A NETWORK TOPOLOGICAL APPROACH to CURRENCY CASCADES

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Abstract

The stability of international financial markets is an important issue for academics and policymakers. Crises in currency markets have become increasingly common with the 1990s in particular experiencing major episodes of currency turmoil. The causation and frequency of these crises is a puzzle, especially for semi-free-floating currencies.

In this thesis recent currency crises are introduced and examined. Theories and methodologies which evolved in complexity and network sciences are then shown to have analogies to currency crises and to offer insights for finance. Common factors of recent currency crises are shown to be explainable using complexity and network sciences, and that price determinant influences exhibit characteristics of a complex network. An alternative approach to currency crises based on binary choices using an agent-based model in an explicit topological sparsely clustered network is proposed. This is shown to be capable of generating complex dynamics, including cascades.

A proxy topology of currency influences is then extracted from the international foreign exchange price matrix and shown to exhibit a robust taxonomy. This topology is then subjected to cascade simulation analysis. The results show that node threshold values and the density of external links are the key parameters in terms of cascade propagation. It is thus shown that a simple parsimonious model of trader interaction within a foreign exchange network can produce dynamics which are complex and contingent, and match the proposed stylised facts of currency crises. Policy issues flowing from these findings are discussed. The results increase our understanding of price dynamics in financial markets.

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Chapter One – Introduction

1.1 International Financial Market Stability

The stability of international financial markets is an important issue for policymakers and academics. Crises in currency markets have become increasingly common since the end of the Bretton Woods system (Bordo, Eichengreen, Klingebiel & Martinez-Peria, 2000), with the 1990s in particular experiencing major episodes of currency turmoil; the European exchange rate crisis in 1992-93, the Latin American "Tequila Crisis" in 1994-95, and the crisis that swept through Asia in 1997-98, and spread to Russia in 1998 and Brazil in 1999. According to Kaminsky (2003) 96 instances of currency crises occurred in twenty selected countries over the period 1970 to 2001.

The size and frequency of these crises is also a puzzle. Typically finance models assume that financial markets are inherently stable. This is a consequence of an assumption of perfect arbitrage behaviour, allied with constant volatility. In such models large discontinuous jumps in asset prices are regarded as infrequent and are treated as exceptional events. The observed frequency of crises of this size in financial markets, however, is closer to once every ten years. The size is also large. The 1987 stock market collapse, for example, embodied a movement of five standard deviations, with asset prices falling by 23% in one day. Under the usual assumptions of normality, the expectation of this event is one occurrence every billion billion years, or in more practical terms, never. This poses the question of whether international markets are inherently less stable than theorised, with these crises being normal (rather than anomalous) events.

For foreign exchange markets the 1997/98 Asian currency crisis raises similar challenges to conventional explanations of crises, as there was a one-day drop of 14.5 standard deviations for the MYR/USD. The major problem was that nearly all the countries involved had not appeared to be vulnerable to such an event. Nearly all these countries were well regarded in terms of macroeconomic management and financial supervision prior to the crisis. The majority of multilateral agencies, observers and investors had not detected increased susceptibility. Not only were there few predictions of the crisis, its scope and its scale were also not widely predicted (Radelet & Sachs, 1998b).

The macroeconomic explanations of crises (e.g: Eichengreen, at al. 1998) emphasise policy failures. These normally involve inconsistent government policies allied with indefensible currency pegs. Policy authorities are advised to adopt policies which avoid zones of vulnerabilities, provide better information and strengthen financial systems.

An alternative view of the Asian crisis is that it was an instance of international market failure. De Brouwer (2001) argues the September/ October 1998 crisis in particular affected investors' beliefs about financial market stability as it generated a global panic, producing a pronounced substitution towards low-risk products. This suggests that herd behaviour was a significant factor in the dynamics of this crisis.

Two points emerge from the literature; firstly, distinguishing causal events which spark crises from similar events which do not is problematic. Most models cannot successfully accomplish this. Even models geared to the Asian crisis are often not generalisable to other crises, and have weak predictive power. Secondly, crises can spread to countries with sound macroeconomic and financial regulatory systems through contagion. Given these problems, it is appropriate to investigate alternative approaches.

1.2 The Research Question

The focus of this thesis is on basic aspects of asset market dynamics, using recent developments in the areas of *complexity science* and the related area of *network analysis*. These approaches originally were derived from research in the areas of physics, biology and engineering.

Since 1998 network analysis in particular has matured and is offering novel insights into a range of areas; from cell biology, to the structure of the internet, to the interlinking of company directorships. The use of complexity science in finance, however, has been limited despite Johnson, Jefferies and Hui (2003) arguing that "financial markets are fascinating examples of complexity in action" (p. 2). Most of the research has also been by non-finance academics. Given that international financial systems are composed of a complex network of money flows, complex science and network theory have the potential to offer new insights into finance.

Based on this approach, the research question considered in this thesis is:

Does the use of theories derived from complex systems and network science enable insights to be gained concerning recent currency crises?

1.3 The Anticipated Contribution

The occurrence of discontinuous large changes in response to seemingly trivial causes is a recurring phenomenon in a diverse range of research areas. For example, a small number of books or movies by obscure artists become hits while a large number are ignored. These events share similar dynamics, yet the basic elements involved are different. If the dynamics of diverse systems are similar, there must be laws that apply to complex systems which do not relate to the system components.

In this thesis the question of whether or not ideas evolved in relation to other complex systems offer insight into discontinuous phenomena in finance is investigated. Models and methods created in complex systems research will be used as a basis to propose a dynamic currency crisis network model. If the structure of the international financial system can be successfully modelled as a complex network of financial flows, there are implications for both currency crisis modelling and for policy makers. The thesis includes a consideration of these possibilities.

The rest of this thesis is organised as follows; chapter two contains a review of currency crisis models as possible foundations of an alterative model. Chapter three contains a review of complexity science before an alternative network-based model is presented. In chapters four and five a proxy international markets network topology is derived. This topology will then be examined via simulation in chapter six. In chapter seven the thesis is concluded, policy issues are discussed and the contributions of this work are highlighted.

Chapter Two – Modelling Currency Crises

2.1 Introduction

2.1.1 Overview of crisis models

The objective in this chapter is to review and explore the broad range of models currently used to explain crises in currency markets. There are two aims in doing this. Firstly, to assess the ability of these models to explain currency crises. Secondly, to explore rules about trader behaviour which can be used as a foundation for an alternative model of currency crises.

A few broad conclusions will emerge from this review of current models. One conclusion is that it is difficult to explain the dynamics of modern currency crises using macro-based crisis models. This is especially evident in the tendency for the key determining metrics of macro-based models to show only a limited relationship to the countries affected by the '97/98 Asian crisis, or its timing, or its size. This same failure of theory to adequately capture the facts is also evident in macroeconomic models of currency determination (Frankel & Rose, 1995). There seems to be more to international currency crises than is captured by current macro-based models. Another conclusion is that the macro-based models have weak micro underpinnings. In particular they fail to explain why traders act in the way which is assumed. Kirman (1992) argues that one problem with macro-theories is that they ignore the behaviour of individual traders in favour of aggregate behaviour by assuming rational self-interest, yet this aggregate behaviour exhibits both individual and collective irrationality.

While recent advances in micro-structure theory (e.g. Lyons, 2001) have improved crisis models by added in more institutional and trader detail, Hirshleifer and Teoh (2003) identify three remaining weaknesses in micro models. These are that the payoff and interaction matrices of economic agents are assumed to be homogenous, the structure of agent interaction is assumed to be homogeneous, and models are static rather than dynamic. Kirman (1992) also argues that micro theories focus on reasons for individual behaviour yet ignore the dynamics of collective market behaviour. Some aspects of recent behavioural models are useful in closing these gaps, as are liquidity and sudden stop models. An additional weakness is that in terms of the dynamics of cascade behaviour even the most complex macro and the micro theories do not display all the richness of dynamics that a simple complex network model exhibits.

2.1.2 Developing trader behavioural rules

Setting simple rules for the behaviour of traders is an important part of modelling networks. Johnson et al. (2003) argue that while the macroscopic behaviour of complex networks can not be directly derived from analysis of network components (*nodes* - the traders), it can be derived from the behaviour of, and the interaction between, the nodes of the network. Careful specification of node behaviour is a vital aspect of this.

Lyons (2001) argues that one of the key reasons why current foreign exchange models do not explain short-term market dynamics well is that there is a dichotomy between how the behaviour of traders is modelled and how traders actually behave. Lyons argues that real traders behave in ways that need to be modelled; traders try to make profit but are overwhelmed by information, they diversify too widely to observe any single asset closely, they lack sound theoretical models for asset pricing, and due to problems with available liquidity they can not hold positions over time. These issues lead to information and asset specialisation occurring: so that traders concentrate on understanding restricted types of trades and follow informally recognised market leaders in all other types.

Those who formulate trader behaviour rules also need to recognise that short-term prices are set by the flow and pattern of interactions between traders. Asset prices do not evolve from the actions of any one trader, but are determined by mutual trader interaction. This means that financial markets are best modelled as a form of co-operative behaviour (Kim, Lee, Kim & Kahng, 2001). Traders will also face a trade-off between the amount of private market information that they collect and the cost/ time involved.

Traders will thus observe the behaviour of other traders as a lower cost proxy for direct collection of market information.

There will be a balance between the wish to observe as many other traders as possible so as to maximise information gain, and the cost of the observation, especially once the pool of physically proximate traders is exhausted. While traders will be conscious of the need to observe the actions of other traders they will be unable to observe more than a minimal subset of worldwide traders. Each individual trader will thus have to make an idiosyncratic choice about the number and type of other traders whose behaviour s/he directly observes. This implies that each trader will receive information from, or observe the actions of, a heterogeneous subset of all market traders, in their own submarket as well as in the broader markets.

Traders will also be limited in the extent of information that they can each assimilate and be limited in their capacity to assess the information they have. This reflects agents' uncertainty about both the validity of their private information, which is related to the level of information noise in the market, about the validity of their analysis of public information, and uncertainty about their assessment of the credibility of the observed actions of other agents. This will lead to uncertainty about the validity of observed trends or market herding. There will also be heterogeneity in leverage and payoff, which will create uncertainty as to whether the observed behaviour of other traders is due to differing information or differing trading ability. These factors imply that traders will differ in their level of confidence about their own ability to assess future prices. There will thus be heterogeneity in weightings placed on public versus private information. Given these limitations on information and analysis, traders will also tend to exhibit inertia in trading decisions.

The above patterns of trader behaviour are particularly evident in information cascade and other behavioural models. In chapter three the trader rules developed in this chapter will be used as the basis for proposing an alternative model of currency crises

2.2 Macroeconomic Feedback Models

2.2.1 Basics

The traditional workhorse model of currency crises, the *macroeconomic feedback model*, has been the main source of macro explanations for currency crises, for predictions of coming crises, and for solutions to those crises. These models may be divided into three types, called *generations*, based on the typology developed by Eichengreen, Rose and Wyplosz (1996a, 1996b).

These models assume fixed exchange rates then postulate reasons for a speculative attack. They are based on the idea that some economic variable feeds back in an adverse way and makes devaluation more likely. They normally involve speculators launching an attack on a particular currency in the expectation of a gain.

2.2.2 First generation models

First generation models, or *exogenous-policy* models, were initially posited by Krugman (1979) and developed by Flood and Garber (1984). They assume rational reasons for a speculative attack. These include faulty economic policy stances or structural imbalances. These models view currency crises as an unavoidable outcome of the unsustainable policy. An attack occurs when a particular key variable passes a specific trigger level. Normally these models yield a single equilibrium. Up until the 1990s first generation models did fit the facts of currency crises reasonably well.

There are three important aspects to these models. Firstly, there has to be fundamental factors causing the structural imbalance and ultimately the speculative attack. The viability of an exchange rate peg is determined by those exogenous fundamental factors, and is unrelated to the behaviour of economic agents. Market participants base their expectations on the presumption that their actions will not affect fundamental macroeconomic statistics. There is assumed to be no relationship between the expectations of economic agents and the actual outcome.

Secondly, a devaluation of appropriate size resolves the contradiction, so thereafter the country can be expected to rapidly and monotonically return to stability. Currency overshooting to any significant extent is not expected.

Thirdly, the size, timing and duration of any crisis will bear a proportional relationship to the macroeconomic imbalance. There is no theoretical justification to a crisis which grossly exceeds the causal factor in size, duration or timing.

First generation models do, however, add that once rational forward-looking traders anticipate devaluation they will liquidate their holdings of domestic currency in anticipation of profit. Faced with sustained speculative attack a central bank will not last long. The exhaustion of reserves can then take the form of a sudden speculative attack, rather than a gradual running down. This implies long periods of calm punctuated by sharp shocks.

An important implication of this is that a speculative attack may be triggered by the market participants' *expectations* of an unavoidable future devaluation. What matters are what expectations of *future* policy stances are, not what *past* policy stances have been. This means that the observed current macroeconomic figures may not be a good indication of the possibility of future currency crises.

2.2.3 Second generation models

Second generation, or *endogenous-policy*, models were created because the first generation models did not seem to explain the facts of the EMS crisis of 1992/3 or the Latin American crises of the 1990s. Grilli (1986) and Obstfeld (1986) provided the modifications of first generation models, which were extended into genuine second generation models by Obstfeld (1991, 1994) and Morris & Shin (1998, 1999).

Rangvid (2001) argues there were three major motivations for the creation of a new generation. Firstly, the notion that limited foreign exchange reserves plays the key role in resisting speculative currency attacks is hard to reconcile with the modern international financial system where unlimited reserves are available. Secondly, it is difficult to understand why a competent government would knowingly run a fixed exchange rate policy alongside an inconsistent macroeconomic policy, if this may ultimately lead to crisis. Thirdly, empirical studies have difficulty predicting recent currency crises, as no secular trend existed in the fundamentals. Instead, economic agents seemed to "suddenly" change their behaviour.

The essence of second generation models is the inclusion of economic agents' expectations as a variable. These expectations are used in a policy feedback between the expectations and actual outcomes, which creates an interaction between policymakers and speculators. Policymakers are assumed to react to macroeconomic shocks so as to achieve some optimal policy outcome. The government's decision to devalue is thus made endogenous, which widens the set of variables in traders' information sets. Fundamentals consequently account for only part of the motive for speculative attacks.

These models emphasise that the interaction between policymakers and speculators can lead to self-fulfilling crises. They also allow multiple rational expectations equilibria, though most model specifications create two equilibria. Second generation models thus add more depth to the analysis of how governments behave in the period leading up to a crisis, and partly explain the weak empirical relationship found between economic fundamentals and the timing of speculative attacks. The interactions generate a pattern of sudden changes in asset prices after long periods of calm.

Note that there does not have to be any actual change in the country's economic fundamentals for a crisis to arise. There is thus no strict correspondence between fundamentals and results.

To summarise; second generation models enable us to distinguish between two kinds of currency crises, one related to volatility in financial markets, and another related to volatility in a country's fundamentals. Second generation models do not, however, offer explanations for the shifts in market expectations.

2.2.4 Problems with the first two generations of models

The first two model generations provided the main conceptual frameworks used to analyse currency crises until the Asian crisis. That crisis however emphasised two important features which these models did not explain well.

Firstly, empirical studies (such as Demirgüc-Kunt & Detragiache, 1998; Glick & Hutchinson, 1999; Kaminsky, 1999; Kaminsky & Reinhart, 1999a) argue that currency and banking crises in emerging countries should be seen as twin events. The feedback mechanism between the two events can generate a cycle by amplifying each other and this has to be incorporated into any crisis model. This means that both the timing and the strength of any currency crisis can depend strongly on the health and stability of the financial sector (see Buch & Heinrich, 1999; Burnside, Eichenbaum, & Rebelo, 1998). Flood and Marion (2001) argue this cycle was a key feature in the Asian crisis.

Secondly, is the quick spread of recent crises between countries, normally referred to as *contagion.* It is analytically useful to follow Masson's (1998) lead and separate contagion models into three types, contagion models involving common external causes affecting several unrelated countries, called "*monsoonal effects*", contagion models where a crisis in one country affects the fundamental variables in another country, called "*spillover effects*" and pure contagion models, where changes in expectations are self-fulfilling, creating multiple equilibria, called "*sunspots*". Various reasons have been advanced for contagion; common shocks, trade linkages, financial interdependence (Claessens, Dornbusch, & Park, 2000) and information herding (Kodres & Pritsker, 2002).

2.2.5 Third generations models

Third generation models were created to address these issues, especially the overreaction of the markets and the subsequent expansion of currency crises into a general financial and economic collapse. The two distinguishing features of these models are the focus on the role which expectations of private agents play in capital flow reversal and the focus on the role of the capital account rather than the current account.

Three model types have been created. Firstly, bank-based models which emphasise insolvency problems (e.g. Chinn & Kletzer, 1999), secondly, portfolio equity-based models which emphasise capital flows (e.g. Calvo, 1998a), and thirdly, bank-panic models which emphasise illiquidity. These models extend the second generation models by exploring the role of financial markets, both domestically and internationally.

These models also integrate fundamentals and self-fulfilling expectations, and extend the definition of fundamentals from just macroeconomic factors to financial and institutional variables. Three basic issues are debated; details of the economic policy trade-offs, reasons for contagion, and reasons for changes in expectations.

A major problem with these models is that the conceptual framework is currently chaotic. There is little consensus on key areas like the nature of macroeconomic equilibrium, the relevant variables, and the relative role of fundamentals versus expectations. There is also no benchmark conceptual model.

2.2.6 General criticisms of macro-feedback models

There are three main criticisms of macro-feedback models. Firstly, causal linkages typically take time to operate. This means that expectations may have to be focused on the "bad" equilibrium for an extended period, which seems unlikely.

Secondly, expectations of investors are assumed to be coordinated in some manner, but how they are coordinated is not normally modelled. The models suit one large speculator, as they are silent on why multiple agents will shift equilibria at the same time. Introducing heterogeneous agents into these models removes the possibility of multiple equilibria (Herrendorf, Valentinyi & Waldmann, 2000).

Thirdly, there is scepticism at the growing number of model variations. Rodrik (1998) in particular regards these models as analytically weak if every new crisis spawns a new generation of models.

Fourthly, these models normally allow multiple solutions only within a restricted range of values. Outside that zone only unique solutions exist, and thus a sudden crisis cannot occur. Yet the economic fundamentals of some affected countries prior to the

1997 crisis were outside the crisis zone (Berg & Patillo, 1999). While useful, there seems to be more to the Asian crisis than is captured by third generation models.

2.3 Liquidity and Bank Run Models

Another approach to currency crises is to use the insights developed by bank run theory. This literature features multiple solutions and illiquidity theory which may usefully extend currency crisis models. Sachs (1984), for example, applied the Diamond and Dybvig (1983) model to international lending, in a form that is more directly relevant to currency crises. He showed that, when a country's indebtedness to international lenders is within a target range relative to its income, panics can occur when each bank believes other banks will stop lending. So even if they have no direct reason, all banks will stop lending. This is regarded as a liquidity crisis rather than a solvency crisis. Note, however, that there can be an identity problem since crises will occur only at a high level of indebtedness.

Sachs, Tornell and Velasco (1996) argue that modified bank-run models fit the 1994 Mexican crisis and Radelet and Sachs (1998a) argue that they fit the Asian Crisis. Chang and Velasco (1998a, b & c) in a series of papers extend these models to include a connection between international crises and domestic bank runs and develop an international liquidity model. They found five distinguishing elements that identify a liquidity crisis. Firstly, international illiquidity is a necessary and sufficient condition for a crisis. Secondly, over-fast financial liberalisation is necessary. Thirdly, bad policy must not be to blame. Fourthly, the collapse of a fixed exchange rate occurs because stabilising banks and maintaining the exchange rate peg become mutually incompatible. Fifthly, the punishment exceeds the crime, so that moderately weak fundamentals, together with a small change in external circumstances, lead to a major collapse in asset prices.

The liquidity crisis model allows for uncoordinated agents, in contrast to the macro feedback models. However, in their current form, liquidity crisis models when applied to currency crises require sequential market transactions, to ensure a first mover advantage. This is possible only with a fixed exchange rate, as under a floating regime those who panic will suffer a capital loss. It is also important to note that these models do not provide any causal mechanism to jumpstart the crisis.

2.4 Micro Structure Models

A criticism of the macro models reviewed is that they make only limited attempts to explain the rationale behind the activities of the economic agents. Since 1981 there has been a growing stream of research that has tried to rectify this by focusing on the micro-structure of financial markets. There has been a limited attempt to integrate this research into currency crisis models but this has been restricted to fixed exchange rates models and has not been applied to contagion (e.g.; Garber & Lall, 1998; Garber & Spencer, 1995; Lall, 1997).

2.4.1 Behavioural finance models

Rationality in finance theory means two things; firstly, agents' beliefs are correct, secondly, agents make choices that are normatively acceptable. Behavioural finance theorists argue that real world market reactions can be understood only when some economic agents are modelled as not fully rational. This leads to the conclusion that markets are not asset price efficient.

The first strand of behavioural finance involves relaxing one or both of the assumptions about rationality. Agents may hold beliefs that are not completely correct or make choices that are normatively questionable.

A second strand of behavioural finance involves establishing limits on market arbitrage. Several reasons are advanced. Firstly, riskless arbitrage at no cost is rarely available. The arbitrageur always faces the fundamental risk that further news may adversely move prices. Secondly, is noise trader risk, where irrational investors may increase the degree of mispricing (De Long, Shleifer, Summers & Waldmann, 1990). Thirdly, is implementation difficulties, especially involving the short selling of securities. Fourthly, is model risk, where arbitrageurs are unsure if the mispricing exists.

2.4.2 Positive and negative feedback models

Some researchers argue that financial markets show both under- and overreaction to financial news (Barberis, Shleifer & Vishny 1998; Bernard & Thomas 1989; Chan, Jegadeesh & Lakonishok, 1997; Cutler, Poterba & Summers, 1991; Fama & French 1998; Jegadeesh & Titman 1993; Shleifer 2000). One reason for this is a behavioural heuristic known as *representativeness* (Tversky & Kahneman, 1974). This is the tendency of financial agents to view events as typical or representative of some specific class, and ignore any laws of probability in the process. Other heuristics are *conservatism*, which is the slow updating of models in the face of new evidence, *underreaction* which occurs when economic agents hear new information and underestimate its significance, and *overreaction* which occurs when repeated news leads to an over-estimation of its significance.

The interaction of these heuristics can lead to an asset pricing pattern of a long period of stable prices followed by sudden sharp reactions to seemingly trivial events as economic agents underreact to individual pieces of information then overreact to conspicuous patterns.

2.4.3 Rational bubble model

Shiller (1989) argues that many financial variables have long periods when they go too high, or too low, with their value bearing no relationship to underlying fundamentals. While some models use irrational behaviour, rational bubble models advance rational reasons.

One reason is that if markets react slowly, then speculators will incur both holding costs and the risk of a paper loss if the price moves against them. Thus uncertainty about how long the bubble will last will hinder counter-speculation. Traders may instead react by following the price trend. This may make counter-speculation even more difficult, further expand the price bubble, and lead to herd behaviour. Frankel and Rose (1995) argue that this can occur frequently in foreign exchange markets as there are few commonly accepted pricing models and an overwhelming mass of information.

2.4.4 Information flow models

Information flow models question the perfect information assumptions of traditional theory. They focus on one of three co-ordination problems; interaction with noise traders, principal agents' concerns and information cascades. These models provide a theoretical justification for the coordination of agent behaviour which is missing in the macro currency crisis models yet is often observed in markets. Calvo and Mendoza (1996a) and Calvo (1998a) argue these models successfully fit recent currency crises.

These models use the argument that market information is costly to obtain so that traders will tend to specialise in particular products and generate imperfect information sets. Traders will be aware other actors have differing information sets, which may be superior to their own for some types of markets, and will thus observe and follow the actions of specialists for each particular product or situation. Traders may also have a differing private information sets. Information availability is thus argued to be both imperfect and asymmetrical.

O'Hara (1995) argues that prices perform market clearing and information aggregation. These functions imply that the sequence of pricing can be informative, and uninformed traders can gain new information from watching price trends. A new signal can tip the balance of sentiment from net optimism to net pessimism, or vice versa, leading to an avalanche of orders. Hirshleifer and Teoh (2003) conclude that for these reasons herding is epidemic in financial markets.

These changes to information modelling assumptions also underlie related cascade models[1]. These models use the argument that under some circumstances agents' decisions do not reflect the private information that agents personally hold but instead reflect the decisions of individuals who have acted before them. Agents thus acquire information in a sequential manner by observing other individuals' past actions.

Information gathering and analysis problems are more likely to occur in the foreign exchange markets than in other markets because of the lack of price information

[1] see Bikhchandani, Hirsheifer & Welch, 1998 for detail on herding vs cascades.

centralisation. This is also likely to be worse in emerging markets where correct information can be scarce. For example, the IMF (1998) concluded that herding occurred during the 1995 Mexican crisis because foreign investors, who relied on local investors for information, panicked when they found that these local investors had been aware of the crisis whilst they had not. A similar argument can be applied to the Asian crisis.

Calvo (1998a & b) argues that since traders cannot perfectly read the minds of other speculators they will be unsure about the exact position and nature of currency equilibrium. This will cause anxiety and extreme sensitivity to any "new" information that comes from the "market", as opposed to coming from changes in fundamentals. In these situations behaviour can arise that is *conformist* as traders end up making the same choices, *fragile* as it can easy break down with the arrival of minor new information, and *idiosyncratic* as random events combined with the choices of the first few players determine herd behaviour.

The key point is that once a critical number of traders have moved in one direction the weight of observed behaviour inevitably outweighs contradictory private information, and all traders will thereafter follow the observed behaviour, thus starting a cascade. Small irrelevant shocks will determine the timing and path of cascades. Frivolous rumours can result in massive switches of capital flows from individual countries.

These information cascade models have been shown to be empirically robust. In this thesis their information modelling assumptions will be used as the basis for the alternative model's trader behaviour rules. The major modification that will be made is the introduction of trader heterogeneity, which has only occasionally been used in these models. Instead, information cascade models typically assume homogeneity in trader payoff and interaction matrices and in the structure of agent interaction.

2.5 Application of these models to the Asian Crisis

2.5.1 The wider Asian crisis

One of the motivations for recent development of new models is the failure of pre-1997 models to match the experience of the Asian crisis. It is hard to argue that the first two generation macro-feedback models fit the experience of the Asian crisis, apart from Thailand. This is for two reasons. The first is that the strong prior macroeconomic position of the affected countries is not consistent with a macroeconomic fundamental cause.

The second is that the first two generation macro-feedback models assume that devaluation will end a crisis, with the currencies stable afterwards and economies recovering. Yet the currency crisis spread to the banking sector and resulted in a general economic crisis in all the affected countries. Bank loans at their peak affected 33% of total loans and 59 of the 91 financial companies in Thailand, 65-75% of total loans and 70 banks in Indonesia, 25-35% of total loans in Malaysia and 30-40% of total loans in South Korea. Bordo et al. (2000) highlighted the importance of twin crises as the key to the growing severity of crises.

The third generation macro-feedback, the illiquidity-based and the insolvency-based bank panic models are easier to apply. South East Asian countries did show signs of international illiquidity pre-crisis as there was an increasing ratio of short-term debt to international reserves, especially in Korea, Indonesia and Thailand. In contrast the less affected Latin American countries had stable ratios generally below one. The ratios of domestic deposits to international reserves in Asia were also rising. All the affected SE Asian countries had short-term international liabilities which exceeded short-term international assets. This made them vulnerable to a panic. Note, however, that the liquidity theory does not provide an initial cause for the crisis. This theory provides only the mechanism for the crisis once an international panic has started.

2.5.2 The twin banking/currency crisis

It is important to examine the role of illiquidity in causing the wider crisis. One reason is that empirical research supports a role for a cascade-type panic in the international trader network with interlinking between the twin currency and the banking crises. Rajan (2000b), for example, applied an international illiquidity model to the wider Asian crisis and found that the predominant capital flows in the Asian crisis originated from the reversal of funds in the banking sector rather than from the portfolio equity investments as premised by Calvo (1998b). Rajan points out that the most affected East Asian countries saw a reversal in net capital flows of almost \$130 billion between late 1996 and late 1998. This reversal was mainly due to net short-term lending by foreign commercial banks, with a net outflow of almost \$30 billion in 1997/98.

The example of Thailand is useful as initial causation seems to have been in the non-bank sector. Rajan (2000a) argues that portfolio flows show a net outflow only during November and December 1997. In contrast bank funds flowed into the country up to July then reversed on a massive scale, with a net turnaround of over US\$10 billion between the first and second halves of 1997. Net bank outflows totalled almost US\$14 billion between July 1997 and December 1998.

This growing crisis was worsened by the reaction of the international rating agencies, who overreacted by issuing multiple downgrades, after failing to predict the crisis. Moody's, for example, rapidly downgraded Thailand from "Prime-2" to "Prime-3" on October 2, 1997 and then to "Prime-4" on November 28 1997. These downgrades forced many banks and portfolio managers to withdraw their funds, leading to an extra round of capital withdrawals in late 1998.

Rajan (2000b) argues that Thailand initially faced insolvency problems only in the financial sector but this led to a bank panic. This subsequently created a systematic illiquidity crisis which then spread more widely in South East Asia. These initial illiquidity crises then created region-wide economic and banking crises.

Kaminsky and Reinhart (1999b) construct a series of contagion vulnerability indices for the subsequent spill-over from the initial Thai crisis, based on trade and finance links between the affected countries. Their indices show that a regional pattern to bank lending can be used to partly explain which countries were affected. US banks were minimally exposed to Asia (their major exposure was to Latin America), whilst Japanese banks were particularly exposed to SE Asia[2], especially Thailand, and European banks were particularly exposed to NE Asia. Kaminsky and Reinhart thus argue that the Thai crisis of July 1997 consequently affected Japanese banks the worst, and they reacted by rapidly withdrawing funding from SE Asia is particular, spreading the crisis to Malaysia and Indonesia. This initial crisis then affected the other major borrowers from Japanese banks. The subsequent crisis of January/February 1998 can be explained by the withdrawal of funds by European banks[3] which spread the crisis to South Korea and NE Asia. The pattern of the network of international bank loans thus played a vital role in the timing and location of the crisis.

Corbett and Vines (1999) argue that the currency crisis by itself would not have caused a collapse. The financial sector in nearly all of the countries could also have been bailed out in a manageable process. It was the interaction of the two panics that was lethal. Once traders feared sovereign insolvency, even if the fears were unrealistic, shifts in traders' expectation of nominal exchange rate anchors meant that the pegs had to be abandoned.

2.5.3 Empirical Research

There is a growing volume of empirical work on currency crises. The major empirical analyses of the causes of the Asian crisis include: Corsetti, Pesenti & Roubini (1999), Bahttacharya, Claessons, Ghosh, Hernandez and Alba (1998) and Radelet and Sachs (1998b). In these studies the choice between fundamentals-based and financial-panic-based explanations is examined. They generally end up opting for the latter. Radelet and Sachs, in particular, argue that "to attribute the crisis fully to fundamental flaws in the

[2] Japanese banks had aggressively tried to expand their loan portfolios in SE Asia to make up for stagnant home markets. The exposure of Japanese banks to Thailand prior to 1997 was similar to exposure of US banks to Mexico prior to 1985.
[3] European banks actually increased their exposure to emerging Asia slightly between June and Nov 1997.

pre-crisis system is to judge that the global financial system is prone to sheer folly, or somehow expected to avoid losses despite the flaws" (p. 30).

The importance of capital flows is now emphasised. Radelet and Sachs argue that "at the core of the (East) Asian financial crisis were the massive capital inflows that were attracted into the region during the 1990s" (p. 8). Dooley (1997) shows that nearly all emerging market currency crises have been preceded by large private capital inflows, then sudden outflows. These studies give legitimacy to the concept that decisive changes in the flows of capital were an important factor in the crisis.

De Brouwer (2001) argues that information cascade models have strong relevance to the Asian crisis as the macro hedge funds played a strong role as information leaders, and that multi-dimensional compound uncertainty existed. One of the reasons was that proprietary trading desks accepted they had had limited understanding of Asia. The conditions set by Avery and Zemsky (1998) for increasing information uncertainty were met and markets acted on this. De Brouwer also argues that Asian markets were more susceptible to herding as limited size and liquidity aided price manipulation and short squeezes. The general conclusion which can be drawn is that the structure of trading, the pattern of financial flows, and the network of international traders all played a vital role in creating and spreading the Asian crisis.

2.6 Conclusion

The aim in this chapter was to review and explore the broad range of models currently used to explain extreme movements in financial asset markets in general and currency markets in particular. Firstly, it was shown that current macro models have limited ability to explain the Asian crisis. Liquidity and herding models seem better fitted. It was shown that patterns in the flow of funds were an important factor in the Asian crisis. If we accept that illiquidity played a major role in the Asian crisis and this illiquidity was caused by the interactions between traders in the international network of financial flows, then it should be useful if the network of trader interaction was explicitly modelled. One of the motivations for proposing an alternative model is to directly focus on the role of the pattern of financial funds flow in currency crises.

Secondly, it was shown that useful rules regarding the behaviour of currency traders could be derived from existing models, especially the information cascade models. These rules will be incorporated into the proposed alternative model of currency crises. The creation of this alternative model will be the focus of chapter three.

Summary of Currency Crisis Models

First generation macro-feedback model

Strengths:

a) Explained Latin American style fixed exchange rate crisis up to 1990's well.
b) Can include expectations of policy variables

Weaknesses:

a) Does not allow for traders' expectations to be an endogenous variable
b) Fixed exchange rate assumed
c) Currency devaluation should end crisis
d) Currency overshooting not allowed
e) Crisis can not exceed causal factor in size, duration or timing
f) Ignores role of private & banking sectors
g) No role for contagion

Asian Crisis:

Does not fit facts of '97 Asian crisis well

Second generation macro-feedback model

Strengths:

a) Allows inclusion of traders' expectations as endogenous variable
b) Government's decision to devalue is made endogenous
c) Allows multiple equlibria
d) Distinguishes between volatility due to fundamentals and due to financial markets

Weaknesses:

a) Do not offer explanations for shifts in market expectations
b) Ignores role of banking/ financial sector
c) Fixed exchange rate assumed
d) No role for contagion

e) Does not explain how traders coordinate speculation

Asian Crisis:

Does not fit facts of Asian crisis well

Third generation macro-feedback model

Strengths:

a) Allows for contagion

b) Role for banking/financial sector

c) Provide details for economic policy trade-offs

d) Explain how a currency crisis can turn into a general downturn

Weaknesses:

a) No generally accepted benchmark conceptual model

b) Fixed exchange rate generally assumed

c) Causal links take time to operate

d) No role for uncoordinated or heterogeneous agents

e) Assumes a fundamental-based rather than a liquidity crisis

f) Only allow multiple equilibria within a restricted range of values

Asian Crisis

Fits a number of aspects of Asian crisis, but not generalisable to other crises

Liquidity & bank-run models

Strengths:

a) Recognises role of international illiquidity in generating crises

b) Allows for homogeneous uncoordinated agents

Weaknesses:

a) Restricted to specific circumstances

b) Require sequential market transactions

c) No role for heterogeneous agents

d) Provide no causal mechanism for starting crises

Asian Crisis

Fits liquidity aspects of crisis

Information flow models

Strengths:

a) Recognises restrictions on trader information

b) Incorporates realistic micro-structure

c) Able to generate herding and cascades

d) Empirically robust

Weaknesses:

a) Inability to realistically incorporate heterogeneous agents

b) Non-robust to heterogeneous agents due to linear sequential decision making

c) Do not tie in to macro-dynamics and agent macro-cooperation

Asian Crisis

Fits some aspects of Asian crisis but limited in applicability

Summary based on Dooley (1997), Masson (1998) and Fourçans & Franck (2003)

Chapter Three – An Alternative Approach

3.1 Introduction

There are three objectives in this chapter. Firstly, to survey the literature on complex and network science models. Secondly, to extract those aspects which are useful for currency crises. Thirdly, to propose an alternative currency crisis model.

Complexity science studies *the structure and dynamics of complex systems. Complex systems* are defined as *systems which are intermediate between orderly and chaotic* (Arrow, McGrath & Berdahl 2000). It takes as its basic assumption that these systems cannot be understood solely by study of the parts that comprise them. *Complexity* instead argues that the *focus of attention should be on the interaction between the parts. Network science* is a related field which *examines how the topological structure of the interconnected parts of a complex system affects the behaviour of the system.*

One reason for this focus on systems rather than parts is that systems themselves fit together in very intricate ways, arrangements which are impossible to create by starting with the components. Another reason is that when researchers from diverse fields of study created maps of the pattern of interconnectivity between things, the *topology,* they found that these maps were very similar. These patterns also had powerful impacts on the way the systems worked. This led scientists to acknowledge that there must be very simple and far reaching natural laws which govern the structure and evolution of all complex systems. Because of the diversity of those systems these laws can not relate to the composition of the individual components. Furthermore these systems are dynamic and their patterns of behaviour can not be deduced from analysis of the parts.

A growing area of this research is the dynamic stability of complex systems. The stability of the systems that have been studied in the physical sciences exhibit varying degrees of robustness under internal or external shocks, with often paradoxical results.

This is obviously an important issue when looking at the ability of financial systems to withstand speculative runs.

Until the mid 1990s the use of network methods in science was limited due to theoretical immaturity. Since then the creation of a whole new range of models has led to novel insights and the discovery of general laws. The applicability of complex science models outside the field of the natural sciences was delayed as the underlying organising principles of organic systems were assumed not to be applicable to social sciences. A series of papers has, however, recently showed that the same basic principles occur in nearly all complex systems. Arthur (1999), for example, showed that the adaptive microscopic behaviour of individual agents plays a crucial role in asset pricing in economic networks. Publications in the area of finance are increasing in number but are still scarce. These papers are also mostly applied to stock markets, with only a few papers relating to foreign exchange (for example: Johnson, Jefferies & Hui, 2005; Onnela, Chakraborti, Kaski & Kertész 2003).

3.2 Theoretical Issues

3.2.1 Theoretical foundations

Network science grew from the publications of the mathematician Euler[1] who showed that pathways through regular networks are dependent on their structure. Erdős and Rényi advanced the theory in a series of publications after 1948[2] by showing that if links (*edges*) between isolated nodes (*vertices*) are made randomly, rather than being made regularly, then the dynamics are different. Erdős and Rényi also showed that if a random network is large enough, then after a critical level all nodes end up with approximately the same number of links. This implies that few nodes are different from the norm.

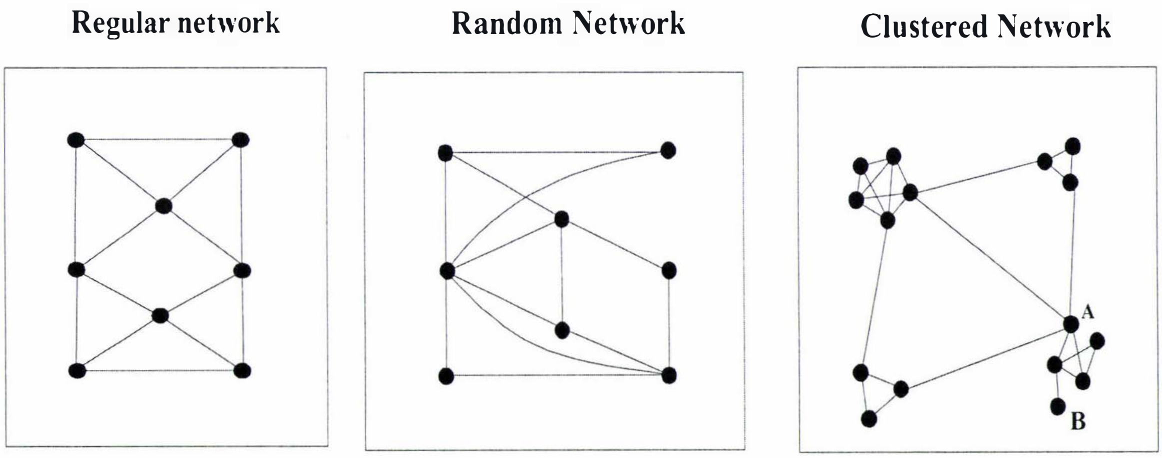
The first breakthrough for modern theory was the discovery that in real-life networks the density of node linkages is very uneven, and at the centre of these networks are a

[1] Available in Euler's collected works; *Opera Omnia* (1913), Birhäuser Verlag AG.
[2] Summarised in Erdős and Rényi (1960).

very small number of nodes with substantially more linkages than any other nodes. These are called *hubs* or *connectors*, and they are special as they dominate networks and determine network stability. They also found that whether or not any particular node is defined as a hub is not generally an inherent characteristic of the node itself but is instead a property of the node's relationships to other nodes.

The second breakthrough was the recognition that most real-life networks are not composed of a uniform interlinked nodes, but are instead composed of relatively isolated *clusters* of nodes (Barabási & Albert, 1999). These clusters have many internal (*strong*) links. These clusters are then linked to each other by sparse external (*weak*) links. The difference between regular, random, and clustered networks is illustrated in Figure 3.1.

Figure 3.1 – Regular versus Random versus Clustered Networks



The third breakthrough was the recognition that the sparse external links are actually more important than the many internal links (Granovetter, 1983). This is because an agent will already have the same information set as the other agents in their cluster, whereas an externally linked agent is connected to a different information set. Watts and Strogatz (1998) argue that external links are a key to network dynamics as they spread information between clusters, especially between distant clusters. Even a few external links drastically decrease the average separation between clusters. This is especially true if those few links are between distant clusters. Thus examining the structure and strength of the external ties is an important factor in network analysis. Networks with these external links are called *small world* because pathways between even distant nodes tend to be short. Watts and Strogatz showed that a sparsely clustered network will form in any situation where there is a reason why there is clustering, and a reason why there are external links.

Barnes (1969) introduced the concept of *density*, which is the proportion of all the possible links that actually occur. Granovetter (1973) added the concept of *clustering coefficient* which is how strong the links within a cluster are compared to the idealised maximum. This co-efficient will be between 0 and 1[3]. Networks with clusters whose members are strongly interlinked will have a high clustering coefficient, whereas networks whose cluster members know as many non-members as members will have a low clustering coefficient. A large randomly connected network will have a cluster coefficient close to 0. Real-life networks often have coefficients closer to 0.5 or higher, showing that clustering is a very common network phenomenon (Watts & Strogatz, 1998).

Note that with clustered graphs there will be a need to separately define the tendency of a node to connect internally to another node within its cluster versus its tendency to connect externally to a node in another cluster. The tendency to connect externally also needs to be differentiated into two separate aspects. Firstly, there is the overall propensity to connect, with some nodes being more likely to connect to outside clusters than other are nodes. Secondly, there is the propensity to connect at distance, with some nodes more likely to connect to distant clusters than are other nodes. The pattern and density of external links is vital for this thesis as it is a key parameter in the effective propagation of information across an entire global network.

3.2.2 The power-law distribution

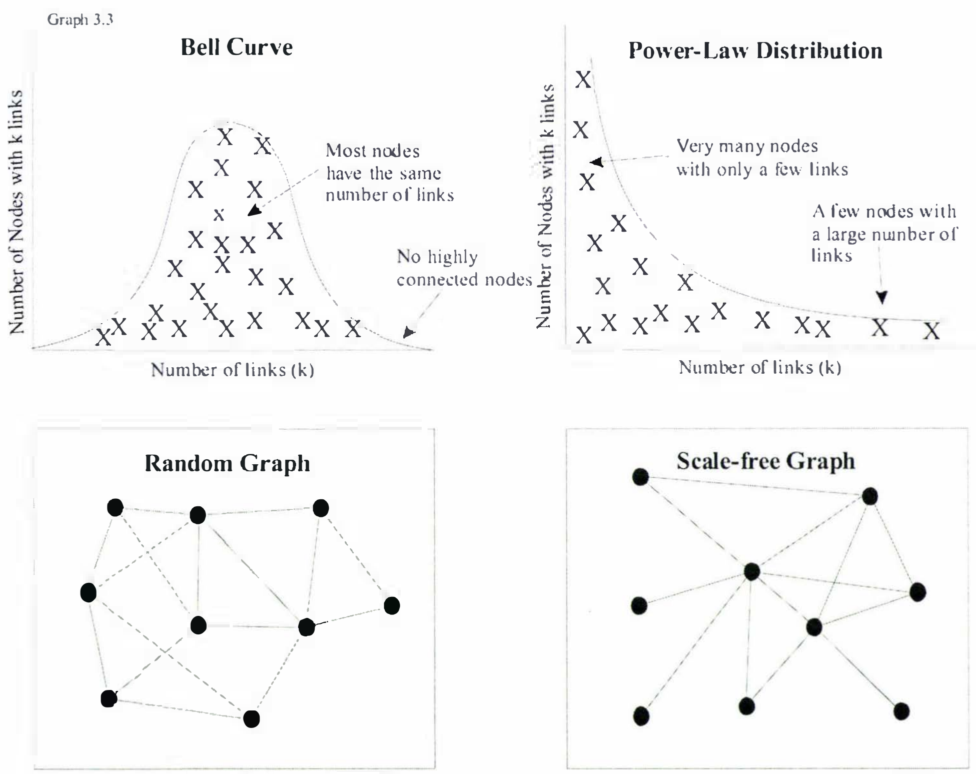
The introduction of the concept of hubs into network theory led to the re-discovery of Mandelbrot (1982)'s work (based on Lévy, 1925 and Stanley, 1971). This argued that the distribution of linkages in non-random networks nearly always follows what is called a *power-law* distribution, rather than the normal or poisson distributions as had been

[3] The node involved is not included as an element of its neighbourhood so the co-efficient can be zero.

assumed. While power-law distributions are a lot less common in social systems than normal distributions they are common in physical systems, and are vital to the dynamics of networks.

A power-law distribution is one where some quantity N can be expressed as a power of another quantity k, and is of the form $N(k) \sim k^{-\gamma}$, where the parameter γ is called the *degree exponent*, and is a non-peaked, continuously declining infinite distribution. The slope of a power-law distribution in a log-log plot is the degree exponent value. The decay factor in a power law distribution is smaller than in a bell distribution, so that large events are more common, as shown in Figure 3.2

Figure 3.2 – Power-law versus Normal Distributions



The key element which power-law distributions introduce to networks is an extreme differentiation between the bulk of local links and the sparse global links; with many small events co-existing alongside a medium number of moderate events and a small number of large events. The tail is infinite so extremely large events are more common than for a normal distribution.

Power-law distributions also have no characteristic node and no average size node. Therefore as the size of the network is scaled up the pattern remains the same. There is also no upper bound to the distribution (*scale*) in terms of the number of connections a node can reasonably have. Thus power-law distributions are commonly referred to as *scale-free distributions.*

Power-law distributions have been found in a number of very diverse areas, for example: cell chemistry, size of earthquakes, fjord geometry, species extinction events, computer chip wiring, the distribution of city size, income distribution, variation in cotton prices, internet linkages and citations in the academic research community. The fact that such a simple empirical relationship is produced by such an array of complex systems is another indication that general rules underlie complex systems.

Research has shown that power-laws are the norm in complex networks, though not the only possible structure. The more complex a network is the higher is the chance of it exhibiting a power-law. The existence of a power-law is thus often taken as evidence that a complex network exists. Jensen (1998) argues that power-law distributions tend to emerge in any network situation if there is considerable interaction between components of the system and those components are *meta-stable*; in the sense that they do not change their characteristics unless some threshold force is applied. Barabási and Albert (1999) argue power-laws occur whenever two characteristics occur; when a network is growing and is therefore dynamic, and when certain nodes attract a disproportional number of new linkages, called *preferential attachment*. The discovery of these characteristics established the basics of network dynamics.

Note that *dynamics* has two meanings. The first is the evolving structure of the network, the changes as it grows and evolves; the *dynamics of network formation*. The second is changes inside a fixed, static network, where the individuals are being influenced in their actions by what their neighbours are doing; the *dynamics of network interaction*. It is the second meaning that will be used in this thesis.

Watts (1999b) suggested that the creation of a small world network required *effective* external links. This means that most links must be local, so that there is clustering, but there also must be a small fraction of globally long external links which connect distant parts of the network. The imposition of any type of external scale on the physical length of links would limit the effectiveness of links as transmission devices. Examination of the scale of external links is thus a key part of empirical network research.

The power-law structure has proved to be generally robust to model modification. Krapivsky, Redner and Leyvraz (2000) find that when preferential attachment in generalised to follow complex non-linear functions the power-law can disappear. They conclude, however, that most of the alternative complex networks generated are unlikely to occur in practice. This is an area which requires further research.

3.3 The Stability of Network Systems

3.3.1 Basics

The most relevant aspect of recent theoretical developments for this thesis is the stability of scale-free systems. Particularly important is the "robustness" of complex network systems under external shock.

One generally noted fact is that natural systems have a higher degree of robustness than human designed or social systems, commonly surviving major catastrophes. Key aspects behind this robustness are that natural systems have a degree of redundancy so alternative routes exist, and self-organising control and feedback mechanisms exist. Albert, Jeong and Barabási (2000) showed the structure of networks was also vital, and nature has typically evolved towards the most robust possible network structure. They labelled this *topological robustness*; robustness based on network structure.

Research has shown that networks generally cope with random node failure until a critical level is reached, whereupon a system-wide breakdown into isolated clumps occurs. This is not a gradual breakdown but an abrupt failure occurring at a defined point, called a *critical error threshold*. Watts (1999a) shows that these phase transitions are very common in relational[4] (scale-free) non-random graphs or in spatial graphs

[4] Relational graphs create new links as a function of pre-existing links, rather than according to a probability distribution defined in terms of distance between nodes (spatial graphs).

whose distributions do not have a finite cut-off and are independent of the graph substrate and degree of clusteredness.

Albert et al. (2000) showed that a scale-free network is far more robust than a random network in the face of random failure or attack[5]. This occurs because the scale-free network is similar in pattern at any scale. The key to this robustness is the existence of hubs. If the nodes fail randomly then the existence or non-existence of any other node is not important to system stability, as long as the hubs survive. Given that the hubs are a small percentage of the total nodes the chance of hub failure from random errors is correspondingly low.

Albert et al. (2000) and Cohen, Erez, ben-Avraham and Havlin (2001), however, argue that the attack tolerance of scale-free networks is different under intentional attack. This occurs because intentional attacks do not target nodes randomly, but directly target the hubs. The removal of several hubs can shatter a scale-free network. Once a realistic size is reached most scale-free networks can survive the removal of one or two hubs, even the most important hubs, but if many more are removed then the system suddenly collapses.

Collapse after hub failure creates a pattern of smooth operation for a number of years, with node failure generating only small fluctuations, followed by a spectacular collapse when hubs fail. The size of this collapse will be out of all proportion to the size of prior fluctuations. The size will be also inexplicable under bell curve assumptions, as the standard deviation based on fluctuations in the prior stable period will predict a system-wide failure as extremely unlikely. The extreme size of the collapse may thus seem to belong to a different error regime from the stable period. It is interesting to note that this pattern reflects some aspects of the dynamics of recent currency crises.

3.3.2 Cascading failure

The vulnerability of networks to the failure of hubs does not by itself constitute a serious problem as the chance removal of several hubs at the same time is rare under

[5] Up to 80% of the nodes could be randomly removed in some examples before system failure occurred.

random failure. Hubs are also normally robustly designed and far less vulnerable to attack than nodes. Thus vulnerability to hub failure becomes a problem only if there is an intentional attack, and it is difficult for an outsider to simultaneously knock down a number of well designed hubs.

