker (2006, p. 185) notes that traditional economics focuses on the exogenous causes for oscillations the first factor in Table 1; 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 while modelling participants with zero intelligence, finding institutional structure largely determines behaviour, and emulating the rational expectations hypothesis produces unrealistic outcomes. The rational expectations hypothesis (Muth 1960, 1961) 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 of the stock including dividends. They find 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, 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 the study, the hyper rational agent is represented by the rational expectations hypothesis (Muth 1960, 1961). For such an agent emergence is a nonexistence property because any difference between their profit expectations and profit actualisation 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 in how many periods the agents remember their adaptive and interactive components. This study uses the current period and last period for the adaptive expectations and the current period for interactive expectations. Section 5 discusses other memory options including the dynamic cognitive model (Yu 2008). Section 2.3 discusses the rational expectations hypothesis (Muth 1960, 1961) further and its role as the hyper rational benchmark for the AIE model.

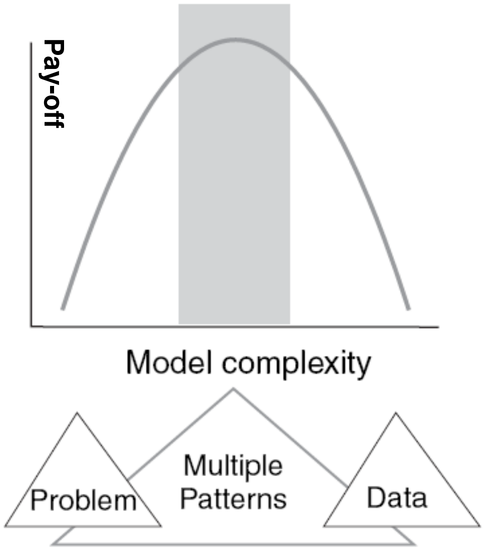
Further to agent sophistication and model complexity, Grimm et al. (2005) note that there lacks a unifying framework for designing, testing, and analysing bottom–up models (agent based or network models). They suggest adapting the Medawar Zone from science to bottom–up models. The Medawar Zone finds the optimal pay–off to model complexity.

Figure 1 shows their proposed adaption 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.

Ideally this would be the case and the Bell (2009a) adopt this approach, however the current AIE version would require too many parameters, making the approach impractical.

Therefore, this paper adopts the traditional scientific approach of falsificationism on the aggregate model using temporal predictions. Initially the AIE model and its benchmarks are calibrated against the D&B (2008) profit expectations data. Predictions are made with the calibrated models and compared. If the AIE model has less predictive power than the rational expectations hypothesis then the agents require more intelligence or memory. If the AIE model has less predictive power than the adaptive expectations model then the agent's interactive component requires adjustment. Section 4.3 compares the predictions of the AIE and adaptive expectations models and section 5 discusses the results. In comparison to agent based modelling, a narrative approach to describing the process of profit expectations formation is unfettered by the practical considerations such as limited computing power and time and data availability and 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. Section 5 discusses increasing model complexity further.

Figure 1 Medawar zone



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

Considering the relationships among agent based modelling, narrative and traditional mathematical approaches to economics, Miller and Page (2007, pp. 78-9) note that agent based models are an interesting trade off between the precision of traditional mathematical tools used in economics and the flexibility of narrative. Agent based models 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 agent based models 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 show similar and more active patterns, denoting more cognitive effort, than the fMRI of the certain gain. They postulate that the preference for certainty over risk is a matter of minimising cognitive effort.

2.2 Profit Expectations Index and Phase Transitions

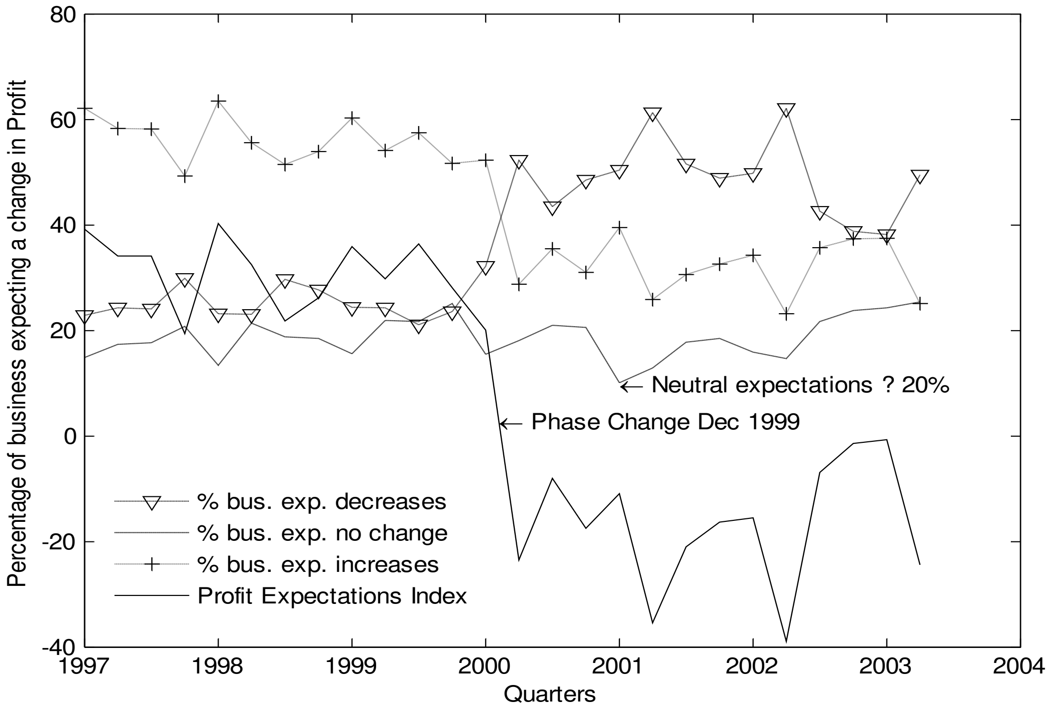
This section discusses the profit expectation indices used in the study and a phase change in profit expectations investigated in the study.

Figure 2 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 as displayed in Figure 2. 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 study. However it does illustrate three important features. First, the components of a profits expectation index formulated in equation (1).

$$\text{Profit Expectations Index} = \%\text{ business expecting increases} - \%\text{ business expecting decreases} \quad (1)$$

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 study uses the percentage of businesses who expect 'no change' in profit from Figure 2 to decompose the all–firms profit expectations indices from Figure 3 into the number of firms holding positive, neutral and negative expectations. Each firm is assigned a profit expectation value of 1, 0 or –1 respectively.

Figure 2 Components of the Profit Expectations Index and Phase Change



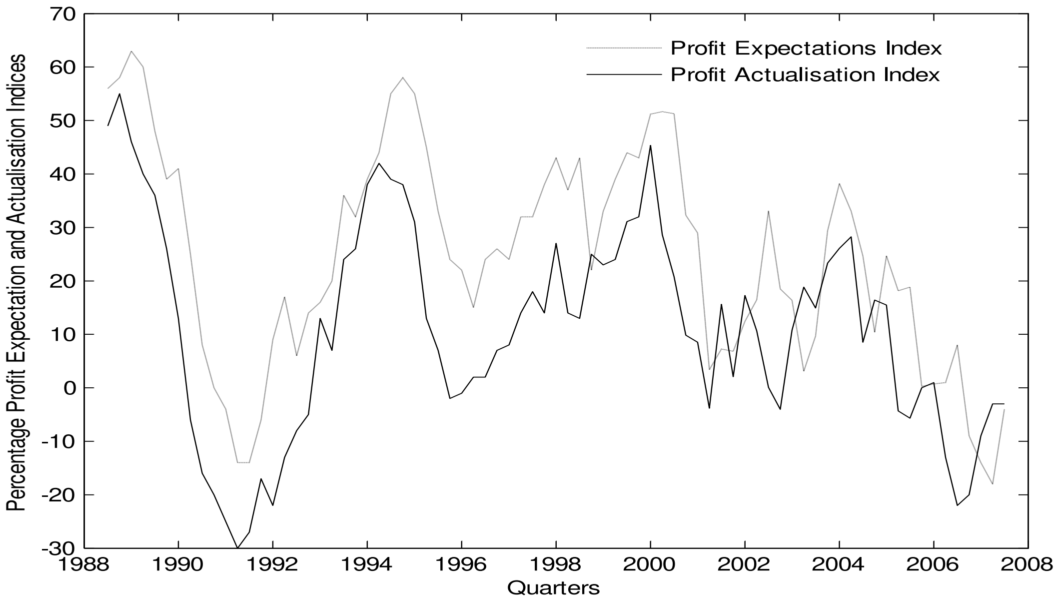
(Source: ABS 2002 Cat. No. 5250.0 tbl. 2)

