ACCOUNTING FOR CRISES[#]

Venky Nagar
University of Michigan
venky@umich.edu

Gwen Yu
University of Michigan
gowoonyu@umich.edu

November 2009

[#] We are grateful to George-Marios Angeletos, Luzi Hail, Stephen Morris, Hélène Rey, Joel Slemrod, and seminar participants at the University of Michigan, Carnegie-Mellon University, 2009 AAA FARS Conference, 2009 Utah Winter Accounting Conference, the 4th Tinbergen Conference on Crashes and Systemic Crises, and 2009 UNC Global Issues in Accounting Conference for their comments.

ACCOUNTING FOR CRISES

Abstract

We provide one of the first tests of recent macro global-game crisis models that show that the precision of public signals can coordinate crises (e.g. Angeletos and Werning 2006; Morris and Shin 2002, 2003). In these models, self-fulfilling crises (independent of fundamentals) can occur only when publicly disclosed fundamental signals have high precision; fundamentals are thus the sole driver of crises in low-precision settings. We affirm this proposition on 39 currency crises by exploiting a key publicly disclosed fundamental driving financial markets, namely accounting data. We find that fundamental accounting signals are stronger in-sample predictors of crises in low-precision countries.

ACCOUNTING FOR CRISES

I. Introduction

A key question in international economics, explored in a series of recent crisis models such as Angeletos and Werning (2006), Angeletos et al. (2006), Angeletos et al. (2007), Rey (2000), Atkeson (2000), Morris and Shin (2002), and Morris and Shin (2003), is whether economic fundamentals or speculators' self-fulfilling beliefs drive crises. While diverse in their settings and modeling approaches, the models all point to the precision of public information as the key driver. If public information is precise enough relative to speculators' private beliefs, it can coordinate multiple self-fulfilling speculator beliefs largely independent of economic fundamentals. The belief coordination role of public signals in crisis models is a stark departure from neoclassical asset pricing models, where high precision signals can only *tighten* the link between fundamentals and prices, not *weaken* them. Yet, this central and robust role of public signals in the analytical crisis models has received scant empirical attention, perhaps due to the difficulty in finding a public signal that institutionally comports with the crisis models and whose precision is measurable. This paper argues that accounting data provide such a signal and uses accounting data to test the central result of recent crisis models.

All the crises models above share three basic steps (see Figure 1): first, the initial fundamentals are realized. Next, the speculators coordinate (the market is too large for any individual speculator) over an action such as interim financing or withdrawing capital. This coordinated action in conjunction with the initially realized fundamental has a real effect on the underlying asset's value. In the final step, this new value translates into asset price.[1]

[1] As any observer of the recent Wall Street turmoil will immediately recognize, both speculator beliefs about fundamentals and speculator beliefs about other speculators' willingness to supply interim financing play a key role in asset valuations (Mollenkamp et al. 2008).

The main point of these crisis models is that speculators' beliefs about each other in the second step can be self-fulfilling, especially when public signals have high precision, thus divorcing the final value of the asset from its initial fundamental realization. For example, suppose each speculator is unsure of the measure of speculators it takes to unravel a currency. An accurate public signal released in the financial markets says that this measure is 30%. This 30% is thus the initial fundamental strength of the currency. If every speculator believes every other speculator will attack (i.e., withdraw capital), everyone will attack. The currency will then fall, for the measure of attackers is 100%, which exceeds 30%. On the other hand, if every speculator believes that no one will attack, a small individual attack only wastes that speculator's money. No one will attack and the currency will stand. The accurate public signal thus supports two self-fulfilling equilibria over its realization range (0%, 100%), i.e., any realization of the initial fundamentals in this range can lead to either of the attack or no-attack outcome.

The above example assumes that the public signal is precise. If this is not the case, the crisis models we test show that speculators will weigh their private information more heavily. Because this private information varies across speculators, each speculator is unsure what the other speculators are thinking. Each individual speculator is then more fearful of losing money in an unsuccessful uncoordinated attack. In such settings, poor initial fundamentals become the main point of coordination and thus the main driver of crises.

In this paper, we test this key comparative static of the crisis models described above using accounting data. Specifically, we argue that realized accounting data should more strongly predict currency crises in countries where the accounting data are *less* precise. We use accounting data for several reasons. First, public corporations' accounting data are a key source of public information on assets traded in a country's financial markets. Second, the accounting literature has extensively examined the notion of accounting quality, or the precision with which accounting measures reflect economic reality. In particular, this literature argues that there is considerable variation in the precision of accounting information across countries, due to variation in legal, enforcement, and rule-making institutions (La Porta et al. 1998; Ball et al. 2000). Such institutional variation is essential to our empirics. More important, these precision measures capture the *noise* in the accounting signals. By contrast, the variance of alternative public signals such as stock prices is the *sum* of the fundamental variance and the noise variance. Additionally, price signals that are the outputs of financial market trading are themselves subject to multiplicity and excess volatility (Angeletos and Werning 2006), confounding empirical estimation. Accounting data, by contrast, are inputs into the financial markets and bypass this problem. Finally, our proxy for accounting data quality measures public signal precision relative to private signal precision, as required by the crises models.

Our setting comprises 39 currency crises in 21 countries from 1981 to 2005. Using prior literature, we construct a composite score of accounting precision for each country (based on all its firms). We use this composite score to split the countries into two groups: high-precision and low-precision. Our birfurcation of the sample follows Angeletos and Werning (2006, Figure 1) who show that the switch from uniqueness to self-fulfilling equilibria is not gradual as the public signal precision increases, but occurs suddenly at a precision threshold.

We then aggregate all the firms in each country every year to yield three annual country-based measures of realized performance: earnings, accounting accruals (accounting adjustments to cash flows to yield earnings), and volatility of earnings. We test the in-sample power of these measures to predict crises.

Graphical analyses (Figure 2) are consistent with our predictions. Figure 2 indicates that the realized performance measures are relevant to crises: relative to tranquil years, they are quite choppy around the crises onset years, especially for low precision countries. Further, the confidence intervals of realized performance measures around crises are much larger in low precision countries. However, despite their noise, we find that public signals have the power to predict crises in low-precision countries.

Specifically, we test the in-sample power of realized accounting performance measures to predict crises. We control for a rich list of other leading indicators as well as country fixed effects and contemporaneous cross-sectional shocks (contagion). In the overall sample, the inclusion of accounting measures significantly improves our in-sample ability to predict crisis one year in advance: the explanatory power increases from 0.245 to 0.283, a 15 percent increase. Much of the predictive power arises from accruals (i.e. *accounting* adjustments to cash flows). This is a particularly interesting result, for it shows that the application of accounting rules to measure firm operations is what generates critical asset-pricing information.

More important, we show that most of the predictive improvement comes from the sub-sample of countries with low accounting precision. The F-statistic for the realized accounting performance measures one year prior to crises is 14.17 in low precision countries, but 1.31 for the high precision countries. By contrast, when we examine accounting data one year after the crisis onset year, we find that both low precision and high precision accounting countries show significance: the F-stats are now 17.67 and 26.62 respectively. So accounting data in high precision countries do appear to reflect the consequences of a crisis; they just don't have ex ante predictive power. We then conduct a series of comparative statics involving institutions, the nature of the crises, the specific precision thresholds, and specific industry sectors. Our main results continue to hold in all these tests.

Our findings make three contributions to the literature. First, we empirically validate a key prediction of recent crisis models, namely that fundamentals are more important than self-fulfilling beliefs in precipitating crises when fundamentals have low precision. Second, and perhaps more important, it is difficult to test self-fulfilling beliefs directly: one can only show that fundamentals don't matter. But then, it is not clear if the result is due to self-fulfilling beliefs or lack of statistical power. By showing settings where fundamentals matter as well as settings where they don't, our study overcomes this objection. Finally, our very use of accounting data is an innovation in empirical crises studies, which have typically used macro, institutional, and trade factors to predict crises (Martin and Rey 2006; Raincere et al. 2008). Our results indicate that accounting data offer significant incremental power beyond these factors to predict crises.

Section II places our research question in the context of prior literature. Section III describes our data and our empirical constructs. Section IV presents the main results. Section V tests the robustness of our results. Section VI concludes.

II. Background

Perhaps the simplest way to frame the crises literature is to use equations from undergraduate macro (e.g., Mankiw 2003, Ch. 13),

$$Y = C(\overset{(+)}{Y}) + I(\overset{(-)}{r}) + G + NX(\overset{(+)}{\varepsilon}) \tag{1}$$

$$\frac{M}{P} = L(\overset{(-)}{i}, \overset{(+)}{Y}) \text{ where } i = r + \pi_e \tag{2}$$

$$NX(\overset{(+)}{\varepsilon}) = CF(\overset{(+)}{r^* - r}). \tag{3}$$

The three endogenous variables are the domestic GDP Y, the domestic real interest rate r (the nominal interest rate i is simply the inflation adjusted version), and the exchange rate ε (the price of foreign currency). Equation (1) states that the GDP is simply consumption plus investment plus government expenditure plus net exports. Investment declines when the cost of borrowing is high. Net exports follow the Marshall-Lerner conditions and increase when the domestic currency is cheaper. Equation (2) says that the supply of real money equals money demand L. People demand more money when the GDP is high and less money when the opportunity costs or the interest rates are high. The supply of money M is set by monetary policy. Equation (3) is simply an accounting identity: any imbalance in the trade of goods has to be balanced with an IOU or capital flows. CF is capital outflows from the domestic country, which is more likely if the foreign interest rate r^* is high.