The major problem with scale-free networks is their vulnerability to *cascading failure*. *Cascades* are defined as *large, system-wide, shocks triggered by small initial shocks*. Cascades occur because the individual components stop acting in an asynchronous individualised fashion and start acting in a synchronous co-ordinated fashion. Cascades are not the random failure of a high number of individual nodes or the spread of failure between nodes. Cascades are also not the result of the aggregation of many small errors. Instead cascades are *contingent failures*, *whereby the failure of one node increases the likelihood of another node failing*. They are an inherent property of a connected flow model. These interaction patterns are called networks' *coupling topology*.

Cascades occur in scale-free networks when a network acts as a transportation or information system for flows. Disturbance of a local hub results in widespread disturbance of system flows and thus the spread of the disturbance to other links and their associated hubs. This can, under some conditions, generate a rapidly escalating catastrophic system-wide breakdown called a *global cascade*. Key aspects to a cascade are the strength of the initiating impulse and its speed.

Watts (2000) argues that most cascades are not actually sudden and unexpected. He instead argues that in most cases the problem has been building unnoticed for a while, as hubs or links drop out, until the critical error threshold is reached. He further argues that attempts to decrease the frequency of these cascades by strengthening hubs normally lead to fewer but far more severe cascades, as the cascades which occur will, by their nature, succeed only if they have a high momentum. A network that was able to withstand these hub failures would have *dynamic robustness*.

This area of network theory is still fairly undeveloped as it involves the dynamic properties of complex systems, rather than the static properties like the topological robustness explored earlier. However, research indicates that the properties of topology, robustness and vulnerability have to be considered together.

3.3.3 Contagious disease models

A useful source for understanding the dynamics of currency is the network models of contagious disease spread, as the propagation of diseases is similar to the propagation of financial panics. A useful class of disease models is the Susceptible, Infectious, Removed (SIR) model. This was developed by Rapport and others (1953a, 1953b, 1957) based on work by Kermack and McKendrick (1927, 1932, 1933). The key element of these models is some form of spreading mechanism to propagate the disease (Watts, 1999a). These models show that differing structures of the network will give different results. They also show that the degree of vulnerability to transmission and the degree of external links to contagion propagation are the two important parameters. The modelling framework provided by these models is adapted in a modified form as the basis of the alternative network currency crisis model introduced later in this chapter.

In SIR models there are three types of agents. Susceptible agents are vulnerable to infection, but are not yet infected. Infected agents are both infected and capable of infecting others. Removed agents are either immune or dead. When a disease is introduced it goes through three phases. With only a few infected agents at the start there is only slow growth. As the number of infected agents expands the disease spreads rapidly. Eventually the reducing number of still to be infected agents causes the disease to burn out.

The dynamics exhibit a threshold effect, with initial slow propagation then a seemingly sudden outbreak. This is called an *epidemic threshold* or a *tipping point*. The point where the epidemic tips is inherently no different from any other point

A series of articles by Schelling (1971, 1978), Granovetter (1978) and Granovetter and Soong (1983) helped to define the three main rules of epidemic dynamics. These rules are; that contagiousness is vital, that most big events have little causes and that change happens in one dramatic moment rather than gradually. Note that these reflect the cascade dynamics of complex systems discussed in section 3.3.2.

Watts (1999a) argues that the SIR model and its variations need modification as none of them treats the problem of disease spreading as a function of the population structure or use only simple topologies based on extreme cases without a constant node degree (e.g., Hess, 1996a, 1996b). Watts argues that because the connectivity of social systems is unknown the way to approach the problem is to consider as wide a range of coupling topologies as possible so as to elicit the principles underlying disease dynamics. The focus should be on subtle changes in network structure rather than changes in connectedness.

Watts' model then yields two types of dynamics; *permanent-removal dynamics* which is *the spread of a lethal disease* and *temporary-removal dynamics* which *is the spread of a non-lethal disease.* The permanent-removal model exhibits a pattern where once a certain probability of infectiousness is reached then initial slow diffusion turns into rapid spread after a tipping point. The permanent-removal model is of more interest for this thesis, as the lethal disease analogy implies the removal, or the inability to trade, of a country or traders from the international financial system until the crisis has passed. Watts shows that this model is highly sensitive to the connective topology of the population, with pandemics occurring at low levels of connectivity.

Another key result Watts finds is that as the network was adjusted from one extreme of completely random to the other extreme of a fixed lattice, the threshold infectiousness required for an epidemic drops rapidly. The implication is that even in highly clustered networks only a few weak links are needed to create the small world characteristics required to induce rapid spread between seemingly isolated clusters.

3.3.4 Physical science contagion models

Another useful source for understanding the dynamics of network collapse is the percolation models used in the physical sciences. These show that the important factor in the dynamics of collapse is the pattern of nodes connected by open links. This is called a *percolating or vulnerable cluster*, which is defined as *the largest linkage of susceptible nodes joined by open links which permeates the entire network* (Newman & Watts, 1999). In the absence of a big enough percolating cluster there would only be localised cascades.

The pattern of percolation in the vulnerable cluster has been shown to be more important than its size. This percolation cluster can be situation or time dependent, with sites or bonds changing their susceptibility depending on conditions. Analysis of the percolating cluster will thus play a part in the examination of the topology of international currency flows in the next chapter.

Bak and Chen (1991)'s sand-pile model is a key physical model as it shows that the full range of complex systems dynamics can be obtained from an extremely simple model, where every node is identical and obeys simple laws. They argue the simplicity of this model proves that the properties of complex systems have to be an inherent property of the interrelationship between nodes rather than related to the properties of the nodes themselves. System dynamics can not be predicted from study of the nodes. The proposed alternative currency model will follow the sand-pile model by simplifying node behaviour as much as possible.

A key outcome of Bak and Chen's model is that local behaviour is monotonous until the global system reaches the critical level, after which local behaviour will become dependent on what happens globally; it will become contingent. A local observer will observe calm most of the time, then bursts of unexplained and large cascades.

Bak (1996) argues power-law dynamics generally lead to the evolution of *self-organized critical systems* rather than *equilibrium systems*. Self-organised critical systems display four phenomena; regular catastrophic events, fractal geometry, 1/f noise and Zipf's law based on a power-law of unitary degree. A crucial property of these systems is that they are highly unstable so that Pareto optimality can not be re-achieved after a disturbance. Complex systems are thus not naturally in a state of balance, which implies equilibrium is not the normal characteristic of these systems. Instead, instability and catastrophes are normal in complex systems. Any short-term periods of calm are merely statistical illusions, periods of low noise between periods of volatility; a pattern called *punctuated equilibria* (from Gould, et al. 1977). Note the similarity of the four phenomena to the cascade dynamics in section 3.3.2. In section 4.4.6 evidence for the four phenomena in currency markets will be examined.

Gould (1989) argues change within a dynamic complex system is neither one of constant linear progress nor of random chance. Instead, dynamic complex systems lead to contingency, which implies the creation and destruction of nodes or clusters involves a complex system of alternative paths. The overall system choice between pathways depends on contingent random shocks, which can be trivial. Any outcome is possible from the start point even though progression within each pathway is internally consistent and predicable. This implies the shape of future evolution of a complex system is inherently unpredictable.

Bak (1996) argues punctuated equilibrium is the product of a large number of diverse periodic behaviours interacting within an overall system. The larger the degrees of freedom the more likely it is that complex system behaviour will arise. This behaviour occurs naturally in a complex system without the need to be near a critical value or external modification. Bak also argues critical systems display a full range of volatilities, from small to very large ordered as a power-law, rather than just calm or crisis. This implies the same causal mechanism must be involved in both large and small shocks. Crises are not unique events. They are simply rare large fluctuations. There is thus no point distinguishing between large and small events. There is also no periodicity to large events as they display a constant probability of occurring.

Bak and Chen (1991) further argue there is no general pattern to the global structure so the details of any particular cascade depend on the entire history of the model up to that point in time, which is unknowable to a local observer. Importantly, even knowing the historical record does not provide much insight, despite the fact that in this simple model each step follows logically from the prior step. This is because local observation alone can not explain why any particular arrangement generated a large cascade instead of a small one, or why the global system reached a state of criticality.

Also, there is not much an observer can do to prevent cascades. Even if a particular cascade can be prevented, this just builds the propensity for a later, probably larger, cascade. The local structure can be rearranged to reduce local propensities, but there is little that can be done to prevent a cascade which originates in a distant cluster. Nagel and Paczuski (1995) show any complex flow system subject to random shocks is impossible to reorganise into an optimal pattern. Instead, a critical system involving constant fluctuations is the best result achievable.

Moss (2001) argues many economic systems are complex self-organising systems, and therefore generally exist in a critical state rather than in an optimal state. He argues this is particularly true of intermediated markets once a sufficient density of traders exists. He notes that international foreign exchange markets are densely intermediated. Zhou and Sornette (2005) find critical system results in finance markets by using a related Ising model. The implication of these results is that policymakers may have to accept the foreign exchange system as subject to unpredictable inherent fluctuations.

3.3.5 The dynamic properties of cascades in random networks.

This thesis is concerned with the dynamic properties of cascades within a static network so this area needs to be examined in more detail. The key paper is Watts (2002) who examines the conditions within random network structures which create global cascades rather than local cascades. His results establish the basic rules of cascade propagation, and crisis dynamics. These dynamics show a striking similarity to the dynamics of currency crises, and thus may be directly applicable.

Watts makes three main conclusions. Firstly, even though the generating mechanisms vary, the mechanism of transmission of social science cascades is very similar to mechanisms in physical networks. Secondly, the initial impulse which generates cascades is normally minor and irrelevant. Cascades are thus inherently unpredictable even when the individual elements of the network are well understood. Global cascades inherently bear little relationship to the initiating cause. Thirdly, networks generally show a high level of prior stability in the presence of both continuous small and large shocks. Causal shocks thus are indistinguishable from non-causal shocks. This means it is inherently impossible to determine which type of events will cause a collapse as the vast majority of events which do not cause a cascade are absolutely similar to the few events which do cause a cascade.

Watts shows the above properties are inherent characteristics of certain types of network topology. The task of finding the cause of cascades is not achieved by looking at individual events, but is achieved by looking at the structure and dynamics of the network at the time when cascades happen, and differentiating them from the structure at times when cascades do not occur. Watts concludes these characteristics imply random networks will appear to be robust and stable for long periods of time, withstanding many external shocks, and then suddenly and seemingly inexplicitly exhibit fragility by collapsing due to a seemingly minor problem.

Watts argues instead that the dynamics of cascades depend critically on the states of the neighbours to the initiating node. The effect of a random disturbance is thus subject to *local dependence*; results will differ depending on which cluster the disturbance starts in and on the parameter levels of the nodes in that cluster. The key metrics are the probability that a global cascade will be triggered by a single node and the expected size of the global cascade once triggered.

Watts found an initial node will affect its immediate neighbours only if one of them has a threshold level low enough to be activated by a single node. This is unlikely and will lead to most disturbances being immediately dampened. However, once other nodes have been activated null nodes will then probably face disturbances from more than one link. The chance of these later nodes being activated will depend on the node's parameter level and pattern of links.

Watts also found a disturbance will successfully spread only if enough of the nodes in the initial cluster have either low enough parameter values or dense enough links. This will allow the disturbance to spread to a sufficient number of nodes to enable them to jointly overwhelm any nodes with medium parameter values. These are nodes which require a significant fraction of neighbours to have been disturbed.

The disturbance will spread outside the initial cluster only if the externally linked node (or nodes) also has a low threshold and is thus activated. This blockage possibility will again dampen most disturbances. The disturbance will then spread past a weakly connected node only if enough of the nodes in its cluster which it is linked to have sufficiently low parameter values. In summary, a *vulnerable percolating cluster* of an appropriate size and structure is necessary. This implies there needs to be sufficient interconnected nodes with low parameters, and these nodes need to be both sufficiently interconnected to each other and further connected to a sufficient number of nodes with medium parameter value. These conditions allow the disturbance to percolate out past the initial disturbed nodes and overwhelm any remaining medium adaptor nodes. Both the pattern of threshold values and the pattern of connectivity will be important.

For a cascade to continue to develop, Watts then argues the disturbance needs to be continually infecting a growing number of nodes and clusters at a sufficiently fast rate. There is thus a momentum parameter.

An important metric is the *average early adaptor cluster size*, or *vulnerable cluster,* which must be a certain critical size to generate the required momentum. Watts shows the frequency of global cascades is positively related to the size of the early adaptor structure as the larger it is the more likely it is that a randomly chosen node will be part of it. The frequency is also positively related to the level of initial momentum which can be generated.

The frequency of global cascades is also positively related to the size of what Watt calls the *extended vulnerable cluster*, which includes all the medium adaptor nodes immediately connected to the early adaptor cluster. This is because it is the impact of disturbances of the early adaptors on the medium adaptors which propagates the momentum past the early adaptors. This is equivalent to the percolating cluster in section 3.3.4.

Watts further shows the average size of global cascades is primarily determined by the connectively of the network rather than the size of either of the above clusters. He argues this is because a random disturbance can occupy the entire vulnerable cluster and still die out, unless the impact on medium and late adaptors of multiple disturbances from this vulnerable cluster is enough to percolate out past the early adaptors. The percolation momentum will be a product of both the average level of connectivity and the pattern of that connectivity. He concludes by arguing the problem of determining whether or not a global cascade can occur in a particular system is thus reduced to showing whether a percolating cluster of the right characteristics does, or does not, exist.

Watts then shows that these results imply differing network distributions lead to differing patterns of percolation. This further implies a critical distinction between *threshold heterogeneity* and *network heterogeneity*, even though both are related by the fractional threshold condition. The former parameter is the degree of skewness in threshold levels, the latter parameter is the degree of skewness in connectivity levels. Watts shows networks with highly skewed degree distributions (e.g., power-law) display high overall stability, even though they display vulnerability to hub attack with that hub collapse disproportionately likely to trigger global cascades. Networks with lower skewness (e.g., uniform random or bimodal) do not display this property, and cascades are as likely to start from an average node as from a hub. For these networks shocks which cause global cascades are inherently no different from the shocks which do not. Thus the value of a strategy of targeting hubs depends critically on the global degree distribution.

Another important conclusion is systems' heterogeneity has a mixed impact on stability. Increased heterogeneity of threshold levels increases the likelihood of global cascades, while increased heterogeneity of nodes appears to reduce it.

Watts' work provides useful dynamic rules. However, his work was limited to randomised networks (apart from applying power-law rules in one section), so the conclusions are indicative only for sparsely clustered networks. Further research is needed in this area.

3.3.6 Node centrality and importance

Watts' results have a direct relevance to currency crises as a number of recent authors (e.g., Eichengreen, 2003) stress the importance of the structure of financial flows to the generation of crises. Kaminsky and Reinhart (2000, 2003) and Bae, Karolyi and Stulz (2000) focus on the role of financial sector links in crisis propagation, whilst others examine the role of trade links (Abeysinghe & Forbes, 2005; Claessens & Forbes, 2001; Forbes & Rigobon, 2002). These authors, however, only found weak or ambiguous empirical evidence for the impact financial/ trade links on currency crises. This has led to doubt being cast on the importance of financial flows.

Network theory would explain these weak results by stressing that the characteristics of an individual node within a complex system are not important. What are important are the pattern of links the node has, its position within the network, and the position of the nodes that the node in question is directly linked to. The entire topology has to be examined as a particular node may be linked to many other nodes, but if those nodes are not very important, or if they constitute an isolated cluster, then those links will not be as influential as a single link to a central node.

This concept means metrics of node centrality are important to understanding the propagation of flows. These metrics measure either the importance of the direct links a node has, or the importance and centrality of the linked nodes. The latter is a superior metric, as it is a better indication of the overall pattern.

These metrics have not been applied to finance, though Kiyotaki and Moore (1997, 2002) explore the propagation and dampening of contagion via full balance sheet model of trade flows (without recognising the relevance of networks) and Kali and Reyes (2005) provide some centrality measures of network contagion.

3.4 Currency Crises : A Network Model Approach

3.4.1 Price dynamics in foreign exchange markets

In this section the modelling ideas derived from chapters two and the sections above will be used to propose an alternative adaptive-agent network model of currency crises. The rules relating to trader behaviour will be examined in order to proxy how a foreign currency network would realistically work.

The similarity of the behaviour of the complex networks outlined above to that of recent currency crises suggests that the network models surveyed can be usefully applied to currency crises by modelling financial networks as sparsely clustered self-organising complex systems. It is useful to note that Watts (2002) for example argues that the characteristics of the initiating node are usually unimportant in network dynamics. This is because the initiating node only affects its immediate neighbours. What is important is the extent to which the entire vulnerable cluster can percolate a disturbance. This percolation ability is a product of the network topology rather than any specific characteristics of the initiating node. This result will apply to complex networks in general.

Examination of the details of science-based models, however, shows some modifications will be needed. One of these is elements within a financial system will have more self-awareness and ability to change their own behaviour and information flows over both time and state than elements in science-based models have. Modification to incorporate this implies increased parameter heterogeneity, but decreased node heterogeneity. This should generate differences in the system dynamics.

Within the area of financial models it is useful to distinguish between behaviour in stock markets and behaviour in foreign exchange markets. The three most important differences are; the foreign exchange market has no commonly agreed pricing models (Meese & Rogoff, 1983), there is no centralising of price data, and there is a high level of short-term noise trading. Daniel, Hirshleifer and Teoh (2002) also argue the overwhelmingly large wealth and complexity of the information available in foreign exchange markets, and the difficulty of its analysis, will diminish the worth of traders' private information vis-à-vis the public information set. This will result in private agents placing a lower weighting on their private information and analysis, and a higher weight on the observation of others. De Brouwer (2001) argues foreign exchange markets cope with these problems by a far higher level of specialisation than is evident in stock markets. Information asymmetry between participants is thus greater. Liquidity constraints also play a larger role in the foreign exchange market.

De Brouwer concludes these differences mean that the foreign exchange market has a greater potential for sudden price shifts. In terms of network theory the increased information constraints in the foreign exchange market will lead to greater dependence by market participants on trying to second guess the behaviour of those market participants who are regarded as being influential in each specialist market segment. This will lower threshold parameters and induce a higher degree of clustering with strong currency hubs around either regions or types of trade.

3.4.2 Trader behavioural assumptions

The international financial network can be modelled as hundreds of thousands of individual currency traders each connected by flows of information or financial funds to other traders. The characteristics of any individual trader are not relevant, their collective behaviour is. This collective behaviour adds up to network behaviour which is more complex than the aggregation of the parts. Furthermore, this international financial network is itself dynamic. Resultant behaviour is thus partly dependent on how the network itself evolves and behaves. Note individual traders can not determine what kind of network they are involved in as they are aware of only their local cluster. They are also not aware of the extent of the vital weak links, or the structure of the entire network.

It is not the attributes of each individual agent which defines each agent. Instead it is the structure of each agent's connections within the network which defines and describes the role of each agent. This assumption creates a fundamental difference in the way the model is constructed. It also implies a difference in the way data are arranged, as network datasets involve a set of relationships between nodes rather than attributes of individual nodes.

The proposed model will use a binary choice model framework by assuming foreign currency traders in a crisis are faced with a binary choice to either hold or sell. Within this framework bounded rationality will be assumed. Information will also be assumed to be scarce and costly to gather, requiring commitment of time and resources. Traders will thus be assumed to not have all possible information or the capacity to analyse it fully. They will make up for this by observation of other traders' actions.

Anderson and Holt (1995) showed that using the observations of others as part of ones information set is a rational response to a complex situation. Arthur, in Arthur et al. (1997) argues a complex system approach views agents as having to cognitively structure the problems they face. Agents have to make sense of the problem as well as solve it, and do this with limited cognitive resources in a world where information is dynamic. Agents thus generally do not optimise but use experience and observations of others to interpret reality as best they can.

We will also assume large costs are involved in making a wrong choice. Traders will thus exhibit inertia in switching between states. There may also be different weightings placed on the observations of others in crisis versus non-crisis times, resulting in possible regime switches. Dvořák (2005) showed this was true for the Asian crisis, where local investors had differing information, and once outsiders learnt this they switched their behaviour.

The proposed model will also assume connections between traders in the currency markets obey a power-law or similar small-world distribution rather a normal or related distributions. This is because traders are far more likely to observe the actions of the major traders in particular currencies than they are to observe any other trader at random. These specialists can be analogised as hubs, with many more links than average. The US$ market will thus be more likely to be observed than another market, in a power-law relationship to its comparative size.

Because the cost of gathering information rises with physical and cultural distance, due to the cost of relationship building, the structure of the international financial network will be assumed to have strong local links inside each cluster and to have weak links between clusters. The nodes could be either a regional market or a type of trade. Furthermore, inter-cluster links will be denser than intra-cluster links. The network will thus be modelled as sparsely clustered nodes consisting of currency markets, with region size and link density based on a power-law. The evidence in favour of this will be examined in chapter five. However, as was noted earlier in this chapter, sparsely clustered self-organising complex networks tend to form when there is a reason for clustering via multiple internal links and for a reason for external links. Financial networks have these characteristics; traders will specialise and trade intensively within particular types of trades (internal links) and traders will observe a limited number of recognised experts in the general market (external links). Clusters of traders will also be assumed to be heterogeneous in structure and in size.

An assumption of heterogeneity in the agent payoff matrix and in parameter characteristics will be made. Informational herding theories generally assume homogeneity; given the same information set each agent will reason identically, and will respond identically to each new set of information. This assumption is inherently unjustifiable in the foreign exchange market, as has recently been extensively explored in the microstructure literature (e.g., Lyons, 2001).

3.4.3 Cascades in currency networks.

Complex network analogies can then be applied to currency cascades by arguing that generating currency crises is not generally the aim of market participants. Each trader is simply reacting to external events in a manner consistent with his/her individual best interest. Each participant, however, has limited market information and limited time and is thus generally forced to react to the behaviour of those traders s/he immediately observes. Asset market cascades are thus created by an unconscious consensus arrived at by a large enough number of individual traders, each observing the behaviour of other traders. The net impact of sufficient prior individual behaviours then generates cascades with the necessary momentum to force subsequent traders to react in favour of the cascade even if they can see the net adverse impact of the cascade. Short-term irrational reaction overrides a longer-term considered response.

Currency cascades can then be seen as examples of contingent failure; whereby the collapse of one financial node increases the chance of failure of another financial node. The power of the influence of one node on another is dependent on the weight which is given to the disturbing node and to the network topology. The flow element which is required for cascade failure can be seen as the selling pressure and negative psychology of financial funds flow. Any financial node hit by a crisis can then be seen as a collapse of financial confidence. This collapse will induce further selling pressure at nodes connected to the collapsed node. Contagion can thus be seen as a particular node being affected by the collapse of a sufficient proportion of the nodes to which it is connected.

Other modelling alternatives exist, especially in game theory. Examples include random networks, like Föllmer's (1974), characteristic defined networks like those of Gilles and Ruys (1989) and stochastic networks like those of Kirman, Oddou and Weber (1986), including non-possible switches of state (see Allan, 1982). These alternative models however, do not fit into a cascade network framework for currency markets so will be ignored. Social network connections will also be omitted, even though these often play a part in crises, as their inclusion would make the research intractable. For similar reasons of tractability a static, non-growing, network will be assumed. These assumptions limit the analysis but are appropriate for a short-term crisis.

3.4.4 Theoretical assumptions of a bootstrap binary model

Applying the above discussion an alternative model of foreign exchange crises can be created. The assumptions of the model follow:

(i) The international foreign exchange network exists with a fixed, finite number, n, of bounded rational agents trying to maximise trading profits, $I = \{1, 2, \ldots.. n\}$. Noise traders are absent.

(ii) Each agent is completely characterised by his/her current state, $\omega_t(i) = a_{i,t} \in A$, and the network as a whole is described by $\omega_t = \{\omega_t(i), i \in I\}$, where $\omega_t \in \Omega = A^I$.

(iii) Each agent, *i*, is linked informationally to a finite and limited subset of other agents, $j \in J \in I$. The links represent the network of interpersonal influences governing the information that individuals have about the world, with each agent observing the actions of only a small subset of the total cluster.

(iv) The linkages of agents to that network exhibit heterogeneity, organised according to a power-law relationship.

(v) These agents are organised into a sparsely clustered international network, organised according to a power-law. Most links are local but a small percentage is global.

(vi) The network is assumed to have heterogeneity in terms of cluster size, called *network heterogeneity*. There is a network of *n* nodes each joined to *k* neighbours with probability P_k (the degree distribution of the graph), with the average number of neighbours being $(k) = z$ (the average degree).

(vii) Links are undirected.

(viii) Agents are affected only by disturbances in those neighbours to whom they are directly linked. Proximate contact dominates, though global influences may impact indirectly via changes in their private information.

(ix) Agents exhibit homogeneity in their information importance in terms of influence per link. The network links are unweighted.

(x) The network is subject to an initial shock, which affects one randomly chosen agent enough to induce him/her to sell. Each shock is idiosyncratic to the node. No common causal factor is assumed as this has no effect on dynamics. There is no additional shock of any substance.

(xi) The choice facing agents is binary; they hold or sell a single product. The agents can be in either state but once they switch from a hold state they stay in the active state. The dynamics are modelled by starting with all agents in hold.

(xii) Agents respond to disturbance with a set minimal delay.

(xiii) Agents will decide their actions based on a well-defined decision rule, $R_{i,t}$, which depends on a weighted mixture of internal, private, information (which includes their own analysis of already public information) and the outside information conveyed by actions of the connected subset of agents J at time $t-1$, so that $R_{i,t}$ depends on $\omega_{t-1}(J)$, by observing their state (either 0 or 1).

(xiv) Agents observe the actions of other agents, but not the information set possessed by other agents or their payoffs.

(xv) The reactions of agents to new information exhibit heterogeneity, in terms of the resistance level to outside information, called *threshold heterogeneity*, $R^c_{i,t}$. This is expressed in terms of a parameter threshold before a decision to sell is taken that weighs the mixture of inside and outside information. Each agent is assigned a threshold level (randomly drawn from a chosen distribution) of directly linked neighbours who have to switch before s/he will. This is expressed as an absolute figure of the agent's neighbours who have sold. Thus $R^c_{i,t}$ is $f(\omega_{t-1}(J))$. This is called their *threshold parameter*. We will assume $1 \leq R^c_{i,t} \leq 4$.

(xvi) In the case of a weighting deadlock they will not act, thus a hold will result.

(xvii) Reaction heterogeneity will group agents into three sectors;

(a) *Early adaptors* are very uncertain about the validity of their own information or analysis of external information so place a higher value on the actions of others, and can be influenced by the observation of a single other agent. The weighting for their private information will be set at ½.

(b) *Medium adaptors* place a higher weighting of 2 on their own internal information and analysis of external information, so they need to observe a small number of agents acting in a concerted direction, before they will follow it. Their threshold will be set at 3.

(c) *Late adaptors* place a high weighing of 4 on their own internal information and their analysis of it. They will be influenced only by the actions of a substantial number of agents, maybe enough to threaten to inflict portfolio losses that exceed their capacity to cope. Their threshold will be set at 5. For tractability no agents are assumed to have internal information weightings higher than 4.

This model can be placed into the generic class of *binary decisions with externalities* models. Key aspects of this generic class are; agents face binary choices based partly or wholly on the decisions of a number of locally connected other agents, called *local dependency,* and the number and pattern of those local links are heterogeneous. This distinguishes the model from epidemiological models which assume contagion occurs between pairs of agents, and from random-field Ising and majority voting models which typically assume regular lattices. The assumption of an absolute number threshold makes the model similar to bootstrap percolation and self-organising criticality models.

3.4.5 Sequential agent behaviour in a single decision bootstrap model

Despite the simplicity of node assumptions, the model generates complex dynamics. This is because of the mutual interaction between the agents and the network. Every single micro-action uniquely defines the current configuration of the system. These current configurations then affect future micro-behaviours. These repeated direct interactions generate a dynamic reaction process in which system variables are time-dependent and transition rules can be established on the basis of micro-behaviour. The ultimate outcome of any disturbance will depend on system topology as outcomes will differ depending on the parameter threshold pattern surrounding the initiator node. Different network arrangements will respond differently to the same initial disturbance.

These dynamics can be illustrated by the simplest model, which involves a sequence of agents making sell or hold decisions in response to a single new piece of information. A randomly chosen agent, i, is the first to act, and will act based on the new information and the private information which s/he possesses. This private information will include his/her estimation of whether or not other agents will receive that new information and how they will respond to it. Disturbances will only start only if the agent decides to change from a hold to a sell.

Agent $i + 1$ acts on both his/her private information and the observed behaviour of i. If this private information points to the same decision that i made, then $i + 1$ will respond in the same way. However if this private information points to a contrary decision, the action of $i + 1$ will depend on his/her weighting of outside versus inside information, called the *preset threshold level*. This will reflect his/her assessment of the validity of his/her private information, the validity of analysis of public information and the credibility of the observed actions of other agents. If this threshold level is low, an early adaptor, s/he will follow the observed actions of agent i and sell. If his/her threshold level is medium or high s/he will follow his/her own private information.

Agent $i + 2$ acts on the basis of his/her private information and his/her observations of the actions of agents i and $i + 1$. If i and $i + 1$ have acted the same way (either hold or sell) and $i + 2$'s private information points to the same decision then $i + 2$ will respond in the same way. However if i and $i + 1$ have acted in contrary ways, or if his/her private information points to a contrary decision, $i + 2$'s action will be complex and will depend on his/her preset threshold level. The following outlines possible choices:

(i) If $i + 2$ is an early adaptor and i and $i + 1$ have agreed then $i + 2$ will follow that decision.

(ii) If $i + 2$ is an early adaptor and i and $i + 1$ have disagreed, $i + 2$ has gained no useful information. S/he will thus follow his/her personal information.

(iii) If $i + 2$ is a medium adaptor and i and $i + 1$ have agreed, $i + 2$ will not follow that decision as the weighting is 3:2.

(iv) If $i + 2$ is a medium adaptor and i and $i + 1$ have disagreed, $i + 2$ has gained no useful information. S/he will thus follow his/her personal information.

(v) If $i + 2$ is a late adaptor, $i + 2$ will follow his/her own private information as s/he will need at least 4 outside agents to concur before s/he will be influenced.

The actions of agent $i + 3$ will be even more complex. $i + 3$ will act on the basis of his/her private information and observations of the actions of the three prior agents. If all prior agents have acted the same way and $i + 3$'s private information points to the same decision then $i + 3$ will respond in the same way. If all prior agents have acted in contrary ways, or if *i + 3*'s private information points to a contrary decision, then *i + 3*'s action will depend on his/her preset threshold level.

(i) If *i + 3* is an early adaptor and at least two of the three prior agents have agreed, s/he will follow that decision (any possible combination of the binary choice will have that outcome). If we weight his/her private information at ½, then any decision will have at least a 2:1½ outcome.

(ii) If *i + 3* is a medium adaptor and the three prior agents have agreed, and his/her private information disagrees, *i + 3* will hold, as the weighting will be 3:3.

(iii) If *i + 3* is a medium adaptor and only two of the prior agents agree, *i + 3* will follow their private information, as the weighting will be 3:2.

(iv) If *i + 3* is a late adaptor s/he will follow his/her own private information, as *i + 3* will need at least 4 outside agents to concur before being influenced.

This logic sequence can be continued for all subsequent agents $i + 3 + j$. Note the above analysis refers only to the impact of immediately linked agents. This will be true if the supply is elastic (i.e. a fixed exchange rate), as price is unchanged regardless of the total number of agents selling. The only impact on an individual agent is s/he would notice sales by the agents with whom s/he is in contact.

If supply is inelastic (i.e.; a floating exchange rate) and more agents in total decide to sell, then the price of the currency will drop. Late adaptors will thus suffer portfolio losses, which will increase pressure on non-sellers and increase the likelihood of a cascade. Note the actions of individual traders in this model are never blind as they always include in their decision rule their full private information set.

3.4.6 Cascade conditions

If the above sequence is worked through it can be ascertained that once there is a five or greater gap between the choices, all subsequent agents will follow the decision regardless of their private information. This will result in an irreversible cascade. If the gap is less than five, then a cascade will propagate only if the affected agents have low enough thresholds.

Note that implications of differing topologies of links between clusters have been ignored. Instead the implicit assumption has been made that the network is big enough and links are ample enough to ensure there will be sufficient alternative percolation routes available to allow any high value nodes/clusters which block percolation to be by-passed. If we modelled the parameter value as a percentage, then this problem would not arise as a sufficiently high combination of linked neighbours would always, by definition, overcome any node's resistance.

Note once the cascade starts the gap will be ever increasing subsequently. This means that the observed behaviour of agents after that point will give no indication as to the content of their private information. Each agent $i + 6 + j$ is in the same position informationally, gaining no additional information from the observed behaviour of others. There will also not be a gradual breakdown but an abrupt failure occurring at a defined point, called a *critical error threshold.* In this case this occurs once a gap of 6 has been created. After the critical error threshold the network changes from a collection of individualised traders to a synchronised group.

The subsequent accelerating cascade wave will tend to overshadow the initial slower percolation of the initial disturbance. Market movements prior to the critical threshold and those subsequent to the critical threshold will seem to be quantitatively and qualitatively different, in terms of both aggregate market behaviour and individual trader psychology. The slower initial percolation can often be ignored by analysts.

The dynamics depend critically on the states of the neighbours to the initiating node which implies the effect of any random disturbance is subject to local dependence; results differ depending on which cluster the disturbance starts in and the parameter levels of the nodes in the cluster. The initial affected agent will affect its immediate neighbours only if one of them has a threshold level low enough. Once more than one agent has been affected, however, subsequent agents will face disturbances from more than one link. The chance of later agents being activated will depend on their parameter level and the number of links to affected nodes. The disturbance will spread only if enough agents in the initial cluster have low parameter values. This will allow the disturbance to spread widely enough to jointly overwhelm any medium adaptor agents. The density of linkages is an important parameter.

Another important parameter is the distribution of the threshold heterogeneity. Under the assumption of a normal distribution, the number of early adaptor nodes will be limited so most disturbances will be dampened. Other distributions will give different results. This will be explored further in chapter six.

The distinguishing feature between disturbances that cause global cascades and those that do not is a matter of topology. It is the pattern of early adaptor agents, rather than the nature of the initial agent disturbed or the nature of the disturbance, which determines the ultimate spread of the cascade.

There is no centralising agent or key player dictating the behaviour of the network. Instead, network behaviour is dictated by its topology. While there are key agents, those weakly connected via distant linkages, these agents are essentially reactive in a cascade, rather than initiating. Each crisis may have a key core of agents vital to the propagation of the cascade, but this core is accidental. The next crisis will arise differently with a different core. The core also does not determine the evolution of the crisis. It is the evolution of the crisis that determines who is in the core. The core that percolates the cascade also does not have to include the agent who initiated the cascade.

3.4.7 A fractional decision model

The model above uses an absolute definition for the threshold parameter. Agents with many links will be more unstable than agents with only a few links, as the possibility of disturbance increases with the number of links. A useful modification, and one that is normal in network models, is to express the threshold conditions as positively related to the proportion of links disturbed. The reason is agents will always have some level of uncertainty about whether or not their private information accurately reflects the market. If an increasing proportion of the agents whom they observe act in a contrary fashion, then their level of uncertainty will increase, increasingly their propensity to act contrary to their private information.

This modification is achieved by assigning each node a threshold level of the fraction of linked neighbours who would have to switch before they would be influenced. This is drawn from a random distribution and is called a *fractional threshold*. This modification adds complications in theoretical modelling but is easier to simulate, so will be adopted in chapter six.

The most important result of this modification is the most stable nodes would be those with many links, the most unstable those with only a few links. This is the opposite result from the bootstrap model. This modification also implies the strength of the influence of each of a node's neighbours is inversely proportional to the number of linked neighbours.

A fractional decision model also creates more reasons why cascades would not happen. This could be because everyone's thresholds are high, so no-one will ever change. Or, it could be because the system is not connected enough with disturbances unable to propagate. One the other hand the network could be too connected, so each node exerts too small an influence on its neighbours.

Watts (2003) makes the point that in a weakly clustered social network, as opposed to a biological network, agents who are very widely connected may have limited influence. This is because they may be expressing a view contrary to most other links and contrary to private information. Locally clustered agents will be more influential as they will be more likely to express a view similar to other linked nodes, and similar to existing private information and analysis. The hubs will be influential only if nodes have a restricted number of links. In a well connected network, hubs may thus play only a minimal role in building up cascade momentum. The key parameter will be the level of inertia of local clusters.

3.4.8 Sequencing

It is vital to note that s*equencing* within a network model is not the same as sequencing within the traditional cascade model. Most financial herding models have a single linear sequence occurring, where every agent is affected by its immediate predecessor in an ordered queue (Bikhchandani & Sharma, 2000). This implies the cascade can be dislodged or temporarily halted if one agent in the sequence is heterogeneous in response to the information. This could occur because s/he places stronger weight on contrary inside information or because s/he receives an additional contrary outside signal. Gale (1996) also shows the speed of information aggregation is vital to cascades picking up the required momentum. The lack of robustness of financial information cascade models is an important reason for their lack of popularity.

Sequencing in network models is different from this as it simply requires that agents are influenced by the observations of the prior actions of agents to whom they directly link. Since nodes will generally have more than one linkage, multiple streams of disturbance will be created instead of a single stream. The existence of multiple streams implies blockages due to the encountering of high threshold agents in any one stream will have only a minor impact on the momentum of a cascade. While some streams will be expected to be blocked, other streams will continue and may bypass, or feedback, to overcome those blockages. Cascades can be dislodged only if a number of nodes collectively block every possible cascade pathway. These blocking nodes do not have to be significant in their inherent characteristics. They simply have to collectively block the generation of sufficient momentum. The important parameters in cascade development are thus the pattern and the level of disturbance multiplicity. The network topology of flows is important rather than the characteristics of the nodes.

This aspect also means the introduction of model modifications involving additional outside signals, or of deviant agents with blocking thresholds, can be expected to have minor effects on network propagation. This is contrary to the strong effect these modifications have in linear sequential finance herding models.

3.5 Conclusion

In this chapter the main strands of network theory and complex systems science have been surveyed, with particular emphasis on elements of stability and the principles of cascade formation. Aspects of cascade dynamics were examined. Complex science and network models have been found which propose patterns of asset prices which are similar to those found in currency crises. These patterns arise as a natural outcome of even simple models, and require assumptions which are realistic.

In this chapter aspects of trader behaviour which could be used in modelling have also been examined. Then a simple alternative model of currency crisis based on a binary choice framework with adaptive-agents was proposed. The model assumed sparse clustering and focused on dynamic aspects of financial flow topology. Some implications of the model were drawn.

The next chapter examines methodological alternatives used in examining network topology. In chapter five foreign exchange price data will be examined to elicit if it can be modelled as a sparsely clustered network. Finally, data will be used to extract a proxy topology of international capital flows. That proxy map will be examined by simulation in chapter six.

Chapter Four – Topological Methodology

4.1 Introduction

4.1.1 Overview

This chapter looks at the methodologies useful for extracting topological information from an international currency network. Extracting price influences from foreign exchange data of the type needed to model cascades in network is not a straightforward task. The theoretical model in the prior chapter is based on interactions between individual traders. It is not appropriate, however, to use individual traders in an empirical model. One reason is data on flows of trade between individual foreign exchange traders (or companies) is not generally available for reasons of commercial sensitivity. Another reason is the international financial system involves hundreds of thousands of traders, resulting in an empirical model which would be too complex to yield tractable results. An additional reason is data involving actual short-term momentum trading would introduce a substantial amount of noise. A better result is instead achieved by treating the group of traders in each type of trade or country as a node and ignoring trade inside the node. This creates a parsimonious network from which international price influences can be extracted.

4.1.2 Outline of methodological issues

The major source of data used was high frequency cross-correlation matrices. One of the recognised problems with large data sets is the high number of non-zero coefficients. Given the number of cross-correlation grows by n(n-1)/2, the size of a correlation matrix can make it difficult to extract system dynamics. Another problem is that large financial correlation matrices can be dominated by noise (Bouchaud & Potters, 2003). Typically, only the major eigenvectors have values consistently different from those produced by random number sets. These problems mean it is vital to selectively extract information when identifying meaningful behavioural interrelationships. Thus it is important for the methodology used to be able to discriminate between data those influences which play a key role in price determination and minor influences, and only extract key influences. A fully described network would provide an overwhelming level of detail and noise.

Network theory argues that the interactions between nodes are vital, including the issues of link position and centrality. For example, a few links to powerful currencies may be more important than many links to minor currencies. This information, however, can not be obtained from analysis of either the raw data or the correlation matrix. It must be determined by techniques which examine link percolation and dynamics. The methodology must thus be able to extract information on the pattern of how price influences are transmitted between currencies.

It would be useful to determine whether or not a time causal linkage exists between currencies. Kullmann, Kertész and Kaski (2002), however, found that even when using high frequency interday NYSE data the causal effect was too quick to capture. McDonald et al. (2005) argue the effect is faster for foreign exchange markets. Thus, analysis of daily lagged correlations may not yield useful time causal results. Kullmann et al. (2002) therefore concluded that causal influence was instead best elicited by indirect examination of those assets which are the most highly traded and connected.

4.2 Methodological Techniques

4.2.1 Econometric techniques

Econometric methods have methodological problems when evaluating network data and crisis dynamics. One issue is that data obtained from crisis periods are scarce. Use of data from a non-crisis period to evaluate crises is also problematic due to differing causal determination. The infrequency of crises also means significant variation in the data is rare and parameter estimates are imprecise. Crises also differ in causation.

Another problem, according to Arthur et al. (1997), is an adaptive nonlinear network does not act in terms of simple stimulus and response, but includes anticipation. Agents act based on limited cognitive responses, which do not need to be explicit, coherent or mutually consistent. Thus, the tools of linearity - fixed points and systems of differential equations - have to be replaced by combinational mathematics and simulation.

Network data are also gathered on a different basis from traditional statistics. Data are not presented as a regular array, with different variables on the columns and the rows, and the information encoded as the data in each element. Network data is instead arranged in a two-dimensional element by element matrix, with the same variables on columns and rows, and information encoded as the relationship between variables. Network elements are also chosen for their association with each other, so are non-independent by design. There are correspondingly no population-based statistics with which comparisons can be made. Thus normal statistical inference methods do not work well with network data. Instead, network methods are centred on the probability of a parameter relative to some ideal theoretical baseline. This baseline can be obtained by use of randomness, or an extreme arrangement, or by a simulation.

4.2.2 Hierarchical structure theory

Hierarchical structure theory has a long and distinguished history in mathematics (see Rammal, Toulouse & Virasoro, 1986). This theory is routinely used in the physical sciences and has been used by several physicists to analyse complex systems in finance. The main use of hierarchical structure methods in finance is to ascertain the structure of asset price movements within a market and extract the essential information from the hidden structure. It does this by using the synchronous correlation coefficient matrix of daily difference of log prices to quantify the pricing distance between assets in terms of the inherent hierarchical structure. This structure can be then used to give some indication of the taxonomy of an assets' portfolio, and generate an assets' hierarchy. This will be the first technique used in the next chapter.

The first technique of hierarchical structure theory used is the creation of *a minimal spanning tree* (MST). The MST T is a graph of a set of n elements of the arrangement of the nodes in an *ultrametric space*[1]. Mantegna (1999) and Bonanno, Vandewalle and Mantegna (2000) show use of MST is sound for financial assets and the resultant taxonomy displays meaningful clusters. Onnela (2002) argues use of MST also helps to overcome the empirical problem of noise in a historical correlation matrix (summarised in Laloux et al. 1999). McDonald et al. (2005) and Bonanno, Lillo and Mantegna (2001) show the links created by MST analysis for currencies exhibit a geographical/ economic integrity and substantial single-step survival over time as well as identifying price causality. The MST technique is also attractive as it an easy visual guide to relative currency pairings.

The second technique used in this chapter is the creation of an *ultrametric hierarchical tree* structure. This technique gives a determination of the hierarchical structure of a network. It is particularly useful for determining if hubs exist (as described by Laloux et al. 1999 and Plerou et al. 1999). The focus in the use of these two techniques in this chapter will be on the extraction of price influences rather than on determinants of market activity.

Hierarchy structure theory argues a pair of assets' correlation coefficient can not be used as an asset space metric in terms of the *distance* between assets because it does not fulfil the three axioms which define a metric. Gower (1966) argues the appropriate Euclidean distance metric can be obtained by the following transformation;

Let $C_i(t)$ denote the vector of logarithmic returns for currency i. If we normalise $C_i(t)$, and if we then let the subscript k specify the k^{th} component $C_{ik}(t)$ of the N-

[1] An ultrametric space is a space endowed with a distance which obeys the inequality $d(A,C) \leq \mathrm{Max}\{d(A,B), d(B,C)\}$.

dimension vector $\hat{C}_i$, we can then define the Euclidean distance between the currency vectors $\hat{C}_i$ and $\hat{C}_j$ as;

$$d_{ij}^2 = \left\| \widetilde{C}_i - \widetilde{C}_j \right\|^2 = \sum_{k=1}^{N} \left(\widetilde{C}_{ik} - \widetilde{C}_{jk} \right)^2 \qquad 4.1$$

We can simplify this by noticing $\sum_{k=1}^{N} \widetilde{C}_{ik}^2 = 1$. For the squared distance we get;

$$d_{ij}^2 = \sum_{k=1}^{N} \left(\widetilde{C}_{ik}^2 + \widetilde{C}_{jk}^2 - 2\widetilde{C}_{ik}\widetilde{C}_{jk} \right) = 2 - 2\sum \widetilde{C}_{ik}\widetilde{C}_{jk}. \qquad 4.2$$

If we then define A_{ij} as the cross-correlation matrix we can then use the compact expression for ultrametric Euclidean distance;

$$d(i,j) = \sqrt{2(1 - A_{ij})} \qquad 4.3$$

Gower argues for symmetrical normalised correlation or association matrices: this equation gives a direct and easy method to measure the distance between the ith and the jth individuals. Mantegna and Stanley (2000 – chpt. 13) show equation 4.3 approximates the standardized Euclidean distance measure between two time series x_i and x_j. This formula appears counterintuitive because it is given in terms of the correlation between the two time-series rather than as a sum over series elements. Mantegna (1999) argues that equation 4.3 can be used as an appropriate metric for correlation coefficients as it does fulfil the three axioms of a metric distance[2]. Mantegna and Stanley (2000) argue spin glass theory[3] has proven that the *subdominant ultrametric space* associated with this metric provides a well defined topological arrangement.

The value of the distance metric will be 0.00 for a perfect positive (+1) relationship and 1.4142 (√2) for no relationship, 2.00 for perfect negative (-1) relationship and 1.00 if $A_{ij} = 0.5$. An increase in the size of the metric implies a weaker relationship between two nodes. This non-linear mapping generates a better distribution of results when the vast majority of correlations are positive.

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[2] Proofs are given in Kaufman & Rousseeau (1990)
[3] A good summary and proofs of spin glass theory is provided in Mezard et al. (1987).

The distance matrix D of $d(i,j)$ elements is used to determine the MST connecting the n assets of the portfolio (Papadimitriou & Steiglitz, 1982). The *subdominant ultrametric distance*, $d^{<}(i,j)$ is defined as the maximum value of any Euclidean two-point distance detected by moving through the shortest path connecting the two points, i & j in the MST. The non-diagonal elements of the distance matrix D are arranged in order of increasing value and the MST is progressively built up by linking all the elements of the set together in a graph characterised by a minimal distance between assets on d values.

The major issue with using MST analysis is, while it is robust for strongly clustered networks, it has a tendency to link poorly clustered groups into chains by successively joining them to their nearest neighbours (Kaufman & Rousseeuw, 1990). These chains are non-robust to data variation. MST is thus less robust for larger distances. This is important as Hirst (2003) argues the choice of clustering procedure has more effect on the quality of clustering than the choice of distance metric. MST analysis uses the single-linkage clustering method which builds up clusters by starting with distinct objects and linking them based on similarity. Since Kaufman and Rousseeuw (1990) argue other clustering techniques have their own disadvantages, the issue of clustering methods is left to future research.

In summary, MST and the hierarchical tree provide a well established and robust methodology for creating asset pricing dynamics taxonomy. These methods will be used to determine groupings of currencies and for establishing hierarchical relationships. The understanding gained from these methods is the first step in constructing an international foreign exchange currency network. These techniques, however, are limited as they extract information on the strongest links only and are not robust for weak relationships. The information obtained should thus be used with care and be combined with other techniques if possible.

4.2.3 Matrix network methods

Matrix network methods are newer methods which provide a set of tools useful for cross-checking the information obtained on first-order relationships from hierarchical structure methods. They also provide information on second and higher order relationships as well as on how the pattern of links influences price determination.

Two main methods are used to create an initial causal mapping. The first method is to select the central node and establish its strong links. Then the strong links are established for the subsequent nodes. This is repeated until a set number of links has been established. This creates a mapping of the pattern of strong causal links. Information on the strengths of links is ignored. The second method is to select a cut-off point in terms of relationship strength and mapping all resultant links. This is less arbitrary than imposing a set number of links but excludes nodes with only weak links.

Having created an initial mapping of currency linkages, network methodology provides a range of tools for analysing different aspects of the linkage pattern. These are based on either graphical or statistical analysis. Graphical techniques allow the primary price determinant influences of each currency to be examined, while statistical techniques examine link patterns.

Block and cut-point analysis evaluates nodes in terms of potential for blockages. *K-Core analysis* identifies clusters by density of linkages. *One-step ego net analysis* extracts those nodes linked by one step. *Univariate analysis* analyses the number of links that each individual node has versus the theoretical maximum. *Network density* shows the sum of all ties divided by the number of possible ties and is the measure of the density of links in the immediate neighbourhood of the nodes. The *global density* metric can then be compared to the neighbourhood density metric to get an indication of the level of clustering. A high neighbourhood density in comparison to the global density indicates a sparsely clustered network.

Centrality, as discussed in section 3.3.5, measures the importance of each node's influence in percolating disturbances across the network. Centrality is a structural attribute of nodes in a network, not an attribute of the nodes themselves. *Centralisation* is the corresponding metric that measures the extent to which a network revolves around a single node. It is the proportion of all centrality possessed by the most central node. A substantial amount of centralisation indicates that the power of individual nodes varies substantially.

Centrality metrics have to be interpreted carefully for cascades as they have an ambiguous meaning. A country (or agent) at the centre of a network, possibly with many links, would have a higher chance of being affected by a randomly occurring crisis as there are many pathways through which a crisis could disturb it. Having many links, however, gives a highly connected country more avenues to diversify away a disturbance. Thus, a disturbance from any particular pathway would be proportionally smaller. Measures of centrality for cascades should thus be considered alongside network structure.

The programme used for this method, Unicet©, provides three *Freeman statistics* for centrality (Freeman, 1979). *Degree* which is the number of ties to others, *Closeness* which is the graph-theoretic distance of a given node to all other nodes, and *Betweenness*, which is the number of geodesic paths that pass through a node. There is also a metric for *network centrality*. This compares the network to the perfect centrality of a star network.

Freeman's statistics assign equal weighting to links and take no account of their importance. A link to a powerful node, however, is normally more important than a link to an isolated node (Salancik, 1986). Unicet thus provides an additional metric involving *the eigenvector of geodesic distances*. This measures node centrality in terms of all the network linkages. Unicet's metric uses the principal eigenvector of the adjacency matrix of a network, and is a recursive version of degree centrality (based on Bonacich, 1972) weighting each node based on its path centrality. This metric can then be compared with the wider range of information obtained from Freeman's metrics.

Results for density, centrality and closeness together provide a range of information on the structure and properties of the network. This can be added to the information on the pattern of links provided by graphical methods to add depth to the primary order information obtained from hierarchical structure theory. The graphical techniques are also useful as complexity can be added or subtracted to explore different levels.

In summary matrix network techniques provide a range of information which is different to that provided by the more established hierarchical structure techniques. Matrix network techniques will thus be used in extensively in the next chapter.

