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Systemic Financial Crises, Balance Sheets, and Model Uncertainty

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Abstract

This paper empirically examines the probability and intensity of financial crises during the 1990s with a view to informing crisis prevention and mitigation policies. The econometric analysis uses a decision-theoretic approach, rather than the more standard general-to-specific approach, to address the high degree of model uncertainty. The results affirm the importance of balance sheets in the probability and intensity of financial crises, especially corporate balance sheet stresses and foreign exchange liquidity shortfalls. Model uncertainty is a bigger problem for estimating crisis intensity compared to crisis probability.

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Contents

I. Introduction

This paper examines the probability and intensity of financial crises during the 1990s with a view to improving crisis prevention and mitigation policies. The motivation is the new mandate for the IMF and World Bank to undertake comprehensive assessments of the vulnerability of the financial sectors of member countries, as well as the need for national policymakers to formulate crisis prevention and mitigation policies.[2] This paper aims to extend the financial crisis empirical literature to help inform these assessments and policies.

The paper appears to make three contributions to the literature. First, the empirical results affirm the key role of balance sheets in financial crises. Specifically, corporate liquidity and leverage and foreign exchange liquidity are robustly related to crisis probability and intensity, even after controlling for a wide array of indicators. The importance of corporate liquidity is a novel result, and suggests that crisis prevention policies should include careful monitoring of corporate balance sheets and improvements in corporate governance. In addition, the robustness of private capital inflows in explaining crisis intensity suggests that in forming crisis mitigation policies, e.g., countercyclical monetary and fiscal policy responses, governments should account for the magnitude of the crisis-triggering capital inflow cutoff.

Second, this paper uses a decision-theoretic approach to address the serious econometric problems posed by model uncertainty in empirical analysis of financial crises. Model uncertainty is in the form of a lack of a unifying theoretical model, collinearity, uneven numbers of observations across indicators, and parameter heterogeneity. These aspects of empirical financial models mean that application of the standard general-to-specific approach to indicator selection may raise important problems that would render the results less useful for policy formulation. To measure the degree of uncertainty regarding indicator selection, a set of data based weights are calculated as a metric to evaluate particular specifications. An additional advantage is that the decision-theoretic approach used in this paper more closely corresponds to the crisis indicator identification procedure practiced by policymakers.

Third, this paper addresses both the probability and the intensity of financial crises. The analytical division of crises into disparate pre-and post crisis dynamics is based on recent theoretical analyses of financial crises, as well as casual observation. Crisis probability is estimated using binary response models, as is typical in the literature. Crisis intensity can be thought of as the distance that the economy travels from the pre-crisis equilibrium measured along the output dimension. This definition is useful for policy because governments care most about the welfare costs of financial crises, and welfare costs have a higher correlation with real GDP than with financial sector indicators. Empirically, crisis intensity is gauged by the change in real GDP relative to the pre-crisis trend, conditional on the occurrence of a crisis. The

[2] The joint World Bank-IMF Financial Sector Assessment Program (FSAP) was introduced in May 1999 to assess financial system soundness in member countries.

analysis of both crisis probability and intensity using the same dataset allows comparison of the underlying structure, and provides policy implications for crisis mitigation.

It is worth noting at the outset that this paper takes a different tack than the high frequency early warning system (EWS) literature (Berg et al., 1999; Kaminsky and Reinhart, 1999; and Mulder et al., 2001). An increasing number of studies are developing EWS's, typically with monthly data. These EWS's aim to identify a small number of leading crisis indicators or even a composite measure of vulnerability to provide relatively quick warning signals of impending crises to trigger countervailing policy adjustments. The goal of this paper, rather, is to help enhance the effectiveness of annual or even less frequent assessments of crisis vulnerability. These assessments can be used to reduce crisis vulnerability by identifying indicators closely related to financial crises that should be closely monitored, and motivating structural reforms.

This paper is organized as follows. The empirical methodology used in this paper is described in Section II, and data issues and model specification are presented in Section III. The crisis probability and intensity results are reported in Sections IV and V. Section VI concludes with a summary of the results and their implications. The theoretical and empirical literature on crisis probability and intensity is reviewed in Appendix I, and data sources are documented in Appendix II.

II. Econometric Methodology

The starting point of the econometric approach taken in this paper is the real-life situation of a policymaker aiming to identify and collect economic data with a view to preventing and mitigating financial crises. The policymaker can be interpreted either as the IMF/World Bank aiming to determine which crisis indicators to employ in their new role of assessing financial vulnerability, or as a national policymaker aiming at formulating crisis policies.

Policymakers aiming to utilize empirical models of financial crises face serious problems posed by model uncertainty. One problem is the lack of a unifying theoretical model. Another is that the set of indicators potentially useful for crisis policies is very large and in constant flux. Many key indicators are available only on a limited basis across countries and time periods, and some have to be developed from scratch. Further, the underlying structure of crises may be different across groups of countries. These problems reflect the ever changing underlying structure of economic crises—indeed, if crises were not changing in cause than they would be anticipated, and thus would not occur in the first place. By contrast, other policies, can be—and often are—based on a single empirical economic model following from a unified theoretical framework estimated over a reliable dataset. Examples of policies driven by a single empirical economic model include time series models for monetary policy, and large microeconomic models used for welfare policy.

In this context, a useful way for the policymaker to proceed would be as follows. First, extract useful crisis indicators from the data by imposing priors based on the literature. Second, choose those indicators that explain the probability and intensity of historical financial crises. Lastly, pay the costs of collecting these data on a regular basis.

This paper applies an econometric methodology—the decision-theoretic approach (DTA)—which to a large extent approximates this procedure. The DTA rather than the more standard general-to-specific approach (GTSA) is used here because the former better addresses the specific econometric problems posed by empirical analysis of financial crises. The GTSA involves beginning with a general model that provides testable hypotheses, and then employs a sequence of tests to narrow down the number of explanatory variables to a manageable number.[3] Empirical analysis of financial crises pose four problems for the GTSA which are addressed by the DTA:

- *Lack of a unifying theoretical model*—The large number of overlapping and evolving theoretical models of crises imply that there is no single "true" underlying model. Thus, there is no valid starting point for the indicator reduction procedure of the GTSA. Application of GTSA in the absence of an underlying model implies path dependence in the order of the tests, which could erroneously lead to the omission or inclusion of indicators that could be useful for policy. In addition, under the GTSA standard likelihood ratio tests for nested models, and modified likelihood in the case of non-nested models are not helpful for binary comparisons given the assumption that one of the models considered is the true model. The lack of confidence in a starting model for the analysis suggests that the DTA offers fewer pitfalls than the GTSA in the effort to uncover the "data generating process".

- *Collinearity*—The combination of large number of candidate indicators and small sample size is likely to result in collinearity and a large number of candidate models that differ marginally.[4] For example, the absence of a single unifying model and the large number of candidate indicators gives a favorable statistical advantage to whatever

[3] A good explanation of the GTSA is as follows: "(1) Formulate a general model that is consistent with what economic theory postulates are the variables entering any equilibrium relationship and which restricts the dynamics of the process as little as possible; (2) Re-parameterize the model to obtain explanatory variables that are near orthogonal and which are 'interpretable' in terms of the final equilibrium; (3) Simplify the model to the smallest version that is compatible with the data ('congruent'); (4) Evaluate the resulting model by extensive analysis of residuals and predictive performance, aiming to find the weaknesses of the model designed in the third step." (Pagan, 1995). See Davidson and Hendry (1981) for a discussion of the limitations of GTSA, and for recent applications of GTSA see, for example, Campos and Ericsson (2000) and White (1999).

[4] See Davidson and Hendry (1981) for a discussion of the limitations of GTSA, and for recent applications of GTSA see, for example, Krolzig and Hendry (2000), Campos and Ericsson (2000) and White (1999).

happens to be chosen as the null model. Thus, in the testing of crisis indicators, the policymaker could erroneously conclude that the null model crisis indicators have explanatory power. Under the DTA, tests would be applied to both models. Of course, if there is no single data generating process than neither approach will produce parsimonious results. Further, a large number of candidate indicators will generate a large number of models using either the GTSA or the DTA.

- *Uneven numbers of observations across indicators*—Owing to an uneven number of observations across the candidate indicators, the larger the number of crisis indicators included in the analysis, the smaller the number of observations available for inference. Therefore, a large number of candidate indicators in the starting model reduces the sample size, and undermines inference. This does not affect estimation using the DTA since models are evaluated separately and not in a top down fashion.

- *Parameter heterogeneity*—The parameters which describe crisis probability and intensity may well be different across country groups and time periods. For example, less developed and more open countries may be more vulnerable to a sudden cutoff of capital inflows. Parameter heterogeneity can be introduced into the GTSA by shift dummies or other parametric adjustments, or simply by dividing up the sample of observations. However, the implications of model uncertainty across sample subsets cannot be measured under the GTSA, but is explicitly addressed using DTA.