This simple model illustrates many well-known features of international economics. The government cannot use M to control two endogenous variables, i and ε simultaneously, unless it is willing to restrict the CF function. This is the famous international policy trilemma. Purchasing power parity is simply a specific structure of the NX function (high elasticity around $\varepsilon = 1$), while the open interest parity requirement imposes similar restrictions on the shape of the CF function.

More broadly, the key implication of this model for our paper is that any explanation of exchange rate (including its sudden drop) has to be grounded in issues such as monetary policy, trade, and capital flows. This is precisely the route that the prior literature has taken. Krugman shows how rational speculators in fixed exchange economies foresee the drop in foreign exchange component of the monetary reserves M, and drive the currency down via capital flows CF. Empirical tests of earlier crises (e.g., Blanco and Garber [1986]) supported this theory, but later crises appeared to less influenced by factors such as reserves (equation (2)), and driven more by activities in the financial markets supporting productive activities in the economy (equations (1) and (3)).

The search for other factors led Obstfeld (see his 1996 summary) to model crises as arising from speculators' self-fulfilling beliefs. He modeled a financial market where each speculator is too small to affect the currency. But if speculators collectively coordinate and withdraw sufficient capital from a country, its currency will collapse. Consequently, if a country's fundamentals are moderately strong, but a large measure of speculators is pessimistic, these speculators' beliefs by themselves can precipitate a crisis. Obstfeld's study generated a large spate of models (see Fourcans and Franck's [2003] excellent survey).

Identifying speculators' beliefs in the data, however, proved to be hard. Jeanne (1997) and Jeanne and Masson (2000) used non-linear empirical tests with Markov switching to identify these beliefs in the devaluation of the French franc in 1987. Markov switching is a maximum likelihood estimator that spots large shifts (the switch) in the time-series of the franc exchange rate. Because these switches are unrelated to the already controlled-for fundamentals, they can potentially represent self-fulfilling beliefs. But the concern with such tests is that the inability of the fundamentals to predict crises could arise from low statistical power and not from self-fulfilling beliefs. The ease of achieving multiple-equilibria analytically and the difficulty in spotting them empirically led Angeletos and Werning (2006) to label economists' relation to multiple equilibria as 'love hate'.

Summarizing the state of affairs, Obstfeld (1996) called for more explicit modeling of the *interaction* between fundamentals and speculator beliefs. This next step was undertaken by Morris and Shin (1998). They showed that even if each speculator has an epsilon amount of private information available, each speculator becomes unsure of other speculators' private information and whether they will participate in an attack. This uncertainty is key because speculators lose money if they are not in sufficient numbers. As a result, speculator coordination necessary for self-fulfilling beliefs does not obtain: poor fundamentals then remain the key driver of crises.

Atkeson (2000) and Rey (2000) (as well as Morris and Shin [2002, 2003]) pointed out that the key driver of Morris and Shin's result was not the precision of the speculators' private information per se, but its strength relative to public information. If the public information were precise enough, it would provide a coordinating point for speculators to coordinate their attack even if the currency were moderately strong (see Section I of this paper for a numerical example). In particular, Atkeson (2000) pointed out that such public information could arise from trades among privately informed speculators. Angeletos and Werning (2006), Angeletos et al. (2006), and Angeletos et al. (2007) flesh out this intuition by endogenizing various aspects of the trading model, namely dividends, price, payoffs, etc. More important, they also endogenize the policy response to the crisis. Their main conclusion is that, despite such endogeneity, there is a range of realized fundamentals where endogenous public information is sufficiently precise relative to speculators' diverse private information to trigger speculator coordination and self-fulfilling beliefs. Consequently, fundamentals cannot predict crises in these ranges because self-fulfilling belief triggers can occur over the entire range (note that these belief triggers are not guaranteed at any specific point in this range, only their possibility is).

This is a stark departure from traditional asset pricing models where high precision signals tighten the link between realized fundamentals and prices. Why the departure then? The key assumption in the crisis models is that the eventual price depends on the initially realized fundamental and a coordinated activity (such as interim financing) by all speculators. This coordinated activity --- and coordination is necessary because the market is too large for any individual agent --- can affect the asset's ability to generate cash flows and thus its eventual price. Agents therefore use public information not just as a signal to uncover the underlying fundamental but also as an important strategic tool to form higher order beliefs of others' actions. It is this strategic role of public information that generates information externality that leads to self-fulfilling beliefs.

On the other hand, if public information is relatively imprecise, i.e., below a certain precision threshold, speculators cannot coordinate on their beliefs (they pay too much attention to their own diverse private information and ignore the common public information).[2] As a result, crises happen only

[2] Of course, if speculators' private information is completely precise, everyone knows that everyone else receives the same signal realization. This situation is equivalent to a precise public signal, and we are back to multiplicity (see Angeletos and Werning 2006).

when fundamentals are weak enough for a sufficiently large mass of speculators to feel confident that they will profit in attacking the currency: poor fundamentals are thus the sole determinant of crises.

These features are all especially salient in international financial markets where traders are small relative to the market and their collective supply of ongoing interim capital financing is key to survival. When international traders withdraw capital from a country's financial market, a currency crisis ensues. Consequently, if we assume a) that variation of the absolute precision of the public information across countries reflects variation of precision of public information relative to private information, b) that we can use the data to nominate the precision threshold necessary for self-fulfilling beliefs to be feasible, and c) that countries where self-fulfilling beliefs can occur do experience such events (i.e., multiplicities are empirically *realized*), we have:

Hypothesis: Realized public disclosures of fundamentals should predict currency crises more strongly in the subsample of countries where these disclosures have low precision.

Accounting data form a natural setting for testing this prediction, for several reasons. Accounting data are a key publicly disclosed fundamental not just in debt and equity markets, but also for bank loans (Dichev and Skinner 2002). Accounting information's relevance to bank loans is especially important because banks are an important financing vehicle in many countries.

Second, the use of accounting data in the pricing of securities and loans has prompted extensive accounting research on the notion of accounting precision. This research also explores the causes and the consequences of variation in accounting precision across countries (Section III has the details). We exploit this institutionally driven variation for our purposes.

Third, we can measure the variance of the *noise* in the accounting signal. By contrast, the variance in other public fundamentals such as prices that arise from trading in asset markets incorporates both fundamental variance and noise variance. Further, prices are subject to multiplicity and excess volatility (Angeletos and Werning 2006), making it difficult for the empirical researcher to uncover the underlying precision of the public information from realized values. In many instances, the assets may not be traded sufficiently often to yield a liquid price (Greenlaw et al. 2008). Accounting data circumvent these problems because they are inputs into the financial markets.

Fourth, the notion of precision of public information in the crises models we study is defined relative to the speculator's private information. Our measure of accounting precision captures this concept. Numerous empirical studies have shown that higher quality accounting information is associated with reduced bid ask spreads and less privately informed trading (Leuz and Verrecchia 2000; Daske et al. 2008).[3] These findings suggest that higher precision in the public accounting information also reduces the precision of the private information among agents. Thus, empirical proxies of accounting precision used in our study represent the relative precision of public information over private information as in Angeletos and Werning (2006).

Despite these advantages, there has been no attempt in the early warnings literature (at least to our knowledge) to use accounting information to predict currency crises.[4] Instead, prior literature has primarily focused on macro measures to predict crises. For example, Ranciere et al. (2008) and Martin and Rey (2006) show that countries with high growth skewness and high trading costs are more likely to suffer crises. We include country indicators to account for such across-country variations. That is, our tests are *timing* tests that operate on a within-country model. In addition, we also conduct our analyses

[3] For example, Daske et al. (2008) show that when countries shift to a higher quality financial reporting regime, both bid-ask spreads and trading costs of the firms in the country decline by 12 basis points.
[4] Swanson et al. (2003) study the information content of accounting figures *following* the 1994 Mexican currency devaluation.

using only the tradable sectors. Finally, Yuan (2005), among others, shows that correlation across equity markets can propel crises (contagion). We use cross-sectionally correlated errors to account for contagion.

III. Data and Variable Definitions

III.A Currency Crises and Financial Data

Since our goal is to predict in-sample crises, we limit ourselves to countries that have had crises. Given the financial market setting of our analytical models, what currency crises are empirically best suited to analyze our hypotheses? While crises are heterogeneous, the financial markets are typically an important contributing factor (Kaminsky and Reinhart 1999, Reinhart and Rogoff 2008). We therefore use all the crises as our sample, and then conduct sensitivity analyses over specific crises subsets.

Kaminsky and Reinhart (1999) define currency crisis as an event of a steep decrease in exchange rates and/or reserves. They provide an extensive list of crisis events (Kaminsky and Reinhart 1999, Table II), which Caprio et al. (2005) and Kaminsky (2003) subsequently update. We define the crisis onset year as the year a crisis started in the Kaminsky (2003) and Caprio et al. (2005) datasets. This procedure yields 68 crises episodes from 21 different countries as shown in Table I.[5]

Table I classifies the different types of crises based on Kaminsky (2003, Table IV). Table I shows that 78 percent of the crises events can be classified as either financial excess or sovereign debt. These types of crises typically arise from financial illiquidity problems following a period of high expansionary credit growth (Tornell and Westerman 2005). Financial markets thus are important drivers of these crises, making them an appropriate setting for our study.

[5] Some countries experience multiple types of crises in the same year. Our analyses count these events as one event.

We collect firm level financial data from Thompson Datastream, which contains accounting information from annual reports of publicly traded companies around the world. To be included in the sample, a country must have more than five firm-year observations with non-missing values for a number of accounting variables such as total assets, current assets, current liability and net operating income.