4.2.4 Ln - Ln diagrams

An alternative approach to identifying the structure of a network system is to determine whether or not a power-law distribution applies. As noted in Section 3.2.2 power-laws were one of the defining characteristics of a sparsely clustered network. Tests normally examine the number of links, k, attached to each node. This is called the "degree", γ, of the node. The degree distribution can be estimated by plotting the logarithm of the probability versus the logarithm of the variable. In a log-log diagram a pure power-law distribution will be a straight line with the slope being the degree exponent. In the next chapter this method is applied to financial flows, to market correlations and to comparative market size.

The main methodological issue associated with use of these plots is that real-life networks are finite so a cut-off always occurs, unlike the infinite theoretical distribution which has no cut-off point. Thus, rather than a simple straight line, tests normally show two or three regions; the straight line scale-free distribution and curved end-regions. Indeterminacy at the bottom end occurs due to most small events passing unrecorded, at the top end due to the scarcity of large events. This can make it hard to distinguish between power-law distributions and normal distributions for small samples. The proportion of line which is straight in the Y axis is taken an indication of the strength of the proof of the existence of a power-law as well as an indication of the quality of the data.

Barabási and Albert (1999) argue that a value of γ between 2 and 4 is common in scale-free networks. A value higher than 4 shows an extremely strong level of global connectivity, between 3 and 4 shows a strong level, between 2 and 3 showing a moderate level, and below 2 showing a sparsely connected network. Bak (1996) argues values close to 1 indicate a strong self-organising system. The cascade theory explored in chapter three requires γ values below 2, as this would imply a strongly locally connected, weakly globally connected, sparsely clustered network.

In summary, while the information which can be obtained by ln-ln diagrams is restricted, it does provide additional information. Use of ln-ln diagrams is thus a useful addition to the other methods.

4.2.5 Eigenvalue analysis

Another useful methodology is to use the *eigenvalues* of a population covariance matrix to determine the approximate factor structure (Chamberlain & Rothchild 1983). Bouchaud and Potters (2003) argue the presence of large eigenvalues located far from the rest is a strong positive indication of the existence of a scale-free network. They argue these large eigenvalues reflect the presence of collective behaviour on the part of elements, rather than randomised individual behaviour. This also reflects the sub-ordination of some financial assets price-making determinants to others.

Since the matrix $A_{i,j\,j}$ (equation 4.3) is symmetric and real, all the eigenvalues (also called *characteristic roots*) should be real and the largest eigenvalue should not be degenerate. Relative rankings of eigenvalues, as represented by the *eigenvector*, can then be used to give an indication of the hub and node structure of capital flows. The influence of countries or capital market centres in terms of influence is determined by the relationship between the corresponding eigenvalue sizes.

Some authors (Brown, 1989; Chiu & Xu, 2004; Shukla & Trzcinka, 1990) have argued a bias towards large factors exists. This bias means while eigenvalue analysis is useful, its results need to be compared with the results from other methods.

4.3 Methodology Summary

This chapter has evaluated five possible methodologies for extracting the mass of information revealed in a covariance or correlation matrix. The later four methods will be used in the next chapter. Econometric methods are not used because of the problems mentioned. All the methods used have differing strengths and weaknesses, but their combination should create a result that is robust.

These methods will be used to examine whether or international currency markets can be modelled as a sparsely clustered network. These methods will also be used to extract information about the network structure which will be used to create a proxy international foreign exchange influence network.

The next chapter will show that network structures and topological results obtained from the range of tests are substantially similar, which indicates the methodologies used are robust. The derived topology of international currency markets is found to be a sparsely clustered network, indicating complex system dynamics would be generated.

Chapter Five – Topological Analysis

5.1 Introduction

This chapter has two main objectives. The first objective is to examine whether or not patterns of price influence within international financial flows indicate the foreign exchange network can be modelled as a sparsely clustered complex system. The positive result obtained as detailed in this chapter indicates that they can. The second objective is to create a proxy topological map of the price influences within the foreign exchange network. The proxy topology obtained is useful in its own right as well as being suitable for simulation analysis of currency cascades in the next chapter.

The four methodologies outlined in chapter four are applied to network structures and show that topological results obtained from a range of tests were substantially similar, which indicates the methodologies used are robust. A derived topology of international currency markets is created and shown to be a sparsely clustered network. This indicates complex system dynamics would be generated. The repetition of tests for crisis and non-crisis periods indicates that while price determination structures do differ during currency crises the essential topology is unchanged.

5.2 Data Summary

5.2.1 Introduction

Three different types of data were used. These data have differing strengths and weaknesses and each reflects different information about international currency markets. The combination of results from these three types of data will create a final result that is richer and more robust than that obtainable from any one data source. This information includes both influence links between currency pairs and the flow of influence between more distance pairs, which gives information on relative importance and centrality of currencies.

The first type of data used is the correlation matrix of daily currency exchange rates. This should give some idea of how international currencies interact, how the currency nodes are clustered, and the pattern behind price influences. These data are extensive in terms of time period and are accurate. The major problem with this data is that they are indirect. Direct data on flows of trades between traders are, however, not suitable or available, as mentioned in chapter four. Data on the direction and volume of currency flows are available only for a limited network of currencies, and are incomplete. They are thus not suitable to network analysis, which requires complete relationship pairs. Kullmann et al. (2002) argues that use of distance metric data based on the indirect data gives a reasonable proxy.

The second type of data used is monthly trade data for key countries. Use of these data allowed the inclusion of countries, like China, that have to be excluded from the first data set because they fixed or linked exchange rates. It also gave an alternative linkage arrangement of currencies that can be used to test the robustness of the first set of results. In addition, it gave some idea of the structural arrangement and size of overall international financial flows. McDonald et al. (2005) also argued short-term capital flows can be proxied by trade data. Trade data also introduce some indication of directionality of price influences due to differences between export and import flows.

The third type of data used is the proportional size of international currency trading centres. Use of these data will give some idea of the degree of both centralisation and competitiveness of international currency markets.

These three data types covered differing periods for reasons of data availability. The similarity of results from these differing periods indicates further result robustness.

5.2.2 Exchange rate data

Exchange rates against the United States dollar (USD) were obtained for the 44 countries listed in Table 5.1 in the Appendix. These currencies were chosen because they were generally free floating, covered the data period (23/10/95 - 31/12/01) as well as for either their dominance in currency markets or their representative nature for a region. The data ended at 2001 as the Euro was introduced on 01/01/02. Daily exchange rates were also obtained for the Malaysian ringgit versus the US dollar (USD), the British pound (GBP), the German deutschmark (DEM), the Japanese yen (JPY), Singapore dollar (SGD), and the South Korean won (SKW). The same sample period was used for all currencies. Data were sourced from Oanda.com at Olsen and Associates, which is an internationally recognised source of reliable high frequency currency data.

All rates were daily average inter-bank ask rates as determined in Zurich. The Mexican peso and Russian rouble were used in their format prior to currency reforms, which removed three zeros. Daily data for a long-time period were used rather then inter-day data, in order to reduce the level of noise. The use of longer periods (six or nine years) of daily price changes also removed the illiquidity and correlation issues, which can occur with minor currencies due to periods of minimal price change.

5.2.3 Trade data

Trade data were obtained for 22 countries, representing the major trading countries in all regions; Argentina (AG), Australia (AU), Brazil (BR), Canada (CA), China (ex HK) (CN), France (FR), Germany (GR), Hong Kong (HK), Indonesia (ID), Italy (IT), Japan (JP), Malaysia (MY), Mexico (MX), New Zealand (NZ), Philippines (PH), Russia (RU), Singapore (SP), South Korea (SK), Spain (ES), Thailand (TH), United Kingdom (UK) and United States (US). Monthly export and import data were obtained for the twelve years from 15/01/ 1992 to 15/01/2004. This period covers the Asian crisis and has sufficient data to be subdivided into three adequate size groups. A longer time period (fourteen years) than for the foreign exchange data was used due to the lower monthly data frequency. These data were obtained from Datastream, a reliable source.

5.2.4 FX centre turnover data

Data on the global foreign exchange trading turnover were also obtained for the top 40 global centres listed in Table 5.6 in the Appendix. Data showed daily average turnover in April for 1998, 2001 and 2004, in US$ Billion. These data were obtained from the Bank of International Settlements (BIS), a reliable source. The data was adjusted for local double counting by the BIS.

5.3 Topological Results

5.3.1 Hierarchical structure theory

5.3.1.1 Introduction

One of the problems uniquely encountered in foreign exchange research is that no independent numeraire exists. Currencies are priced instead against each other. Any currency chosen as a numeraire will be excluded from the results, yet its inherent patterns can indirectly influence overall patterns. There is no standard solution to this issue or a standard numeraire candidate. Gold was considered, but rejected due to its high volatility.

This issue is important for MST analysis. Different numeraire choices will give different results if strong multidimensional cross-correlations are present. For example, there are large negative correlations for the GBP/USD and USD/CHF, and correspondingly large positive correlations for the USD/GBP and CHF/USD. Any correlation differences will show up in the GBP/CHF cross. Different bases can also generate different tree structures. The inclusion or exclusion of currencies from the sample can also give different results. This implies undue emphasis should not be placed on any particular MST result, and result robustness should be checked by comparison with other methods or samples.

The approach used in this thesis was to repeat the test. Initially the New Zealand dollar was used as the numeraire. It is a minor currency which can be easily excluded, and it does not impose any strong default pattern. The results obtained show the predominant first-order relationships between currencies, including the US dollar. However the overwhelming dominance of the US dollar tends to submerge secondary influences. The tests were then repeated using the US dollar as the numeraire to obtain second-order relationships between currencies. These results need to be treated with care as the exclusion of the US dollar can impose a default pattern due to cross-correlations. The issue of numeraire bias is left for future research.

The sample size was restricted for the NZ dollar tests as six currencies with strong ties to the other currencies were excluded for clarity (BOB, CZK, SEK, KZT, PGK, PLN). The SAR, which is fixed to the US dollar, is included in both samples as a cross-check on robustness. The full sample size was used for the US dollar tests to allow regional clusters to be developed. Most of the remaining currencies were not included due to infrequent price movement, not spanning the period, or fixed relationships.

An alternative approach to MST graphs is the use of all currency pairs (McDonald et al. 2005). This is a valid approach but it does add more complexity, and gives visual results which are difficult to interpret. The approach is also impractical if additional causal links in addition to the primary link are examined, or if the sample size is larger than ten. There are also problems caused by the impact on correlations of cross-quotations, as this imposes a default structure.

5.3.1.2 NZD matrix

Daily ln-ln changes were calculated on a NZ dollar basis for 44 countries and the correlation matrix[1] was calculated. Correlations are generally low but there are currency groupings with high values. Predominant is the European exchange rate mechanism (ERM) pairs, like DKK-FIM, DKK-ITL, NLG-BEF (all above 0.9), currencies linked to the USD like QAR or INR, and local pairs like the CAD-USD (0.8920) or MYR-SGD (0.7628). Inter-SE Asia correlations are higher than other pairs, but still relatively low at 0.5 - 0.7. This indicates SEA currencies had only weak causal links pre-crisis. The North Asian currencies do not seem to be correlated to the SE Asian currencies. The highest Asian correlation belongs to the Malaysian ringgit- German deutschmark, MYR-DEM, pair (0.8653). The most isolated currency is the RUB.

A distance-metric matrix was calculated based on equation 4.3 and the correlation matrix (Table 5.2 in the Appendix). This was created using Pajek© software (Baragelj &

[1] Non-included correlations, distance matrices and statistical tables available on request from the author.

Mrvar, 2005) and Kruskal's algorithm[2]. Low values of this metric indicate similarity in currency dynamics. Close pairs are NLG-BEF 0.1743, NLG-FRF 0.1805, and BEF-FRF 0.2125. Again the DEM is not close to any of the ERM countries, even its Benelux currency partners. But it is reasonably close to the MYR (0.5191). MYR-SGD (0.6888) was the only close currency pair in SE Asia, though inter-Asian values tend to be lower than intra-Asian.

From this distance matrix, a minimum spanning tree (MST) was created, as shown in Figure 5.1. This will give an indication of primary influences in price-setting behaviour. The technique is to start with the pair with the smallest value, in this case USD-SAR. The graphed distance corresponds to the distance value. Those two currencies are eliminated from further consideration. The next lowest distance value is then added, in this case a separate pair, NLG-BEF 0.1743. This is inserted in a different part of the graph. The next lowest pair was NLG-FRF 0.1805, so the FRF was added to the NLG-BEF link. The MST was progressively built up following this technique.

The MST in Figure 5.1 indicates the USD is the dominant world currency, and the hub of an international cluster. Only the ERM cluster is separate. As noted, the DEM is not part of the ERM cluster or directly linked to the USD. It is instead closely linked to the MYR. The IDR is also linked via the MYR. The THB and PHP are linked to the SGD rather than the USD directly. These results indicate inter-SEA FX linkages are stronger than in other (non-ERM) regions. Note also the UK pound, GBP, links to the USD in preference to the ERM and the AUD links via its commodity cousin, the CAD, rather than directly to the USD. Two other commodity currencies are also linked, the BRL and the CLP. It needs to be noted some currencies had slightly closer links to the SAR rather than to the USD. These linkages were ignored however; as it was assumed these links arose due to joint correlation to the USD and the driver was the USD.

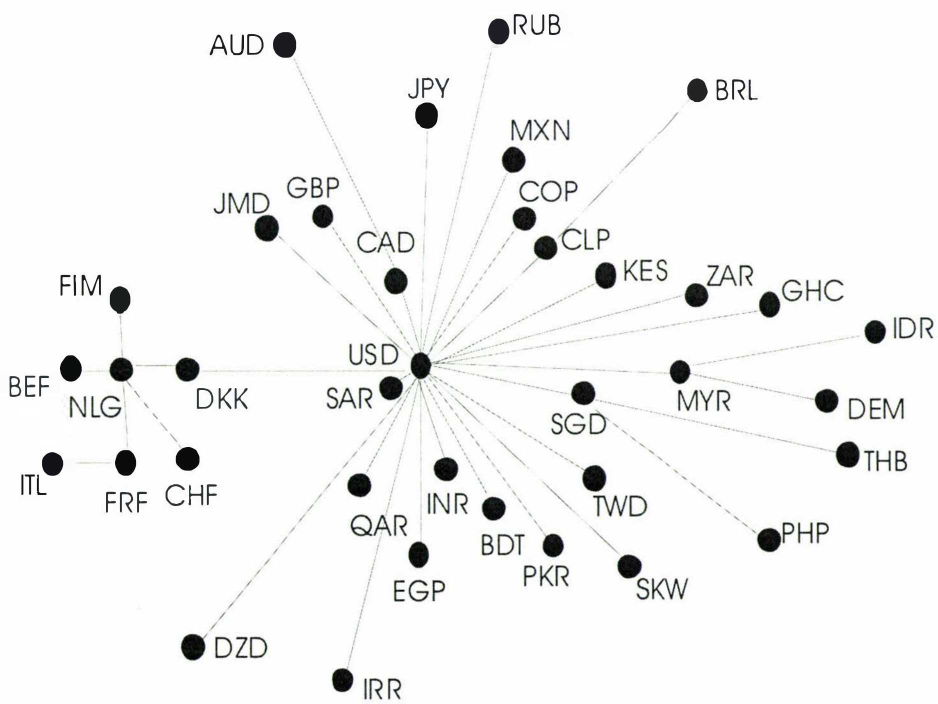
The linking of the DEM to the MYR is a puzzle as the mechanism of the EMS implies close correlations between EMS members. This implication is backed by

[2] Details of this algorithm are given in Cormen et al. (1990)

correlation based empirical evidence [12, 13, 14]. One possible explanation is that as the lead currency within the EMS the value of DEM is determined by global influences and these are best reflected in the value of the MYR. Other EMS currencies are followers so do not respond on a daily basis to global factors. It may indicate the Malaysian central bank was targeting the DEM (or ECU) rather than the USD prior to 1997 (MYR-USD is 0.63). Alternatively it may simply indicate a common response by two highly trade-dependent countries to external events. Another explanation is that since the distance metric is based on log daily changes with no lag component it reflects short-term movements within the EMS band. For the DEM these may not be related to the intra-band movements of other EMS currencies. This issue needs further analysis. The DEM result emphases the causation made in section 1; that hierarchical structure techniques need to be used with care and combined with other techniques if possible.

Fig 5.1 – NZD-based FX minimum spanning tree (1995-2001)

This gives a graphical representation of minimal distance metrics for currencies quoted against the NZD This gives an indication of the basic first-order price causation determination. The USD is shown as the hub, with an attached ERM cluster.



MST analysis shows the key determinant European currency is the Dutch guilder, NLG. The key link between these two US and Euro clusters is the USD-DKK. It is of interest that currencies which are isolated, like the RUB or the IRR, still have the USD as their main determinant link. When currencies not in the sample were added, in related research, they fitted the MST pattern, with most linked to the USD base (e.g. the Costa Rican colon) and the remainder ERM based (e.g. the CZK). This showed the MST is robust to excluded currencies.

Vandewalle, Brisbois and Tordoir (2001) classified node topology into three types. "Important" were *nodes which are the prime price determinators* (like GM). "Links" were *nodes which mediate information between branches* (like Yahoo). "Dangling ends were *nodes which only receive influences*. Using this terminology the USD and the NLG can be classified as important nodes, the DKK, MYR and SGD are links, and the rest are dangling ends. The geographical/ economic integrity of node placement helps confirm the validity of the method. The only disadvantage to the initial result is that the overwhelming dominance of the US dollar restricts the extent of information on secondary influences.

It is also useful to compare these results with those obtained by Mantegna (1999) for stocks used in the Dow Jones Industrial and the Standard and Poor's 500 indexes during 1989-1995. Mantegna found the closest stock pair had a distance of 0.949, with most in the 1.09 to 1.3 range. There was a web-like structure with four distinct clusters for the DJIA, 16 major clusters for the S&P with 44 minor clusters, and 18 key stocks acting as linkages between S&P clusters. Bonanno et al. (2000) and Vandewalle et al. (2001) found a similar topology for stocks on the Nasdaq, NYSE and AMEX. They found appropriate placed nodes around the sectional indices, a power-law with degree 2.2 for the distribution of links per node, and the non-random nature of the MST remained remarkably consistent over time. Onnela (2002) found a more structured star-based network for the S&P 500 index.

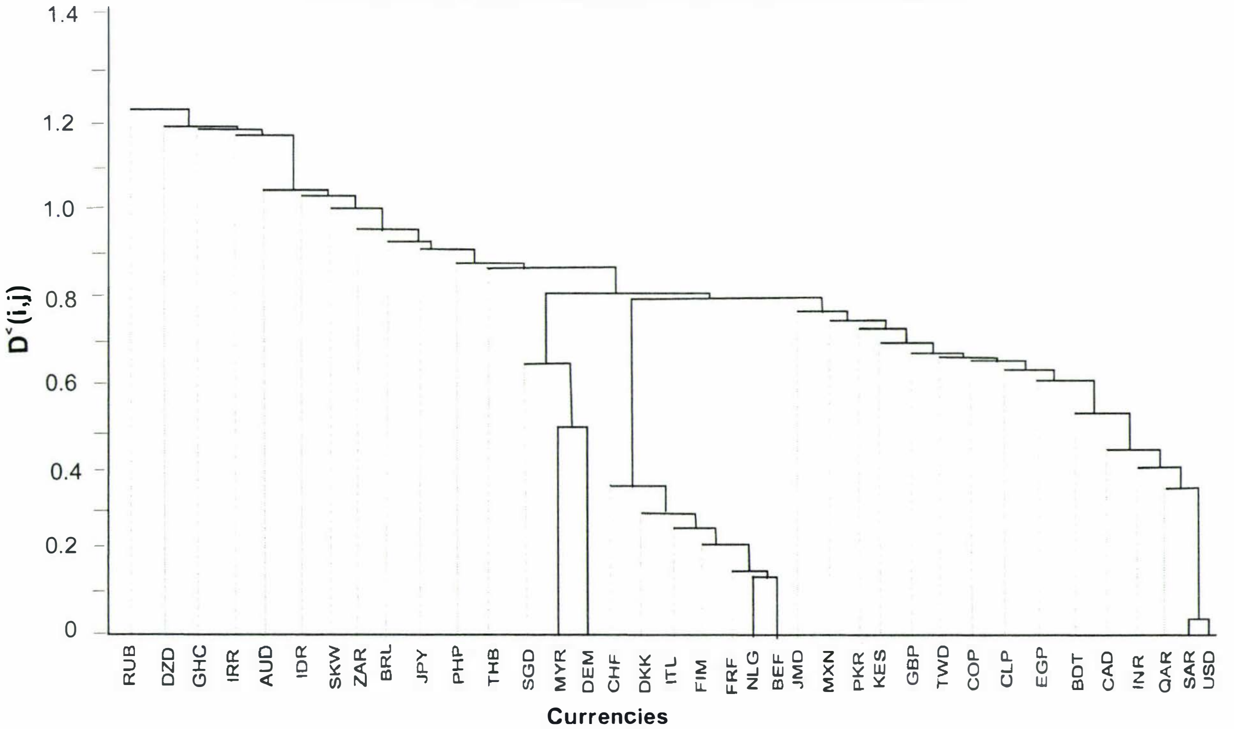
Our results show a more centralised arrangement than the US stock market. The distribution of links per node is more centralised than a power-law would dictate, as shown by the concave curve in Figure 5.2 (in the Appendix). The slope is 0.8, indicating a strong element of self-organisation in the international financial system. These results imply that either currencies are all linked by common economic factors or currency traders pay more attention to USD movements than to local factors. The spread of most distance values in the 0.8 to 1.16 range also reinforces the point that price setting in currency markets is generally more homogeneous than price setting in stock markets.

The next stage was to construct a hierarchical tree of the subdominant ultrametric space associated with the MST, by determining the subdominant ultrametric matrix, $D^{<}$. This was used to create a graphical hierarchy by linking assets horizontally with distance on the vertical axis.

The hierarchical tree is shown in Figure 5.3. The smoothness of the hierarchical tree shows the dominance of the USD, as all currencies aside from the ERM cluster and the DEM-MYR-SGD triage link off the main tree. The large distances involved for IRR, GHC, DZD and RUB in Figure 5.3 show them to be largely isolated.

Fig 5.3 – NZD-based FX hierarchical tree of subdominant ultrametric space (1995-2001)

Hierarchical grouping of distances metrics for currencies quoted against the NZD. This gives an indication of how currencies should be grouped into clusters, based on primary causal link. This shows that price determination leads off the USD with Asian and ERM clusters.

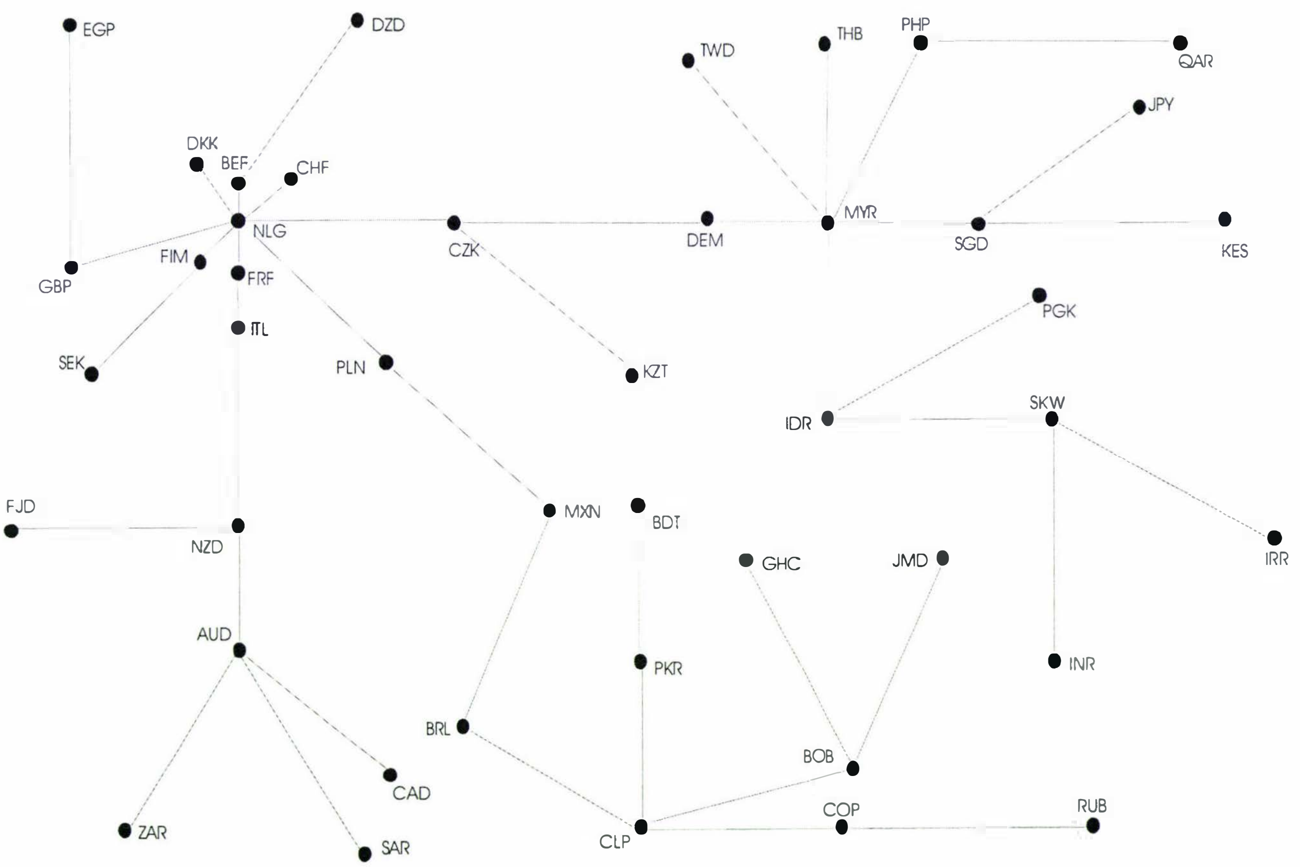


5.3.1.3 USD matrix

The analysis was repeated using the USD as the base for the reasons outlined in section 5.3.1.1. In general the distances matrix (available on request) shows weaker links than for the NZD matrix, with a number of links close to the no-relationship value of 1.4142. This is expected as we are exploring secondary influences, and some currencies may not have influential secondary linkages. The USD based minimum spanning tree, shown in Figure 5.4, indicates a number of relationship groupings between currencies, which seem to have valid economic foundations.

Fig 5.4 – USD-based FX minimum spanning tree (1995-2001)

Graphical representation of minimal distance metrics for currencies quoted against the USD. This gives an indication of the second order price causation determination. This shows a sparse clustering compared to Figure 5.1.



The overall network structure is more clustered than the NZD MST star diagram, with groups nested within other groups. Visually relationships overall seem weaker than in Figure 5.1, though care is needed due to page scaling. Care is also needed when interpreting second order trees. Relationships between nodes can be created indirectly by a joint association to the missing hub, the USD, rather than to any direct relationship between the nodes. Results should be checked against economic reasons for price linkages or against other samples or methods.

The ERM hub still exists and has strong ties, as would be expected from a linked currency arrangement. This hub is stable as dropping out the USD does not affect price causation. The removal of the USD has, however, affected most other currency relationships. The GBP is now showing its second order link to the ERM as is the DZD. There also may be a minor Scandinavian grouping with the SEK linked to the NLG by the FIM rather than the DKK.

The MST in Figure 5.3 has a number of dangling pendants. While these need to be treated with caution, as discussed, there does tend to be economic causation behind most of the linkages. The strongest economic clusters are the two commodity clusters. The first is the AUC, CAD, ZAR, SAR cluster. The AUD is conventionally used in currency markets as a play on commodity prices (Frankel, Galli, & Giovannini, 1996), and as such has a higher volume of foreign exchange turnover than its own economic size would dictate. The linking of the commodity economies to the AUD lends support to this convention. The NZD and FJD are also linked. Contrary to this commodity cluster argument is the instance of the Middle Eastern oil currencies of which only the SAR is linked to a commodity cluster. Note, however, the other oil currencies have linked relationships to the USD, so secondary influences may be weak.

Another commodity cluster is grouped around the CLP (copper, various). This involves the COP (oil), RUB (oil, various), BOB (copper), GHC (copper) and the JMD (bauxite). This cluster also links to the Indian subcontinent currencies of PKR and BDT. The distances involved in this cluster indicate only weak relationships. The linkage of this commodity cluster back to the ERM cluster via the MXN-PLN link involves long distances, indicating the linkage may be spurious. The CLP cluster may thus be isolated in terms of secondary relationships. The distance involved with the RUB link indicates it is also isolated.

The BOB, PKR and BDT links are problematic as they were pegged to the USD for part of the data period and have thin markets, generating irregular daily changes. The raw data do however indicate price changes occur at approximately the same time.

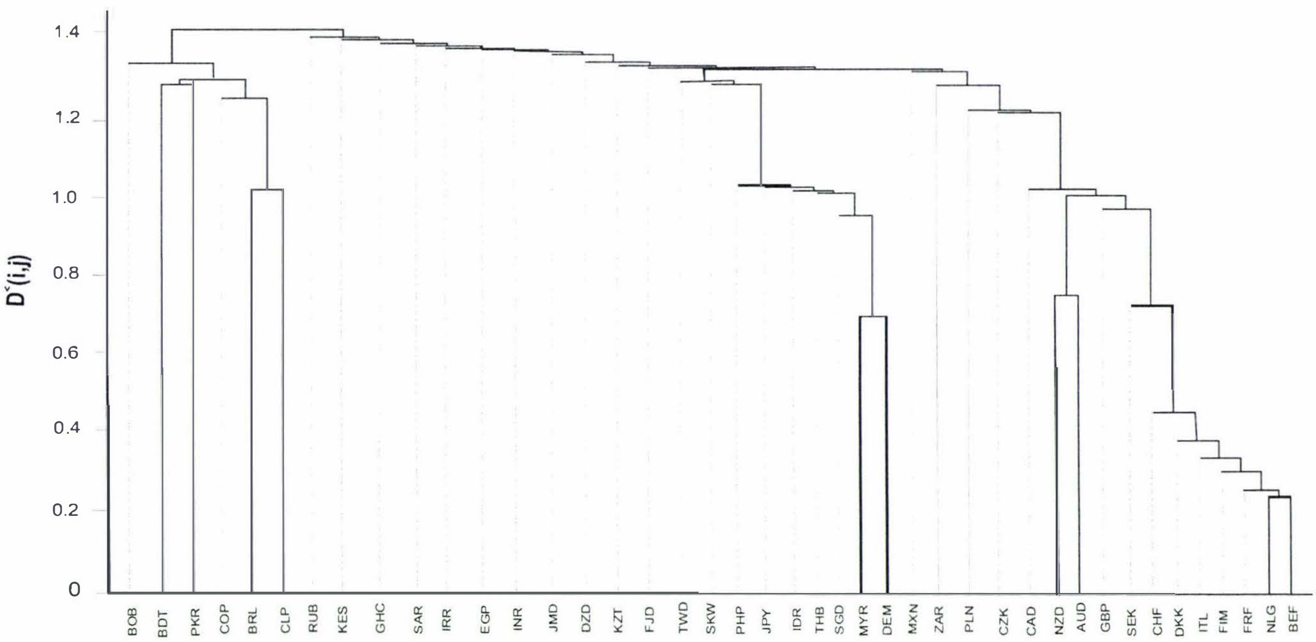
The link between the ERM cluster and the rest of the world is via the CZK-DEM-MYR link, which provides the backbone to the system. Note the KZT branches off this link rather than the RUB, and the PLN relates to the NLG rather than to the DEM.

A SE Asian cluster is evident, centred on the MYR and linked via the DEM. This indicates that after the primary USD link shown in Figure 5.1 there was inter-regional linkages pre-crisis. Why the MYR is the hub is unclear. The SGD seems to be linked externally instead of inter-Asean as illustrated by its JPY link. There seems to be no economic reasoning for the SGD/ KES link and its weak strength implies it is spurious, as is the PHP/QAR link. Similarly the distances involved in the cluster attached to the IDR imply spurious links.

The overall impression of the USD-based MST is of a common core of currencies consisting of a tree-like structure with linkages between the AUD, NLG, CLP, DEM and MYR providing the core. The other currencies are located within the clusters which branch off that common core. Once these secondary linkages are added to the primary linkages in Figure 5.1, we have the basic topology we need to create a foreign exchange network. The distribution of node links of the USD MST is more varied than the NZD MST, with an approximate power-law distribution of degree 1.5 ($R^2 = 0.95$). This is graphed in Figure 5.5 in the Appendix.

The USD MST was then used to construct the associated hierarchical tree of the sub-dominant ultrametric space, as shown in Figure 5.6. From this we can see three main secondary clusters emerging, the ERM, with low distances, the North/SE Asian, with medium distances, and the Latin American/South Asian grouping. Outside those clusters distances tend to be high, indicating ties are weak. The hierarchical tree helps to clarify the main ties exposed by the USD minimum spanning tree, but does give additional information on linkages between clusters that seemed otherwise graphically isolated. For example the hierarchical tree makes it clear that the AUD based commodity cluster is clearly part of the dominant USD/ERM hierarchy rather than an isolated cluster. Conversely the hierarchical tree confirms that the Latin American-South Asian cluster is isolated from the main tree, and has a separate price determinate process, though inter-region linkages are weak. Note there is no separate South-Asia cluster.

Fig 5.6 – USD-based FX hierarchical tree of subdominant ultrametric space (1995-2001)
Hierarchical grouping of distances metrics for currencies quoted against the USD. This gives an indication of how currencies should be grouped into clusters, based on secondary causal links. This shows ERM, Asian, and Latin American clusters.



Overall the information obtained gives a good starting point to the creation of a proxy network of foreign exchange price setting determination. The results also provide an indication that the price determination structure of international currency markets is sparsely clustered. This implies dynamic behaviour related to complex networks can be applied to currency markets. These results will be further cross-checked with other samples and methods.

5.3.1.4 NZD Crisis matrix

The analyses were repeated for the Asian crisis period, 1st August 1997 to 31st October 1998. The rationale is that several empirical studies have indicated that causal determination behind currency movements differs between crisis periods and non-crisis periods. In particular, regional correlations tend towards unity during a crisis. It is useful to verify these results with MST analysis, as this may aid our understanding of cluster dynamics during market crises. The results can also be compared to the stock market topological crisis studies of Onnela et al. (2003) and Araújo and Loucã (2005).

This period was chosen as by the 1st August the crisis had spread from Thailand to nearly all SE Asian countries and by 31st October of the next year markets were starting to calm down. The IRR was dropped from further analysis as it was fixed to the USD during this period and provided no additional information.

The crisis period correlation matrix for the NZD, the USD and the associated distance-metric matrices show that during the crisis period correlations within SE Asia increased, in most cases by 50 to 100%, approximating inter-ERM correlations. This can be seen by comparing the NZD crisis matrix in Table 5.3, with the total period matrix in Table 5.2 (both in the Appendix). North Asian currencies, which had high distances to SE Asian currencies during the normal period, had low distances during the crisis period. This could imply currency traders started to treat the crisis countries as a distinct bloc during the period of the crisis.

An interesting result was also obtained for the Bangladesh currency, BDT, which was mainly linked within South Asia during the normal period. During the crisis period, however, the BDT became strongly linked to the SE Asian currencies. The same result is found for the BRL, the RUB, and the currencies tied to the USD (SAR, QAR & IRR). The GBP was similarly affected, though not as strongly. Linkages of all Asian crisis-affected currencies to the USD strengthened, including a weakening of the previously strong MYR-DEM pair. In contrast to these results inter-ERM distances increased, indicating this linkage was under stress despite the pressure for currency alignment prior to the establishment of ECU.

While these results provide support for the hypothesis that crisis affected countries formed a closely tied cluster, these conclusions need to be treated with care as the decrease in distances of all the affected countries to the USD raises the alternative hypothesis of an increase in power of the USD in price setting. The crisis-affected countries could be seen as individually increasing their joint co-movement against the USD, and only indirectly moving together.

These changes are illustrated in the crisis period NZD-based minimum spanning tree, shown in Figure 5.7 (in the Appendix). The total period two-cluster network shown in Figure 5.1 is still retained during the crisis period. The ERM cluster is largely unchanged, though the distances are increased and the GBP and JPY have been picked up. The USD cluster structure is also largely unchanged though some relative distances have changed. In particular the RUB is now closer to the USD. The Asian offshoot is retained but now the THB is the key currency with MXN and SKW now linked. This acknowledges the effect of the crisis on those countries, though they failed to propagate the crisis further.

Figure 5.7 helps confirm the hypothesis that channels for crisis propagation were within the network of US traders impacting on one country after another, instead of one currency directly affecting another. The distributions of links for nodes in the NZD crisis MST are basically unchanged from the non-crisis period. These conclusions are strengthened by examination of the hierarchical tree of the subdominant ultrametric space, shown in Figure 5.8 (in the Appendix). This tree shows that despite the increased correlations within the Asian currencies, there are still only two dominant clusters. The pattern of network clustering is unaltered. The only noticeable change is that previously isolated currencies, like the RUB, IRR or GHC, are now a part of the international financial network.

5.3.1.5 USD Crisis matrix

The crisis period USD based correlation and ultrametric distance (available on request) inter-Asia distances are lower than for the total period but not substantially. Inter-ERM distances are higher though not universally. The ITL is now the closest currency to the still dominant NLG, rather than the BEF. The links found in the NZD-based distance matrix between the Asian crisis countries and the BDT, BRL and RUB are now not evident. However, the MYR-DEM linkage is substantially stronger.

The crisis period MST (Figure 5.9 in the Appendix) shows that a slightly different pattern of secondary influences arises compared to the normal period MST in Figure 5.4. The primary core of NLG-CZK-SGD-MYR-DEM still exists, with branches based on PLN, IDR and AUD-NZD. The basic structure is retained with a defined ERM cluster, an Asian cluster, and a developing country commodity cluster. However, there are some changes. The Latin American-developing country commodity branch is broken up, the FJD is attached to a disparate developing country branch rather than the NZD, the PHP is sprouting a major branch network, the SGD is more central and currencies with more distant links have randomly re-arranged themselves. Despite these changes the basic structure of shock transmission is not greatly changed from the normal period. The distribution of node links has a slightly more even distribution, with a power-law distribution of degree 1.4 (Figure 5.10 in the Appendix).

These conclusions are reinforced by the hierarchical tree of the subdominant ultrametric space (Figure 5.11 in the Appendix). The ERM cluster is still present and the Asian-based cluster is weakened, with only the DEM-MYR-SGD triage present. Other Asian currencies tend to co-move with this triage only as part of a global currency co-movement. Most non-ERM-Asian currencies have weak distances. The Latin-American/ South Asian cluster has disappeared. The overall impression is of less regional clustering during the crisis and more of a common global cluster, especially outside the ERM.

5.3.1.6 Conclusions

In this section two results have been established. Firstly it has been shown that price determination in international currency markets displays sparse clustering. Secondly information has been extracted which can form the basis of a network topology. The network created has a simple tree-like structure with a dominant spine rather than the more complex web structures found for S&P 500 by Mantegna (1999). This is similar to the tree-like structure found by McDonald et al. (2005) for bilateral foreign exchange rates. Underneath the predominant influence of the USD and the ERM, there are clear secondary relationships based on economic or regional factors.

We have also gained an understanding of the differences between crisis and non-crisis periods. The results indicate a transmission process for cascading shocks through the USD/ERM spine and through links outside of that spine. They also show that, while the correlations between currencies increase and ultrametric distances decrease during a crisis, the topological structure does not show major change.

5.3.2 Matrix network methods

5.3.2.1 Introduction

While the information obtained from MST analysis provides useful and clear results from established methodology, it can not be used as the sole basis for a topological map as it is restricted to extracting the dominant influences. Nor does it provide information on the relative position of nodes within a network, or on the dynamics of percolation of disturbances between nodes, or on the density and centrality of links.

To provide information on these aspects matrix network methods as outlined in section 4.2.3 were applied to the distance matrices. This was done via a number of different methods and types of data to allow a full range of information to be extracted. The crisis period data were also examined, so some indication of crisis dynamics could be obtained. The combination of MST and matrix networks methods will allow the creation of a more robust topological map. An examination of international currency market price influences of this type has novelty.

5.3.2.2 NZD 5 link matrix

The initial method involves the five strongest correlations from the NZD distance matrix per currency at a maximum value of 1.0, with a minimum of one link. The value of 1.0 was chosen as it provides the optimal balance between strong and weak ties. Links are dichotomised as binary. Note if a currency provides the strongest link to many other currencies then it may end up with more links than its own five strongest links. Note also that direction of causation is not implied, and a two-way link is always assumed.

The advantage of this approach compared to the hierarchical tree methodology is that it includes all the strong causal links between currencies, not just the primary link. The disadvantage is dichotomising removes any indication of the relative importance of those links in price determination. Results should be assessed together with the information on the relative importance of primary causal links obtained from the MST. Dichotomisation is normal with network analysis as valued matrix data have a limited range of statistical network methods available.

Using these criteria a network graph was created and analysed. The software used is UCINET© (Borgatti, Everett & Freeman, 2002) together with the related programs NetDraw©, Pajek©, and Mage©. Node positions were calculated by an algorithm-based technique called *Spring Embedding*. This iteratively allocates position to put those with the shortest path lengths closest together in the graph. The software allows a measure[3] of node repulsion to prevent nodes from being indistinguishable. Lengths are calculated based on the similarity of all pathways between node pairs and not just direct links. Borgatti, et al. (2002) show the technique places nodes in a good approximation of their influence in price determination. The graph, Figure 5.12, thus gives some idea of appropriate node position and appropriate node length of the price determination in the international currency network.

The robustness of the method is shown by the similarity in the basic structure of the currency network between Figure 5.12 and the MST Figure 5.1. The main difference is the network in Figure 5.12 has multiple price setting influences, so is more complex and harder to analyse. Two clusters exist; an ERM group and a USD group.

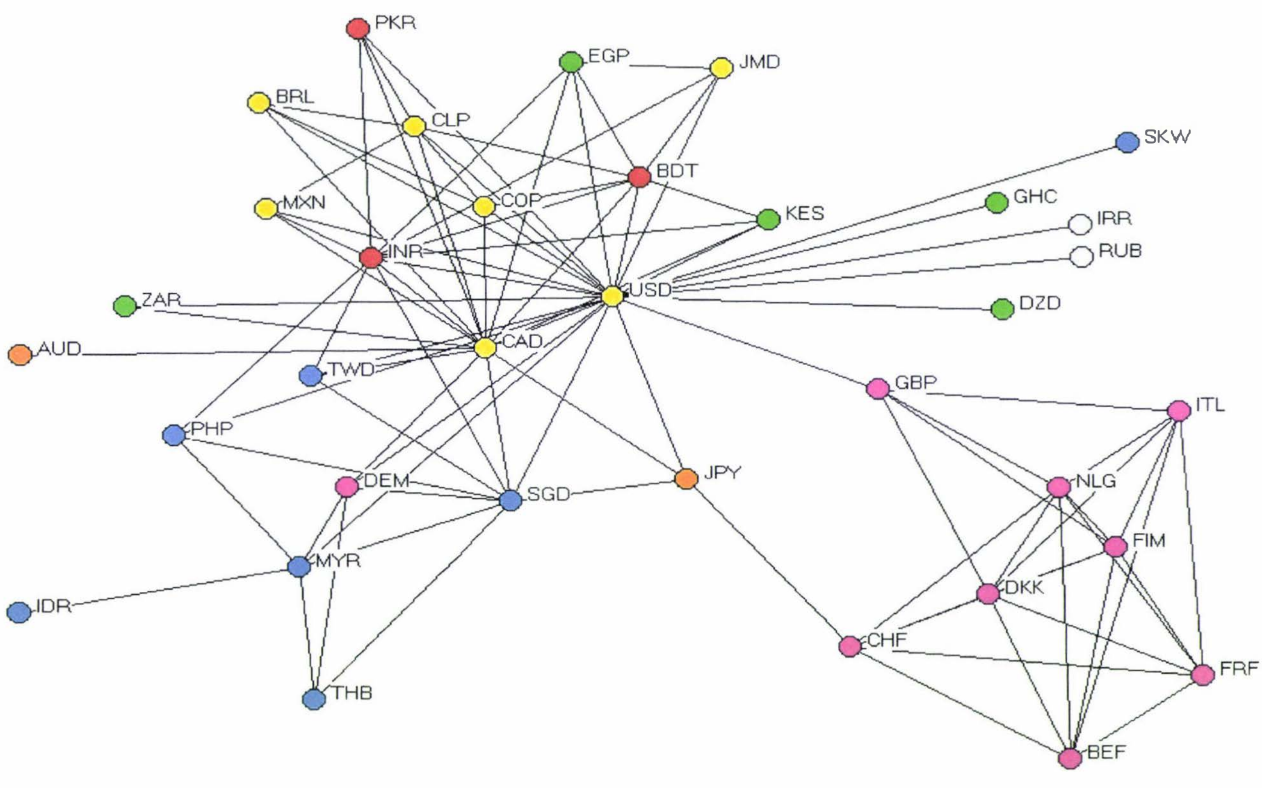
Other points to note are the SGD has taken on a more central role, the link from the USD cluster to the ERM is via the JPY and GBP, and the USD has only five currencies which are dangling pendants. The GBP was identified as part of the USD group rather

[3] This measure is calculated by the software as the minimum needed to avoid two nodes which have similar price movements from being drawn too close to be distinguishable.

than the ERM. There are indications of a Latin American/ commodity currency sub-cluster at the top and an Asian currency subcluster at the bottom. These are, however, sub-clusters embedded in the USD cluster. Graphical network techniques identified USD, CAD and MYR as nodes with potential to block disturbance percolation.

Figure 5 .12 NZD-based Network Graph of Binary 5-link Distance Matrix

Graphical representation of currency network based on 5 strongest links up to 1.0 based on spring-embedding algorithm of currencies quoted against the NZD. This gives an indication of the basic first order price causation determination. When compared to Figure 5.1, the basic structure is retained, with two clusters.



One-step ego nets for selected currencies (Figure 5.13 in the Appendix) show the role of SGD, DEM, INR and CLP as links between their local cluster and external nodes. The MYR is the hub for SE Asia, with limited external links. The SGD acts as the regional "broker", transmitting price behaviour to and from regional currencies to the developed currencies of JPY, CAD and USD. The FRF is by contrast isolated from global influences, influenced only by ERM currencies. The INR plays an interesting role of linking a number of otherwise disparate currencies with the key regional currencies. The longer lengths involved in INR cluster, however, indicate weak relationships.

Univariate analysis rank USD, QAR, CAD, IDR and SGD as the most linked and highlighted the highly uneven nature of price determination links, indicating a hierarchical structure (graphical and statistical results are available on request). Network global density (matrix average) is 0.1794 (17.9% of all possible links are present). The neighbourhood clustering coefficient is 0.765 unweighted and 0.479 weighted[4]. The low global density metric compared to the high neighbourhood density indicates links in the NZD network are sparsely clustered rather than uniform or random.

Centrality statistics rank the most central nodes as USD, CAD, GBP, JPY, INR, SGD, MYR, BDT and CLP. These currencies can be regarded as the key hubs in terms of transmitting price influences to their regional subclusters. Network degree centrality is 57% based on local connections (vs. a star network). This is a substantial amount of centralisation, and indicates the power of individual nodes varies substantially. While these results are partly due to the restriction to five unvalued links, further research indicated the use of a valued weighting would increase centralisation but would not change the essential network structure.

Eigenvectors of geodesic distance statistics show overall centralisation in terms of the total network is 49.22%. Comparison to the Freeman metric of 57% indicates the network is as centralised at a global level as it is at the local level. This supports sparse clustering and a global hierarchy. Eigenvalues indicate 25.2% of the overall pattern of distances is accounted for by the first-order global pattern and only an additional 16.0% by the second-order pattern. The NZD binary network is thus only weakly patterned at a global level.

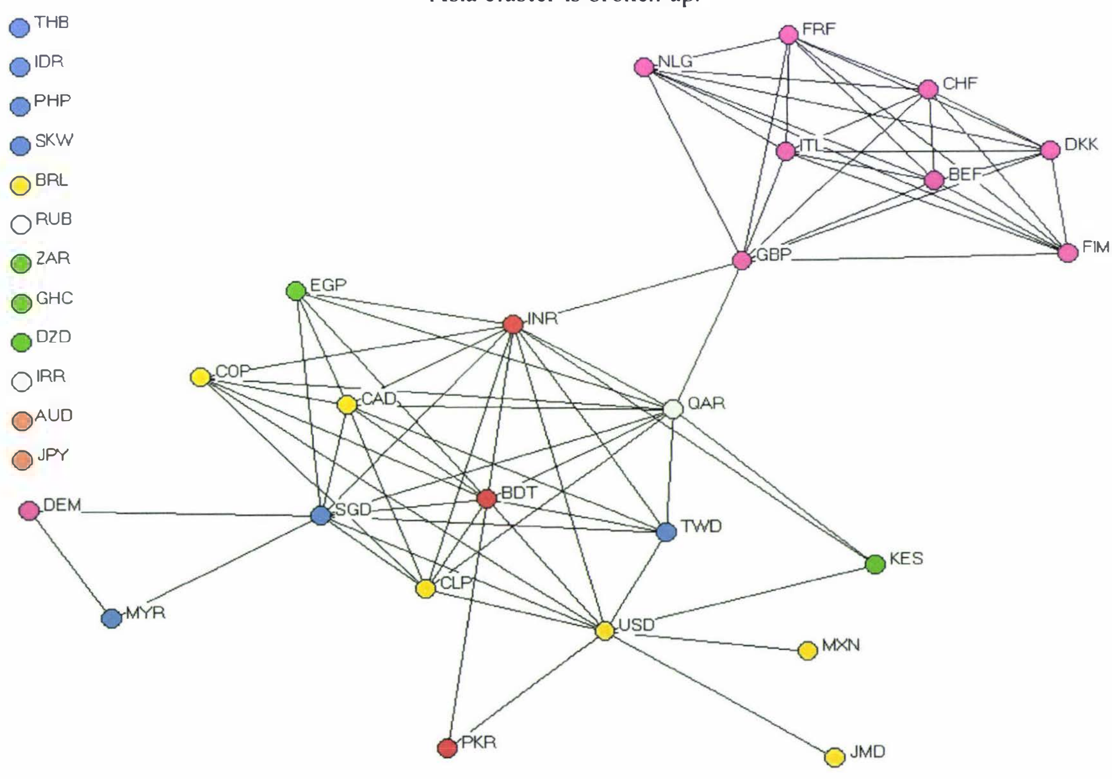
These results indicate the NZD-based major links dichotomised matrix is a sparsely clustered network which exhibits both centralisation, and a strong tendency to local clustering. Dynamics indicate more than just the USD domination. While two clear clusters exist, the ERM and the USD clusters, defined subclusters exist within the USD cluster. Only a few currencies are completely isolated.

[4] Since larger networks are often less dense a weighting is normally used.

5.3.2.3 NZD dichotomised matrix

The 5-link method allowed the inclusion of all currencies, and is a robust method which gave an initial indication of the overall network structure and node placement. However, the method has some weaknesses. The first is it includes links which are weak and can wrongly imply a relationship. The second is it artificially restricts the links hub currencies can have. An alternative methodology was thus used to cross-check results. This also establishes the robustness of the results and will identify isolated currencies. This method uses all links below a cut-off point. The dichotomisation value used was 0.8, which is approximately the mean value. Further research showed the network structure was robust to changing this value, with only the number of isolates changing. A higher value linked nearly all nodes, making analysis difficult.

Figure 5 .14 NZD-based Network Graph of Dichotomised Distance Matrix.
Graphical representation of currency network dichotomized at 0.8 distance metric based on spring-embedding algorithm of currencies quoted against the NZD. This shows only the strong first-order links. Same structure as Figure 5.12, though the USD is now less central. GBP and INR are key links. The SE Asia cluster is broken up.