Third, Figure 2 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 all–firms profit expectations index in Figure 3. Additionally, such phase changes are in agreement with the observations made by Flieth and Foster (2002) and Bowden and MacDonald (2006). This study uses the June 2000 phase change as a break point to test a hypothesis about the phase change. If the phase change concept is true then calibrating a model over shorter time series will provide greater predictive power.

2.3 Adaptive Expectations and Rational Expectations Hypothesis

This section discusses the adaptive expectations model (Hicks 1939) and rational expectations hypothesis (Muth 1960, 1961). Both models form benchmarks for the AIE model. In addition to being a benchmark, the adaptive expectations model (Hicks 1939) provides AIE model with a link between the profit actualisation and expectations indices. This connection is important because the interactive expectations model (Flieth & Foster 2002), which is also incorporated into the AIE model, provides only a narrative linking actualisation and expectations. Figure 3 compares the all–firms profit expectations and profit actualisation indices of the respondents to D&B (2008); the AIE model uses these indices. Figure 2 shows the ABS (2002 Cat. No. 5250.0 tbl. 2) neutral expectations; the AIE model also use this dataset.

Figure 3 All–firms Profit Expectations and Actual Indices



(Source: D&B 2008)

In Figure 3 the 'all–firms' division is an aggregate of the respondents from the manufacturing, retail and wholesale divisions. Equation 2 shows that the actualisation indices are calculated in a parallel manner to the expectations indices in equation 1.

$$\text{Profit Actualisation Index} = \%\text{ business with actual increases} - \%\text{ business with actual decreases} \quad (2)$$

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 paper is on a single economic indicator for brevity and the indicator profits because profits embody most factors of production. Figure 3 matches the actualisation for the quarter with the expectations for that quarter. Noteworthy is the persistence of the profit expectations index above the profit actualisation index. This is in contradiction to the rational expectations hypothesis, where profit expectations index curve ought to be centred randomly about the profit actualisation index curve.

This paper uses model variance, the mean of the 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 variable T is the number of quarters in the dataset. The model variance for the ration expectations hypothesis (Muth 1960, 1961) is simply the SSE/T between the profit expectations and profit actualisation 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 2–1 shows the adaptive expectations model in its simplest form.

$$P = A_{t-1} + \lambda\,(P_{t-1} - A_{t-1}) \quad (3)$$

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. Alternatively for $-1 < \lambda < 0$ we have rapid error correction.

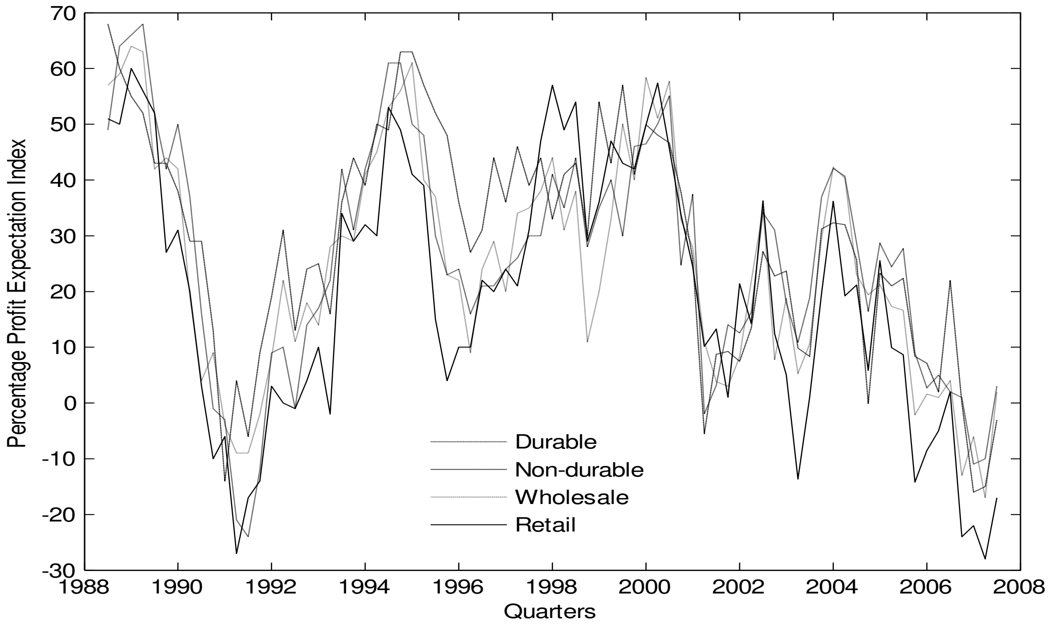
Section 3.1 discusses the incorporation of equation 3 within the AIE model. Section 5 discusses the dynamics cognitive model (Yu 2008) as a refinement of the adaptive expectations model for further research.

2.4 Interactive Expectations

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 (2006) find heard 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 2.5 to extend interactive expectations (Flieth & Foster 2002) with a small world network (Watts & Strogatz 1998). Section 2.1 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 4 shows the profit expectations indices for the durable, non–durable, wholesale and retail divisions from D&B (2008). Figure 3 shows the profit expectations indices for the aggregate of these four divisions called 'all–firms'. The retail and wholesale divisions match those of the same name in the ABS (2006) Australian New Zealand Standard Industrial Codes (ANZSIC). The durable and non–durable divisions span the ANZSIC manufacturing division. The durable and non–durable divisions match section 3 and section 2 of the Dun and Bradstreet (2006) Standard Industrial Classification (D&BSIC). Generally, the durable and non–durable subdivisions in the ANZSIC and the D&BSIC match, excepting ANZSIC's 'Furniture and fixtures' are considered "durables" and ANZSIC's 'Rubber, plastics and leather' are considered "non–durables".

Figure 4 Wholesale, Retail, Durable and Non–durable Expectation Profit Indices

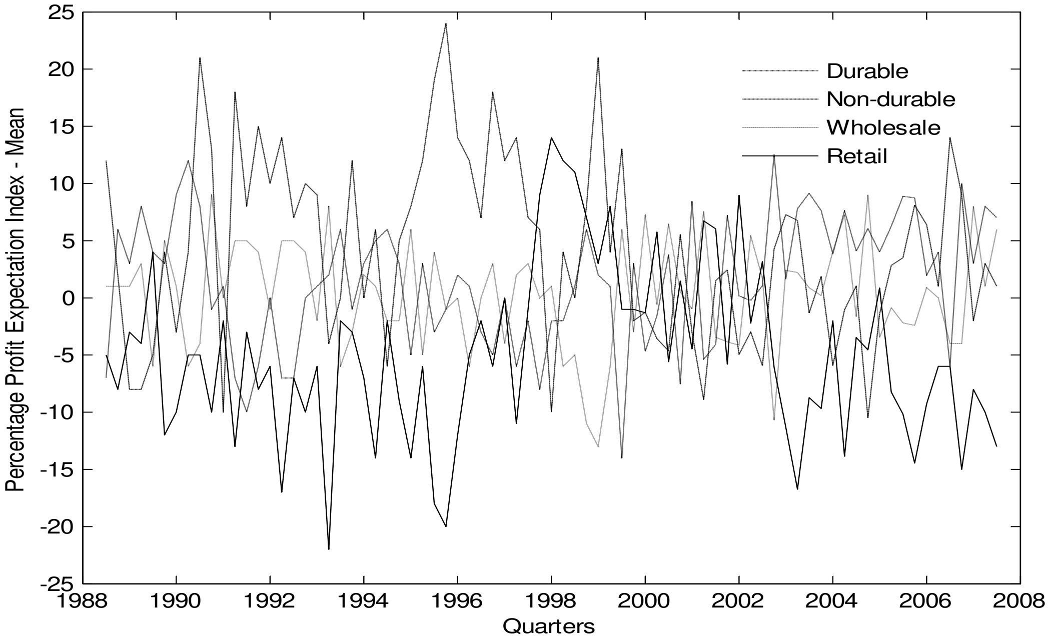


(Source: D&B 2008)