The DTA is used here to address these problems.[5] [6] The DTA is predicated upon the identification of a candidate set of variables, say Ω of dimension v. In the absence of any constraints the total number of possible models is 2^v, and the objective of the policymaker is to reduce Ω to a smaller subset of unknown dimension κ (κ can also differ across pre-identified periods and/or country groups) upon which to base crisis policies. For crisis intensity, the dependent variable is y_j and x_{ji} determine the crisis intensity through a linear relationship:

(1) $$y_j = \sum_{i \in \kappa} \beta_i x_{ji} + \varepsilon_j,$$

[5] Burnham and Anderson (1998) provide an overview of the DTA to model selection, and Pesaran and Weeks (1999) evaluate the DTA and the GTSA in the context of model selection.

[6] The approach used here is similar in spirit to recent revionist approaches to modeling economic growth, which poses several of the same econometric challenges as does analysis of financial crises. Brock and Durlauf (2000) explicitly analyze theory uncertainty and parameter uncertainty using a decision-theoretic framework. Fernandez, Ley and Steel (2001) address the robustness problems posed by the coincidence of a large number of potential explanatory variables and the relative weakness of economic theory by using a full Bayesian approach.

where $\varepsilon \sim N(0,\sigma^2)$.[7]

The policymaker's priors are based on the financial crisis literature (as discussed in Appendix I), and previous experience with crises episodes.[8] Based on the priors of the policymaker, Ω is partitioned into S crisis channel indicator groups, say $\omega^{(1)},..\omega^{(S)}$. For example, $\omega^{(1)} = (x_1^1, x_2^1, ..., x_l^1)'$ might denote indicators of corporate balance sheet channels (e.g., total debt to common equity and the ratio of total debt to total assets) which are believed to be critical determinants of the probability and intensity of crises episodes. Individual indicators *within* each crisis channel group are indexed by $i = 1, ..., l^S$ with the notation allowing for a varying number of indicators per crisis channel. The policymaker is faced with considerable uncertainty given that theory is weak, or completely impotent, in selecting, for example, the appropriate indicators within the crisis indictor groups.

The number of potential indicators per group $\omega^{(s)}$ is subject to one of two constraints to minimize collinearity, and reduce the cost of data collection for the policymaker, which can be considerable. Under the first constraint, *one* indicator is chosen from each $\omega^{(s)}$ (l^S=1). Under the second constraint, *none or one* indicator is chosen from each part of Ω ($l^S \leq 1$) to allow for the possibility that one or more crisis channels (and measures therein) are not important determinants of crisis likelihood and intensity. The constraints are introduced by parameterizing the above model as follows:

(2) $$y_j = \sum_s^S \sum_{\{i;\gamma_i^s=1\}}^{l^s} \beta_i^s x_{ji}^s + \varepsilon_j$$

where $\gamma_i^s \in 0,1$ is a switch variable that determines whether indicator i in crisis channel s is to be included. Under the first set of constrained priors $\sum^{l^s} = 1$ and for the second set of unconstrained priors $\sum^{l^s} \leq 1$, for all S channels.

The Akaikes Information Criterion (AIC; Akaike, 1973) is used here as the objective function for model selection. The AIC is based upon the notion that an exactly true model does not exist,

[7] Modelling of the likelihood of crisis the procedure is exactly the same, with the only difference being that maximum likelihood is used to estimate binary probit models.

[8] Brock and Durlauf (2000) discuss the use of qualitative information in establishing identifying assumptions in empirical analysis of growth models.

and that the purpose of model selection is simply to find the best approximating model of the data generating process. [9] The AIC objective function is:

(3) $$AIC = -2\ell(\hat{\theta}(y)) + 2k$$

where, for any given model, k denotes the number of candidate indicators in the actual regression plus one (for σ), $\hat{\theta}$ is a vector of estimated parameters, and $\ell(\hat{\theta}(y))$ is the log-likelihood evaluated at $\hat{\theta}$. The model with the smallest AIC is considered to be the best approximating model of the data generating process. The AIC captures the bias-variance trade-off in that the addition of more parameters may shrink the first term as the approximating model gets closer to the true model, but since these parameters are *estimated*, adding more parameters will also increase variance. The policymakers' objective function is proxied by:

(4) $$\min_{\kappa\in\Omega} AIC \quad st \quad \kappa \leq S, \qquad \sum_{i=1}^{I_s} \gamma_i^s \leq 1$$

The first inequality limits the number of regressors to the number of crisis channels *S*. In the second inequality, elements of a (0,1) vector γ^s are set equal to 1 for the *ith* member of each *sth* indicator group $s=1,\ldots,S$, if that element is included in the model. Given that $\sum_s^S \sum_i^{I^s} \gamma_i^s = \kappa$, this constraint specifies that only specifications (combinations of indicators) with at most one indicator from each crisis channel will be considered.

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[9] This criteria is distinct from a number of alternate DTA objective functions, such as the Bayesian Information Criterion (BIC) derived by Schwarz (1978) which Burnham and Anderson (1998) note, are "dimension consistent." The BIC is used to locate the "true" model, which is fixed as sample size increases, and assumed to lie within the candidate set of models. Consistency means that as sample size increases, the probability of locating the true model approaches one. In the context of empirical analyses of financial crises, an increase of sample size corresponds either to a larger set of countries, e.g., extending the dataset from the standard 30 or so large emerging market countries to include smaller emerging market countries, or to a large set of indicators, e.g., extending the dataset to include corporate or legal indicators. The problem is that both extensions may well introduce an alternative data generating process, thereby violating consistency.

The extent of model uncertainty for a given sample of countries and years is gauged by comparing the AIC statistic across a set of specifications. This comparison is made using the AIC differences, which for specification p are given by

$$\Gamma_p = AIC_p - M_*, \tag{5}$$

where M_* denotes the model with minimum AIC over the set of specifications, such that $\Gamma_p \geq 0$. Γ_p facilitates direct comparison of AIC across the set of specifications, such that although M_* might be identified as the best approximating specification, as Γ_p increases the less plausible is p as the best specification.

Finally, for ease of comparison, Akaike weights are based on the AIC differences, and following Akaike (1983) are constructed as follows:

$$w_p = \frac{\exp(-\frac{1}{2}\Gamma_p)}{\sum_{m=1}^{Z} \exp(-\frac{1}{2}\Gamma_m)} \tag{6}$$

where $w_p \in (0,1)$ and $m = 1,\ldots, Z$ indexes the set of Z specifications that minimize Γ_p. Here, Akaike weights are used as a measure of how well the best specification approximates the unknown data generating process vis-à-vis the next Z-1 best specifications.

III. Data Issues and Model Specification

This section describes the empirical approach taken in this paper. For the empirical analysis, choices must be made regarding: the sample countries and years, the definition and measurement of crisis probability and intensity, selection of the candidate indicators for gauging the crisis channels, and presentation of the results.

A. Sample Countries and Years

The selection of the sample countries and years entails tradeoffs. For example, a larger sample can provide more precise inference, but only if the parameters are stable across countries. Moreover, the number of countries is limited because countries need to be of a certain size before they have full access to international capital markets and thus can become vulnerable to a financial crisis. This suggests a compromise: used here are 49 medium and large countries that have access to international capital markets and thus could potentially have spillover effects on other countries (Appendix II).

The time period for the regression analysis is 1992–99. An earlier starting point would, again, provide more data for inference, but would call into question the implicit assumption of parameter stability, since by their very nature the causes and dynamics of crises evolve through time. Further, the purpose of this paper is to inform forward-looking policies. Finally, as a practical matter, much of the key data used in the analysis is available only for the 1990s. To determine the extent to which both the determinants of the probability and intensity of financial crisis have changed during the 1990s, separate regressions are run for 1992–95.

B. Definition and Measurement of Crisis Probability

A binary crisis indicator is used as the dependent variable in the crisis probability regressions. A binary indicator allows direct estimation of crisis probability and type 1 and type 2 errors. Moreover, a binary indicator can be used to gauge not only the occurrence of a currency crisis, but also a bank crisis, which is difficult if not impossible to gauge with a continuous quantitative indicator. The disadvantages of a binary crisis indicator are that indicators cannot be ranked, and false signals cannot be take into account.

The financial crisis episodes are chosen using standard methodologies. The source of the pre-1997 currency crises was Aziz et al., (2000) who employed an index of weighted averages of exchange rate changes and reserve changes normalized to have equal variance. A crisis is defined as when the index exceeded 1½ times the pooled standard deviation plus the pooled average. They identified episodes from January 1975 to November 1997, and episodes covering December 1997 to December 1999 were added to the data used here based on the same methodology. The banking crises were taken from Caprio and Klingebiel (1996), who employed a necessarily judgmental approach to identify crises from the late 1970s to the mid-1990s. Again, the sample was extended to 1999 using the same approach.