The network graph, Figure 5.14, shows a similar structure to the MST result of Figure 5.1, and the 5-link result of Figure 5.12. This establishes result robustness. The main changes from Figure 5.12 are the exclusion of isolates and a reduction in the number of linkages for most currencies. The key global linkage currencies are the GBP, INR and QAR. Analysis of the latter is ambiguous as it was in a semi-fixed relationship to the USD, so could be acting as a proxy. The prior GBP-USD link has disappeared. There is no defined SE Asian cluster, with DEM and MYR in a pendant cluster. The role of the SGD as a linking hub is confirmed. Additionally there is no defined Latin American / commodity cluster. Graphical analysis identified USD, GBP and SGD as the key hubs, and univariate analysis rank the most linked nodes as the USD, GBP, SAR, QAR, INR and BDT (results available on request). The network has a density (matrix average) of 0.1351 and an overall graph clustering coefficient of 0.736 unweighted. These measures show the network is more sparsely clustered than the 5-link network.

The distribution of node links obeyed a power-law relationship with a degree of 1.65 ($R^2 = 0.93$) (shown in Figure 5.15 in the Appendix). This indicates a high degree of clustering, as it is below the critical level of 2. In particular the USD is dominant to a high degree compared to other networks (1.8 for the US stock market, 2.1 for the internet and 2.3 for Hollywood (Kim et al., 2001)).

Freeman's network centralisation statistics rank the most central nodes as SAR, INR, SGD, QAR, BDT, USD and GBP. The one-step ego-net diagrams illustrate the role of SGD, INR and CLP as regional hubs (Figure 5.16 in the Appendix). The eigenvector metric of overall centralisation of 41.4% compared to the neighbourhood Freeman metric of 26% indicates the network is more centralised at a global level than in terms of local connections. Eigenvalues indicate only 22.5% of the overall pattern of distances is accounted for by the first-order pattern, the overall global pattern. Only an additional 18.2% is contributed by the second-order pattern. The combination of results implies that the dichotomised network is not patterned at a global level, but is clustered. These results confirm the basic network structure from the last section and the robustness of the results. It provides additional information on relative link strengths and on relative node position. The results again provide a strong indication that the international financial market is sparsely clustered.

5.3.2.4 USD dichotomised matrix

We then examined the USD-based data as a binary dichotomised matrix. This will give second-order relationships as USD influences will be absent. A higher cut-off distance value of 1.3 was used since the second-order distances were longer than for the NZD-based matrix[5]. Further research showed the network structure was robust to changing this value, with only the number of isolates changing. A cut-off below 1.0 left only a few connected nodes, the ERM cluster, and AUD-NZD, SGD-MYR-DEM links.

Figure 5 .17 USD-based Network Graph of Dichotomised Distance Matrix.
Graphical representation of currency network dichotomised at 1.3 distance metric based on spring-embedding algorithm of currencies quoted against the USD. This gives an indication of the second-order price causation determination. Comparison to Figure 5.4 shows a similar structure with ERM cluster connected to the AUD cluster and a defined SE Asian cluster. The Latin American/ developing commodity cluster is now separate.

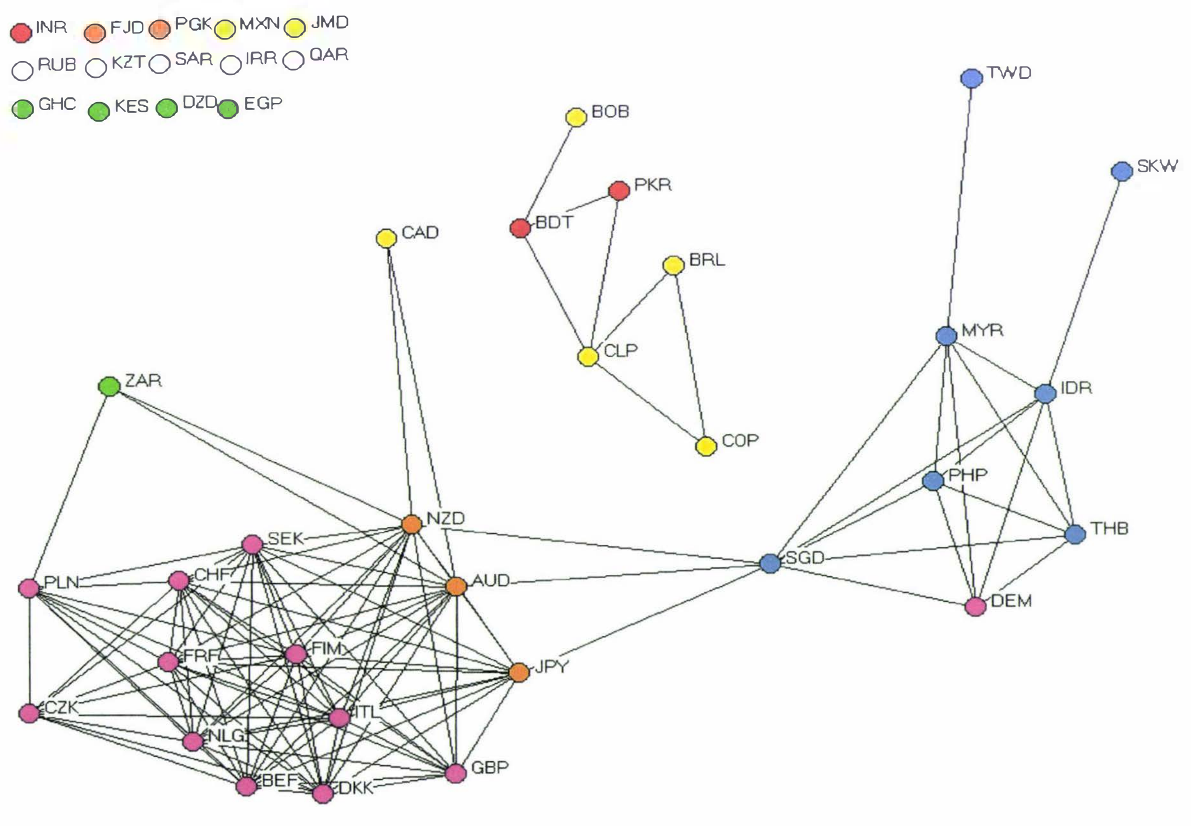


Figure 5.17 shows the resultant second order network. Comparison to Figure 5.4 shows a similar structure with an ERM/ AUD cluster and a defined SE Asian cluster.

The doubts raised in section 5.3.1.3 about the worth of some of the longer links are confirmed here. More currencies are shown as isolates, no strong currency links exist outside the USD, and the Latin American/ developing commodity cluster is separate. The AUD and JPY are now shown as link currencies and the position of the SGD as an external link for SE Asia is emphasised. The DEM is still grouped with the Asian countries. The ego-webs emphasise the hub positions of the AUD, SGD and CLP (Figure 5.18 in the Appendix). The MYR is shown to be no more central to its cluster than other currencies. The ego-web for the FRF shows the ERM currencies have high triad closure and are relatively closed to external influences. This includes the East European currencies.

Univariate analysis ranks the most linked nodes as the AUD, NZD, CHF, FRF, NLG, BEF, DKK, ITL, FIM and SEK. The network has a density (matrix average) of 0.1216 while the overall graph clustering coefficient is 0.839 weighted. The low global density compared to the high neighbourhood density show the network is sparsely clustered rather than uniform (graphical and statistical results available on request).

Freeman's metrics rank the most central nodes as NZD, AUD, SGD, JPY, FRF, NLG, BEF, FIM and SEK, which is a reflection of the tight interlocking of the ERM cluster. The network centrality is 21.23% based on local connections, which is a low metric. When compared to the NZD-based matrix metric of 56.64% the network appears to be only weakly centralised. The eigenvector metric of network centralisation of 32.97% compared to the Freeman's metric indicates the network is more centralised at a global level than at a local level. Eigenvalues indicate only 12.12% of the overall pattern of distances is accounted for by the overall global pattern and only an additional 5.14% by the second order pattern. Thus the USD binary network is only weakly patterned at a global level.

The results from the first three network analyses confirm the basic tree and branch structure found from the MST analysis. Detail has been added, however, like the

[5] A distance value of 1.4142 means no relationship

regional hub role of the AUD, SGD and INR as transmitters of price influences. The Latin American cluster has been shown to be isolated, and the existence of a SE Asian cluster confirmed. The combined results from the three analyses provide information from price matrices on node linkages, node position and node centrality.

The similarities of results from the different methods act as a cross-check and indicate robustness. The results indicate the international financial system can be modelled as a sparsely clustered network. The results will also be very useful in the creation of a topological map of foreign exchange price influences.

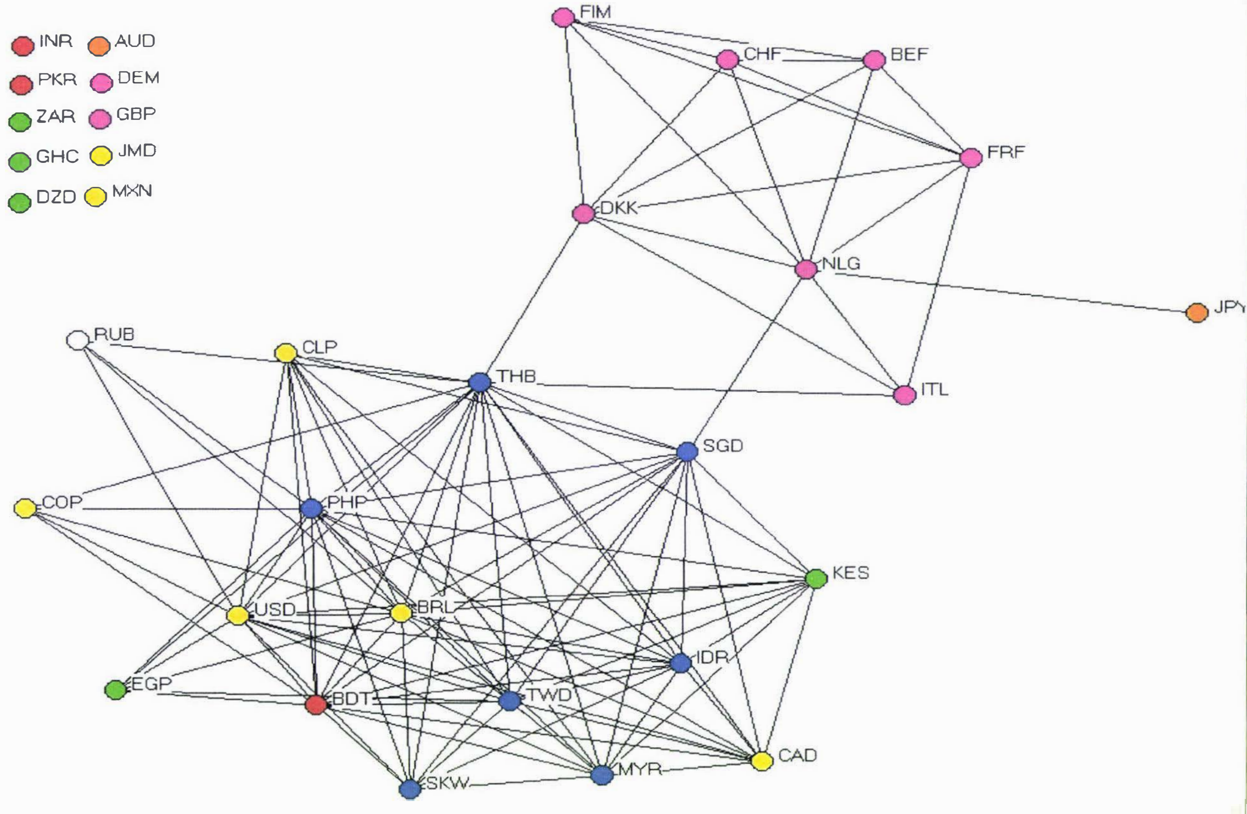
5.3.2.5 NZD crisis matrix

For the reasons outlined in section 5.3.1.4, results were re-examined for crisis period data, dichotomised at 0.8, as per section 5.3.2.3. The resultant network in Figure 5.19 shows a similar structure to the non-crisis network in Figure 5.14. The major change is an increase in the overall density of connections within the USD cluster. This is the same result found for the MST in section 5.3.1.4. This implies an increase in global price-determinant behaviour. Other changes are the integration of RUB and PHP, and the regional hub role of THB. Conversely the DEM, GBP and AUD are now isolates, indicating a decrease in their transmission role. The change in the ego-webs from the normal period emphasise the increase in link density (shown in Figure 5.20 in the Appendix). The SE Asian currencies in particular are now strongly globally connected. The entire USD cluster is now well integrated, with no single node acting as a bloc.

The univariate statistics rank the most connected nodes as THB, PHP, BRL, USD, BDT, SGD, TWD and MYR. The average density of links is now 0.2417, nearly double the normal period 0.135, and the clustering coefficient is 0.861 or 0.838 weighted, indicating that 83% of neighbouring nodes are connected. The lower global metric compared to the high local metric indicates a high level of clustering as a network, though less than for the normal period (results available on request).

Network centrality is now 33.17%, compared to 26% for the normal period, with the most central nodes being THB, BRL, PHP, USD, NLG, BDT, SGD, TWD and IDR using Freeman's three measures. Overall centralisation is 12.30%, indicating low centralisation and a wide dispersal of links. The power of the USD on price determination has fallen. Eigenvalues show overall centralisation is 22.55%, indicating the network is more centralised at the global level than at the local level.

Figure 5 .19 Crisis Period NZD Network Graph of Dichotomised Distance Matrix.
Graphical representation of currency network dichotomized at 0.8 based on spring-embedding algorithm of currencies quoted against the NZD during crisis period. This gives an indication of the basic first-order price causation determination. Comparison to Figure 5.14 shows a similar structure but fewer isolates and a higher density.



5.3.2.6 USD crisis matrix

Results for the crisis period US matrix[6] show similar changes (Figure 5.21 in the Appendix). The major change is a higher density of linkages and the merging the previously separate clusters of the ERM, Pacific, Asian and Latin-American-South Asia into one price determinant cluster. Fewer currencies are also isolated, though PKR and BDT are now isolates. Within the SE Asian subcluster THB has moved into a central position. The ego-webs confirm this and emphasise the hub roles of the AUD and SGD (Figure 5.22 in the Appendix). Thus, while the THB has moved into a more central

[6] Dichotomised at a distance metric of 1.3 as previously.

position with regard to Asia, it is the SGD which acts as a transmission mechanism for the spread of price-setting impulses outside of Asia. No block-points exist and no nodes act as hubs. K Core analysis shows the ERM and Asian subclusters are still more densely interlinked with each other than with other nodes, though SGD is equally linked to all areas (results available on request).

Univariate statistics rank the most connected nodes as AUD, NZD, JPY, SEK, CZK, PLN, BEF, DKK and FIM. The average density of links is now 0.1934, 60% more than the normal period 0.121, and the clustering coefficient is 0.721 or 0.726 weighted, indicating that 72% of neighbouring nodes are connected. The lower global metric compared to the high local metric still indicates a high level of clustering as a network, though less than for the normal period. Network centrality is now 35.77%, compared to 21.23% for the normal period. Overall centralisation is 35.77%, nearly double the normal period. Although this is still low it indicates a wide dispersal of links and no central hubs. Eigenvalues give an overall centralisation of 30.19%, indicating the network is now less centralised at the global level than at the local level, the opposite of the normal period.

Overall the results for the two crisis periods show a sharp increase in global price co-determination, with inter-regional links and intra-region links growing stronger. While the USD increased in its price-determining power, many other cross-currency links also strengthened. This indicates that during the crisis traders were taking notice of a more complex range of information, with a wider range of currencies being observed and becoming influential. Despite these changes the overall structure is similar for the crisis and non-crisis periods. This result indicates that the price dynamics did not radically change during the crisis. There was only an intensification and diversification of links. The consistency of the overall structure from the various methods used helps to reaffirm the techniques' basic validity.

5.3.2.7 Trade matrix

Trade data were analysed for the reasons given in section 5.2.1, as a proxy for capital flows and to allow the inclusion of countries with fixed exchange rates. Twenty-two countries were used, as shown in Table 5.4 (in the Appendix). Interestingly when countries were ranked by export volume as a percentage of total world trade and graphed on a ln-ln plot, (Figure 5.23 in the Appendix), the ranking is surprisingly close to a power-law. The degree is 1.1, with an adjusted R^2 of 0.795. This indicates the international trade network is sparsely clustered and hierarchical.

Export data for each country were dichotomising at a set percentage of each country's export to the total exports of sample countries. This was done to exclude minor influences and focus on the major patterns of financial flows. Exports values are used as it is argued that they proxy the dependency of one country on another and thus price influences. To explore any difference between major and minor trade influences and to explore sensitivity, two cut-off values, 5% and 10% of trade, were used. Since the matrix is not symmetrical the network is now directional and arrows are used to indicate the direction of trade flows. The introduction of directionality adds additional detail to the proxy network.

Figure 5.24 - Network Graph of Dichotomized Trade Flows at 5%
Graphical representation of trade network based on export % within sample, dichotomization at 5%. This gives an indication of the trade derived price causation determination. It shows an integrated world trade network, with the US and CN at the centre. SE Asian and EU clusters are evident.

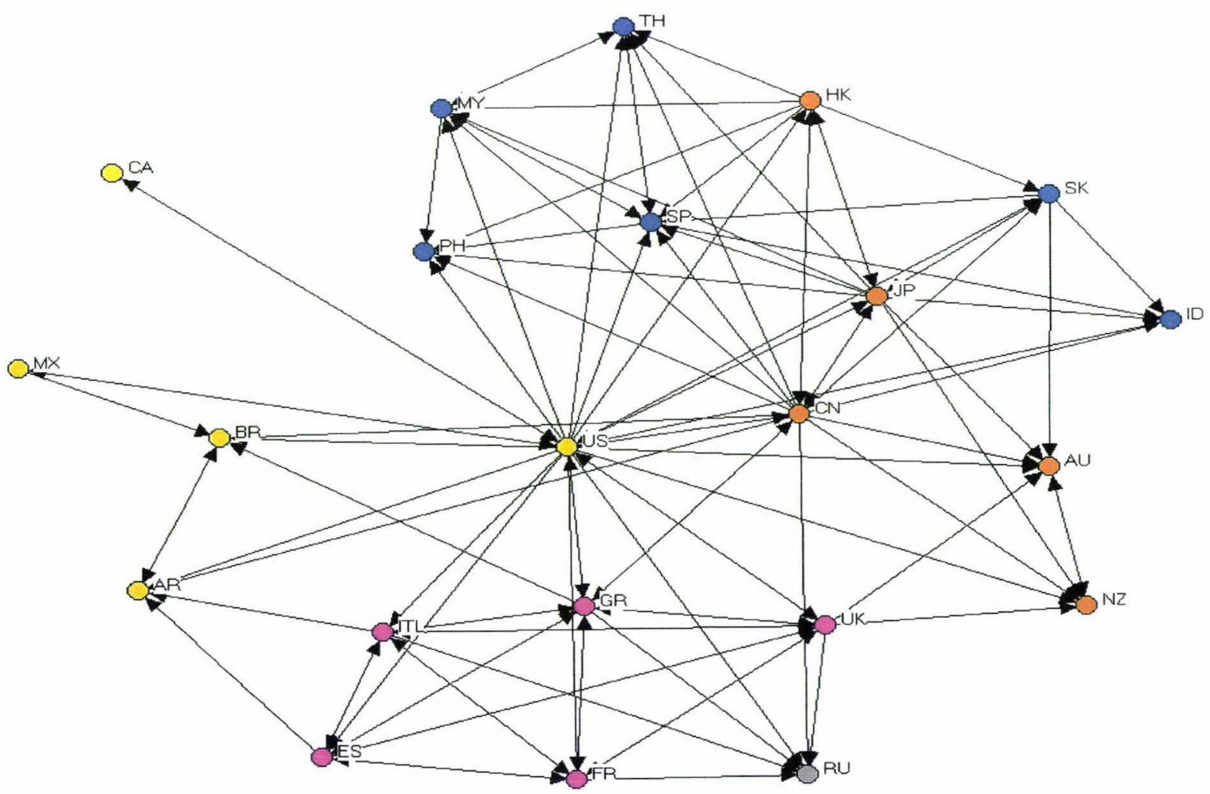
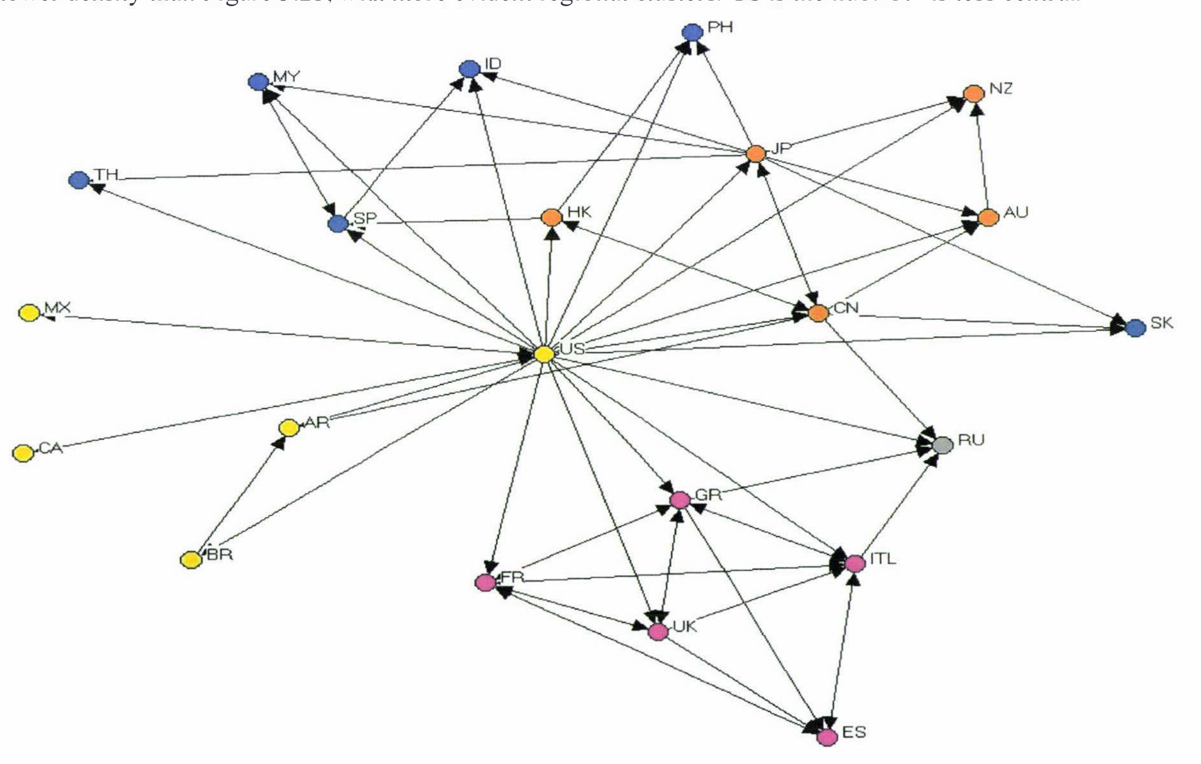


Figure 5.24 shows the network for the 5% cut-off. When the MST networks in Figure 5.1 and 5.4 and the price networks in Figures 5.15 and 5.17, are compared a similar structure can be seen. This is useful conformation of prior results. Figure 5.24 has the US and China (CN) at the centre, with links to most nodes. Distinct clusters exist for Europe, SE Asia, and Latin America, which are confirmed by K-core. Note Germany (GR) is now at the centre of the European cluster. Singapore (SP) is the hub of SE Asia. The ego webs shown in Figure 5.25 confirm these results. Australia (AU) is shown as important in linking currencies across the Pacific basin. The European cluster shows the highest level of symmetry in the direction of arrows.

The 10% graph, which restricts the network to major links, is in Figure 5.26. This emphasises the hub position of the US as well as the regional clusters. Arrow directions for US indicate that it influences but is not influenced. Note some currencies, like the ID, are now influenced only as shown by the lack of back links. CN is less important.

Figure 5.26 - Network Graph of Dichotomized Trade Flows at 10%

Graphical representation of trade network based on export % within sample, dichotomization at 10%. This gives an indication of the trade derived price causation determination. Note the arrow directions. It shows a lower density than Figure 5.23, with more evident regional clusters. US is the hub. CN is less central.



Freeman and eigenvalue centrality metrics rank the most central nodes as the US, CN, JP, SP, HK, UK, and GR. The 5% network has a network density of 0.2316 and a clustering co-efficient of 0.540 unadjusted and 0.388 adjusted. This shows the 5% network is only moderately clustered, when compared to the price matrix results in earlier sections (0.179 & 0.765).

The 5% network has a Freeman centralisation metric of 71.9% and an eigenvalue metric of 44.76%, which indicates the network is more centralised at the local level than at the global level. This indicates a sparsely clustered and patterned network. The 10% network has a network density of 0.1364, a clustering co-efficient of 0.428 unadjusted, 0.223 adjusted, Freeman centralisation of 80.84% and eigenvalue centralisation is 66.91%. The similarity of the results from 10% with those from 5% shows only a moderate sensitivity in price influence to cut-off value. The main difference is the lower centralisation for the 10% network. This is not surprising as the 10% cut-off value favours countries with fewer trading partners, and increases the importance of the US.

The export network is more centralised than the import network. The out-degree (exports) links at 5% displaying a power-law of degree 1.07, (Figure 5.28 in the Appendix), whereas the in-degree (imports) does not display a power-law ($R^2 = 0.76$). If we see import demand as creating dependence by the exporter on the importer then it is the out-degree that counts. This implies large countries like USA, China or Japan have a disproportionate power as they take a large proportion of most countries' exports. The fact the US takes at least 10% of total exports from 20 of the 21 sampled countries emphases its centrality.

The node ranking in terms of centrality metrics indicates the potential for each country to generate a cascade. Interestingly, countries which are relatively minor in terms of world GDP, like Malaysia or Thailand, have a surprisingly high ranking, particularly in terms of the eigenvector results. The ranking is also different to the ranking of trade to GDP. Kali and Reyes (2005) used a 1% cut-off to analyse centrality in a trade network of 182 countries with 1990's data and found countries which were at the heart of recent crises like Brazil (18), Indonesia (24), Malaysia (23), Russia (14), South Korea (11), Thailand (13) and Turkey (17) were amongst the top thirty five most central countries. They were also becoming more important over time. These results emphasise the importance of a country's central positions in the trade finance flow network to currency crisis percolation. This aspect is important to the understanding of why minor countries can generate a global currency cascade.

5.3.2.8 Foreign exchange centre turnover

Another source of data on the structure of the international foreign exchange network is the relative size of the different centres for global foreign exchange trade. The data on global FX turnover for the top 40 centres are shown in Table 5.5 in the Appendix. The ln-ln plot (Figure 4.29 in the Appendix) indicates turnover follows a power-law, with a degree of 1.03 ($R^2 = 0.98$). The fit gets less close as the centre size gets smaller. The possible reason is a proportion of each centre's turnover relates to local demand and is non-transferable. The law holds over a wide range of degree, however, so can be regarded as robust. This is further indication that the international financial market is a sparsely clustered network.

5.3.2.9 Conclusions

The use of matrix network methodology and ln-ln plots has enabled us to expand our analysis from the strongest links to additional links. Analysis of the relative importance of nodes was undertaken as well as the additional details from use of trade data obtained. The similar network graphs for both daily prices and trade to the MST graphs indicate the methods are robust and consistent. The results are a solid indication the international financial network can be modelled as sparsely clustered. We also have a solid basis of information to construct a simplified network of international financial flows for analysis of cascades in terms of both node links and node position.

5.3.3 Eigenvalue analysis

Using the NZD and the USD based foreign exchange data, a correlation matrix of ln-ln price changes was created and eigenvalues derived (via a programme module for SAS©). For both data sets the eigenvector corresponding to the largest eigenvalue is large compared to the rest (Tables 5.6 and 5.7 in the Appendix). The NZD-based data have 29.3% of the eigenvector located at the first eigenvalue (USD), and 43.56% located at the first two eigenvalues. The USD-based data have 15.3% of the eigenvector located at the first eigenvalue, and 28.5% located at the first two eigenvalues. These results are reinforced by the eigenvector results (available on request).

These results indicate a few, hub, currencies strongly influence the rest. The difference in the results between the USD and NZD-based data indicate currency topology involving the USD is more centralised than currency topology not involving the USD. These results confirm and enhance the results obtained in earlier sections, and is further indication the international foreign exchange market is sparsely clustered, probably involving a power-law distribution. These results also confirm our finding that the price-determinate process is more centralised in the foreign exchange market than is the stock market (Bonanno et al., 2000).

5.3.4 Power-laws and 1/f noise in the MYR market

As discussed in section 3.3.4, Bak (1996) argues that most power-law dynamics lead to the evolution of *self-organized critical systems* rather than *equilibrium systems*. These are *systems which display four phenomena; regular catastrophic events, fractal geometry, 1/f noise and Zipf's law based on power-law of unitary degree*. The dynamics of critical systems led to episodes of severe volatility which exceeds their normal pattern of volatility. There is also no correlation between the fundamental factors behind crises and the crisis timing and size.

In this section the presence of the last three phenomena in the ringgit market will be examined. The evidence for the first was examined in chapters one and two. The descriptive statistics for the MYR versus its six major trading partners are presented in Table 5.8. The percentage daily change in the MYR/USD rate shows volatility is state and time dependent, with an extraordinary level of volatility in 1997/98, and lesser levels in 1994 (Figure 5.30 in the Appendix). In comparison to a normal curve the MYR daily change shows a high level of leptokurtosis, whether examined in nominal terms or as a percentage (Figure 5.31 in the Appendix). This is confirmed by the rejection of the Jarque-Bera normality statistic for all currencies. The tails are long as indicated by the extreme daily change for the USD 18.81 standard deviations from the mean, or the extreme daily change in the SKW 23.4 standard deviations from the mean.

Table 5.8 MYR Descriptive Statistics

Descriptive statistics of MYR versus six currencies for 24/10/93 to 31/12/201

MYR Descriptive Statistics – percentage change

Common Sample: 24/10/1993- 31/12/2001

	%ΔDEM	%ΔGBP	%ΔSGD	%ΔSKW	%ΔUSD	%ΔYEN
Mean	6.53E-05	0.000147	8.89E-05	2.59E-05	0.000147	9.68E-05
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.078007	0.081497	0.064386	0.223973	0.075499	0.082951
Minimum	-0.067169	-0.066127	-0.056250	-0.167991	-0.063715	-0.057501
Std. Dev.	0.007075	0.006329	0.004359	0.010437	0.005196	0.007379
Skewness	0.474936	0.417094	0.670319	2.706870	0.965070	1.099969
Kurtosis	20.58716	31.32293	52.12139	160.9408	61.61581	21.45304
Jarque-Bera	38660.00	100059.4	300933.0	3112459.	428652.5	43039.81
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.195370	0.439695	0.265908	0.077396	0.440611	0.289598
Sum Sq. Dev.	0.149669	0.119780	0.056809	0.325733	0.080737	0.162798
Observations	2991	2991	2991	2991	2991	2991

Quantile-quantile tests for the USD against the exponential and logistic distributions. Cramer-von Mises, Watson, Anderson-Darling and Maximum Likelihood tests also found against those distributions, for both the full sample and a restricted sample[7] (shown by Figure 5.32 and Tables 5.9 & 5.10 in the Appendix). The same empirical tests for the other currencies also found against those distributions. An ln-ln plot of the larger half for the pre-fixing absolute MYR/USD price changes indicates that they follow a power-law with a degree of 1.7. These results indicate that daily changes in the MYR against its major trade partners indicate that the distribution is described by a power-law rather than randomly generated by a normal curve or a fat tailed distribution like a Student's t.

To exclude the possibility of two regimes tests were conducted on both the pre-crisis sample (before 30/ 08/97) and on the crisis period. Results are similar for both periods showing volatility is not generated by a random variable, the mean is zero, skewness is non-significant and a high level of leptokurtosis exists. The generating process seems the same for both periods. The results indicate the volatility process is not state dependent, as there was no difference between crisis and non-crisis periods. Analysis of daily changes for each year and for selected months indicates that while the size of volatility varies between years, the overall pattern and the power-law nature of volatility does not vary. The pattern indicates an absence of scale, remaining the same at finer time intervals. This supports the hypothesis of a scale-free distribution. This phenomenon is called "1/f noise". The overall signal can be seen as a superposition of periodic signals of all time scales, exhibiting peaks of all sizes, rather than the variation seen in white noise signals.

This observation is important as it indicates the generating process is a complex system following a low degree power-law. The evidence also shows the crisis period exhibits the same dynamics as the non-crisis periods. It does not follow a random generator with a separate crisis period process. Mandelbrot (1963) showed a similar volatility pattern exists for monthly cotton prices and is a general characteristic of commodity prices.

5.4 Creation of a Proxy Topological Map

Based on the results above a topological map of the main nodes in the international network of financial flows was created, as shown in Figure 5.33. This map was created using the information extracted from the minimum spanning trees, the graphical and statistical output from the matrix network methodology, from the log-log diagrams and from the eigenvalue analysis.

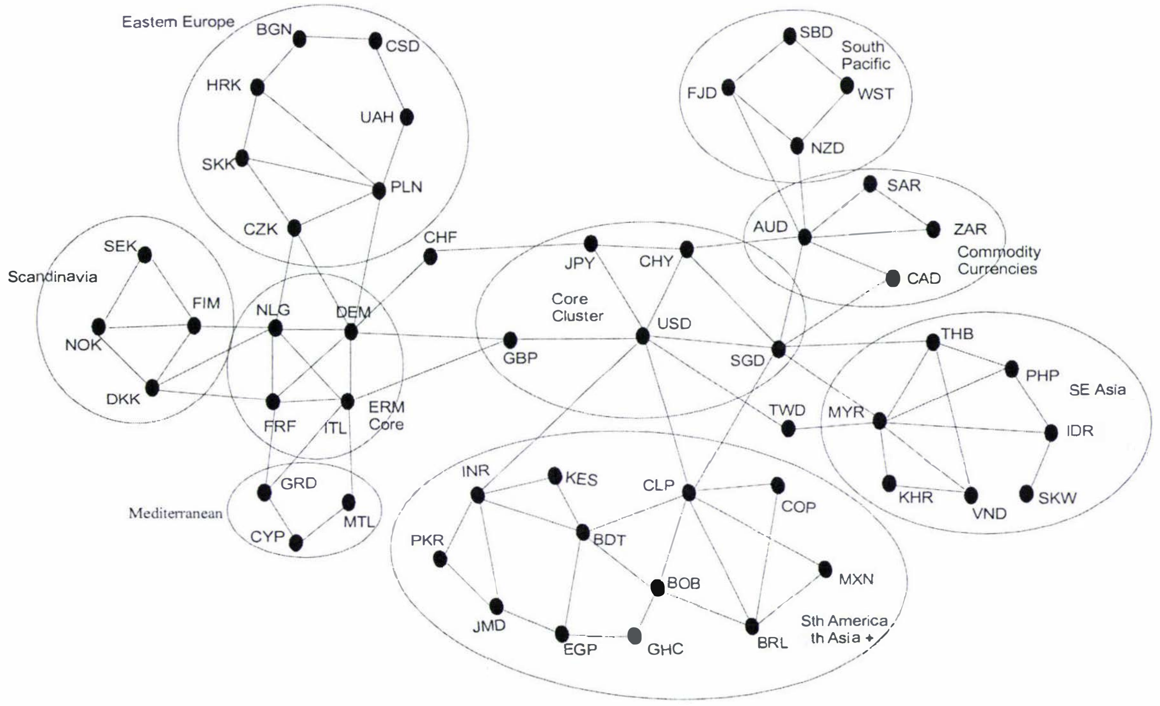
The creation of a topological map has many key elements. One has to decide which nodes should be included, and whether isolates or pedants should be included. Nodes are then classified as hubs, links or dangling. One also has to decide on the position of nodes in relation to each other, and the links that each node has to other nodes. One also has to

[7] Tests against a normal distribution could not run due to non-positive likelihood values

decide on the arrangement of each cluster in relation to other clusters. The density of internal cluster links and the density of external cluster links then have to be specified. One also has to decide on the distribution imposed on the arrangement of links and of clusters. One also has to decide on the existence and the pattern of multiple financial flow pathways. Lastly one has to decide on the overall topology which is imposed.

Figure 5.33 - Derived International Financial Flows Network

Simplified network of currency nodes using derived information



These criteria were used to design Figure 5.33, using information provided by the prior sections. Particularly important here was information on the relative strength of currencies in terms of price influence, as well as each currency's centrality in the network. Results from prior sections also informed decisions on which nodes were linked in clusters, on the density of linkage, on the size of clusters, on the global versus cluster density distribution, as well as whether power-laws could be applied. The topology was designed to be as parsimonious as possible. Only the strongest links were used, particularly between clusters. A key reason for this is eigenvalue studies show that past a certain level price determination becomes largely noise.

Consideration of these criteria meant the essential tree structure of earlier results was retained. A core of the US, Japan and China was created with distinct regional clusters.

GBP and SGD were chosen as the key link currencies, with DEM, NLG, INR, CLP, MYR and AUD acting as the regional hubs. These regional hubs have not been picked out for their own intrinsic importance but because of their influence on the price determination of their neighbours. The density of internal cluster links averaged 60% and the density of external cluster to cluster links averaged 15%. To add clarity distant links were avoided so only directly adjacent nodes were linked. The major change was the dropping of multiple direct links to the USD. Excluding these links has minimal effect on system dynamics though it does have a substantial visual simplifying effect.

Additional currency nodes were added to fill out the European, Asean and South Pacific regional clusters[8]. These nodes were not included in the earlier analysis because data are available only for a subperiod. A few of the currency nodes included in earlier sections were excluded either because they were in a fixed relationship to another currency (e.g. QAR) or they were isolated (e.g. RUB). For example, the ERM cluster was simplified as the excluded currencies added no additional dynamics. The isolates tend to tie solely to the USD and would add visual complexity without adding any additional dynamics.

The map is based on the long run determinants over our entire data period and patterns of normal period behaviour. While information was obtained on the dynamics of behaviour during the Asian crisis, the map uses normal period data as the key issue is to investigate cascade crises using normal topology.

The end result is a simplified topology that is realistic and sound in terms of economic/ deterministic links. This map will be the basis of further research. To the author's knowledge, a derived topology of international financial markets of this type has never previously been created.

The derived topological map does, however, need modification and enhancement before it can be used for simulation of cascades. One reason is it includes needless complexity so is not as parsimonious as it could be. Another reason is that the essentially tree-like structure hinders the exploration of the dynamic behaviour of cascades as there are insufficient alternative routes. Also it does not include a wide enough variety of cluster formations and triad closures. Thus to add tractability in simulation an enhanced topology was created, as shown in Figure 5.34. This will be used as the basis of simulation in chapter six.

Figure 5.34 - Simulation Topological Map

This is the modified topological map derived from Figure 5.33 which will be used for simulation

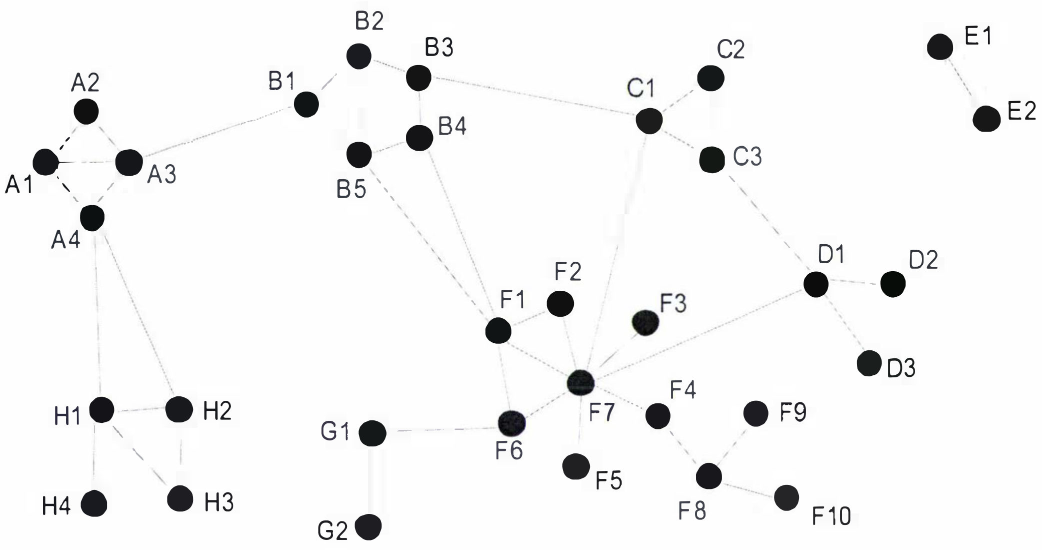


Figure 5.34 has the same tree structure as Figure 5.33, but additional alternative routes have been added from the central core. As well it exhibits a sparsely clustered arrangement of nodes, a wide range of cluster sizes, diverse degrees of triad closure and external linkage, a power-law derived density of links to individual nodes, and a diverse array of pendants and isolates. It has eight clusters based on a power-law ranging in size, from 2 nodes to 10 nodes. One cluster, F, dominates and one cluster, E, is an isolated island. There is a semi-star pattern around node F7, which can be regarded as the global network hub (e.g., USA). Other hubs can be regarded as smaller regional hubs, (B cluster could be ERM, A cluster Asia, etc.). The degree of triad closure varies on a power-law basis between 100% for cluster C to 50% for cluster F, as does the density of external linkages. The density of internal and external linkages approximate the topology

[8] BGN Bulgarian lev; CSD Serbian dinar; CYP Cyprus koruna; HRK Croatian kuna; GRD Greek drachma; KHR Cambodian riel; MTL Maltese lira; NOK Norwegian kroner; SBD Solomon Islands dollar; SKK Slovak koruna; WST Samoan Tala; UAH Ukrainine hyyvnia; VND Vietnam Dong

derived in chapter four. The isolated cluster, E, represents the undeveloped, non-integrated, countries (e.g. most of Africa) and will be ignored in the simulation exercise. The percentage of actual links used to the potential link is listed in Table 5.11 in the Appendix.

5.5 Conclusion

There were two main objectives in this chapter. The first objective is to examine whether or not patterns of price determination within international financial flows indicated that the foreign exchange network can be modelled as a sparsely clustered complex system. Results obtained from three data sources and four contrasting methodologies have indicated that price determinant influences in international currency can be modelled as a sparsely clustered complex system. The similarity of results from a range of data and tests give confidence in the robustness of the results. This is an important outcome as it implies the complex system dynamics outlined in chapter three may be present in currency markets and may be a contributing factor in the propagation of currency crises.

The second objective in this chapter was to create a proxy topological map of the price influences within the foreign exchange network. The methodologies used enabled the key nodes to be identified, their role as hubs, brokers or pendants clarified, and the basic topological framework extracted. Figures 5.33 and 5.34 show the result. This will be used as the basis of simulation testing in the next chapter.

The authors of most complexity science papers are satisfied to prove the existence of a complex system and then imply the resultant applicability of general complex network results. In the next chapter the analysis will go further by exploring a few characteristics of the proxy currency network. This analysis will give insights into some dynamics behind recent currency crises, like Asia in 1997/98. It will also provide a few implications for improvement in policy prescriptions. These will be presented in chapter seven.

Chapter Six – Simulation Analysis

6.1 Methodology

6.1.1 Introduction

In this chapter the conditions under which currency crises spread are investigated. A currency crisis is represented as a global cascade. There are three related issues. The first is to discover which parameters increase the likelihood of a global cascade. The second is to discover which parameters hinder the occurrence of such cascades. The third is to explore how a cascade spreads through a geographically explicit network.

Two different approaches to modelling this problem were considered. These approaches were to use a network game theoretic model, or to use a Monte Carlo simulation. It was determined that a simulation would be more appropriate for the research question which was posed.

Game theory models study the behaviour of individual nodes (players). This is done in an endogenous framework in which some (or all) nodes are assigned objective functions and try to meet these objectives. For reasons of tractability, such network models typically involve a small number of nodes. Solving large numbers of objective functions either simultaneously or sequentially is not a trivial task. This research is less concerned with the behaviour of individual nodes. Instead the research is concerned with determining which exogenous factors are important for global cascades. Hence game theory was less appropriate for the research objective than simulation.

There are, however, important features which distinguish this research from traditional simulation models. The most important is that many simulation models are concerned with estimating a final value for the objective variable. For example, simulation might be used to generate a hedging strategy. Cascade research is not concerned with estimating a final value. Rather it is the path followed by a disturbance flow, and the stage in the path at which it stalls, which are of interest. It is this focus on the dynamics, the breakdowns and the interactions between nodes which increase the novelty of this research.

Simulation is one of the most commonly used methodologies for the exploration of complex systems characteristics (Bak, 1996). Simulation involves creating either a theoretical- or a data-based model based on the flow of data or actions through a series of nodes. Each node generally operates on simple rules. Simulation starts by setting initial values for decision making and criteria values. The simulation is then repeated a number of times, altering parameter values using a suitable distribution. No prior assumptions are made about appropriate parameter values and no discovery exercise is undertaken to find actual values. Parameter values are instead selected randomly from preset distributions. This process can accommodate sparsely clustered networks as it allows multiple influence pathways.

6.1.2 Simulation methodology

The derived network was simulated using 1,000 repetitions at each of the 31 nodes (31,000 total repetitions). Each repetition involved a change in the selected parameter values using random values chosen from one of the three distributions: the uniform, the normal and the power-law. The simulation analysis was achieved via especially written software using Matlab©, using a programmer.

The three parameters selected for simulation were: the pattern of internal linkages within clusters, the pattern of external linkages between clusters, and the threshold parameter value. Each of these parameters was initially simulated with the others fixed. Two types of output were collected from the cascade results; the size of cascades that started from each node and which nodes were contained in each cascade. The first output is each node's propensity to initiate cascades. The second output is each node's propensity to propagate cascades. *Small cascades* were arbitrarily defined as *those results which involved less than 50% of nodes being disturbed*, *medium cascades* were defined as *those which involved between 50% and 80% of nodes being disturbed*, and *large cascades* were defined as *those which involved over 80% of nodes being disturbed*. These terms have no generally accepted definitions but the above definitions are those implicitly used by Watts (2002).

During cascade results analysis a distinction will be made between *initiating* difficulties and *momentum* difficulties. The *former* involved *a node finding enough neighbours with low parameters to initiate a cascade* and the *latter* involved *a cascade being able to find sufficient alternative routes to either avoid or overwhelm a high value blocking node to sustain its momentum.*

6.2 The Simulation Model

When creating a theoretical model it is preferable if the model is as parsimonious as possible as this enables basic underlying principles to be extracted. It is also preferable for it to be as generalisable as possible. Yet it is also preferable for the model to be rich enough to allow complex dynamics to be captured. The way these preferences were achieved in this thesis was by simplifying the node behavioural rules, and then introducing complexity in terms of node and cluster interactions. This allows the focus to be on the characteristics of network flows rather than node behaviour.

The network which was simulated was Figure 5.34 which is based on the cascade model developed in section 3.4.3. The following assumptions were made during simulation:

(i) The structure of the network is fixed. This includes the number of nodes and their placement.

(ii) Core units are nodes, which represent clusters of traders. These clusters can be visualised as regional financial centres or trade types, with internal trade aggregated.

(iii) The choice facing nodes is binary. Traders hold or sell a single product.

(iv) Each node, i, is linked informationally to a finite and limited subset of other nodes.

(v) The nodes are organised into a sparsely clustered international network. The network is assumed to have heterogeneity in terms of cluster size, where the number of nodes per cluster is organised according to a power-law.

(vi) Links between nodes are differentiated according to whether the link is internal (within the cluster) or external (between clusters).

(vii) Internal linkages have a lot higher density than external linkages. Both linkage densities have parameters which exhibit heterogeneity based on a pre-set distribution.

(viii) Links are undirected, unvalued and bi-directional.

(ix) All nodes and all clusters are assumed to have the same propensity to resist cascades. Nodes in bigger clusters, or hubs, are not more developed or robust than nodes in small clusters. This means differences in results can be related to only differing cluster size or structure

(x) Nodes will decide their actions based on a well-defined decision rule. This rule exhibits heterogeneity. It is expressed by terms of a parameter threshold as the number of neighbours required to be active before a decision to sell is taken.

(xi) Threshold parameter values are expressed as percentages rather than absolute. This implies the more links to a node the weaker the influence of each link.

The last assumption was introduced for computational ease and means the parameter value at any node is dependent on the number of links connecting to that node. With a normal distribution, $\mu = 0.5$, a node with 10 links will have an average parameter value of 5. A node with 3 links off it will have an average parameter value of 2. A node with just one link has to have a parameter value of 1.

6.3 Experiments with threshold parameter distributions

6.3.1 Results from differing distribution metric on parameters

6.3.1.1 Introduction

The initial experiment involved examining the effect on cascade propensity of imposing variations in the distribution used to choose the threshold parameter values. Initially the normal distribution was simulated, then the power-law, then the uniform. The network was otherwise held constant with the internal and external linkages as per Figure 5.34. The simulation procedure is described in the Appendix.

Three different types of output were produced for this section. The first was a table which shows how far in the network a disturbance spreads for each starting node. Based on 1,000 repetitions at each node the table lists the mean value of cascades, the minimum and maximum disturbances, as well as the percentage of the simulations that passed set cascade levels; 50%, 60%, 70%, 80% and 90%. For global cascades it is the cascades over 70% that are the focus of attention. The second type of output is a graph which summarises the percentile cascade size versus the initiating nodes. This shows which nodes are more likely to initiate cascades, as well as whether that differentiation changes as cascade size increases. The third type of output is a 3D graph which shows the size of all cascades experienced by each node. This graph has as the X axis the initiating node, numbered 1 to 31 as defined in Table 6.3. The Y axis is the size of the cascade (0 – 31 nodes infected). The Z-axis is the number of repetitions linked to each node that generate a cascade of a particular size (from 1,000 repetitions at each node).

6.3.1.2 Normal distribution

Initially the experiment used the normal distributions with (0.3, 0.28), (0.4, 0.28) and (0.5, 0.28). The standard deviation remained unchanged. The first simulation involved a mean value of 0.3, which implies that on average a node will require 30% of its neighbours to be activated before it activates. This should make activation easier than the higher metric distributions and encourage more global cascades.

The results presented in Table 6.1 (in the Appendix) confirm there were a high number of cascades with all nodes reaching 100% global cascades on at least 1% of repetitions. The average cascade size was 26.8% (8 nodes), indicating about two clusters affected. Global cascades were frequent with 21% of all repetitions affecting more than 50% of nodes, and 4.8% infecting more than 80%. The nodes most likely to cause a cascade if initiated were nodes F7 (52.1% infection on average), F1 (43.0%) and B5 (39.3%). Global cascades were least likely to begin at nodes H3 and H4. This indicates changing the mean value does not affect patterns of cascade, only the average size. Differences in the level of momentum achieved by the nodes is illustrated visually in

Figure 6.1 (in the Appendix), where the ridges leading out from nodes 16, F1, and 22, F7, are prominent. Figure 6.2 (in the Appendix) shows differentiation between the nodes tends to decrease as cascade size increases. The results are summarised in Table 6.2.

Table 6.2 - Normal Distribution

Cascade statistics from simulation. Nodes are ranked in order of propensity.