Figure 4 shows the four divisions roughly moving in phase with one another. There is interaction between the firms in the divisions or interactive expectations. Figure 4 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 paper is to model this interactive component as an emergent property.

Figure 5 shows the profit expectations indices of each division in Figure 4 less the all–firms profit expectations index to more easily make comparisons between the divisions. Figure 5 also illustrates that the retail division most often holds the lowest profit expectations and the non–durable most often holds the highest profit expectations.

Figure 5 Wholesale, Retail, Durable and Non–durable Profit Expectation Indices less the All–firms Profit Expectations Indices

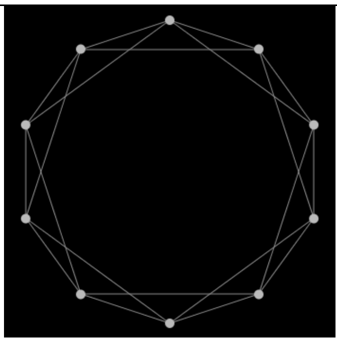
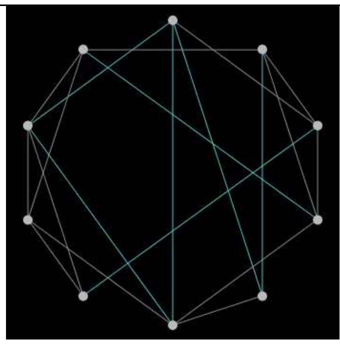
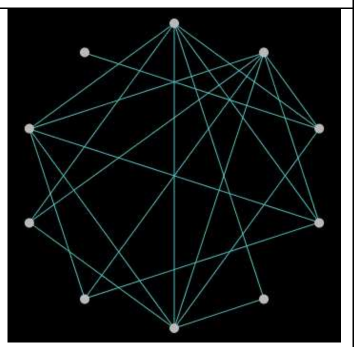


(Source: D&B 2008)

2.5 Small World Networks

This section discusses small world networks (Watts & Strogatz 1998) that form a component of the AIE model. Specifically they extend Flieth and Foster's (2002) interactive expectations model to allow a network rather than a statistical physics approach to information flow, as section 2.1 discusses.

Figure 6 Regular, Small World and Random Networks.

Regular	Small–world	Random
		
ρ = 0	ρ = 0.3	ρ = 1

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

In the AIE model the nodes in Figure 6 represent the firms and the links represent the flow of profit expectation between the firms; the link are undirected, that is, information can flow both ways. The AIE model uses similar network topologies to Bowden and McDonald (2006, p. 9), as they also study how differing network topologies affect interactive expectations formation. Figure 6 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 6 shows $\rho = 0$, 0.3 and 1 representing a regular, small world and random network respectively and sets $n = 10$ to allow for easier viewing whereas the AIE model sets $n = 200$ and has 11^2 possible network topologies by ranging $\rho = 0, 0.1, 0.2, \ldots, 1$ and $L = 2, 4, 6, \ldots, 22$. These network parameters are tuned to find a suitable proxy for the interactive network. Section 4.5 presents a visualisation of this tuning and section 5 discuss it further.

It is noteworthy that 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.

2.6 Combining forecasts: Model Averaging to Equilibria Averaging

This section discusses 'model averaging' (Bates & Granger 1969) because the AIE model has multiple equilibria and combining these equilibria for forecasting potentially could 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). In contrast this paper combines the differing equilibria of the AIE model to improve forecast accuracy or perhaps more aptly named 'equilibria averaging'. Acknowledging, it could be argued that the AIE model is in fact a collection of models, reasoning that each network topology is an entirely different structure therefore a different model. So, the term 'model averaging' (Bates & Granger 1969) would suffice. However each network topology has multiple equilibria. For simplicity, the term model averaging is retained. Section 3.3 discusses 'optimal calibration model averaging', which uses multiple equilibria. The literature supporting the component parts of the AIE model is now in place ready to discuss the methodology.

2.7 Research Questions

The research questions arising from the literature review are listed for review.

Research question one tests the expectations phase change concept.

Research question two benchmarks the AIE model against the adaptive expectations model to test the interactive component of the AIE model.

Research question three benchmarks the AIE model against the rational expectations hypothesis to determine the appropriate level of intelligence of the agents.

Research question four tests the efficacy of the optimal calibration model averaging technique.

Research question five evaluates the efficacy of fine tuning a small world network and the interactive power to match the flow of interactive expectations.

3 Methodology for the AIE Model

This section discusses the methodology for the AIE model. The AIE model combines the adaptive expectations model (Hicks 1939) and the interactive expectations model (Flieth & Foster 2002) extended with small world networks (Watts & Strogatz 1998) within an agent based model (Wilensky 1999).

Supplementing the components above, the AIE model introduces two techniques: (1) a '*pressure to change profit expectations index*' (p^x) to replace the probabilistic treatment in the interactive model (Flieth & Foster 2002), and (2) *'optimal calibration model averaging'* to enhance prediction.

Each run of the AIE model has a unique set of parameters and a model variance. The model variance is the SSE/T between the all–firms profit expectations index of the AIE models and of the D&B (2008) profit expectations survey. The model's multiple equilibria are located by finding the runs with low model variance or the local minima. An alternating gradient and limited broad sweep search method is used to find the multiple equilibria in the AIE model. These multiple equilibria are then used in 'optimal calibration model averaging' to enhance prediction.

The structure of this section is as follows. Section one discusses linking the macro level indices with the micro level firms' behaviour and initialising the AIE model. Section two discusses the calculation of the p^x. Section three discusses searching for local minima or equilibria in the AIE model. Section four discusses optimal calibration model averaging. Section five discusses refinements to the research questions.

3.1 Emergence: Linking Macro Indices to Firms' Micro Behaviour

The AIE model starts with and uses macro level all–firms profit indices (D&B 2008) to assign profit expectations and actualisation levels to individual firms. To do this the profit expectations index is decomposed into the percentage of firms expecting profits to increase, to undergo no change and to decrease, using equation (1). Additionally, the profit actualisation index is decomposed into the percentage of firms whose profits actually increase, undergo no change and decrease, using equation (2). The decomposition requires the ABS (2002 Cat. No. 5250.0 tbl. 2) aggregate of the percentage of firms that expect 'no change' in profits. This 'no change' dataset is used to represent the D&B (2008) 'no change' data for both the profit expectations and actual profits. This 'no change' data is the best that could be found. 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, to undergo no change or decrease, using the percentage breakdowns. The actualisations ($a_{i,t}$) are assigned similarly. So far these assignments reflect the D&B (2008) indices.