The unconditional probability of crisis for the sample is 11.5 percent based on the incidence of fifty two crisis episodes during 1992–99 for the 49 sample countries. Of these episodes, thirty-seven episodes are currency crises, fifteen are bank crises, and seven are concurrent crises. For the sake of comparison, the unconditional probability of crises during the prior 1977–91 period was also 12 percent, suggesting the incidence of crises did not shift in the 1990s compared to the prior period. The number of crises per year peaked in the mid-1980s with the sovereign loan defaults, and in the mid-1990s including the tequila and East Asian episodes (Figure 1). The incidence of currency crises is three times that of bank crises over the entire sample period. However, the number of bank crises increased in the 1990s, whereas the number of currency crises remained broadly unchanged. The number of concurrent crises quadrupled from two during 1977–91 to six during 1992–99, indicating the increased symbiosis of currency and bank crises.

The incidence of crisis differed sharply across regions and time periods (Figure 2). The lowest incidences, at around 7½ percent were for the European emerging market countries and the industrial countries. In contrast, the three African countries experienced crisis in 25–30 percent of the years. Latin American, Asian, and Middle Eastern countries all had crises in

15–20 percent of the observations. A 1977–91 and 1992–99 comparison of crisis incidence suggests a surprising level of stability over time, although this comparison masks the sharp fall in crisis in industrial countries in the late 1990s.

C. Definition and Measurement of Crisis intensity

Crisis intensity is gauged by the change in real GDP relative to the pre-crisis trend conditional on the occurrence of a crisis. The output shortfalls for these episodes are measured as the percentage deviation of actual GDP from its trend. The trend is calculated using a Hodrick-Prescott filter with standard parameter settings. Since the measurement of crisis intensity involves a duration component, another key specification issue is what duration to choose in the absence of a complete empirical macroeconomic model that would control for all the factors influencing output (Hoggarth et al., 2001). Measuring intensity using output data for the year of the crisis would seem too short, and there is also the problem of crises that start late in the year. On the other hand, using data for say four or five years after the onset of crisis would surely introduce other extraneous shocks. Alternatively, a variable duration could be employed based on the number of post-crisis years for which GDP remained below trend. But a variable duration can also introduce extraneous shocks and, moreover, raises difficult problems of defining explanatory indicators, e.g., should averages of indicators be used, or at the beginning of the crisis. For these reasons, the shortfall of output from trend for the crisis year and the following year was used. This approach introduces an extra source of measurement error at the gain of consistent definitions, and interpretations of explanatory indicators. However, estimation with alternative different definitions of duration suggested that the results are robust with respect to the term of the duration.

Financial crises caused output to contract by 4 percent on average across the entire sample (Figure 3). The impact on output of the crises on average for each year during 1977–99 has been negative, except for four years, mostly covering industrial country crises. Generally, the most severe crises occurred during the mid-1980s, 1997, and to a lesser extent during the early 1990s, although it should be kept in mind that the differential number of crises per year distorts these annual averages.

Crisis intensity varies widely with an average annual range of some 14 percent. Indonesia in 1997–98 experienced the largest output contraction of 30 percent. On average, developing countries are hit harder in comparison to industrial countries, and the range of the crisis impact is wider. An exception are the developing countries in Europe who experience a less adverse and even a positive impact on output during the 1990s (mostly EMU crisis observations) probably reflecting their ties to industrial countries which are less prone to financial crises. The Asian country crises during 1993–99 had the most deleterious impact on output across the regions and time periods (Figure 4). Most of the other episodes ordered in this way had average contractions in the -4 to -2 percent range.

D. Crisis Channel Indicators

Specification of the probability and intensity models is motivated by the literature review and by the practicalities of assessing the vulnerability of the financial sectors. The review of the theoretical literature in Appendix I, as well as practical experience, suggests the following crisis channels: the external sector, banking sector, corporate sector, collateral, financial breadth, foreign exchange liquidity, and the legal environment. Indicators gauging the vulnerability of each of these channels can then be chosen largely based on data availability (Table 1).

Table 1. Crisis Channel Indicator Groups 1/

External sector
- Imports to GDP (Imp/GDP) +
- Real effective exchange rate, deviation from trend (REER) +
- LIBOR +
- Net liabilities of nonbanks to banks residents in BIS reporting countries to GDP (Ext Liabs) +
- Current account balance to GDP (CA/GDP) +

Banking sector
- Leading four year change in private credit to GDP (4 yr ChPCr) +
- Domestic credit to GDP (DomCred) + or -
- Broad money to GDP (BrdMgdp) -

Corporate sector
- Total debt to common equity (TotDCE) +
- Equity to total capital (EqTC) -
- Current ratio - Ratio of total current assets to total current liabilities (CurrR) -
- Working capital to total capital (WCapTC) -
- Long-term debt to common equity (LTDCE) +
- Quick ratio — Ratio of cash and equivalents plus net receivables to total current liabilities (QuickR)
- Long-term debt to total capital (LTDTC) +

Financial Breath
- Ratio of outstanding bonds plus stock market capitalization to bank credit (FBr2) -
- Private bond market capitalization to GDP (PBM_gdp) -

Foreign Exchange Liquidity
- Broad money/International reserves (Broad$) +
- Change in capital inflows (ChPC/GDP) -

Legal Environment
- Rule of Law (ROL) -
- Antidirectors Rights (AntiDirR) -

Other
- Annual average CPI inflation (CPI Inf) +
- Income development (1 = high income,…., 4 = low income) (Idevl) -
- Real GDP deviation from trend (R_GDPhpt) +

1/ Signs indicate hypothesized impact of each indicator on crisis probability (the impact on crisis intensity is of the opposite sign).

Descriptive statistics for the twenty-one crisis probability indicators are shown in Table 2. The maximum number of observations per indicator is 392 (nine years of data for 49 countries), but there are sizable holes in the data, especially for foreign exchange liquidity, legal environment and corporate sector indicators.

Table 2. Crisis Channel and Indicator Groups 1/

Indicator	Mean	Standard Deviation	N
External Sector			
PrivCF	65.709	34.203	382
90dLIB	-0.399	2.674	392
TofT	102.019	12.157	292
Imp.	64.539	154.571	383
Banking Sector			
4YrChPCr	-0.484	5.019	392
DomCred	15.580	22.136	384
BrdMgdp	13.717	174.760	384
Corporate Sector			
TotDCE	6.742	1.274	392
EqTC	17.417	45.028	363
CurrR	75.428	37.857	375
QuickR	10.082	11.065	373
Financial Breadth			
FBr2	23.327	9.709	392
PBM-gdp	61.648	12.830	304
Foreign Exchange Liquidity			
Broad$	18.700	31.896	366
ChPC/GD	26.745	33.664	390
Legal Environment			
ROL	0.094	0.292	392
AntiDirR	0.038	0.192	392
Others			
CPI Inf	-37.026	28.686	392
R_GDPhpt	1.813	5.060	392

Sources: See Appendix II.

1/ Data arc for 49 countries, and an uneven number of years.

E. Presentation of the Results

For both crisis probability and intensity six "runs" are reported. All of the runs are constrained such that either one ($l^S=1$) or one or no ($l^S \leq 1$) indicators are selected for each candidate indicator group. The runs are as follows: (i) using data for the period 1992–99, covering all sample countries with one indicator chosen from each of the seven candidate indicator groups; (ii) the same as i but without the legal indicator candidate group and one indicator chosen from each of the six remaining groups; (iii) the same as ii but allowing one or no indicators to be chosen from each of the six groups; (iv) the same as iii but without the contagion indicator; (v) the same as ii using data for 1992–95; and, (vi) the same as ii using data for nonindustrial countries only.

The top half of the regression tables reports the p-value for each of the selected indicators whose combination minimizes the constrained AIC statistic (4); blanks correspond to indicators that are not selected. P-values less than .05 are marked in bold, and a negative sign denotes a negative parameter estimate. The bottom half of each table reports diagnostics, including: the number of observations; the pseudo r-squared; type1 error; and type 2 errors for the probability regressions;[10] r-bar-squared for the intensity regressions; the AIC statistic; and the Akaike weights for the 10 specifications that minimize the AIC statistic, in decreasing order. P-values for a test of heteroscedasticity and normality are also presented.

IV. Crisis Probability Regression Results

The results reported in the first column of Table 3 are based upon a search over models which are constrained to include one indicator from each of the seven crisis channel groups ($l^S = 1$). These regressions utilize only 284 observations out of a possible 396 mainly because they include the legal environment indicators, which are not available for twelve of the 49 countries. The indicators with the most explanatory power are the size of the banking sector, the corporate current ratio and the money to international reserves ratio, and the contagion indicator, all of which have the expected sign. The financial breadth indicator, and external indicators with p-values at just below 10 percent are marginally significant, whereas, none of the legal or other indicators were significant, in contrast to other empirical studies (Kaminsky and Reinhart, 1999; Mulder et al, 2001). The diagnostic results show that the model that minimizes the AIC statistic does not predict 40 percent of the sample crises (type 1 error), and falsely predicts a crisis (type 2 error) for about 16 percent of the observations. The sequence of AIC differences, which

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[10] The pseudo r-squared equals 1 when the model is a perfect predictor of crisis events; type 1 errors represent the percentage of crisis observations that we were predicted as non-crisis; type 2 errors represent the percentage of non-crisis observations that were predicted to be crises (false alarms).

serve as a measure of model uncertainty for each run, suggest that the explanatory power of the specifications for those observations is low relative to the other runs.

