The Dynamics of Global Financial Crises

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Abstract

This thesis presents a Markov chain model of the transmission of financial crises. Using bilateral trade data and a measure of exchange market pressure, it develops a method to determine a set of transition probabilities that describe the crisis transmission dynamics. The dynamics are characterized by one month conditional crisis probabilities and the probability of a crisis occurring within one year. Calculations of the transition probabilities for a three country example suggest that minor trading partners can increase the likelihood of a crisis in the home country through their effect on major trading partners.

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Title: Harris & Harris Group Professor
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Chapter 1

Introduction

Over the past decade, several financial and economic crises hit a number of developing countries. While some of these crises appeared to be isolated incidents affecting one country, for example, in Turkey and Argentina, a far greater number of them had effects beyond the borders of the initial country. In particular, the European Monetary System crisis of 1992, the Mexican crisis of 1994, the East Asian crisis of 1997, and the Russian crisis of 1998 affected more than the initial country.

The volatile nature of these crises resulted in economic hardship, political instability, and the toppling of a few governments. What made the crises even more disturbing was how they spread from country to country in an unexplained manner. The real difficulties associated with these financial crises prompted calls for the implementation of a variety of remedies from capital controls and currency boards to restrictions in the flow of foreign direct investment.

This thesis develops a small discrete-time stochastic model of the spread of a financial crisis from one country. The model is used to explore the paths a crisis can take through different countries and attempts to compare how actual crises spread. Chapter 2 reviews the existing literature on the spread of crises and the notion of contagion. Chapter 3 presents trade networks between the major economies from 1980 to 2000. Chapter 4 articulates a model based on Markov chains that give rise to dynamic behavior similar to the spread of a crisis. Chapter 5 presents the results of simulations of the Markov chain model in the two country and three country case.
Chapter 6 defines a notion of crisis and develops methods to estimate the probability of a crisis. In this chapter, we use extreme value distributions to estimate how often crises occur. Chapter 7 presents empirical estimates of the exchange market pressure and crisis probabilities and Chapter 8 concludes.
Chapter 2

Literature Review

2.1 Types of Contagion

There are several related but distinct types of contagion. The most often analyzed type, financial contagion refers to the spread of crises from one country to one or more other countries. Typically, the spread of crises is marked by a sharp deterioration of several macroeconomic and financial variables such as a fall in an index of the stock market, a depreciation of the currency, decreased or negative GDP growth rates, net outflows of foreign investment, and the collapse of property prices. Although recent crises such as the East Asian crisis of 1997 have been accompanied by all of these effects, some of the recent literature has chosen to focus on currency crises as the signal that a crisis has occurred.

It is possible to imagine the contagion of other types of crises as well. One country may default on its sovereign debt, causing defaults in other countries (default contagion). The stock market in an emerging market might drop significantly followed by similar drops in other markets independent of a currency crisis (stock market contagion). Political upheavals may destabilize regions promoting turmoil in neighboring countries (political contagion). A few papers have looked at contagion using these other indicators of crisis (see, for example, Baig and Goldfajn, 1999).

There is no consensus on what constitutes contagion. Forbes and Rigobon (2001) review some of the definitions of what constitute contagion. Early papers often point
to some empirical phenomenon (for example, increased co-movement in short term interest rates, see Gerlach and Smets 1995) and try to explain it without explicitly defining contagion. The implicit assumption is that contagion has occurred and the papers tackle the question of defining its causes.

Testing for contagion of crises requires a definition of crisis. Several papers (see for example, Glick and Rose, 1999) use popular press accounts to determine the approximate start of a crisis. These types of tests have the appeal of attempting to explain the spread of an intuitive (or popular press) notion of crisis. Eichengreen, Rose, and Wyplosz (1996) point out that focusing only on instances of devaluation of the exchange rate could miss other significant episodes of market pressure. A crisis is often preceded by a speculative attack which hastens the devaluation of the currency. However, the monetary authorities could repel a speculative attack by raising interest rates. Additionally, the authorities could increase monetary reserves in non-crisis periods to preempt an attack. To account for these additional periods, Eichengreen, Rose, and Wyplosz devised an index of exchange market pressure (EMP) that incorporates the key tools that a monetary authority has at its disposal. Using the EMP index as a proxy for the incidence of a crisis, they estimate a binary probit model to test for the significance of various macroeconomic variables in explaining contagion.

2.2 Is There Contagion?

Rigobon (2001) explores a number of pitfalls in commonly used tests for contagion. Tests for contagion must account for simultaneous equations, omitted variables, and heteroskedasticity in the data. He specifically looks at the more widely adopted tests of contagion including linear regressions, logit-probit regressions, and tests based on Principal Components. He develops procedures to correct for these problems under special conditions. Forbes and Rigobon (2001) review the four different approaches that have been used to test for contagion: analysis of correlation coefficients, GARCH frameworks, cointegration, and probit models.
2.3 Mechanisms of Transmission

The literature on contagion has divided explanations for the transmission of financial crises into two types: fundamental links among economies and the behavior of investors (Dornbusch, Park, and Claessens 2001). The fundamental links often cited as conduits of crises are trade and capital flows. Others point to rational and irrational investor behavior as another mechanism of crisis transmission.

2.3.1 Fundamental Mechanisms

Forbes (2001) reviewed the recent literature on the role of trade in transmitting crises. Gerlach and Smets (1995) present empirical evidence on the co-movement of interest rate spreads in Nordic countries during the 1992 EMS crisis. From this, they go on to develop a three-country model based on the Flood-Garber speculative attack model. They derive the time path of the exchange rates and show the dependence of the exchange rate collapse of one country on the collapse of another country. They build a story of how the collapse of the exchange rate in country 1 leads to a real appreciation of the exchange rate of country 2. This leads to a decrease in money demand in country 2 and an erosion of reserves. A decreased ability to defend the exchange rate in country 2 eventually leads to collapse. They predict that contagion effects would be stronger when wage flexibility is low and the degree of trade integration is high between the two countries relative to the anchor country.

In addition, a number of papers empirically estimate the importance of trade in transmitting crises. Glick and Rose (1999) attempt to distinguish the importance of trade and macroeconomic mechanisms in the transmission of crises. They regress the incidence of crises on an index of trade integration involving bilateral trade data. They find that trade better explains the spread of crises than macroeconomic similarity. Forbes (2001) uses bilateral trade data broken down by industry and attempts to separate the macroeconomic effects of changes of different types of trades. She divides the implications of changes in trade into three types: a competitiveness effect, where a depreciation in another country’s exchange rate decreases the first country’s ability
to export similar goods; an income effect, where a depreciation will sharply reduce exports to that country; and a cheap import effect, where the input prices will be reduced.