The first two periods of a dataset from the D&B (2008) survey are used to initialise the each firm's level of profit expectations and actual profits. Section 3.2 discusses how these firms change their expectations based upon the p^x for each successive period. Once the AIE model calculates the expectations of each firm for each period, the AIE model's expectations index is calculated using equation (1). A measure of the goodness of fit of the model run is the model variance between the all–firms profit expectations index of the AIE model's run and D&B (2008). The runs with the lowest model variance are local minima or equilibria. Section 3.3 discusses searching for the equilibria and section 3.4 discusses optimal calibration model averaging.

3.2 The Pressure to Change Profit Expectations Index

The $p^x_{i,t}$ is calculated for each firm *i* each quarter *t*. Rather than using a probability to assign a change in expectations to an agent, which is common in the expectations literature, see Flieth and Foster (2002) and Bowden and McDonald (2006), this paper introduces the p^x as a subjective measure representing decision making in the face of uncertainty as opposed to a probability, which is more useful in representing a known risk. Each agent in the model is subjected to pressure to change their profit expectations. Section 3.2.1 discusses how the maximum and minimum p^x is restricted to 100 and –100 respectively. In addition to the index's suitability to measure decision making under uncertainty, 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, bypassing 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. Equation 3 shows the calculation of the p^x (a) for firms who currently expect profits to decrease, (b) for firms who currently expect no change on profits and (c) for firms who currently expect profits to increase.

These basic tendencies (β) 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 neutral (β^0) could be interpreted respectively as optimism, pessimism, or neutral feelings that permeate the economy. Looking at Figure 3, it appears that there are overly optimistic expectations, because profit expectations exceed profit actualisations most of the time, so 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.

The interactive influence (I) in equation 3 indicates the influence of other firms holding a certain level of profit expectations on the firm. This is adapted from Flieth and Foster (2002), see equation 4. Equation 3 differs from equation 4 in that it connects the firm via a network rather than assuming total connectivity. Section 2.5 discusses the AIE network topology (L and ρ) and parameters ranges. Note to ease comparison between equation 3 and equation 4 that the variable names in equation 4 have been made consistent.

Equation 3 – 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

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

(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

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

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

The pressure to decrease expectations

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

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

β^0 = basic tendency to neutral expectations

β^- = basic tendency to decrease expectations

A = adaptive influence this quarter

A_{-1} = adaptive influence last quarter

$a_{i,t}$ = 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)

Equation 4 results in a probabilistic treatment of the whole population's expectations, whereas Equation 3 considers each firm within a network of interactive influence. These two differing approaches are appropriate to the situation being studied. Flieth and Foster (2002) examine interactive expectations using an electoral opinion poll, whereas this paper examines interactive profit expectations among the manufacturing, wholesale and retail divisions. Flieth and Foster's (2002) approach more closely approximates a complete graph as individuals are exposed to regular national media coverage of political events, which includes regular surveys of the voting population. The AIE model's approach more closely resembles a network of interconnected supply chains as firms are linked to one another via orders in expectation of sales as discussed in the 'beer distribution game'. Admittedly, the two approaches are not as black and white as portrayed, but more different shades of grey.

Equation 4 – Interactive Influence from Flieth and Foster (2002) to compare with the AIE interactive component in Equation 3

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

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

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

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 (2006). This ensures that the design of the AIE model's network builds upon the existing literature. However the results in section 4.5 show that an alternative network approach is required, a point taken up in the section 5.

The AIE model also relaxes the assumption of Flieth and Foster (2002) that the interactive power in Equation 4 is two by allowing the power to vary from 1 to 3 by 0.2 increments to test their assumption.

In addition to the network lattice, the AIE model differs from Flieth and Foster (2002) in that it also incorporates an adaptive expectations influence (A) from Hicks (1939). This allows a connection between profit actualisations and profit expectations, which Flieth and Foster's (2002) Interactive Expectations lacks. In Equation 3(a), the parameters A and A_{-1} act as weights in the p^{x} and the parameters ($a_{i,t} - e_{i,t}$) and ($a_{i,t-1} - e_{i,t-1}$) form a link between the profit actualisation and profit expectations. The AIE model uses the current and last quarter only, assuming a cognitive bias called the recency effect holds. Additionally, the model reflects the fact that a firm lacks full information about the actual profits for the current quarter until the following quarter, so a firm behaving adaptively would use the full information available from last quarter and the partial information available about the current quarter.

Equation 5 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 the firm holds for the next quarter ($e_{i,t+1}$).

Equation 5 – 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 5 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 next quarter as per Equation 1. 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 is the process for a single run to find the model variance for a single set of parameter values. Section 3.3 discusses the process used to search the parameter space for local minima of model variance or equilibria.

3.2.1 Maximum and minimum pressure to change index

Equation 6 shows how the weights in the p^x are set to 100. The constraint allowed the elimination of one parameter from the parameter sweeping; the basic tendency neutral (n) was chosen for elimination. In Equation 3, because the parameters $a_{i,t}$, $e_{i,t}$, $a_{i,t-1}$ and $e_{i,t-1}$ can all take the values 1, 0 or –1, this can result in doubling the weight of A or A_{-1} on the p^x. The factor of two in Equation 6 reflects this.

Equation 6 – Setting the maximum and minimum p^x to 100 and –100 respectively

$$100 = \beta^+ + \beta^0 + I + 2 * [A + A_{-1}]$$

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

3.3 Searching the parameter space for local minima or equilibria

This section discusses the search for minima or equilibria in the AIE model. The search for the lowest model variance between the profit expectations index of the AIE model and of D&B (2008) combines the gradient method with a limited broad sweep to prevent the gradient method becoming lodged on a local minimum and to reduce the risk of missing other local minima, which may be equally plausible solutions to a global minimum. These equally plausible equilibria become candidates for inclusion in optimal calibration model averaging discussed in section 3.4. Additionally the limited broad sweep provides for visualisation, see section 4.5.

Each run is defined by the eleven parameters: β^+, I, L, δ, A, A_{-1}, ρ, p^+, p^{++}, p^- and p^{--}. The gradient and limited broad sweeps method involves setting an initial value for the 11 parameters. The 11 parameter values to initialise the gradient method are based upon reason and assumptions. Each parameter value is allowed to vary plus or minus one increment: $\beta^+ \pm 1$, I±1, L±2, $\rho \pm 0.1$, $\delta \pm 0.2$, A±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. The minimum parameter values are L = 2, δ = 1 and $\beta^+ = \beta^0 = I = A = A_{-1} = \rho = p^+ = p^{++} = p^- = p^{--} = 0$. The condition in equation (6) 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. 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±5, L = (2, 4, 6, …, 22), δ = (1.0, 1.2, 1.4, …, 3.0), ρ = (0, 0.1, 0.2, …, 1), A±5, $A_{-1} \pm 5$. This gives 11^6 parameter combinations or runs. 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.

3.4 Optimal Calibration Model Averaging

This section discusses the optimal calibration model averaging technique for combining forecasts to enhance predictions (Bates & Granger 1969). The process involves a calibration and a forecast phase.

In the calibration phase, the runs are arranged in an ascending order of model variance; see the dashed line in Figure 10. A calibration model average is produced from the two runs with the lowest model variance by averaging their profit expectations indices for each quarter. The calibration model averaging process is repeated for three runs, four runs, and so on. The model variance between the all–firm profit expectations indices of the model average and of D&B (2008) is shown by the solid line in Figure 10. The minimum model variance on the solid line determines the optimal number of runs to average, hence the name optimal calibration model averaging.

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 dashed line in Figure 16 shows the model variance of the predictions. The solid line in Figure 16 shows the model variance of the model average of the predictions. The following model variances of the prediction are compared to evaluate the effectiveness of the technique: the model average of the optimal calibration model average number of runs and single prediction run using the parameters from the calibration run with the lowest model variance.

3.5 The Research Questions

Research question one involves using prediction to test the expectations phase change concept. This requires calibrating the AIE model over a long and a short period and using their respective predictions to test the concept. The long calibration period is June 1988 to December 2006 and the short calibration period is March 2000 to December 2006. The prediction period is March 2006 to June 2007.