		Mean Metric		
		$\mu = 0.3$	$\mu = 0.4$	$\mu = 0.5$
Mean Cascade Size		26.80%	14.68%	9.24%
Infection Rate	cascades > 50%	21.01%	4.33%	0.64%
	cascades > 80%	4.85%	0.31%	0.00%
Nodes with 100% cascades		all	A3, C1	none
Nodes with largest cascade		all	A3, C1	A1, A3, F7
Nodes with most @50% cascades		F7, F1	F7, F1	F7, F1
Nodes with most @80% cascades		F7, F1, A3	F7, F1, B5	A1, A3, F7[1]
Nodes with most @90% cascades		F7, F1, H1	A3, B5, C1, F1, F6	none
Nodes with least @50% cascades		H4, H3	H4, H3	A2, H1, H3, H4
Nodes with least @80% cascades		F9, F10, H4	D2, D3, F9, F10, H4	all

(1) @ 70%

Next the simulation was repeated using a mean of 0.4. This implies that on average each node will require 40% of its neighbouring nodes to be activated before it will also activate. This should impede cascade generation. Nodes D1, F7, F8, G1 and H1 always infect another node beside themselves. The size of the mean cascade varies between a high of 35% (11 nodes) for F7 to a low of 7.4% for H4 (2 nodes) (detailed results are available on request). The position of a node within its cluster and the density of internal links seem to be important factors in determining the mean value. For example D2 and D3 have lower means and lower momentum than D1 or the C cluster, probably because of the incomplete triad linkage and fewer external links. The range of mean values exhibits a low order power-law distribution (0.5 degree), which implies a high level of differentiation between the initiating nodes. These results indicate the structural position of the initiating node can have an impact on cascade outcomes. The low average of the mean values (14.7%, 5 nodes) indicates that nearly all disturbances end up local. This is therefore a stable system.

For the analysis of currency crises the size and distribution of the large cascades are relevant rather than the smaller cascades. Only two nodes, A3 and C1 achieved 100% cascades, with a wide range of results between nodes, as shown in Figure 6.5. Nodes B1, B5, F1, F5 and F7 have the most 80% cascades. Interestingly F7, F1 and B5 achieved this despite having no 100% cascades. Cascades over 80% were rare events, achieved by only 0.3% of disturbances. Only 4% of disturbances generated cascades over 50%. The differentiation between nodes within the same cluster confirms node centrality is important to the propensity to generate large cascades.

Finally, the simulation was re-run with a 0.5 mean. This implies 50% of neighbouring nodes have to be affected which should lessen global cascades. The summary of results in Table 6.3 confirm this (detailed results are available on request). The mean cascade is only 9.14% (3 nodes) which implies that most cascades remain within the local cluster. Global cascades are rare with 0.64% of simulations infecting over 50% of nodes. No cascades occur over 71%. The most prominent node is the centralised node F7 which generates 50% cascades 3.3% of the time. Nodes F1 and B5 also prominent at the 60% level reinforcing the prior results. The importance of topology is shown by nodes A1 and A3, which have low means but high momentum at the 70% level. Disturbances starting at H1, H2 or H4 in contrast don't generate 50% cascades, even though H1 and H2 have high mean values. This is probably because H nodes find it hard to break out of both H and A clusters as both have poor external connections. These results reinforce the earlier contention that for large cascades the position of a node with the entire network is more important than its position within the local cluster.

Overall there is only weak correlation between the size of mean cascades and the size of strong cascades. Some nodes with small means and fewer cascades in general, like node A3, achieved more large cascades than did the central node, F7. The momentum propensity of large cascades also does not seem to be related to the frequency of smaller cascades. Occupying a key blocking position, like node A3 does, seems to be vital. Conversely, A2 - the only node without external links - has substantially fewer cascades than the other three A cluster nodes. The H cluster is consistently the least likely to generate 50% cascades, but retains a higher momentum than do F9 and F10, which generate more 50% cascades but fewer 80%. Cascade propensities between nodes from the same cluster also tend to even out as cascades develop. This indicates it is the cluster that a node belongs to which is important for global cascades, not the individual node's characteristics.

These results emphasise the importance of the concept of node centrality, explored in sections 3.3.5 and 5.2.3, for cascade propagation. Another conclusion for large cascade propagation is that it is the position of a node or cluster in terms of its control over flows within the network which is important, rather than the size of its originating cluster or the density of its intercluster links.

The results show changing the metric for a normal distribution does impact strongly on the propensity to generate cascades. This change is also nonlinear. The results, however, also show that despite the differences in detail between the three normal simulations, changing the metric does not have a strong impact on the pattern of cascade generation. The relative ranking of node importance is stable.

6.3.1.3 Power-law distribution

The experiment was then repeated for four power-law distributions using degrees, 1.2, 1.5, 18 and 2.1. This gives a good indication of the impact on cascade generation of varying the degree. In research for sparsely clustered networks it is common to see a degree of between 1.8 and 2.3 (Internet 2.1, US Stocks 2.2). In section 5.3 we found a degree of 1.65 for the NZD distance matrix, 1.5 for the USD MST, 1.08 for the trade matrix. The degrees used span this range.

Increasing the degree of the power-law will concentrate the distribution, which will increase the number of low threshold values. This should both encourage cascades to start and encourage momentum, generating more global cascades. Lowering the degree will spread out the distribution, increasing the number of medium and high threshold values and thus generate fewer cascades due to the higher momentum requirement and a greater chance of a blockage.

The simulation was initially done using a degree value of 1.5. A power-law distribution of threshold values will give a higher number of low value parameter nodes, but a lower number of middle value parameter nodes, and few high value parameter nodes. This should encourage cascade generation and encourage momentum. Table 6.3, in the Appendix, contains the results. These confirm the system is more prone to cascades than the normal distribution. All the nodes generate a 100% cascade with 40% of repetitions generating a 50% cascade, 10% over 80% and 5% of all disturbances producing cascades affecting over 90% of all nodes. Figure 6.3, in the Appendix, shows nodes F7, F1 and B5 are the most strategic nodes. It also shows clusters A and H are the least prone to medium-size cascades. Figure 6.4, in the Appendix, shows that, while variability in results between nodes is initially high, it decreases as the cascade size increases. This is similar to the earlier results for the normal distribution. These results show a system with a power-law distribution of threshold values would be prone to system-wide breakdowns.

Table 6.4 - Power-law Distribution

Cascade statistics from simulation. Nodes are ranked in order of propensity.

		Degree Metric			
		$\rho = 1.2$	$\rho = 1.5$	$\rho = 1.8$	$\rho = 2.1$
Mean Cascade Size		12.26%	39.58%	67.27%	82.68%
Infection Rate	cascades > 50%	1.34%	40.13%	74.22%	87.40%
	cascades > 80%	0.01%	10.44%	49.35%	73.51%
Nodes with 100% cascades		none	all	all	all
Nodes with largest cascade		F4, F6, F7	all	all	all
Nodes with most @50% cascades		F7, F1	F7, F1	F7, F1	F7, F1
Nodes with most @80% cascades		F4, F6, F7	F7, A3, A4	F7, A3, A4, B1	F7, A3, B1
Nodes with most @90% cascades		none	F7, A4, F1, A3	A4, A3, F1	A4, F7, A2
Nodes with least @50% cascades		H4, H2, H3	H4, H3	H4, F8, H3	F9, F10
Nodes with least @80% cascades		nearly all	F9, F10	F9, F10	F9, F10

The simulation was then repeated with the degree reduced to 1.2. The results are summarised in Table 6.4 (detailed results are available on request). The mean cascade size falls to 12%, with 1.3% of cascades infecting over 50% of nodes, and 0.01% over 80%. There are no 100% cascades. Nodes F4, F6 and F7 are the only ones to achieve 80%. F6 has the highest maximum cascade but F7 has more large cascades. G2 has the fewest cascades. As previously, A and H clusters have lower mean values but sustain high occasional cascades. This indicates on the occasions when they can break out of their relative isolation, they can build up momentum. Interestingly, F8 has the same minimum start size as F7, which means it is always overcoming its neighbours (F4, F9 and F10), but does not overcome F7 often. Note this distribution generates a lower mean value of cascades than a normal distribution with $\mu = 0.3$.

The simulation was then repeated with degree 1.8. As predicted, increasing the degree generates a substantial increase in the number of large cascades (detailed results are available on request). All the nodes now generate 100% cascades and the mean cascade size is now 67.3% (20 nodes). Seventy-four per cent of repetitions generate 50% cascades, 49% generate 80% cascades and 36% generate 90% cascades. These results imply most disturbances start a cascade that affects multiple clusters. Nodes F7, F1 and B5 are still the most strategic nodes, with disturbances starting at F7 to affect over 81% of all nodes on average. Variability in cascade propensity between nodes is high, though there is a tendency for these propensities to even out with cascade size. This system would be unstable with frequent system-wide breakdowns.

The simulation was then repeated with the degree increased to 2.1. The results show another increase in cascade propensity; with the mean cascade value now 82.6% (26 nodes) (detailed results are available on request). This indicates most cascades turn global. Seventy-three per cent of repetitions generate 80% cascades and 65% generate 90% cascades. Again differentiation between clusters evens out as cascade size increases. A high degree power-law distribution imposed threshold parameters for a tree network will generate an unstable system.

The power-law results confirm changing the metric for the distribution imposed on threshold values has a marked effect on the propensity to generate cascades, though a lesser effect on the pattern of cascade propagation. Variation between degrees is non-linear as cascade size increases. The results also confirm the importance of centrality to the propensity to generate cascades, and the decreasing importance of the initiating node as cascade size increases. The results, however, also show that despite the differences in detail between the four simulations, changing the metric does not have a strong impact on the pattern of cascade generation. The relative ranking of node importance is stable.

6.3.1.4 Uniform distribution

The experiment was then repeated using the uniform distribution (range = 0-1) to determine parameter values. The uniform distribution provides a higher number of low value parameter nodes and a lower number of middle value parameter nodes. This encourages cascades to start but may hinder momentum build-up. Blockages may also occur due to a larger number of high value parameter values.

Table 6.5, in the Appendix, and Table 6.6 show the uniform distribution generates fewer global cascades. The size of mean cascades is lower for all nodes; with an average mean cascade size only 10.9% (3 nodes) indicating the average cascade was local. No node generated a 100% cascade, with only 3 nodes generating over 80% cascades, and only one node, F7, over 90%. While nodes A3, F6 and F7 are again the most likely to generate large cascades, consistent with the normal (0.4) results, nodes B5 and C1 are now not as likely to generate large cascades. Nodes C1 and F1 generate a large number of 60% cascades, but these lack momentum and do not reach 80%.

Table 6.6 - Comparison for Uniform, N(0.4), PL (1,2) Distributions

Cascade statistics from simulation. Nodes are ranked in order of propensity.

		Uniform	normal 0.4	PL 1.2
Mean Cascade Size		10.87%	14.68%	12.26%
Infection Rate	> 50%	1.19%	4.33%	1.34%
	> 80%	0.01%	0.31%	0.01%
Nodes with 100% cascades		F7	A3, C1	none
Nodes with largest cascade		F7, F6	A3, C1	F4, F6, F7
Nodes with most @50% cascades		F7, F1	F7, F1	F7, F1
Nodes with most @80% cascades		F7, F6	F7, F1, B5	F4, F6, F7
Nodes with most @90% cascades		F7	A3, B5, C1, F1, F6	none
Nodes with least @50% cascades		H3, H4	H4, H3	H4, H2, H3
Nodes with least @80% cascades		nearly all	D2, D3, F9, F10, H4	nearly all

Figure 6.5, in the Appendix, shows that with an even spread of threshold values the larger cascades can arise from isolated clusters even though these nodes generate smaller cascades on average, For example A3 generates more momentum than F1, even though it has a lower mean cascade size. While there is a lower level of cascades than the normal (0.4), and the Z-axis is scaled down, it can be seen there is a more even spread of cascades. For example, compare the results for clusters B, C and F once cascades reach 20 nodes.

Figure 6.6 shows a similar pattern of the differences in the ultimate cascade size between nodes within clusters as occurred with the normal (0.4) results. In terms of their propensity to produce larger cascades, nodes within clusters A, B and C become more even as cascade size increases. This shows that once cascades break out of their home clusters disturbances from all nodes face similar external conditions. This may be because the larger cascades nearly always affect all three of these clusters.

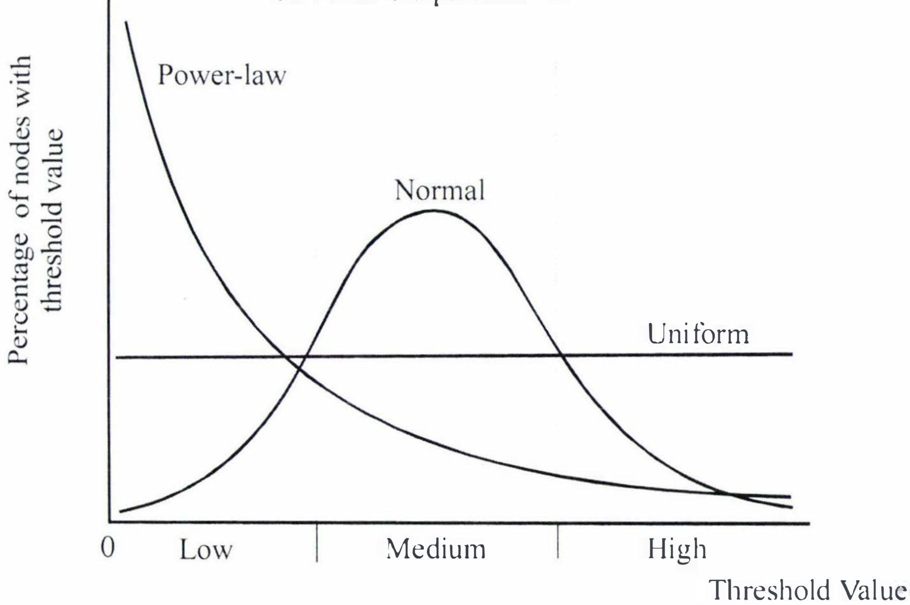
The results from the uniform distribution again emphasise the importance of node centrality. The results also show this centrality can not be defined by one-step link networks, or by pictorial centrality. What is important is the propensity of all possible pathways from a particular node to propagate a cascade outwards to a substantial proportion of the network. For example, nodes in H clusters find it hard to break out of both H and A clusters so generate few large cascades. In contrast, nodes in the F cluster dangling pendant find it easier to generate large cascades than H cluster nodes do when they break out of their isolation. This result illustrates the importance of considering the topology of the entire system when estimating the propensity of nodes to generate cascades.

6.3.1.5 Conclusion

In general, the results of the simulation indicate imposing a differing distribution on threshold parameters has an impact on results. The power-law distribution seems to generate more global cascades than the normal or the uniform distributions, as was expected. Some interesting insights did result, especially the idea that the mean size of a cascade generated by a node may differ from its propensity to cause large global cascades. The position of a node in terms of the percolating cluster seems to be an important property, as does the importance of external links. Local linkage density seems to be less important.

Different distributions will generate differing ratios of low, medium and high threshold value nodes, as illustrated in Figure 6.7. These differing ratios should produce different cascade results. The power-law distribution, which has a high number of low threshold value nodes and few high threshold value nodes, should generate cascades nearly all the time. The normal distribution should generate fewer cascades as it has fewer low value thresholds. However once started, normal distribution cascades may have higher momentum as they have the highest number of middle value nodes. The uniform distribution should generate a moderate number of cascades based on the medium number of low and medium value nodes, but will tend to suffer more blockages due to its having the largest number of high threshold values.

Figure 6.7 - Effect of varying distributions on threshold parameters



It also needs be remembered that for the purposes of analysing financial crises, it is not the regular small cascades which are important but the more irregular large cascades. Attention needs to be on the individual 80% and 90% results rather than the means. The results for the larger cascades indicate the importance of any individual country in the international financial system, or even the importance of its network of neighbours, is not a strong determinant of global cascades. The propensity of a disturbance spreading far enough from each country into the wider international financial network seems to be a stronger determinant. The key factor here is the ability to generate sufficient momentum to become a cascade which is able to overcome or avoid blockages. These results emphasise the importance of the centrality metrics outlined in section 4.2.3. The topologies of crises matter and thus should form part of analysis and policy.

An additional result is that there does not seem to be an increasing strength to cascade momentum as size grows, as proposed by Watts (2002). Instead there is a steady decline in the percentage of simulations that achieve the set cascade sizes, even for larger cascades.

6.3.2 Analysis of how many cascades of a given size contain a given node

6.3.2.1 Introduction

The second experiment examined whether or not the position of a particular node is special in terms of its propensity to propagate or block global cascades. Since nodes in a sizable network will be involved in propagating many more cascades than they will initiate, the role of a node in propagating a cascade can be more important than its role in initiating a cascade. This experiment will thus examine the role of topology in the distinction between cascade initiation and cascade propagation.

This additional analysis will also help to confirm or reject our initial analysis that the key aspect of generating a cascade is the position of a particular node within the percolating cluster, rather than its position within the originating cluster. This should also give us useful information on the dynamic characteristics of cascade propagation.

Note results presented as a 3D graph use a different Z axis scale from that used in the prior section. This is because a node could be in a cascade initiated at any node so there is a possible maximum of 31,000 cascades available for each node. This is different from the 1,000 maximum used previously.

6.3.2.2 Normal distribution

The first experiment involved the normal distribution, initially normal (0.3, 0.28) distribution for threshold values. Table 6.7 and Figure 6.8, in the Appendix show inclusion in cascades is common for nodes, with all nodes being contained in at least one global cascade. Most of these inclusions were in small cascades, with a lower number of inclusions in medium size cascades. Results between nodes vary at smaller cascade sizes but even out as cascade size increases. Comparison of Figure 6.1 with Figure 6.8 shows a number of differences. Pronounced horizontal ridgelines are evident along the x-axis which indicates nodes tend to fall in pairs or triples. Once cascades reach a medium size differentiation between nodes within each cluster decreases. F1 and F7 occur in the highest number of medium cascades but run out of momentum. The B cluster and the F cluster pendant occur in the least number of 90% cascades, with the valley around F9 and F10 clearly evident. Interestingly, nodes in the A and H clusters are contained in the least number of medium cascades but the highest number of large cascades. This may be due to the pendant position of A and H clusters. This makes it difficult for cascades started elsewhere to affect them, but those cascades which do are large. Note as well, the hub node, F7 does not have to be in the largest cascades. The F pendant and the B cluster are included in the least number of large cascades. These results illustrate the importance of network topology in generating cascades. It is also evident that local cascades tend to infect clusters in pairs so that if cluster H is infected then cluster A is likely to also be infected, or vice versa. There is no visible relationship between the tendency of nodes to be included in small cascades and the tendency to be included in large cascades.

Table 6.8 - Comparison of node inclusion in cascades

Cascade results from simulation. Nodes are ranked in order of propensity

		Nodes contained in cascades			
	Mean	Most @ 50%	Most @ 80%	Least @ 50%	Least @ 80%
normal (0.3)	50.3%	F7, F5, F3	H1, A3, H2	A cl, H cl	F pd, B cl[1]
normal (0.4)	29.4%	F7, F5, F3	F7, H1, F1	A cl, H cl	F pd
normal (0.5)	17.9%	F7, F1, D1	F8, F7, G12	A cl, H cl	H cl[2]
P-L (1.2)	22.6%	F7, D1, C1	A3, A4, H cl, D1	H cl	F pd
P-L (1.5)	61.1%	F7, F3, F5	H cl, A cl	H cl, A cl	B4, F2, F1, B3
P-L (1.8)	82.9%	F7, F1	H cl, A cl	H cl, A cl	G2, F6, F2, G1
Uniform	21.1%	F7, F1	F7, F pd, A3	H cl	H4, B3, G2, C cl

(1) cl = cluster, pd = pendant
(2) @ 70% as no cascades at 80%

Results for the normal (0.4) distribution, summarised in Table 6.8, show a lower inclusion in moderate and large cascades compared to normal (0.3) (detailed results available on request). The same cascades patterns are evident, although there is now a greater differentiation between nodes and clusters. F7 and F1 now have a high propensity to be included in the largest cascades. The pattern of A and H clusters showing a high percolation momentum is still evident.

Results for the normal (0.5) distribution show limited inclusion in medium size cascades, with no cascades at the 80% level. The same cascades patterns are evident, though the H cluster is now the least likely to be included in large cascades. This is probably due to the higher average parameter threshold ensuring it is too hard to overcome H cluster's relative lack of connections. This is also true of clusters C, D and the F pendant. Due to the rarity of large cascades, no node stands out as acting as a block to global cascade generation.

6.3.2.3 Power-law distribution

The next experiment involved the power-law distribution. The results for the power-law 1.2, summarised in Table 6.8, (detailed results available on request) show the propensity for nodes to be included in cascades is similar to the normal distributions, though there seems to be more momentum to cascades as evident by a more even inclusion in moderate cascades. The variability between nodes is more pronounced, however, especially for inclusion in small cascades. Again clusters A and H are the least included in medium cascades, and the most included in large cascades. Interestingly, D1 is now a pivotal node. Note clusters C and D tend to fall together, indicating if one cluster is affected, then the other is more likely to be affected.

The results for the power-law 1.5 distribution show more inclusion in medium size cascades. This indicates a strong momentum factor. Otherwise cascade patterns are similar. Again there is little correlation between the results for small cascades and the results for large cascades. Figure 6.9, in the Appendix, shows strong ridges along the X axis, indicating nodes tend to be infected as clusters.

The results for the power-law 1.8 show a high rate of cascade inclusion. The frequency of cascade inclusion has altered the patterns with limited inclusion in small or medium cascades. All nodes are included in a large number of global cascades, and most cascades show a lot of momentum. Once again, clusters A and H are not included in many medium size cascades but are included in the highest number of large cascades. The small cascades (size 3 or so) mainly involve clusters G and D, indicating unless they penetrate cluster F, cascades from those clusters can not propagate far. Clusters A and H also have hills at 9 nodes, indicating those cascades which failed to break out. No node stands out as a blockage or a booster.

The results for the power-law 2.1 distribution show a very high rate of cascade inclusion. The patterns in the lower degree power-laws are still evident, with clusters G and D present in small cascades and clusters A and H present in slightly bigger cascades. Large cascades have x-axis ridges, indicting that there is little node differentiation for larger cascades.

6.3.2.4 Uniform distribution

Results for the uniform distribution are shown in Figure 6.10, and summarised in Table 6.8. The absolute number of nodes included in cascades is very low compared to the normal distributions results (the Z axis is reduced to 10% of the previous value). The pattern of results, however, is similar to prior results. The main difference is F cluster is more likely to be included in large cascades than A and H clusters. The F pendant is involved in few cascades above size 12. The scarcity of large cascades above 21 nodes, as well as the sharp ridge at that value indicates clusters A, H and the F pendant act as blocks in the creation of large cascades.

6.3.2.5 Conclusion

The analysis of the inclusion of nodes in particular size cascades has produced some interesting insights. When compared with the node-initiating graphs for the corresponding distributions, (e.g.; Figure 6.1 with Figure 6.8) one sees less prominent Y axis ridges. This indicates individual nodes are not as differentiated in hindering or boosting cascades as they are in initiating cascades. Instead all nodes inside a cluster seem to play a similar role. This is similar to the role nodes play in disturbances for the larger cascades in the initiation graphs. In a large network, where individual nodes are submerged, these results could be more evident.

These results indicate once a cascade has generated a certain amount of momentum then nodes with any cluster play a similar role in cascade propagation. They also indicate the generation of a large cascade requires a jump in percolation between blocks of clusters. This indicates the structural position and the external linkages of clusters are more important for cascade percolation than individual node characteristics.

The results also show that while changing the metric or the distribution type does have a strong impact on the mean cascade propensity, it has only a minor impact on the pattern of cascades. It is also evident that nodes/ clusters differ in their propensity to propagate a global cascade from their mean propensity to propagate.

6.3.3 Threshold experiment conclusion

Simulation analysis of different distributions for threshold parameter values shows changing the distribution has an impact on the propensity to transform local cascades into global cascades within a sparsely clustered network. It also shows that where the disturbance originates matters and the position of nodes within the network matters. This is different from Watts' (2002) result for random networks.

In general a power-law distribution of threshold values has the highest propensity to generate global cascades. The higher the degree of the power-law is the higher this propensity. This result implies that sparsely clustered networks which have a higher level of heterogeneity in agents' behaviour, in terms of the relative weighting placed on internal versus external information, will have more volatile price patterns.

It was noted in chapter three that modern microstructure theory argues information overload and asymmetries in foreign exchange markets lead to the establishment of price leading specialists in each submarket. As markets expand and become more complex the relative amount of information any one agent can assimilate in these complex markets will fall. This increased heterogeneity implies cascade-type problems may become an inherent part of asset pricing. This problem would be worse in markets with higher levels of information asymmetry due to problems with availability or access to information. Emerging markets will thus tend to have more asset price instability.

The other conclusion is that the pattern of which nodes initiate or propagate the larger cascades is reasonably stable over all distributions and metrics. This implies the topology of a network imposes defined patterns on cascades generation. Topology matters.

6.4 Experiments with Linkage Densities

6.4.1 Introduction

The next set of experiments examined the impact of varying either the density of internal links within clusters or density of external links between clusters. The structure of nodes and threshold values were left constant.

The major change in procedure is that the analysis was done by clusters rather than individual nodes. This was because the random generation of links between clusters meant links between any two nodes were equally likely. The linkages in Figure 5.24 no longer apply. This means starting from a particular node in a cluster was not different from starting from another node in the cluster. The simulation procedure is explained in the Appendix. The simulation was conducted using 100 repetitions of the chosen distribution for each of 100 repetitions of linkage density. This gave 10,000 repetitions for each starting node. All threshold parameter values were drawn from a normal distribution with (0.3, 0.28). All density values were drawn from a uniform (0-1) distribution. Examination of the impact of changing both linkage density and threshold values is left to future research.

Note the parameter value at each node is dependent on the number of links at each node. For example, for a normal distribution with $\mu = 0.5$, we would expect a node with 9 links coming off it to have a parameter value average of 5, whereas a node with 4 links will have an average parameter value of 2. Since a value of zero was excluded, any node with one link always had a parameter value of 1.

The uniform distribution used to create linkages implies the more nodes a cluster has the more links it should attract on average. The proportional definition of parameter threshold values, with no differentiation made between internal and external links, implies the more links a node has the higher will be the node's average threshold parameter value. This occurs because an individual link will be a smaller proportion of links for a node with more links. A node with many links will thus be more robust to a disturbance affecting any single link. This implies a disturbance starting inside a larger cluster will face lower blockage difficulties than one starting inside a small cluster.

6.4.2 Changing internal cluster density

The third experiment examined the effect of changing the density of links within clusters. External linkage density was set at 6%. The internal linkage density was examined at 40%, 60% and 80%. The sizable differentiation between these two densities was needed to create a sparsely clustered nature of the network. These values were derived based on the topological results in chapter four. The results are summarised in Table 6.9 (detailed results are available on request).

Table 6.9 - Effects on global cascades of varying % internal linkage

6% external links, normal (0.3, 0.28)

Shows how the % of simulations reaching a given cascade size changes as % of external linkage changes for clusters

			% of internal links		
	Node Size	% Cascade	40%	60%	80%
Cluster	G 2	50%	36.5	37.5	35.9
		80%	27.3	30.8	28.9
	C 3	50%	33.6	42.1	38.5
		80%	24.9	34.4	31.0
	D 3	50%	30.5	42.7	38.3
		80%	22.5	34.7	30.8
	A 4	50%	36.8	46.6	47.8
		80%	27.2	38.2	39.0
	H 4	50%	35.6	46.0	49.5
		80%	26.3	37.6	39.9
	B 5	50%	41.6	50.6	53.6
		80%	30.8	41.3	43.6
	F 10	50%	61.6	72.5	77.6
		80%	43.8	58.4	61.6
	Ave	50%	39.4	48.3	48.7
		80%	29.0	39.3	39.3

These results present the size of cascades that start within the cluster. Since these results include cascades starting at any node within a cluster they give a higher mean size for a cascade than do the results in sections 6.3. Note that the larger the cluster, the more chance that a cascade started within the cluster will form a global cascade, due to the greater number of exit points from the cluster into the surrounding network.

The table shows that increasing the percentage of links with clusters increases the occurrence of global cascades. However, the impact on cascade generation is proportionally small, especially for the larger cascades. A 33% increase in internal link density yields only at most a 7% change in the number of cascades. Increasing the internal links past 60% has minimal impact, mainly for larger clusters. This is because each link has a decreased value, and the bigger the cluster the greater the chance of a global cascade starting at the node. Note also for the three smallest clusters increasing internal link density from 60% to 80% actually reduces cascades.

A 33% reduction in internal link density reduces the number of cascades by only 17%. Note it has a larger effect on the larger clusters, with minimal effect on cluster G. This result is probably because cascades move more slowly through clusters due to less interlinking being available to avoid blockages caused by high parameter nodes.

These results occur because once a cascade leaves its originating cluster the organisation of the cluster is irrelevant. The degree of internal linkage in the originating cluster is no longer of relevance. The minimal effect on larger cascades may indicate it is the links between clusters which hinder flows rather than links inside clusters. However, it needs to be remembered that since larger clusters have average parameter values which are higher, larger clusters will be harder to penetrate on any single external link.

The density of internal linkages thus does not have a strong impact on the propagation of global cascades. In terms of currency crises this implies links between countries inside an affected region may not be an important aspect of generating global financial crises. Even if a crisis spreads easily inside a region, it does not become global unless it can escape the region.

6.4.3 Changing external linkage density

The fourth experiment involved changing the density of external linkage between clusters to determine whether or not this affects the results. Internal linkage density was left unchanged at the reference level of 60%. The external density was examined at 4%, 6% and 8%. Table 6.10 summarises the results (detailed results available on request).

These results show decreasing external linkage density has a marked effect, particularly on the smaller clusters, with the number of cascades starting at small clusters dropping by 25% or more. This is probably due to the larger clusters being harder to penetrate as they have fewer external links, yet still the same number of internal links. Starting in the large cluster it is harder to get out with a decreased number of >50% sized cascades, and a large decrease in the number of >80% cascades.

Table 6.10 - Effects on global cascades of varying % external linkage

60% internal links, normal (0.3, 0.28)

Shows how the % of simulations reaching a given cascade size changes as % of external linkage changes for clusters

	Node	Size	% Cascade	% of external links 4%	6%	8%
Cluster	G	2	50%	25.75	37.48	48.95
			80%	17.44	30.79	43.95
	C	3	50%	31.71	42.09	50.08
			80%	21.73	34.37	44.71
	D	3	50%	30.08	42.67	49.18
			80%	20.89	34.68	44.51
	A	4	50%	36.54	46.62	55.04
			80%	24.74	38.23	49.43
	H	4	50%	36.94	46.03	55.05
			80%	25.95	37.55	49.54
	B	5	50%	39.73	50.6	58.77
			80%	27.72	41.34	52.84
	F	10	50%	67.61	72.54	75.96
			80%	43.57	58.36	68.31
		Ave	50%	38.34	48.29	56.15
			80%	26.01	39.33	50.47

Increasing the external linkage density has a marked effect on cascades. The mean cascade increases strongly, as does the number of large cascades. The increase is particularly pronounced for the smaller clusters. This result is expected as there are more routes available to get around blockages. The increase is most pronounced when cascades start in the small clusters. For example the G cluster, with 2 nodes, has a 33% change. This difference in that response between clusters is probably because of initial problems in cascade generation due to the restricted number of external links. However, once a cascade has achieved some momentum it can move smoothly through the smaller clusters until it is able to affect the larger clusters via multiple links. The results also show disturbances starting in larger clusters have a higher chance of causing a global cascade.

The density of external linkages thus does have a strong impact on the propagation of global cascades. This result occurs because a global cascade can propagate successfully only if can link with a sufficient momentum between clusters. Comparison of Tables 6.9 and 6.10 shows the contrast between the impact of changing internal and external linkage densities, with the change in external density producing a larger impact than the change in internal density.

6.4.4 Conclusions from changing linkage densities

The results indicate the most important parameters related to cascade generation in sparsely clustered networks are the density of external linkages and threshold values of individual nodes. There are indications both variables have non-linear profiles. Both the threshold parameter and the external density parameter are less important for larger clusters. There is also an indication that individual node threshold parameters would be less important as network size grows. The importance of network size for the external density parameter is ambiguous.

In terms of currency crises this result implies links between regions is a more important parameter than links between countries in generating global instead of local financial crises. It is only when a crisis can spread easily between regions that an initially local crisis can become global.

Note that, contrary to Watts' (2002) model, there is no evidence once the cascade reaches a certain size a global cascade becomes inevitable. This is shown by the percentage of cascades steadily decreasing as cascade size increases. It is possible this result may not hold for larger networks. This is left for future research.

6.5 Simulation Conclusions

In this chapter it has been shown that the specification of a complex network is important to the potential of the system in generating global cascades. The position of nodes within clusters, the position and composition of clusters in relation to each other, the density of triad closure within clusters, the density and distribution of linkages between clusters and the definition and distribution of threshold parameter values are all important variables. In summary, the topology of nodes matters for the propagation of currency cascades.

The distribution and metric of the density of external linkages and distribution and metric of the threshold parameter were shown to be the most important variables. Within a simple model the exact topology of complex networks plays an important role in terms of the likelihood of cascades and the dynamics of propagation. Cascades within the network are commonly localised on one or two clusters, but a limited number are global.

The model was specified so the nodes were identical in everything apart from threshold values and the disturbances were random and identical. The range of results therefore is solely the product of the variation in the network topology created by the repetitive drawing from the chosen distribution. The results are not due to any inherent differences in the initiating cause, any alterations in the state of the nodes or any differences in the timing of the disturbance.

It is useful to note the pattern of results produced by this simulation analysis matches the proposed stylised facts of chapter one. It has also been shown that simulation of a network with explicit sparse clustering produces results different from those obtained from the simulation of a random network by Watts (2002).

In terms of currency crises, these results imply that links between the affected region and the rest of the financial world are an important aspect of the generation of global financial crises. Even if a crisis spreads easily inside a region, it does not become global unless it can escape the region. This also implies it would be useful for currency crisis researchers to examine the links between regions in terms of their propensity to spread a crisis between regions. In terms of this model SE Asia can be seen as a region more likely than regions like South Asia or Africa to generate global crises. This is due to a higher density of both internal and external trade and financial linkages. This density has grown in the last few decades as the region has integrated, and grown in market size. In contrast Africa is extremely unlikely to generate cascades due to the lack of external links.

The non-linearity in the density parameter which was found may indicate the parameter is ambiguous at higher levels. It could be posited there is a bell-shaped propensity to crises in terms of the density of external linkage. This would start at low propensity due to small market size and few external linkages (e.g. Africa), then increase as internal market size and internal and external linkages grow (e.g. Asia), but ultimately decrease again as the large number of external links (e.g. North America) will reduce the impact of disturbances on any one link and allow a region to pass on a shock. This suggestion would correspond with empirical research which shows middle-income, emerging, countries are most likely to percolate currency crises. This issue is left for further research which uses large networks.

Chapter Seven – Conclusion

7.1 Overview

7.1.1 Thesis objectives

In this thesis the following question was considered:

Does the use of theories derived from complex systems and network science enable insights to be gained concerning recent currency crises?

The answer to this question is that theories and methodologies which evolved in complexity and network sciences have analogies to currency crises and offer insights for finance. Analysis of the pattern and characteristics of price determination was shown to be a useful aspect of market instability analysis.

The use of complex network analysis can usefully address the causes of currency crises and offer policy suggestions. The approach is also capable of handling interesting and practical modifications, as will be outlined in section 7.4.

7.1.2 Thesis summary

In this thesis recent advances in complex network science were examined and the question of whether or not these approaches could prove useful when understanding currency crises was considered. In chapter one the motivations for the research were outlined and the research objectives introduced.

In chapter two existing currency and other financial crisis models were reviewed. This showed that the characteristics of recent currency are not well explained by older currency crises macro-feedback models. Possible theoretical bases for rules for the modelling of trader behaviour were also developed.

In chapter three recent developments in complex systems and network science were reviewed, as well as useful literature from the biological and physical sciences. This review led to the conclusion that complexity science models had the ability to explain currency crises. This is because the price patterns seen in the dynamics of recent currency crises could be seen as characteristic behaviours of complex systems rather than characteristics generated by either individual currency markets or the international market.

From the review of chapter two and three, an alternative approach to modelling currency crises was proposed. This alternative approach was a binary choice model based on the adaptive micro-behaviour of adaptive agents arranged in the explicit topology of a sparsely clustered network. This model was designed to be parsimonious but capable of handling the complications which arise from network topology considerations. It was also shown to be capable of generating complex dynamics. This approach differs from earlier herding models which assumed a linear sequence of affected agents with a single disturbance path. The alternative approach creates complex dynamics as any initiating disturbance has multiple pathways open to it, and the pattern of these pathways differs depending on the initiating node. These theoretical dynamics of this model were presented and examined.

Chapter then four introduced and evaluated useful topological methodologies. In chapter five the topology of price influence in international currency markets was examined by the application these methodologies. These results indicated the pattern of exchange rate prices could be treated as a sparsely clustered complex network of financial flows. It was shown that these methodologies produced useful and robust topological results. It was also shown that the ringgit market exhibited fractional pricing patterns. This led to the creation of a proxy topological map of international foreign exchange price determination.

In chapter six simulation methodology was used to extract the characteristics and parameters of the proxy topology map developed. It was shown that the proxy topology could be used to generate cascades which yielded useful and logical results. Outcomes of the simulation analysis indicate that knowledge concerning currency crises may be enlightened by use of network analysis.

7.2 Summary of Results

The results in this thesis indicate novel insights in the propagation of global cascade currency crises if complexity theory is applicable. One insight is that the topology of trader networks matters for global currency crises. Another insight is that the characteristics of the initiating country are not as important as the pattern of links tying that country to its regional neighbours. Another insight is that the pattern of links the region has to the rest of the global network is more important than inter-region links. The two most important parameters of the global network's reaction to regional shocks are the level of a regional cluster's threshold against external shock, and the density of a region's links to non-affected regions.

A number of conclusions arose from the review and the simulation. One conclusion is that for a global cascade to develop there needs to be a sufficient fraction of markets/ agents being early adaptors and these early adaptors need to be sufficiently connected for a disturbance to affect most clusters. Also, if the largest cluster is affected, then this builds momentum which creates a pattern of multiple activations and impacts on medium adaptor nodes via several links. The impact of early adaptors' disturbances on that extended vulnerable cluster is also vital as this extends the momentum past the early adaptors, thereby transforming a regional crisis into a global crisis. Thus the frequency and pattern of global cascade crises will depend on the structure of the extended vulnerable cluster.

The important parameters in the structure of an extended vulnerable cluster are the pattern and distribution of threshold parameters and the pattern and distribution of external extra-cluster linkages. This means differing network distributions lead to contrasting patterns of percolation. A network with a low average level of connectiveness will tend to have frequent local cascades but these will die out before becoming global as the vulnerable cluster will occupy only a relatively small fraction of the network. Conversely, a network with a higher average level of connectiveness will tend to be stable most of the time. But an occasional disturbance in the right place will create a cascade which turns global as the vulnerable cluster is tightly bound into the entire network so that effective propagation is achieved.

7.3 Contributions

7.3.1 Theoretical contribution

This study made several contributions to knowledge. Firstly: it has been shown that complex science and network theory have the potential to offer useful insights for finance.

Secondly: an alternative approach to currency crisis cascade modelling has been proposed, which has special relevance to the experiences of recent currency crises. Johnson et al. (2003) argue that the only common element in all financial markets that could generate the required dynamic behaviour is the existence of complex networks of traders. In this thesis the way in which a sparsely clustered complex network of traders could be modelled to generate these dynamics has been suggested. To the author's knowledge this is the first attempt to apply this type of model to finance. Johnson et al., in a survey of the field, found no similar approach.

Another contribution is that the price determination patterns embodied in the stylised facts of recent currency crises can be explained by complexity and network sciences. This offers an explanation for how crises can occur in free-floating currencies.

7.1.3 Methodological contribution

In this thesis methods which were novel to finance were used to show that price determination in international currency markets exhibits characteristics of a complex network. As part of the work involved a proxy topology which was shown to exhibit a robust taxonomy, was extracted from the price matrix. Simulation techniques were also used to elicit cascade dynamics from the proxy topology. The focus on the dynamics, the breakdowns and the interactions between nodes in these simulations has novelty in finance.

7.1.4 Empirical contribution

Johnson et al. (2003) argued that the patterns of dynamic behaviour typically characterised by complex networks are present in all financial markets. In particular it was shown that currency markets exhibit the four phenomena, regularity of catastrophic events, fractal geometry, 1/f noise and Zipf's law, which indicate the existence of a complex network.

This thesis examined in detail price influences in the international currency markets and created a proxy topological mapping of foreign exchange price determination. This kind of examination is novel especially as it includes secondary linkages and centrality metrics.

The proxy topology was subjected to cascade simulation analysis, which yielded several useful insights into currency crises. It was shown that node threshold values and the density of external links were key parameters in terms of cascade propagation. It is of interest that these parameters were also found to be the key parameters in contagious disease models. It was also shown that simulation of the dynamics of a sparsely clustered network produces results that differ from those of random networks. It was also shown that a simple parsimonious model of trader interaction within a foreign exchange network can produce dynamics that are complex and contingent.

7.4 Theoretical and Policy Implications

7.4.1 Theoretical implications

Complexity science authors argue that the existence of complex networks tend to imply a particular set of characteristics and dynamic behaviours (e.g.; Mantegna & Stanley, 2000 and Watts, 2002). For example these authors argue that large and small cascades obey the same general principles, with the initiating impulse the same for both. Global cascades are not extreme events with different initiating causes. They are random outcomes which can be expected occasionally from the dynamics of a complex network. This is because the size of any particular cascade from a disturbance is a factor of the percolating cluster surrounding the node disturbed at that time. Most of the time the percolating cluster will dampen regional disturbances, but as long as initiating disturbances regularly occur in differing nodes, global cascades will eventually occur. This is a global condition rather than any characteristic of the disturbed node or the originating cause. There is also no periodicity to global cascades. The chance of another global cascade occurring is not a function of past disturbance patterns.

When a global cascade does occur, percolation to the entire vulnerable cluster will be a discontinuous phase transition, starting slowly then jumping from the initiating cluster to the entire network. It is the size of the jump required which will determine the frequency and dynamics of global cascades. If the jump required is small, global cascades will be common and the system will be regarded as unstable. If the jump required is sizable, most local cascades will die out. This will lead to the observation that the system is stable. This stability can continue for a long time, until a disturbance seeming to be exactly the same as past disturbances, achieves the phase transition and becomes a global cascade. This generates the pattern of long-term stability with occasional crises whose size is out of proportion to past stability. It is important to note it does not matter if global cascades are rare as long as the possibility of occurrence exists. A network may have a low average cascade size yet have the ability to generate the occasional global cascade.

Since the occurrence of global cascades is a global rather than a local condition, the initiating country does not need to be special or highly connected. Being connected is less important than being connected to individuals who can be easily influenced, and who are also connected to traders who are easily influenced. The vital condition is that the percolating cluster is accessible from the initiating node. This is a centrality condition. Countries which are unimportant by themselves and have a low average cascade size can generate more global cascades than important countries if they occupy an important position in the network structure. There is often no direct connection between the characteristics of the initiating node or cluster and the outcome.

Small disturbances can create global cascades if the percolating cluster is accessible. Thus there is often no direct connection between the characteristics of the initiating disturbance and the outcome.

The dynamic of complex network imply the predominant pattern of asset pricing is punctuated equilibrium. This implies contingent patterns where the creation of cascades involves a complex system of alternative paths. The overall system choice between pathways is based on contingent random shocks. This implies the shape of future system evolution is inherently unpredictable. Complex systems involve regular extreme movements which are inevitable. This implies that financial policymakers may have to live with occasional, unpredictable, currency crises.

The topology of information and money flows within the international financial system will also have to be analysed before an understanding of the international financial system can be obtained. Topology and geography matter. This will require use of the complex systems and network methodologies and tools.

7.4.2 Policy implications

The dynamic characteristics embodied in complex networks, which are described above, are often presented in the form of stylised facts (Mantegna & Stanley, 2000 and Watts, 2002). If these are modified to suit currency crises they become;

(i) Financial markets exhibit a "normal state" of stability with limited reaction to frequent external shocks, and then occasionally exhibit sudden extreme instability in response to a shock.

(ii) These crises seem to be substantially out of proportion to the size of the causal shock.

(iii) The causal shocks seem indistinguishable from the non-causal shocks.

(iv) The determination of markets/ countries affected often seems to bear only a limited reasonable relationship to fundamental factors.

(v) The timing of the crises often seems to bear only a limited reasonable relationship to fundamental factors.

(vi) These stylised facts mean that crises can not be understood simply by examining the markets/ countries involved either individually or as a group.

If the international financial markets do embody aspects of complex networks and the above stylised facts are applicable then some policy conclusions regarding global cascades can be implied. These differ substantially from those offered by conventional currency crisis theory. Note that these policy conclusions apply solely to the generation of global rather than regional crises.

Firstly, the characteristics or importance of any individual country in the international financial system does not play a major role in the propagation of global currency crises. Even the characteristics or importance of its network of neighbours is not very important. What is important is the likelihood of a disturbance spreading from that country into the wider international financial network, and the likelihood of the disturbance building enough momentum to become an irresistible cascade. Policymakers keen to prevent global cascade crises thus have to focus on the structure of the network of countries which the vulnerable country is linked to, and the propensity of this pattern of links to percolate a crisis.

Secondly, policymakers need to be focused on improving the capacity of the system to cope with shocks rather than trying to solve specific causes. Each crisis will have unique causes, with the scale of the resultant crisis dependent on the peculiar state of the network at the time of the crisis, rather than any inherent characteristics of the initiating cause.

Thirdly, given that the international financial system is ever growing in size and complexity this system can be expected to increasingly display the characteristics of a complex system. This is one possible reason for the changing dynamics of currency crises since 1990.

Fourthly, cascade pricing patterns can be expected to be more prevalent in markets which have problems with availability or access to information due to lower threshold parameter values. This implies a higher level of asset price instability in emerging markets. These markets have to move towards increased information accessibility. This is particularly important for countries whose markets act as financial hubs or regional brokers in terms of either information or finance flows. Daniel et al. (2002) and Kim & Pantzalis (2000), however, argue that herding takes place because of the difficulties involved processing the breadth and richness of financial information and product choice, rather than lack of information. Calvo (1998c) also shows that diversification reduces investor ignorance. The implication of these arguments is that release of full information will be insufficient to prevent future herding problems.

Fifthly, global cascade crises are best handled by changing the topology of international financial flows to minimise a shock's percolation ability. Policymakers in individual countries have five possible methods to achieve this outcome. The first method is to strengthen the ability of a country to withstand external financial shocks (Radelet & Sachs, 1998a). This will mean that fewer crises will initiate from a particular country and fewer crises will be propagated through that country. Note, however, the cascades which still occur will by definition be more severe as they will succeed only if they have high enough momentum to overcome system barriers. Calvo and Mendoza (1996b) argue that liquidity crises will become more common and the consequences of these will exceed any errors made by policymakers.

The second method is the issue of non-recourse sovereign bonds which carry an implicit risk rating. This may allow economic problems in individual countries to be foreseen and allow market traders to act in advance. These could be tied to compulsory collective action clauses, which would lessen first mover advantages. Similarly, Rogoff (1999) stresses creating a system of international simultaneous transaction processing would remove first mover advantages.

The third method is to isolate the financial market of a country from international markets. The isolation of financial markets in most areas in Africa is a reason why they suffer fewer crises. But this isolation would impose substantial economic costs that would not be acceptable to most policymakers.

The fourth method is to reduce the strength of information and financial flow linkages between regions, by partly isolating financial markets. Agénor, Bhandari and Flood (1992) show a high enough capital control tax can delay the outbreak of crises. These measures would, however, run counter to the trend towards increasing global financial integration, which will have been increasing the propensity for crises to spread. It may, however, be possible to reduce the connection of the real side of an economy to international financial markets at an acceptable cost. Eichengreen (2003) argues for a range of measures which emerging countries can use to reduce the degree of capital flows, especially inflow during the booms which precede crises, eg; the capital inflow into SE Asia in the period leading up to 1997. Krugman (1998) argues that capital controls should play a major role during currency crises. Rodrik (1998) finds no evidence that capital account liberalisation provides benefits which counter the obvious dangers.

The fifth method is to hinder the spread of contagion outside the currency markets into the real markets. Chapter two emphasised one of the factors in recent crises has been the twinning of currency and banking crises. Miller (1999) thus suggests that regulating bank loan activity is a key component of any plan to avoid crises.

The experience of Malaysia during the Asian crisis provides two lessons. Firstly, that policy measures which focus on improving the situation in one country or type of market have limited value during global currency cascades if a crisis originates in another market, especially one in another regional cluster. The assumption that speculators will leave a well run country alone during a global crisis is doubtful. Malaysia had a well regulated financial sector, limited bank borrowing, declining official borrowing, and private sector borrowing which was substantially hedged on the swaps market (Jomo, 2001). Malaysia had liberalised its capital markets largely in the sequence recommended by Eichengreen (2003). Despite these advantages Malaysia was still affected by a liquidity panic which originated in a neighbour, which was less well run. Secondly, markets can react adversely to the imposition of controversial measures, thereby negating the positive impact. Eichengreen, (2003) argues that the experiences of Indonesia, which had little in common economically which Thailand or Malaysia apart from physical proximity, or the experiences of the North Asian countries which had even less in common, indicate financial markets take limited heed of fundamentals during a crisis.

The major lesson is policy authorities have to create regional or system-wide circuit breakers that reduce the momentum of cascades. The depth and breadth of the crisis of October 1998 indicate that once a global currency cascade has gained momentum it is hard to stop. Failure to create circuit breakers within a system of punctuated equilibrium implies policymakers will have to accept occasional, unpredictable, global crises.

These conclusions show that the application of the concepts and methods of complexity science offer novel insights. It needs to be cautioned however that the application of the theory and methods derived from complexity and network sciences to financial markets is still an immature research area. It is also still largely the preserve of physicists rather than financial academics, and as such often suffers from lack of appropriate modifications. Yet financial markets are arguably the largest and best documented complex system available for research. The potential of these methods to explain the dynamic patterns of financial crises needs to be explored further.

7.5 Model Extensions and Future Work

The model was designed to be as parsimonious and generalisable as possible. This has enabled generalised conclusions to be drawn. There are, however, a number of ways in which the analysis could be usefully extended. These methods are left for future research.

Firstly, it would be useful to examine if the results still held for a far larger sparsely clustered network of thousands of nodes. There are some indications in chapter five that the topology of groups of clusters, rather than attributes like cluster linkage density would become more important with size. For example, in chapter five it is suggested that as cascade size grows the density of external linkages would become more important than threshold values.

Secondly, issues related to heterogeneity in node fitness or robustness could also be usefully examined. North America may, for example, have higher inherent robustness, and this could impact on results. It needs to be remembered, however, even a system with a low potential to generate global cascades can have the potential to generate the occasional large system collapse. Global collapses can thus arise from any region if the global topology is suitable at that moment. Percolation models argue that changing node characteristics in physical systems has only a minor affect on network dynamics.

Thirdly, a repetitive simulation could be usefully examined. This could allow for agents' repeated responses to a developing cascade. While this may generate differing dynamics, the effect will be limited within a currency crisis context because most currency traders are subject to short-term trading limits. If traders were allowed to reallocate their new portfolios in reaction to the prices created by the initial reallocation, then dynamics might be affected. Watts (2002) indicates a repeated decision model using a random network does not lead to permanent long-run solutions so are more difficult to analyse. Whether or not this result applies to explicitly clustered networks is an open question.

Fourthly, the network could be made dynamic so that it changes over time, maybe growing or the position of links changing. This would enable us to study the dynamics of network formation, since the network is growing or changing and therefore is dynamic.

These modifications show that the model used in this thesis has a lot of room for exploration.