2.3.2 Investor Behavior

In 1998, a crisis in Russia led to a series of financial crises in a number of emerging markets seemingly unrelated by trade or other fundamentals to Russia. To explain this, Calvo (1999) develops a model where uninformed investors observe the actions of informed investors. The uninformed investors face a signal extraction problem where they are not sure whether the sales of assets by informed investors reflects negative information or margin calls. The actions of these uninformed investors tend to amplify movements in the price of emerging market securities even where the markets may not be linked by trade. In general, the co-movement of financial indicators in emerging economies may be explained by their dependence on a common set of investors.

2.4 Toward a Model of Dynamics

Although the literature on contagion has grown quite large, much of the recent work has focused on presenting and testing the significance of various linkages between economies (for example, regional similarities, trade, and common investors). Less emphasis has been placed on explicit modeling of the dynamics of the spread of a crisis. The course of a global crisis has large ramifications for investors, multinational corporations, and the people of the afflicted countries. When a neighboring country experiences a severe and unexpected financial crisis, it matters a lot whether your country will be next. The remaining chapters of this thesis present a model of global financial crises that illustrates the time path of contagion and allows for the analysis of contagion dynamics. The two contributions of this thesis are, first, the application of Markov chain analysis to crises dynamics, and, second, the use of a crisis index to estimate country crisis probabilities.
Chapter 3

Mapping Global Networks

This chapter maps global trade data among major countries. Bilateral trade flows among the major industrialized countries are plotted in Figures 3-1 to 3-8.\footnote{Direction of trade data were obtained from the IMF's Direction of Trade Statistics database (available on http://econ.bc.edu). Bilateral trade data are available on a monthly basis from 1980. Three categories of data are available: exports, imports CIF (cost, insurance, and freight), and imports FOB (free on board).}

Figures 3-1 and 3-2 detail total annual trade flows in US dollars among 9 countries (United States, Canada, Germany, United Kingdom, Mexico, France, China, Italy, and Brazil) from 1980 to 2000. The thicknesses of the arcs have been normalized to the largest trade flow in that particular year (usually Canada to the United States).\footnote{Except where noted, the rest of the arcs in all of the maps are scaled in the following manner: largest flow, 5 pt; 90% of largest flow, 4.5 pt; ..., 10% of largest flow, 0.5 pt.}

Figures 3-3 and 3-4 detail year-on-year percentage changes in total annual trade flows among the 9 countries. The thicknesses of the arcs have been normalized to the largest percentage change in that particular year. Negative percentage changes are indicated by a dotted arc.

Figures 3-5 and 3-6 detail total annual trade flows in US dollars among the 9 countries from 1980 to 2000. The key difference from Figures 3-1 and 3-2 is that the thicknesses of the arcs have been normalized to the largest trade flow in the entire 21 year period (Canada to the United States in 2000).

Figures 3-7 and 3-8 detail total annual trade flows in US dollars among 17 countries (United States, Canada, Germany, United Kingdom, Mexico, France, China,
Figure 3-1: International Trade Flows (Relative) for Nine Countries, 2000.
Figure 3-2: International Trade Flows (Relative) for Nine Countries, 1980-2000.
Figure 3-3: Changes in International Trade Flows for Nine Countries, 1999 to 2000.
Figure 3-4: Changes in International Trade Flows for Nine Countries, 1980-2000.
Figure 3-5: International Trade Flows (Absolute) for Nine Countries, 2000.
Figure 3-6: International Trade Flows (Absolute) for Nine Countries, 1980-2000.
Figure 3-7: International Trade Flows (Absolute) for 17 Countries, 2000.
Figure 3-8: International Trade Flows (Absolute) for 17 Countries, 1980-2000.
Italy, Brazil, Belgium, Netherlands, Switzerland, Spain, Australia, Hong Kong, India, Singapore) from 1980 to 2000. The thicknesses of the arcs have been normalized to the largest trade flow of all trade flows over all years. In this case the largest flow was from Canada to the United States in 2000 ($240 billion). Trade flows below 10% of the largest flow are not drawn.

Figures 3-1 and 3-5 indicate that U.S.-Canada trade represents the largest cross-border trade flows in U.S. dollars. Figure 3-2 shows that the relative sizes of the trade flows have been fairly stable over time among the 9 countries. In current U.S. dollars, Figure 3-6 shows that trade has grown over time. Notice that U.S.-Mexico trade has grown over time even in relative terms, particularly in the 1990’s. Figure 3-8 shows that the first nine countries account for much of the flow of trade, with many of the flows to and from the remaining eight countries below the 10% threshold of $24 billion per year.
Chapter 4

The Dynamics of Financial Crises

4.1 Markov Chain Analysis

The dynamics of a financial crisis can be modeled using a Markov chain. Consider a discrete-time Markov chain, in which the state changes at specific discrete time steps. At each time step $n$, there is a current state, denoted by $X_n$, which belongs to a finite set $S$ of possible states.\(^1\) The Markov chain is described by a set of transition probabilities $p_{ij}$ that denote the probability that the next state is equal to $j$ given that the current state is $i$. Explicitly,

$$p_{ij} = P(X_{n+1} = j | X_n = i) \quad i, j \in S. \quad (4.1.1)$$

The key assumption underlying a Markov chain is that the transition probabilities $p_{ij}$ apply whenever state $i$ is visited with no dependence on the history of states visited in the past.

A Markov chain model specifies: (a) the set of states $S = 1, \ldots, m$, (b) the set of possible transitions, namely, those pairs $(i, j)$ for which $p_{ij} > 0$, and (c) the numerical values of those $p_{ij}$ that are positive.

An initial approach to modeling global financial crises as a Markov chain might specify each country as a separate state. If the current state is country $i$, this means

\(^1\)For a general treatment of Markov chains see Drake (1967).
that country $i$ is in crisis. Transition probabilities measure the probabilities of the spread of a crisis from country $i$ to country $j$. A self-loop with probability $p_{ii}$ denotes the probability that given that a country $i$ experienced a crisis at time $t$, it continues to experience a crisis at time $t + 1$.

This first approach exhibits some of the conditional crisis probabilities we are trying to analyze, unfortunately, this model fails to capture the possibility that simultaneous crisis events in two countries might interact to increase the crisis probabilities worldwide. For example, given that Malaysia is currently experiencing a crisis, we are able to ask what the probability that Japan will experience a crisis within the next 12 months is? However, if a crisis in Malaysia leads to a crisis in Thailand through a contagion mechanism, it is possible that the crisis in Thailand positively contributes to the probability of a crisis in Japan. That is, Japan may be more likely to develop a crisis given that both Thailand and Malaysia are in crisis than if Malaysia alone were experiencing a crisis. The possibility of these multi-country interactions suggest the approach to modeling financial crises presented in the rest of this section.