Research question two involves using predictions to test the AIE model against its benchmark the adaptive expectations model. This comparison with the adaptive expectations model determines the predictive power of the interactive component of the AIE model.

Research question three compares the AIE model with its other benchmark the rational expectations hypothesis (Muth 1960, 1961) to determine if the level of intelligence of the agent is adequate. Sections 4.1 and 4.3 present the calibrations and predictions respectively to address research questions one, two and three.

Research question four tests the efficacy of the optimal calibration model averaging technique. Sections 4.2 and 4.4 present the evaluation of the technique.

Research question five evaluates the efficacy of fine tuning the network parameters (L, ρ, δ) to find a proxy for the interactive network using a visualisation. Section 4.5 presents a visualisation of the model variance dependent on the network parameters.

4 Results

This section presents the results that address the research questions in section 3.5.

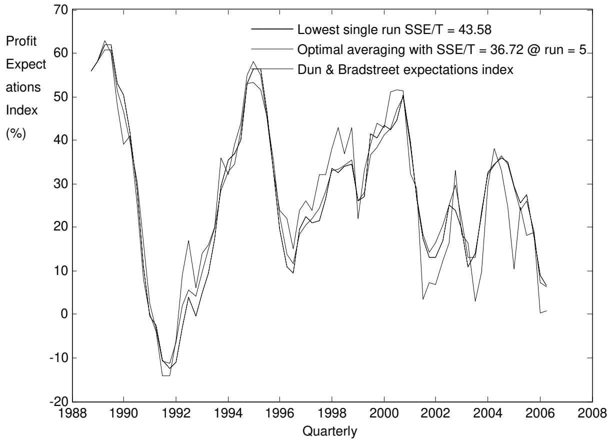
The structure of this section is as follows. Section one presents the results of the short and long calibration of the AIE model and the short calibration of the adaptive expectations model, so addressing the calibration phase for research questions one, two and three. Section two presents the results of the calibration using the ‘optimal calibration model averaging’ technique, so addressing the calibration phase for research question four. Section three presents the predictions based upon the calibrations in section one, so addressing the prediction phase for research questions one, two and three. Section four presents the result for the predictions using the ‘optimal calibration model averaging’ technique based upon the calibration in section two, so addressing the prediction phase for research question four. Section five presents a visualisation of using parameters to fine tune the network topology and the effectiveness of using an interactive power of two, addressing research question five.

4.1 Calibration

Figure 7, Figure 8 and Figure 9 have three lines each. The dashed line represents the all–firms profit expectations index of D&B (2008); the line the model is trying to emulate. The dotted line represents the model's run with the lowest model variance. The solid line is from the 'optimal calibration model averaging' in section 4.2. The model variance is the measure of the mean of the sum of the square of the errors (SSE/T) between the all–firm profit expectations indices of the D&B (2008) and of the AIE or the adaptive expectations model.

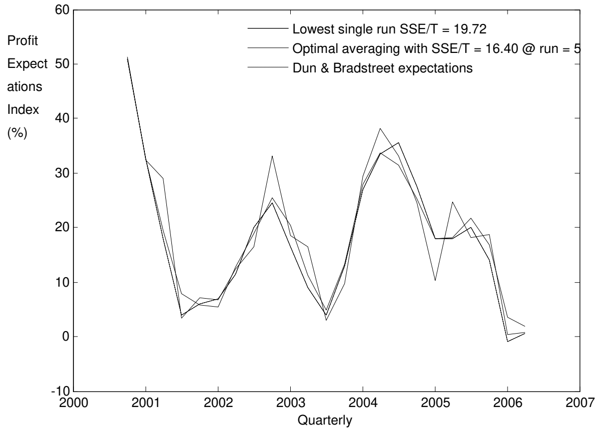
Addressing research question one: comparing Figure 7 and Figure 8 shows that the AIE model for the long calibration has a higher model variance than the short calibration. However to ensure that this result is not just the product of fitting the AIE model to fewer data points; a prediction is performed in section 4.3. Section 4.5 presents a visualisation containing the 'Lowest single run' model variance in Figure 8.

Figure 7 Comparing the Long Calibration of the AIE model against the D&B Index



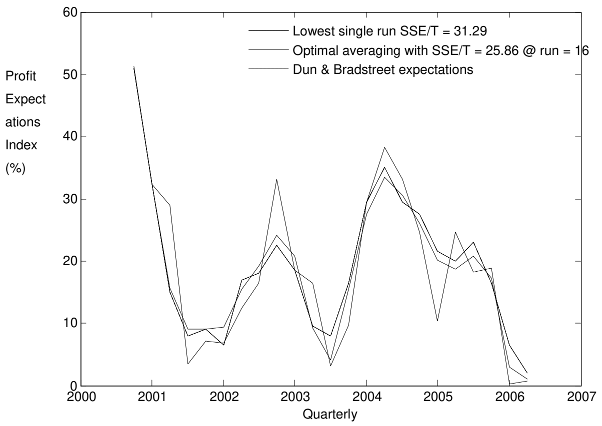
Addressing research question two: comparing Figure 8 and Figure 9 shows that the AIE has a lower model variance or better fit in than the adaptive expectations model. To make sure this is not just a product of modelling the same number of points with more parameters a prediction is performed in section 4.3. The adaptive expectations model lacks the interactive components, so has fewer parameters to allow fine tuning of the model.

Figure 8 Comparing the Short Calibration of the AIE model against the D&B Index



Addressing research question three: the model variance of the rational expectations hypothesis over the long and short calibration periods is 317 and 183 respectively. Both these values are higher than the long and short calibrations of the AIE and of the short calibration of the adaptive expectations. Note in calculating the model variance for rational expectations hypothesis the profit expectations indices of the first two quarters are set to zero percent to ensure consistency with the initialisation requirements and model variance calculation of the AIE and adaptive expectations models.

Figure 9 Comparing the Short Calibration of the Adaptive Expectations model against D&B Index



4.2 Using Model Averaging to Minimise the Model Variance

Addressing research question four: this section finds the optimal number of runs to include in model averaging to minimise the SSE/T for three models in section 4.1.

Figure 10 illustrates minimising the SSE/T using model averaging for the AIE model for the long calibration period. The upper dashed line in Figure 10 shows the SSE/T value between the all–firms profit expectations index of the D&B (2008) and of the AIE model for the two hundred best fitting runs in ascending order.

The lower continuous line in Figure 10 shows the SSE/T value between the all–firms profit expectations index of the D&B (2008) and of AIE model averaging. The optimal number of runs for model averaging is 5 runs where the SSE/T is 36.72.

Figure 10 shows that optimal model averaging reduces the SSE/T for the individual run from 44 to 37. Figure 11 shows that the SSE/T reduction for the AIE short calibration is from 20 to 16. Table 2 shows the parameters of the 5 runs included in the optimal model averaging. Figure 12 shows that the SSE/T reduction for the adaptive expectations short calibration is from 31 to 26.

Optimal calibration model averaging reduces SSE/T in the calibration phase, but, more importantly, the question "How does it perform during prediction?"