We acknowledge that our analysis is limited to the publicly traded sector; activities of private companies that do not trade publicly are not captured directly (except through their effect on public firms). However, note that public firms typically tend to be the larger firms, and can thus have a large impact on the country's economy. Thompson Datastream defines each firm observation by the unit of equity it issues. Thus, if a firm issues equities on two different exchanges, it will count as two firm observations. Since securities listed on a foreign exchange are also subject to accounting rules of the foreign country, we delete all securities cross-listed on foreign stock exchanges. This deletion ensures that the accounting signals of each country are an outcome of the local accounting standards.[6]

Our procedure yields 101,492 firm-year observations from 21 different countries in our final sample. The limited availability of firm year observations in earlier years restricts our analysis to crises episodes after 1981. This truncation removes some early reserves based crises and makes the sample more relevant to our financial market based hypothesis. We then aggregate the firm-years into country-years (we do not over-weigh country-years with more firm-year observations). This aggregation yields 331 to 371 observations depending on the regression. These country-years include 39 crises.

Table II reports the onset year of each crisis in different countries, as well as the number of public firms in our sample for each of the country-years. There is considerable variation in the number of firm-

[6] The results are robust to including the cross-listed firms.

year observations across countries, reflecting differences in the level of industrialization, financial market development, and also data availability.

The shaded areas in Table II show considerable variation in the spread of crises across countries and time. Crises have a slight tendency to be clustered in the early 1990s and late 1990s, reflecting the existence of the well known ‘contagion effect’ (Allen and Gale 2000; Kaminsky et al. 2003; Yuan 2005).

III.B Precision of Accounting Signals

B.1 Measures

Our main prediction is that accounting fundamentals are a stronger predictor of crises in countries with low accounting precision. We now describe our composite measure of accounting precision for each country.

The accounting literature --- see summaries in Dechow and Skinner (2000) and Healy and Wahlen (1999) --- has extensively researched the precision or the ability of accounting measures to capture economic fundamentals. The source of accounting (im)precision arises from the following problem: period t cashflows are not period t economic earnings. For example, the manager may have spent cash on investments that will pay back in the future, so the cash outflow is not a pure economic loss. Alternatively, assets may have declined in value leading to an economic loss, but there is no cashflow impact because the assets are not sold. Accounting therefore adjusts the cashflows to construct a measure of earnings or profits. This adjustment is called accruals. The noise in these adjustments is then our proxy of the precision of the public signals. Note again that we are not measuring the variance of the *overall* performance signal, we are measuring the noise in the accounting *adjustments*. This is precisely the measure that the crisis models require.

To users of financial statements, these accrual adjustments are *relevant*, but their *reliability* can be imperfect. Specifically, the reliability or the precision can be impaired because management can make estimation mistakes, or can misuse their discretion over accruals to conceal economic reality (both these factors are evident in the current U.S. mortgage crisis, for example).

But what factors restrain management accounting choices? Recent accounting research indicates that the deeper institutional factors that determine firms' accounting choices are accounting rules, legal enforcement, and the legal regime (e.g., Ball et al. 2000). These factors vary across countries, yielding us an institutionally driven cross-country variation in accounting precision in our data.

While recognizing accounting precision's conceptual and institutional importance, the accounting literature has not converged to a universally accepted measure of accounting precision. Different accounting studies pick a different property of accruals to deduce the precision of accounting measures. We employ six commonly used measures that capture various dimensions along which accounting information reliably reflects relevant firm fundamentals. Table III defines in full detail the six measures we use, as well as their sources in the literature. We aggregate each measure to the country level by using the median of the firm year observations. We sign the measures so that lower values reflect higher precision.

Our first measure of accounting precision, accruals quality (=AQ^1), captures the estimation errors in the accounting process by measuring how well accrual estimates map into cash flow realizations. Following Dechow and Dichev (2002), we operationalize this measure as the standard deviation of the residual from a country-level regression of current accruals on multi-period operating cash flow. Low standard deviation implies higher accounting precision.

Our second measure AQ^2 proxies for the level of management discretion, often known as the 'smoothing' behavior (Fudenberg and Tirole 1995; Trueman and Titman 1988). Smoothing refers to managers misusing their reporting discretion to conceal economic shocks by over-reporting poor performance and under-reporting strong performance. The accounting literature has traditionally used a strong negative correlation between changes in accruals and operating cash flows to proxy for management intervention over and beyond the natural level of accruals accounting (e.g., Francis et al. 2005). The negative of this correlation is then our AQ^2 measure.

The remaining four measures of accounting precision (=AQ^3, AQ^4, AQ^5 and AQ^6) are various measures of the magnitude of accruals. Sloan (1996) suggests that large accruals involve higher degree of subjectivity that can often result in both intentional and unintentional reporting errors. Leuz et al. (2003), on the other hand argue that the larger the absolute magnitude of accruals, the more room the manager has to exercise discretion in reporting earnings. We measure both these concepts both with current accruals (=AQ^3, AQ^4) that arise from operating activities, and total accruals (=AQ^5, AQ^6) that include accruals from both operating and financing activities. We scale the accruals as per the original papers.

Then, as defined in Table IV, we construct a composite measure of accounting precision from the six AQ measures to eliminate potential measurement error. We rank each measure across all countries and take the mean of the six ranks as a composite country index of accounting precision. This is our country-based measure of the precision of the public signal.[7]

Table IV sorts the countries in ascending order based on the composite index with lower scores reflecting higher accounting precision. All six individual measures exhibit large variation across countries but similar rankings in terms of relative magnitudes. The magnitudes of the measures conform by and large with prior literature (Bhattacharya et al. 2003, Table I and III; Leuz et al. 2003, Table II) with small difference due to different sample periods.

[7] In Section V, we report the robustness of our main results to alternative measures of country-level accounting precision.

The crisis models in Section II have a specific precision threshold at which self-fulfilling beliefs are feasible. We therefore need to partition the sample based on this precision threshold. But it is not clear how to translate the analytical precision threshold to the data. Table IV therefore dichotomizes the sample at the median into countries with high and low accounting information precision.

In-sample ranking can distort the relative ranking of the 21 crisis countries if accounting precision makes countries more (or less) prone to crises. Hence, we re-examine the accounting precision ranking of the 21 sample countries after including 27 additional countries that did not suffer any crisis. Untabulated results show that including the 27 countries has minor effect on the relative ranking of the 21 sample countries. In particular, the expanded sample categorizes 10 countries (i.e., 47% of the 21 sample countries) as countries with high accounting precision when the sample median is used as the precision threshold.[8]

In addition, with some exceptions such as Australia, the country classification of high and low accounting precision groups confirms prior studies that suggest that institutional characteristics (La Porta et al. 1997) and enforcement of contracts (Ball et al. 2000) are related to the accounting information environment. For example, Table IV shows high ranks for European countries such as Denmark, Finland, Spain and Sweden, while developing countries like Argentina, Brazil and Greece rank among the countries with low accounting precision. The fact that some countries from common law origin are classified in the low precision group (i.e., Malaysia and Thailand) is consistent with Ball et al. (2000), who argue that common law influence does not guarantee accounting information quality when the enforcement of legal contract is weak. In the following section, we directly examine the relationship between our measure of accounting precision and various institutional characteristics.

[8] We test the robustness of the results to alternative dichotomies in Section 5.

B.2 Sources of variation in accounting precision across countries and over time

Accounting practice emerges in response to stewardship and valuation demands for accounting information from institutions and capital markets. In Table V, we directly examine the relationship between our accounting precision measures and various proxies of legal and institutional environment culled from prior literature. Table V, Panel A shows the country ranks of each institutional variables sorted by the level of accounting precision. We use the well-known anti-director index (La Porta et al. 1998; Djankov et al. 2008) and the creditor rights aggregate score (La Porta et al. 1997; Djankov et al. 2007) to proxy the level of investor protection ($LEGAL_c$). To address the common criticism that it is the law enforcement rather than the rules itself that define the legal environment, we also examine various measures of law enforcement from the prior literature. The enforcement variable ($ENFORCE_c$) is a combination of the rule of law index from the *International Country Risk Guide* and the debt contract enforcement measure from Djankov et al. (2006). Finally, we collect the measure of disclosure quality ($DISCLOSE_c$) from La Porta et al. (2006).

The correlations in Table V, Panel B show that accounting precision is indeed positively correlated with the quality of legal institutions and the levels of law enforcement. Specifically, the accounting precision measures (AQ_c) show a strong positive association with level of enforcement ($ENFORCE_c$, $\rho = 0.505$). However, the legal rule itself ($LEGAL_c$, $\rho = 0.067$) is weakly correlated. One possible explanation for this weak correlation is the additional variation in accounting precision due to firm-level incentives such as investment opportunities, external financing and ownership structure (Durnev and Kim, 2005). Finally, the $DISCLOSE_c$ measure is positively associated ($\rho = 0.226$) with our accounting precision measure, providing additional construct validation.

We aggregate each of our AQ_c measures across firms and across time to create country specific measures. However, accounting policies themselves can evolve in response to crises (Angeletos et al.

2006; Angeletos et al. 2007). As countries implement such rule changes, temporal shifts in the cross-section of accounting precision can occur. We directly examine our precision measures' time series stability with AR(1) correlations.