This representation takes snapshots of the world as the current state at a given time. For example, one state can represent the world free of crises; the second state can represent only Malaysia in a crisis; the third state can represent Malaysia, Thailand, and Japan in a crisis. In this context, transition probabilities measure the probability of going to a particular snapshot of the world. With this model it is possible to answer questions such as: given that no country is in crisis, what is the probability of Malaysia having a crisis, or what is the probability of all three countries, Japan, Malaysia, and Thailand, experiencing crisis?

4.1.1 An Example with Two Countries

For the sake of concreteness, let us start with two countries, denoted $A$ and $B$. If country $A$ is experiencing a crisis, denote that $A^C$. If country $A$ is not in crisis (troughil), denote that $A^T$. In the two-country model, there are $2^2 = 4$ possible states of the world:
1. $A^T B^T$
2. $A^T B^C$
3. $A^C B^T$
4. $A^C B^C$

Let any of the four states transition to any other state. This implies that there are $4^2 = 16$ transition probabilities which can be arranged into a state transition probability matrix.

$$P = \begin{bmatrix}
  p_{11} & p_{12} & p_{13} & p_{14} \\
  p_{21} & p_{22} & p_{23} & p_{24} \\
  p_{31} & p_{32} & p_{33} & p_{34} \\
  p_{41} & p_{42} & p_{43} & p_{44}
\end{bmatrix}.$$  \hfill (4.1.2)

The transition probability matrix, $P$, has only three linearly independent columns because each row must sum to one, that is,

$$\sum_{j=1}^{4} p_{ij} = 1, \quad \forall i,$$  \hfill (4.1.3)

A graphical representation of the states and transition probabilities is depicted in Figure 4-1. The states are represented by the numbered circles. The two smaller circles within each state represent country A and B. A white circle is tranquil; a black circle is crisis. Each arrow represents one of the transition probabilities $p_{ij}$, where country $i$ is the base (start) of the arrow and country $j$ is the head (end) of the arrow. All of the transition probabilities are needed to fully describe the global financial network.

We make the following assumptions:

1. The incidence of crisis in one country next period is independent of future events in other countries,

$$P(A^Z B^Z | A^Y B^Y) = P(A^Z | A^Y B^Y) P(B^Z | A^Y B^Y), \quad Z, Y \in \{C, T\}. \hfill (4.1.4)$$

2. A country is either in crisis or not in crisis.
3. The transition probabilities are calculated as follows:

\[ p_{ij} = \mathbb{P}(S_j|S_i) = \mathbb{P}(A^{f(S_j)}|S_i)\mathbb{P}(B^{f(S_j)}|S_i), \tag{4.1.5} \]

where \( f(S_j) = C \) or \( T \) depending on state \( S_j \). For example,

\[ p_{23} = \mathbb{P}(A^C B^T|A^T B^C) = \mathbb{P}(A^C|A^T B^C)\mathbb{P}(B^T|A^T B^C). \]

We might be concerned that the assumption of independence may be too strong. If we make our time steps short enough, it is unlikely that the incidence of crisis in one country would depend on the simultaneous triggering of a crisis in another country as opposed to dependence on the same previous state. The spread of crisis to two countries is still captured because they both depend on the same state in the previous period.

As shown in Table 4.1, with \( n \) countries, the number of states is \( 2^n \), and the number of transition probabilities is \( 2^{2n} \). Additionally, with the independence assumption, the
<table>
<thead>
<tr>
<th>Number of Countries</th>
<th>Number of States</th>
<th>Number of Transition Probabilities</th>
<th>Number of Independent Transition Probabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>4</td>
<td>16</td>
<td>8</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>64</td>
<td>24</td>
</tr>
<tr>
<td>n</td>
<td>$2^n$</td>
<td>$2^{2n}$</td>
<td>$n2^n$</td>
</tr>
</tbody>
</table>

Table 4.1: Number of Transition Probabilities.

The number of independent transition probabilities is $n2^n$.

4.1.2 Using Linear Programming to Find Values of the Transition Probability Matrix

Our next step is to find values of the transition probability matrix that (a) obey the probability laws, (b) are consistent with the assumptions presented above, and (c) are derived from data on bilateral trade flows and incidence of crises.

4.1.3 Total Probability Constraints

The sum of the outgoing probabilities must equal 1 as in equation (4.1.3),

$$\sum_{j=1}^{4} p_{ij} = 1 \quad \forall i. \quad \text{(4.1.6)}$$

So in the two country example, the outgoing transition probabilities from state 1 must sum to 1.

$$p_{11} + p_{12} + p_{13} + p_{14} = 1$$

or

$$P(A^T|A^TB^T)P(B^T|A^TB^T) + P(A^T|A^TB^T)P(B^C|A^TB^T) +$$
$$P(A^C|A^TB^T)P(B^T|A^TB^T) + P(A^C|A^TB^T)P(B^C|A^TB^T) = 1$$
4.1.4 Long Run Probability Constraints

Let $\pi_k$ denote the unconditional probability of a crisis in country $k$,

\[ P(A^C) = \pi_A \]

\[ P(A^T) = 1 - \pi_A. \]

By the law of total probability, form additional constraints on the conditional probabilities:

\[ \pi_A = P(A^C|A^T B^T)(1 - \pi_A)(1 - \pi_B) + P(A^C|A^T B^C)(1 - \pi_A)\pi_B + P(A^C|A^C B^T)\pi_A(1 - \pi_B) + P(A^C|A^C B^C)\pi_A\pi_B \]  
(4.1.7)

\[ \pi_B = P(B^C|A^T B^T)(1 - \pi_A)(1 - \pi_B) + P(B^C|A^T B^C)(1 - \pi_A)\pi_B + P(B^C|A^C B^T)\pi_A(1 - \pi_B) + P(B^C|A^C B^C)\pi_A\pi_B \]  
(4.1.8)

4.1.5 Bilateral Flow Data Constraints

Define the dependence of country A on country B as the sum of imports and exports between country A and B divided by the GDP of country A,

\[ H_{AB} = \frac{F_{AB} + F_{BA}}{\text{GDP}_A}. \]  
(4.1.9)

Similarly, the dependence of country B on country A is

\[ H_{BA} = \frac{F_{BA} + F_{AB}}{\text{GDP}_B}. \]

Define a related parameter to indicate the influence of crisis within a country on crisis next period,

\[ G_A = \max \left\{ 0, \frac{\text{GDP}_A - F_{AB} - F_{BA}}{\text{GDP}_A} \right\}. \]  
(4.1.10)

$G_A$ plays a similar role to $H_{AB}$ by indicating the percentage of the economy that is non-traded. Next, let the differences between related conditional probabilities be
represented as
\[ \delta_{A1} = P(A^C | A^C B^C) - P(A^C | A^T B^T) \]
\[ \delta_{A2} = P(A^C | A^C B^C) - P(A^C | A^T B^C) \]
\[ \delta_{A3} = P(A^C | A^C B^C) - P(A^C | A^C B^T) \]  \( (4.1.11) \)