Figure 10 Using model averaging to minimises the model variance for the AIE long calibration

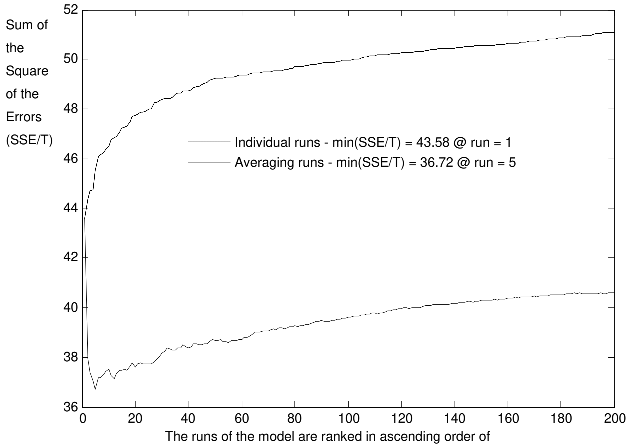


Figure 11 Using model averaging to minimises the model variance for the AIE short calibration

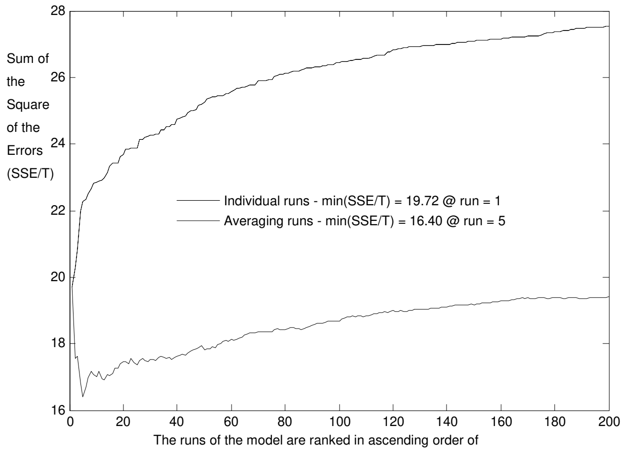
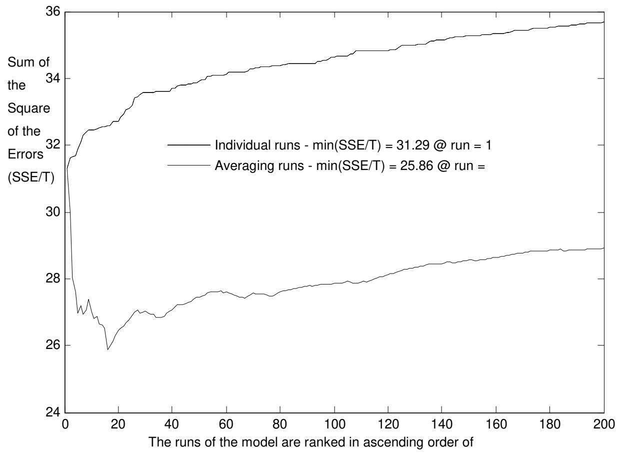


Figure 12 Using model averaging to minimises the SSE/T for the adaptive expectations short calibration



4.3 Prediction

This section presents the results of the predictions based upon the three calibrations in section 4.1. Figure 13, Figure 14 and Figure 15 have three lines each. The dashed line represents the all–firms profit expectations index of D&B (2008); the line the model is trying to emulate. The dotted line represents the model's prediction based upon the calibration run with the lowest model variance in section 4.1. The solid line prediction is based upon the optimal calibration model averaging in section 4.3.

Addressing research question one: comparing Figure 13 and Figure 14 shows that the shorter calibration period has greater predictive power. Additionally 'optimal calibration model averaging' has slightly less predictive power than the 'Lowest SSE/T single run from the calibration' in the AIE model over the short and long calibration period.

Addressing research question two: comparing Figure 14 and Figure 15 shows that the adaptive expectations model in Figure 15 makes the predictions with the lowest model variance for both 'optimal calibration model averaging' and the single run. The prediction of the

Figure 13 Prediction and SSE/T for the AIE model based upon a long calibration

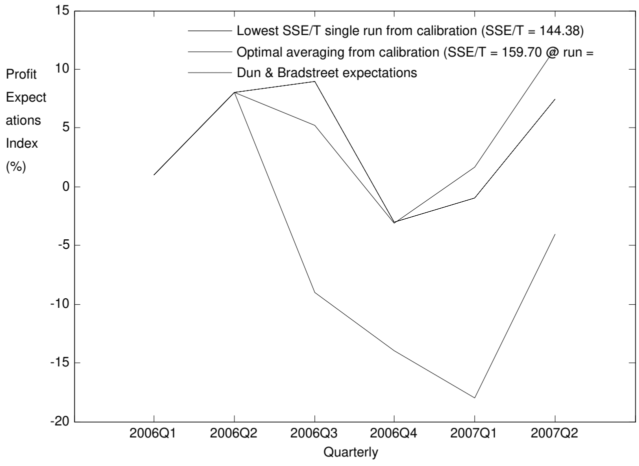


Figure 14 Prediction with SSE/T for the AIE model based upon a short calibration

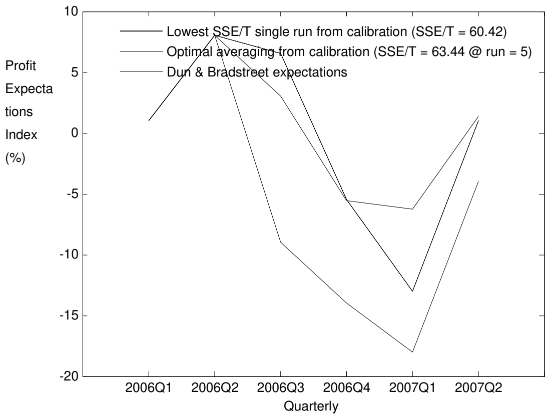
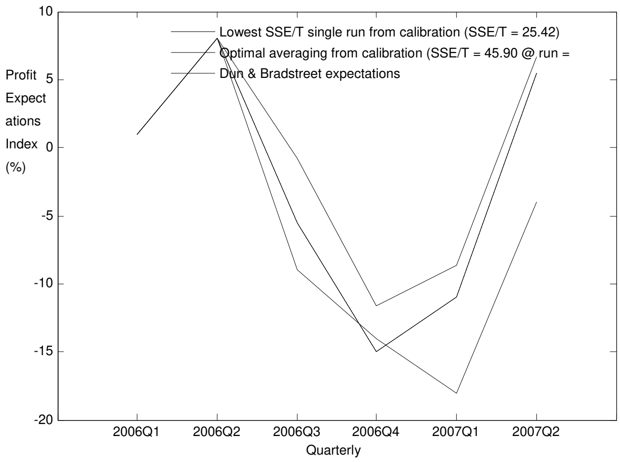


Figure 15 Prediction with SSE/T for the adaptive expectations model based upon a short calibration



adaptive expectations model, the benchmark, has outperformed the prediction of the AIE model. This indicates that the interactive component requires improving and is discussed further in section 5.

Addressing research question three: the model variance of the rational expectations hypothesis over the prediction period is 62. This model variance is much higher than the adaptive expectations model's, slightly higher than the AIE model's run with the lowest model variance and slightly lower than the AIE model's 'optimal calibration model averaging'. This indicates that the amount of memory in the AIE model may be correct. Section 5 discusses this further.

4.4 Reviewing the Prediction Performance of Optimal Calibration Model Averaging

Addressing research question four: this section reviews the predictive performance of 'optimal calibration model averaging' described in section 3.3. The solid (dashed) lines in Figure 16, Figure 17 and Figure 18 show the model variance between the all–firms profit expectations indices of D&B (2008) and of the model averaging (individual runs) for the predictions based upon the calibrations in section 4.2.