Table V, Panel C shows the AR(1) times series correlation of each AQ measure of 21 countries spanning the years 1981 to 2005. Across all AQ measures, the association between each AQ measure in successive non-overlapping sub-periods of three or five years is significantly positive, suggesting that the accounting precision is persistent ---- it is institutionally difficult to change accounting rules and enforcement quickly (unlike say interest rates). Individual accounting rules may change, but overall accounting precision is unlikely to change rapidly in a country. That said, the three year AR(1) correlations are much stronger than the five-year AR(1) correlations suggesting that the five year shifts in the data are more substantive. Obviously, we cannot tell whether these shifts are noise or true variation, so we repeat our main analyses with the five-year aggregation period.

III.C Macroeconomic Leading Indicators in Prior Literature

The general conclusion in the crisis prediction literature is that an effective warnings system should consider a large variety of indicators (Kaminsky and Reinhart 1998). We adopt the leading indicators proposed in Kaminsky and Reinhart (1998, Table IVA) and Edison (2003, Table V). Following Edison (2003), we group the list into five major categories: current account indicators, capital account indicators, real sector indicators, domestic financial indicators, and global indicators.

Table VI, Panel A provides definitions of all the seventeen leading indicators, their data sources (primarily the International Financial Statistics), and the predicted direction of changes prior to a currency crisis. All indicators are defined as a percentage change from the previous year, except for the indicators already measuring deviation from a trend.[9]

The descriptive statistics of all the leading indicators are in Table VI, Panel B. Some leading indicators have extreme values. The extreme values for the currency overvaluation variable are from Indonesia and Mexico during periods of high inflation. The extreme values for excess real M1 balances are due to EU countries that experienced a discontinuity in M2 measures in 1999. To ensure that these extreme observations do not dominate our empirical tests, we repeat all our empirical tests after excluding these two variables and find similar results.

Table VII provides descriptive statistics for each leading indicator variable across different countries, along with additional country information, sorted by the countries' accounting precision. A comparison of the cost of crises, measured by foregone outputs as well as the actual loss of reserves incurred in defending the speculative attack (Bordo et al. 2001), indicates that countries with low accounting precision appear to have suffered more severe crises. Countries with low accounting precision also tend to have higher inflation and GDP growth over the sample period. Given that volatile and unstable countries are more likely to have institutionally weaker accounting regimes (e.g., Ball et al. 2000), this table provides additional support for our accounting precision partition method.

III.D Realized Accounting Fundamentals

Table VIII provides the definition of the three accounting signals we use to operationalize the realization of fundamentals. These measures are a) accruals, b) earnings or profits, and c) volatility of earnings. We do not include cashflows because they are simply earnings less accruals (cashflows and

[9] The two indicators are excess real exchange rate and excess real M1 balances.

accruals are correlated at 0.9 in our sample). We obtain the median of each measure for each country year and nominate it as the countrywide measure for that year.

While the list of potential accounting measures and accounting ratios useful for evaluating firm performance is very large (Ou and Penman 1989), the measures we choose are widely recognized as key accounting measures of firm performance (Dechow 1994; Dechow and Schrand 2004). More detailed accounting measures and ratios may not be equally valid across a diverse set of firms and countries, and also have limited data availability.

There is some overlap in the data underlying our accounting precision metrics and the data underlying realized accounting fundamentals, notwithstanding different aggregation procedures. With some exceptions, the realized fundamentals are typically first-moment effects, where as the accounting precision metrics are variance-covariance second-moment effects. More important, our analyses include country fixed effects, so any across-country variation in the measures in Table IV will have no impact on the results; we will assess only the within-country effect in our regressions.

D.1 Realized Accounting Signal: Accruals

The first accounting signal we employ, $Accruals_{c,t}$, represents the adjustment to cash flows to yield accounting earnings. These adjustments play a key role in reporting firm performance, especially in times of rapid downturns and upturns, for cashflows are not yet impacted. For example, banks typically do not wait for loans to default before writing them off. Such advance writeoffs generate large negative accruals.[10] Likewise, in upturns, firms may recognize revenue before the cashflows from customers have materialized. Of course, the extent to which accruals systematically predict future firm

[10] In his Congressional testimony on Feb. 28th, 2008, Fed chairman Ben Bernanke partly implicated the writeoffs resulting from the mark-to-market accounting rule as a driver of the current U.S. mortgage crisis (http://www.bloomberg.com/apps/news?pid=20601039&sid=a_XUPMYKChM0&refer=columnist_berry). Also see Greenlaw et al. (2008).

performance is highly controversial in the accounting literature. Although it has been well shown that the accrual component is less persistent than the cash flow component of earnings (Sloan 1996), recent studies such as Hirshleifer et al. (2009) find that at the aggregate level, accruals are positively associated with future performance. We therefore expect accruals to be large and negative prior to a downturn or a crisis.

We follow prior literature (Jones 1991; Dechow et al. 1995; Sloan 1996) and focus on current accruals including the reversal of certain non-current operating asset accruals by subtracting depreciation and amortization. We compute accruals from balance sheet and income statement information, and then compute cash flows as operating income minus accruals. We do not use the cash flow statement to compute accruals because of limited data availability of cash flow information across countries and time.

Table VIII, Panel B indicates that the mean of accruals is -0.01, similar to Sloan (1996, Table I) who reports accruals of -0.03. Note that accruals, though aggregated in an entirely different manner, also form the basis of our measure of the precision of accounting information (Section III.B). Although the empirical measure is identical, it is important to note that we implement the two in very different ways. The level of accrual as a proxy for accounting precision captures the variation across countries. On the other hand, the accruals level as a signal for fundamental is employed to capture within-country variation over time. Therefore, our definition of accruals as an accounting fundamental applies only within each country. In any event, we revisit this issue in Section V where we downplay the importance of accrual levels as measures of accounting precision.

D.2 Realized Accounting Signal: Operating Profitability

Operating profitability or operating earnings require little motivation. We define operating profitability as the country median of firm-level net operating income scaled by beginning total assets. Table VIII, Panel B indicates that operating profits average to a reasonable 8.5 percent of assets.

D.3 Realized Accounting Signal: Earnings Volatility

Following studies such as Ranciere et al. (2008), which implicate higher moments as the predictors of crises, we include volatility of the reported earnings as our last accounting signal. Volatility is the standard deviation of operating income (scaled by beginning total assets) over a three-year backward rolling window. Crises are troubled periods with high uncertainty; we therefore predict a positive association between crisis onset and earnings volatility.

D.4 Correlations

Table IX, Panel A presents the correlation matrix of all crises predictors, including accounting signals and leading indicators from prior literature. Simple examination of the correlation increases our confidence in the validity of our measures. For example, industry output is positively correlated with equity prices (= 0.34, Spearman) and commercial bank deposit is positively associated with domestic real interest rates (= 0.34, Spearman). Also, the associations of our accounting signals are plausibly signed: accruals and profitability show a positive relation (0.37, Spearman). More important, there also appears to be little evidence of multicollinearity; our three accounting signals thus capture different dimensions of realized fundamentals.

Table IX, Panel B presents the time series correlation of all the three accounting signals. The association of the contemporaneous and lagged accounting measure is stable. For example, the correlation between Profitability$_{c,t-2}$ and Profitability$_{c,t-1}$ (= 0.549, Spearman) is close to the correlation between Profitability$_{c,t-1}$ and Profitability$_{c,t}$ (= 0.559, Spearman). More important, the AR(1) effect in the realized accounting fundamental measures is significant. Our empirical tests therefore incorporate various lead-lags of the realized accounting fundamentals to get a better understanding of the predictive timing effects. We turn to these tests next.

IV. Results

IV.A The Story in Pictures

We first present a graphical representation of the movements in accounting signals for the periods leading up to and immediately following the currency crisis. Following Eichengreen et al. (1995), we compare the behavior of each accounting signal during 'tranquil' periods as well.

Figure 2 reports the movement in accounting signals three years before and after the 39 currency crises. The horizontal axes represent the number of years before and after the crisis (or tranquil) year. The bands represent the upper and lower 25% quartiles of the realization of each accounting signal.

Accounting signals show much movement during crises, especially for low accounting precision countries. Profits decline for these countries. Accruals do so as well and enter negative territory, suggesting considerable write-offs. Volatility of profit increases as predicted. By contrast, in the tranquil years, the data are indeed tranquil across both sets of countries, suggesting that the movement during crises years is not entirely spurious.

The univariate nature of the figures necessitates caution in any inference. For example, the movement of accounting signals in low precision countries also comes with larger confidence intervals. We therefore turn to a more formal analysis of the data.

IV.B Multivariate Analysis of Crisis Prediction

We examine the relation between accounting variables and the occurrence of a currency crisis in a regression framework. Our unit of observation is a country-year. The majority of the early warnings literature takes the signals approach (Kaminsky and Reinhart 1998), where indicators issue a signal whenever they move beyond a certain threshold. However, our ability to estimate the optimal threshold is impaired by the limited frequency of annual accounting data. Thus, we use multivariate probit models as in Frankel and Rose (1996) to test the in-sample statistical power of accounting signals to predict currency crises. Berg and Pattillo (1999) also use the probit model to assess the out-of sample performance of binary indicators and find that probit model outperforms the signal approach in terms of scores and goodness-of-fit.

