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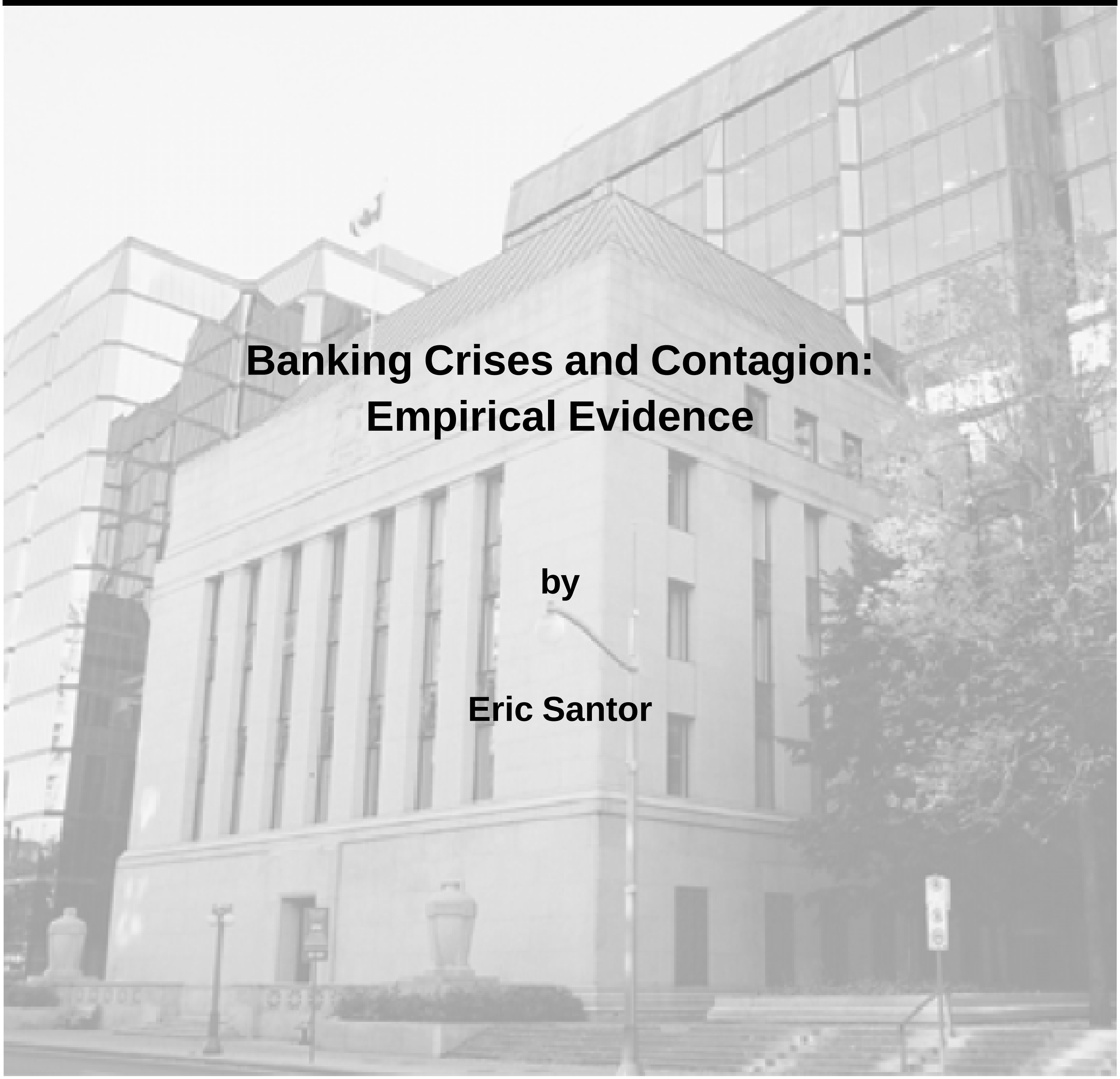

Banking Crises and Contagion: Empirical Evidence

by

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Abstract

Recent events, such as the East Asian, Mexican, Scandinavian, and Argentinian crises, have sparked considerable interest in exploring how shocks experienced by one country can spread vis-à-vis real and nominal links to other countries' banking systems. Given the large costs associated with banking-system failures, both economists and policy-makers are interested in predicting the onset of banking crises and assessing the likelihood of contagion during crisis events. The author uses cross-country panel data to examine contagion across banking systems in developed and developing countries. Particular attention is paid to the construction of the cross-country sample: matching-method techniques are used to construct a suitable control-group sample analogue to the set of crisis countries to accurately quantify the probability of the occurrence of a banking crisis and the probability of banking-system contagion. The author finds that the sample choices of previous studies introduced bias into the estimates of the probability that a banking crisis would occur, owing to differences between the supports of the conditioning variables for the crisis and non-crisis country groups. Furthermore, the probability of a banking crisis increases when countries have macroeconomic characteristics similar to those that have recently experienced a crisis, regardless of the degree of actual economic linkages between the countries. This suggests that information contagion plays a larger role than previously suspected.

JEL classification: F30, G20
Bank classification: International topics

Résumé

Les événements récents, tels que les crises qui ont secoué l'Asie orientale, le Mexique, la Scandinavie et l'Argentine, ont suscité un vif intérêt pour l'étude de la façon dont les chocs se propagent d'un système bancaire à l'autre du fait des liens d'ordre réel ou financier qui existent entre les pays. Étant donné les coûts importants associés aux défaillances des systèmes bancaires, les économistes tout comme les autorités cherchent à prévoir le déclenchement des crises bancaires et à évaluer leur risque de contagion. Dans son étude, l'auteur examine la contagion au sein des systèmes bancaires de pays développés et en développement à l'aide de données longitudinales multipays. Soucieux de quantifier avec précision la probabilité qu'une crise bancaire survienne et qu'elle se propage d'un système bancaire à l'autre, il apporte un soin particulier à la sélection de l'échantillon et utilise des techniques de rapprochement afin de constituer un groupe témoin analogue au groupe des pays victimes d'une crise. L'auteur constate que, dans les études antérieures, le choix des échantillons introduisait un biais dans les estimations de la probabilité d'une crise bancaire parce que les supports des variables explicatives n'étaient pas les mêmes entre les deux groupes de pays considérés. Il observe en outre que la probabilité d'une crise bancaire augmente dans les pays dont les caractéristiques macroéconomiques ressemblent à celles des pays qui ont récemment connu une crise, quelle que soit l'importance des liens économiques réels entre ces pays, ce qui donne à penser que la contagion mimétique joue un rôle plus grand qu'on ne l'avait d'abord soupçonné.

Classification JEL : F30, G20
Classification de la Banque : Questions internationales

1. Introduction

The role of central banks, the International Monetary Fund (IMF), and national governments in preventing and mitigating the negative consequences of banking crises and "contagion" is a subject of ongoing research for many institutions. Despite considerable efforts to model empirically the nature of banking crises, the results of current empirical analyses are not robust to alternative specifications.[1] Likewise, little is known with respect to the presence, and effect, of contagion across banking systems. This paper seeks to answer the following questions left unanswered in the literature. First, given the limitations of the data, can the onset of a banking crisis be accurately predicted? Second, does the theoretical literature of banking crises and contagion provide suitable hypotheses that can be empirically tested? And third, conditional on the ability to predict banking crises, can the existence of information contagion be assessed? That is, does the occurrence of a crisis in one market allow the prediction of crises in other markets, over and above the effects of macroeconomic interconnections?

The impetus for this research is clear: a recurring problem of financial markets throughout the twentieth century was their tendency to experience crises. More recently, financial deregulation and the global integration of markets has led to a heightened awareness of the potential fragility of financial systems in the face of crisis events. Banking crises are numerous: Glick and Hutchinson (1999) document 90 banking crises since 1975 across a sample of 90 developing and developed countries. High-profile examples of banking crises, such as the Mexican, East Asian, Scandinavian, and Argentinian crises, reinforce this empirical reality. The

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[1] The determinants of banking crises can vary widely, depending on sample choice and specification, resulting in different interpretations of the relevance of macro predictors across different empirical models. Given the current emphasis of the IMF and central banks on constructing "early warning systems" (EWS) and "stress indicators" to quantify the potential risks in the financial system, it is important to be confident of the methods of empirical assessment used in these processes.

very nature of banks renders crises more costly than for most other groups of firms.[2] Through payment and settlement systems, interbank deposits and loans, and due to their wide participation in financial markets as market-makers, the failure of one bank can affect the liquidity and/or solvency of many market participants.[3] Banks are also potentially more fragile than other firms, since they can function only if depositors feel that their savings are safe. This inherent fragility renders banks susceptible to deposit runs, both within and across banking systems.

The implications of the special nature of banking crises, and the potential for contagion to propagate their adverse effects, have not been ignored by policy-makers. The recent East Asian crisis provoked considerable discussion about how to best design the global financial system to limit the scope and impact of any particular banking crisis.[4] This event also highlighted the fact that banking crises are often associated with currency crises, and that the combination of these two events can have serious macroeconomic consequences for the affected countries. It is thus clearly recognized among policy-makers that the ability to predict banking crises (and the potential for contagion) is critical for the sound management of the world financial system, particularly in light of continued weakness in the Japanese banking system, high-profile corporate bankruptcies in the United States in the aftermath of the sharp decline in asset prices, and the operational risks associated with highly integrated markets.

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[2] The potential costs of banking crises are large: Frydl (1999) estimates, for a sample of 29 developed and developing countries, the average cost of a banking crisis, in terms of lost output and resolution costs, to be over 8 per cent of GDP, while Hoggarth, Reis, and Saporta (2001) use a sample of 24 countries and measure lost output at 15–20 per cent of GDP annually per crisis episode.

[3] The role of banks as intermediaries for savings also emphasizes their importance to the economy.

[4] During the East Asian crisis, Thailand, Indonesia, Malaysia, South Korea, and the Phillipines all suffered banking crises.

This paper is organized as follows. Section 2 defines and describes contagion and how it can occur within and between banking systems. Section 3 reviews the existing theoretical and empirical models of banking crises and contagion. Section 4 discusses the empirical issues surrounding existing empirical models of banking crises, paying particular attention to issues of functional form and sample selection. Section 5 describes an empirical model of cross-country contagion and banking crises. Section 6 offers data, descriptive statistics, and results, and it augments the empirical analysis by using matching method techniques. Section 7 offers conclusions and suggestions for future research.

2. Defining Contagion[5]

Throughout the literature, the term contagion describes the process by which a crisis in one market affects outcomes in financial markets, currency markets, and/or banking systems. This section focuses on two definitions of contagion—fundamental and investor-based—and assesses how they can lead to banking crises.

2.1 Fundamentals-based contagion

Fundamentals-based contagion describes shocks that affect markets owing to economic links The term covers three categories: common shocks, trade linkages, and financial linkages (Dornbusch, Park, and Claessens 2000). Crises can result from common shocks such as changes in U.S. interest rates, the price of oil, or the growth rate of the OECD countries, which can then lead to contagion due to the normal interdependence of economies. Trade linkages can also be a pathway for contagion. Because a crisis affects a country's demand for imports, exporting countries will be negatively affected by the new, lower level of demand. Likewise, the crisis country may be forced to engage in a competitive devaluation, thereby affecting other exporting

[5] This section draws heavily on Dornbusch, Park, and Claessens (2000).

countries. Lastly, a crisis can affect other countries by reducing the direction and magnitude of capital flows. In such cases, contagion is not caused by investor panic or herding, but by real-side interdependencies. The impact of such shocks can be contagious in that they undermine the quality of a bank's loan portfolio through credit exposures, thus leading to insolvency if credit risks are not well-managed. While fundamental contagion is seemingly very important, it has not been the focus of most studies. It is relatively straightforward to anticipate the consequences that common shocks will have on the probability of a banking crisis occurring, or their effect on financial system fragility.[6] Of greater concern is when contagion is caused by factors other than fundamentals, since those shocks are less likely to be anticipated, and their negative impacts are more difficult to assess.

2.2 Investor-based contagion

The term investor-based contagion describes the process by which shocks that affect one market are transmitted to related markets despite the lack of actual fundamental relationships between the respective markets. Contagion is transmitted by two primary channels: (i) liquidity and incentives, and (ii) the sharing of information (Dornbusch, Park, and Claessens 2000). In the former case, shocks to one market can cause a decline in asset prices, which, in turn, can have implications for other markets. This is particularly true for banks that utilize Value-at-Risk models, where there can be balance-sheet effects (Schinasi and Smith 2000). A decline in one market's asset prices may lead the bank to reduce its overall exposure to similar assets with correlated outcomes. For instance, if an emerging economy experiences a banking crisis that causes the asset prices for that country to fall, a bank's Value-at-Risk model may require similar

[6] That is, the effect of a recesssion on banking systems is well-known and supposedly accounted for by regulatory capital requirements, due diligence, and credit-rating agencies. Normal banking-system stress due to the business cycle is not a primary concern of the banking-crisis and contagion literature.

type assets to be sold off from the portfolio.[7] This balance-sheet effect may lead to a deterioration in the prices of assets held in countries which are not experiencing a crisis, but which appear to be similar to the crisis country. In this way, a banking crisis in one country could lead to a crisis in another country.

The information-driven channel of investor-based contagion results from the fact that the onset of a crisis in one market may lead investors to reassess the risks associated with investments in other markets. This "visible similarity" contagion is also known as the "wake-up call," and is often characterized by "herding" behaviour (Ahluwalia 2000).[8] Given that there is imperfect information in asset markets and assuming a fixed cost to collecting information, small investors may be forced to follow the actions of a few large (and seemingly well-informed) investors (Agenor and Aizenman 1997).[9] Thus, the arrival of information regarding a crisis in one country may lead to wake-up calls in similar countries. This would lead to behaviour that would induce asset prices to fall in the affected countries, thereby undermining banks' balance sheets. While such behaviour may be collectively irrational, individual rationality implies that the crisis event could lead to contagion.