Exclusion of the legal environment indicators to increase the number of observations, and because they were not significant in the first run, does not qualitatively change the results. Omitting the legal indicators increases the number of observations from around 284 to 312, with most of the new observations for poor countries. The development indicator now has the lowest p-value of any indicator, suggesting that the legal indicators are a proxy for stage of development, and that the nonindustrial countries are more prone to crisis. Interestingly, none of the banking indicators are now significant at even the 10 percent level, and the p-value of the foreign exchange liquidity indicator drops. The type 1 errors are higher and type 2 errors are broadly unchanged from the previous run. The inclusion of observations for lower income countries increases the degrees of freedom, but does not improve the predictive power of the model, perhaps because the data generating process is different for the lower income countries. The higher AIC weight for the first specification indicates that model uncertainty for this set of observations is less than that of the previous run.

For the third run, indicator groups that do not contribute to a lower AIC statistic are eliminated ($l^S \leq 1$). Interestingly, this adjustment to the algorithm did not lead to the elimination of any of the indicator groups, i.e., the results were identical to the constrained results. Thus, all of the six included groups help explain crisis probability.

The contagion indicator was then excluded in the fourth run to examine whether contagion has an independent impact on crisis probability. Comparison of the third and fourth columns of Table 3 show that excluding contagion raises the type 1 error by 8 percentage points, suggesting that contagion does has predictive power in and of itself. Moreover, the results for the other indicators were not qualitatively changed. This outcome suggests that contagion has an impact on crisis probability autonomous from the wide array of candidate indicators used here.

The model was than run using the 180 observations over 1992–95 to discern heterogeneity in the determinants of crisis probability during the 1990's. The results for the early subsample are qualitatively similar to the results for the entire 1992–99 sample, as can be seen by comparing the third and fifth columns of Table 3. The increase in the value of the p-statistic for the contagion indicator is consistent with increased capital market integration during the 1990s, and financial breadth no longer contributes to the objective function. Interestingly, the lower type 1 error suggests that crises were *easier* to predict in the earlier period. At the same time, the incidence of type 2 errors is higher. Another surprising result is that the AIC weights indicate that one specification fits the 1992–95 data relatively better than the next best specifications chosen by the algorithm. This indicates that the 1992–95 data are better captured by a single model relative to the 1992–99 data, i.e., model uncertainty increased during the 1990s.

Table 3. Crisis Probability Results 1/

Indicator	(i) All Countries 1992–99 (One)	(ii) All Countries 1992–99 No Legal (One)	(iii) All Countries 1992–99 No Legal (One or none)	(iv) All Countries 1992–99 No Legal No Contagion (One or none)	(v) All Countries 1992–95 No Legal (One or none)	(vi) Non-Industrial Countries 1992–99 (One or none)
External Sector						
Imp/GDP						
REER						
LIBOR	-0.0740			**-0.0458**		**-0.0198**
Ext liabs		0.0692	0.0692		**0.0250**	
CA/GDP						
Banking Sector						
4YrChPCr		-0.1280	-0.1280	-0.1911	-0.0904	-0.3773
DomCred/GDP	**-0.0108**					
BrdMgdp						
Corporate Sector						
TotDCE						
EqTC						
CurrR	**-0.0058**	**-0.0081**	**-0.0081**	**-0.0059**	**-0.0104**	**-0.0186**
WcapTC						
LTDCE						
QuickR						
LTDC						
Financial Breadth						
FBr1						
FBr2	-0.0914	-0.1408	-0.1408	-0.0893		-0.1987
PBM-GDP						
Foreign Exchange Liquidity						
Broad$	**0.0007**	0.0618	0.0618	0.0536		**0.0050**
ChPC/GDP					**-0.0080**	
Legal Environment						
ROL						
AntiDirR	-0.2011					
Others						
CPI Inf						
IdevI	0.2118	**0.0010**	**0.0010**	**0.0030**	**0.0058**	0.1406
R_GDPhpt						
RealRr						
Contagion	**0.0081**	**0.0023**	**0.0023**		0.0605	**0.0087**

Table 3. Crisis Probability Results (continued)

Indicator	(i) All Countries 1992–99 (One)	(ii) All Countries 1992–99 No Legal (One)	(iii) All Countries 1992–99 No Legal (One or none)	(iv) All Countries 1992–99 No Legal No Contagion (One or none)	(v) All Countries 1992–95 No Legal (One or none)	(vi) Non-Industrial Countries 1992–99 (One or none)
Diagnostics						
N	284	312	312	312	180	175
Pseudo R-squared	0.810	0.814	0.814	0.81	0.761	0.754
Type 1 error	0.405	0.405	0.405	0.48	0.200	0.333
Type 2 error	0.158	0.152	0.152	0.14	0.247	0.238
AIC	186.8	211.4	211.4	220.8	144.3	138.2
AIC weights						
1	0.201	0.242	0.242	0.272	0.375	0.138
2	0.150	0.171	0.171	0.226	0.121	0.137
3	0.125	0.117	0.117	0.103	0.105	0.134
4	0.111	0.113	0.113	0.085	0.068	0.124
5	0.110	0.097	0.097	0.067	0.066	0.102
6	0.098	0.069	0.069	0.061	0.062	0.098
7	0.054	0.054	0.054	0.052	0.055	0.076
8	0.052	0.048	0.048	0.049	0.054	0.073
9	0.052	0.047	0.047	0.043	0.051	0.065
10	0.046	0.043	0.043	0.042	0.043	0.054

1/ "One" and "One or none" refers to the number of indicators constrained to be chosen from each indicator group.

Finally, to examine differences between the industrial countries and the others, the high-income country observations were excluded from the results reported in the sixth column of Table 3, leaving 175 observations. The type 1 error is higher for the medium and low-income countries, but the type 2 errors increase. The shape of the AIC weights suggest that there is no single specification that applies to the nonindustrial countries, perhaps reflecting their heterogeneity. Comparisons of columns three and six of Table 3 indicate that the external and foreign exchange indicators are more important for the nonindustrial countries. The sequence of AIC weights is much flatter for the nonindustrial countries, indicating that model uncertainty across specifications is higher for this subsample relative to the entire sample.

In summary, these regression results suggest that corporate liquidity, contagion, foreign exchange liquidity, the level of development, and external sector indicators help explain financial crisis probability during 1992–99. The legal indicators do not enter significantly, implying that their influence independent of the other indicators is minimal. Similarly, the banking and financial breadth indicator results are mixed, indicating that they may be conduits of corporate distress rather than have an independent role in crisis vulnerability. The indicators selected for the early subsample and for the nonindustrial countries compared to the entire sample are not qualitatively different. However, the improvement in type 1 errors for the subsamples suggests policymakers should separate country groups in formulating crisis policies.

Moreover, model uncertainty is a bigger problem for the non-industrial countries, and for the late 1990s.

V. Crisis Intensity Regression Results

Crisis intensity regression results are presented in Table 4. As noted earlier, crisis intensity is measured as the accumulated deviation from trend GDP during the crisis year and the following year. Ordinary least squares is used to generate the parameter estimates.

As in the probability regressions, the first column results are constrained to include one indicator from each of the crisis indicator groups, allowing a total of 36 observations. The adjusted r-squared is 41 percent, suggesting a useful degree of explanatory power. The significant parameter estimates are for imports/GDP, the corporate current ratio, the cutoff of capital inflows, and contagion, all with the expected sign. The AIC weights suggest a high degree of model uncertainty across specifications.

Exclusion of the legal environment indicators, as shown in the second column, adds an extra six observations for a total of 42, but does not qualitatively change the results. Significant parameter estimates are obtained for the same four crisis indicators, and the adjusted r-squared is marginally higher. Interestingly, model uncertainty as gauged by the sequence of AIC weights is much improved compared with the previous run, indicating improved robustness arising from the extra observations afforded by the exclusion of the legal indicators.

Lifting the constraint that one indicator is chosen from each category, as reported in column three, does not qualitatively changes the results. The current account/GDP replaces the import/GDP as a significant external sector indicator, while corporate leverage replaces corporate liquidity. The adjusted r-squared rises slightly.

In a similar vein, exclusion of the contagion indicator, as reported in the fourth column of Table 4, does not qualitatively changes the results or the fit. Thus, contagion appears to be less important for crisis intensity vis-à-vis crisis probability.