We estimate the following probit model for the full sample of country-years. We include country fixed effects, a common time trend, and contemporaneous cross-sectional correlations:

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{3} \beta^i \times Accounting\ Signal^i_{c,t-n} + \sum_{k=1}^{18} \gamma^k \times Leading\ Indicators_{c,t-n} + \varepsilon_{c,t}. \quad (4)$$

Table X reports the results for various lead-lags in the full sample. The coefficients represent the marginal effect averaged over all observations. Results show that accounting signals two years prior have no ability to predict crisis onsets. However, the situation is different for a one-year lead. Accounting signals are now collectively significant, and the F-statistic for the three accounting measures is 17.97 (p-value <0.001). The goodness-of-fit, measured using McFadden's pseudo R-square, increases from 0.245 to 0.283 with the inclusion of accounting signals.[11] Finally, contemporaneous accounting signals in the last column are also significant. However, since the crisis has already occurred this significance could partially reflect the toll of the crisis on firm performance.

[11] Since McFadden's pseudo R-square can increase even with an inclusion of irrelevant variables, we also assess the model's explanatory power using adjusted-McFadden's R-square. Unreported results show that including accounting signals one year prior to the crises increases adjusted-McFadden's R-square by 8%.

Interestingly, Table X shows that many of the leading indicators also do not have statistically significant coefficients. Among the leading indicators, some domestic financial variables such as commercial bank deposit and Excess real M1 balances appear to be statistically significant in the predicted direction. On the other hand, coefficients of real interest rate differential, domestic real interest rate and lending/deposit rate show reverse signs.[12] This is consistent with the early warnings systems finding that even the best model has limited predictive power (Kaminsky and Reinhart 1998, Table I).

IV.C The Accounting Precision Dichotomy

We now expand equation (4) to compare coefficients across the two groups of accounting precision. We specify the following stacked probit model:[13]

$$D\_crisis_{c,t} = \sum_{i=1}^{3} \beta_H^i \times [I_{C_H} \times Accounting\ Signal_{c,t-n}^i] + \sum_{i=1}^{3} \beta_L^i \times [I_{C_L} \times Accounting\ Signal_{c,t-n}^i] + \sum_{k=1}^{18} \gamma^k \times Leading\ Indicator_{c,t-n}^k + \varepsilon_{c,t}. \tag{5}$$

I_{C_H} (I_{C_L}) is an indicator equal to 1 when the crisis is in a country with high (low) accounting precision and 0 otherwise (there is no intercept term). The coefficients β_H^i (β_L^i) measure the associations between accounting signals from countries with high (low) accounting precision and the onset of a crisis.

Table XI presents the result of the probit estimations. As in Table X, accounting signals two years in advance have no power to predict crises. However, the one-year prior F-tests clearly show that

---

[12] This finding is consistent with other empirical research in the early warnings system literature. In particular, Edison 2003 (Table XIV) finds that the real interest differential and real interest rates have the lowest probability of issuing a signal during the 24-month period prior to a crisis.

[13] See Maddala (2001) for a discussion of stacked regressions. Under the assumption that the error terms from each regression have the same distribution, this technique captures any (potential) correlations across the error terms. Stacking also allows statistical tests of coefficients across the stacked equations.

accounting signals have more statistical power to jointly predict crisis among countries with low accounting precision. In particular, the in-sample prediction power of realized accounting signals is significant for low accounting precision countries (F-stat = 14.17, p-value = 0.003), and insignificant (F-stat = 1.31, p-value = 0.726) for high precision countries. This is precisely the prediction of models such as Angeletos and Werning (2006).

An alternative explanation for the insignificance of the accounting signals in the high precision countries is lack of power. The aftermath model in the last column of Table XI dispels this possibility. For the first year following a crisis onset, the accounting signals appear to be jointly significant for both the high (F-stat= 26.62, p-value< 0.001) and the low (F-stat= 17.67, p-value< 0.001) accounting precision subsamples. Accounting signals in high precision countries thus reflect the consequence of crises: they simply cannot predict them.

The individual coefficients of the realized accounting signals in Table XI are somewhat difficult to interpret. We cannot directly read off the profitability coefficient, for we have to keep the accrual component constant. We therefore examine the measures individually in Table XII.

We get the same result as in Table XI, namely that two out of the three prior-year accounting measures are strongly predictive of crises in low precision countries.[14] Nothing is significant in the high precision countries. Accruals in low precision countries are negatively significant, suggesting declines before the crises. Accruals decline if firms increase their write-offs or decrease their inventory buildup. Inventory buildup, a particularly important measure of economic health, is a positive accrual because it consumes cash but does not affect earnings.

[14] Unreported results indicate that no measure individually has any power to predict crises in both subsamples two years in advance. For one year following a crisis, some signals are significant in both high and low precision countries. The results thus mirror Table XI.

The prior-year profitability in low precision countries is significant but has the opposite sign (it does so in Table XI as well). One explanation is that although accruals are declining, prior-year cashflows are still booming, causing total profits to increase before the crisis (a la Ranciere et al. 2008). But then, once the crisis hits, this boom disappears. Commensurately, the profitability in the crises years (Table XI) does significantly decline.

In sum, therefore, our results for the low precision countries mirror Ranciere et al. (2008), who show growth (captured by our profit measures) as improving before the crises. Our key additional insight is firms anticipate a growth slowdown and reduce accruals. Accounting adjustments thus play precisely the role they are supposed to. This is a particularly valuable result because it shows that *accounting* rules matter: it's the application of these rules to measure firm operations that generates critical asset-pricing information.

IV.D Institutional Factors and Time-Varying Measures of Accounting Precision

One concern with the above results is that they reflect the underlying institutions in Table V, Panel A and not accounting precision. This is especially true of institutions that are strongly correlated with accounting precision. In this subsection, we examine this concern directly. Table V, Panel B shows that, of all the institutional features, legal enforcement is most strongly associated with accounting precision. We divide the sample into high and low enforcement countries and examine the predictive power of the realized accounting signals.

Table XIII, Panel A shows that in the year before the crisis, realized accounting signals are stronger predictors only in low quality law enforcement countries. We interpret this result as follows. Modern research on economic growth has explored several channels through which institutions affect growth. In most of these channels, which range from financial development to trading costs (e.g., Martin and Rey

2006; Acemoglu and Guerrieri 2008; Ranciere et al. 2008), excess volatility and self-fulfilling crises due to luck and other sunspot phenomena are more likely in less-developed countries with features such as poor enforcement. Prescriptions on capital account liberalizations also routinely start with the assumption that less-developed countries are more susceptible to sunspot volatility (e.g., Prasad and Rajan 2008).

The above line of reasoning therefore would then suggest that fundamentals are *less* likely to predict crises in such countries. Our results in Table XIII, Panel A are exactly the opposite. So the channel which does seem to be operating in Table XIII, Panel A is likely the one in Table XI, namely that high enforcement countries have high precision accounting signals (Table V, Panel B), which then fall into the purview of our analytical crisis models. Therefore, albeit indirect, Table XIII, Panel A also provides support for our main prediction.

Another aspect of institutions is that they can change with time, especially in response to crises. Angeletos et al. (2006) and Angeletos et al. (2007) analytically show that our main prediction is robust to such endogenous institutional changes. As discussed in Section III.B.b, we re-sort the countries into high and low accounting precision every year, based on the accounting precision score over the previous five-year period. Table XIII, Panel B presents the main results in Table XI using this time-varying dichotomy. As in Table XI, the accounting fundamentals can predict crises only in the low precision countries. Our main result thus continues to hold.

V. Additional Analyses

V.A Different Types of Crises

Our approach so far has not differentiated among different types of crisis. In this section we relax this assumption and drop all the seven fiscal deficit, current account, and sudden stops crises in Table I.

These crises are more a product of government monetary and macro policies than information-based speculative behavior in financial markets.

Table XIV, Panel A provides the test results for the 32 remaining banking crises. The model specification and estimation strategy is identical to equation (5). The results of the banking crises subsample are similar to that of the comprehensive crises sample. Prior-year accounting signals are strongly predictive of crises in low precision countries and are insignificant in high precision countries.

Another implication of Kaminsky and Reinhart (1999) is that crises in the same country in consecutive years may not be independent. We therefore collapse consecutive crises years in the same country into the first year (the effect is that we are mostly dropping currency crises that follow a banking crisis). This procedure reclassifies 12 out of 37 crises as non-crises, but our results continue to remain unchanged. For this version of Table XI, we find that the predictive chi-squares of the realized fundamentals in the year before the crises are 17.99 (p-value <0.001) for the low accounting precision countries and 3.32 (p-value = 0.345) for the high precision countries. Furthermore, mirroring Table XI, both sets of countries show a significant change in fundamentals one year after the crises hit.

V.B Country classification of High and Low Accounting Precision

The switch from multiplicity to a region of uniqueness in the analytical crisis models is not gradual, but occurs suddenly at a certain threshold (Angeletos and Werning 2006, Figure 1). Empirically, we have used the sample median as the precision threshold after sorting the countries by the composite index described in section III. In this section, we examine the sensitivity of our results to several alternative thresholds.

We first repeat our analysis after redefining the countries with high accounting precision as those with a composite index smaller or equal to the sample mean (instead of the median) of the composite index. Italy and Mexico are now categorized as counties with high accounting precision. Table XIV, model (1) of Panel B shows the results using this alternative precision threshold. The results are robust. Prior-year accounting measures are strongly predictive of crises in low precision countries and have no predictive power in high precision countries.

Our accounting precision measures AQ^3- AQ^6 are very similar in that they measure accrual levels. This factor is thus not only similar to one of our realized performance measures but also may have a disproportionate influence on our precision threshold. We therefore only use AQ^1- AQ^3 as accounting precision measures and re-sort our sample countries on the median. Most countries retain their original standing. Only the countries that lie close to the precision threshold switch precision groups: France and Japan are now in the low precision group and Italy and Mexico are in the high precision group. Thus, our precision rankings are robust to alternative definitions of the precision measures. In addition, Table XIV, model (2) of Panel B shows that our main results continue to hold. Prior-year accounting measures are strongly predictive of crises in low precision countries and have no predictive power in high precision countries.