If we define the strength of the interdependence of two economies as the difference between the conditional probabilities in equation (4.1.11), then we interpret \( \delta_{A1} \) as a distance. Stronger interdependence corresponds to a greater distance. In particular, let the bilateral flow data constraints be

\[ \delta_{A1} \geq \beta_{A1}(G_A + H_{AB}) \]
\[ \delta_{A2} \geq \beta_{A2}(G_A) \]
\[ \delta_{A3} \geq \beta_{A3}(H_{AB}) \]  \( (4.1.12) \)

where \( \beta_A \) is a parameter that keeps the constraint from specifying infeasible probabilities. To interpret the constraint in equation (4.1.12), note that \( \delta_{A1} \) represents the difference between the conditional probability of country A experiencing a crisis given that the current state is \( A^C B^C \) and the conditional probability given that the current state is \( A^T B^T \). The two states differ in the status of both countries, so we include both connectivity terms in the distance constraint. For \( \delta_{A2} \), the states only differ in the status of country A. Therefore, we only include the connectivity measure of country A, \( G_A \), in the distance constraint. An additional constraint is necessary to insure that \( \delta_{A1} \) is larger than \( \delta_{A2} \) and \( \delta_{A3} \).

\[ \delta_{A1} \geq \delta_{Ai} \ \forall i \neq j. \]  \( (4.1.13) \)

To find a feasible solution to the model, solve the linear program with the decision variables,

\[ P(A^C | S_i), \ i = 1, 2, 3, 4 \]
\[ P(B^C | S_i), \ i = 1, 2, 3, 4 \]  \( (4.1.14) \)

subject to the constraints in equations (4.1.6), (4.1.7), (4.1.12), and (4.1.13) for both country A and country B. By applying Phase I of the two-phase simplex method,
we can determine whether our problem is infeasible or if feasible, we can find a basic feasible solution. For a large number of countries, this linear program in underconstrained, therefore there are many feasible transition probability matrices consistent with the constraints. Since a larger $\delta$ implies a greater value of information given knowledge of the existing state of the world, we search for the feasible solution that minimizes $\sum_k \sum_i \delta_{ki}$ for countries $k$ and all $i$.

### 4.2 Conditional Probability of a Crisis

If we are interested in the probability that a particular country develops a crisis within some time horizon, we can calculate the probability directly from the transition probability matrix. Let $J$ represent the set of states where the country of interest is in crisis. In the two country example, country $A$ is in crisis in state 3 and state 4. Then starting from state $i$, the probability that country $A$ will be in crisis for the first time at time $n$, denoted $f_i^n$, is:

\[
f_i^0 = 0,
\]

\[
f_i^n = \sum_{j \in J} P\{X_n = j, X_k \neq p, k = 1, \ldots, n - 1, p \in J | X_0 = i\}, \tag{4.2.15}
\]

where $i$ is an element of $S$. The probability of country $A$ being in crisis within the next year starting from state $i$ (where the time step in one month) is:

\[
\epsilon_i^{12} = \sum_{n=1}^{12} f_i^n. \tag{4.2.16}
\]

In order too calculate $f_i^n$, form the reduced transition probability matrix, $\tilde{P}$, by dropping the columns and rows corresponding to states in $J$. Let $I$ be the set of these remaining states (i.e. $I = S \setminus J$ with $J = \{S_3, S_4\}$). In the two country

\[\text{\footnote{See, for example, Bertsimas and Tsitsiklis (1997).}}\]
example,

\[ \tilde{P} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}. \] (4.2.17)

We have dropped the columns and rows corresponding to states 3 and 4. The first
transition probability becomes:

\[ f_i^n = \sum_{j \in J} p_i' \tilde{P}^{n-2} p_{Ij}, \] (4.2.18)

where \( p_i' \) and \( p_{Ij} \) are vectors. The matrix \( \tilde{P} \) is raised to the power \( n - 2 \) because
we are considering the probability of paths that enter the states represented by the
reduced matrix on its first step, remain there for the next \( n - 2 \) steps, and enter one
of the states in \( J \) on the final step.
Chapter 5

Analyzing the Dynamics of Financial Crises

This chapter presents the results from applying the Markov chain analysis from Section 4.1 to a two country example and a three country example. We present the transition probability matrices computed from hypothetical parameters for GDP, trade flows, and crisis probabilities and analyze the dynamics implied by these matrices.

5.1 An Example with Two Countries

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td></td>
</tr>
<tr>
<td>Country A</td>
<td>100</td>
</tr>
<tr>
<td>Country B</td>
<td>10</td>
</tr>
<tr>
<td>Trade flows</td>
<td></td>
</tr>
<tr>
<td>A to B</td>
<td>5</td>
</tr>
<tr>
<td>B to A</td>
<td>5</td>
</tr>
<tr>
<td>Crisis probability, $\pi$</td>
<td></td>
</tr>
<tr>
<td>Country A</td>
<td>0.01</td>
</tr>
<tr>
<td>Country B</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table 5.1: Parameters for the Two Country Example.

Using the parameters given in Table 5.1, a transition probability matrix was com-

39
puted for the two country example using the constraints outlined in Section 4.1. Setting conditional probability distance scaling factors, $\beta_{ij}$, for all countries $i$ and conditional probability differences, $\delta_{ij}$, to 0.8, we obtain an objective function value $\sum_k \sum_i \delta_{ki}$ of 3.22 and a transition probability matrix (see equation (4.1.2)) of

$$P = \begin{bmatrix}
0.99 & 0.01 & 0.00 & 0.00 \\
0.18 & 0.76 & 0.01 & 0.05 \\
0.28 & 0.00 & 0.71 & 0.01 \\
0.04 & 0.16 & 0.15 & 0.65
\end{bmatrix}.$$  \hspace{1cm} (5.1.1)

What is particularly striking is the high values of the self-transition probabilities, $p_{33}$ and $p_{44}$. However, this is consistent with small probabilities of transitioning to state 3 or state 4 in the first place. The "persistence" of state 3 and state 4 may be high if the probabilities of reaching those two states are extremely low from state 1 or state 2. Next, we can calculate the probability that country A develops a crisis given a particular state of the world over the 12 months as defined in equation (4.2.16). Notice that this is a different quantity than the long run probability of crisis (i.e., what is the probability that country A is in crisis at any point in time).