2.3 Banking contagion within and across countries

In spite of the independence of a failing bank, there are three main pathways by which its (or a banking system's) failure can affect other banks. First, other banks can be affected through exposures in payment systems, otherwise known as systemic risk.[10] For instance, the failure of a bank that participates in a payments system can lead to liquidity problems for banks that did not

[7] For instance, a fall in the price of Brazilian debt may lead the bank to reduce its exposure to Mexican debt.
[8] While herding may seem irrational at the macroeconomic level, for the individual, such behaviour may be rational.
[9] Alternatively, since many large investors are managed by agents who face mean-performing incentives, the desire to replicate the actions of others may lead to herding behaviour.
[10] The relative importance of each channel naturally varies from country to country. Nevertheless, given the ever-increasing integration of financial markets, each pathway is important in its own right.

receive expected payments in a timely fashion. Banks that face such liquidity shortages could then be forced to withhold repayments themselves, leading to further liquidity shortages and ultimately to insolvency. Given the wide participation of banks in multiple payments systems both domestically and internationally, the potential for contagion associated with systemic risk is substantial.

Second, bank failures can be transmitted through banks' exposures to each other in the interbank market, in which banks that are short on liquidity borrow from those that have excess liquidity, often on an overnight basis.[11] Interestingly, the vast majority of interbank lending is conducted on a non-collateralized basis. Consequently, the failure of a bank to either repay an interbank loan or to extend credit to meet the liquidity needs of another bank through interbank lending could quickly lead to insolvency. Given the large volumes of funds that are exchanged on interbank markets, there is considerable potential for contagion to occur. Therefore, if a crisis that occurs in one country affects the willingness of banks to extend interbank credit, liquidity problems, and ultimately insolvency, can occur.[12]

Third, the failure of one bank can cause agents to reassess (accurately or not) the viability of other banks. This pathway of information contagion can be considered the typical "bank-run" episode that was more a feature of the 1930s than of modern-day banking crises. The idea that one bank failure can reveal information about other potential bank failures should not be dismissed, however, since the potential impact of "herding" behaviour based on information can be significant in financial markets. In this instance, no actual linkage between banks or banking

[11] The size and scope of the international interbank market is impressive. Bernard and Bisignano (2000) estimate total interbank claims at over $6.5 trillion.

[12] Specifically, there is anecdotal evidence that the Asian crisis was largely the result of the withdrawal of funds by Japanese banks from the interbank market that had transferred liquidity to East Asian banks. As Thailand fell into crisis, other banks reconsidered their interbank exposures, and adjusted their portfolios accordingly (Bernard and Bisignano 2000).

systems is required: rather, banks may be subject to runs simply due to their apparent similarity to a set of banks that have experienced a crisis.

The existence of multiple channels of contagion increases the probability of any particular shock having widespread consequences on banking-system stability. That is, both real shocks and shifts in investor sentiment can generate effects that cause individual banks to fail, and the interdependence of banks can lead to further transmission (or amplification) of these shocks. Furthermore, the linkages through which contagion between banks can occur exist not only at the national level but also at the international level. Section 3 briefly reviews how the theoretical and empirical literature has attempted to address these issues.

3. Literature Review

3.1 Theoretical models of banking crises and contagion

While there are numerous theoretical models of banking crises, dating from Diamond and Dybvig's (1983) seminal work, there are few corresponding theoretical models of contagion and banking crises, from either a domestic or international perspective.[13] The most notable example of contagion literature is Allen and Gale (2000). Utilizing a standard Diamond and Dybvig framework where depositors consist of two types—those with early and those with late liquidity preferences—they show that, when banks are spatially separated, the existence of idiosyncratic liquidity shocks will lead to the rise of an interbank market. Assuming that there is no aggregate liquidity risk, the interbank market will ensure that regional liquidity shocks will not cause any bank to fail. Regardless of the nature of interbank linkages, optimal risk-sharing through the interbank market will occur and shocks will not lead to contagious events.

[13] See Lai (2002) for a complete survey of the banking-crises literature. Typically, most models of contagion describe a domestic banking sector, but extension to an international setting (for spatial models) is conceptually straightforward.

In their study, Allen and Gale (2000) then introduce a zero-probability aggregate liquidity shock. Contagion can occur in this environment, since banks suffer unanticipated liquidity shocks that cannot be insured against in the interbank market. The liquidity shock can cause one bank to fail, which implies that its obligations in the interbank market will not be honoured, leading to a liquidity shortage for its counterparties. This liquidity shortage can then spill over to the affected bank's counterparties, as it fails to meet its interbank obligations. The essential feature of the Allen and Gale model is that the effect of contagion depends entirely on market structure, which is exogenously determined. If interbank markets are "incomplete," then contagion will be limited to banks in the immediate region of the failing bank. Greater completeness, however, means that while the chances of contagion are higher (in that more banks will suffer liquidity shocks), the chances of a bank failure are lower, since the shock is spread across more banks.

Alternatively, Chen (1999) provides an example of how the arrival of new information can lead to contagion in interbank markets. In his model of informational contagion, there are multiple banks that invest in risky projects, and investments are positively correlated across banks. Some depositors observe perfectly the outcome of their own bank's risky project. In a subset of banks, when depositors observe the failure of the risky project, they run on their banks. Depositors at other banks, some of whom are uninformed, run on their own bank, since they believe the bank's risky project to be unsuccessful. Thus, contagion can occur even without direct linkages between banks or banking systems. The relative lack of theoretical modelling of banking crises and contagion is not surprising, since crises are difficult to model as an equilibrium outcome.[14] In fact, Allen and Gale (2000) need to impose a zero-probability

[14] Rochet and Tirole (1996) are another notable example. In their model, contagion is viewed as a disciplining device, and as a result it is hard to draw testable predictions.

aggregate liquidity shock and an exogenous interbank market structure to generate contagion. Consequently, few models can adequately explain why contagion occurs across and within banking systems.

3.2 Empirical models of banking crises and contagion

Substantial empirical literature seeks to determine whether banking crises can be characterized and/or predicted. Demirgüç-Kunt and Detragiache (1997, 1998, 2002), Eichengreen and Rose (1998), Eichengreen and Arteta (2000), Glick and Hutchinson (1999), Hardy and Pazarbasioglu (1998), Kaminsky and Reinhart (1998), and Hernandez and Valdes (2001), among others, provide mixed evidence for the determinants of banking crises. The potential usefulness (and motivation) of these studies is obvious: if the conditions under which banking crises occur can be established using widely available macroeconomic data, then policy-makers can take appropriate preventative actions.[15]

Standard empirical models of banking crises utilize cross-country macroeconomic panel data to assess the determinants of the onset of a crisis event. Data are typically gleaned from the IMF's International Financial Statistics (IFS), World Economic Outlook (WEO), and similar cross-country data sources. Early studies (Kaminsky and Reinhart 1998, Demirgüç-Kunt and Detragiache 1997) use small samples of 15–40 countries, while more recent studies (Glick and Hutchinson 1999) include up to 90 countries. Common to all studies is the underlying empirical relationship, which is defined as follows:

$$\text{Prob}(Crisis_{it} = 1) = F(X_{it}\beta) + \varepsilon_{it}, \qquad (1)$$

where $Crisis_{it}$ is a bivariate variable that takes the value of 1 if there is a banking crisis and 0 otherwise, and X_{it} is a matrix of macroeconomic indicator variables, often current or lagged.

[15] The IMF has developed the EWS based largely on this approach.

Studies include the real GDP growth rate, current account (or proxies, such as the terms of trade), government deficit, inflation rate, real interest rates, measures of credit growth, reserves, and other indicators of oncoming financial stress. Studies also include institutional information, such as the level of accounting standards, legal standards and/or the existence of deposit insurance, or recent financial liberalization. Estimation typically uses a simple probit or logit technique.

The results of these studies, while not uniformly robust, provide a few stylized relationships. Banking crises are related to slow economic growth, high inflation, high real interest rates, declining terms of trade, poor legal and accounting standards, and lower per-capita income. With respect to institutional features, Demirgüç-Kunt and Detragiache (1998, 2002) find that deposit insurance is positively related to banking crises, as is financial liberalization. The results of these studies have important policy implications, since the underlying relationships can be (and are) used to generate "stress" indexes.[16]

The treatment of contagion in the empirical literature mirrors its exposition in the theoretical literature. While numerous studies estimate the likelihood of banking crises, few, if any, examine the existence of contagion.[17] Several studies have tried to simulate the occurrence of contagion by assessing the impact of the failure of a bank in the payments system. For instance, Furfine (2001) uses Fedwire data to show how the failure of the largest bank(s) in the payments system would affect the liquidity position of its counterparties. Upper and Worms (2000) conduct a similar analysis using simulated interbank exposures in the German banking system. They estimate the optimal exposure of interbank market participants and simulate the

[16] The estimates of the coefficients can be used to generate the "weights" of the components of a stress index.

[17] There is considerable empirical literature on the incidence of contagion in financial markets and with respect to currency crises. See Rigabon (2001) for a standard treatment.

effect of a failure of the largest interbank participant.[18] The striking result of both these simulation studies is that it is difficult to induce large-scale contagious banking failures through a default in the payments system or interbank market. With a different approach, using aggregate bank data on bank capital flows, Van Rijckeghem and Weder (2000) provide evidence that banking crises in one country predict capital flows to other countries. They show that the onset of a crisis affects the flow of capital to other countries if those countries share common lenders. Van Rijckeghem and Weder, however, do not extend the analysis to predict the occurrence of banking crises per se through contagion. Before an empirical model of contagion is described, a close examination of the econometric shortcomings of banking-crises studies will highlight the difficulties associated with this type of analysis.

4. Econometric Issues: Are Existing Empirical Methodologies Sound?

4.1 Defining a banking crisis

The first issue is to define the term banking crisis. Demirgüç-Kunt and Detragiache (1997) define the term to mean that the ratio of non-performing loans to total assets is greater than 10 per cent, rescue operations cost more than 2 per cent of GDP, and/or the nationalization of banks occurs, or a bank holiday, or a guarantee of deposits.[19] Alternatively, Caprio and Klingebiel (1999) use loan losses and the erosion of bank capital to define a banking crisis. Other studies simply combine these definitions (for instance, Glick and Hutchinson 1999). In either case, banking crises are defined as binary variables, indicating that there is a discrete difference or some threshold value that differentiates a crisis from a non-crisis situation.[20] However, most studies (as does this one) conduct sensitivity analysis and the results are

[18] Their study, however, relies upon strong assumptions with respect to market structure (since it cannot be observed).
[19] Demirgüç-Kunt and Detragiache (1997) vary the magnitudes but find little difference.
[20] It could be the case that small changes in the threshold levels would produce widely differing results.

generally robust to reasonable definitions of what constitutes a crisis (as opposed to just normal variation around the business cycle). While sensitivity analysis to different definitions of banking crises is important, it is not the focus of this study.

4.2 Functional form

A more pressing concern for this paper is the sensitivity of the results to the choice of functional form. Given that there are typically few actual crisis events, the results may be affected by whether one utilizes probit, logit, or panel-data techniques. For instance, inappropriate assumptions over the distribution of the error term may lead to incorrect assessments of the likelihood of default. That is, there may be country-specific effects that are unobservable in the data: if these effects are not controlled for, then the estimates of the coefficients may be biased if the unobserved country-specific effect is correlated to observables. Therefore, a probit random-effects specification may be warranted. In this framework, the underlying assumption is that there is a randomly distributed error component, v_i (that is uncorrelated with the *X*'s), in addition to the individual-error component. Specifically, the random-effects model is:

$$\text{Prob}(Crisis_{it} = 1) = F(X_{it}\beta) + \varepsilon_{it}, \tag{2}$$

where the error term has two components:

$$\varepsilon_{it} = v_i + u_{it},$$

with v_i being a specific individual effect and u_{it} a random-error term. The error terms are normally distributed with zero means and are independent. Therefore, normalizing σ_u^2:

$$\text{Var}[\varepsilon_{it}] = \sigma_v^2 + \sigma_u^2 = \sigma_v^2 + 1,$$

and

$$\text{Corr}[\varepsilon_{it}, \varepsilon_{is}] = \rho = \frac{\sigma_v^2}{\sigma_v^2 + 1}.$$

If the random-effects model is true, then ρ, defined as the proportion of the total variance contributed by the country-level variance component ($\rho = \sigma_v^2 / (\sigma_v^2 + 1)$), should be significantly different from zero. Failure to control for this country-specific effect will result in biased estimates of the coefficients.[21] In this context, the error component v_i will capture country-level unobservables such as risk type or bank supervisorial competence. The assumptions necessary for panel-data techniques to be consistent may not be met in this environment. Under the random-effects model, if v_i is correlated with the regressors, then β will be inconsistent (essentially, this is equivalent to an omitted-variables problem). If, however, the data are sufficiently rich, then the random-effects model is feasible if the random effect is orthogonal to the regressors.[22] This paper will estimate a random-effects model in addition to the standard probit technique. The feasibility of applying panel-data techniques, and the appropriate test of orthogonality, will be addressed in future research.

4.3 Sample selection

Criticism of the banking-crisis literature centres on (and legitimately so) the issues of data quality, the definition of banking crises, and the question of which set of macro variables best quantify impending banking-system stress.[23] The issue of sample selection is largely ignored. Early studies, such as Kaminsky and Reinhardt (1998), used only 20 countries, all of which had a crisis. If it is believed that there are country-specific fixed effects that affect the probability of having a crisis, then this approach will produce biased results—the regression is essentially estimating the probability of having a crisis, conditional on having a crisis. More recent studies,

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[21] An alternative approach to the random-effects model is the logit fixed-effects model. The difference between these two models is largely "heuristic," since it amounts to believing whether the unobserved individual effect is a shift in the intercept or a difference across coefficients (Greene 2000).
[22] Fortunately, the orthogonality assumption can be tested using a simple Hausman test. See Greene (2000) for details.
[23] These shortcomings are widely acknowledged by the authors of these studies.

such as Demirgüç-Kunt and Detragiache (1997), expand their sample to include countries that have not experienced a crisis. The addition of a "control group" is critical to produce unbiased estimates of the coefficient vector. Subsequent studies following Demirgüç-Kunt and Detragiache (1997), such as those by Glick and Hutchinson (1999) and Eichengreen and Arteta (2000), include all countries for which data are available.