To gauge changes in crisis intensity during the 1990s, regressions were run using the 30 observations covering 1992–95, a disproportionate number of which were industrial countries owing to the ERM crisis. Results are presented in the fifth column of Table 4. The r-squared is much lower at 18 percent. In contrast to the results for the entire sample, none of the external indicator indicators are significant, nor is the contagion proxy. The relatively low AIC weight for the best specification run indicates that the earlier period is characterized by a higher degree of model uncertainty.

Finally, results are reported for the nonindustrial countries, leaving 30 observations, in the last column. Comparisons of columns three and six shows, perhaps surprisingly, a better fit, according to the adjusted r-squared of 53 percent, and a relatively low degree of model uncertainty. The indicators with significant parameter estimates are import/GDP, corporate leverage, and the capital inflow indicator, whereas contagion is not significant.

Table 4. Crisis Intensity Results 1/ 2/

Indicator	(i) All Countries 1992–99 (One)	(ii) All Countries 1992–99 No Legal (One)	(iii) All Countries 1992–99 No Legal (One or none)	(iv) All Countries 1992–99 No Legal No Contagion (One or none)	(v) All Countries 1992–95 No Legal (One or none)	(vi) Non-Industrial Countries 1992–99 (One or none)
External Sector						
Imp/GDP	**0.0472**	**0.0216**		**0.0091**		**0.0170**
REER						
LIBOR						
Ext liabs					0.1326	
CA/GDP			**0.0198**			
Banking Sector						
4YrChPCr	-0.2000	-0.2338	-0.2986	-0.2947	-0.4316	-0.2197
DomCred/GDP						
BrdMgdp						
Corporate Sector						
TotDCE			**-0.0009**			**-0.0057**
EqTC						
CurrR	**0.0221**	**0.0023**		**0.0019**		
WcapTC						
LTDCE					**-0.0268**	
QuickR						
LTDC						
Financial Breadth						
FBr2	0.4646	0.6679	**0.0902**	0.6847	0.1110	0.4615
PBM-GDP						
Foreign Exchange Liquidity						
Broad$						
ChPC/GDP	**0.0022**	**0.0010**	**0.0001**	**0.0006**	**0.0136**	**0.0002**
Legal Environment						
ROL						
AntiDirR	0.7081					
Others						
CPI Inf	0.4149					
IdevI		-0.4183				
R_GDPhpt						
RealRr						
Contagion	**-0.0247**	**-0.0154**	0.1711		-0.2158	0.1015

Table 4. Crisis Intensity Results (continued)

Indicator	(i) All Countries 1992–99 (One)	(ii) All Countries 1992–99 No Legal (One)	(iii) All Countries 1992–99 No Legal (One or none)	(iv) All Countries 1992–99 No Legal No Contagion (One or none)	(v) All Countries 1992–95 No Legal (One or none)	(vi) Non-Industrial Countries 1992–99 (One or none)
Diagnostics						
N	36	42	42	42	30	30
R-bar squared	0.412	0.417	0.428	0.420	0.180	0.531
AIC	135.5	153.0	151.5	151.8	93.4	110.4
AIC weights						
1	0.125	0.220	0.230	0.232	0.127	0.289
2	0.115	0.197	0.198	0.190	0.121	0.139
3	0.106	0.174	0.108	0.127	0.108	0.110
4	0.105	0.150	0.097	0.104	0.107	0.108
5	0.098	0.107	0.089	0.087	0.106	0.072
6	0.096	0.071	0.086	0.086	0.098	0.068
7	0.095	0.021	0.074	0.073	0.089	0.064
8	0.095	0.020	0.053	0.038	0.085	0.056
9	0.082	0.019	0.035	0.035	0.084	0.054
10	0.081	0.019	0.030	0.026	0.076	0.039
Heteroscedasticity test (p-values)	0.918	0.926	0.718	0.715	0.032	0.882
Normality test (p-values)	0.036	0.052	0.023	0.015	0.243	0.20

1/Dependent variable is the change in real GDP for the crisis year and the following year (t to t + 1) relative to the pre-crisis trend (calculated using an HP filter); no legal indicators.

2/"One" and "One or none" refers to the number of indicators constrained to be chosen from each indicator group.

In summary, these regression results suggest that corporate balance sheet indicators, the cutoff of private capital inflows, corporate liquidity, and to a lesser extent imports to GDP and contagion are the most robust indicators for crisis intensity. The adjusted r-squareds suggest a reasonable degree of explanatory power. The importance of the external indicators, which did not show up in the crisis probability regressions, indicates that external sector adjustment plays an important role in shaping the response of output to a financial crisis. Further, banking sector and financial breadth indicators do not seem to independently drive crisis intensity.

The importance of the cutoff of capital inflows suggests that the magnitude of the crisis-triggering shock is crucial to the output consequences of a financial crisis. Indeed, crisis intensity may reflect more the magnitude of the crisis-triggering shock than the underlying balance sheet dynamics. More specifically, the results support the Krugman (1999) explanation of crisis intensity which stresses a cutoff of capital inflows triggering a large upward swing in the current account balance, a sharp depreciation of the exchange rate, and worsening corporate balance sheets.

VI. Conclusion

This paper examined the probability and intensity of financial crises during the 1990s with a view to improving crisis prevention and mitigation policies. The motivation was the new mandate for the IMF and World Bank to undertake comprehensive assessments of the vulnerability of the financial sectors of member countries, as well as the need for national policymakers to formulate crisis prevention and mitigation policies. This paper aimed to extend the financial crisis empirical literature to help inform these assessments and policies.

Balance sheet indicators dominated the crisis probability results. In particular, corporate and foreign exchange liquidity are quite robust empirical determinants of crisis probability across a wide array of indicators. The importance of corporate liquidity is a novel result, and suggests that governments should have corporate sector balance sheet data sufficient in quantity, quality and timeliness to alert them to crisis threats. Crisis prevention policies should also focus on structural reforms that forestall corporate liquidity problems, such as improvements in corporate governance. The empirical results also support the ongoing theoretical efforts toward modeling the roles of corporate balance sheets (Caballero and Krishnamurthy, 2000) and foreign exchange liquidity (Chang and Velasco, 1999) in systemic financial crises. The level of development, external indicators and contagion also appear to be important determinants of crisis probability.

The results for crisis intensity, defined as the loss of real GDP relative to trend during a crisis, indicate that the magnitude of the crisis-triggering shock may matter as much as the underlying balance sheet dynamics. The cutoff of private capital inflows, corporate balance sheet indicators, and to a lesser extent imports to GDP and contagion are the most robust indicators. The adjusted r-squareds suggest a reasonable degree of explanatory power. The importance of the capital inflow and import/GDP indicators highlights the importance of external sector adjustment in shaping the response of output to a financial crisis (Krugman, 1999b). Thus, in forming crisis mitigation policies, e.g., countercyclical monetary and fiscal policy responses, governments should pay careful attention to the magnitude of the crisis-triggering cutoff of private capital inflows.

In contrast to other studies, the legal indicators do not enter significantly, suggesting their influence independent of the other indicators is minimal. Similarly, the banking and financial breadth indicator results are mixed, indicating that they may be conduits of corporate distress and liquidity constraints, rather than have an independent role in crisis vulnerability.

This paper employed an decision-theoretic approach to address the model uncertainty that inherent to empirical analysis of financial crises. Thus, the crisis indicators identified in the results may be relatively robust compared to other studies using the more standard general-to-specific approach. The DTA also provided for uneven numbers of observations across indicators, which is relevant here since the extra number of observations provided by the exclusion of the legal indicators seemed to reduce model uncertainty.

The DTA also allowed for explicit comparisons of model uncertainty between crisis intensity and probability and across sample subsets. Model uncertainty, judging by the AIC weight sequences, is more of a problem for crisis intensity than for crisis probability. Of course, this may reflect the fewer observations available for intensity. Interestingly, for 1992–95, the analysis of crisis probability was marked by *less* model uncertainty than for the 1992–99 period, indicating that uncertainty has increased during the 1990s. Nonindustrial countries demonstrated more model uncertainty, perhaps not surprisingly in light of their greater within-group structural differences. For crisis intensity, by contrast, model uncertainty was higher for the earlier subsample, and uncertainty was lower for nonindustrial countries.

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Literature Review

This section reviews the theoretical and empirical financial crisis literature with a view to motivating the empirical model.

A. Theoretical Literature

Ideally, the supporting theory for an econometric analysis provides a single or small number of conceptual models with testable hypotheses. However, the theoretical work on systemic financial crises is marked by a multiplicity of explanations and lack of a unifying framework. In particular, the literature is constantly in flux because financial crises themselves are, by definition, ever changing. A practical way to proceed is to arrange the information posed by the evolving facets of the theoretical literature into: (i) *shocks* that trigger a crisis event; (ii) *channels* that propagate the shock into the financial and real sectors; and, (iii) the *consequences* of the crisis for the economy. Crisis shocks are largely observable and relatively amenable to analysis. The consequences of crises, such as the impact on the real sector or on asset prices, are more or less observable. Crises channels, in contrast, are difficult to observe and understand.