<table>
<thead>
<tr>
<th>Initial State</th>
<th>Probability, $c_{iA}^{12}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. $A^TB^T$</td>
<td>0.02</td>
</tr>
<tr>
<td>2. $A^TB^C$</td>
<td>0.19</td>
</tr>
<tr>
<td>3. $A^C B^T$</td>
<td>0.72</td>
</tr>
<tr>
<td>4. $A^C B^C$</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Table 5.2: Probability that Country A will Develop Crisis Within 12 Months.

In actual episodes of contagion, it is popularly believed that when one country experiences a crisis, other countries are more likely to follow suit. The 12 month crisis probabilities, $c_{iA}^{12}$, given in Table 5.2 confirm that when country B is in crisis, country A is more likely to develop a crisis within 12 months. In particular, being in state $A^TB^C$ leads to a 12 month crisis probability of 0.19, more than nine times higher than if the world had started in state $A^TB^T$. In contrast, if the two countries
experienced crisis independently then we could treat possibility of crisis as a series of Bernoulli trials with probability equal to the long run probability of crisis, \( \pi_A \). In this case, the 12 month probability would be 0.11. That \( c_{2A}^{12} \) is much higher than \( c_{2A}^{11} \) is not surprising, country A’s effect on itself is large so once it goes into crisis, it is very likely to stay in crisis. Notice that the parameters and constraints yielded a feasible transition probability matrix. The linear program was also computed with alternative objective functions. In particular, when the transition probability matrix was computed using the maximization of \( \Pr\{A^C|A^TB^T\} \) as the objective function, slightly different 12 month crisis probabilities were obtained.

### 5.2 An Example with Three Countries

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td></td>
</tr>
<tr>
<td>Country A</td>
<td>100</td>
</tr>
<tr>
<td>Country B</td>
<td>20</td>
</tr>
<tr>
<td>Country C</td>
<td>10</td>
</tr>
<tr>
<td>Trade flows</td>
<td></td>
</tr>
<tr>
<td>A to B</td>
<td>10</td>
</tr>
<tr>
<td>B to A</td>
<td>10</td>
</tr>
<tr>
<td>A to C</td>
<td>5</td>
</tr>
<tr>
<td>C to A</td>
<td>5</td>
</tr>
<tr>
<td>B to C</td>
<td>5</td>
</tr>
<tr>
<td>C to B</td>
<td>5</td>
</tr>
<tr>
<td>Crisis probability, ( \pi )</td>
<td></td>
</tr>
<tr>
<td>Country A</td>
<td>0.01</td>
</tr>
<tr>
<td>Country B</td>
<td>0.02</td>
</tr>
<tr>
<td>Country C</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table 5.3: Parameters for the Three Country Example.

As in the two country example, a transition probability matrix was computed using the parameters given in Table 5.3. In this case, we set the conditional probability distance scaling factor, \( \beta_{ij} \), to 0.4 for countries \( i \) and conditional probability differences, \( \delta_{ij} \), to insure that we do not specify meaningless constraints. If the scaling factor is set too high, the constraint as defined would require that the difference be-
tween two conditional probabilities be greater than 1. This would lead immediately to an infeasible transition probability matrix. We minimize the objective function, \( \sum_k \sum_i \delta_{ki} \), to 7.2 to obtain the transition probability matrix,

\[
P = \begin{bmatrix}
0.97 & 0.03 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.45 & 0.32 & 0.11 & 0.08 & 0.02 & 0.01 & 0.01 \\
0.31 & 0.23 & 0.21 & 0.16 & 0.03 & 0.02 & 0.02 \\
0.06 & 0.29 & 0.09 & 0.43 & 0.01 & 0.04 & 0.02 \\
0.70 & 0.02 & 0.00 & 0.00 & 0.27 & 0.01 & 0.00 \\
0.31 & 0.22 & 0.08 & 0.06 & 0.15 & 0.11 & 0.04 \\
0.22 & 0.16 & 0.15 & 0.11 & 0.13 & 0.09 & 0.08 \\
0.04 & 0.20 & 0.06 & 0.30 & 0.03 & 0.13 & 0.04 \\
\end{bmatrix}
\]  \hspace{1cm} (5.2.2)

We then calculate the conditional probability that country A will develop a crisis in the next 12 months as defined in equation (4.2.16).

<table>
<thead>
<tr>
<th>Initial State</th>
<th>Probability, ( c_{iA}^{12} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. ( A^T B^T C^T )</td>
<td>0.05</td>
</tr>
<tr>
<td>2. ( A^T B^T C^C )</td>
<td>0.10</td>
</tr>
<tr>
<td>3. ( A^T B^C C^T )</td>
<td>0.15</td>
</tr>
<tr>
<td>4. ( A^T B^C C^C )</td>
<td>0.20</td>
</tr>
<tr>
<td>5. ( A^C B^T C^T )</td>
<td>0.32</td>
</tr>
<tr>
<td>6. ( A^C B^T C^C )</td>
<td>0.36</td>
</tr>
<tr>
<td>7. ( A^C B^C C^T )</td>
<td>0.41</td>
</tr>
<tr>
<td>8. ( A^C B^C C^C )</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Table 5.4: Probability that Country A will Develop Crisis Within 12 Months.

Once again, the conditional 12 month crisis probabilities, \( c_{iA}^{12} \), for country A are higher when either country B or country C is experiencing a crisis when compared to the tranquil state. Country B has a greater impact on \( c_{iA}^{12} \) than country C. This is not surprising because country B has greater trade flows with country A. Interestingly, \( c_{iA}^{12} \) is lower than the independent 12 month crisis probability of 0.11, but country C does contribute to increases in \( c^{12} \) when both country B and country C are in crisis. This suggests that small trading partners do not increase the likelihood of a crisis in
the home country when their problems are isolated, but could amplify the impact of a crisis in major trading partners on the home country.

In both the two country example and the three country example, we are able to obtain a feasible transition probability matrix consistent with a small set of reasonable constraints. By assuming that the world is governed by dynamics implied by that transition probability matrix, this chapter characterizes the probabilities of events of interest such as the probability that a particular country will develop a crisis within the next year. Both of these examples contained a small number of decision variables (8 and 24, respectively). If we were to increase the number of countries to over 40, the number of decision variables as described in Table 4.1 would quickly reach levels beyond current LP solvers. Reducing the number of countries to 20, however, would reduce the number of decision variables to about 2.1 million, which would be well within the capability of current solvers.
Chapter 6