Simply adding as many control countries as possible may not lead to more accurate estimates of the determinants of banking crises, since it must be considered whether the control-group countries are actually comparable to the crisis countries. For instance, in Demirgüç-Kunt and Detragiache (1997), the list of countries in the control group may seem arbitrary. While the authors acknowledge the need to exclude certain countries on the basis that they may be not be comparable to the countries studied (such as some transition economies), this process is not formalized. Does including Togo and Seychelles as "control" countries make sense when the set of countries experiencing crises consists of OECD members and the emerging economies of East Asia?

The importance of choosing an appropriate control sample should not be underestimated. Heckman et al. (1996) show that the utilization of standard estimation techniques can produce biased estimates if the distributions of the characteristics of the treatment group and control group are not over the same interval and exhibit dramatically different densities when they do share values. For example, Heckman et al. show that, when evaluating the impact of job-training programs on labour-market outcomes, it is important to ensure that the control group is "similar" to the treatment group. It could be the case that the individuals who take up the program are young females with high levels of education, and that the non-participants are old males with low levels of human capital. Thus, estimating the average impact of the program across groups would not produce accurate estimates, since the program would have widely different effects for each group. In terms of the banking-crisis literature, whether the crisis countries are sufficiently similar to the control group in terms of their characteristics must be considered. That is, do the respective countries in the crisis and control groups share similar institutional and macroeconomic features that would render them comparable when exposed to a shock that could induce a banking crisis? If the latter group is not sufficiently "close," then estimation may be biased. To address this issue, this paper will utilize matching methods to construct a suitable set of control-group countries.

4.4 Matching methods

The non-experimental estimation techniques typically used in the banking-crisis literature rely on the fact that the crisis and control groups are comparable and imply common supports for the distribution of country characteristics. In particular, many banking-crisis studies assess the impact of particular country-level institutional features on the probability of a crisis. For example, to examine the impact that the implementation of deposit insurance has on the probability of a banking crisis, as in Demirgüç-Kunt and Detragiache (2002), a standard treatment-effects model would estimate the difference between deposit insurance participants and non-participants:

$$\alpha = E(C_1 \mid DI = 1) - E(C_0 \mid DI = 0) . \qquad (3)$$

Where C_1 is the outcome of some crisis variable when the treatment is taken up, and C_0 is the outcome of some crisis variable when the treatment is not taken up, deposit insurance $DI = 1$ if the country is "eligible" to take up the treatment and 0 otherwise. Controlling for self-selection would help to reduce the potential bias from endogenous placement into the treatment group (in this case, taking up deposit insurance). The estimated effect of deposit insurance, however, would still be biased, since equation (3) estimates the impact between all those who took up the program and all those who did not. To accurately assess the impact of deposit insurance, the effect of the treatment (deposit insurance) on the treated (those who could implement deposit insurance) must be calculated. That is,

$$\alpha_T = E(C_1 \mid DI = 1) - E(C_0 \mid DI = 1)\,. \tag{4}$$

Unfortunately, the second term on the right-hand side of equation (4) does not exist in the data, since it is not observed. We do not observe those countries that were "eligible" to take up the treatment but declined to do so. Ideally, the researcher could create $E(C_0 \mid DI = 1)$ by implementing a randomized experiment: some countries would randomly introduce deposit insurance, while others randomly would not. If this were true, a true control-group sample analogue could be created and used to determine the difference between the outcomes of those countries that implemented deposit insurance and those countries that did not. While the implementation of randomized experiments has been successfully executed in certain settings, evaluation techniques of this sort are not readily accepted by development practitioners to evaluate the impact of deposit insurance.

A solution to this evaluation problem is to create the counterfactual $E(C_0 \mid DI = 1)$ by matching treatment and control countries along observable characteristics. If there are many dimensions along which to match countries, however, the dimensionality of the match becomes very large, and it becomes difficult if not impossible to find matches. Rosenbaum and Rubin (1983) show that the probability that the country participated in deposit insurance can be matched along $P(X)$ rather than along X, and consistent and unbiased estimates of the effect of deposit insurance on the treated country can still be produced. The aim of matching is to ensure that the characteristics of the treatment group are similar to those of the control group. To quantify whether matching is necessary, Rosenbaum and Rubin (1983) measure the differences between the two groups utilizing the "standardized difference." The standardized difference in per cent is the absolute value of the mean difference as a percentage of the average standard deviation:

$$\text{Std Diff} = 100\ (x_1 - x_2)/\left[\left(s_1^2 + s_2^2\right)/2\right]^{1/2} \ ,$$

Where, for each variable, x_1 and x_2 are the sample means in the treated group and the control group, and s_1^2 and s_2^2 are the corresponding sample variances. Rosenbaum and Rubin (1983) suggest that, if the standardized difference is greater than 10, then there is covariate imbalance and matching is required. Similarly, it is possible to compare the kernel density of the respective distribution of characteristics between the treatment and control group.[24] If the two distributions do not share common supports or similar densities, estimation of treatment effects will produce biased results.

Several methods of matching can be considered: "without replacement," "with replacement," and nearest-neighbour techniques (Dehejia and Wahba 1998).[25] For the purposes of this study, matching is done with replacement.[26] The ability of matching method techniques to construct a suitable control-group sample analogue depends on the following crucial assumption:

$$E\left(C_0 \mid P(X), DI = 1\right) = E\left(C_0 \mid P(X), DI = 0\right). \tag{5}$$

That is, conditional on the propensity score, the outcome in the non-participation state is independent of participation. The conditioning variables must determine participation in the treatment such that the outcome in the non-participation state is the same for participants and

[24] Kernel densities are approximations of the distribution *f*(*x*) of the data.
[25] See Appendix A for a description of these techniques.
[26] For a description of the trade-off between the three techniques, see Dehejia and Wahba (1999).

non-participants. For this result to hold, Smith and Todd (2001) suggest that the data must possess two criteria. First, the data for the control and treatment group must come from the same source; second, the data must be "sufficiently rich" that equation (5) holds true. The limitations of matching methods are a function of these conditions. In particular, the matching technique relies heavily on the second criterion, the availability of a rich set of conditioning variables. The ability to create suitable counterfactuals to the treatment group depends on the ability to match along observable characteristics. If the process of selection into the participation and non-participation states is a function of unobservables that are not captured by the observable data, then the control group may not be properly specified. In this sense, the limitation of utilizing the propensity score as a measure of "comparability" is determined by the availability of sufficient conditioning variables. If the decision to participate in the program is poorly measured, the treatment and control groups will be poorly matched, and any inferences on the effect of the "treatment on the treated" will be biased in an undetermined manner. In this way, matching may actually accentuate the biases caused by selection on unobservables (Smith and Todd 2001).

If the observable data sufficiently determine participation, then the benefits of matching are large. By reducing the dimensionality of the match to a univariate measure, for each country in the treatment group its sample analogue can be generated in the control group. Matching methods allow for a straightforward assessment (along $P(X)$) to determine whether the supports of the distribution of the control-group characteristics are different from those of the treatment group. Those countries in the control group that fall outside the support of the treatment group are discarded from the sample. Likewise, treatment-group countries that have no comparable control-group analogues are removed from the assessment procedure, since no counterfactual exists. In this way, the most directly comparable control-group sample analogue is utilized in assessing the impacts of deposit insurance participation. Matching, in theory, allows the effect of the treatment to be isolated.

Although this study is not directly interested in evaluating the effect of deposit insurance, accounting standards, financial liberalization, or other policies per se on the probability of a banking crisis occurring, the underlying premise of constructing a suitable control group based upon this type of criteria is still relevant. To properly assess the likelihood of a banking crisis, it must be ensured that the control group is properly specified. This study introduces matching method techniques to (i) assess whether the control groups suggested by Demirgüç-Kunt and Detragiache (1997) are suitable and, if they are not, (ii) construct a control-group sample analogue. Section 5 describes the results from the application of matching methods to the sample of treatment and control groups, and it also describes the standard descriptive statistics and regression results.

5. Theoretical Predictions and Testable Hypotheses: Constructing an Empirical Model of Banking Crises and Contagion

Chen's (1999) theoretical model suggests possible candidate empirical tests of banking crises and informational contagion.[27] The key to this test is that measures of real linkages between banking systems need not be found. Rather, Chen suggests that "information" may be sufficient to cause a banking crisis. For instance, if a banking system fails, it may cause uninformed investors in another country to reassess the viability of their own (or other) banking systems, since they may believe that there is a positive correlation between the loan portfolios of the respective banking systems.[28] Subsequently, they will run on their own banking system, despite the non-existence of any real-side connections to the initially failing banking system. In terms of

[27] The theoretical model of Allen and Gale (2000) does not lend itself well to empirical tests. See Appendix B for a description of possible empirical tests of their model.

[28] The existence of correlated projects across banks (or, in this case, banking systems) is an assumption of the model.

testable implications, this suggests that if two banking systems belong to economies that share similar characteristics, then the occurrence of a crisis in one system may predict the occurrence of the crisis in the other system, even if there are no real linkages between the markets. This test can be implemented by augmenting the benchmark model of banking crises (1) with a proxy of informational contagion:

$$\text{Prob}(Crisis_{it} = 1) = F(X_{it}\,\beta) + CT_{it-1} + \varepsilon_{it}\,, \tag{6}$$

where the Xs are the standard macroeconomic variables and CT_{it-1} is a proxy for informational contagion. The measure of "informational contagion" can be defined, as suggested by Ahluwalia (2000), by the following contagion index:

$$CT_{jt} = \sum_{m=1}^{n} CRI_{mt} \times I[\sum_{i=1}^{K} I(X_{ijt} > \overline{X}_{ij}) \times I(X_{imt} > \overline{X}_{im})], \tag{7}$$

where j indexes the non-crisis country, m indexes all the countries other than j, i indexes the macro variable from a set of K macro variables, X_{ijt} are macro fundamentals for the year t, $\overline{X}_{jt}$ is the threshold value of X, I is an indicator function that takes a value of one if the argument $X_{ijt} > \overline{X}_{jt}$ and $X_{imt} > \overline{X}_{im}$ is true, and CRI_{mt} is a dummy variable that takes the value of one if the country experiences a banking crisis in period t.[29] The indicator variable determines whether the macro variable takes a value greater than some threshold value that would indicate that a crisis is occurring. In this case, whether the variable is one and a half or more standard deviations greater than its mean is the measure of a "crisis" value for that variable.[30] The crisis index adds a value of one if the non-crisis country shares a crisis indicator in common with the crisis country. Thus, if there are four countries in crisis with a macro variable above the

[29] This analysis can be extended to consider the effect of currency crises.
[30] For variables where low values are a sign of crisis, we assume that the indicator function includes a "less than" operator. Varying the threshold does not qualitatively affect the results. Utilizing 1.5 standard deviations as the threshold level generates stress for 3–7 per cent of the total observations.

threshold and country j's macro variable is also above the threshold, then CT_{jt} takes a value of four. Alternatively, one can define the contagion index as:

$$CTM_{jt} = \sum_{i=1}^{10} I \sum_{m=1}^{n} CRI_{mt} \times I(X_{ijt} > \overline{X}_{ij}) \times I(X_{imt} > \overline{X}_{im}). \tag{8}$$

Instead of counting the number of countries that are similar, CTM_{jt} counts the number of macro variables greater than the threshold that country j has in common with any country that is experiencing a crisis at time t. In both cases, the contagion index captures the notion of the visible similarities of the non-crisis country to the crisis country. If these visible similarities provoked investor-based contagion, one would expect the probability of a crisis to be higher in the next period if the contagion index takes values greater than zero.

Both indexes can be refined to capture visible similarities that are related to income or region. For instance, CT_{jt} and CTM_{jt} can be refined to count values only when country j is in the same income group as the crisis country, or the same region: Thus,

$$CTR_{jt} = \sum_{m=1}^{n} (CRI_{mt} \times DR) \times I[\sum_{i=1}^{10} I(X_{ijt} > \overline{X}_{ij}) \times I(X_{imt} > \overline{X}_{im})], \tag{9}$$

where DR takes a value of one when countries m and j belong to the same region, and 0 otherwise. For instance, if Mexico experienced a crisis and its real interest rate was more than one and a half standard deviations above its mean, then, for any country in the region that also had real interest rates above the threshold, that value of *CTR* would also take a value of one. Similarly, CTI_{jt} and $CTMI_{jt}$ are contagion indexes where countries are identified not by region but by income quartile:

$$CTI_{jt} = \sum_{m=1}^{n} (CRI_{mt} \times DR) \times I[\sum_{i=1}^{10} I(X_{ijt} > \overline{X}_{ij}) \times I(X_{imt} > \overline{X}_{im})]. \tag{10}$$

DR takes a value of 1 if countries *m* and *j* both come from the same income quartile. For this study, CTI_{jt} and $CTMI_{jt}$ are also calculated for when *CRI* is a dummy variable indicating the occurrence of a currency crisis.

The intuition underlying the contagion indexes is simple: if a country experiences a banking crisis, investors will be "woken up" and prompted to reassess the viability of their portfolios in countries that share similar traits. If countries share "visible similarities," this will cause banks or other market participants to adjust their portfolios accordingly. This could lead to a decline in asset prices, withdrawal of interbank deposits and loans, or other effects that would undermine the viability of the non-crisis country's banking system and increase the likelihood of a banking crisis in the near future. Interestingly, this analysis precludes the need for any change in fundamentals (although they are controlled for the regressions). That is, if contagion occurs simply due to the effect of the crisis occurring, and not due to a change in fundamentals, then informational contagion potentially exists.