Not surprisingly, the evolving facets of the literature are basically defined by their emphasis on different crisis channels. For example, in recent years foreign exchange liquidity and collateral channels have emerged as new facets of the literature. Moreover, policymakers interested in preventing and mitigating crises will tend to think in terms of how policies bear on different crisis channels. For these reasons, this section reviews the theoretical crisis literature with an emphasis on crisis channels. This should lead naturally to groups of related indicators that are amenable to empirical analysis, and, ultimately, to their use by policymakers. The theoretical literature is reviewed here in terms of the following crisis channels: the external sector, bank sector, foreign exchange liquidity, collateral, financial breadth, and the legal environment.

The early theoretical crisis literature focused on *external sector currency crises* and can be summarized in terms of "generations" of models. First generation models are concerned with the abandonment of a fixed exchange rate regime owing to fiscal channels. They show how a fixed exchange rate policy combined with monetization of expansionary fiscal policies inevitably leave the exchange rate vulnerable to speculative attack (Krugman, 1979). Second generation models emphasizing multiple equilibria were developed in response to the absence of apparent fiscal instability in the ERM devaluations of 1992–93. In these models, central banks abandon a fixed exchange rate, shifting the economy to a bad equilibrium, when the expected costs of defending the peg outweigh the expected social costs in terms of unemployment and recession (Obstfeld, 1994). Thus any channels which enter into the government's calculation regarding the tradeoffs on currency defense are relevant e.g., domestic interest rates and the cost of government debt (Obstfeld, 1994), unemployment (Jeanne, 1997) and the banking sector (Calvo, 1995).

Modern models of *bank crises* mostly stress the interplay between bank balance sheet and balance of payments. The traditional theoretical models of bank crises are not directly applicable to the financial crises of the 1990s because they emphasize deposit runs and government guarantees[11] A more relevant strand of the literature focuses on a combination of financial liberalization and weak supervision and deposit guarantees that can boost the quantity but undermine the quality of bank lending. Velasco (1987) tied together this approach with currency crises by modeling a government guarantee of bank liabilities that leads to a rate of credit expansion that ultimately triggers a devaluation. Thus, the channels posited by this approach are bank credit growth prior to the crisis, and the size of the banking sector. New channels raised by the intertwining of banks and the balance of payments were raised beginning in the mid-1990s. According to Mishkin (1996), a devaluation is especially damaging if banks hold a large share of their liabilities denominated in foreign currency. Goldfajn and Valdes (1995) show how the intermediating role of banks amplifies international interest rate and capital flow shocks into an exaggerated business cycle that ends in bank runs and financial crises. Empirical indicators suggested here include pre-crisis bank credit growth, money and credit relative to GDP, and bank foreign liabilities. .

The relatively recent *foreign exchange liquidity approach* explicitly addresses crisis channels arising from a shortfall of foreign exchange liquidity. Liquidity can be defined as the difference between potential short-term obligations in foreign currency and the amount of accessible foreign currency in the consolidated financial system. In the framework of Chang and Velasco (1999) a balance of payments crisis is viewed as a situation in which a central bank runs out of international reserves to fight a financial crisis. The absence of reserves dries up foreign exchange liquidity, which propagates throughout the economy, and creates a new crisis channel. Corporations must cut back production or even shut down, and bank capital can be wiped out by projects not undertaken owing to a lack of liquidity, worsening the crisis. These models have a key market failure: private decision makers have no incentive to take into account the increase in crisis vulnerability arising from their borrowing. Calvo (1998) analyzes the impact of sudden stops in capital inflows via import dependence, bankruptcies, and external debt maturity. Indicators of the shocks that raise a crisis liquidity channel include the cutoff of capital inflows and world interest rates. Indicators of the channels raised by the foreign exchange liquidity approach are the ratio of broad money to international reserves, and the ratio of short-term external assets to liabilities and short-term debt to total debt.

Many of the more recent and successful theoretical models of crises are rooted in the emergence of a *crisis collateral channel*. The precursor of this approach is the financial accelerator literature, which was originally developed to explain balance sheet channels of monetary policy (Bernanke and Gertler, 1995). According to this approach, corporate net worth plays the role of collateral owing to information asymmetries. Net worth can constrain financing corporations and thereby amplify the impact of changes in interest rates engineered by monetary policy. Gertler, Gilchrist and Natalucci (2000) show that the corporate balance sheet channels are even

[11] Sundararajan and Baliño (1991) and Goldstein and Turner (1996) provide overviews of bank crises. More recent bank crises are not characterized by extensive runs on deposits (Demirgüç-Kunt et al., 2000). Government guarantees are stressed by by Dooley (1997) and Krugman (1999a) but these seem to have receded as a focus of the crisis literature.

more important in an open economy framework. Natalucci and Driessen (2000) apply this framework to monetary policy during the Asian crisis. In the related model of Krugman (1999b) a loss of confidence leads to a cutoff of capital inflows and prompts a large upward swing in the current account balance. This upward swing requires a sharp depreciation of the exchange rate, which, given the onerous weight of foreign debt, worsens corporate balance sheets, reduces investment, validates the loss of confidence, and may trigger a recession.

Kiyotaki and Moore (1997) fleshed out a new more direct collateral channel emphasizing macroeconomic rigidities in the form of underdeveloped domestic financial sector and corporate and financial sector balance sheets. The dynamic interaction between credit limits and the prices of assets used for collateral is a powerful crisis channel. Caballero and Krishnamurthy (1999 and 2000) extend this model to use shortfalls of the collateral that is necessary to get domestic and international financing to explain crisis vulnerability. These shortfalls are rooted in weak governance and legal systems. Adverse terms of trade or interest rate shocks squeeze external borrowers by reducing the value of international collateral. External borrowers sharply bid up interest rates by selling assets in an effort to obtain domestic collateral to trade for foreign collateral. The resulting drop in asset prices weakens domestic banks, reducing intermediation, and exacerbating the crisis. Their model also has a crucial market failure: private decision makers do not have the incentive to hold sufficient international collateral to forestall crisis; a centralized decision market would improve welfare by introducing incentives to hold higher levels of collateral. A similar emphasis on wasteful capital sales from a drop in collateral value is modeled by Kim and Stone (1999). In their model, highly leveraged firms facing a cutoff of capital inflows are threatened by bankruptcy. These firms respond by eliminating investment and selling their capital goods—at a discount—to try to stay afloat. Lower investment and wasteful capital sales shrink the aggregate capital stock, trigger deflationary pressures, and contract overall output. Owing to data unavailability, the impact of collateral crisis channels cannot be directly estimated. Possible indirect indicators of the impacts of collateral are corporate leverage, corporate liquidity, and the quality of corporate governance.

An absence of *financial breadth*, or the availability of a broad range of financing alternatives to the private sector, can also create a new crisis channel. Financial breadth is only now beginning to attract theoretical and empirical analysis. The large output contraction caused by the recent Asian crisis has been attributed in part to the lack of nonbank financing alternatives, whereas nonbank financing helped limit the impact of the slowdown of American bank lending in 1990 that resulted from a collapse in the value of real estate collateral (Greenspan, 1999). Davis (2000) used flow of funds data to look at post-crisis changes in the composition of corporate financing for industrial countries. Stone (2000) looked at the implications of corporate leverage on aggregate output for emerging market countries in 1997. There appear to be no cross-country studies utilizing aggregate emerging market country data. Empirical indicators of financial breadth are the size of equity and corporate bond markets compared to bank credit.

Finally, the *legal environment* is also seen as a crucial cause of crisis even though this concept is also difficult to define and analysis of this issue is limited. Many crises are rooted in interventionist government policies that concentrated lending in selected banks and corporations, result in highly leveraged and undiversified balance sheetsPoor governance—

reflecting lax shareholder rights, opaque accounting, and weak law enforcement—undermined the resiliency of the private sector to external shocks. Hard evidence on the implications of rule of law for crisis vulnerability is hard to put together, but the available evidence suggests it plays an important role (Claessens et al., 2000).

Finally, *contagion*, or the spreading of crisis of crisis from one country to another, that has been a feature of financial crises of the 1990s has been the subject of considerable analysis (Masson, 1998). Contagion can be driven by a common shock across countries e.g., an increase in world interest rates; a devaluation by one country that undermines the competiveness of its trading partners, or through herd behavior on the part of investors reflecting information asymmetries (Calvo and Mendoza, 1997). Empirical analysis has shifted from an emphasis on trade linkages (Eichengreen et al 1996) to financial linkages (Hernandez and Valdes, 2001).