Figure 16 AIE long optimal calibration model averaging prediction performance

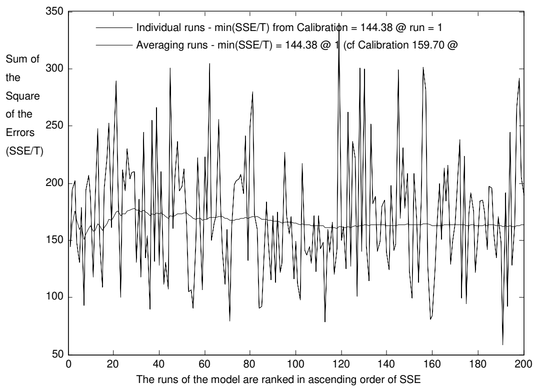
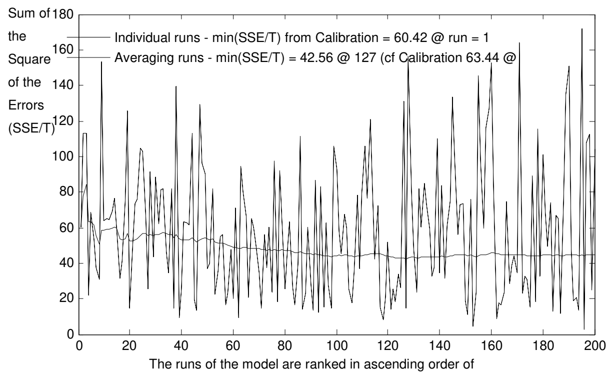


Figure 17 AIE short optimal calibration model averaging prediction performance



To ease evaluation, the model variance from the 'optimal calibration model averaging' (lowest single run) from Figure 13, Figure 14 and Figure 15 are presented.

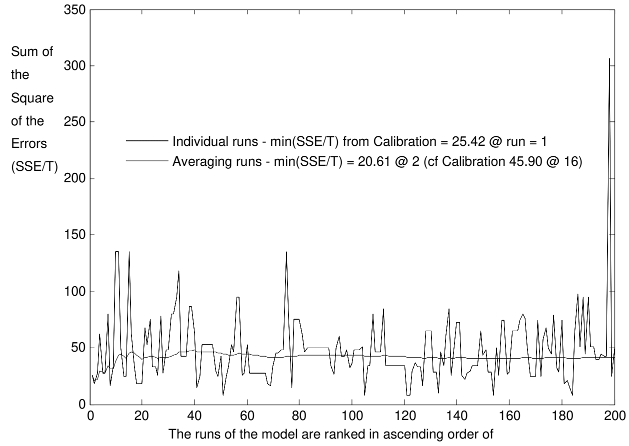
Figure 16 shows that the optimal calibration model averaging technique appears ineffective in the AIE model long calibration, because the lowest model averaging for the prediction is at run one; this compares to run five for the optimal calibration model averaging technique.

Figure 17 shows that the technique appears ineffective in the AIE model short calibration case, because the lowest model averaging for the prediction is at run 127; this compares to run 5 for the technique.

Figure 18 shows that technique appears ineffective in the adaptive expectations model short calibration case, because the lowest model averaging for the prediction is at run 2; this compares to run 16 for the technique.

Section 5 discusses these findings further.

Figure 18 Adaptive expectations short optimal calibration model averaging prediction performance



4.5 Visualisation to evaluate finetuning the network topology

This section shows how varying the network topology (L and ρ) and interactive power (δ) affects the model variance. L, ρ and δ determine the interactive component of the p^x.

Figure 19, Figure 20 and Figure 21 show how varying the network topology affects the model variance for δ = 1.0, 1.2 and 1.4 respectively. The dark patches are the low model variance values and the white patches the high model variance values. Thinking of dark green valleys and the white tops of mountains is a helpful analogy. The figures show multiple equilibria or minima. The minimum in Figure 20 shows the run from Figure 8 with the lowest model variance at 19.72; Table 2 shows the parameters values for the five runs with the lowest model variance, including run 1 from Figure 8.

Table 2 Parameter values for the five runs with the lowest model variance (SSE/T) for the short calibration of the AIE model

Run	SSE/T	δ	ρ	L	β^+	I	A	A_{-1}	p^+	p^{++}	p^-	p^{--}
1	19.7	1.2	0.6	16	3	27	13	18	45	117	48	122
2	20.3	1.8	0.9	22	5	24	10	19	45	117	48	122
3	20.8	2.8	1	12	4	30	9	18	45	117	48	122
4	22	1.4	0.3	22	4	28	12	22	45	117	48	122
5	22.3	1.8	0.8	8	4	30	9	19	45	117	48	122

Notable is that p^+ and p^{++} are smaller in magnitude than p^- and p^{--} respectively. This is consistent with the all–firms profit expectations indices being greater than the actualisation indices seen in Figure 3. Note also that the values of L, δ and ρ are widely spread. This is consistent with Figure 19, Figure 20 and Figure 21 showing widely spread minimums.

Figure 19 SSE/T for various L and ρ for δ = 1.0

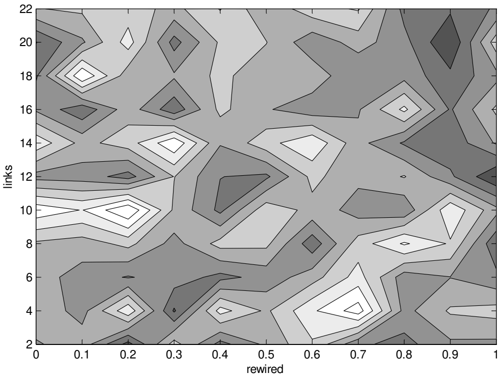
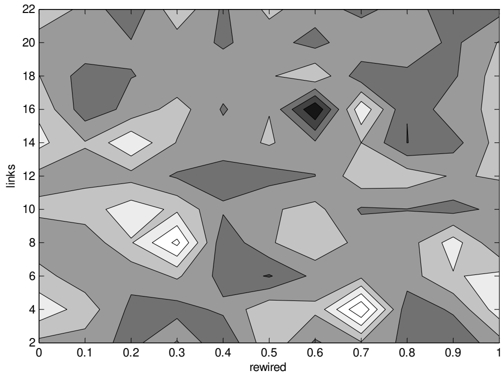


Figure 20 SSE/T for various L and ρ for δ = 1.2



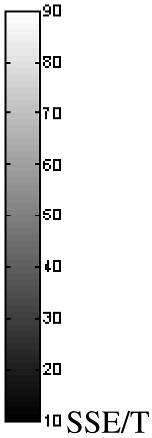
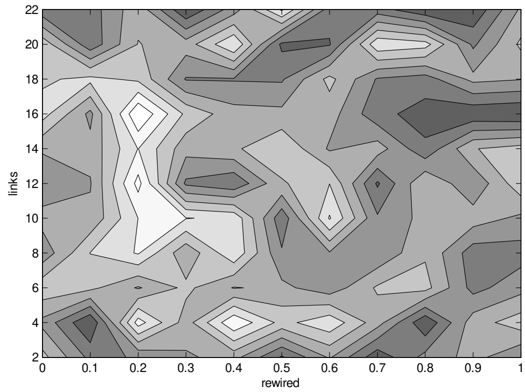


Figure 21 SSE/T for various L and ρ for δ = 1.4



4.5.1 *Visualisation to evaluate finetuning the interactive power*

This section investigates whether a δ of 2 is significant in finding low model variance in the AIE model.

Figure 22, Figure 23 and Figure 24 show that a δ of 2 does not appear to play any finetuning role in the AIE model. Figure 22, Figure 23 and Figure 24 contain run 1 with the lowest model variance of 19.72 from Figure 8, whose parameters are shown in Table 2.

This result is significant for future AIE model development, because retaining δ as a parameter to sweep appears necessary.