Measuring Financial Crises

6.1 Exchange Market Pressure

The exchange market pressure index introduced by Eichengreen, Wyplosz, and Rose (1996) captures the notion of a currency crisis in a measure that can then be used to test for the explanatory power of macroeconomic variables. The EMP index incorporates the three elements that are impacted by a speculative attack: the exchange rate, short-term interest rates, and central bank reserves. This chapter follows the version of the EMP used by Forbes (2001),

\[ \text{EMP}_{i,t} = \alpha \%\Delta e_{i,t} + \beta [(i_{i,t} - i_{U,t}) - (i_{i,y} - i_{U,y})] - \gamma (%\Delta r_{i,t} - %\Delta r_{U,t}) \]  \hspace{1cm} (6.1.1)

where: \( e_{i,t} \) denotes the price of U.S. dollars in country \( i \)'s currency at time \( t \); \( i_{i,t} \) is country \( i \)'s interest rate; \( i_{U,t} \) is the U.S. interest rate; \( i_{i,y} \) is country \( i \)'s interest rate calculated as a rolling average for the previous year starting at time \( t - 1 \); \( i_{U,y} \) is the U.S. interest rate calculated as a rolling average for the previous year starting at time \( t - 1 \); \( r_{i,t} \) is the ratio of country \( i \)'s international reserves to narrow money (M1); \( r_{U,t} \) is the ratio of international reserves to narrow money (M1) in the U.S. The weights \( \alpha, \beta, \) and \( \gamma \) are set to the inverse of the standard deviation for each series to equalize conditional volatilities. \( %\Delta \) is measured as the weekly percentage log difference, for
example,
\[ \%\Delta e_{i,t} = 100(\ln e_{i,t} - \ln e_{i,t-1}) \]

To identify periods of crisis, a critical value of EMP is determined using the mean and standard deviation of all EMP observations. In particular, if

\[ \text{EMP}_{i,t} > \mu_{\text{EMP}} + 5\sigma_{\text{EMP}}, \] (6.1.2)

then country \( i \) is designated to be in crisis at time \( t \), where \( \mu_{\text{EMP}} \) is the mean of the EMP series, and \( \sigma_{\text{EMP}} \) is the standard deviation over all countries and observations in the sample. Additionally, we follow the convention of Forbes (2001) by grouping all crisis weeks within one year of the initial crisis event into one crisis event. Subsequent crisis weeks beyond one year are labelled as part of a separate crisis event.

### 6.2 Extremal Value Theory

The probability of a crisis in a country can be obtained by dividing the number of crisis weeks by the total number of EMP observations. However, for countries that do not experience a crisis during the sample period, this value would be zero and imply that a crisis is impossible in these countries. Alternatively, to estimate the probability of crisis events, assume that the EMP of each country is a random variable with the right tail distributed according to the following extreme value distribution\(^1\)

\[ F(x_k) = 1 - D_k x_k^{-\alpha}, \quad x_k > 0, \] (6.2.3)

where \( x_k \) take on the EMP values of country \( k \); \( \alpha_k \) is a parameter greater than zero to be estimated. We assume that \( D_k = u_k^{\alpha_k} \) and that \( u_k \) is equal to the sample mean plus one sample standard deviation,

\[ u_k = \mu_k + \hat{\sigma}_k = \frac{1}{n} \sum_{j=1}^{n} x_j + \sqrt{\frac{n \sum_{j=1}^{n} x_j^2 - (\sum_{j=1}^{n} x_j)^2}{n(n - 1)}}. \] (6.2.4)

\(^{1}\)See Embrechts, Klüppelberg, and Mikosch (1997), pages 330-331.
The cutoff, $u_k$, is chosen so that the density function is convex and thus better approximated by the extreme value distribution. Only EMP values for country $k$ that are greater than the cutoff, $u_k$, are used to estimate the distribution. Hill's maximum likelihood estimator of $\alpha_k$ is (Embrechts, Klüppelberg, and Mikosch, 1997)

$$\hat{\alpha}_k = \left(\frac{1}{t} \sum_{\{x_{j,k} \geq u_k\}} \ln \left(\frac{x_j}{u_{j,k}}\right)\right)^{-1},$$

(6.2.5)

where the $t$ values of $x_{j,k}$ are greater than the cutoff, $u_k$. Estimate $\alpha_k$ for each country separately. Let $\bar{C}$ be the value of the crisis cutoff. Then the estimated probability of a crisis for country $k$ is

$$P_k(X_k > \bar{C}) = 1 - F_k(\bar{C}) = u_k^{\hat{\alpha}_k} \bar{C}^{-\hat{\alpha}_k}.$$

(6.2.6)
Chapter 7

Empirical Results

This chapter presents the results of an empirical study of the crisis probabilities of 44 countries. We first tabulate values of the exchange market pressure and then use the EMP time series as a measure of crisis in each country. Estimates of the long run crisis probabilities, \( \hat{\pi} \), of each country can then be used to calibrate the model of financial crisis dynamics.

7.1 EMP Calculations

We measure the incidence of crisis using the version of the exchange market pressure index used by Forbes (2001). Using equation (6.1.1), we calculate EMP time series for 44 countries from 07/01/94 to 06/30/99. The countries were chosen to match the ones included in the Forbes data set to facilitate comparison. Countries in the sample are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Czech Republic, Denmark, Ecuador, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Peru, Philippines, Poland, Portugal, Russia (after 1996), Singapore, Slovak Republic, South Africa, Spain, Sweden, Switzerland, Thailand, the U.K., and Venezuela. As the reference country, the U.S. is included, but cannot experience a crisis by definition. Five years of data for 44 countries produced 11,440 weekly EMP data points.
In order to calculate the EMP time series, we use data on exchange rates relative to the U.S. dollar, interest rates, international reserves, and the money supply.

### 7.1.1 Exchange Rates

All exchange rates are downloaded weekly from Datastream under *Reuter's Spot Rates*. Exchange rates are expressed as the local currency per U.S. dollar with the exception of the Slovak Republic where the national exchange rate as reported by Datastream was used because the spot rate was not available. The starting date for all exchange rate data is the first week of July, 1994. Exchange rates for the Czech Republic and Poland were filled in from the Bloomberg spot rates from July, 1994, to January, 1995. Exchange rates for Ecuador and Morocco were filled in from the Bloomberg spot rates from July, 1994, to December, 1994.

### 7.1.2 Interest Rates

Interest rates were downloaded starting from July, 1993 (to calculate the rolling average of the interest rates) from Datastream. If available, weekly interbank rates for each country were used; if not available, the money call rates were used. If neither were available, the shortest-term rates available were used. For the U.S. interest rate, we used the Federal Funds rate. For Brazil, the earliest data were from October, 1994, when they fixed their interest rates to U.S. rates. Only monthly rates were available for Greece, Hungary, and Peru, so the weekly data were interpolated. For Israel, the interest rate data appear suspiciously stable over several months, but no correction was made. Missing values were backfilled with the first available values for each of the following countries: Brazil (10/14/94), Chile (08/26/94), Ecuador (01/07/94), Korea (08/06/94), Malaysia (08/13/94), Morocco (12/31/94), and Venezuela (12/02/94).