6. Results

6.1 Data

The data used in the study are taken from the IFS, WEO, and other IMF databases. Over 90 countries have sufficiently complete data from 1975 to 1998. The banking and currency crisis dates are taken from Demirgüç-Kunt and Detragiache (1997) and Glick and Hutchinson (1999), respectively. The explanatory variables for predicting a crisis are those suggested by Demirgüç-Kunt and Detragiache (1997) and are as follows: GDP growth rate, current account surplus, depreciation rate of the currency, real interest rate, inflation rate, government deficit, ratio of M2/reserves, ratio of private credit-to-GDP, growth of real private credit, per-capita income, existence of deposit insurance, and a measure of law and order. The predicted signs, as suggested by Demirgüç-Kunt and Detragiache, are as follows. Poor macro fundamentals will adversely affect bank balance sheets negatively: low real GDP growth, declining current account balances, and high real interest rates should be positive predictors of a crisis. High inflation and currency depreciation will lead to a higher likelihood of banking crises, as will larger government deficits. The former implies higher nominal interest rates and, in general, economic mismanagement, while the latter reduces the ability of the government to address banking-system problems. To control for liquidity, the ratio of M2-to-reserves is also included, since lower liquidity implies a greater likelihood of default. Conversely, excessive credit growth implies overlending (often associated with real-estate booms) and thus should predict banking-system distress. Lastly, institutional variables should be taken into account. Higher per-capita GDP and law and order imply a smaller probability of a banking crisis. However, the sign for deposit insurance is not clear. While it should reduce the likelihood of a bank run, insurance could induce moral-hazard problems. This would lead to riskier lending and thus a higher likelihood of a banking crisis. Appendix C gives a detailed description of these variables.

The above specification naturally raises many questions regarding the problem of underidentification. While macroeconomic variables are important indicators of possible banking-system stress, they are by no means the only determinants, since the likelihood of a crisis depends upon many typically unobservable characteristics. These would include bank industry-level loan-loss indicators, Value-at-Risk measures, and other measures of financial fragility. Institutional features such as the degree and effectiveness of bank regulators are also omitted. Likewise, it is difficult to measure the pathways that would lead to informational contagion, since the effect of contagion depends on the degree of interconnectedness between respective banking systems. To quantify this effect, it would be necessary to observe the existence, breadth, and depth of interbank markets, whether asset markets and banking systems are connected through institutional investors, and so on. Consequently, in the empirical analysis that follows, it must be remembered that measures of contagion, which may show the existence of the pathway, are but one step towards understanding how contagion can affect banking systems.

6.2 Descriptive statistics

Table 1 lists sample statistics for those countries that suffered a crisis at some time during the sample period, and for those that did not. Several important characteristics stand out. Over the time frame of the sample, countries experiencing banking crises had a greater depreciation of their currency (relative to the dollar), higher inflation, and larger government deficits. In addition, crisis countries had, overall, lower private credit-to-GDP, per-capita income and lower levels of law and order. The contagion index was constructed as per Ahluwalia (2000) using the nine macro variables identified in section 6.1. Overall, 6.4 per cent of all country-years had a contagion index score of 1 or more (results not shown) with respect to banking crises ($CRI = 1$ if a banking crisis occurs). The contagion indexes were also constructed using currency crises for the dummy variable *CRI* – 7.3 per cent of all country-year observations having a contagion index score of 1 or more for currency crises.

6.3 Matching methods

Table 1 also lists measures of sample matching through the standardized difference of the crisis and control groups. Following Rosenbaum and Rubin's (1983) rule of thumb, if the standardized differences are greater than 10, then there exists covariate mismatch that may lead to bias in the estimated coefficients. Column 3 of the table shows that the standardized differences are large: the crisis and non-crisis countries are significantly different in terms of many of the explanatory variables, such as depreciation, inflation, and other measures. To correct for this potential source of bias, matching methods are utilized. The difficulty is that it is not obvious which characteristics are most appropriate to match.[31]

For the purposes of this study, two criteria for matching are considered: (i) a measure of financial liberalization, and (ii) whether the country takes a positive value of the contagion index. The motivation for using financial liberalization (although other candidate matching criteria, such as a binary financial development measure are possible) is twofold—it indicates a level of financial development and it is empirically related to the onset of financial crises (Demirgüç-Kunt and Detragiache 1998).[32] First, a probit regression is estimated (see Table 2 for results), and then each crisis country-year is matched to its nearest neighbour from the non-crisis country-year, based on its propensity score for financial liberalization. The full set of available countries is used in the probit regression and the process is done "with replacement." Financial liberalization is predicted using the level of GDP, the level of openness, exports, and a variety of institutional variables. The key identifying variable is legal origin—if the country does not have U.K. legal origin, financial liberalization is well-predicted.[33]

The second matching criterion is whether the country takes a positive value of the contagion index. In that case, the contagion index can be considered to be the "treatment." The contagion index is predicted using the levels of macroeconomic variables and regional and income-level dummies. These last two variables help to identify the contagion index directly, but are at the same time exogenous (in that countries do not choose their region nor their relative income, at least over the short run). The objective of the matching process is to attempt to isolate

[31] Typically, in the labour literature, the dependent variable of the probit regression used in generating the propensity score is program participation.
[32] Demirgüç-Kunt and Detragiache (2000) argue that liberalization and deregulation initially leads to overlending, as inexperienced bank managers underestimate risk.
[33] This variable is used in other studies as an "instrument" for financial development (Ragan and Zingales 1998).

the effect of the "treatment"—in this case, the occurrence of a banking crisis in a country with visible similarities. Table 1 shows results of the matching exercise; in most cases, the degree of covariate imbalance is mitigated by the matching process. Figures 1 to 4 show kernel density estimates for the distribution of three macro variables and the propensity score of financial liberalization for unmatched and matched data. Matching has two effects that are readily discernible. First, the distributions are more closely matched in terms of the kernel density. For instance, in the case of per-capita GDP, private credit to GDP, and the propensity score, the matched control group's kernel estimate distribution is more similar to the crisis group than to the control group from the unmatched data. Second, as in the case of the macro variable "Government Surplus/GDP," the supports of the distribution are closer than the unmatched data. This is not surprising, given the characteristics of the countries that are removed from the control group. Matching by financial liberalization (or by contagion crisis index) removes Paraguay, Jamaica, Bahrain, Syria, the Democratic Republic of Congo, Seychelles, and Togo.

Consequently, one would expect the remaining control-group countries to be better "matched" to the crisis countries. One problem that remains to be addressed is whether there is a sufficiently large pool of control-group countries. Presumably, as the time frame enlarges, almost all of the countries could experience a banking crisis, thus removing them as potential control-group candidates. The purpose of matching, however, is to generate a control-group sample analogue for a given sample of countries over a given time period. In this way, matching formalizes the process by which countries are chosen, given the sample at hand.

6.4 Regression results

Table 3 lists the results of estimating the simple banking-crisis equation. Banking crises are more likely to occur during periods of slow economic growth, high inflation, and high real interest rates and fiscal laxity, although this last measure is not statistically significant (column 1). [34] Inclusion of credit and money variables does not significantly alter the results. High private credit-to-GDP ratios and credit growth are positively related to banking crises (column 2). These two measures imply that the credit growth associated with booms may eventually lead to a crisis. Unfortunately, the coefficients for the credit and money variables are insignificant. Although the lack of significance for the depreciation rate and credit and money variables may seem troubling, it is not surprising given the nature of the data. The high variance, and the fact that many of these macro variables are jointly determined, reduces the likelihood that any particular measure will be well-identified.[35] For instance, depreciation and the inflation rate are highly correlated, and so it is problematic to identify empirically one effect from the other. Inclusion of institutional characteristics does not alter the results (columns 3 and 4). The model is re-estimated utilizing a probit random-effects model. The results do not change, however, and one cannot reject the null hypothesis that $\rho = 0$. This suggests that country-specific effects are adequately controlled for by the inclusion of institutional variables.

The regressions are re-estimated with matched data to check the robustness of the results (Tables 4 and 5). The macro variables retain their magnitude and significance, but there are several notable differences. First, the coefficient on per-capita GDP is a significant predictor of a banking crisis, as is the size of the government deficit. The benefit of matching can be seen through its impact on the precision of the estimates. In this case, the matching process removes observations from the data that do not share similar characteristics with the control group.

[34] The use of current values (instead of lagged values) naturally raises the question of endogeneity. Following Demirgüç-Kunt and Detragiache (2000) and Glick and Hutchinson (1999), however, current vales are used.
[35] This is also reflected in the low pseudo R^2 of the regression. Banking crises are essentially micro-level phenomena, while the explanatory variables are macro-level aggregates. The subsequent mismatch in the data renders any close association unlikely.

Consequently, outliers are removed from the sample, leading to more reliable results. While this result could be achieved by simply removing outliers arbitrarily, matching formalizes the process.[36]

The incidence of contagion, conditional on fundamentals, is assessed by estimating equations (9) and (10) with the inclusion of the contagion index, lagged one period, as suggested by Ahluwalia (2000). If contagion exists, conditional on fundamentals, the coefficient should be positive and significant. Table 6 lists the results. The contagion index positively predicts future banking crises when the previous crisis event was a banking crisis from a country of a similar income group (columns 1 and 2). This result did not hold when the contagion index was constructed by region, or when the contagion index was based on previous currency crises (columns 3-8). It could be the case, however, that the contagion index is simply picking up the fact that in the previous period the defaulting country's macro variables were above their threshold. As a check, lagged dummies (taking the value of one if the macro variable was above the threshold) were added to control for this effect; the contagion index was still significant (results not shown). The results hold when matched samples are used (Tables 7 and 8). The banking contagion index is a positive predictor of the occurrence of a banking crisis. Interestingly, the contagion index based upon currency crises is not a significant predictor of future banking crises.

[36] The results shown in Table 1 suggest that sample selection may be important, since there is a large degree of covariate imbalance. While matching served to mitigate this problem, there still exists some degree of differences between the "treatment" group and the "control" group. These differences exist partly due to the ad hoc nature of the matching process. That is, the need to use macro variables to predict a country's status in the control and treatment group is a shortcoming that is difficult to address. Consequently, while matching did serve to produce better estimates of the probability of a banking crisis, this line of empirical research still requires further study.

7. Conclusion

This paper has surveyed the empirical literature of banking crises and highlighted several econometric weaknesses. Most notably, the need to consider the choice of control-group countries has been shown to affect the estimation of the determinants of banking crises. The empirical evidence shows that the ability to predict banking crises may depend on the choice of the sample of non-crisis countries: failure to construct a suitable control group of non-crisis countries can lead to biased results. For instance, although the government surplus was not an important determinant of a banking crisis for the unmatched sample, a result that is consistent with Demirgüç-Kunt and Detragiache (2002), the matching results revealed that large government deficits are correlated to banking crises.

An empirical model was described of information contagion based upon Chen (1999). The empirical evidence indicates that information contagion may play an important role in predicting future banking crises. Interestingly, it is only the occurrence of a banking crisis that leads to information contagion; currency crises do not provoke contagious banking-crisis events. This is consistent with previous evidence that suggests that banking crises and currency crises are either concurrent events or that currency crises are preceded by banking crises (Kaminsky and Reinhart 1999b). While this evidence is far from conclusive, it suggests future avenues of research. Most notably, are the results robust to the inclusion of measures of financial integration? Potential candidate control variables could be gleaned from BIS exposure data, or based on whether a country's banks have exposures to the interbank markets, payments systems, or other forms of banking-system integration. Better identification of the contagion effect, however, is not possible until the degree of banking-system integration is controlled for. Consequently, there is still considerable room for future research.

Bibliography

Agenor, P. and J. Aizenman. 1997. "Contagion and Volatility With Imperfect Credit Markets." IMF Working Paper No. 97127.

Ahluwalia, P. 2000. "Discriminating Contagion: An Alternative Explanation of Contagious Currency Crises in Emerging Markets." IMF Working Paper No. 0014.

Allen, F. and D. Gale. 2000. "Financial Contagion." *Journal of Political Economy* 108: 1–33.

_______. 2001. "Financial Fragility." University of Pennsylvania. Photocopy.

Baig, T. and I. Goldfajn. 1998. "Financial Market Contagion in the Asian Crisis." IMF Working Paper No. 98155.

Beck, T., A. Demirgüç-Kunt, and R. Levine. 1999. "A New Database on Financial Development and Structure." World Bank Working Paper.

Berg, A. and C. Pattillo. 1999. "Predicting Currency Crises: The Indicators Approach and an Alternative." *Journal of International Money and Finance* 18: 561–86.

Bernard, H. and J. Bisignano. 2000. "Information, Liquidity and Risk in the International Interbank Market: Implicit Guarantees and Private Credit Market Failure." BIS Working Paper No. 86.

Blaschke, W. et al. 2001. "Stress Testing of Financial Systems: An Overview of Issues, Methodologies, and FSAP Experiences." IMF Working Paper No. 0188.

Bussiere, M. and C. Mulder. 1999. "External Vulnerability in Emerging Market Economies: How High Liquidity Can Offset Weak Fundamentals and the Effects of Contagion." IMF Working Paper No. 00135.

Calvo, G. and E. Mendoza. 2000. "Rational Contagion and the Globalization of Securities Markets." NBER Working Paper No. 7153.

Caprio, G. and D. Klingebiel. 1999. "Bank Insolvencies: Cross-Country Experiences." World Bank Policy Research Paper No. 7272.

Caramazza, F., L. Ricci, and R. Sanilgado. 2000. "Trade and Financial Contagion in Currency Crises." IMF Working Paper No. 0055.

Chai, J. 2000. "An Incentive Approach to Identifying Financial System Vulnerabilities." IMF Working Paper No. 00211.

Chen, Y. 1999. “Banking Panics: The Role of First-Come, First-Serve Rule and Information Externalities.” *Journal of Political Economy* 107: 946–68.

Choueiri, N. and G. Kaminsky. 1999. “Has the Nature of Crises Changed? A Quarter Century of Currency Crises in Argentina.” IMF Working Paper No. 9152.

Dehejia, R. and S. Wahba. 1998. “Propensity Score Matching Methods for Nonexperimental Causal Studies.” NBER Working Paper No. 6829.