B. Empirical

Empirically, a *currency crisis* is typically defined to occur when a weighted average of the exchange rate, international reserves and in some cases interest rates passes a predefined threshold. An early example is Eichengreen, Rose, and Wyplosz (1996), who applied probit analysis to quarterly data for 20 industrial countries during 1959–93 to assess impact of crisis in other countries controlling for macroeconomic variables. Sachs et al., (1996) concluded that vulnerability of the exchange rate of 20 emerging market countries to the Mexico crisis is explained by real exchange rate appreciation, bank lending growth, and a high ratio of M2 to reserves. Berg and Patillo (1999) employ a general probit-based model with the dependent variable defined by an exchange rate and reserve based index to predict currency crises. Tornell (1999) concludes that bank credit growth, real appreciation, and the ratio of M2 to reserves explain both the Mexico and Asia currency crises.

Empirically, *bank crises* are almost always gauged with a binary indicator because they are difficult, if not impossible, to measure with a continuous indicator. Eichengreen and Rose (1998) found that banking crises result from domestic fragilities and global conditions—especially high world interest rates. Bank crises produce output growth declines of 2–3 percent compared with noncrisis countries, but last only about a year. Demirgüç-Kunt and Detragiache (1999a) emphasize vulnerability to large capital inflows, bank deposit insurance, and the legal system. Demirgüç-Kunt and Detragiache (1999b) found that banking crises associated with macroeconomic problems were characterized by high loan/deposit and foreign borrowing/deposit ratios and high credit growth. (Demirgüç-Kunt et al., 2000) looked at the pattern post-bank crisis output contraction during bank crises over 1980–95 and found that they last only a year or two, even though credit growth recovers quite slowly.

There has been relatively little *joint empirical analysis of currency and bank crises*, probably reflecting the difficulty of defining the latter. A notable exception is Kaminsky and Reinhart (1999), who examined the macroeconomic background and predictability of the "twin crises" using a sample of 20 countries over 1970–95 with monthly data. They concluded that bank and currency crises have become more intertwined in the 1980s and 1990s. Problems in the banking sector typically precede a currency crisis; the currency crisis deepens the banking crisis, activating a vicious spiral, and financial liberalization often precedes banking crises. Kaminsky and Reinhart conclude that the output contraction from concurrent crises (8 percent below non-crisis periods is more severe than for single crises. They found that financial liberalization and increased capital inflows set the stage for crises, and that they are preceded by recession, which is attributable to a mix of terms of trade shocks, an overvalued exchange rate, and rising credit costs. Mulder et al., (2001) used several of the private sector balance sheet indicators employed in this paper in their estimation of an EWS. They applied the general-to-specific approach to model selection using monthly data for 19 emerging market countries. They found that the corporate indicators of leveraged financing and short-term debt to working capital help predict crises. In addition, shareholders rights had an important impact of crisis probability. This result held even when controlling for more standard macroeconomic crisis prediction indicators.

Recently, a few studies have looked at *crisis-induced output contractions*, or what we refer to as the intensity of crises. Stone (2000) looked at the impact of financial crisis on output via the corporate sector and concluded that crisis-induced output contractions are associated with high levels of corporate debt, openness, and exchange rate over appreciation. Bordo et al., (2000) examined output contractions over the past 120 years and concluded that the probability of crisis has increased but intensity has not. They attribute the increased probability to capital mobility and financial safety nets.

DATA DOCUMENTATION

Indicators 1/	Sources
External Indicators	
Imports to GDP	WEO
Real Effective Exchange Rate, deviation from HP trend	IFS
LIBOR	WEO
Net liabilities of nonbanks to banks resident in BIS reporting countries to GDP	BIS
Change in Current Account to GDP	WEO
Banking Sector Indicators	
4-Year Change in Private Credit to GDP	IFS / WEO
Domestic credit to GDP	IFS
Broad money to GDP	IFS
Corporate Sector Indicators 2/	
Total debt to Common equity	Worldscope
Equity to Total capital	Worldscope
Current ratio: total current assets / total current liabilities	Worldscope
Working capital to Total capital	Worldscope
Quick ratio: Cash & equivalents + receivable net / total current liabilities	Worldscope
Total debt to Total assets	Worldscope
Financial Breadth Indicators	
Financial Breadth 1: ratio of outstanding bonds (national corporations) to bank credit	WEO/Beck et al.
Financial Breadth 2: Ratio of outstanding bonds (national corporations) + stock market capitalization to bank credit	WEO/Beck et al.
Private bond market capitalization to GDP	Beck et al.
LT debt to Common equity	Worldscope
LT debt to Total capital	Worldscope
Foreign Exchange Indicators	
Broad money/International reserves	IFS
Change in capital flows to GDP	WEO
Legal Environment Indicators	
Antidirectors Rights	La Porta
Rule of Law	La Porta
Other Indicators	
Annual Average CPI Inflation	IFS
Income development indicator	Beck et al.
Real GDP//Hodrick-Prescott trends	IFS
Real interest rate	IFS
Contagion	–

1/Stock indicators enter with a lag to limit the possibility of endogeneity.
2/ Corporate indicators are the median of all non-financial corporations that trade in the local stock market, adjusted for extreme values; data for 1992 and 1993 are estimates based on 1994 data.

List of Countries (49)

Argentina
Australia
Austria
Belgium
Brazil
Canada
Chile
China
Colombia
Czech Republic
Denmark
Egypt, Arab Rep.
Finland
France
Germany
Greece
Hong Kong
Hungary
India
Indonesia
Ireland
Israel
Italy
Japan
Jordan
Korea, Rep.
Malaysia
Mexico
Netherlands
New Zealand
Norway
Pakistan
Peru
Philippines
Poland
Portugal
Russia
Singapore
South Africa
Spain
Sri Lanka
Sweden
Switzerland
Thailand
Turkey
United Kingdom
United States
Venezuela
Zimbabwe