### 7.1.3 International Reserves

Monthly international reserves data are from the IMF *International Financial Statistics* CD-ROM (line 1L.dzf). Weekly data were interpolated from the monthly data.
7.1.4 Money Supply

Monthly money supply data are from the IMF International Financial Statistics CD-ROM for 31 countries (line 34..zf). The countries were Argentina, Australia, Brazil, Canada, Chile, Colombia, Czech Republic, Denmark, Ecuador, Hungary, India, Indonesia, Israel, Japan, Korea, Malaysia, Mexico, Morocco, New Zealand, Norway, Peru, Philippines, Poland, Russia (after 1996), Singapore, Slovak Republic, South Africa, Switzerland, Thailand, the U.S., and Venezuela. We interpolated weekly data from the monthly data and converted the data from national currency to U.S. dollars. For the other countries, narrow money supply (M1) data from Datastream were used.

7.1.5 Comparison of Crisis Events

Reserve to money supply ratios were calculated by first converting international reserves from local currency to U.S. dollars. Then, M1 values were converted from local currency to U.S. dollars using the exchange rates. The weights $\alpha$, $\beta$, and $\gamma$ in equation (6.1.1) were calculated as the inverse of the standard deviation for each series. Standard deviations were calculated using all data points over time and across countries. As shown in Table 7.1, with the exception of the May, 1997, crisis event in Venezuela and a crisis event in Japan in late 1998 and early 1999, there is agreement between our calculations of crisis events and the calculation from Forbes (2001). Minor differences in EMP values can be attributed to the use of slightly different time series, particularly for the short-term interest rates and the narrow money supply. Using lower critical values to define crisis events (for example, $1.5\sigma$ or $3\sigma$) does not have a large impact on the resulting classification of crisis events.

7.2 Crisis Probabilities

From the EMP time series for each country, we can estimate the probability that the country will experience a crisis in any period. If we treat the data in our sampling period as draws from an underlying distribution, we can estimate the right tail of
<table>
<thead>
<tr>
<th>Country</th>
<th>Crisis Weeks (EMP value)</th>
<th>Forbes (2001)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Mexico</td>
<td>12/02/94 (12.6); 02/24/95 (13.4); 03/03/95 (10.71); 03/24/95 (12.73); 03/31/95 (9.12)</td>
<td>12/19/94-12/25/94; 01/16/95-01/29/95; 02/27/95-03/05/95; 03/13/95-03/19/95</td>
</tr>
<tr>
<td>2. Ecuador (1)</td>
<td>01/27/95 (9.53); 02/03/95 (30.13); 02/10/95 (20.28); 11/03/95 (14.17)</td>
<td>01/23/95-02/12/95; 10/30/95-11/05/95</td>
</tr>
<tr>
<td>3. Ecuador (2)</td>
<td>11/16/98 (7.89); 01/15/99 (7.31); 01/22/99 (10.39); 01/29/99 (7.58)</td>
<td>10/19/98-10/25/98; 01/11/99-01/17/99; 03/01/99-03/07/99</td>
</tr>
<tr>
<td>4. Venezuela (1)</td>
<td>07/08/94 (10.03);</td>
<td>12/11/95-12/17/95; 04/15/96-04/21/96</td>
</tr>
<tr>
<td>5. Venezuela (2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Thailand</td>
<td>06/19/98 (18.04); 12/11/98 (8.27)</td>
<td>06/15/98-06/21/98; 09/14/98-09/20/98</td>
</tr>
<tr>
<td>7. Philippines</td>
<td>10/03/97 (9.21); 10/10/97 (8.52)</td>
<td>07/07/97-07/13/97; 09/29/97-10/05/97</td>
</tr>
<tr>
<td>8. Indonesia</td>
<td>11/07/97 (11.44); 01/30/98 (37.77); 02/06/98 (12.36); 02/13/98 (7.46); 03/13/98 (8.76); 03/27/98 (13.04); 04/10/98 (10.82); 05/22/98 (8.26); 07/17/98 (13.34); 08/21/98 (11.06); 10/09/98 (11.85); 10/16/98 (8.45); 11/13/98 (8.64)</td>
<td>08/11/97-08/17/97; 08/25/97-08/31/97; 09/29/97-10/05/97; 12/08/97-12/14/97; 01/19/98-01/25/98; 03/02/98-03/08/98; 05/18/98-05/24/98</td>
</tr>
<tr>
<td>9. Korea</td>
<td>01/16/98 (9.15); 01/30/98 (11.22)</td>
<td>12/29/97-01/04/98</td>
</tr>
<tr>
<td>10. India</td>
<td>01/23/98 (10.66)</td>
<td>01/19/98-01/25/98</td>
</tr>
<tr>
<td>11. Russia</td>
<td>05/29/98 (11.6); 08/07/98 (9.29); 09/11/98 (50.56); 09/25/98 (19.18); 10/02/98 (8.15)</td>
<td>05/18/98-05/31/98; 07/06/98-07/12/98; 08/10/98-09/06/98; 09/14/98-09/20/98</td>
</tr>
<tr>
<td>12. Slovak Republic</td>
<td>10/02/98 (7.69)</td>
<td>09/28/98-10/04/98</td>
</tr>
<tr>
<td>13. Brazil</td>
<td>04/07/95 (7.48); 02/05/99 (7.78)</td>
<td>01/11/99-01/17/99</td>
</tr>
<tr>
<td>14. Argentina</td>
<td>03/03/95 (12.67)</td>
<td>03/06/95-03/12/95</td>
</tr>
<tr>
<td>15. Czech Republic</td>
<td>05/30/97 (9.89)</td>
<td>05/19/97-05/25/97</td>
</tr>
<tr>
<td>16. Japan</td>
<td>10/09/98 (9.92); 04/02/99 (8.44); 05/28/99 (7.84)</td>
<td></td>
</tr>
</tbody>
</table>

Note: 44 countries were evaluated from 07/01/94 to 06/30/99 with $\mu_{\text{EMP}} = -0.14$, $\sigma_{\text{EMP}} = 1.48$, and the critical value ($\mu_{\text{EMP}} + 5\sigma_{\text{EMP}}$) = 7.24. Crisis weeks within 2 weeks of a crisis week in Forbes (2001) are indicated in bold. Crisis events were also found for Austria, the Netherlands, and Portugal for 01/01/99, but were removed because they are probably an artifact of the data related to conversion to the Euro. EMP values were averaged across countries for a given week and then the weekly values were averaged to obtain $\mu_{\text{EMP}}$. Similarly, the standard deviation was calculated across countries for week and the values were averaged to obtain $\sigma_{\text{EMP}}$. 

Table 7.1: Crisis Events from July 1, 1994, to June 30, 1999.
the density function to obtain crisis probabilities. Using the EMP values tabulated in Section 7.1, we go on to estimate the long run crisis probabilities as outlined in Section 6.2. The long run crisis probability estimates, \( \hat{\pi} \), are presented in Table 7.2.