APPENDICES

Chapter Five - Data Appendix

Table 5 .1 Countries selected for Exchange Data
Currency and international quotation code
(23/10/1995 - 31/12/2001)

Currency	Code	Currency	Code
Algerian Dinar	DZD	Italian Lira	ITL
Australian Dollar	AUD	Japanese Yen	JPY
Bangladeshi Taka	BDT	Jamaican Dollar	JMD
Belgium Franc	BEF	Kazakhstan Tenge	KZT
Bolivian Boliviano	BOB	Kenyan Shilling	KES
British Pound	GBP	Malaysian Ringgit	MYR
Brazilian Real	BRL	Mexican Peso	MXN
Canadian Dollar	CAD	New Zealand Dollar	NZD
Chilean Peso	CLP	Pakistan Rupee	PKR
Colombian Peso	COP	Papua New Guinea Kina	PGK
Czech Koruna	CZK	Philippine Peso	PHP
Danish Krone	DKK	Polish Zloty	PLN
Dutch Guilder	NLG	Qatar Rial	QAR
Eqyptian Pound	EGP	Russian Rouble	RUB
Fiji Dollar	FJD	Saudi Arabian Riyal	SAR
Finnish Markka	FIM	Singapore Dollar	SGD
French France	FRF	South Korean Won	SKW
Ghanaian Cedi	GHC	South African Rand	ZAR
German Deutschmark	DEM	Swedish Krona	SEK
Indian Rupee	INR	Swiss Franc	CHF
Indonesian Rupiah	IDR	Taiwan Dollar	TWD
Iranian Rial	IRR	Thai Baht	THB

Table 5 .2 NZD-based FX Distance Matrix (1995-2001)

Matrix of distance metric (equation 4.3) of currencies quoted against the NZD – primary causal links

This shows the relative closeness of currencies in causal terms, scaled from 0.0 (no distance) to 2.0. Values above 1.4142 indicate a negative relationship.

	MYR	THB	SGD	IDR	PHP	SKW	TWD	INR	BDT	PKR	BRL	MXN	CLP	COP	RUB	ZAR	GHC	KES	SAR	DZD	EGP	IRR	QAR	AUD	GBP	JPY	DEM	CHF	FRF	NLG	BEF	DKK	FIM	ITL	CAD	JMD
MYR																																				
THB	0.8913																																			
SGD	0.6888	0.8747																																		
IDR	1.0449	1.1348	1.1182																																	
PHP	0.9318	1.0042	0.8862	1.1793																																
SKW	1.1159	1.1499	1.0716	1.2246	1.1393																															
TWD	0.9238	1.0315	0.7673	1.2468	0.9718	1.0885																														
INR	0.9291	1.0388	0.6781	1.2657	0.9550	1.0632	0.7455																													
BDT	0.9525	1.0775	0.7450	1.2770	1.0096	1.1128	0.7714	0.6441																												
PKR	1.0351	1.1178	0.8768	1.2961	1.0467	1.1579	0.9114	0.8221	0.7987																											
BRL	1.1415	1.1919	1.0191	1.2961	1.1556	1.2297	1.0481	0.9875	0.9738	1.0405																										
MXN	1.0230	1.1149	0.8592	1.2843	1.0690	1.1520	0.9358	0.8497	0.8853	0.9861	1.0411																									
CLP	0.9483	1.0649	0.7762	1.2564	1.0133	1.1423	0.8138	0.7261	0.6909	0.8427	0.9095	0.8819																								
COP	1.0324	1.0910	0.8242	1.2629	1.0463	1.1465	0.8639	0.7475	0.7521	0.9053	0.9568	0.9172	0.7723																							
RUB	1.3141	1.3296	1.2721	1.4195	1.3099	1.3517	1.2843	1.2452	1.2608	1.2922	1.3287	1.2895	1.2683	1.2480																						
ZAR	1.1099	1.1860	0.9899	1.3051	1.1707	1.2201	1.0515	1.0083	1.0340	1.1085	1.1314	1.0364	1.0589	1.0577	1.3116																					
GHC	1.2777	1.3124	1.2385	1.3713	1.2890	1.3211	1.2500	1.2178	1.2406	1.2419	1.2716	1.2833	1.2195	1.2225	1.3647	1.3020																				
KES	1.0112	1.1283	0.8351	1.2843	1.0627	1.1434	0.9099	0.7938	0.8328	0.9550	1.0733	0.9638	0.8765	0.9080	1.2785	1.0822	1.2630																			
SAR	0.8551	0.9996	0.5533	1.2530	0.9160	1.0574	0.6686	0.4196	0.5311	0.7507	0.9486	0.7516	0.6408	0.6639	1.2332	0.9531	1.1976	0.7072																		
DZD	1.2843	1.3095	1.2222	1.3756	1.2966	1.3224	1.2331	1.2281	1.1997	1.2376	1.2937	1.2448	1.2291	1.2348	1.3729	1.2987	1.3592	1.2494	1.1983																	
EGP	0.9888	1.0824	0.7845	1.2937	1.0299	1.1339	0.8409	0.7109	0.7640	0.8837	1.0587	0.9201	0.8214	0.8385	1.2683	1.0166	1.2053	0.8882	0.6112	1.2360																
IRR	1.2759	1.2888	1.2286	1.3968	1.2746	1.2674	1.2382	1.2137	1.2260	1.2588	1.2957	1.2647	1.2450	1.2447	1.3645	1.3005	1.3563	1.2558	1.1925	1.3539	1.2357															
QAR	0.9014	1.0356	0.6400	1.2659	0.9496	1.0822	0.7342	0.5430	0.6257	0.8077	0.9819	0.8177	0.7288	0.7349	1.2456	1.0046	1.2143	0.7739	0.3585	1.2142	0.6859	1.2079														
AUD	1.1834	1.2386	1.1277	1.2985	1.2346	1.2482	1.1680	1.1348	1.1487	1.1921	1.2564	1.1912	1.1700	1.1851	1.3495	1.1962	1.3168	1.1867	1.1054	1.3081	1.1577	1.3309	1.1233													
GBP	1.0174	1.0991	0.8062	1.2870	1.0672	1.1445	0.8814	0.7727	0.8245	0.9506	1.0955	0.9970	0.9031	0.9105	1.2771	1.0626	1.2241	0.9120	0.6756	1.2280	0.8600	1.2479	0.7520	1.1601												
JPY	1.0746	1.1084	0.8546	1.2732	1.0810	1.1783	0.9922	0.9721	0.9994	1.0785	1.1655	1.0710	1.0376	1.0467	1.3669	1.1580	1.3038	1.0581	0.9120	1.2833	1.0152	1.2853	0.9582	1.2169	0.9793											
DEM	0.5191	0.9793	0.7912	1.0951	0.9737	1.1253	0.9652	0.9200	0.9609	1.0382	1.1237	0.9881	0.9582	1.0166	1.3008	1.1369	1.2959	1.0163	0.8579	1.3186	0.9932	1.2782	0.8990	1.2194	1.1574	1.1556										
CHF	1.1146	1.1525	0.9316	1.3386	1.1343	1.2115	0.9898	0.9425	0.9528	1.0497	1.1763	1.1295	1.0149	1.0332	1.3366	1.1450	1.2597	1.0327	0.8631	1.2264	0.9820	1.2834	0.9156	1.2037	0.7500	0.9765	1.3822									
FRF	1.0896	1.1399	0.9131	1.3373	1.1244	1.2118	0.9683	0.9171	0.9324	1.0419	1.1619	1.0981	0.9912	1.0107	1.3145	1.1066	1.2522	1.0111	0.8375	1.2256	0.9636	1.2721	0.8929	1.1809	0.7277	1.0097	1.3826	0.3785								
NLG	1.0963	1.1460	0.9159	1.3372	1.1277	1.2143	0.9711	0.9218	0.9370	1.0419	1.1641	1.0983	0.9945	1.0157	1.3152	1.1101	1.2537	1.0149	0.8426	1.2254	0.9668	1.2734	0.8974	1.1798	0.7289	1.0059	1.3908	0.3739	0.1805							
BEF	1.0966	1.1424	0.9171	1.3357	1.1263	1.2104	0.9697	0.9179	0.9359	1.0426	1.1639	1.0952	0.9927	1.0133	1.3073	1.1081	1.2535	1.0150	0.8414	1.2218	0.9664	1.2729	0.8963	1.1824	0.7345	1.0085	1.3869	0.3968	0.2125	0.1743						
DKK	1.0853	1.1357	0.9018	1.3344	1.1233	1.2068	0.9567	0.9013	0.9229	1.0297	1.1512	1.0735	0.9770	1.0041	1.2970	1.0937	1.2508	1.0014	0.8203	1.2189	0.9500	1.2709	0.8776	1.1762	0.7245	1.0124	1.3608	0.4391	0.3166	0.3027	0.3095					
FIM	1.0923	1.1419	0.9179	1.3346	1.1253	1.2102	0.9636	0.9194	0.9363	1.0443	1.1630	1.0943	0.9961	1.0173	1.3153	1.1105	1.2537	1.0136	0.8411	1.2304	0.9671	1.2726	0.8961	1.1848	0.7324	1.0087	1.3797	0.4243	0.2635	0.2362	0.2547	0.3243				
ITL	1.0917	1.1433	0.9131	1.3360	1.1222	1.2115	0.9652	0.9065	0.9285	1.0390	1.1583	1.0986	0.9890	1.0044	1.3144	1.0989	1.2518	1.0056	0.8292	1.2275	0.9628	1.2641	0.8859	1.1680	0.7275	1.0149	1.3711	0.4416	0.2564	0.2628	0.2944	0.3753	0.2995			
CAD	0.9182	1.0498	0.6874	1.2653	0.9668	1.0923	0.7740	0.6009	0.6888	0.8640	0.9908	0.8088	0.7531	0.7708	1.2571	0.9808	1.2315	0.8103	0.4642	1.2099	0.7685	1.2264	0.5731	1.0802	0.8080	0.9823	0.9149	0.9636	0.9292	0.9335	0.9363	0.9165	0.9273	0.9166		
JMD	1.0553	1.1419	0.9101	1.3052	1.0929	1.1795	0.9576	0.8526	0.8723	0.9788	1.1016	0.9853	0.9294	0.9519	1.2900	1.0913	1.2322	0.9686	0.7746	1.2588	0.9271	1.2610	0.8300	1.2075	0.9794	1.1048	1.0503	1.0745	1.0649	1.0607	1.0620	1.0473	1.0601	1.0601	0.8661	
USD	0.8561	1.0004	0.5534	1.2533	0.9163	1.0570	0.6681	0.4186	0.5311	0.7500	0.9465	0.7523	0.6420	0.6640	1.2337	0.9549	1.1977	0.7067	0.0266	1.1986	0.6109	1.1922	0.3579	1.1054	0.6738	0.9112	0.8596	0.8607	0.8358	0.8408	0.8399	0.8189	0.8395	0.8275	0.4647	0.7747

Figure 5.2 - ln-ln Diagram of NZD MST graph
This figure plots, as ln-ln, the probability distribution of links for nodes on a ranked basis, for the NZ$ MST fig 5.1. The concave curve in the upper portion shows a stronger than power-law relationship

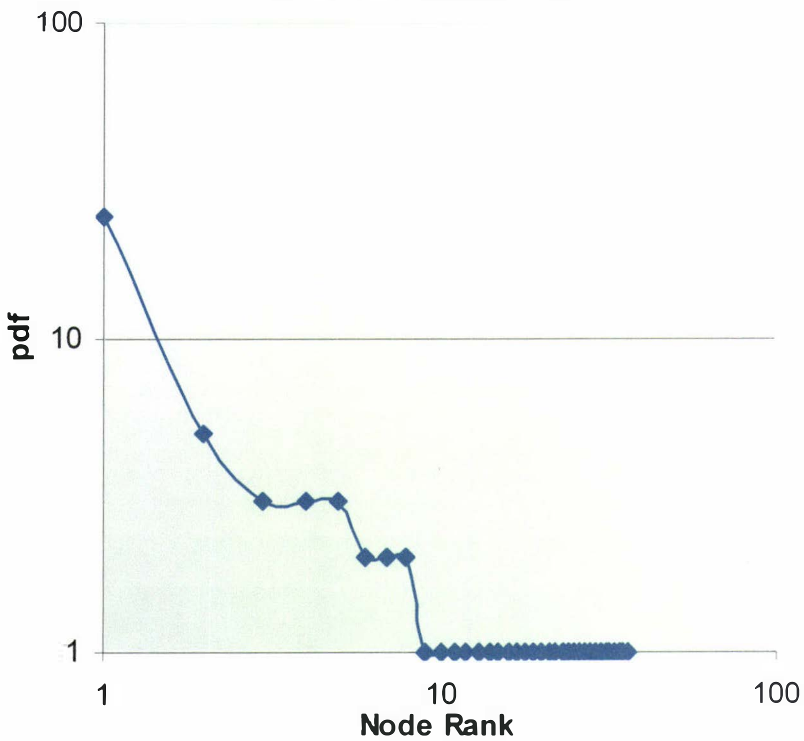


Figure 5.5 - ln-ln Diagram of USD MST graph
This figure plots, as ln-ln, the probability distribution of links for nodes on a ranked basis, for the US$ MST fig 5.4. The upper portion shows an approximate power-law relationship

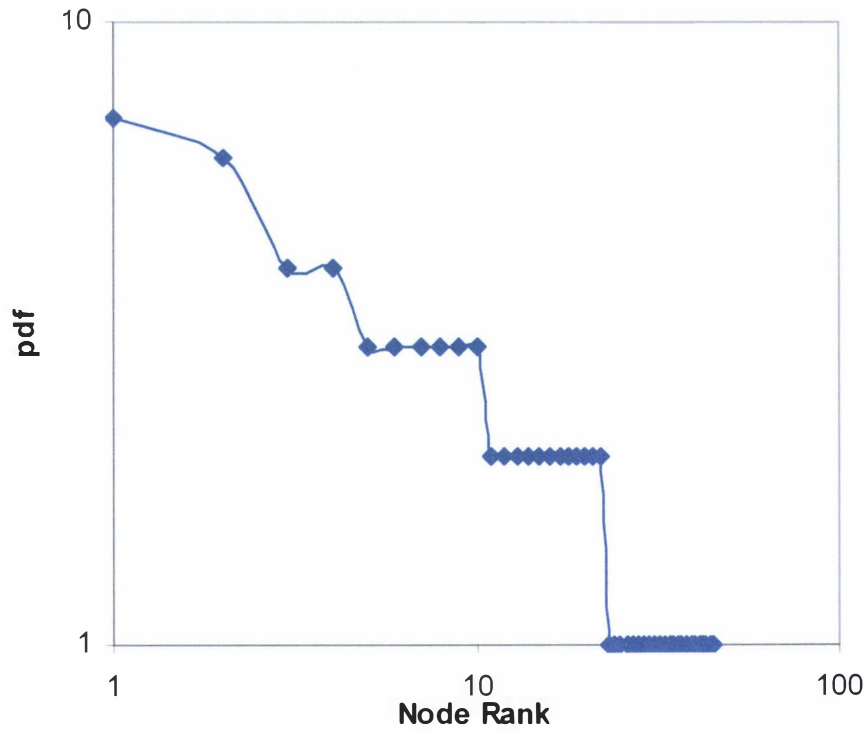


Table 5 .3 Crisis Period NZD-based FX Distance Matrix (1997-98)

Matrix of distance metric (equation 4.3) for crisis period of currencies quoted against the NZD - primary causal links
This shows the relative closeness of currencies in causal terms, scaled from 0.0 (no distance) to 2.0. Values above 1.4142 indicate a negative relationship

	MYR	*THB*	*SGD*	*IDR*	*PHP*	*SKW*	*TWD*	*INR*	*BDT*	*PKR*	*BRL*	*MXN*	*CLP*	*COP*	*RUB*	*ZAR*	*GHC*	*KES*	*SAR*
MYR																			
THB	0.4169																		
SGD	0.5068	0.3664																	
IDR	0.5681	0.4261	0.5626																
PHP	0.5003	0.3271	0.4725	0.4435															
SKW	0.6942	0.6151	0.6573	0.7100	0.6898														
TWD	0.5051	0.3781	0.4669	0.5017	0.4326	0.6516													
INR	0.9757	0.9244	0.9674	0.9544	0.9222	1.0409	0.9769												
BDT	0.4995	0.3685	0.4612	0.4881	0.3865	0.6726	0.4503	0.9385											
PKR	1.0630	1.0588	1.0730	1.0812	1.0749	1.1212	1.0800	1.2512	1.0704										
BRL	0.4884	0.3363	0.4698	0.4275	0.3490	0.6592	0.4404	0.9443	0.3673	1.0523									
MXN	1.1735	1.1535	1.1966	1.1614	1.1546	1.2008	1.1577	1.3384	1.1923	1.3266	1.1688								
CLP	0.7786	0.7322	0.7601	0.7772	0.7748	0.8863	0.7835	1.0641	0.7666	1.1317	0.7585	1.3120							
COP	0.8094	0.7815	0.8186	0.8018	0.7980	0.9610	0.8021	1.0767	0.7916	1.1790	0.7716	1.2419	0.9848						
RUB	0.8400	0.7770	0.8099	0.8288	0.7830	0.9252	0.8213	1.0765	0.8001	1.1781	0.7769	1.2470	0.9858	0.9869					
ZAR	1.0260	1.0249	1.0938	1.0261	1.0518	1.0966	1.0274	1.1942	1.0269	1.2299	1.0254	1.3080	1.1467	1.1273	1.1507				
GHC	1.0486	1.0375	1.0396	1.0335	1.0508	1.1271	1.0451	1.2150	1.0544	1.2623	1.0229	1.2738	1.1051	1.1232	1.1605	1.2350			
KES	0.6636	0.6102	0.6762	0.6683	0.6317	0.8073	0.6477	1.0115	0.6333	1.1112	0.6141	1.2146	0.8693	0.8417	0.8881	1.0832	1.0805		
SAR	0.4187	0.2330	0.3783	0.3928	0.2691	0.6280	0.3597	0.9180	0.2927	1.0520	0.2282	1.1695	0.7252	0.7487	0.7649	1.0205	1.0197	0.5801	
DZD	1.3738	1.4032	1.3658	1.4102	1.3902	1.3778	1.3743	1.4133	1.3798	1.4007	1.3875	1.3308	1.4555	1.3885	1.3911	1.4064	1.3979	1.3849	1.3774
EGP	0.8387	0.7706	0.8260	0.8259	0.7782	0.9053	0.7801	1.0694	0.7629	1.1662	0.7480	1.2605	0.9528	0.9752	0.9638	1.1389	1.1447	0.8935	0.7414
IRR	0.4187	0.2307	0.3762	0.3918	0.2663	0.6278	0.3597	0.9172	0.2923	1.0513	0.2281	1.1702	0.7242	0.7482	0.7647	1.0205	1.0202	0.5789	0.0251
QAR	0.4190	0.2316	0.3763	0.3927	0.2652	0.6294	0.3604	0.9189	0.2926	1.0516	0.2282	1.1698	0.7253	0.7480	0.7636	1.0209	1.0200	0.5800	0.0393
AUD	1.1575	1.1032	1.1159	1.0813	1.0642	1.1156	1.1036	1.2161	1.0812	1.2894	1.0641	1.3328	1.1736	1.1776	1.1549	1.2203	1.2076	1.1009	1.0551
GBP	0.9763	0.8919	0.8757	0.9691	0.9402	1.0044	0.9062	1.1671	0.9238	1.2212	0.9373	1.3025	1.0352	1.0189	1.0667	1.2044	1.1735	0.9624	0.9099
JPY	0.8622	0.8010	0.8043	0.9604	0.9180	0.9266	0.8718	1.1681	0.9248	1.1535	0.9376	1.2152	0.9663	1.0707	1.0666	1.2320	1.2111	0.9879	0.9058
DEM	0.9067	0.9913	1.0593	0.9490	0.9320	1.0591	0.9974	1.1267	0.9495	1.2725	0.9120	1.2877	1.1571	1.0779	1.1046	1.1762	1.2067	1.0115	0.9059
CHF	0.9795	0.9257	0.9142	1.0440	1.0108	1.0483	0.9706	1.2014	0.9944	1.1877	1.0273	1.2861	1.0111	1.1140	1.1353	1.2384	1.2222	1.0667	0.9971
FRF	0.8817	0.8138	0.8056	0.9417	0.9031	0.9555	0.8599	1.1612	0.8876	1.1862	0.8990	1.2721	0.9267	1.0081	1.0072	1.1797	1.1609	0.9547	0.8748
NLG	0.8806	0.8069	0.7859	0.9542	0.9110	0.9574	0.8591	1.1613	0.8998	1.1891	0.9225	1.2638	0.9421	1.0480	1.0469	1.1884	1.1718	0.9802	0.8879
BEF	0.8910	0.8293	0.8141	0.9737	0.9319	0.9730	0.8824	1.1673	0.9340	1.2006	0.9409	1.2554	0.9389	1.0463	1.0468	1.1996	1.1699	0.9910	0.9078
DKK	0.8658	0.7983	0.8093	0.9435	0.8943	0.9583	0.8551	1.1551	0.8930	1.1945	0.9052	1.2555	0.9364	1.0484	1.0258	1.1620	1.1796	0.9754	0.8754
FIM	0.9049	0.8439	0.8603	0.9696	0.9287	0.9925	0.8956	1.1753	0.9246	1.2004	0.9257	1.2617	1.0002	1.0672	1.0699	1.2027	1.1805	1.0051	0.9090
ITL	0.8562	0.7860	0.8136	0.8917	0.8508	0.9543	0.8358	1.1066	0.8571	1.1826	0.8368	1.3154	0.9709	0.9962	1.0215	1.1023	1.1721	0.9036	0.8214
CAD	0.7011	0.6587	0.7093	0.7039	0.6696	0.8270	0.6662	0.9583	0.6655	1.1716	0.6484	1.2249	0.9432	0.8853	0.9163	1.0811	1.0773	0.7965	0.6167
JMD	1.1836	1.1473	1.1756	1.1328	1.1554	1.2025	1.1684	1.2761	1.1541	1.3033	1.1536	1.3251	1.2195	1.2171	1.2446	1.2675	1.2569	1.1918	1.1496
USD	0.4187	0.2307	0.3762	0.3918	0.2663	0.6278	0.3597	0.9172	0.2923	1.0513	0.2281	1.1702	0.7242	0.7482	0.7647	1.0205	1.0202	0.5789	0.0251

	DZD	*EGP*	*IRR*	*QAR*	*AUD*	*GBP*	*JPY*	*DEM*	*CHF*	*FRF*	*NLG*	*BEF*	*DKK*	*FIM*	*ITL*	*CAD*	*JMD*
EGP	1.3859																
IRR	1.3781	0.7410															
QAR	1.3777	0.7424	0.0292														
AUD	1.3441	1.1546	1.0550	1.0544													
GBP	1.3700	1.0493	0.9103	0.9109	1.2124												
JPY	1.4000	1.0595	0.9042	0.9028	1.3765	1.0633											
DEM	1.4108	1.1046	0.9078	0.9081	1.1929	1.4079	1.3655										
CHF	1.3537	1.1100	0.9950	0.9951	1.3265	0.9105	0.8209	1.6009									
FRF	1.3750	1.0067	0.8729	0.8728	1.2535	0.8401	0.8307	1.5230	0.4822								
NLG	1.3734	1.0194	0.8852	0.8854	1.2697	0.8267	0.7977	1.5508	0.4817	0.4257							
BEF	1.3631	1.0260	0.9060	0.9059	1.2697	0.8638	0.8241	1.5340	0.5401	0.4703	0.3605						
DKK	1.3640	1.0148	0.8728	0.8726	1.2481	0.8511	0.8209	1.5186	0.5120	0.4634	0.3790	0.3976					
FIM	1.3846	1.0373	0.9063	0.9056	1.2835	0.8943	0.8790	1.4911	0.6833	0.6308	0.5468	0.6161	0.5012				
ITL	1.3797	1.0453	0.8195	0.8191	1.1703	0.9156	0.9304	1.3468	0.8572	0.7542	0.7518	0.8188	0.7894	0.8269			
CAD	1.3314	0.9216	0.6166	0.6177	1.0810	1.0083	1.0644	0.9539	1.1400	1.0436	1.0515	1.0757	1.0379	1.0309	0.9357		
JMD	1.4012	1.2283	1.1496	1.1493	1.3020	1.2695	1.2776	1.2842	1.2901	1.2854	1.2390	1.2582	1.2347	1.2445	1.2750	1.1757	
USD	1.3781	0.7410	0.0000	0.0292	1.0550	0.9103	0.9042	0.9078	0.9950	0.8729	0.8852	0.9060	0.8728	0.9063	0.8195	0.6166	1.1496

Figure 5.7 – Crisis Period FX NZD-based minimum spanning tree (1997-98)

Graphical representation of minimal distance metrics for crisis period of currencies quote against the NZD. This gives an indication of the basic first-order price causation determination. Minimal changes have occurred compared to Figure 5.1, though lengths are shorter.

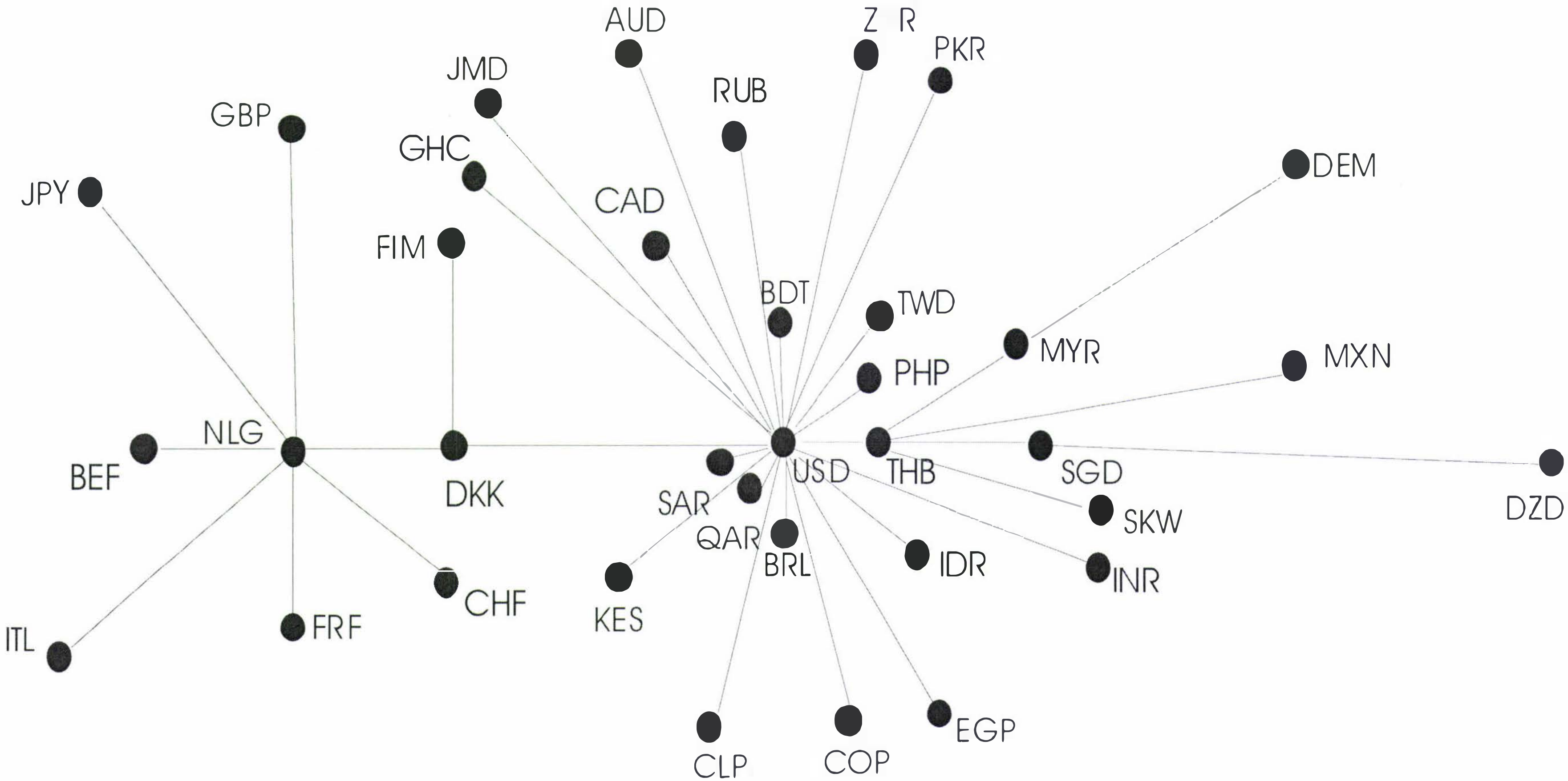


Figure 5.8 – Crisis Period FX NZD-based hierarchical tree of subdominant ultrametric space (1997-98)

Hierarchical grouping of distances metrics for crisis period of currencies quoted against the NZD. This gives an indication of how currencies should be grouped into clusters, based on primary causal link. The main difference from Figure 5.3 is shorter distances.

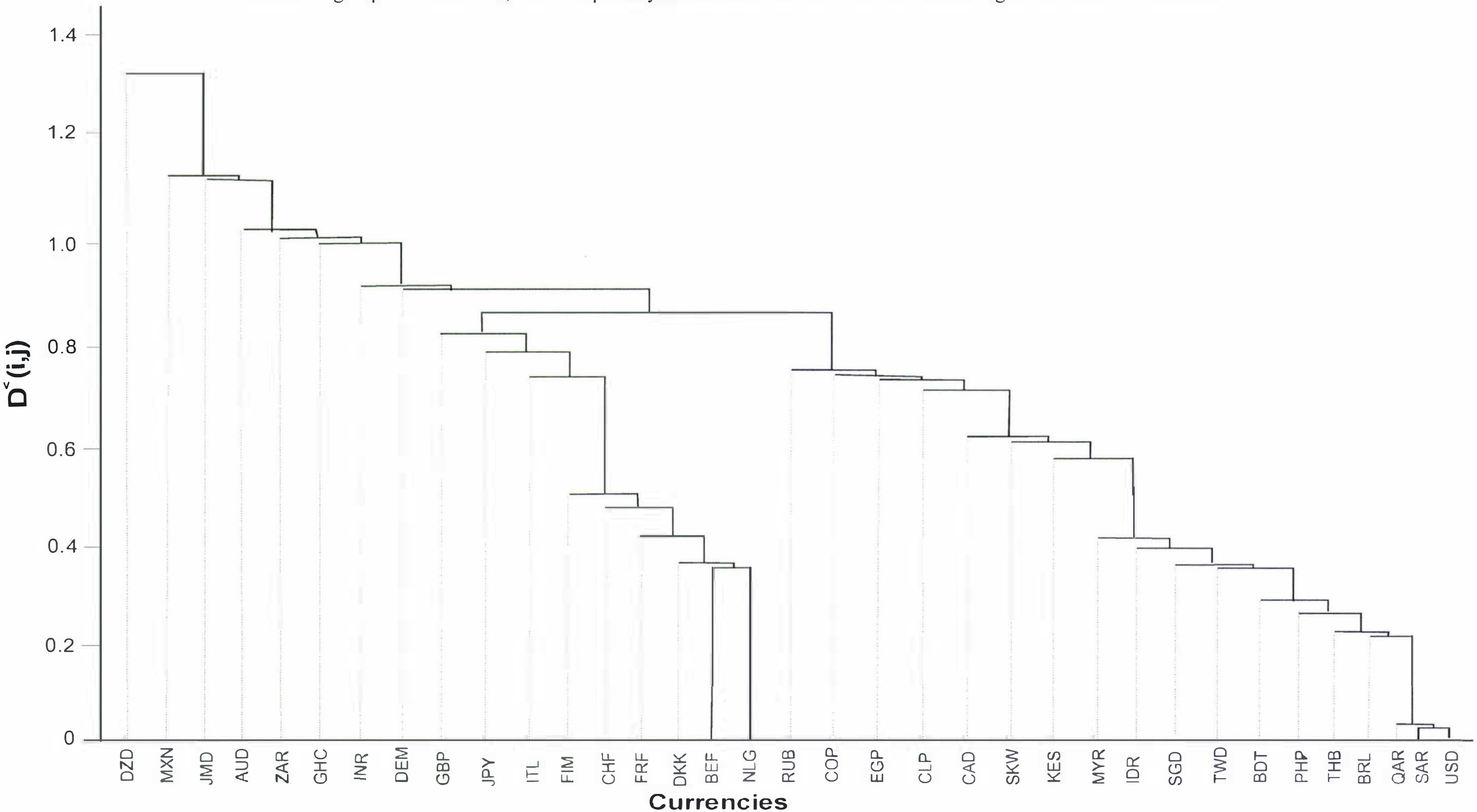


Figure 5.9 – Crisis Period FX USD-based minimum spanning tree (1997-98)

Graphical representation of minimal distance metrics for crisis period of currencies quoted against the USD. This gives an indication of the second-order price causation determination. The major difference from Figure 5.4 is the increased centrality of the Asian cluster.

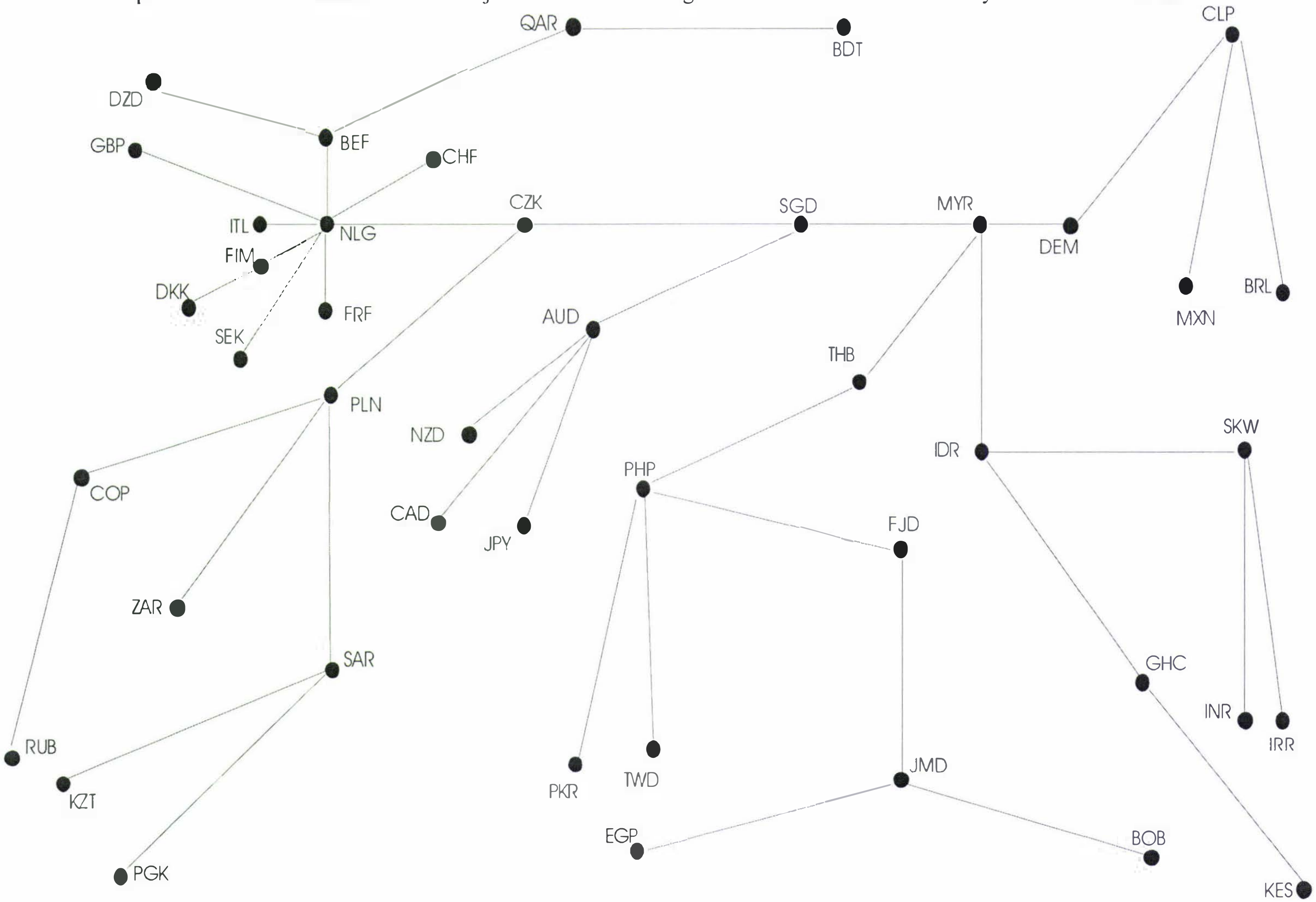


Figure 5.10 - In-In Diagram of USD crisis MST graph
This figure plots, as In-In, the probability distribution of links for nodes on a ranked basis, for the USD crisis MST fig 5.9. The upper portion shows an approximate power-law relationship

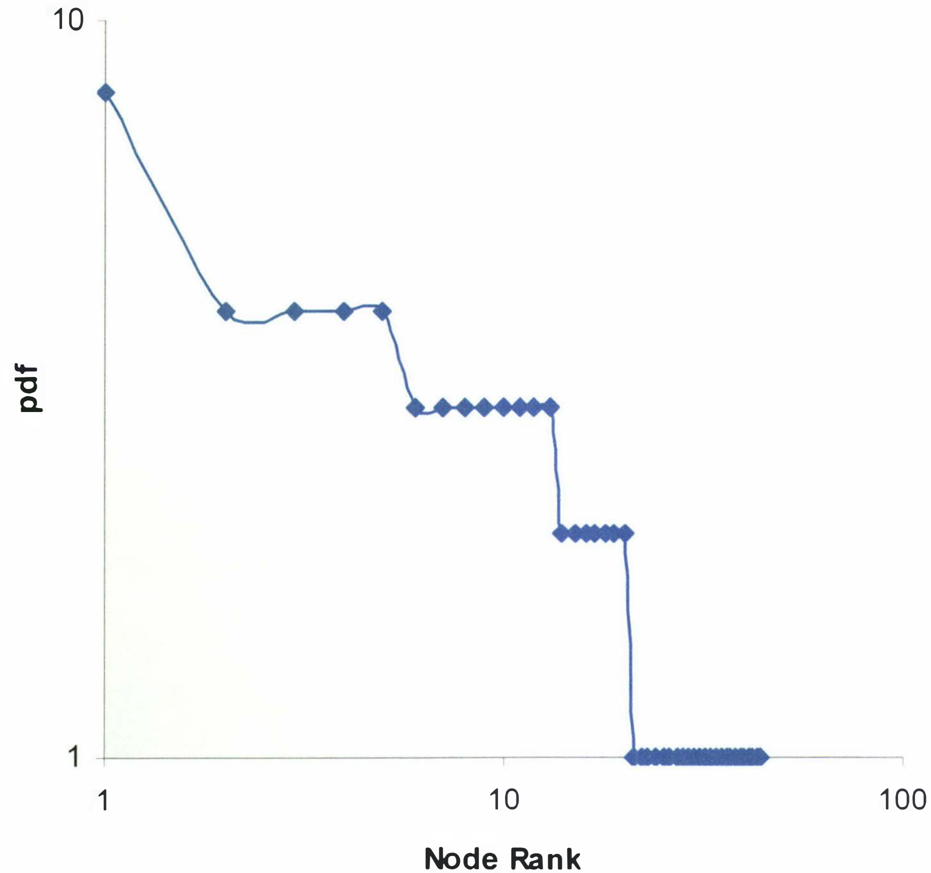


Figure 5.11 – Crisis Period FX USD-based hierarchical tree of subdominant ultrametric space (1997-98)
Hierarchical grouping of distances metrics for crisis period of currencies quoted against the USD. This gives an indication of how currencies should be grouped into clusters, based on primary causal link. When compared to Figure 5.6 fewer clusters are evident.

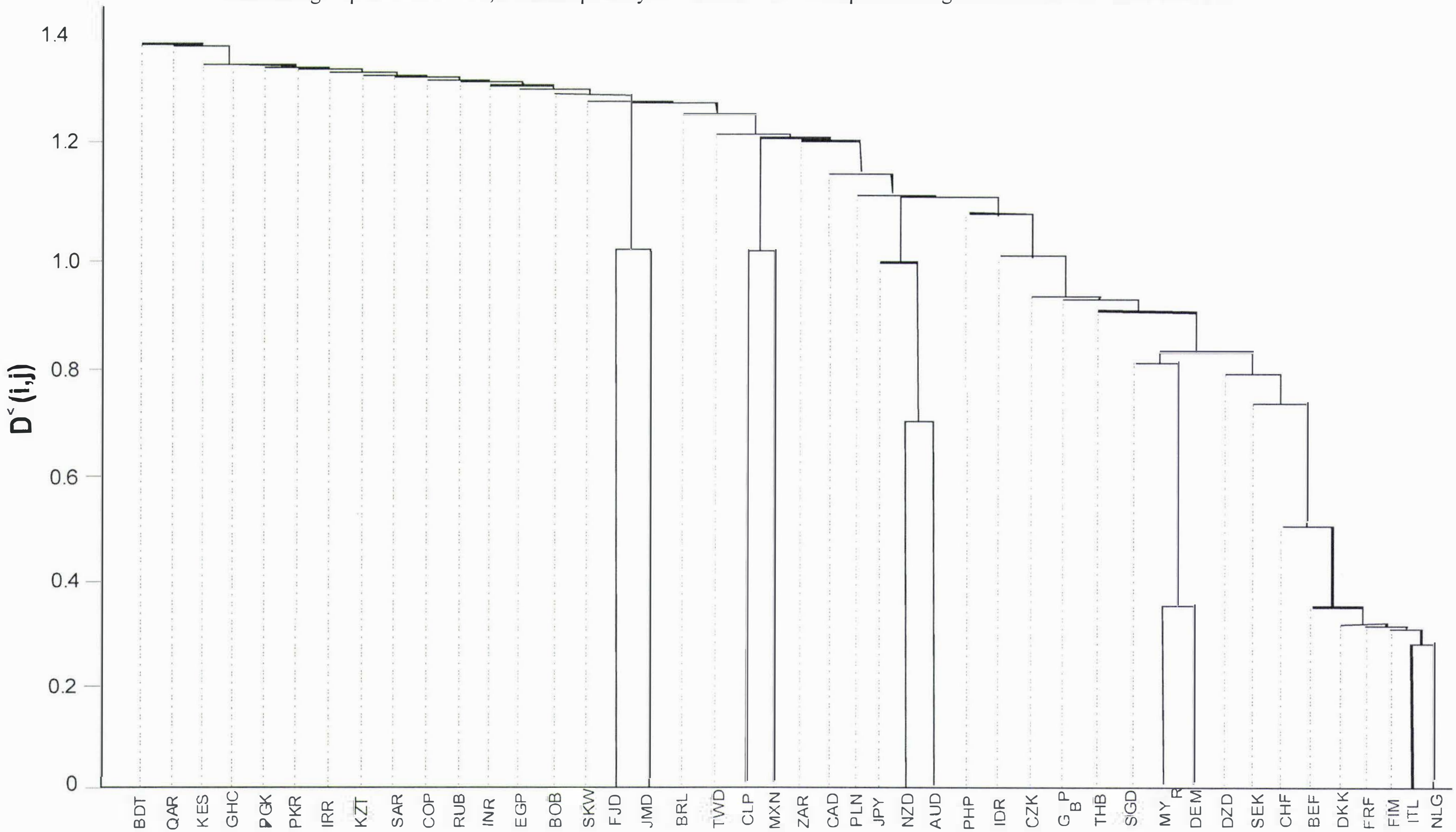


Figure 5 .13 – One-step ego-nets for selected currencies for NZD 5-link distance matrix

Currency network for individual currency nodes based on one step links for 5-link distance matrix. This gives an indication of the price causation determination for selected currencies. The external linkage roles of SGD, DEM, INR and CLP are evident. MYR is the hub for SE Asia.

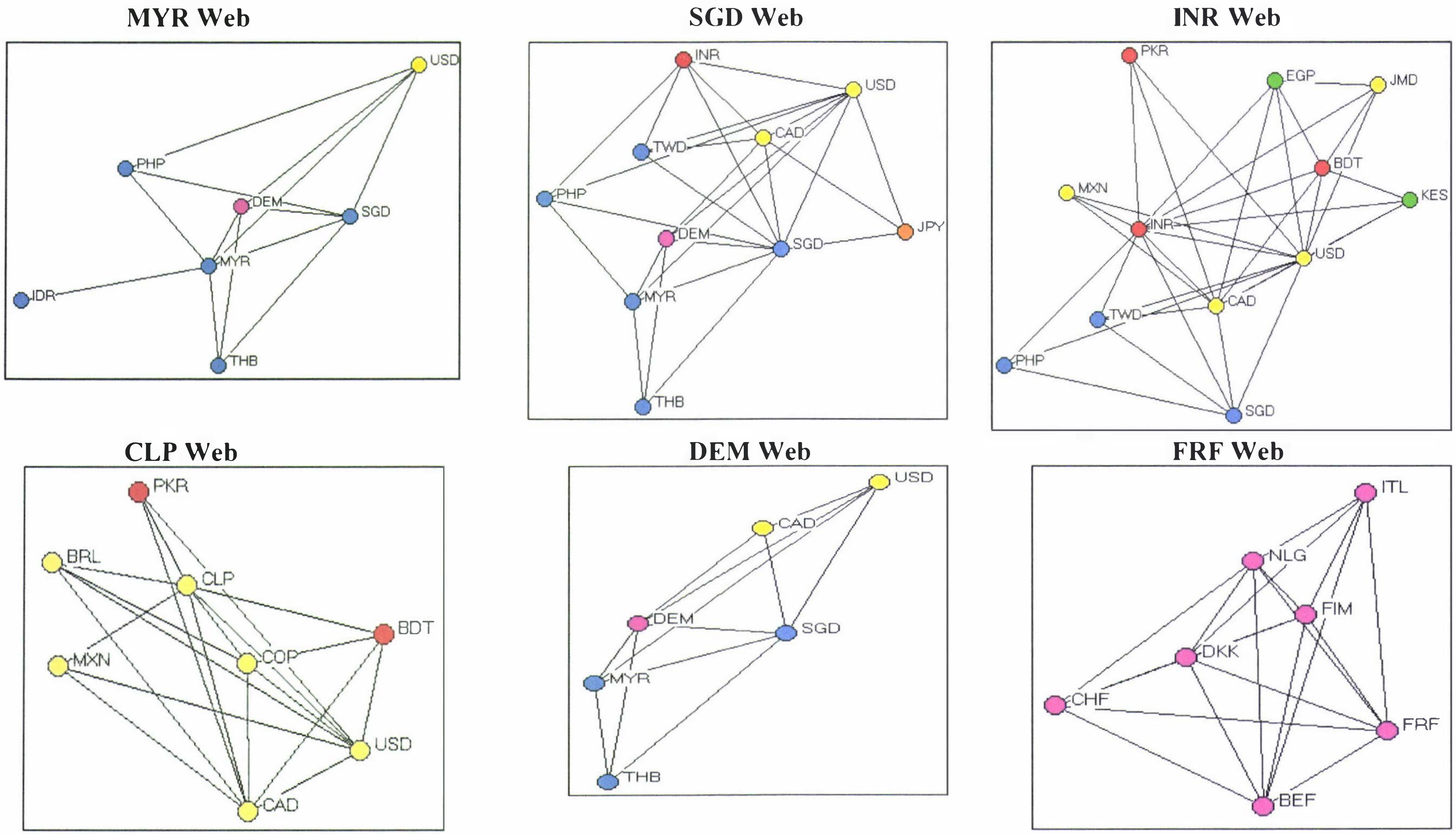


Figure 5 .15 - Ln-ln Plot of Distribution of Links for NZD-based Dichotomised Distance Matrix.
This figure plots, as ln-ln, the probability distribution of links for nodes on a ranked basis, for the NZD dichotomised distance matrix in Figure 5.14. Both the pdf of links and the % are plotted. The upper portion shows a strong power-law relationship.

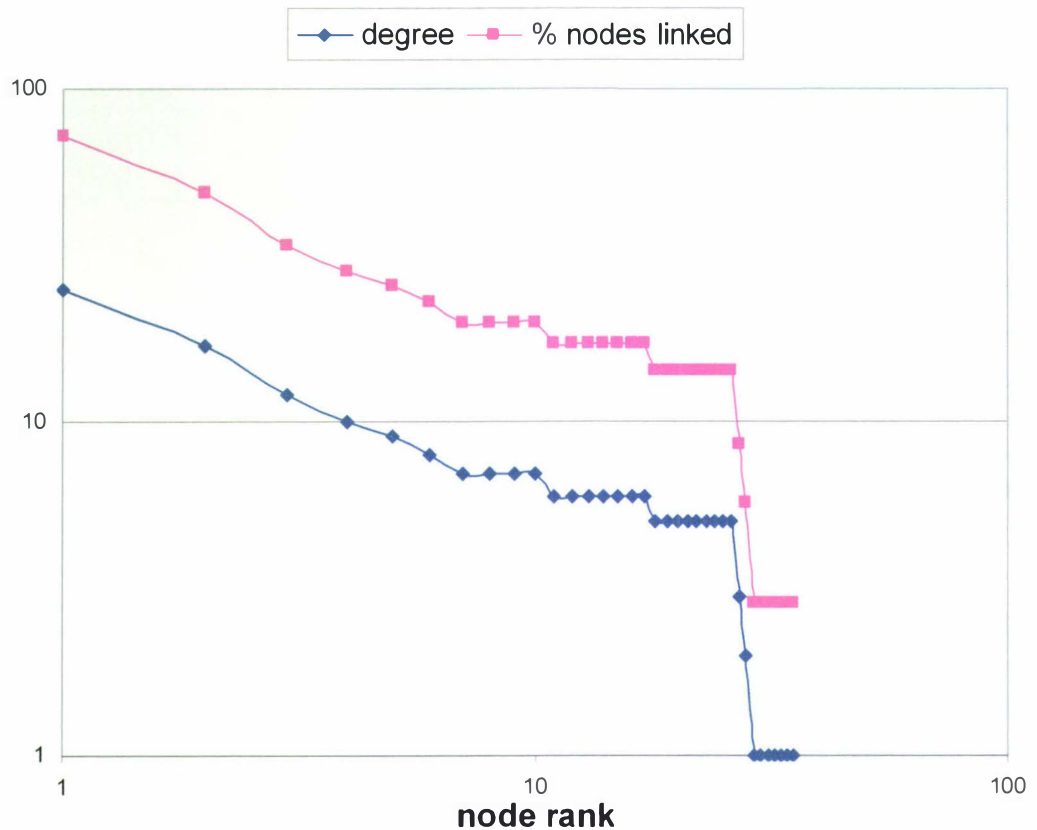


Figure 5 .16– One step ego-nets for selected currencies for NZD-based distance matrix

Currency network for individual currency nodes based on one step links dichotomized at 0.8 distance metric. This gives an indication of the price causation determination for selected currencies. When compared to Figure 5.13 the roles of SGD, INR and CLP as regional hubs are confirmed. MYR is no longer a hub for SE Asia.