Figure 1. Number of Crises, 1977-99

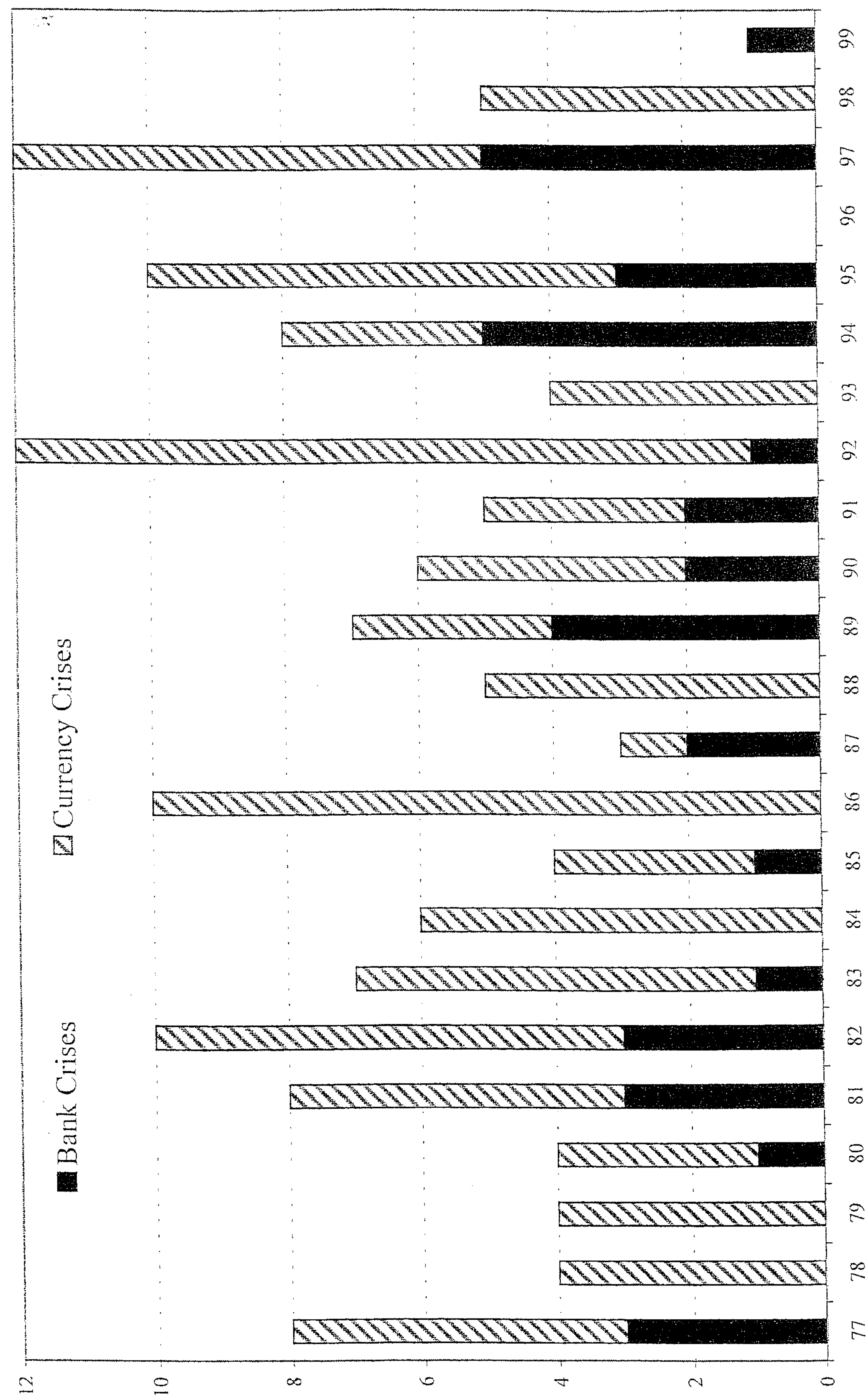
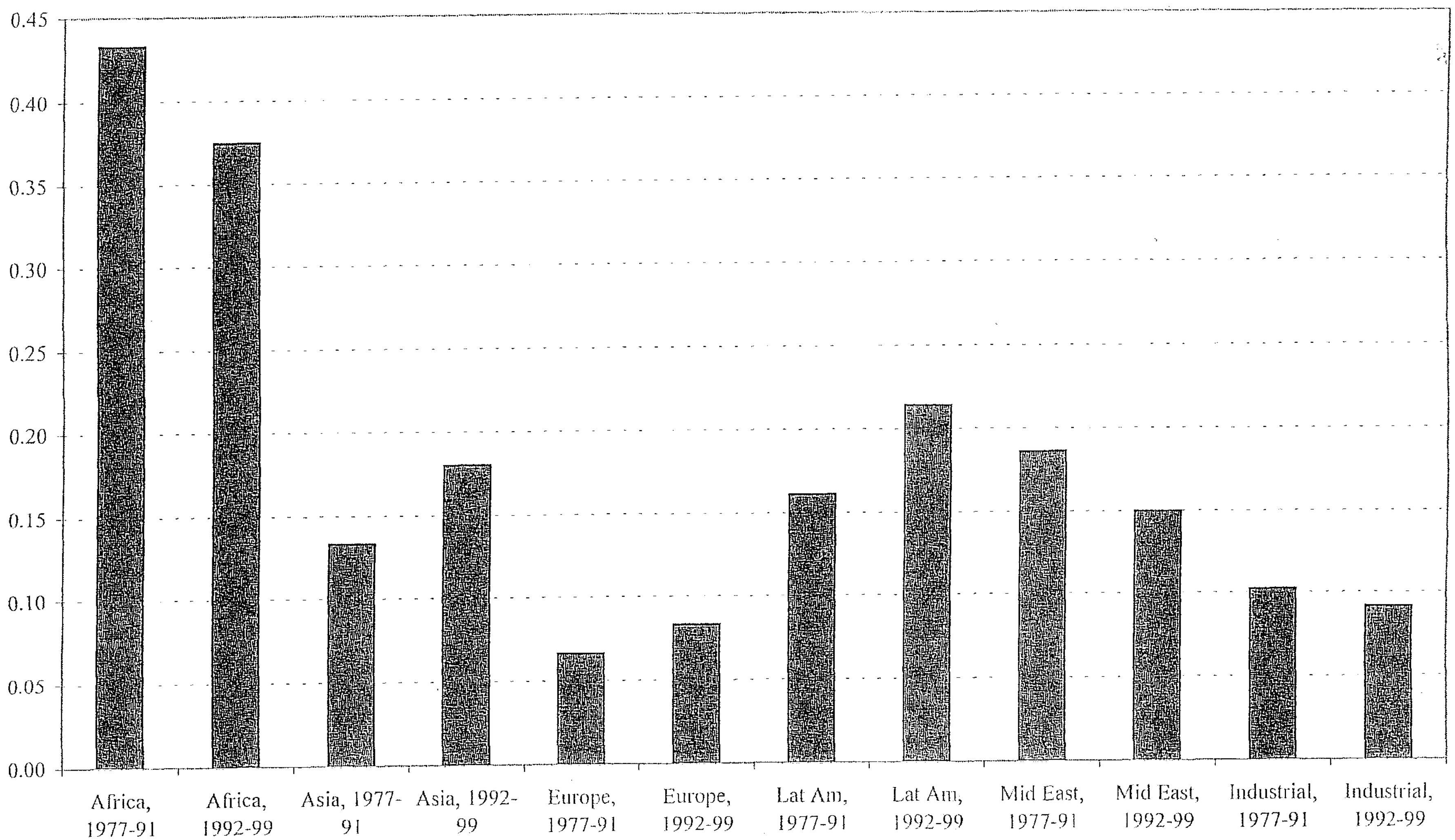


Figure 2. Crisis Incidence by Region and Time Period 1/



1/ Incidence is the ratio of the number of crises per region and time period to the product of the number of countries in the region and the number of years in the time period.

Figure 3. Crisis Output Contractions T to T+1, 1977-99

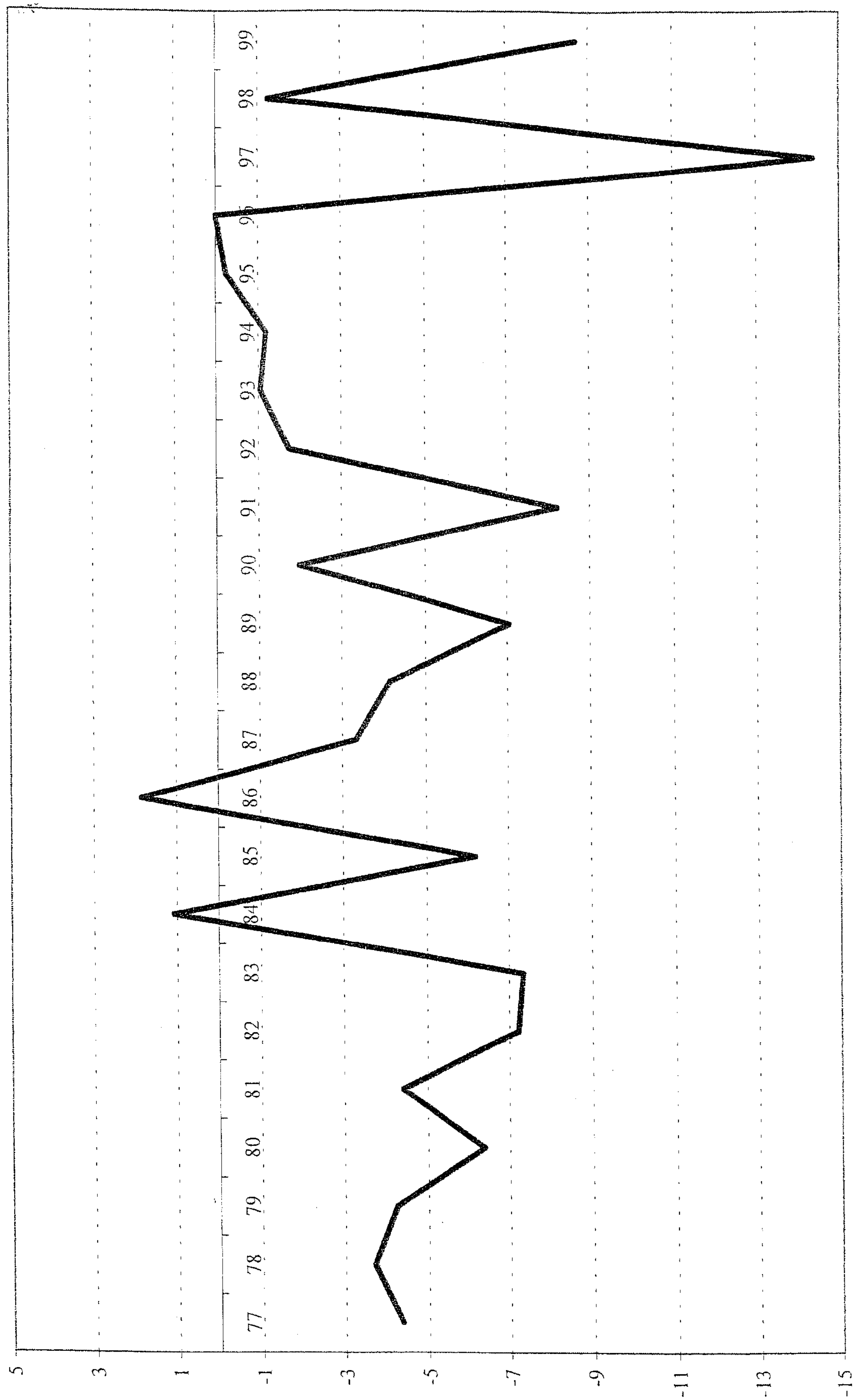


Figure 4. Crisis Output Contractions T to T+1, By Region, 1977-99