Finally, we examine the sub-sample of countries that lie in the interior of the precision categories. Our reasoning is that the behavior of these countries should be robust to movements in the precision threshold. We drop all countries that are relatively close to the precision threshold: France, Japan, Italy, and Mexico. Table XIV, model (3) of Panel B shows the results using this alternative precision threshold. Our main results continue to hold after dropping these countries. Prior-year accounting measures are strongly predictive of crises in low precision countries and have no predictive power in high precision countries.

V.C *Crisis Prediction in Tradable Sectors*

Trade-based crisis models show that trading frictions can cause excess volatility and capital flights (Martin and Rey 2006). While related, trading frictions constitute a different self-fulfilling mechanism than our financial market coordination models. Although we have controlled for across-country variation in trading costs via country fixed effects in our regressions, we control for the trading cost effect directly by eliminating the non-tradable sectors in the computation of accounting signals.[15]

We follow Tornell and Westermann (2005) and define the tradable sectors as all sectors excluding wholesale, retail trade, utilities and transportation industries. Unreported descriptive statistics indicate that on average 84 percent of the firms are categorized in the tradable sectors, but figures vary by country. Firms in the tradable sectors are typically more profitable firms with lower leverage and less volatility in their earnings stream.

Table XIV, Panel C replicates Table XI by using the accounting signals from the tradable sectors. We find strong evidence of coordination-based crises in the tradable sectors, with accounting fundamentals predicting crises only in the low precision countries. Our main results are thus robust to Martin and Rey (2006)-type trading cost effects.

VI. Conclusion

Recent dynamic growth models show that expansions and improvements in financial markets result in higher quality public signals that improve economy-wide resource allocations, thus increasing output and reducing volatility and crises (Acemoglu 2008, Ch. 17). The global games literature revisits this idea by arguing that in large financial markets, traders are individually too small to completely fund assets and therefore have to coordinate their resource allocation and interim financing activities. In such

[15] We continue to retain all sectors in the computation of the accounting precision measure.

settings, precise public signals can exacerbate volatility and multiplicities by coordinating traders' beliefs about each other and precipitating crises independent of realized fundamentals (e.g., Angeletos and Werning 2006; Angeletos et al. 2006; Angeletos et al. 2007).

A key public information source in financial markets is accounting data. The accounting research literature has extensively documented how cross-country variation in the precision of the accounting data arises due to variations in legal regimes, enforcement, and accounting rules. We exploit this variation in accounting data to provide one of the first tests of the public information precision predictions of global games. Subject to the usual econometric caveats, which we discuss at length in the body of the paper and attempt to control using a wide arsenal of econometric tools and experimental design techniques, we find strong in-sample support for global games predictions.

References

Acemoglu, D. 2008. *Introduction to Modern Economic Growth.* Princeton University Press, Princeton, NJ.

Acemoglu, D., V. Guerrieri. 2008. Capital Intensity and Non-Balanced Endogenous Growth. *Journal of Political Economy* 116: 467-498.

Allen, F., D. Gale. 2000. Financial Contagion, *Journal of Political Economy* 109: 1-33.

Angeletos, G-M., C. Hellwig and A. Pavan. 2006. Signaling in a Global Game: Coordination and Policy Traps. *Journal of Political Economy* 114:452-484.

Angeletos, G-M., C. Hellwig and A. Pavan. 2007. Dynamic Global Games of Regime Change: Learning, Multiplicity and Timing of Attacks. *Econometrica* 75: 711-756.

Angeletos, G-M., I. Werning. 2006. Crises and Prices: Information aggregation, multiplicity, and volatility. *American Economic Review* 96: 1720-1736.

Atkeson, A. 2000. Discussion of Morris and Shin's 'Rethinking Multiple Equilibria in Macroeconomic Modeling'. *NBER Macroeconomics Annual* 15, The MIT Press.

Ball, R., S. Kothari, and A. Robin. 2000. The Effect of International Institutional Factors on Properties of Accounting Earnings. *Journal of Accounting and Economics* 29: 1-51.

Berg. A., C. Pattillo. 1999. Predicting Currency Crises: The Indicators Approach and an Alternative. *Journal of International Money and Finance* 18: 561-586.

Bhattacharya, U., H. Daouk and M. Welker. 2003. The World Price of Earnings Opacity. *The Accounting Review* 78: 641-678.

Blanco, H., P. Garber. 1986. Recurrent Devaluations and Speculative Attacks on the Mexico Peso. *Journal of Political Economy* 94:148-166.

Bordo, M., B. Eichengreen, D. Klingebiel, M. Martinez-Peria and A. Rose. 2001. Is the Crisis Problem Growing More Severe? *Economic Policy* 16: 51-82.

Caprio, Jr. G., D. Klingebiel, L. Laeven and G. Noguera. 2005. Banking Crisis Database. In Honohan, P., Laeven, L., *Systemic Financial Crises: Containment and Resolution. Cambridge University Press*, Cambridge and New York.

Daske. H., L. Hail, C. Leuz, and R. Verdi, 2008, Mandatory IFRS Reporting Around the World: Early evidence on the economic consequences, *Journal of Accounting Research* 46(5), 1085-1142.

Dechow, P., 1994. Accounting Earnings and Cash Flows as Measures of Firm Performance: The Role of Accounting Accruals, *Journal of Accounting and Economics* 18, 3-42.

Dechow, P., I. Dichev. 2002. The Quality of Accruals and Earnings: the Role of Accrual Estimation Errors. *The Accounting Review* 77 Supplement: 35–59.

Dechow, P., C. Schrand. 2004. *Earnings Quality*. *The Research Foundation of CFA Institute.*

Dechow, P., D. Skinner. 2000. Earnings Management: Reconciling the Views of Accounting Academics, Practitioners, and Regulators. *Accounting Horizons* 14: 235-250.

Dechow, P., R. Sloan and A. Sweeney. 1995. Detecting Earnings Management. *Accounting Review*: 193–225.

Dichev, I., D. Skinner. 2002. Large-Sample Evidence On The Debt Covenant Hypothesis. *Journal of Accounting Research* 40: 1091–1124.

Djankov, S., O. Hart, C. McLiesh, and A. Shleifer, 2006. Debt Enforcement Around the World, *National Bureau of Economic Research Working paper 12807*.

Djankov, S., R. La Porta, F. Lopez-de-Silanes, and A. Shleifer. 2008. The Law and Economics of Self-Dealing. *Journal of Financial Economics* 88: 430-465.

Djankov, S., C. McLiesh, and A. Shleifer. 2007. Private Credit in 129 Countries. *Journal of Financial Economics* 84: 299-329.

Durnev, A., E.H. Kim. 2005. To Steal or Not To Steal: Firm Attributes, Legal Environment and Valuation. *The Journal of Finance* 60: 1461-1493.

Edison, H. 2003. Do Indicators of Financial Crises Work? An Evaluation of an Early Warning System. *International Journal of Finance and Economics* 8: 11-53.

Eichengreen, B., A. Rose and C. Wyplosz. 1995. Exchange Market Mayhem: The Antecedents and Aftermath of Speculative Attacks. *Economic Policy* 21: 249-312.

Fourcans, A., R. Franck. 2003. Currency Crises: A Theoretical and Empirical Perspective. *Edward Elgar Publishing.*

Francis, J., R. LaFond, P. Olsson and K. Schipper. 2005. The Market Pricing of Accruals Quality. *Journal of Accounting and Economics* 39:295-327.

Frankel J., A. Rose. 1996. Currency Crashes in Emerging Markets. An Empirical Treatment. *Journal of International Economics* 41: 351-366.

Fudenberg, D., J. Tirole. 1995. A Theory of Income and Dividend Smoothing Based on Incumbency Rents. *Journal of Political Economy* 103: 75-93.

Greenlaw, D., J. Hatzius, A. Kashyap and H.S. Shin. 2008. Leveraged Losses: Lessons from the Mortgage Market Meltdown: *US Monetary Policy Forum*, February.

Healy, P., J. Wahlen. 1999. A Review of the Earnings Management Literature and its Implications for Standard Setting. *Accounting Horizons*: 365-383.

Hirshleifer, D., K. Hou, and S. H. Teoh. 2009. Accruals and Aggregate Stock Market Returns. *Journal of Financial Economics:* forthcoming.

Jeanne, O. 1997. Are Currency Crises Self-Fulfilling? A Test. *Journal of International Economics* 43: 263-286.

Jeanne, O., P. Masson. 2000. Currency Crises, Sunspots and Markov-Switching Regimes. *Journal of International Economics* 50: 327-350.

Jones, J. 1991. Earnings Management During Import Relief Investigations. *Journal of Accounting Research*: 193–228.

Kaminsky, G. 2003. Currency Crises: Are They All The Same? *Journal of International Money and Finance* 25: 503-527.

Kaminsky, G., C. Reinhart, and C.Vegh. 2003. The Unholy Trinity of Financial Contagion. *Journal of Economic Perspectives* 17: 51-74.

Kaminsky, G., C. Reinhart. 1998. Leading Indicators of Currency Crises. *IMF Staff Papers* 45: 1-48.

Kaminsky, G., C. Reinhart. 1999. The Twin Crises: The Causes of Banking and Balance-of-Payment Problems. *American Economic Review* 89: 473-500.