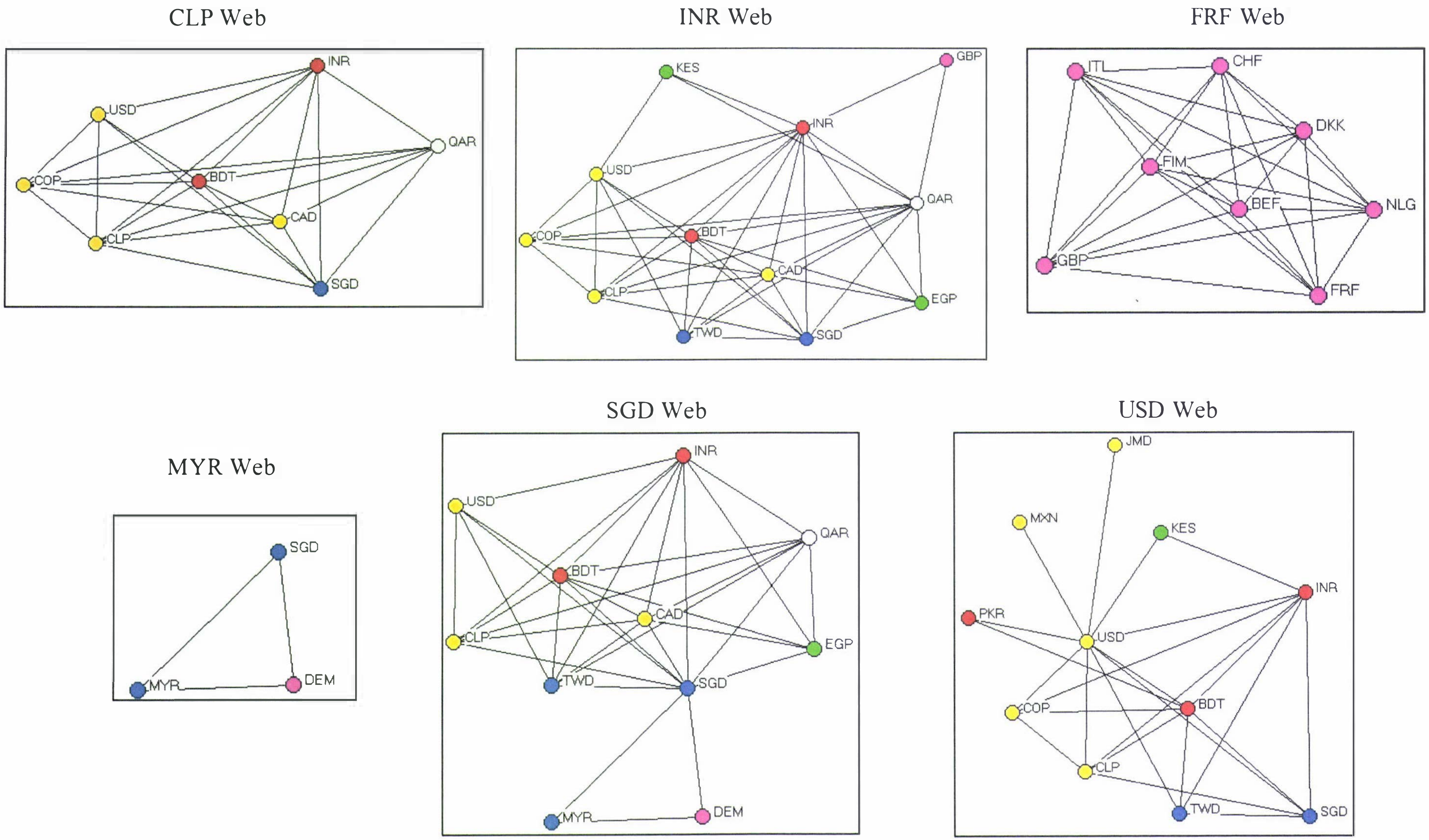
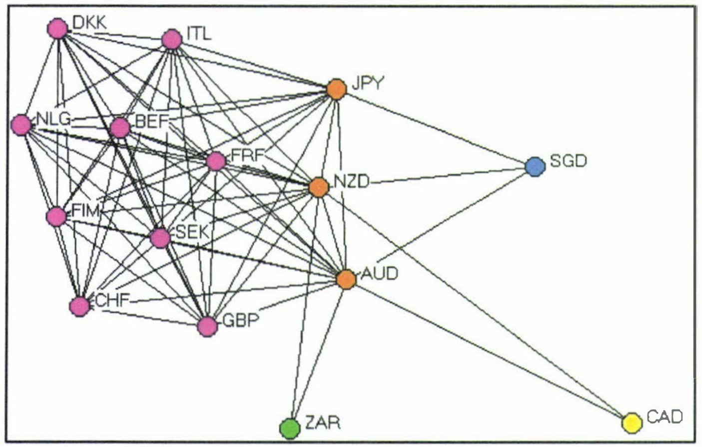


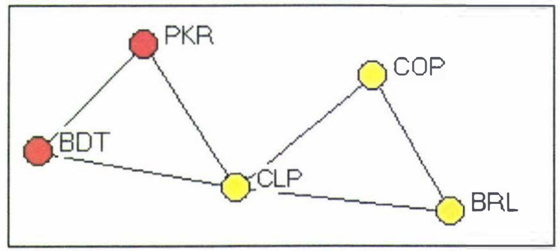
Figure 5 .18 – One-step ego-nets for selected currencies for USD-based distance matrix

Currency network for individual currency nodes based on one-step links dichotomised at 1.3 distance metric. This gives an indication of the second-order price causation determination for selected currencies. These emphasise the hub positions of the AUD, CLP and SGD.

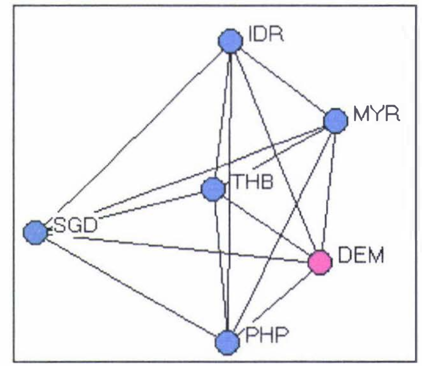
AUD Web



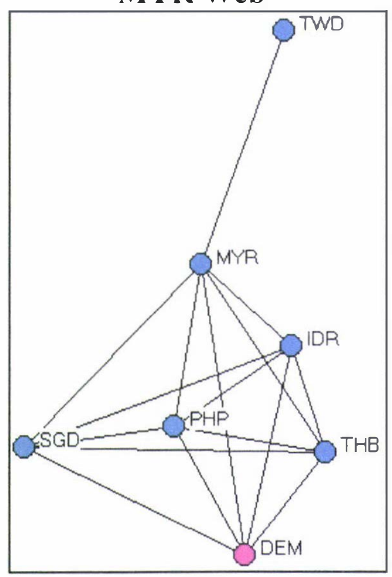
CLP Web



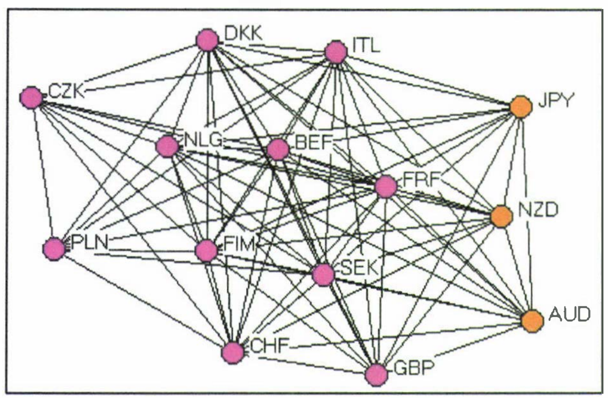
DEM Web



MYR Web



FRF Web



SGD Web

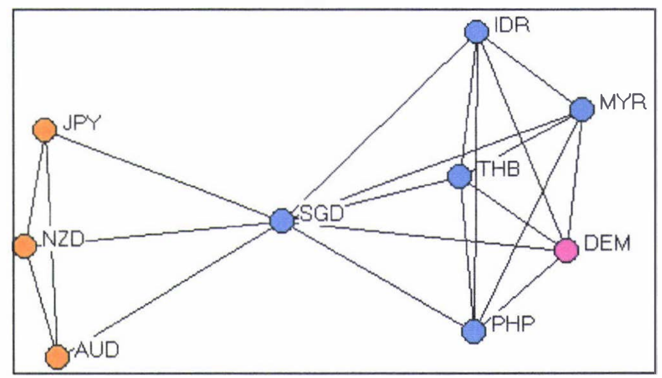


Figure 5 .20 – One-step ego-nets for selected currencies for NZD-based crisis period distance matrix

Currency network for individual currency nodes based on one step links dichotomised at 0.8 distance metric

This gives an indication of the basic first-order price causation determination for selected currencies

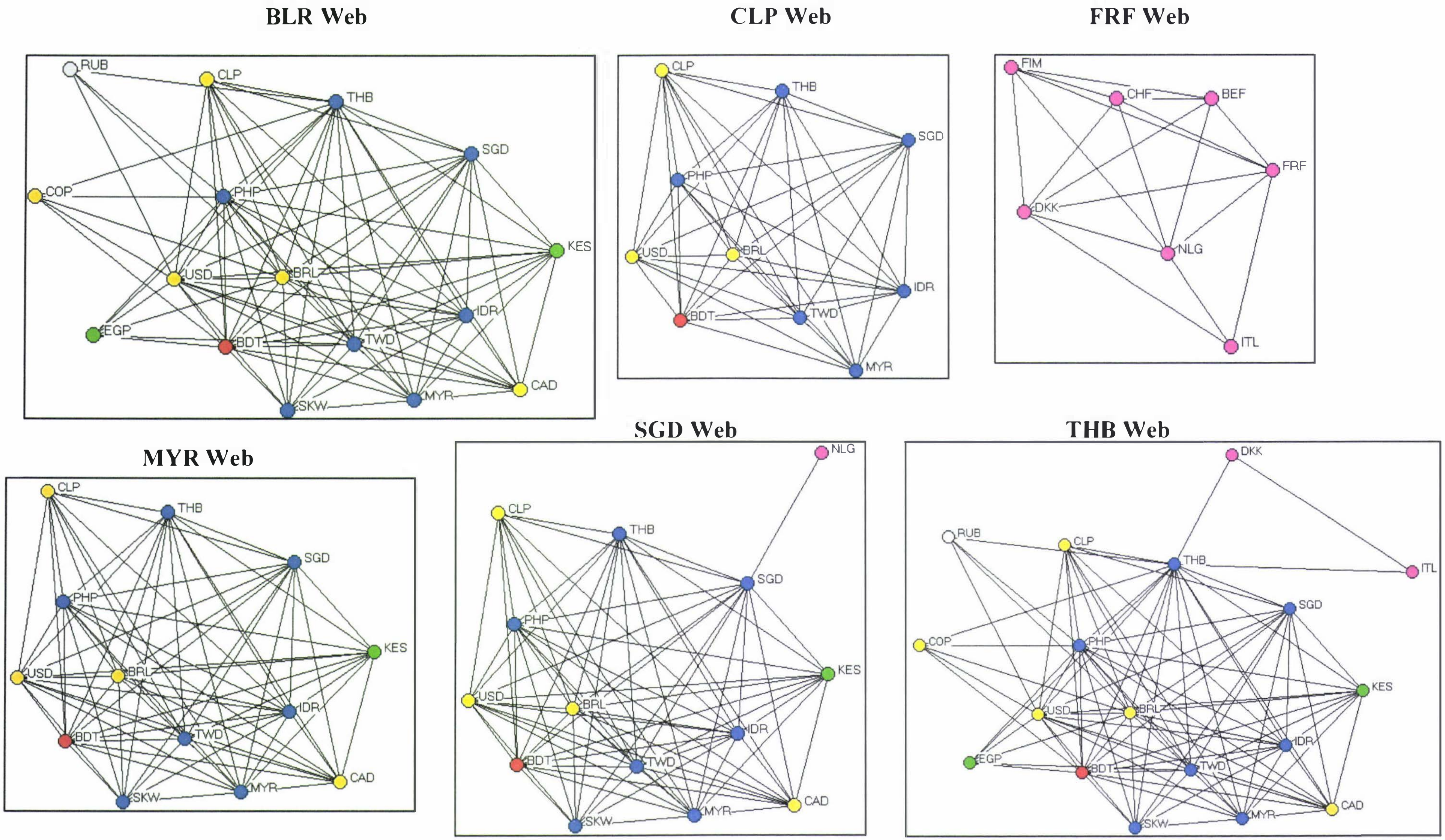


Figure 5 .21 USD-based Crisis Period Network Graph of Dichotomised Distance Matrix.
Graphical representation of currency network dichotomized at 1.3 based on spring-embedding alogrithm of currencies quoted against the USD for crisis period. This gives an indication of the second order price causation determination. Comparison to Figure 5.16 shows the creation of an integrated global network, with high density.

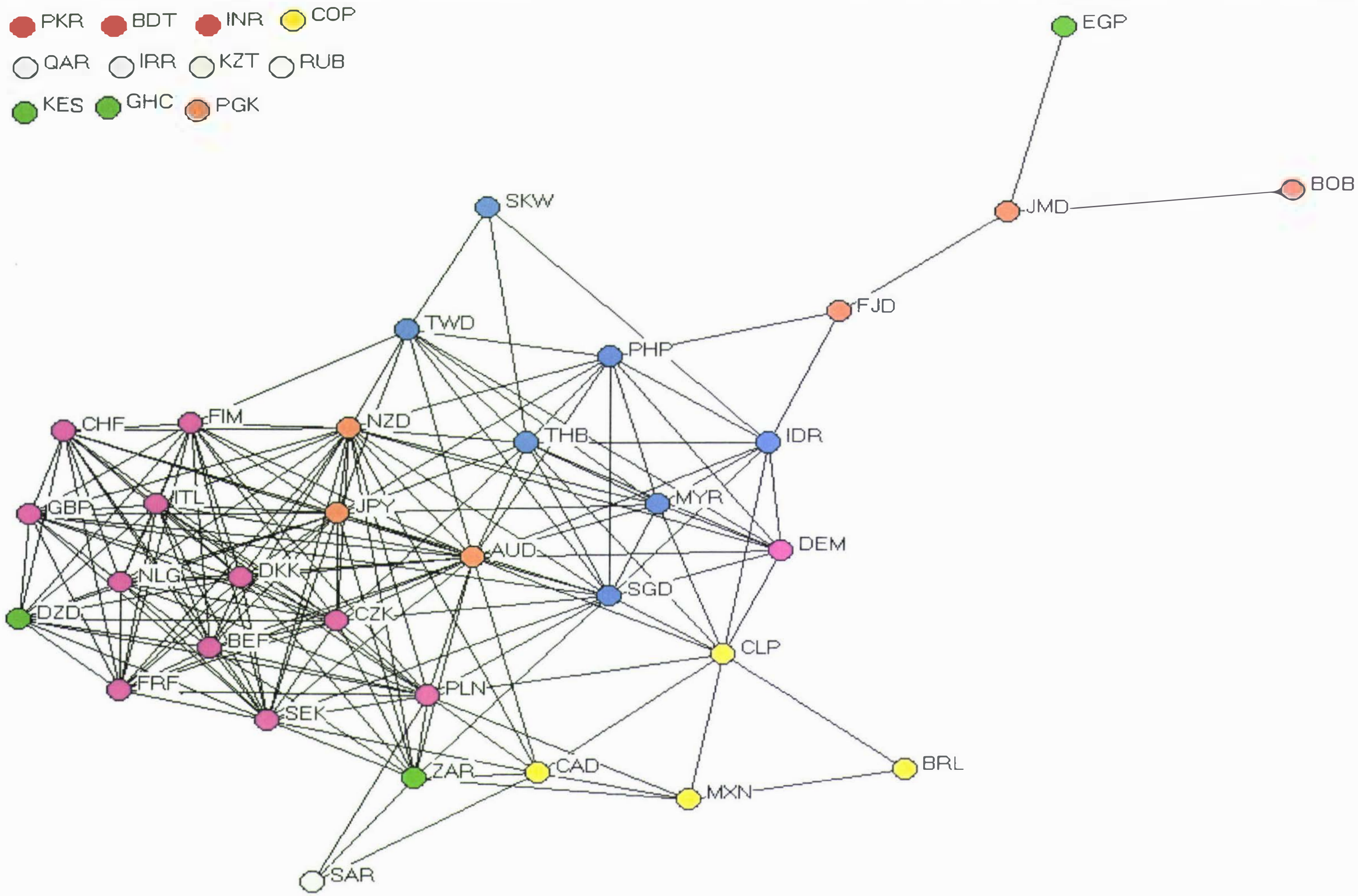
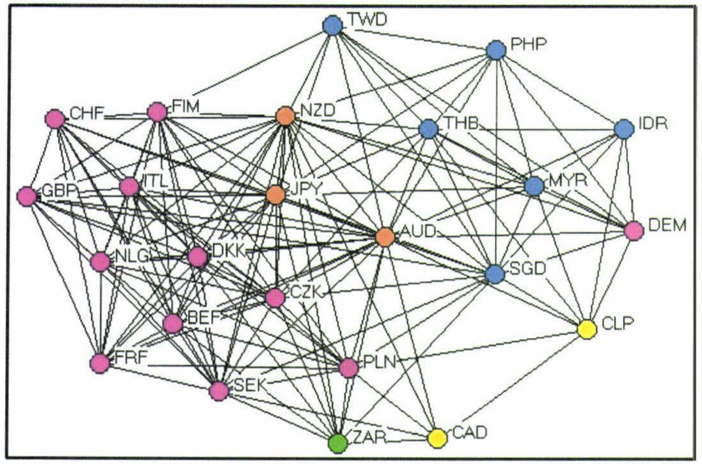


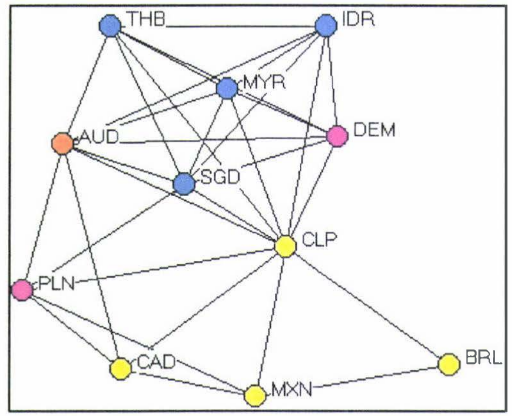
Figure 5 .22 – One step ego-nets for selected currencies for USD-based crisis period distance matrix

Currency network for individual currency nodes based on one step links dichotomised at 1.3 distance matrix. This gives an indication of the second-order price causation determination for selected currencies. Comparison to Figure 5.21 shows a substantial increase in link densities. The centrality of the AUD and SGD is evident.

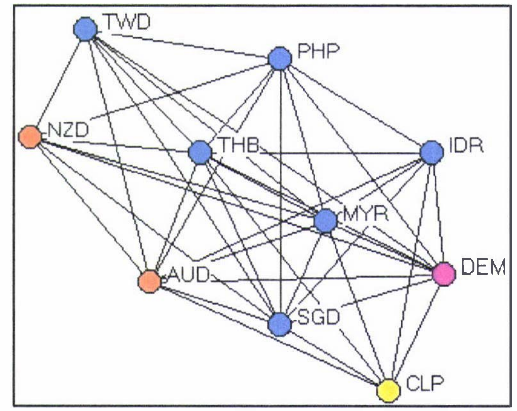
AUD



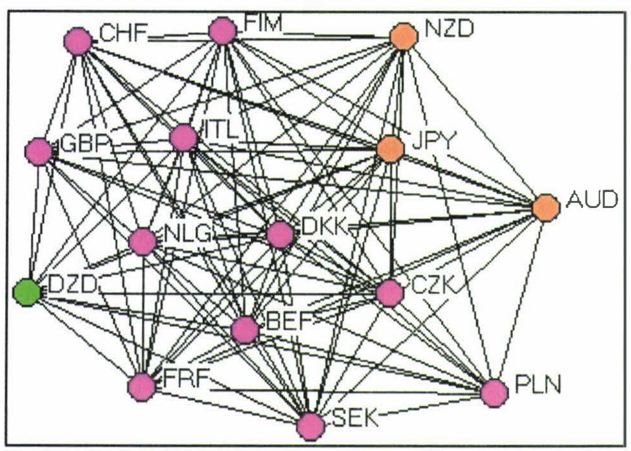
CLP



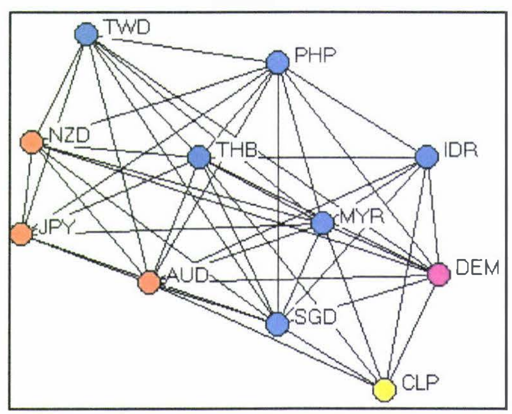
DEM



FRF



MYR



SGD

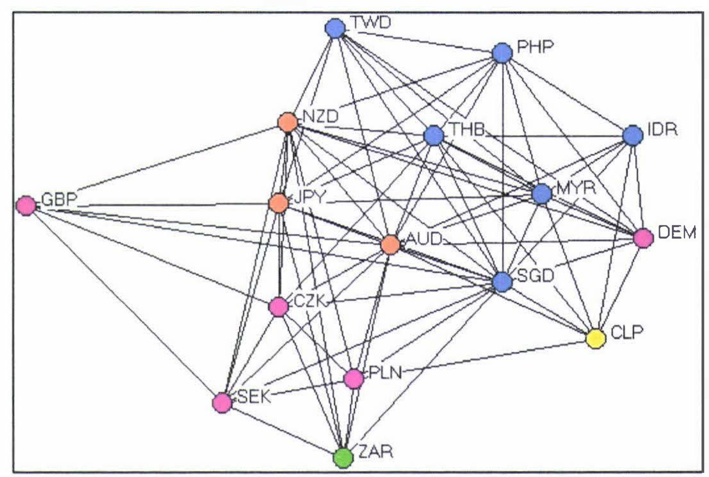


Table 5.4 Matrix of export trade in country percentage terms

(% of total inter-sample monthly exports 15/01/1992 – 15/01/2004)

Exports from

As a percentage of trade for that country

		SP	MY	TH	ID	PH	SK	CN	HK	JP	US	UK	CA	AU	NZ	GR	IT	ES	FR	BR	AG	MX	RU	% of Total
	SP	x	19.39%	9.52%	11.14%	8.30%	3.16%	2.57%	2.35%	4.01%	2.98%	1.50%	0.12%	4.10%	1.42%	1.09%	0.91%	0.31%	1.08%	0.71%	0.06%	0.12%	0.33%	2.61%
	MY	19.82%	x	6.30%	4.88%	8.41%	2.63%	1.78%	1.01%	3.04%	1.96%	0.98%	0.13%	2.49%	2.36%	0.91%	0.57%	0.20%	0.35%	0.48%	1.25%	0.04%	0.88%	2.10%
	TH	5.35%	5.41%	x	2.87%	4.21%	1.72%	1.11%	1.18%	4.33%	1.05%	0.54%	0.12%	2.69%	1.50%	0.54%	0.41%	0.23%	0.35%	0.87%	2.52%	0.03%	0.27%	1.43%
	ID	2.72%	2.50%	3.69%	x	1.01%	2.30%	1.30%	0.51%	1.94%	0.45%	0.42%	0.12%	3.43%	1.69%	0.36%	0.26%	0.22%	0.26%	0.67%	0.43%	0.02%	0.49%	0.91%
	PH	2.81%	1.68%	2.63%	1.95%	x	2.03%	0.89%	1.14%	2.43%	1.44%	0.36%	0.10%	1.14%	2.17%	0.27%	0.16%	0.15%	0.17%	0.24%	1.37%	0.01%	0.38%	1.02%
	SK	5.27%	3.57%	2.57%	8.92%	4.48%	x	5.81%	2.34%	9.40%	4.33%	1.38%	0.50%	9.66%	4.39%	1.59%	1.32%	0.40%	1.01%	2.56%	2.52%	0.12%	2.73%	3.43%
	CN	8.81%	7.99%	9.25%	7.85%	7.32%	23.94%	x	48.84%	15.51%	5.11%	1.82%	1.24%	10.90%	6.08%	5.21%	2.50%	1.30%	2.34%	9.49%	14.38%	0.62%	16.93%	8.46%
	HK	12.54%	7.96%	7.03%	2.44%	10.56%	9.99%	22.07%	x	8.07%	2.43%	2.36%	0.31%	3.41%	2.48%	1.13%	1.75%	0.46%	1.11%	1.45%	0.57%	0.09%	0.67%	5.06%
	JP	8.43%	13.17%	18.49%	28.07%	19.69%	11.78%	17.19%	6.18%	x	9.35%	3.52%	2.15%	23.60%	13.73%	3.38%	2.80%	1.14%	2.68%	4.84%	2.00%	0.75%	4.99%	6.93%
Exports	US	17.88%	24.10%	22.17%	15.24%	24.83%	23.44%	26.79%	21.37%	31.68%	x	27.76%	90.34%	11.29%	18.21%	17.56%	14.23%	6.73%	11.59%	35.39%	18.18%	92.62%	12.62%	26.13%
to	UK	3.98%	2.74%	4.19%	2.34%	2.37%	2.79%	3.13%	3.77%	3.56%	6.09%	x	1.46%	8.68%	6.03%	15.77%	11.59%	15.30%	16.02%	3.98%	2.23%	0.47%	9.90%	6.39%
	CA	0.38%	0.71%	1.53%	0.79%	1.09%	1.83%	1.63%	1.50%	1.99%	30.45%	3.08%	x	2.02%	2.42%	1.38%	1.56%	0.75%	1.24%	2.05%	1.26%	1.94%	0.55%	5.91%
	AU	4.07%	3.07%	3.51%	3.69%	1.39%	2.23%	1.81%	1.40%	2.69%	2.35%	2.16%	0.36%	x	27.22%	1.20%	1.49%	0.68%	0.97%	0.64%	0.67%	0.13%	0.04%	1.83%
	NZ	0.50%	0.42%	0.43%	0.32%	0.12%	0.30%	0.23%	0.18%	0.49%	0.33%	0.33%	0.10%	9.60%	x	0.17%	0.20%	0.08%	0.21%	0.08%	0.06%	0.01%	0.01%	0.40%
	GR	3.87%	2.82%	2.92%	2.93%	4.16%	3.82%	5.07%	3.70%	4.43%	5.18%	18.58%	0.74%	1.53%	3.31%	x	23.08%	19.57%	25.38%	6.57%	4.18%	1.28%	21.33%	7.05%
	ITL	0.36%	0.73%	1.55%	1.74%	0.43%	1.75%	1.92%	1.27%	1.48%	1.90%	7.69%	0.46%	1.90%	2.00%	13.94%	x	15.93%	15.82%	4.62%	5.40%	0.00%	17.30%	4.53%
	ES	0.34%	0.48%	1.00%	2.11%	0.37%	1.38%	1.14%	0.86%	0.99%	1.07%	7.82%	0.23%	0.82%	0.73%	9.29%	11.68%	x	16.33%	3.25%	8.05%	0.94%	2.65%	3.71%
	FR	1.80%	2.08%	1.54%	1.37%	0.74%	1.23%	2.12%	1.45%	1.92%	3.12%	16.80%	0.59%	1.37%	1.74%	19.98%	20.51%	31.47%	x	3.67%	2.01%	0.22%	7.18%	6.20%
	BR	0.20%	0.23%	0.48%	0.51%	0.08%	0.78%	0.62%	0.29%	0.51%	2.02%	0.78%	0.23%	0.56%	0.15%	1.16%	1.05%	1.03%	0.82%	x	27.06%	0.40%	0.52%	0.97%
	AR	0.03%	0.05%	0.07%	0.12%	0.01%	0.11%	0.13%	0.05%	0.07%	0.44%	0.13%	0.02%	0.10%	0.05%	0.20%	0.28%	0.51%	0.18%	9.55%	x	0.15%	0.01%	0.30%
	MX	0.63%	0.62%	0.67%	0.49%	0.38%	1.67%	0.95%	0.47%	0.98%	17.51%	0.65%	0.59%	0.54%	1.85%	1.38%	1.17%	2.57%	0.70%	5.74%	4.62%	x	0.20%	3.54%
	RU	0.22%	0.29%	0.44%	0.23%	0.05%	1.13%	1.75%	0.14%	0.48%	0.44%	1.34%	0.08%	0.18%	0.48%	3.47%	2.49%	0.96%	1.41%	3.14%	1.16%	0.03%	x	1.10%
	% Total	3.18%	2.36%	1.71%	1.34%	0.81%	4.06%	9.56%	5.41%	10.25%	15.40%	4.80%	7.20%	1.50%	0.36%	10.87%	4.84%	2.64%	6.27%	1.32%	0.48%	4.31%	1.33%	100.00%

Figure 5 .23 – Ln-ln plot of countries ranked by export trade.
This shows a ln-ln plot of countries ranked by % of world exports. It shows a weak power-law relationship.

Countries ranked by export %

US	15.40%	SP	3.18%
GR	10.87%	ES	2.64%
JP	10.25%	MY	2.36%
CN	9.56%	TH	1.71%
CA	7.20%	AU	1.50%
FR	6.27%	ID	1.34%
HK	5.41%	RU	1.33%
IT	4.84%	BR	1.32%
UK	4.80%	PH	0.81%
MX	4.31%	AG	0.48%
SK	4.06%	NZ	0.36%

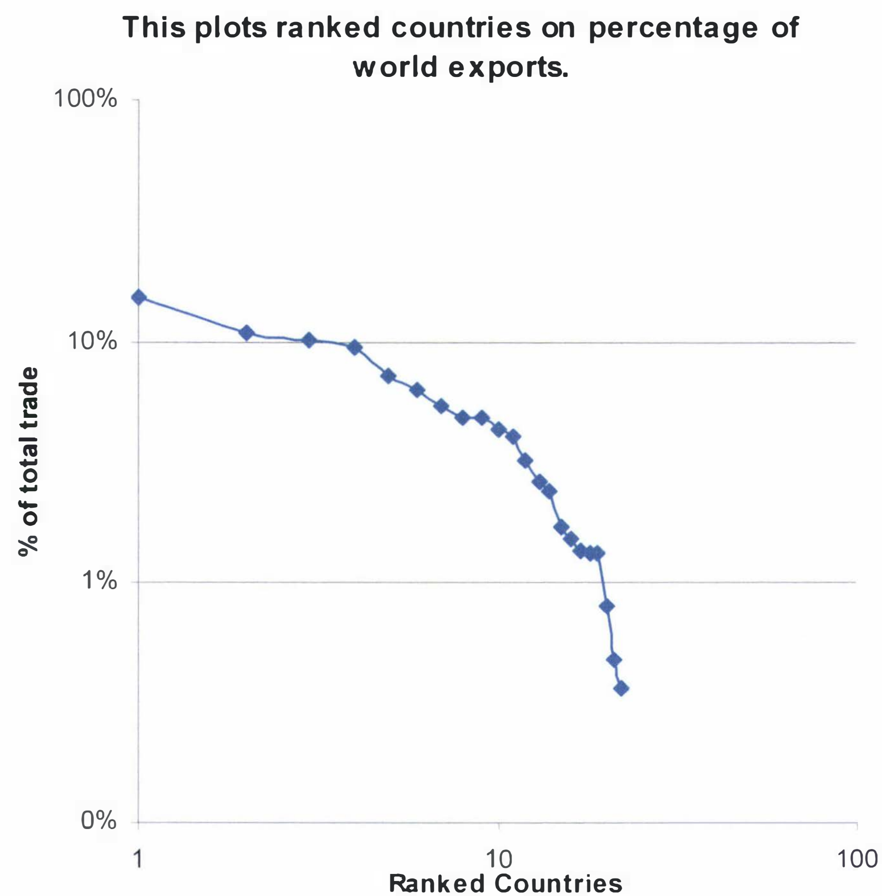
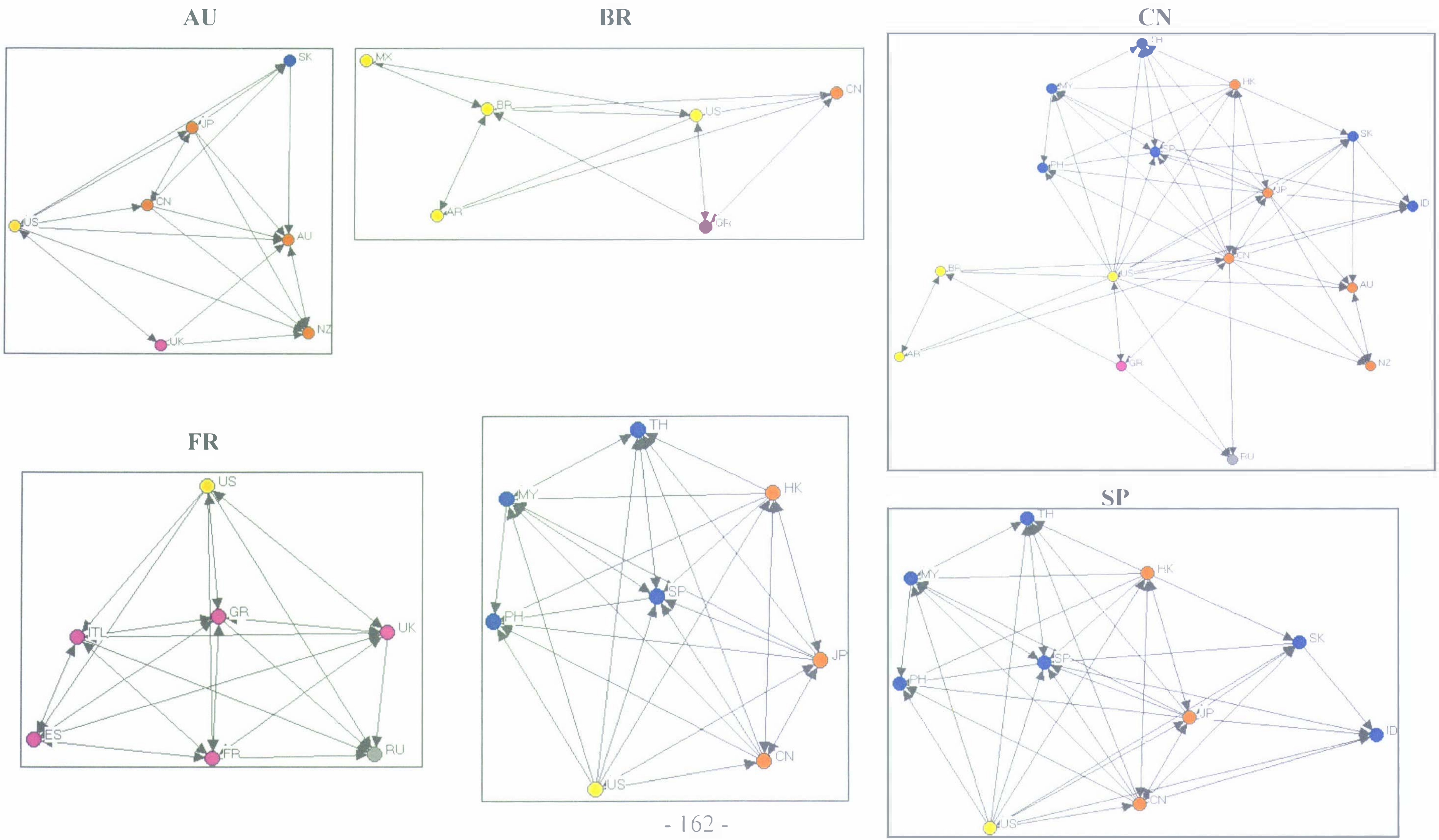


Figure 5.25 – One-step ego-nets of trade flows dichotomized at 5%

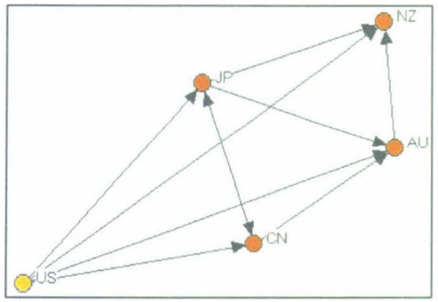
Country networks for trade links based on 5% dichotomization. This gives an indication of the trade derived price causation determination for selected currencies. The roles of CN as a hub and SP as a regional link are evident.



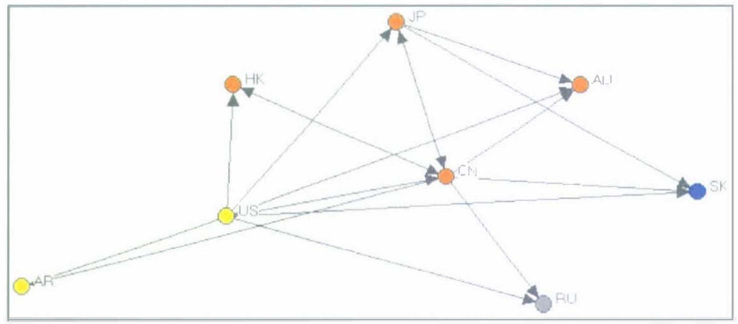
One-step ego-nets of trade flows dichotomized at 10%

Country networks for trade links based on 5% dichotomization. This gives an indication of the trade derived price causation determination for selected currencies. The importance of JP is evident.

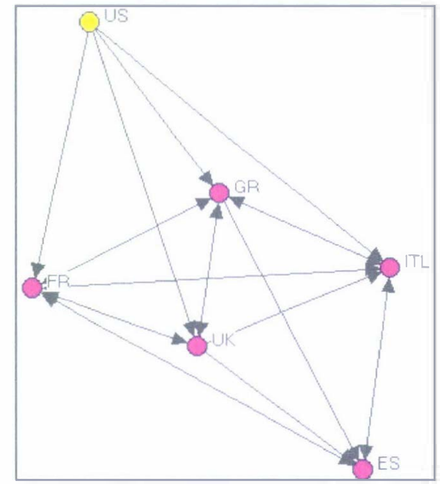
AU



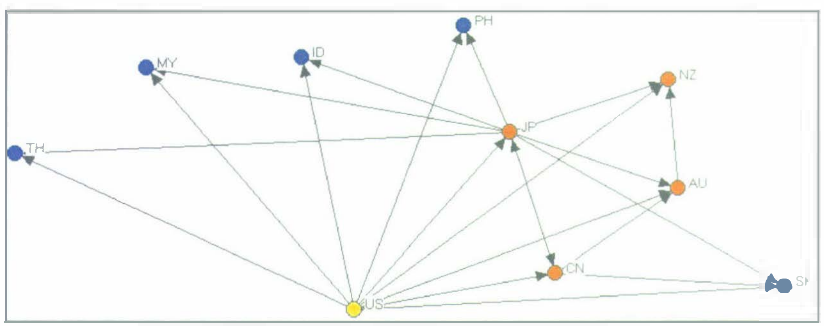
CN



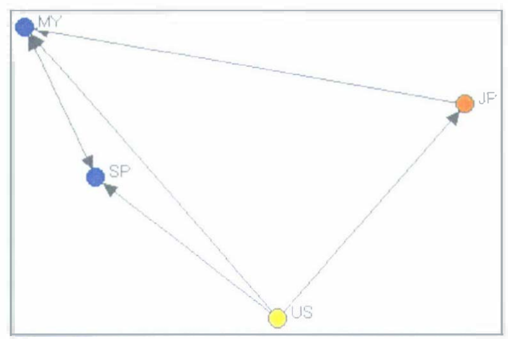
FR



JP



MY



SP

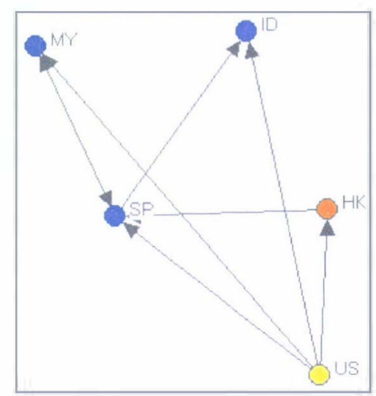


Figure 5.28 – In-In plot of trade links dichotomised at the 5% level.
Plot o ftrade links based on 5% dichotomization, ranked by linkage based on export links. The upper proportion shows a power-law.

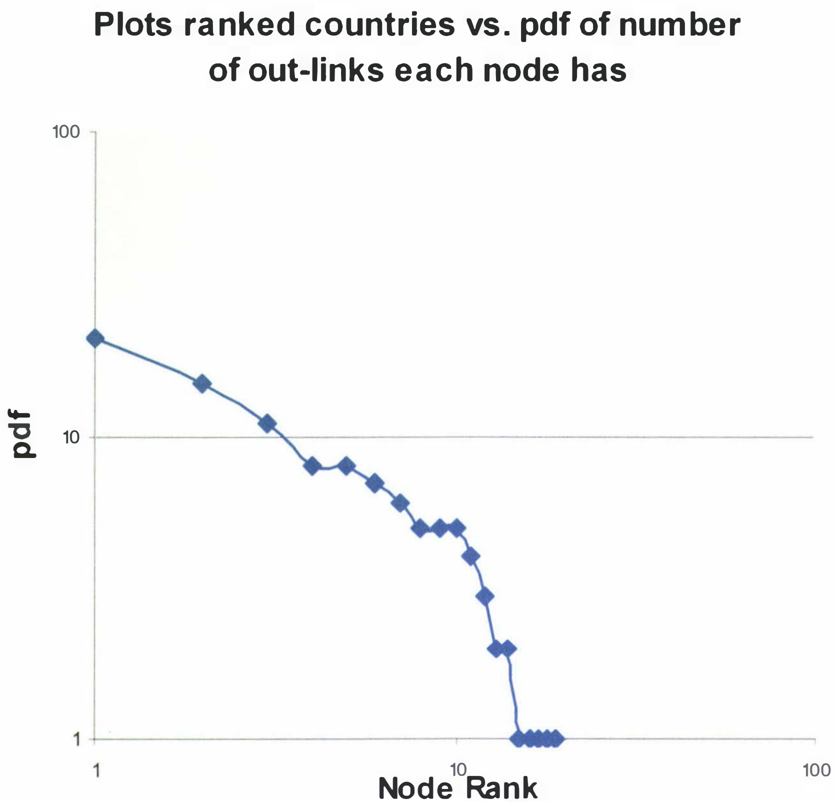


Table 5.5 – Turnover of FX trading by centre

Daily averages in April in US$ B, adjusted for local double counting (BIS).
% of total FX turnover. Ranked by 2004.

	1998		2001		2004	
	Amount	% share	Amount	% share	Amount	% share
United Kingdom	637	32.5	504	31.2	753	31.3
United States	351	17.9	254	15.7	461	19.2
Japan	136	6.9	147	9.1	199	8.3
Singapore	139	7.1	101	6.2	125	5.2
Germany	94	4.8	88	5.5	118	4.9
Hong Kong SAR	79	4	67	4.1	102	4.2
Australia	47	2.4	52	3.2	81	3.4
Switzerland	82	4.2	71	4.4	79	3.3
France	72	3.7	48	3	63	2.6
Canada	37	1.9	42	2.6	54	2.2
Netherlands	41	2.1	30	1.9	49	2
Denmark	27	1.4	23	1.4	41	1.7
Sweden	15	0.8	24	1.5	31	1.3
Russia	7	0.4	10	0.6	30	1.2
Belgium	27	1.4	10	0.6	20	0.8
Italy	28	1.4	17	1	20	0.8
Sth Korea	4	0.2	10	0.6	20	0.8
Mexico	9	0.5	9	0.5	15	0.6
Luxembourg	22	1.1	13	0.8	14	0.6
Norway	9	0.5	13	0.8	14	0.6
Spain	19	1	8	0.5	14	0.6
Austria	11	0.6	8	0.5	13	0.6
Sth Africa	9	0.5	10	0.6	10	0.4
Taiwan, China	5	0.3	4	0.3	8	0.3
India	2	0.1	3	0.2	7	0.3
Ireland	10	0.5	8	0.5	7	0.3
New Zealand	7	0.4	4	0.2	7	0.3
Poland	3	0.2	5	0.3	6	0.3
Greece	7	0.4	5	0.3	4	0.2
Bahrain	2	0.1	3	0.2	3	0.1
Brazil	5	0.3	5	0.3	3	0.1
Thailand	3	0.2	2	0.1	3	0.1
Chile	1	0.1	2	0.1	2	0.1
Czech Republic	5	0.3	2	0.1	2	0.1
Finland	4	0.2	2	0.1	2	0.1
Indonesia	2	0.1	4	0.2	2	0.1
Malaysia	1	0.1	1	0.1	2	0.1
Portugal	4	0.2	2	0.1	2	0.1
Saudi Arabia	2	0.1	2	0.1	2	0.1
Philippines	1	0.1	1	0.1	1	0.1
Total	1,958	100	1,612	100	2,406	100

Figure 5.29 – ln-ln plot of FX Turnover by Centre.
Plot of FX turnover, as ln-ln, for the centres listed in Table 5.6 for 2004, for both total US$B turnover and % of global market. Centres are ranked by size. The upper proportion shows a power-law.

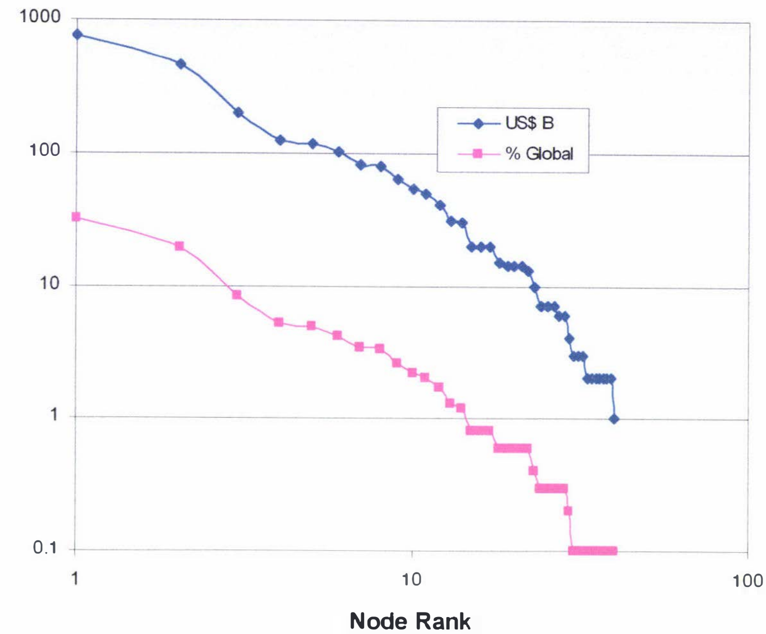


Table 5.6 Eigenvalue of the covariances of NZD matrix
Proportion of covariance explained by each ranked factor for NZD-based distance matrix. The first-order global pattern explains only 29.3% of the variation, the second 14.2%.

Eigenvalues of the NZD Covariance Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	0.00102832	0.00052751	0.2930	0.2930
2	0.00050081	0.00010342	0.1427	0.4356
3	0.00039739	0.00009342	0.1132	0.5488
4	0.00030397	0.00001617	0.0866	0.6354
5	0.00028780	0.00005049	0.0820	0.7174
6	0.00023731	0.00007561	0.0676	0.7850
7	0.00016170	0.00005100	0.0461	0.8311
8	0.00011070	0.00003854	0.0315	0.8626
9	0.00007216	0.00001997	0.0206	0.8832
10	0.00005218	0.00000886	0.0149	0.8981
11	0.00004333	0.00000733	0.0123	0.9104
12	0.00003599	0.00000177	0.0103	0.9206
13	0.00003423	0.00000264	0.0098	0.9304
14	0.00003158	0.00000263	0.0090	0.9394
15	0.00002896	0.00000384	0.0082	0.9476
16	0.00002511	0.00000278	0.0072	0.9548
17	0.00002233	0.00000253	0.0064	0.9612
18	0.00001980	0.00000362	0.0056	0.9668
19	0.00001617	0.00000077	0.0046	0.9714
20	0.00001540	0.00000108	0.0044	0.9758
21	0.00001433	0.00000156	0.0041	0.9799
22	0.00001276	0.00000101	0.0036	0.9835
23	0.00001176	0.00000236	0.0033	0.9869
24	0.00000940	0.00000117	0.0027	0.9895
25	0.00000823	0.00000286	0.0023	0.9919
26	0.00000536	0.00000036	0.0015	0.9934
27	0.00000500	0.00000036	0.0014	0.9948
28	0.00000464	0.00000027	0.0013	0.9962
29	0.00000438	0.00000167	0.0012	0.9974
30	0.00000271	0.00000083	0.0008	0.9982
31	0.00000187	0.00000031	0.0005	0.9987
32	0.00000156	0.00000013	0.0004	0.9992
33	0.00000143	0.00000065	0.0004	0.9996
34	0.00000078	0.00000026	0.0002	0.9998
35	0.00000052	0.00000030	0.0001	0.9999
36	0.00000021	0.00000020	0.0001	1.0000
37	0.00000001		0.0000	1.0000

Table 5.7 Eigenvalue of the covariances of USD-based matrix

Proportion of covariance explained by each ranked factor for USD-based distance matrix. The first-order global pattern explains only 15.3% of the variation, the second 13.2%.