________. 1999. “Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs.” *Journal of the American Statistical Association* 94: 1053–62.

Dekle, R. and K. Kletzer. 2001 “Domestic Bank Regulation and Financial Crises: Theory and Empirical Evidence From East Asia.” IMF Working Paper No. 0163.

Demirgüç-Kunt, A. and E. Detragiache. 1997. “The Determinants of Banking Crises – Evidence From Developing and Developed Countries.” IMF Working Paper No. 99147.

________. 1998. “Financial Liberalization and Financial Fragility.” IMF Working Paper No. 9883.

________. 1999. “Monitoring Banking Sector Fragility: A Multivariate Approach.” IMF Working Paper No. 99147.

________. 2002. “Does Deposit Insurance Increase Banking System Stability? An Empirical Investigation.” *Journal of Monetary Economics* 49: 1373-1406.

Demirgüç-Kunt, A., E. Detragiache, and P. Gupta. 2000. “Inside the Crisis: An Empirical Analysis of Banking Systems in Distress.” IMF Working Paper No. 00156.

Demirgüç-Kunt, A., and T. Solbaci. 2000. “Deposit Insurance Around the World: A Data Base.” World Bank Working Paper.

Detragiache, E. 1999. “Bank Fragility and International Capital Mobility.” IMF Working Paper No. 99113.

Diamond, D. and P. Dybvig. 1983. “Bank Runs, Deposit Insurance, and Liquidity.” *Journal of Political Economy* 91: 401–19.

Diamond, D. and R. Rajan. 2000. “Banks, Short Term Debt and Financial Crises: Theory, Policy Implications and Applications.” NBER Working Paper No. 7764.

Dornbusch, R., Y. Park, and S. Claessens. 2000. “Contagion: How it Spreads and How it can be Stopped?” World Bank. Photocopy.

Dziobek, C. and C. Pazarbasioglu. 1997. "Lessons From Systemic Bank Restructuring: A Survey of 24 Countries." IMF Working Paper No. 97161.

Eichengreen, B. and C. Arteta. 2000. "Banking Crises in Emerging Markets: Presumptions and Evidence." UC Berkeley. Photocopy.

Eichengreen, B. and A. Mody. 1999. "Lending Booms, Reserves and the Sustainability of Short-term Debt: Inferences From the Pricing of Syndicated Bank Loans." NBER Working Paper No. 7113.

Eichengreen, B. and A. Rose. 1998. "Staying Afloat When the Wind Shifts: External Factors and Emerging Market Banking Crises." NBER Working Paper No. 6370.

Eichengreen, B., A. Rose, and C. Wyplosz. 1996. "Contagious Currency Crises." NBER Working Paper No. 5681.

Forbes, K. 2000. "The Asian Flu and Russian Virus: Firm-level Evidence on How Crises are Transmitted Internationally." NBER Working Paper No. 7807.

________. 2001. "Are Trade Linkages Important Determinants of Country Vulnerability to Crises?" NBER Working Paper No. 8194.

Freixas, X., B. Parigi, and J. Rochet. 2000. "Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank." *Journal of Money, Credit, and Banking* 32: 611–40.

Frydl, E. 1999. "The Length and Cost of Banking Crises." IMF Working Paper No. 9930.

Furfine, C. 1999. "Interbank Exposures: Quantifying the Risk of Contagion." BIS Working Paper No. 70.

________. 2001. "The Interbank Market During a Crisis." BIS Working Paper No. 99.

Garcia, G., 1999. "Deposit Insurance: A Survey of Actual and Best Practices." IMF Working Paper No. 9954.

Glick, R. and M. Hutchinson. 1999. "Banking and Currency Crises: How Common are the Twins?" Pacific Basin Working Paper Series PB99-07. Federal Reserve Bank of San Francisco.

Gonzalez-Hermosillo, B. 1999. "Determinants of Ex-ante Banking System Distress: A Macro-Empirical Exploration of Some Recent Episodes." IMF Working Paper No. 9933.

Greene, W. 2000. *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.

Gupta, P. 2000. "Aftermath of Banking Crises: Effects on Real and Monetary Variables." IMF Working Paper No. 0096.

Hardy, C. and C. Pazarbasioglu. 1998. “Leading Indicators of Banking Crises: Was Asia Different?” IMF Working Paper No. 9891.

________. 1999. “Determinants and Leading Indicators of Banking Crises: Further Evidence.” IMF Staff Papers 46, 3.

Heckman, J. 1974. “Shadow Prices, Market Wages, and Labour Supply.” *Econometrica* 42: 679–94.

________. 1978. “Dummy Endogenous Variables in a Simultaneous Equations System.” *Econometrica* 46: 931–59.

________. 1979. “Sample Selection Bias as a Specification Error.” *Econometrica* 47: 153–61.

________. 1990. “Varieties of Selection Bias.” *American Economic Review Papers and Proceedings* 80: 313–18.

Heckman, J. and V. Hotz. 1989. “Choosing Among Alternative Nonexperimental Methods for Estimating the Impact of Social Programs: The Case of Manpower Training.” *Journal of the American Statistical Association* 84: 862–74.

Heckman, J. and R. Robb. 1985. “Alternative Methods for Evaluating the Impact of Interventions.” In *Longitudinal Analysis of Labour Market Data*, edited by J. Heckman and B. Singer, 156–245. Cambridge: Cambridge University Press.

Heckman, J. and J. Smith. 1995. “Assessing the Case for Social Experiments.” *Journal of Economic Perspectives* 9: 85–110.

__________. and J. Smith. 1996. “Experimental and Nonexperimental Evaluations.” In *International Handbook of Labour Market Policy and Evaluation*, edited by G. Schmid et al. London: Edward Elgar.

Heckman, J. et al. 1996. “Sources of Selection Bias in Evaluating Social Programs: An Interpretation of Conventional Measures and Evidence on the Effectiveness of Matching as a Program Evaluation Method.” *Proceedings of the National Academy of Sciences* 93: 13416–20.

________. 1997. “Matching as an Econometric Evaluation Estimator: Evidence From Evaluating a Job Training Program.” *Review of Economic Studies* 64: 605–54.

________. 1999. “The Economics and Econometrics of Active Labor Market Programs.” *Handbook of Labor Economics*, vol. 3a, edited by O. Ashenfalter and D. Card, 1865–2097. Amsterdam: North-Holland.

Hernandez, L. and R. Valdes. 2001. "What Drives Contagion: Trade, Neighborhood, or Financial Links?" IMF Working Paper No. 0129.

Hoggarth, G., R. Reis, and V. Saporta. 2001. "Costs of Banking System Instability: Some Empirical Evidence." Bank of England Working Paper No. 144.

Huang, H. and C. Xu. 2000. "Financial Institutions, Financial Contagion and Financial Crises." IMF Working Paper No. 0092.

Johnston, R., J. Chai, and L. Schumacher. 2000. "Assessing Financial System Stability." IMF Working Paper No. 0076.

Kaminsky, G. and C. Reinhart. 1998. "On Crises, Contagion, and Confusion." *Journal of International Economics* 51: 145–68.

________. 1999a. "The Center and the Periphery: Tales of Financial Turmoil." Photocopy.

________. 1999b. "The Twin Crises: The Causes of Banking and Balance of Payments Problems." *American Economic Review* 89: 473–500.

________. 1999c. "Bank Lending and Contagion: Evidence from the Asian Crisis." Photocopy.

Kaufman, G. 1994. "Bank Contagion: A Review of the Theory and Evidence." *Journal of Financial Services Research* 8: 123–50.

Kaufman, G. and S. Seelig. 2001. "Post-Resolution Treatment of Depositors at Failed Banks: Implications for the Severity of Banking Crises, Systemic Risk and Too-Big-to-Fail." IMF Working Paper No. 0183.

Kruger, M., P. Osakwe, and J. Page. 1998. "Fundamentals, Contagion and Currency Crises: An Empirical Analysis." Bank of Canada Working Paper No. 98-10.

Kyei, A., 1995. "Deposit Protection Arrangements: A Survey." IMF Working Paper No. 95134.

Lai, A. 2002. "Modelling Financial Instability: A Survey of the Literature." Bank of Canada Working Paper No. 2002-12.

Masson, P. 1999. "Multiple Equilibria, Contagion, and the Emerging Market Crises." IMF Working Paper No. 99164.

Munoz, S. 2000. "The Breakdown of Credit Relations Under Conditions of a Banking Crisis: A Switching Regime Approach." IMF Working Paper No. 00135.

Pericoli, M. and M. Sbracia. 2001. "A Primer on Financial Contagion." Bank of Italy. Photocopy.

Pritsker, M. 2000. “The Channels for Financial Contagion.” Board of Governors of the Federal Reserve System. Photocopy.

Ragan, R. and L. Zingales. 1998. “Financial Dependence and Growth.” *American Economic Review* 88: 559–86.

Rigabon, R. 2001. “On the Measurement of the International Propagation of Shocks: Is the Transmission Stable?” MIT. Photocopy.

Rochet, J. and J. Tirole. 1996. “Interbank Lending and Systemic Risk.” *Journal of Money, Credit and Banking* 28: 733–62.

Rosenbaum, P. and D. Rubin. 1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” *Biometrika* 70: 604–20.

Schinasi, G. and R. Smith. 1999. “Portfolio Diversification, Leverage and Financial Contagion.” IMF Working Paper No. 99136.

Smith, J. and P. Todd. 2001. “Reconciling Conflicting Evidence on the Performance of Propensity Score Matching Methods.” *American Economic Review Papers and Proceedings* 91: 112–18.

Upper, C. and A. Worms. 2000. “Estimating Bilateral Exposures in the German Interbank Market: Is There a Danger of Contagion?” Prepared for the Autumn Central Bank Economists’ Meeting of the BIS on “Marrying the Micro and Macro-prudential Dimensions of Financial Stability.” BIS.

Van Rijckeghem, C. and B. Weder. 2000. “Spillovers Through Banking Centers: A Panel Data Analysis.” IMF Working Paper No. 0088.

Table 1: Country Characteristics

Variable	Mean (crisis countries)	Mean (control group unmatched)	Standardized difference	Mean (control group matched by contagion index)	Standardized difference	Mean (control group matched by fin lib index)	Standardized difference
Growth	3.4	3.3	3.27	3.8	9.59	3.3	2.99
Current account/GDP	-0.022	-0.026	3.85	-0.028	5.80	-0.029	6.74
Depreciation	0.113	0.065	21.73	0.07	18.90	0.08	14.63
Real interest rate	2.1	2.4	4.41	1.48	6.26	1.41	6.86
Inflation	14.2	8.8	38.39	9.3	34.68	9.5	31.61
Government surplus/GDP	-0.058	-0.042	11.14	-0.046	11.20	-0.069	9.54
M2/reserves	13.82	11.39	12.05	9.82	21.90	17.09	12.23
Private credit/GDP	0.39	0.46	27.02	0.45	21.28	0.44	19.68
Cash/bank assets	0.113	0.101	10.18	0.115	1.28	0.124	6.74
Real credit growth	6.83	1.48	7.41	3.25	15.88	5.36	19.21
Ln per-capita income	7.80	8.44	43.21	8.22	27.27	8.18	38.65
Deposit insurance	0.24	0.18	14.52	0.19	22.53	0.17	17.95
Law and order	3.54	4.29	47.16	4.11	35.73	4.23	42.44

The standardized difference in per cent is the absolute value of the mean difference as a percentage of the average standard deviation: $100\,(x_1 - x_2)/\left[\left(s_1^2 + s_2^2\right)/2\right]^{1/2}$ where for each variable x_1 and x_2 are the sample means in the treated group and the control group and s_1^2 and s_2^2 are the corresponding sample variances.

Table 2: Probit Regression

Dependent Variable:	Financial liberalization (1)	Crisis event (2)
Growth	-0.001	-0.061*
	(0.012)	(0.017)
Current account/ GDP	1.762	-1.809*
	(0.6323)	(0.789)
Depreciation	-0.246	0.107
	(0.235)	(0.297)
Real interest rate	0.030*	-0.002
	(0.007)	(0.009)
Inflation	0.015*	0.001
	(0.006)	(0.006)
Government surplus/GDP	-0.111	-0.437
	(0.356)	(0.394)
M2/reserves	-0.111	0.005*
	(0.356)	(0.003)
Private credit/ GDP	0.022	0.528*
	(0.233)	(0.295)
Real credit growth$_{t-2}$	0.001*	0.001
	(0.000)	(0.001)
Legal origin	-0.620*	-0.004
	(0.102)	(0.151)
Deposit insurance	0.597*	0.101
	(0.142)	(0.178)
[Poor excluded]		
High income	-0.581*	-0.643
	(0.189)	(0.403)
Middle income	-0.451*	-0.106
	(0.153)	(0.266)
Low income	-0.430*	0.029
	(0.121)	(0.189)
Chi^2	196.47	57.22
Pseudo R^2	0.18	0.11

* indicates significance at the 5 per cent level, ** indicates significance at the 10 per cent level. Robust standard errors.

Table 3: Probit Results–Dependent Variable: Banking Crisis

	Macro variables (1)	Banking variables (2)	Institutional characteristics (3)	Institutional characteristics (4)
Growth	-0.049*	-0.057*	-0.058*	-0.063*
	(0.022)	(0.025)	(0.025)	(0.025)
Current account/ GDP	0.142	0.480	0.165	0.545
	(0.785)	(0.698)	(0.636)	(0.662)
Depreciation	0.375	0.270	0.194	0.236
	(0.205)	(0.397)	(0.415)	(0.415)
Real interest rate	0.021*	0.017*	0.020*	0.018*
	(0.007)	(0.007)	(0.007)	(0.007)
Inflation	0.009*	0.009**	0.010*	0.008**
	(0.004)	(0.005)	(0.005)	(0.005)
Government surplus/GDP	-0.477	-0.393	-0.638	-0.291
	(0.487)	(0.537)	(0.589)	(0.527)
M2/reserves		0.001	0.004	0.001
		(0.004)	(0.004)	(0.004)
Private credit/ GDP		-0.216	0.202	0.084
		(0.313)	(0.398)	(0.396)
Real credit growth$_{t-2}$		0.002	0.002	0.001
		(0.002)	(0.002)	(0.001)
Ln per-capita income			-0.147	
			(0.098)	
Deposit insurance			0.245	
			(0.214)	
Law and order				-0.090
				(0.082)
N	1138	915	905	905
Chi^2	33.14	33.14	37.47	35.01
Pseudo R^2	0.10	0.10	0.12	0.11

* indicates significance at the 5 per cent level, ** indicates significance at the 10 per cent level. Robust standard errors.