Krugman, P. 1979. A Model of Balance-of-Payments Crises. *Journal of Money, Credit and Banking* 11: 311-325.

La Porta, R., F. Lopez-de-Silanes, and A. Shleifer. 2006.What Works in Securities Law? *Journal of Finance* 61: 1-32.

La Porta, R., F. Lo´pez-de-Silanes, A. Shleifer, and R. Vishny. 1997. Legal Determinants of External Finance. *Journal of Finance* 52:1131–50.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer and R. W. Vishny. 1998. Law and Finance. *The Journal of Political Economy* 106(6): 1113-1155.

Leuz, C., D. Nanda and P. Wysocki. 2003. Investor Protection and Earning Management: An International Comparison. *Journal of Financial Economics* 69: 505-527.

Leuz, C., R. Verrecchia. 2000. The Economic Consequences of Increased Disclosure. *Journal of Accounting Research* 28, 91-124.

Mankiw, G. 2003. *Macroeconomics.* Worth Publishers, New York.

Martin, P., H. Rey. 2006. Globalization and Emerging Markets: With or Without Crash? *American Economic Review* 96: 1631-1651

Mollenkamp, C., S Craig, S. Ng, and A. Lucchetti. 2008. Crisis on Wall Street as Lehman Totters, Merrill Is Sold, AIG Seeks to Raise Cash. *Wall Street Journal* Sept 15th.

Morris, S., H. S. Shin. 1998. Unique Equilibrium in a Model of Self-fulfilling Currency Attacks. *American Economic Review* 88: 587–597.

Morris, S., H. S. Shin. 2002. Global Games: Theory and Applications, Advances in Economic theory and Econometrics: Proceedings of the eighth world congress of the Econometric society, *Cambridge University Press*.

Morris, S., H. S. Shin. 2003. Coordination Risk and The Pricing of Debt. *European Economic Review* 48:133-153.

Obstfeld, M. 1996. Are Currency Crises Self-fulfilling? Comment. *NBER Macroeconomics Annual* 11: 393-403.

Ou, J., S. Penman. 1989. Accounting Measurement, Price-Earnings Ratio, and The Information Content of Security Prices, *Journal of Accounting Research* 27: 111-144

Prasad, E., R. Rajan. 2008. A Pragmatic Approach to Capital Account Liberalization. *Journal of Economic Perspectives* 22(3): 149-172.

Ranciere, R., A. Tornell and F. Westermann. 2008. Systemic Crises and Growth. *Quarterly Journal of Economics* 123: 359-406.

Reinhart, C., K. Rogoff. 2008. Is the 2007 U.S. Sub-prime Financial Crisis So Different? An International Historical Comparison. *American Economic Review 93*: 339-44.

Rey, Hélène. 2000. Discussion of Morris and Shin's 'Rethinking Multiple Equilibria in Macroeconomic Modeling'. *NBER Macroeconomics Annual* 15, The MIT Press.

Sloan, R. 1996. Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings? *The Accounting Review* 71: 289-315.

Swanson, E., L. Juarez -Valdes. 2003. The Contribution of Fundamental Analysis After a Currency Devaluation. *The Accounting Review* 78: 875-902.

Tornell, A., F. Westermann. 2005. *Boom-Bust Cycles and Financial Liberalization*. CESifo book series, The MIT press, Cambridge.

Trueman, B., S. Titman. 1988. An Examination for Accounting Income Smoothing. *Journal of Accounting Research* 26 (Supplement): 127-139.

Yuan, K. 2005. Asymmetric Price Movements and Borrowing Constraints: A Rational Expectation Equilibrium Model of Crises, Contagion, and Confusion. *Journal of Finance* 60: 379-411.

Table I: Crisis Onset Years By Different Types of Currency Crises

Country	Type of crises				
	Fiscal deficit	Current account	Financial excesses	Sovereign debt	Sudden stop
Argentina		2002*	1981 1982	1986 1989 1990	
Australia			1989*		
Brazil			1990* 1994* 1999	1983 1986 1989 1990 1991	
Denmark		1979		1993	
Finland				1991 1992	1982
France			1994*		
Greece			1991		
India			1993*		
Indonesia		1978	1983	1986 1997 1998	
Italy			1990		
Japan			1991*		
Korea			1997*		
Malaysia			1997 1998		
Mexico			1994*	1976 1982	
Norway	1992		1978	1998 1999 2000	1986
Philippines			1983 1984	1986 1997	
Spain		1976 1977	1992 1993	1982	
Sweden		1977		1992	1981 1982
Taiwan			1997*		
Thailand	2000	1978 1981	1984 1997*	1997 1998 1999	
Turkey			1994* 2001*	1980 1994	
Total # of crisis years	2	8	26	28	4

Notes: Crises episodes are taken directly from Kaminsky and Reinhart (1999) and the banking crisis database of Caprio et al. (2005). We follow the crisis classification of Kaminsky (2003).
* From the Caprio et al. (2005) banking crisis database.

Table II: Crisis Onset Years and Number of Public Firms

	Number of public firm observations										
Year	Argentina	Australia	Brazil	Denmark	Finland	France	Greece	India	Indonesia	Italy	Japan
1976											
1977											
1978											
1979											
1980											
1981		3				2					
1982		5				3					
1983		5				3				2	
1984		5			6	5				6	
1985		12		4	7	10	2			8	2
1986		18		4	10	13	10			15	11
1987	2	26		5	13	27	31			39	18
1988	6	82	15	36	38	198	33			186	37
1989	7	123	99	96	76	260	33			200	142
1990	7	145	113	125	90	299	35	6	2	207	614
1991	7	150	111	127	90	329	44	6	10	208	933
1992	16	150	148	134	90	342	71	32	86	208	1057
1993	21	156	151	137	89	362	112	137	94	200	1085
1994	26	156	162	143	92	367	128	156	101	191	1127
1995	30	168	197	143	93	367	126	175	106	200	1182
1996	28	206	253	141	93	383	125	256	147	195	1219
1997	37	236	256	171	116	525	164	281	155	210	1255
1998	39	251	278	175	131	600	186	298	161	231	1288
1999	49	282	319	167	130	646	197	305	163	247	1789
2000	60	381	571	154	126	669	240	309	193	262	1791
2001	66	588	561	145	134	668	265	350	262	268	1863
2002	68	965	541	140	132	638	273	412	282	262	2019
2003	68	1000	529	137	128	626	258	437	286	268	2035
2004	64	1069	541	124	132	622	262	510	284	276	2109
2005	61	1211	548	118	132	618	263	574	286	273	2162
Total # of firm-years	662	7393	5393	2426	1948	8582	2858	4244	2618	4162	23738
# of crisis years (sum of shaded cells)	6	1	7	2	3	1	1	1	5	1	1

(Continued)

Table II: Crisis Onset Years and Number of Public Firms (Continued)

	Number of public firm observations									
Year	Korea	Malaysia	Mexico	Norway	Philippines	Spain	Sweden	Taiwan	Thailand	Turkey
1976										
1977										
1978										
1979										
1980										
1981										
1982										
1983		1					1			
1984		3		1			4			
1985		5	7	7		2	4			
1986	1	7	7	12		3	8			
1987	1	10	12	16		8	12			
1988	13	35	38	66		54	85		4	2
1989	73	43	47	82	5	71	113	5	8	10
1990	106	50	48	97	5	76	145	5	21	18
1991	99	55	47	97	10	86	149	5	42	21
1992	100	106	77	96	36	89	154	24	141	24
1993	111	135	90	90	46	92	160	27	231	28
1994	165	138	105	101	52	92	171	44	301	40
1995	194	156	114	97	57	93	184	103	318	38
1996	218	234	112	97	82	97	184	191	346	41
1997	259	267	120	165	87	119	236	210	372	53
1998	299	304	125	172	88	116	270	223	385	73
1999	383	309	164	156	103	117	265	226	375	89
2000	649	342	170	128	113	116	270	367	375	111
2001	667	548	172	129	152	119	263	475	517	131
2002	731	671	173	124	165	114	253	1084	532	140
2003	814	710	167	129	175	113	261	1169	585	169
2004	837	794	162	141	172	117	279	1229	631	179
2005	847	863	155	142	176	110	277	1229	638	177
Total # of firm-years	6567	5786	2112	2145	1524	1804	3748	6616	5822	1344
Total # of crisis years (sum of shadedcells)	1	2	3	6	4	5	4	1	7	3

Notes: Figures in table represent number of public firm observations in each country-year with financial data (total asset, net income from operations, current assets and current liabilities) available in Thompson Datastream. Shaded cells represent the year of an onset of a crisis described in Table I.