	Eigenvalue	Difference	Proportion	Cumulative
1	0.00050311	0.00007146	0.1532	0.1532
2	0.00043165	0.00012193	0.1315	0.2847
3	0.00030972	0.00000601	0.0943	0.3790
4	0.00030370	0.00001416	0.0925	0.4715
5	0.00028954	0.00003911	0.0882	0.5596
6	0.00025043	0.00002840	0.0763	0.6359
7	0.00022203	0.00006018	0.0676	0.7035
8	0.00016186	0.00004342	0.0493	0.7528
9	0.00011843	0.00003548	0.0361	0.7889
10	0.00008296	0.00001454	0.0253	0.8141
11	0.00006842	0.00001787	0.0208	0.8350
12	0.00005055	0.00000744	0.0154	0.8504
13	0.00004311	0.00000376	0.0131	0.8635
14	0.00003935	0.00000341	0.0120	0.8755
15	0.00003594	0.00000092	0.0109	0.8864
16	0.00003502	0.00000188	0.0107	0.8971
17	0.00003314	0.00000166	0.0101	0.9072
18	0.00003148	0.00000213	0.0096	0.9168
19	0.00002935	0.00000238	0.0089	0.9257
20	0.00002696	0.00000049	0.0082	0.9339
21	0.00002648	0.00000364	0.0081	0.9420
22	0.00002284	0.00000210	0.0070	0.9489
23	0.00002074	0.00000247	0.0063	0.9552
24	0.00001827	0.00000066	0.0056	0.9608
25	0.00001761	0.00000157	0.0054	0.9662
26	0.00001604	0.00000216	0.0049	0.9711
27	0.00001388	0.00000146	0.0042	0.9753
28	0.00001243	0.00000196	0.0038	0.9791
29	0.00001047	0.00000032	0.0032	0.9823
30	0.00001015	0.00000155	0.0031	0.9853
31	0.00000860	0.00000038	0.0026	0.9880
32	0.00000822	0.00000242	0.0025	0.9905
33	0.00000580	0.00000055	0.0018	0.9922
34	0.00000525	0.00000059	0.0016	0.9938
35	0.00000467	0.00000023	0.0014	0.9953
36	0.00000443	0.00000059	0.0014	0.9966
37	0.00000384	0.00000117	0.0012	0.9978
38	0.00000268	0.00000107	0.0008	0.9986
39	0.00000161	0.00000020	0.0005	0.9991
40	0.00000141	0.00000063	0.0004	0.9995
41	0.00000078	0.00000025	0.0002	0.9998
42	0.00000053	0.00000027	0.0002	0.9999
43	0.00000026	0.00000024	0.0001	1.0000
44	0.00000002		0.0000	1.0000

Figure 5.30 – Time plot of MYR/ USD
Daily percentage changes 01/1990 to 12/2001

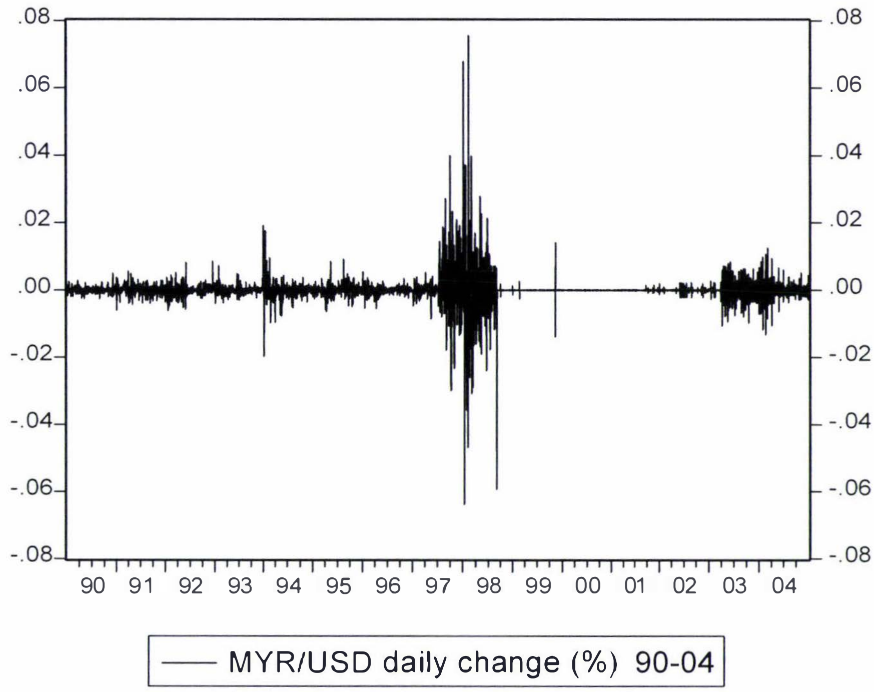


Figure 5.31 – Normality comparison for MYR/ USD
Daily percentage changes 01/1990 to 12/1998

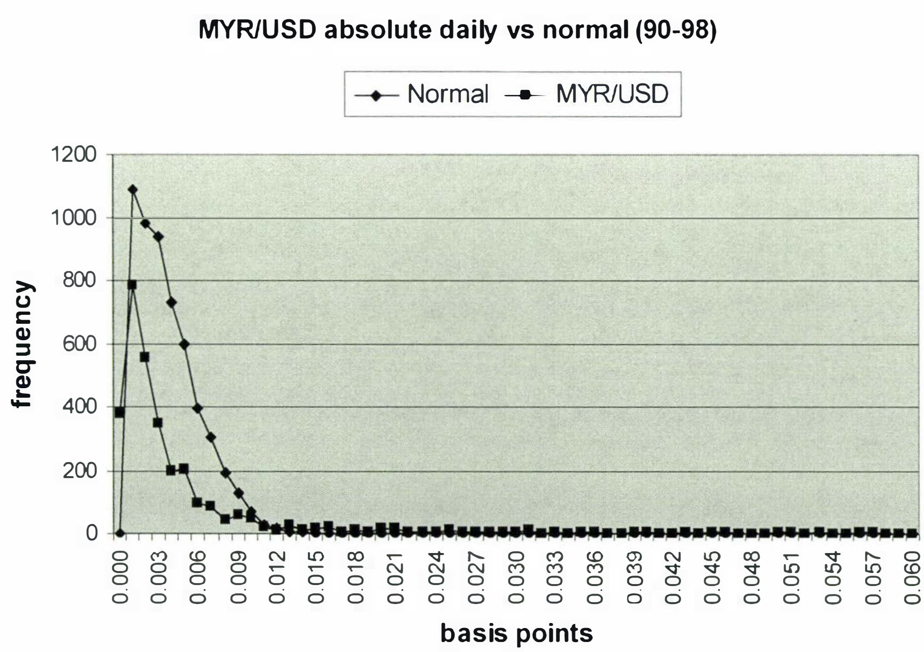


Figure 5.32 – MYR/USD daily change distribution tests.
This shows that MYR/USD daily changes do not fit the exponential or logistic distributions.

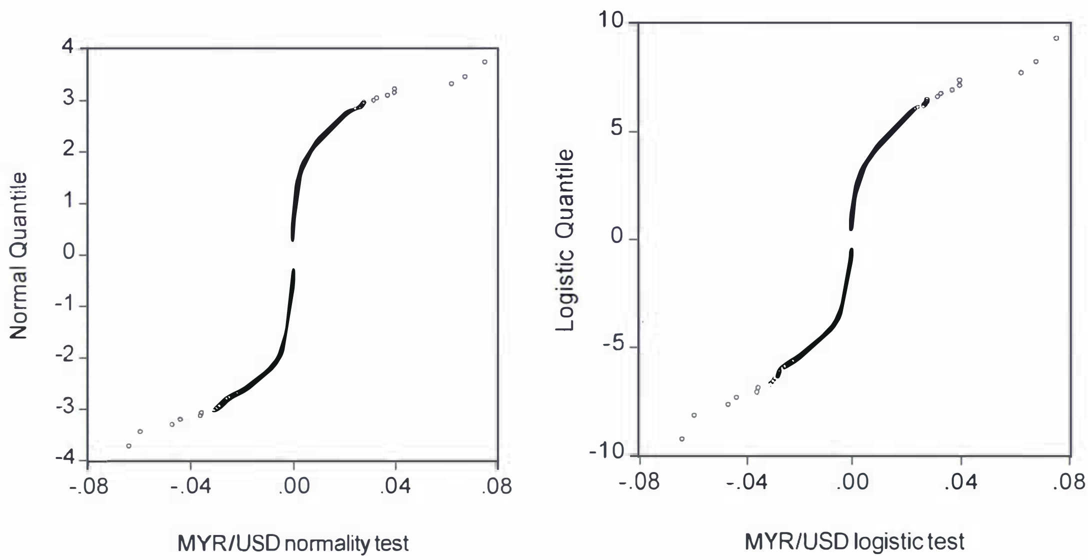


Table 5.9 – MYR/USD daily change distribution tests.

This shows that MYR/USD daily changes do not fit the exponential or logistic distributions.
Full sample – 01/1990 to 12/2004

Empirical Distribution Test for MYR/USD daily changes
Hypothesis: Exponential
Date: 04/07/05 Time: 09:34
Sample: 3/01/1990 31/12/2004
Included observations: 5477
5478 observations used in EDF tests after adjusting for estimated parameter(s)

Method	Value	Adj. Value	Probability
Cramer-von Mises (W2)	514.8719	514.8870	0.0000
Watson (U2)	420.4707	420.4830	0.0000
Anderson-Darling (A2)	2352.423	2352.681	0.0000

Method: Maximum Likelihood (Exact Solution)

Parameter	Value	Std. Error	z-Statistic	Prob.
A	-0.063715	1.16E-05	-5470.997	0.0000
MU	0.063785	1.16E-05	5476.500	0.0000
Log likelihood	9597.019	Mean dependent var.		6.99E-05
No. of Coefficients	2	S.D. dependent var.		0.004013

Empirical Distribution Test for MYR/USD daily changes
Hypothesis: Logistic
Date: 04/07/05 Time: 09:36
Sample: 3/01/1990 31/12/2004
Included observations: 5477
WARNING: test results may not be valid. Coefficient estimator convergence not achieved.

Method	Value	Adj. Value	Probability
Cramer-von Mises (W2)	162.6377	162.6674	< 0.005
Watson (U2)	162.5538	162.5835	< 0.005
Anderson-Darling (A2)	794.9541	794.9904	< 0.005

Method: Maximum Likelihood (Marquardt)
Failure to improve Likelihood after 1 iteration
Covariance matrix computed using second derivatives

Parameter	Value	Std. Error	z-Statistic	Prob.
MU	6.99E-05	9.72E-05	0.719205	0.4720
S	0.002212	0.001934	1.143972	0.2526
Log likelihood	24172.49	Mean dependent var.		6.99E-05
No. of Coefficients	2	S.D. dependent var.		0.004013

Table 5.10 – MYR/USD daily change distribution tests.

This shows that MYR/USD daily changes do not fit the exponential or logistic distributions.
Restricted sample – 01/1990 to 09/1998

Empirical Distribution Test for MYR/USD restricted sample
Hypothesis: Exponential
Date: 04/07/05 Time: 09:50
Sample: 3/01/1990 2/09/1998
Included observations: 3165
5478 observations used in EDF tests after adjusting for estimated parameter(s)

Method	Value	Adj. Value	Probability
Cramer-von Mises (W2)	230.9664	230.9732	0.0000
Watson (U2)	130.4358	130.4396	0.0000
Anderson-Darling (A2)	673565.1	673638.9	0.0000

Method: Maximum Likelihood (Exact Solution)

Parameter	Value	Std. Error	z-Statistic	Prob.
A	-0.063715	2.02E-05	-3158.985	0.0000
MU	0.063836	2.02E-05	3164.500	0.0000
Log likelihood	5543.290	Mean dependent var.		0.000121
No. of Coefficients	2	S.D. dependent var.		0.005114

Empirical Distribution Test for MYR/USD restricted sample
Hypothesis: Logistic
Date: 04/07/05 Time: 09:51
Sample: 3/01/1990 2/09/1998
Included observations: 3165
WARNING: test results may not be valid. Coefficient estimator convergence not achieved.

Method	Value	Adj. Value	Probability
Cramer-von Mises (W2)	54.31710	54.33424	< 0.005
Watson (U2)	54.21548	54.23259	< 0.005
Anderson-Darling (A2)	275.9715	275.9933	< 0.005

Method: Maximum Likelihood (Marquardt)
Failure to improve Likelihood after 7 iterations
Covariance matrix computed using second derivatives

Parameter	Value	Std. Error	z-Statistic	Prob.
MU	0.000108	5.53E-05	1.944336	0.0519
S	0.002018	4.56E-05	44.24575	0.0000
Log likelihood	13546.59	Mean dependent var.		0.000121
No. of Coefficients	2	S.D. dependent var.		0.005114

Table 5.11 - Internal triad linkage density

(% of potential internal links per node used)

Node	% links	Node	% links	Node	% links
A1	1.0	D1	0.5	F10	0.5
A2	0.7	D2	0.5	G1	0.5
A3	1.0	D3	0.5	G2	0.5
A4	0.7	F1	0.6	H1	1.0
B1	0.5	F2	0.4	H2	0.7
B2	0.8	F3	0.2	H3	0.7
B3	0.5	F4	0.3	H4	0.3
B4	0.5	F5	0.2		
B5	0.8	F6	0.4		
C1	1.0	F7	1.0		
C2	1.0	F8	0.6		
C3	1.0	F9	0.3		

Chapter Six – Appendix

Simulation procedure for section 6.3 – threshold parameters

The simulation was undertaken by processing a series of binary matrices and transforming the output into table or graphical representation. One matrix represents the links between nodes, either 1 for linked or 0 for not linked. Another linked matrix holds node activation state values, either 0 or 1. Another matrix holds parameter values. These are stacked and run through a simulation.

The simulation runs as follows:

1. Choose a parameter distribution, and its attributes.
2. Generate the parameter values at each node randomly from the chosen distribution.
3. Activate the first node and run 1000 simulations, recording:
   a) The size of the cascade (in number of nodes).
   b) The affected nodes.
4. Repeat step 3 starting with each node in turn.
5. Repeat from step 2 for as many trials as desired.
6. Collate results:
   a) Size of a cascade given a particular starting node. (e.g., relative frequency of large cascades vs. small cascades).
   b) Size of a cascade containing a particular node. (e.g., nodes which do not appear in many large cascades are critical (likely medium to late adopters), whereas those that appear in a lot of large cascades are more probably early adopters).
   c) Effect of distribution of parameters on the distribution of the resulting cascades.

Simulation procedure for section 6.4 – External and Internal Linkages

Programming this part of the analysis was tricky as varying linkages between nodes meant dropping the pre-defined cluster structure used before. In terms of matrix operations a link meant any cell could now link at random to any other cell. Thus, it was important to partition the matrix into blocks related to the clusters so differential rules could be applied to the density of linkages with a cluster and between clusters.

To ensure a sparsely clustered distribution was created with internal density which was much higher than the external density. No rule or fitness criteria were imposed on which nodes within the cluster those links should attach to. Thus any node had an equal chance of gaining each new link.

The simulation then runs as follows:

1. Choose the network distribution and parameters following the generation rules.
2. Choose a parameter distribution, and its attributes (e.g., uniform, normal (with mean and standard deviation) or power-law (with degree)).
3. Generate the network using the parameters chosen.
4. Generate the parameter values at each node randomly from the chosen distribution.
5. Activate the first node and run the simulation, recording:
   a) The size of the cascade (in number of nodes).
   b) The affected nodes.
6. Repeat step 5 starting with each node in turn.
7. Repeat from step 4 for as many parameter trials as desired.

8. Repeat from step 3 for as many network trials as desired.
9. Collate results:
   a) Size of a cascade given a particular starting node. (e.g., relative frequency of large cascades vs. small cascades).
   b) Size of a cascade containing a particular node. (e.g., nodes which do not appear in many large cascades are critical (likely medium to late adopters), whereas those that appear in a lot of large cascades are more probably early adopters).
   c) Effect of distribution of parameters on the distribution of the resulting cascades.
   d) Effect of distribution of network (particularly links between clusters or within clusters).

All simulation output is after 100 trials at the network and 100 trials at the parameter distribution levels (10000 trials in total) for each starting node.

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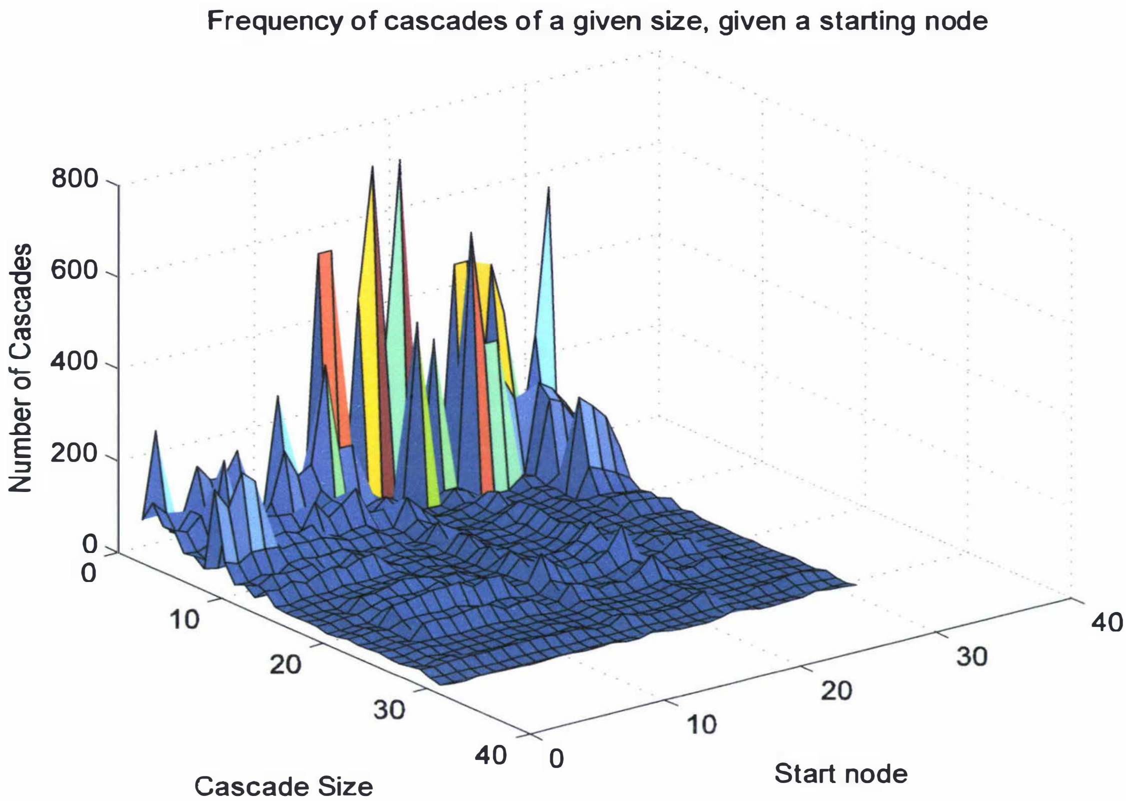
Table 6.1 – Simulation output for Normal Distribution: ($\mu = 0.3$, $\sigma = 0.28$)

Cascade size statistics (minimum and maximum of runs) and % of simulations that pass the set levels

	Cascade size distribution (% nodes)			*% Global Cascades*				
Node	*Min*	*Mean*	*Max*	*(>50%)*	*(>60%)*	*(>70%)*	*(>80%)*	*(>90%)*
1 A1	3.23	27.73	100.00	14.20	11.30	9.20	6.20	3.40
2 A2	3.23	23.16	100.00	11.70	9.30	7.10	4.80	2.90
3 A3	3.23	31.83	100.00	17.70	14.20	10.90	7.50	3.90
4 A4	3.23	29.34	100.00	13.50	11.20	9.30	6.90	3.70
5 B1	3.23	33.22	100.00	28.00	20.00	11.00	5.40	3.30
6 B2	3.23	34.81	100.00	30.20	21.30	11.60	5.50	3.20
7 B3	3.23	34.88	100.00	31.90	22.00	11.10	5.50	3.40
8 B4	3.23	36.00	100.00	34.10	23.10	12.30	6.00	3.60
9 B5	3.23	39.34	100.00	35.70	24.90	13.80	6.80	3.80
10 C1	3.23	37.10	100.00	35.70	24.30	12.90	6.60	3.80
11 C2	3.23	26.48	100.00	24.20	16.80	9.10	4.90	3.00
12 C3	3.23	31.63	100.00	28.60	20.30	10.60	5.80	3.20
13 D1	9.68	31.55	100.00	26.90	20.20	10.50	5.60	3.50
14 D2	3.23	15.84	100.00	12.40	8.70	4.40	2.60	1.60
15 D3	3.23	15.84	100.00	12.40	8.70	4.40	2.60	1.60
16 F1	3.23	43.02	100.00	41.30	28.50	14.60	7.90	4.50
17 F2	3.23	27.73	100.00	27.30	18.50	9.60	4.60	2.60
18 F3	3.23	17.10	100.00	16.30	10.90	5.70	3.00	1.60
19 F4	3.23	21.45	100.00	16.70	11.60	6.40	3.10	1.70
20 F5	3.23	17.10	100.00	16.30	10.90	5.70	3.00	1.60
21 F6	3.23	31.17	100.00	29.60	19.60	10.10	5.10	2.90
22 F7	9.68	52.15	100.00	54.60	36.80	20.00	9.70	5.20
23 F8	9.68	22.81	100.00	15.10	12.10	7.00	3.70	2.00
24 F9	3.23	13.21	100.00	7.60	5.60	3.10	1.60	1.00
25 F10	3.23	13.21	100.00	7.60	5.60	3.10	1.60	1.00
26 G1	6.45	21.45	100.00	17.20	12.30	6.90	3.30	2.00
27 G2	3.23	17.05	100.00	13.30	9.40	5.30	2.80	1.80
28 H1	6.45	26.79	100.00	10.20	8.10	7.10	6.10	4.00
29 H2	3.23	24.83	100.00	9.60	7.80	6.70	5.60	3.70
30 H3	3.23	19.86	100.00	7.10	5.70	4.80	4.10	2.70
31 H4	3.23	12.94	100.00	4.20	3.50	3.00	2.40	1.60
Ave	4.06	26.79	100.00	21.01	14.94	8.62	4.85	2.83
Std dev	2.03	9.57	0.00	11.85	7.83	3.88	1.95	1.07

Figure 6.1 – Frequency of cascades starting at a particular node - normal distribution ($\mu = 0.3, \sigma = 0.28$)

Shows the number of repetitions that start at a particular node of each cascade size



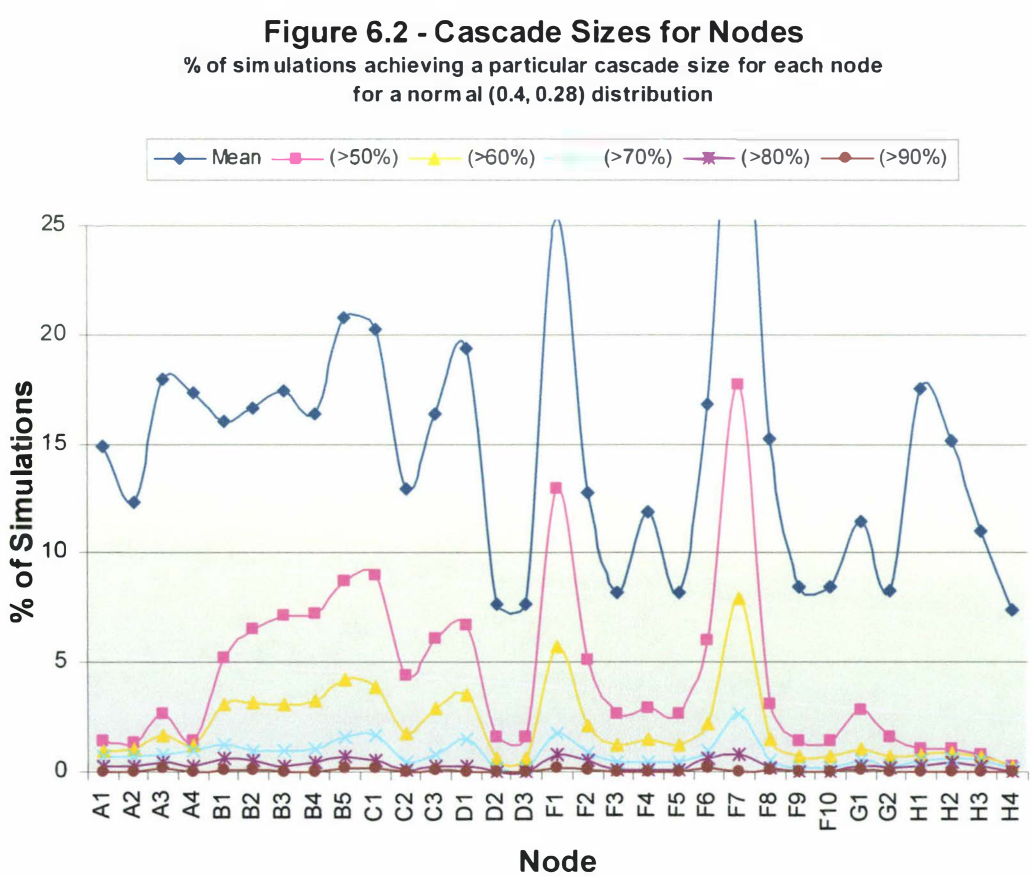


Table 6.3 – Simulation output for Power-law distribution (ρ = 1.5)

Cascade size statistics (minimum and maximum of runs) and % of simulations that pass the set levels

	Cascade size distribution (% nodes)			*% Global Casacdes*				
Node	*Min*	*Mean*	*Max*	*(>50%)*	*(>60%)*	*(>70%)*	*(>80%)*	*(>90%)*
1 A1	3.23	36.72	100.00	29.10	24.90	19.10	12.00	5.40
2 A2	3.23	35.11	100.00	28.70	24.50	18.70	11.50	5.30
3 A3	3.23	44.09	100.00	39.00	33.50	25.60	15.50	6.80
4 A4	3.23	39.84	100.00	30.40	25.90	21.80	15.10	7.50
5 B1	3.23	49.35	100.00	51.40	39.50	26.90	14.20	6.60
6 B2	3.23	48.67	100.00	52.50	37.70	24.50	11.80	5.70
7 B3	3.23	50.86	100.00	56.60	40.60	25.40	12.50	5.80
8 B4	3.23	49.86	100.00	54.80	38.40	23.70	11.00	5.20
9 B5	3.23	51.67	100.00	56.60	40.00	26.20	12.10	6.20
10 C1	3.23	51.35	100.00	57.90	40.20	25.90	12.40	5.60
11 C2	3.23	42.28	100.00	46.30	32.90	20.80	10.00	5.00
12 C3	3.23	45.92	100.00	50.60	35.80	22.90	11.50	6.00
13 D1	9.68	47.64	100.00	52.60	38.90	24.30	12.80	5.50
14 D2	3.23	32.30	100.00	34.40	25.20	16.10	8.10	3.80
15 D3	3.23	32.30	100.00	34.40	25.20	16.10	8.10	3.80
16 F1	3.23	55.11	100.00	62.40	45.10	26.90	13.00	6.90
17 F2	3.23	45.77	100.00	50.90	36.20	22.20	10.50	4.90
18 F3	3.23	31.83	100.00	36.30	25.80	15.80	6.70	2.90
19 F4	3.23	36.49	100.00	39.10	28.20	18.30	8.30	4.00
20 F5	3.23	31.83	100.00	36.30	25.80	15.80	6.70	2.90
21 F6	3.23	48.32	100.00	54.10	38.70	24.40	11.90	5.60
22 F7	12.90	60.31	100.00	70.60	51.30	32.90	16.40	7.70
23 F8	9.68	31.70	100.00	30.40	23.70	15.60	7.10	3.80
24 F9	3.23	23.07	100.00	21.40	16.30	10.80	4.50	2.30
25 F10	3.23	23.07	100.00	21.40	16.30	10.80	4.50	2.30
26 G1	6.45	37.08	100.00	40.00	30.10	19.70	9.60	4.50
27 G2	3.23	28.30	100.00	29.30	22.20	14.40	7.20	3.90
28 H1	6.45	33.35	100.00	22.10	19.20	15.80	11.40	6.50
29 H2	3.23	31.87	100.00	21.70	18.60	14.90	10.50	5.50
30 H3	3.23	29.12	100.00	19.30	16.60	13.60	9.60	5.10
31 H4	3.23	21.84	100.00	13.40	11.50	9.80	7.10	4.20
Ave	4.17	39.58	100.00	40.13	29.96	19.99	10.44	5.07
Std dev	2.38	10.23	0.00	14.79	9.78	5.67	3.05	1.43

Figure 6.3 – Frequency of cascades starting at a particular node - power-law distribution (ρ = 1.5)

Shows the number of repetitions that start at a particular node of each cascade size

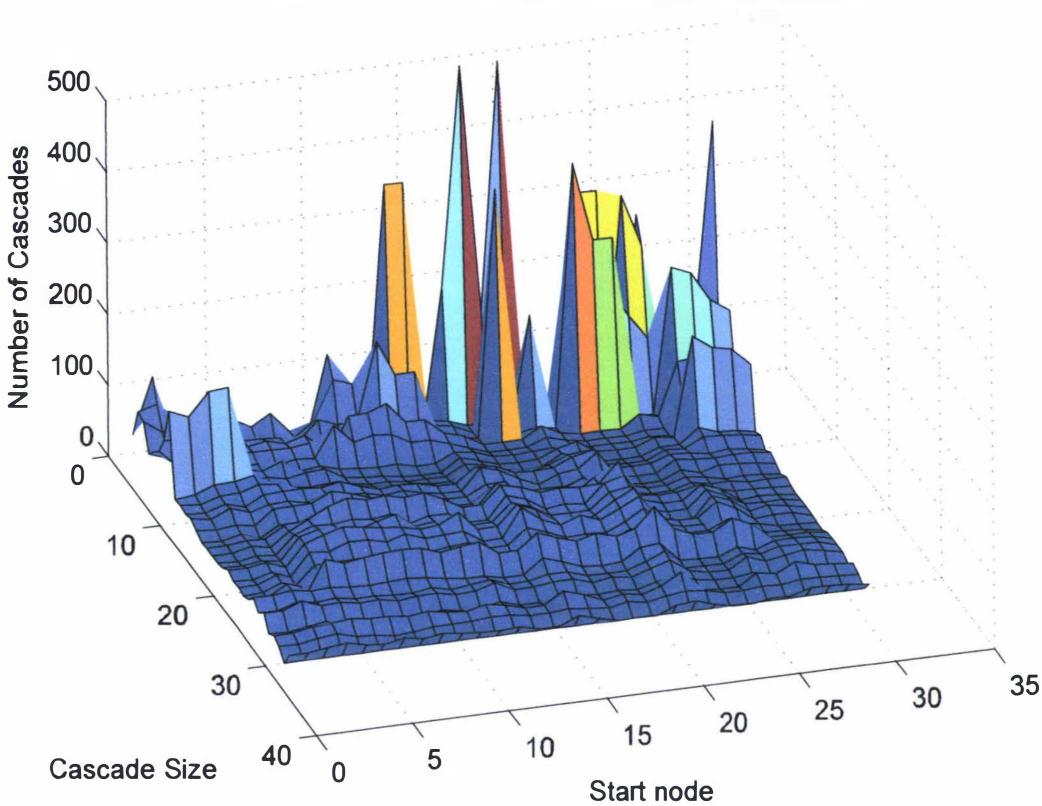


Figure 6.4 - Cascade Sizes for Nodes

% of simulations acheiving a particular size frop each node for a power-law (1.5) distribution

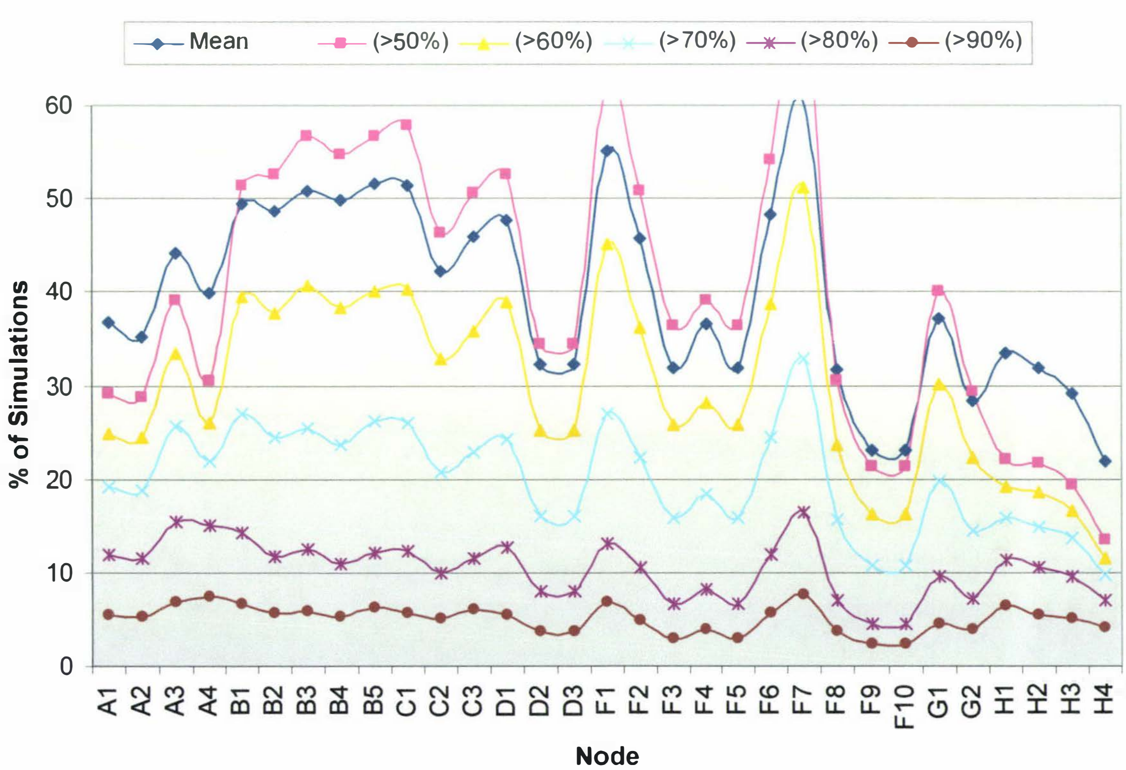


Table 6.5 – Simulation output for Uniform Distribution

Cascade size statistics (minimum and maximum of runs) and % of simulations that pass the set levels

	Cascade size distribution (% nodes)					*% Global Cascades*		
Node	*Min*	*Mean*	*Max*	*(>50%)*	*(>60%)*	*(>70%)*	*(>80%)*	*(>90%)*
1 A1	3.23	11.15	74.19	0.50	0.30	0.10	0.00	0.00
2 A2	3.23	8.09	70.97	0.20	0.20	0.10	0.00	0.00
3 A3	3.23	13.71	80.65	1.00	0.80	0.20	0.10	0.00
4 A4	3.23	13.25	77.42	0.30	0.30	0.10	0.00	0.00
5 B1	3.23	11.75	77.42	1.80	0.70	0.20	0.00	0.00
6 B2	3.23	11.63	77.42	1.80	0.90	0.20	0.00	0.00
7 B3	3.23	11.42	74.19	1.90	0.60	0.10	0.00	0.00
8 B4	3.23	11.74	74.19	1.90	0.80	0.10	0.00	0.00
9 B5	3.23	14.08	74.19	2.30	0.70	0.10	0.00	0.00
10 C1	3.23	14.64	74.19	2.40	1.10	0.10	0.00	0.00
11 C2	3.23	9.17	74.19	1.30	0.60	0.10	0.00	0.00
12 C3	3.23	11.91	74.19	1.80	0.70	0.10	0.00	0.00
13 D1	9.68	15.42	70.97	1.90	1.00	0.10	0.00	0.00
14 D2	3.23	6.28	67.74	0.50	0.40	0.00	0.00	0.00
15 D3	3.23	6.28	67.74	0.50	0.40	0.00	0.00	0.00
16 F1	3.23	17.16	74.19	3.00	1.10	0.20	0.00	0.00
17 F2	3.23	9.06	74.19	1.30	0.60	0.10	0.00	0.00
18 F3	3.23	6.19	67.74	0.80	0.40	0.00	0.00	0.00
19 F4	3.23	9.51	70.97	1.10	0.50	0.10	0.00	0.00
20 F5	3.23	6.19	67.74	0.80	0.40	0.00	0.00	0.00
21 F6	3.23	12.05	80.65	1.60	1.00	0.40	0.10	0.00
22 F7	9.68	26.22	93.55	4.90	1.40	0.40	0.20	0.10
23 F8	9.68	12.57	77.42	0.70	0.20	0.10	0.00	0.00
24 F9	3.23	6.32	61.29	0.30	0.10	0.00	0.00	0.00
25 F10	3.23	6.32	61.29	0.30	0.10	0.00	0.00	0.00
26 G1	6.45	9.33	70.97	1.10	0.50	0.10	0.00	0.00
27 G2	3.23	5.96	67.74	0.30	0.20	0.00	0.00	0.00
28 H1	6.45	13.75	70.97	0.30	0.20	0.10	0.00	0.00
29 H2	3.23	11.17	61.29	0.20	0.10	0.00	0.00	0.00
30 H3	3.23	8.60	45.16	0.00	0.00	0.00	0.00	0.00
31 H4	3.23	5.92	45.16	0.00	0.00	0.00	0.00	0.00
Ave	4.06	10.87	70.97	1.19	0.53	0.10	0.01	0.00
Std dev	2.03	4.28	9.35	1.05	0.36	0.10	0.04	0.02

Figure 6.5 – Frequency of cascades starting at a particular node - uniform distribution

Shows the number of repetitions that start at a particular node of each cascade size

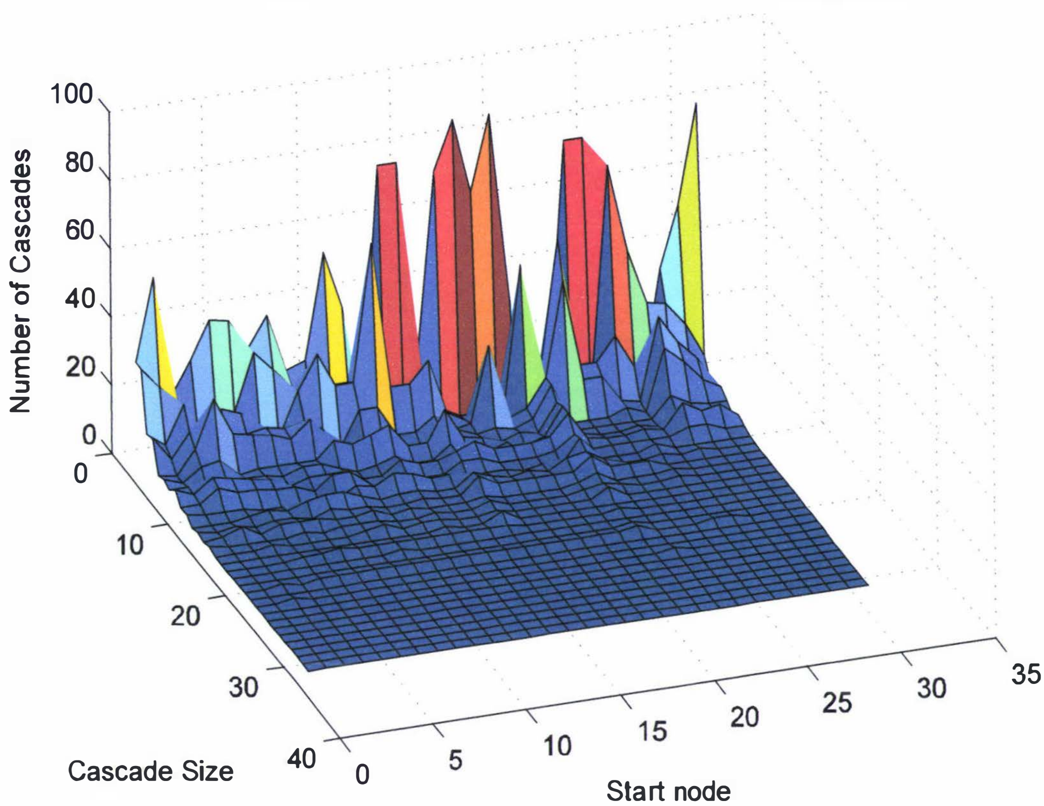


Figure 6.6 - Cascade Size for Nodes

% of simulations acheiving a particular cascade size for each node for a uniform distribution

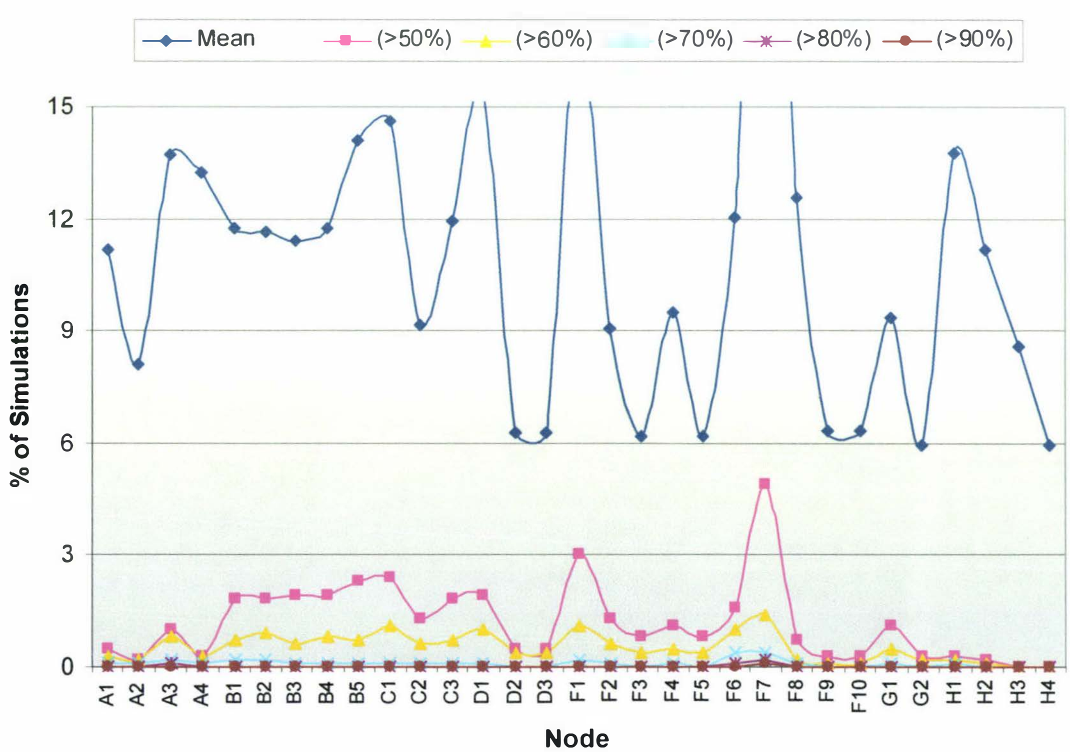


Table 6.7 – Containing simulation output for Normal (0.3) Distribution

Shows the percentage of repetitions that each particular node was contained in for each cascade size

	Cascade size distribution (% nodes)			*% Global Cascades*				
Node	*Min*	*Mean*	*Max*	*(>50%)*	*(>60%)*	*(>70%)*	*(>80%)*	*(>90%)*
1 A1	3.23	45.61	100.00	36.66	30.62	26.08	18.84	11.32
2 A2	3.23	44.82	100.00	36.18	30.36	25.78	18.56	10.86
3 A3	3.23	47.31	100.00	39.05	33.00	27.05	19.31	11.28
4 A4	3.23	44.23	100.00	33.41	28.24	24.59	19.11	12.12
5 B1	3.23	51.63	100.00	53.20	41.03	25.38	14.82	8.66
6 B2	3.23	53.00	100.00	56.85	43.11	26.06	14.65	8.56
7 B3	3.23	53.55	100.00	58.94	44.05	25.69	14.50	8.47
8 B4	3.23	54.39	100.00	60.63	45.11	26.19	14.73	8.61
9 B5	3.23	54.55	100.00	59.34	44.85	26.90	15.13	8.84
10 C1	3.23	54.96	100.00	64.22	47.52	27.70	15.67	9.43
11 C2	3.23	52.48	100.00	61.21	45.89	26.71	15.18	9.29
12 C3	3.23	53.24	100.00	61.65	46.68	27.40	15.67	9.60
13 D1	9.68	54.53	100.00	63.40	49.80	29.23	17.11	10.19
14 D2	3.23	51.03	100.00	59.08	46.41	27.23	15.95	9.50
15 D3	3.23	51.03	100.00	59.08	46.41	27.23	15.95	9.50
16 F1	3.23	56.98	100.00	65.31	47.95	27.91	15.70	9.18
17 F2	3.23	55.18	100.00	63.38	46.32	27.02	15.20	8.89
18 F3	3.23	56.89	100.00	68.19	51.06	30.08	17.00	9.93
19 F4	3.23	51.73	100.00	59.80	45.52	27.48	15.13	10.21
20 F5	3.23	56.89	100.00	68.19	51.06	30.08	17.00	9.93
21 F6	3.23	55.25	100.00	64.69	47.89	28.68	16.04	9.25
22 F7	9.68	61.65	100.00	74.25	55.60	32.75	18.51	10.81
23 F8	9.68	47.55	100.00	52.69	42.23	27.62	14.77	10.10
24 F9	3.23	44.24	100.00	48.77	39.08	25.56	13.67	9.34
25 F10	3.23	44.24	100.00	48.77	39.08	25.56	13.67	9.34
26 G1	6.45	51.37	100.00	60.39	45.98	28.03	15.54	9.68
27 G2	3.23	49.86	100.00	58.50	44.53	27.15	15.05	9.38
28 H1	6.45	41.79	100.00	28.90	24.79	22.75	19.64	13.57
29 H2	3.23	40.95	100.00	27.98	24.20	22.02	19.12	13.05
30 H3	3.23	39.58	100.00	27.01	23.34	21.22	18.44	12.68
31 H4	3.23	38.61	100.00	26.51	22.74	20.88	18.02	12.45
Ave	4.06	50.29	100.00	53.10	41.11	26.58	16.38	10.13
Std dev	2.03	5.80	0.00	13.89	9.17	2.51	1.80	1.40

Figure 6.8 – Frequency of cascades containing a particular node - normal distribution (0.3, 0.28):

Shows number of repetitions which each particular node was present in for each cascade size

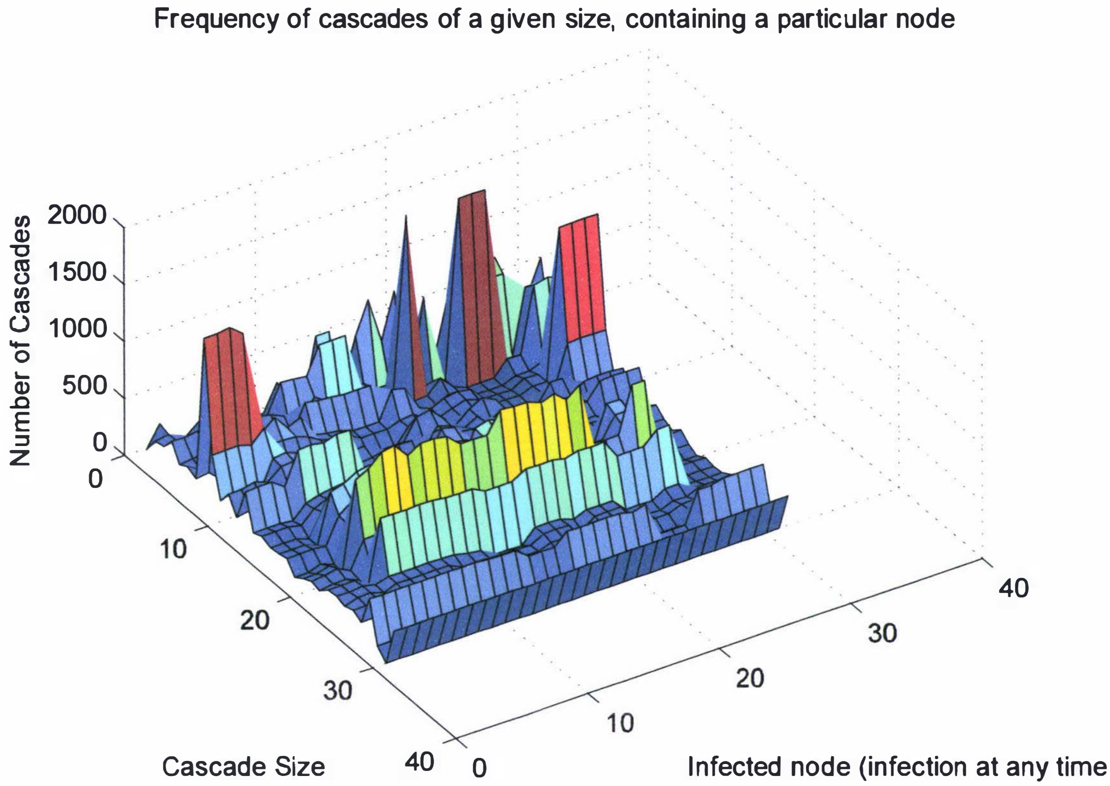


Figure 6.9 – Frequency of cascades containing a particular node – Power-law (p = 1.5)

Shows number of repetitions which each particular node was present in for each cascade size

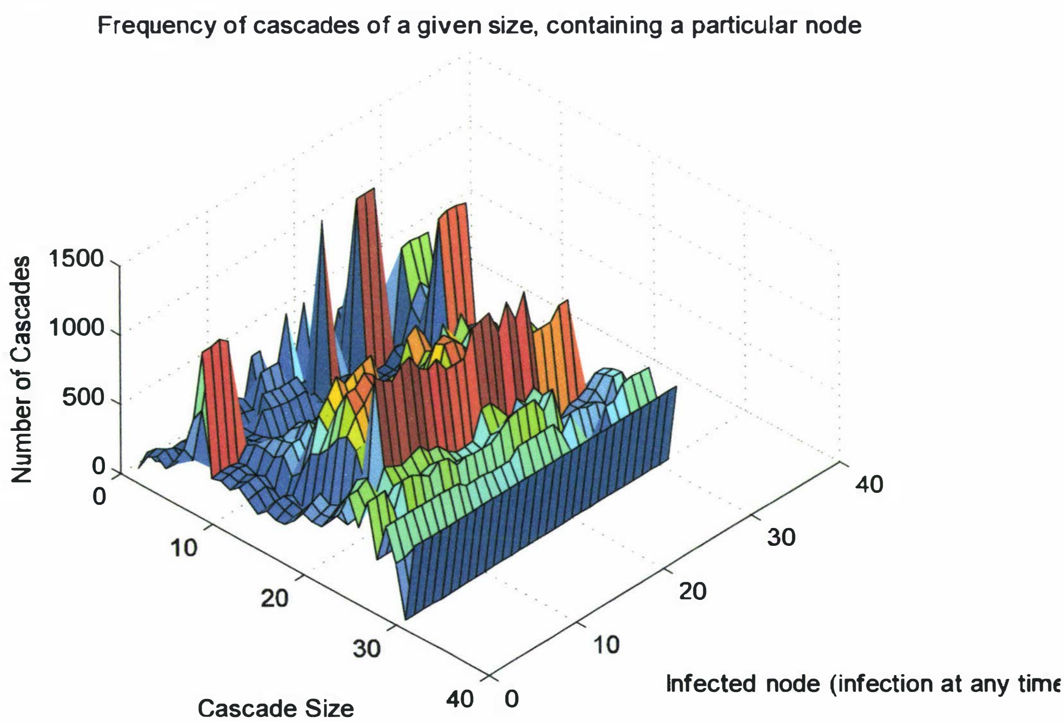
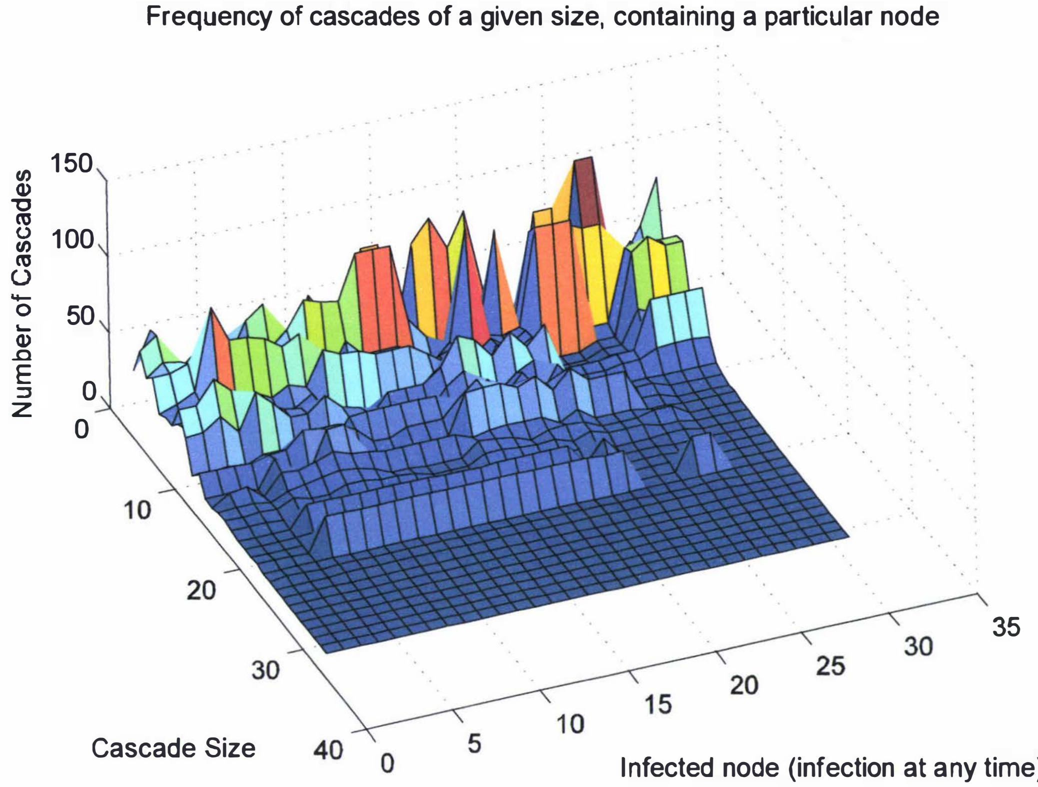


Figure 6.10 – Frequency of cascades containing a particular node – Uniform Distribution

Shows number of repetitions which each particular node was present in for each cascade size



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