Figure 22 SSE/T for various δ and β^+ for I = 27

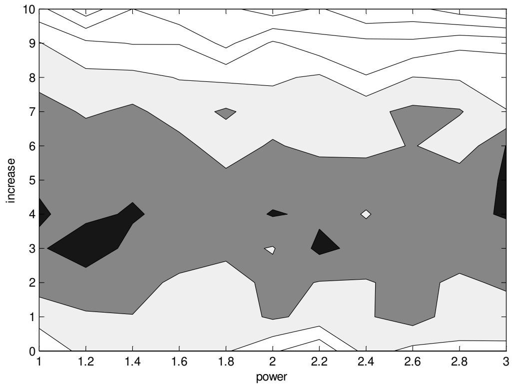
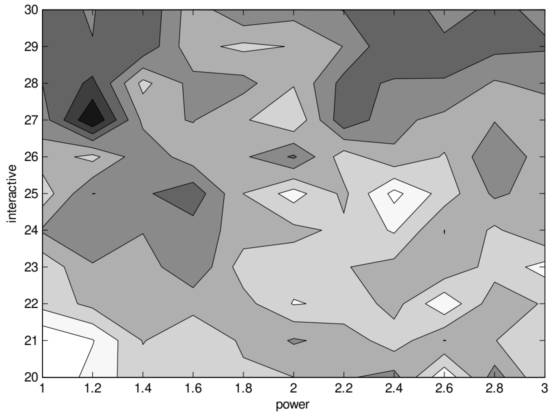


Figure 23 SSE/T for various δ and I for A_{-1} = 18



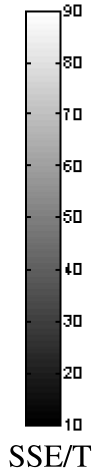
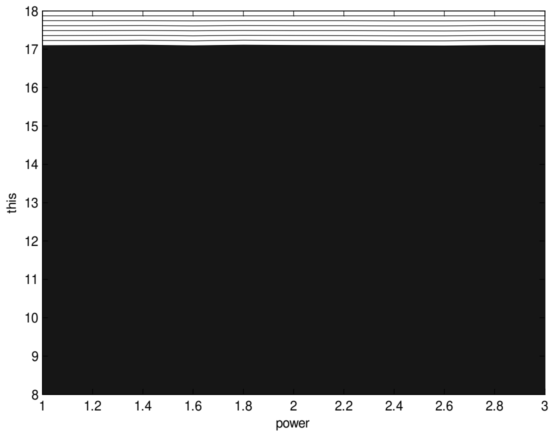


Figure 24 SSE/T for various δ and A for A_{-1} = 18



5 Discussion

The calibration results in section 4.1 show that the AIE model calibrated over the shorter period provides a much closer fit to the D&B (2008) profit expectations index. This could be the product of fitting the same model to fewer data point. However in section 4.3, the prediction of the AIE model calibrated over the shorter period finds a much closer fit to the D&B (2008) profit expectations also. The prediction and calibration are consistent. These findings do not reject Flieth and Foster’s (2002) observation regarding expectations undergoing phase changes.

In addition, the calibration results in section 4.1 show that the AIE model provides a much closer fit to the D&B (2008) profit expectations index than the adaptive expectations model. This could be a product of fitting the adaptive expectations model with fewer parameters than the AIE model to the same number of data points. However in section 4.3 the prediction of the adaptive expectations model finds a much closer fit to the D&B (2008) profit expectations. The calibration and prediction are inconsistent. The prediction of the adaptive expectations model has a lower model variance than the AIE model, so providing more predictive power with fewer parameters. The adaptive expectations model is essentially the AIE model less the interactive components that is the network topology parameters and power, see equation (3). The interactive components in this version of the

AIE model appear to have failed to capture the interactive expectations. Before discussing improvements to the AIE model though, it must be recognised that the AIE model provides a dynamic forecast in that one period's state determines the next. There is feedback in the model and more parameters allow for the model's prediction to become awry. In comparison, the adaptive expectations model's static forecast can stay in sync with profit actualisation values.

One solution to improving the AIE model's predictive ability would be to increase the memory of the agents of the interactive component, although a comparison with the rational expectations hypothesis would suggest an increase in memory is unnecessary. This version of the AIE model only uses the current quarter for establishing the p^x from an interactive influence. This compares with the adaptive influence that uses this quarter and last quarter. However increasing the interactive memory to include the last quarter would mean adding 3 to 4 more parameters to the model, which is already time consuming to analyse and at the limits of the computing power available. Yu's (2008) dynamics cognitive model offers an avenue for further research into increasing the model's memory with a modest increases in the number of parameters. The dynamic cognitive model based upon empirical studies finds that people discount their previous periods' information by 0.75 each period. Discounting is consistent with the adaptive expectations model (Hicks 1939) that is also known as exponential smoothing. Yu (2008) compares Bayesian learning and dynamic cognitive model predictions with the results from empirically based cognitive research and finds that both approaches are consistent. However the dynamic cognitive model is much simpler to calculate.

Section 4.5 shows a visualisation of the AIE model for the short calibration. This visualisation provides a clearer picture of the network topology problem in the interactive component of the AIE model. The current AIE model uses a 200 node ring lattice network whose topology is controlled by two parameters: L and ρ. This approach is based upon the literature (Bowden & McDonald 2006; Watts & Strogatz 1998; Wilensky 2005). Section 4.5 demonstrates multiple equilibria in the model. Many combinations of L and ρ can be calibrated to find a low model variance value. Finetuning the network failed to identify a unique solution; in fact the multiple equilibria are quite disparate. This suggests that the method requires some form of restriction on the network parameterisation. Additionally, any form of simple ring lattice may be unable to represent the interactive network. This is an avenue for further research.

Grimm et al. suggest using the Medawar zone concept to test agent based models using the patterns from multiple levels of emergence. The current AIE model is an aggregate model using a single class of firm with a single class of interactive link of equal size between the firms. Introducing a different class of firm to represent for each division of the D&B (2008) survey would allow for emergence at multiple levels. This entails introducing a different class of directional link between each class of firm to represent the intensity of interactive expectations between each class of firm. Hanneman and Riddle (2005) note that a network can represent informational and material flows. To this end, an input–output table can represent material flows between sectors of the economy and the hyperlinks between businesses on World Wide Web that can represent information flows. Baggio (2008) found a correspondence between the structure of the real world network of social links in the tourist industry and the virtual network of the businesses' hyperlinks. Further research involves testing the AIE at multiple levels using the input-output table and a hyperlink network to represent the intensity of interactive flows between firms. Bell (2009a) uses an AIE model augmented with an input-output table.

The primary motivation for the AIE model is to capture emergence from the endogenous factors. However to do so may require allowance for exogenous factors other than actual change in percentage profits used in the current AIE model. Further research involves identifying the most significant exogenous factors for incorporation into the AIE model, such as a change in interest rate.

Finally, as shown in section 4.4, the optimal calibration model averaging is effective for the improving the calibration of the AIE and adaptive expectations models but ineffective for improving prediction. Further research in this area could consider factors other than ranking the runs by model variance, such as runtime weighting model averaging, which features in Bell (2008, 2009a, 2009b).

6 Conclusion

The AIE model provides an explanatory description of profit expectations formation, exceeding the calibration benchmarks but fails to exceed all the predictive benchmarks. The '*optimal calibration model averaging*' technique has the same fault. Meaning the AIE model and the model averaging technique require improvement before they are ready to investigate policy implications.

A major constraint on improving the AIE model is the number of parameters that can be tested, so a focus of section 5 is determining which parameters to include and how to get the best use out of the parameters. These are considerations for traditional mathematical economics also, but the relative times for testing models are hours compared to weeks for agent based models.

Section 4 shows that the predictive performance of the interactive component of the AIE model is poor relative to the adaptive expectations model but is comparable to the rational expectations hypothesis. However, it needs to be acknowledged that the AIE model is a dynamic model. In all three cases, the 'optimal calibration model averaging' technique improves model calibration but not prediction.

The interactive component of the AIE model may be improved by increasing the interactive memory and or replacing the aggregate model with a divisional model whose interactive links between firms of differing division have magnitudes based upon an output–input table or a hyperlink network.

Beinhocker's (2006) three factors of emergence provide a useful framework to structure the reason why parameters are included in a model: (1) exogenous shocks, (2) participants' behaviour and (3) institutional structure. This paper has identified the following corresponding items for further research: exogenous shocks, the inclusion of the change in interest rates (D&B 2008); participant behaviour, the inclusion of the dynamic cognitive model (Yu 2008); and institutional structure, using a disaggregated interactive network and incorporating an input–output table or a hyperlink network (Baggio 2008). These changes feature in Bell (2009a).

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Figures

Tables