Table 4: Probit Results–Matched Data (by Financial Liberalization) Dependent Variable: Banking Crisis

	Macro variables (1)	Banking variables (2)	Institutional characteristics (3)	Institutional characteristics (4)
Growth	-0.055*	-0.055*	-0.056*	-0.062*
	(0.027)	(0.027)	(0.024)	(0.024)
Current account/ GDP	0.263	0.293	0.162	0.360
	(0.468)	(0.482)	(0.618)	(0.407)
Depreciation	0.219	0.234	0.154	0.205
	(0.420)	(0.401)	(0.424)	(0.424)
Real interest rate	0.016*	0.014**	0.016*	0.015**
	(0.007)	(0.006)	(0.008)	(0.008)
Inflation	0.007**	0.008**	0.010**	0.008*
	(0.004)	(0.004)	(0.005)	(0.004)
Government surplus/GDP	-0.859*	-0.874*	-0.750	-0.691*
	(0.211)	(0.244)	(0.585)	(0.279)
M2/reserves		0.001	0.002	0.001
		(0.004)	(0.005)	(0.004)
Private credit/ GDP		0.074	0.594	0.492
		(0.292)	(0.412)	(0.373)
Real credit growth$_{t-2}$		0.004	0.004	0.002
		(0.003)	(0.003)	(0.003)
Ln per-capita income			-0.151	
			(0.096)	
Deposit insurance			0.194	
			(0.209)	
Law and order				-0.114**
				(0.068)
N	852	852	852	793
Chi^2	62.68	66.24	35.51	59.32
Pseudo R^2	0.09	0.10	0.12	0.12

* indicates significance at the 5 per cent level, ** indicates significance at the 10 per cent level. Robust standard errors.

Table 5: Probit Results–Matched Data (by Crisis Event) Dependent Variable: Banking Crisis

	Macro variables (1)	Banking variables (2)	Institutional characteristics (3)	Institutional characteristics (4)
Growth	-0.055*	-0.055*	-0.056*	-0.058*
	(0.026)	(0.026)	(0.026)	(0.027)
Current account/	0.300	0.357	0.188	0.408
GDP	(0.480)	(0.454)	(0.446)	(0.394)
Depreciation	0.306	0.310	0.245	0.293
	(0.402)	(0.389)	(0.426)	(0.405)
Real interest rate	0.017*	0.017*	0.019*	0.018*
	(0.07)	(0.007)	(0.007)	(0.007)
Inflation	0.008**	0.008*	0.010*	0.008*
	(0.004)	(0.004)	(0.005)	(0.004)
Government	-0.754*	-0.742*	-0.588*	-0.627*
surplus/GDP	(0.228)	(0.266)	(0.268)	(0.289)
M2/reserves		0.003	0.003	0.003
		(0.004)	(0.004)	(0.004)
Private credit/		-0.061	0.438	0.237
GDP		(0.297)	(0.374)	(0.380)
Real credit growth$_{t-2}$		0.002	0.002	0.001
		(0.003)	(0.003)	(0.002)
Ln per-capita			-0.157**	
income			(0.082)	
Deposit insurance			0.258	
			(0.179)	
Law and order				-0.081
				(0.067)
N	845	845	845	779
Chi^2	46.31	55.05	54.13	49.82
Pseudo R^2	0.10	0.11	0.12	0.12

* indicates significance at the 5 per cent level. ** indicates significance at the 10 per cent level. Robust standard errors.

Table 6: Probit Results–Dependent Variable: Banking Crisis

	CTI banking (1)	CTMI banking (2)	CTI currency (3)	CTMI currency (4)	CTR banking (5)	CTMR banking (6)	CTR currency (7)	CTMR currency (8)
Growth	-0.052*	-0.053*	-0.058*	-0.058*	-0.056*	-0.059*	-0.062*	-0.062*
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Current account/	0.255	0.209	0.206	0.159	0.307	0.230	0.210	0.212
GDP	(0.651)	(0.645)	(0.600)	(0.620)	(0.643)	(0.627)	(0.625)	(0.625)
Depreciation	0.225	0.213	0.210	0.191	-0.059	-0.081	-0.106	-0.100
	(0.425)	(0.424)	(0.418)	(0.416)	(0.509)	(0.496)	(0.492)	(0.495)
Real interest rate	0.020*	0.020*	0.020*	0.019*	0.025*	0.024*	0.024*	0.024*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
Inflation	0.010*	0.010*	0.010*	0.010*	0.018*	0.019*	0.019*	0.019*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.007)	(0.007)	(0.007)
Government	-0.527	-0.563	-0.611	-0.643	-0.641	-0.741	-0.769	-0.764
surplus/GDP	(0.618)	(0.609)	(0.596)	(0.590)	(0.627)	(0.596)	(0.587)	(0.588)
M2/reserves	0.003	0.003	0.004	0.005	0.004	0.005	0.005	0.005
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Private credit/	0.175	0.177	0.207	0.201	0.330	0.375	0.365	0.369
GDP	(0.406)	(0.402)	(0.400)	(0.400)	(0.416)	(0.410)	(0.412)	(0.410)
Real credit growth$_{t-2}$	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln per-capita	-0.154	-0.153	-0.149	-0.148	-0.166**	-0.164	-0.159	-0.159
income	(0.096)	(0.098)	(0.099)	(0.098)	(0.099)	(0.101)	(0.103)	(0.103)
Deposit insurance	0.261	0.262	0.249	0.244	0.222	0.204	0.202	0.203
	(0.211)	(0.213)	(0.214)	(0.213)	(0.216)	(0.219)	(0.218)	(0.218)
Contagion index	0.345**	0.212**	0.106	-0.014	0.325	0.080	-0.235	-0.066
	(0.197)	(0.118)	(0.242)	(0.129)	(0.199)	(0.140)	(0.361)	(0.221)
N	905	905	905	905	893	893	893	893
Chi^2	39.93	39.24	37.70	37.47	36.67	37.04	35.85	36.05
Pseudo R^2	0.13	0.13	0.12	0.12	0.12	0.11	0.12	0.11

* indicates significance at the 5 per cent level, ** indicates significance at the 10 per cent level. Robust standard errors.

Table 7: Probit Results–Matched Data (by Financial Liberalization) Dependent Variable: Banking Crisis

	CT banking (1)	CTM banking (2)	CT currency (3)	CTM currency (4)	CTR banking (5)	CTMR banking (6)	CTR currency (7)	CTMR currency (8)
Growth	-0.050**	-0.052**	-0.056**	-0.056*	-0.050**	-0.054**	-0.057*	-0.057*
	(0.028)	(0.028)	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)	(0.027)
Current account/ GDP	0.288	0.220	0.227	0.165	0.197	0.175	0.152	0.158
	(0.449)	(0.451)	(0.406)	(0.450)	(0.432)	(0.450)	(0.478)	(0.471)
Depreciation	0.174	0.153	0.175	0.152	0.184	0.159	0.144	0.147
	(0.454)	(0.454)	(0.446)	(0.444)	(0.444)	(0.442)	(0.440)	(0.440)
Real interest rate	0.017**	0.016**	0.017*	0.016*	0.017**	0.016**	0.016*	0.016*
	(0.007)	(0.008)	(0.008)	(0.018)	(0.007)	(0.018)	(0.008)	(0.007)
Inflation	0.010*	0.010*	0.009*	0.010*	0.010*	0.010*	0.010*	0.010*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Government surplus/GDP	-0.602*	-0.661*	-0.702*	-0.744*	-0.694*	-0.724*	-0.756*	-0.751*
	(0.258)	(0.261)	(0.276)	(0.262)	(0.279)	(0.263)	(0.246)	(0.250)
M2/reserves	0.001	0.001	0.002	0.002	0.003	0.003	0.002	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Private credit/ GDP	0.578	0.602**	0.609**	0.598	0.633**	0.621*	0.598	0.596
	(0.361)	(0.360)	(0.367)	(0.369)	(0.362)	(0.362)	(0.366)	(0.367)
Real credit growth$_{t-2}$	0.003	0.003	0.003	0.003	0.003	0.003	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Ln per-capita income	-0.160*	-0.162*	-0.155**	-0.153**	-0.167*	-0.161**	-0.151**	-0.151**
	(0.076)	(0.078)	(0.082)	(0.080)	(0.074)	(0.077)	(0.080)	(0.080)
Deposit insurance	0.214	0.213	0.199	0.194	0.204	0.194	0.190	0.192
	(0.175)	(0.177)	(0.176)	(0.175)	(0.172)	(0.175)	(0.174)	(0.174)
Contagion index	0.428*	0.246*	0.168	0.007	0.409	0.135	-0.160	-0.036
	(0.191)	(0.105)	(0.205)	(0.083)	(0.271)	(0.143)	(0.332)	(0.194)
N	851	851	851	851	851	851	851	851
Chi^2	73.66	68.85	66.95	63.99	59.71	61.45	68.53	66.11
Pseudo R^2	0.13	0.13	0.11	0.12	0.13	0.12	0.12	0.12

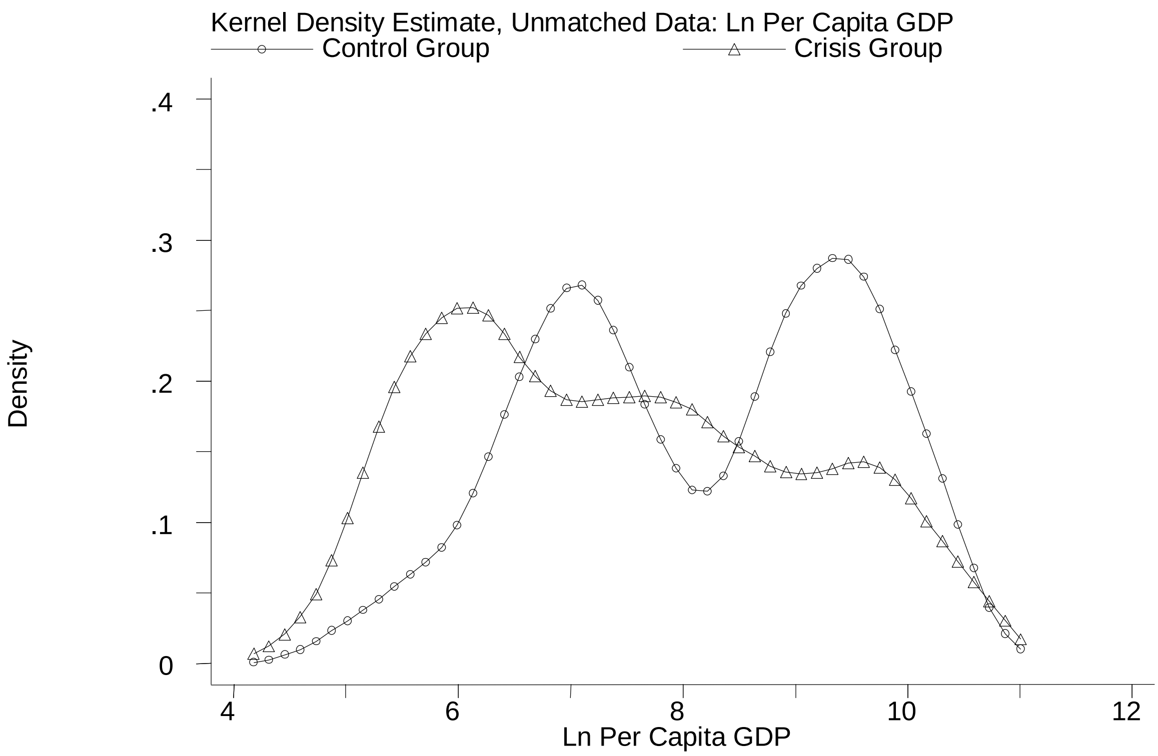
* indicates significance at the 5 per cent level, ** indicates significance at the 10 per cent level. Robust standard errors.