<table>
<thead>
<tr>
<th>Country</th>
<th>Long Run Crisis Probability, ( \hat{\pi} )</th>
<th>Country</th>
<th>Long Run Crisis Probability, ( \hat{\pi} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Argentina</td>
<td>0.071</td>
<td>23. Japan</td>
<td>0.050</td>
</tr>
<tr>
<td>2. Australia</td>
<td>0.023</td>
<td>24. Korea</td>
<td>0.156</td>
</tr>
<tr>
<td>3. Austria</td>
<td>0.015</td>
<td>25. Malaysia</td>
<td>0.170</td>
</tr>
<tr>
<td>4. Belgium</td>
<td>0.031</td>
<td>26. Mexico</td>
<td>0.222</td>
</tr>
<tr>
<td>5. Brazil</td>
<td>0.167</td>
<td>27. Morocco</td>
<td>0.012</td>
</tr>
<tr>
<td>6. Canada</td>
<td>0.010</td>
<td>28. Netherlands</td>
<td>0.023</td>
</tr>
<tr>
<td>7. Chile</td>
<td>0.042</td>
<td>29. New Zealand</td>
<td>0.019</td>
</tr>
<tr>
<td>8. Colombia</td>
<td>0.078</td>
<td>30. Norway</td>
<td>0.040</td>
</tr>
<tr>
<td>9. Czech Republic</td>
<td>0.031</td>
<td>31. Peru</td>
<td>0.051</td>
</tr>
<tr>
<td>10. Denmark</td>
<td>0.023</td>
<td>32. Philippines</td>
<td>0.105</td>
</tr>
<tr>
<td>11. Ecuador</td>
<td>0.375</td>
<td>33. Poland</td>
<td>0.031</td>
</tr>
<tr>
<td>12. Finland</td>
<td>0.013</td>
<td>34. Portugal</td>
<td>0.039</td>
</tr>
<tr>
<td>13. France</td>
<td>0.025</td>
<td>35. Russia</td>
<td>0.585</td>
</tr>
<tr>
<td>14. Germany</td>
<td>0.025</td>
<td>36. Singapore</td>
<td>0.016</td>
</tr>
<tr>
<td>15. Greece</td>
<td>0.029</td>
<td>37. Slovak Republic</td>
<td>0.044</td>
</tr>
<tr>
<td>16. Hong Kong</td>
<td>0.032</td>
<td>38. South Africa</td>
<td>0.126</td>
</tr>
<tr>
<td>17. Hungary</td>
<td>0.024</td>
<td>39. Spain</td>
<td>0.035</td>
</tr>
<tr>
<td>18. India</td>
<td>0.112</td>
<td>40. Sweden</td>
<td>0.011</td>
</tr>
<tr>
<td>19. Indonesia</td>
<td>0.547</td>
<td>41. Switzerland</td>
<td>0.028</td>
</tr>
<tr>
<td>20. Ireland</td>
<td>0.028</td>
<td>42. Thailand</td>
<td>0.090</td>
</tr>
<tr>
<td>21. Israel</td>
<td>0.027</td>
<td>43. UK</td>
<td>0.006</td>
</tr>
<tr>
<td>22. Italy</td>
<td>0.025</td>
<td>44. Venezuela</td>
<td>0.249</td>
</tr>
</tbody>
</table>

Note: Crisis probabilities were estimated from EMP values for 44 countries from 07/01/94 to 06/31/99.

Table 7.2: Estimates of Long Run Crisis Probabilities, \( \hat{\pi} \).  

Countries that experience crisis during the sample period yield crisis probability estimates that are too high. For that reason, it probably makes sense to use the extreme value distribution to estimate crisis probabilities for countries that do not experience a crisis during the sample period. Although some of the crisis probabilities are very large (Indonesia, 54.7% and Russia, 58.5%), many of the crisis probabilities are low, particularly for the developed economies. Note that Russia has a crisis probability almost 100 times larger than that of the U.K. Mechanically, the countries that
experience a crisis during our sample period have higher values of $\hat{\pi}$ than countries that did not experience a crisis. The exceptions are consistent with newspaper coverage of crisis events during this period. In particular, the Czech Republic and the Slovak Republic have low values of $\hat{\pi}$, 0.031 and 0.044, respectively. Coverage of crisis in the Czech Republic and the Slovak Republic was not notable during the weeks in question. In contrast, Malaysia was widely reported to be experiencing crisis as part of the East Asian Crisis of 1997. This is consistent with its relatively higher $\hat{\pi}$ of 0.170.

Along with the bilateral trade data, these estimates of long run crisis probability can be used to calibrate a Markov chain model of global financial crises.
Chapter 8

Conclusion

Several financial crises in the past decade have been marked by contagion, the spread of a crisis from one country to another. These crises have received significant press coverage and stimulated a substantial amount of research. A review of the previous literature shows that while much attention has been paid to testing whether various macroeconomic and trade variables can explain the spread of crises, there has been little focus on explicit modeling of crises dynamics. This thesis presents an unique approach to modeling the dynamics of global financial crises.

Chapter 3 presents a series of maps showing bilateral trade flows from 1980 to 2000. These trade flows along with the long run crisis probabilities become calibration parameters for a model of crises.

Chapter 4 presents the Markov chain model of global financial crises. The main element of the model is a transition probability matrix which is found using a linear program. This linear program includes a set of probability law constraints, total probability constraints, long run probability constraints, and bilateral trade flow constraints. Based on the transition probability matrix, we present a measure of the probability that a country would develop a crisis within 12 months starting from any given state of the world.

Chapter 5 presents the results of two country and three country examples of the Markov chain model. A transition probability matrix was obtained using hypothetical parameters. The results of the examples analyzed in Chapter 5 have some interesting
implications. In particular, they suggest that concern in the home country when a crisis afflicts a major trading partner is warranted. Additionally, officials in the home country should be less concerned about a crisis in lesser trading partners if it occurs in isolation, but become more active once the crisis affects multiple trading partners.

Chapter 6 presents a method to estimate a country’s long run crisis probabilities. The method builds on the notion of exchange market pressure as a measure of crisis by using an extreme value distribution to approximate the incidence of crisis. We estimate the crisis probabilities, \( \hat{\pi} \), using this extreme value distribution.

Chapter 7 presents estimates of the long run crisis probabilities, \( \hat{\pi} \), for 44 countries. When viewed alone, the disparity in crisis probabilities shows that some countries have much higher crisis probabilities. The next step is to use actual trade flows and the empirical estimates of the long run crisis probabilities, \( \hat{\pi} \), to calibrate a Markov chain model of global financial crises.
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