Table 8: Probit Results–Matched Data (by Crisis Index) Dependent Variable: Banking Crisis

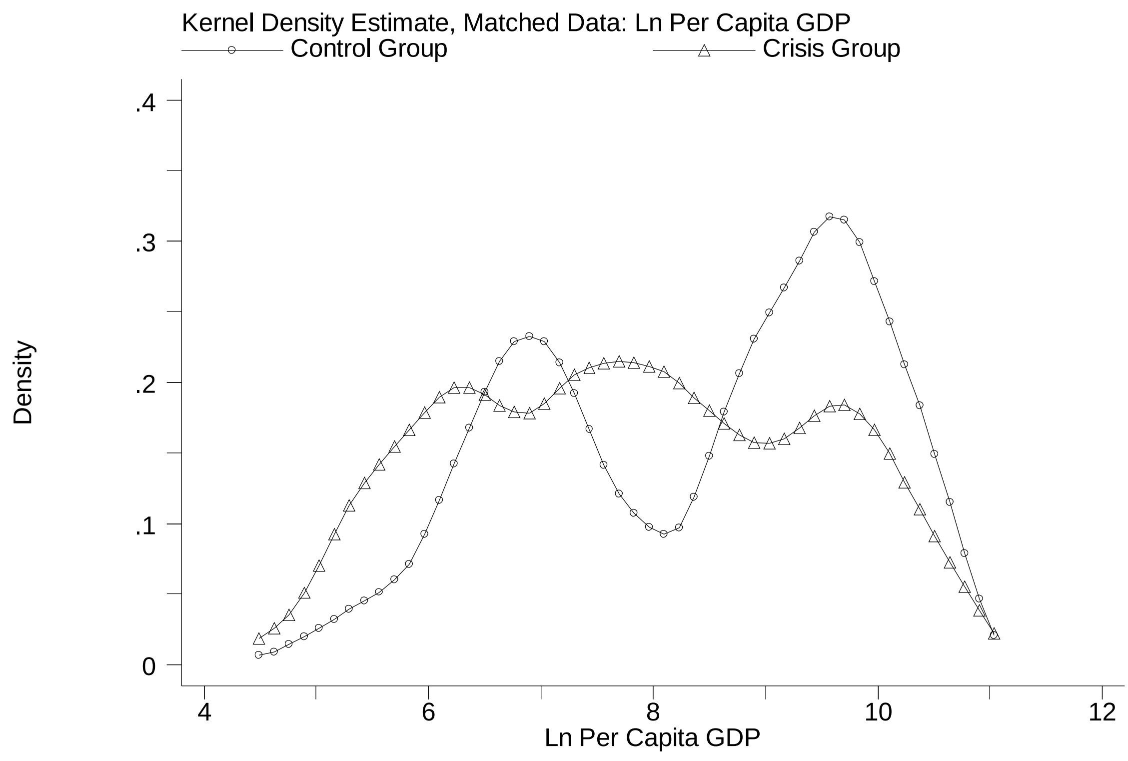
	CTI banking (1)	CTMI banking (2)	CTI currency (3)	CTMI currency (4)	CTR banking (5)	CTMR banking (6)	CTR currency (7)	CTMR currency (8)
Growth	-0.042*	-0.043**	-0.045**	-0.045*	-0.052*	-0.055*	-0.056*	-0.056*
	(0.023)	(0.023)	(0.023)	(0.023)	(0.026)	(0.026)	(0.026)	(0.026)
Current account/	0.253	0.200	0.174	0.130	0.207	0.191	0.150	0.166
GDP	(0.452)	(0.448)	(0.407)	(0.437)	(0.431)	(0.443)	(0.473)	(0.463)
Depreciation	0.303	0.292	0.303	0.283	0.265	0.249	0.233	0.235
	(0.410)	(0.408)	(0.409)	(0.406)	(0.429)	(0.427)	(0.424)	(0.425)
Real interest rate	0.019*	0.019*	0.018*	0.018*	0.020*	0.020*	0.019*	0.019*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Inflation	0.010*	0.010*	0.009*	0.010*	0.010*	0.010*	0.010*	0.010*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Government	-0.555*	-0.602*	-0.674*	-0.702*	-0.565*	-0.584*	-0.613*	-0.608
surplus/GDP	(0.243)	(0.242)	(0.251)	(0.237)	(0.287)	(0.270)	(0.245)	(0.252)
M2/reserves	0.003	0.002	0.004	0.003	0.003	0.003	0.004	0.003
	(0.004)	(0.003)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Private credit/	0.042	0.037	0.095	0.092	0.444	0.439	0.455	0.448
GDP	(0.384)	(0.381)	(0.374)	(0.371)	(0.379)	(0.375)	(0.368)	(0.367)
Real credit growth$_{t-2}$	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Ln per-capita	-0.109	-0.107	-0.103	-0.102	-0.165*	-0.159*	-0.155*	-0.155**
income	(0.078)	(0.080)	(0.082)	(0.081)	(0.078)	(0.080)	(0.081)	(0.081)
Deposit insurance	0.277	0.273	0.265	0.260	0.264	0.258	0.255	0.257
	(0.180)	(0.181)	(0.181)	(0.179)	(0.178)	(0.179)	(0.176)	(0.176)
Contagion index	0.386**	0.226*	0.105	-0.009	0.236	0.033	-0.312	-0.120
	(0.205)	(0.115)	(0.226)	(0112)	(0.243)	(0.124)	(0.326)	(0.202)
N	845	845	845	845	845	845	845	845
Chi^2	65.66	62,24	64.27	62.15	52.70	54.08	59.86	57.73
Pseudo R^2	0.13	0.13	0.13	0.12	0.13	0.12	0.13	0.12

* indicates significance at the 5 per cent level, ** indicates significance at the 10 per cent level. Robust standard errors.

Figure 1

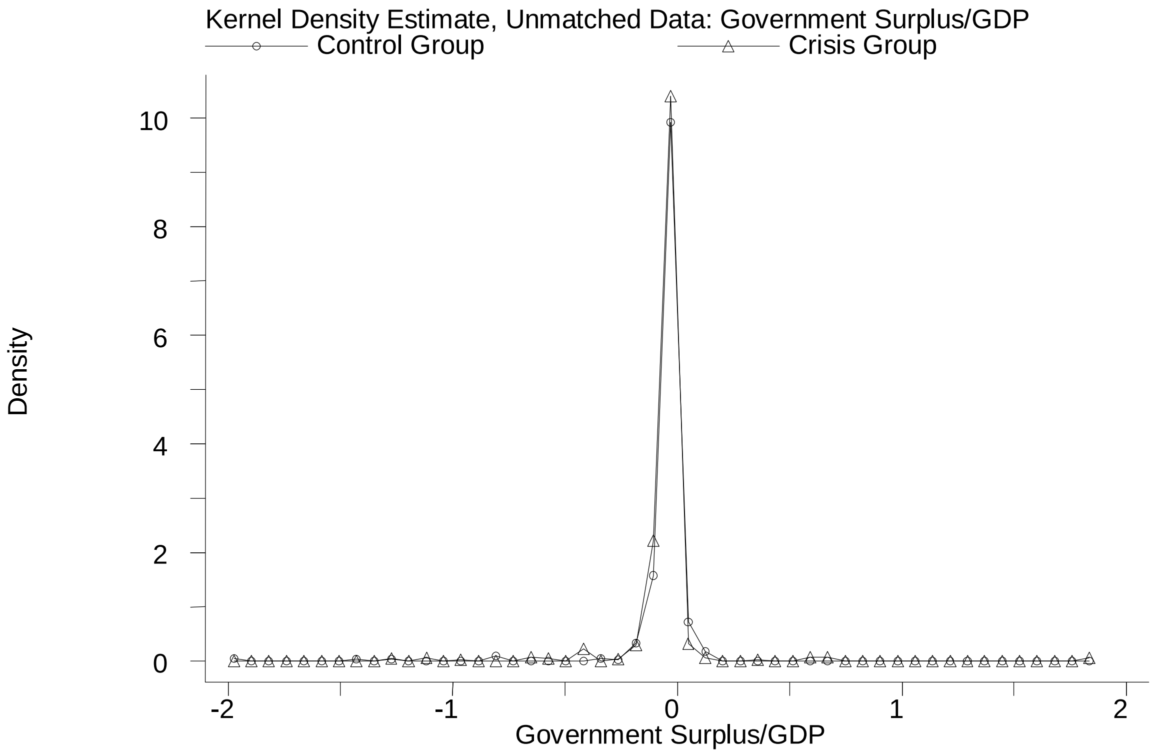


Kernel Density Estimate, Unmatched Data: Ln Per Capita GDP
Control Group
Crisis Group
Density
.4
.3
.2
.1
0
4
6
8
10
12
Ln Per Capita GDP

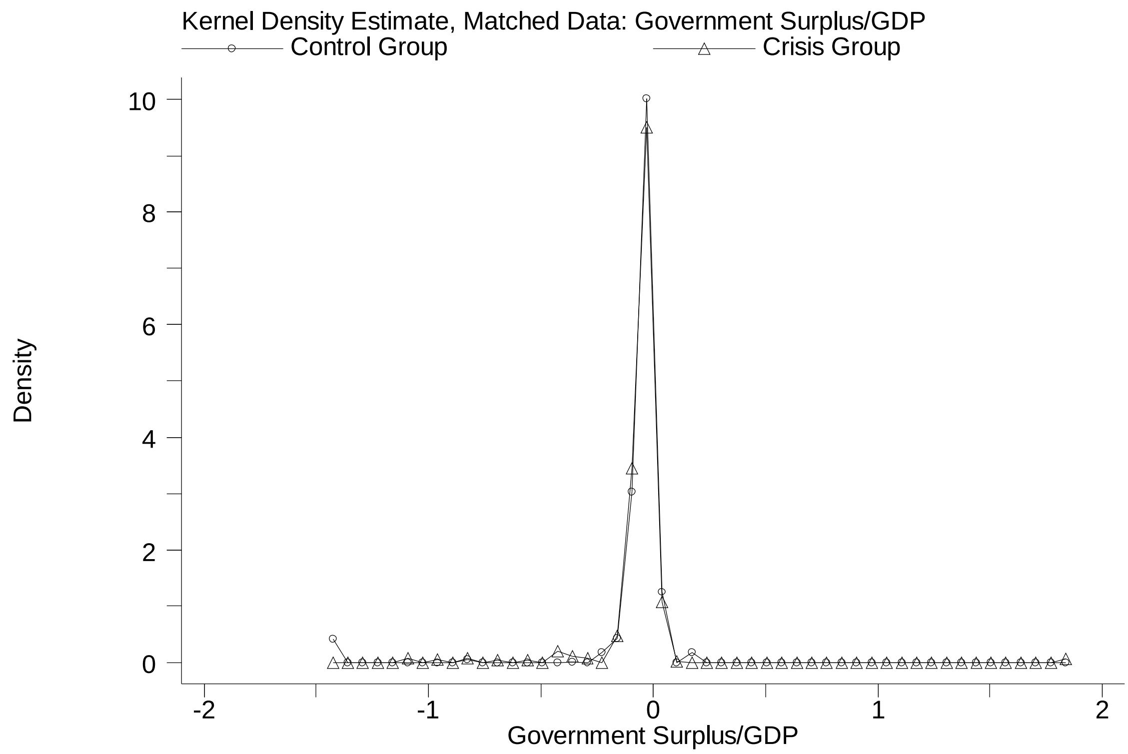


Kernel Density Estimate, Matched Data: Ln Per Capita GDP
Control Group
Crisis Group
Density
.4
.3
.2
.1
0
4
6
8
10
12
Ln Per Capita GDP

Figure 2

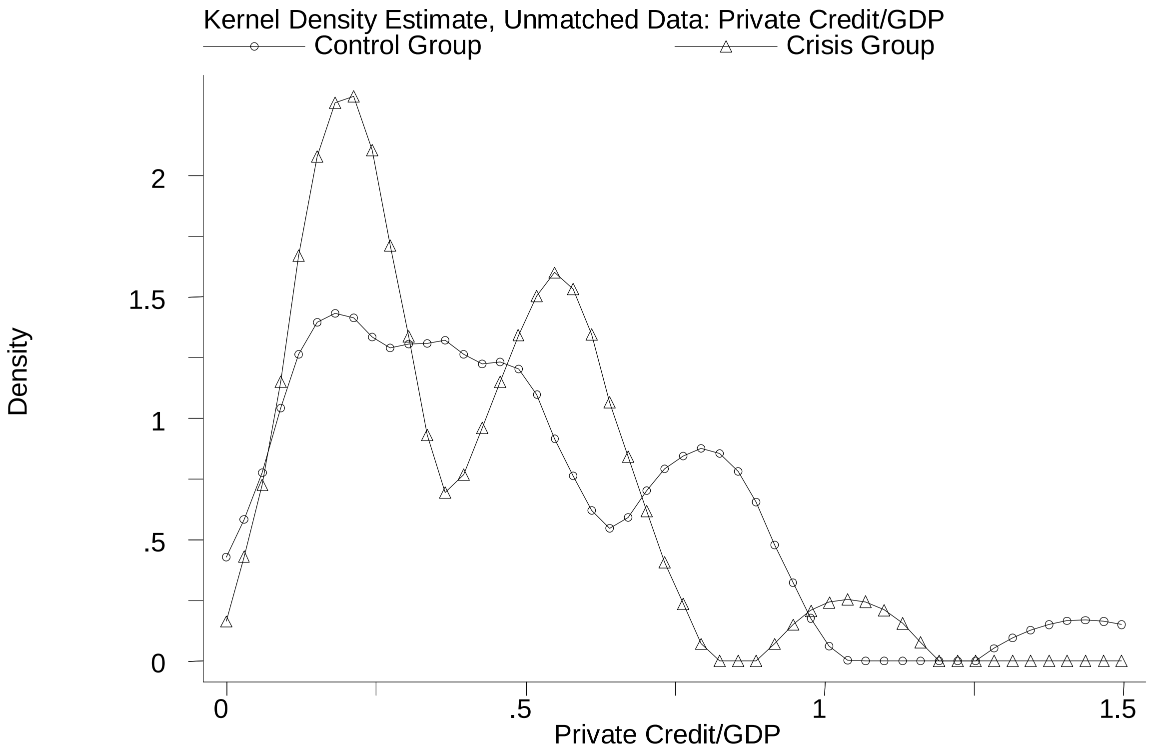


Kernel Density Estimate, Unmatched Data: Government Surplus/GDP
Control Group
Crisis Group
Density
0
2
4
6
8
10
-2
-1
0
1
2
Government Surplus/GDP



Kernel Density Estimate, Matched Data: Government Surplus/GDP
Control Group
Crisis Group
Density
0
2
4
6
8
10
-2
-1
0
1
2
Government Surplus/GDP

Figure 3


Kernel Density Estimate, Unmatched Data: Private Credit/GDP
Control Group
Crisis Group
Density
0
.5
1
1.5
2
0
.5
1
1.5
Private Credit/GDP

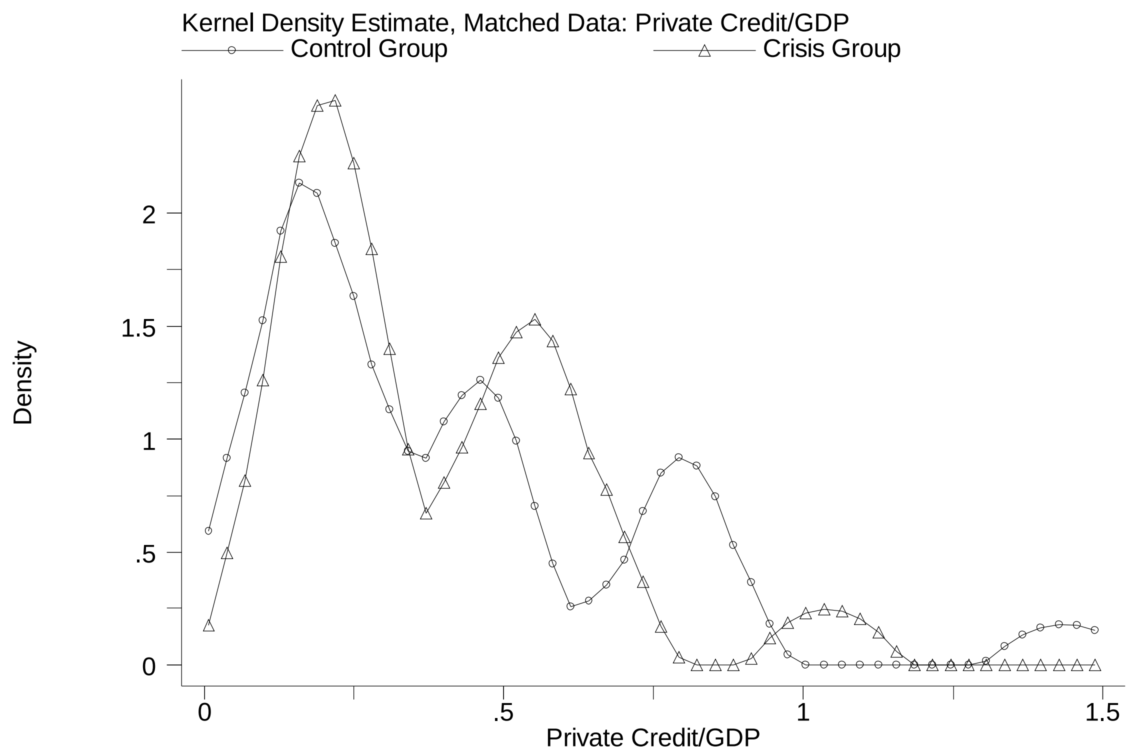
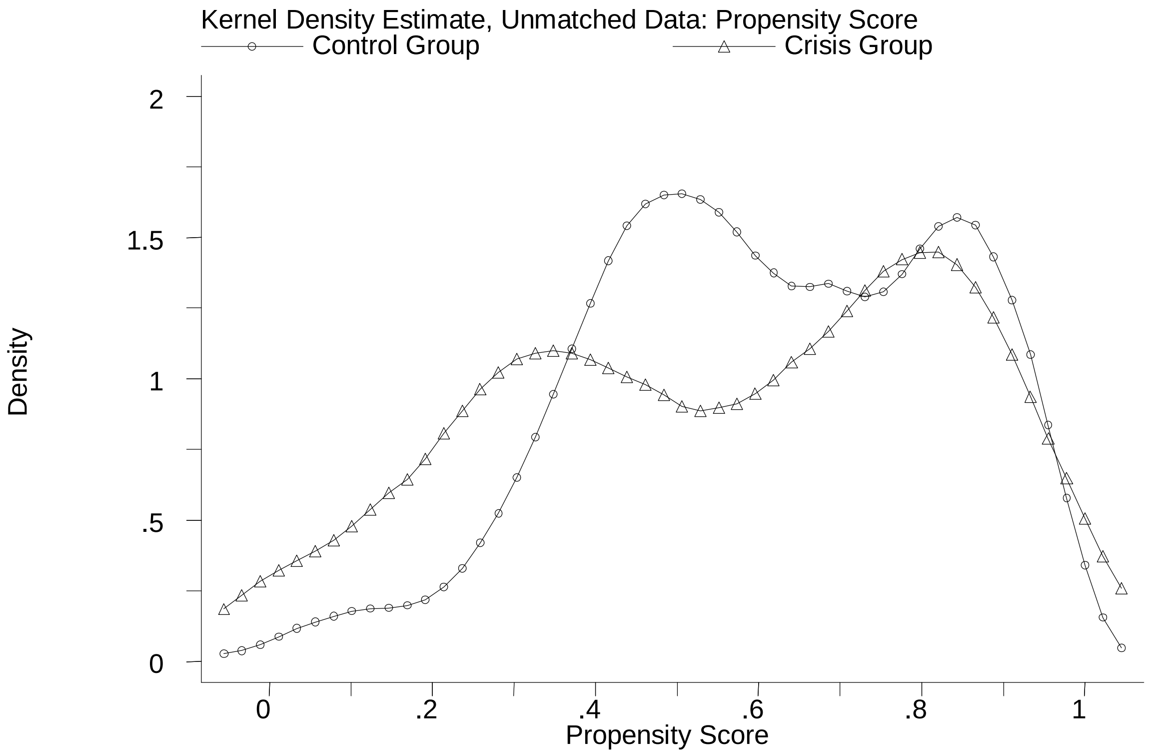
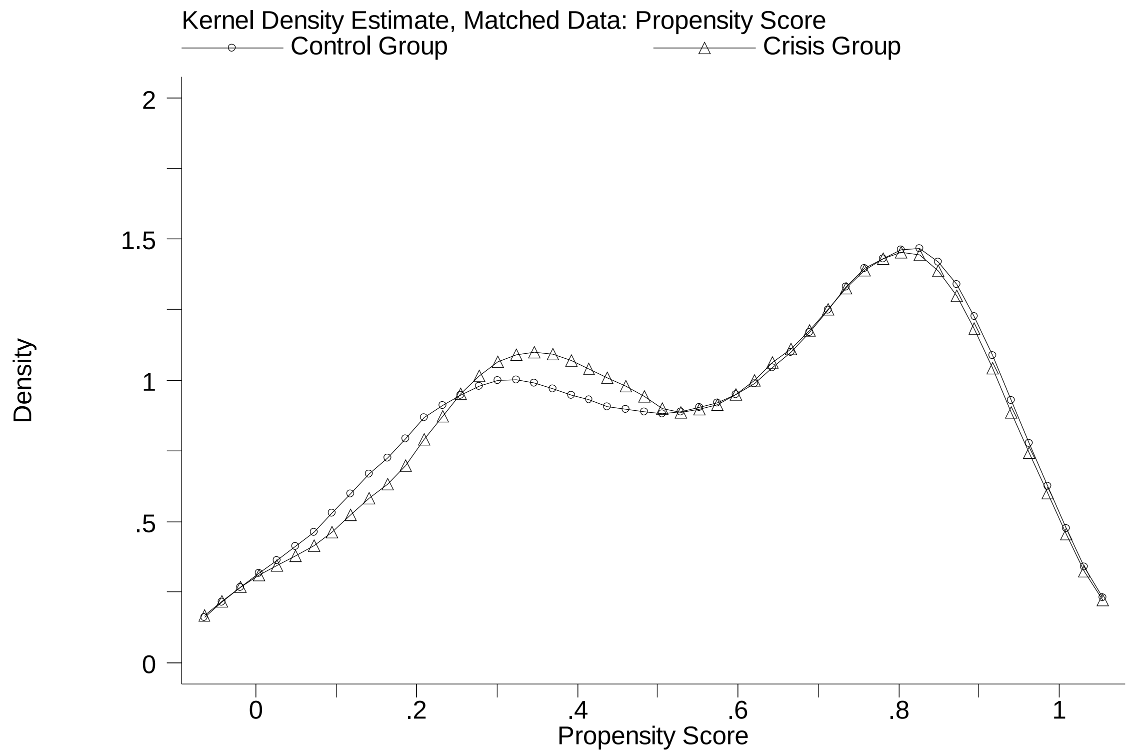

Kernel Density Estimate, Matched Data: Private Credit/GDP
Control Group
Crisis Group
Density
0
.5
1
1.5
2
0
.5
1
1.5
Private Credit/GDP

Figure 4


Kernel Density Estimate, Unmatched Data: Propensity Score
Control Group
Crisis Group
Density
2
1.5
1
.5
0
0
.2
.4
.6
.8
1
Propensity Score


Kernel Density Estimate, Matched Data: Propensity Score
Control Group
Crisis Group
Density
2
1.5
1
.5
0
0
.2
.4
.6
.8
1
Propensity Score

Appendix A: Matching Methods

The standard technique, matching without replacement, is conducted as follows. First, run a logit and/or probit regression to generate a scalar measure of the probability of deposit insurance participation $P(X)$. Match each country in the treatment group to a control country, in descending order, and repeat until each treatment country is matched with a country from the control group.

This technique can also be done "with replacement." In this case, $P(X)$ is estimated and the data are randomly ordered. Then each country in the treatment group is matched with the country from the control group that is its nearest neighbour. Define $P(X)$ as p, C_1 the set of treatment countries, and C_0 the set of control countries. Then, let $C_0(i)$ represent the set of control countries matched to the treatment country i given values of the propensity score p_i. Matching to the nearest neighbour is done as follows:

$$C_0(i) = \min_j \left\| p_i - p_j \right\|.$$

That is, each treatment unit is matched to its closest sample analogue from the control group based upon the propensity score. Furthermore, this technique implies that both the treatment units and control units will share common supports. If a treatment country does not contain a comparable sample analogue in the control unit (and vice versa), the country is removed from the sample. In this way, different treatment countries may have the same control-group analogue. Lastly, one can match each treatment country to those control countries within some radius, δ, of $P(X)$ and take the weighted average of the characteristics of those countries in the radius.[1] That is:

[1] The size of δ is determined by the researcher. Likewise, one can use local linear regression or kernel estimator methods to generate the control group analogue within the range of δ.

$$C(i) = \left\{ p_j \mid \quad \left\| p_i - p_j \right\| < \delta \right\}.$$

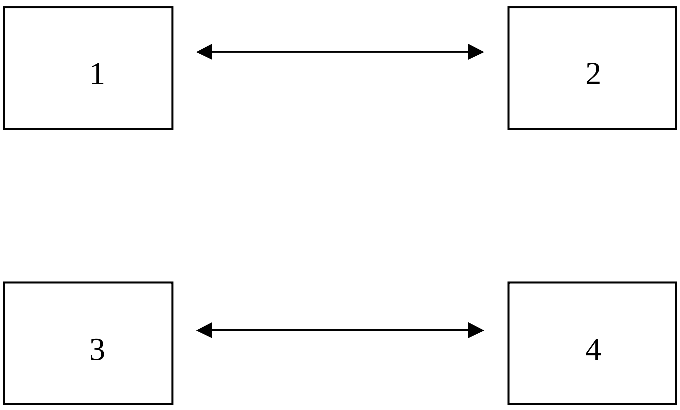
All the control units falling within the radius δ are matched to the treatment unit.

Appendix B: Market Structure (Allen and Gale, 2000)

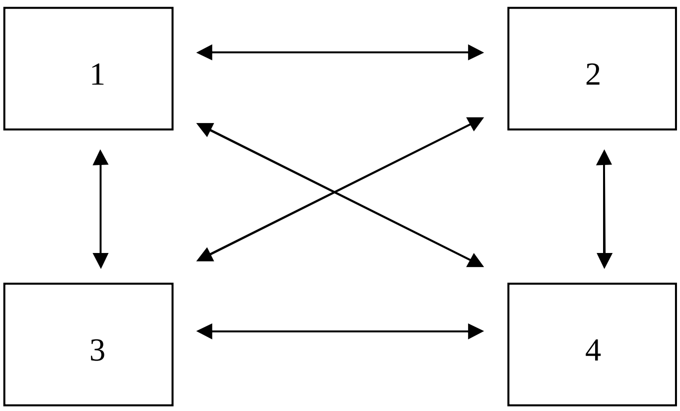
Allen and Gale (2000) show that the more complete the interbank market, the less likely a shock is to lead to contagion that causes a system-wide banking crisis. For example, consider two different market structures as shown in Figure B.1. If a shock hits Bank 2, the likelihood that contagion will spread differs according to market structure. If the market structure is less complete, as in structure A, the idiosyncratic liquidity shock will affect only one other bank, but with a greater likelihood that the other bank will become illiquid (since the shock can be insured only across two banks). The more complete the market structure, as in structure B, the greater the likelihood that the shock affecting Bank 2 can be insured against by the banking system. There is a trade-off, however, since structure B could lead to a complete failure of the banking system in the presence of a very large liquidity shock, while the relatively incomplete market structure A will result in the failure only of two banks The difficulty in testing these respective hypotheses from the Allen and Gale model is that it is hard to find direct empirical measures of "completeness." Conversely, there may be threshold effects, such that completeness, while allowing a greater dispersion of market liquidity when required, can actually help transmit shocks. Unfortunately, the data requirements for testing these hypotheses are extremely high, and so tests of Allen and Gale cannot be conducted.

Figure B.1: Two Different Market Structures

Structure A



Structure B



Source: Allen and Gale (2000)

Appendix C: Description of the Explanatory Variables and Sources

Data were obtained from the IMF and World Bank.

Variable Name	Definition	Source
Growth	Growth rate of GDP	IFS, WEO data base
Current account	Current account surplus	IFS
Depreciation	Rate of change of the exchange rate	IFS
Real interest rate	Nominal interest rate minus the contemporaneous rate of inflation	IFS
Inflation	Rate of change of inflation	IFS
Surplus/GDP	Ratio of central government budget surplus to GDP	IFS
M2/reserves	Ratio of M2 to foreign exchange reserves of the central bank	IFS
Private credit/GDP	Ratio of domestic credit to the private sector to GDP	IFS
Credit growth	Rate of growth of real domestic credit	IFS
Deposit insurance	Dummy variable for existence of a deposit insurance scheme	Kyei (1995), Garcia (1999), World Bank
Law and order	Quality of law enforcement	International Country Risk Guide, World Bank

Source: Demirgüç-Kunt and Detragiache (1997), IFS, World Bank

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