Table III: Individual Countries' Measures of Accounting Signal Precision
[c=country, f=firm, t=year]

	Description	**Measure**
$AQ^1_{c,t}$ *Accruals quality*	Measures how well accruals map into past, current and future cash flow realizations (Source: Dechow and Dichev 2002)	$AQ^1_{c,t} = \sigma_f(\varepsilon_{c,t})$ $Accruals_{c,f,t} = \hat{\alpha}_{c,t} + \hat{\beta}^0_{c,t} \times CFO_{c,f,t-1} + \hat{\beta}^1_{c,t} \times CFO_{c,f,t} + \hat{\beta}^2_{c,t} \times CFO_{c,f,t+1} + \varepsilon_{c,f,t}$
$AQ^2_{c,t}$ *Smoothing*	Measures the extent accounting accruals offset cash flow shocks (Source: Francis et al., 2005)	$AQ^2_{c,t} = -Corr\left\{\Delta\left(\frac{Accruals_{c,f,t}}{TotalAsset_{c,f,t-1}}\right), \Delta\left(\frac{CFO_{c,f,t}}{TotalAsset_{c,f,t-1}}\right)\right\}$
$AQ^3_{c,t}$ *Accruals*	Level of accruals (Source: Sloan 1996)	$AQ^3_{c,t} = Median_f\left(\frac{Accruals_{c,f,t}}{TotalAsset_{c,f,t-1}}\right)$
$AQ^4_{c,t}$ *Absolute accruals*	Magnitude of accruals (Source: Leuz et al., 2003)	$AQ^4_{c,t} = Median_f\left(\frac{\lvert Accruals\rvert_{c,f,t}}{\lvert CFO\rvert_{c,f,t}}\right)$
$AQ^5_{c,t}$ *Total accruals*	Level of total accruals (Source: Sloan et al., 2002)	$AQ^5_{c,t} = Median_f\left(\frac{TotalAccruals_{c,f,t}}{TotalAsset_{c,f,t-1}}\right)$
$AQ^6_{c,t}$ *Absolute total accruals*	Magnitude of total accruals (Source: Leuz et al., 2003)	$AQ^6_{c,t} = Median_f\left(\frac{\lvert TotalAccruals\rvert_{c,f,t}}{\lvert CFO\rvert_{c,f,t}}\right)$
$AQ^i_{c,t,P}$ i= 1..6	Time averaged measure over a P-year rolling window	$AQ^i_{c,t,P} = \frac{1}{P}\sum_{p=1}^{P}(AQ^i_{c,t-p+1}), \forall i$
AQ^i_c i= 1..6	Per-country mean of each measure	$AQ^i_c = Mean_t\left(AQ^i_{c,t}\right)$

Notes: Each measure is defined such that *lower* value represents *higher* accounting precision.

$$Accruals_{c,f,t} = (\Delta CA_{c,f,t} - \Delta Cash_{c,f,t}) - (\Delta CL_{c,f,t} - \Delta STDebt_{c,f,,t} - \Delta TaxPayable_{c,f,t}) - Depreciation_{c,f,t}$$

$$TotalAccruals_{c,f,t} = (\Delta TotalAsset_{c,f,t} - \Delta TotalLiability_{c,f,t}) - \Delta Cash_{c,f,t}$$

$$CFO_{c,f,t} = OperNI_{c,f,t} - Accruals_{c,f,t}$$

Table IV: Countries' Average Measure of Accounting Precision
[c=country]

Panel A: Countries with high accounting precision

Country	# of years	# of firm years	**Level of accounting precision averaged over the sample period**						**Composite country index**
			AQ_c^1	AQ_c^2	AQ_c^3	AQ_c^4	AQ_c^5	AQ_c^6	$= Mean_i\{Rank_c(AQ_c^i)\}$ where $i = 1..6$
Denmark	21	2,426	0.0512	0.8917	-0.0485	0.5567	0.0391	0.6339	5.2
Finland	21	1,948	0.0149	0.8963	-0.0567	0.6056	0.0594	0.6825	6.7
Spain	21	1,804	0.0499	0.9340	-0.0369	0.4484	0.0588	0.6596	6.7
Sweden	23	3,748	0.0519	0.8204	-0.0334	0.4701	0.0662	0.8025	6.8
Norway	22	2,145	0.0621	0.6576	-0.0505	0.5585	0.0496	2.3362	7.7
Taiwan	17	6,616	0.0487	0.9469	-0.0315	0.5697	0.0421	0.7379	8.3
India	16	4,244	0.0519	0.7606	-0.0186	0.4488	0.0899	0.8172	8.7
Philippines	17	1,524	0.0474	0.8479	-0.0288	0.5072	0.0739	0.9692	8.7
France	25	8,582	0.0706	0.9257	-0.0403	0.5685	0.0568	0.6422	9.0
Japan	21	23,738	0.0683	0.9854	-0.0276	0.5307	0.0264	0.7133	9.7

Notes: Definitions of accounting precision measures are in Table III. Sample is described in Table II.

(Continued)

Table IV: Countries' Average Measure of Accounting Precision (Continued)
[c=country]

Panel B: Countries with low accounting precision

Country	# of years	# of firm years	**Level of accounting precision averaged over the sample period** AQ_c^1	AQ_c^2	AQ_c^3	AQ_c^4	AQ_c^5	AQ_c^6	**Composite country index** $= Mean_i[rank_c(AQ_c^i)]$ where i = 1..6
Italy	23	4,162	0.0558	0.9073	-0.0492	0.6570	0.0621	0.9541	10.2
Mexico	21	2,112	0.0491	0.8299	-0.0138	0.4706	0.2293	1.5416	10.5
Thailand	18	5,822	0.0581	0.9186	-0.0303	0.5720	0.0697	0.8302	11.3
Malaysia	23	5,786	0.0826	0.9230	-0.0130	0.5578	0.0527	1.0483	12.3
Indonesia	16	2,618	0.3759	0.9777	-0.0332	0.6353	0.0072	1.0548	12.8
Korea	20	6,567	0.0958	0.9494	-0.0262	0.6229	0.0557	0.9771	13.5
Australia	25	7,393	0.0917	0.8516	-0.0182	0.8697	0.0672	3.2037	15.2
Argentina	19	662	0.0674	0.5242	0.3258	0.9821	2.4680	6.2378	15.3
Turkey	18	1,344	0.1818	0.7641	0.0643	0.6701	0.4428	2.0100	15.5
Brazil	18	5,393	0.3056	0.8400	-0.0206	0.6597	3.5114	4.4988	16.0
Greece	21	2,858	0.0727	0.9381	-0.0001	0.6668	0.1129	1.1765	16.8

Notes: Variable definitions are in Table III. Sample is described in Table II.

Table V: Stability of Accounting Precision Measures Across Different Institutions and Over Time

[c=country]

Panel A: Country rankings of institutional variables sorted by level of accounting precision

Country	**Accounting precision**	**Legal origin**	**Legal system**			**Legal enforcement**			**Security law**
	$AQ_c = Mean_i\{Rank_c(AQ_c^i)\}$ where i =1..6	Common vs. Code Law	Rank (Anti-director)	Rank (Creditor Law)	**LEGAL$_c$**	Rank (Rule of law)	Rank (Debt Enforce)	**ENFORCE$_c$**	**DISCLOSE$_c$**
Countries with high accounting precision									
Denmark	**5.2**	Code (S)	7	1	**4**	1	9	**5**	**11**
Finland	**6.7**	Code (S)	12	14	**13**	1	3	**2**	**15**
Spain	**6.7**	Code (F)	1	5	**3**	10	8	**9**	**15**
Sweden	**6.8**	Code (S)	12	14	**13**	1	7	**4**	**11**
Norway	**7.7**	Code (G)	12	5	**9**	1	4	**2.5**	**11**
Taiwan	**8.3**	Code (S)	16	5	**11**	8	2	**5**	**5**
India	**8.7**	Common (U)	1	5	**3**	19	.	**19**	**1**
Philippines	**8.7**	Code (F)	7	14	**11**	21	18	**19.5**	**4**
France	**9.0**	Code (F)	12	20	**16**	6	12	**9**	**5**
Japan	**9.7**	Code (G)	5	5	**5**	6	1	**3.5**	**5**
Countries with low accounting precision									
Italy	**10.2**	Code (F)	19	5	**12**	9	15	**12**	**10**
Mexico	**10.5**	Code (F)	16	20	**18**	15	10	**12.5**	**11**
Thailand	**11.3**	Code (F)	7	5	**6**	13	11	**12**	**1**
Malaysia	**12.3**	Common(U)	1	1	**1**	11	14	**12.5**	**1**
Indonesia	**12.8**	Code (F)	7	5	**6**	20	17	**18.5**	**15**
Korea	**13.5**	Code (S)	5	1	**3**	15	5	**10**	**5**
Australia	**15.2**	Code (S)	7	1	**4**	1	6	**3.5**	**5**
Argentina	**15.3**	Code (F)	19	14	**17**	15	16	**15.5**	**15**
Turkey	**15.5**	Code (G)	16	5	**11**	18	20	**19**	**15**
Brazil	**16.0**	Code (S)	1	14	**8**	12	19	**15.5**	**21**
Greece	**16.8**	Code (S)	19	14	**17**	14	13	**13.5**	**20**

Note: Each variable is ranked such that *lower* score/rank indicates *higher* quality.

Table V: Stability of Accounting Precision Measures Across Different Institutions and Over Time (Continued)
[c= country, P= Length of non-overlapping consecutive periods over which stability is measured]

Panel B: Correlation of accounting precision and institutional variables

	AQ_c	$LEGAL_c$	$ENFORCE_c$	$DISCLOSE_c$
AQ_c	-	0.067	**0.505****	0.226
$LEGAL_c$		-	0.057	0.409
$ENFORCE_c$			-	0.065
$DISCLOSE_c$				-

Variable definitions (Note: lower scores indicate higher quality):
The legal traditions of code and common laws origins are France (F), Scandinavian (S), German (G), and British (U).
$LEGAL_c$=Mean[Rank(Anti-director index$_c$), Rank(Creditor rights score$_c$)]. The anti-director index (0-6) is an aggregate measure of shareholder rights defined in La Porta et al. (1998) and corrected in Djankov et al. (2007). The creditor right scores (0-4) measure the extent legal provisions protect creditors' rights as defined in La Porta et al. (1997) and updated in Djankov et al. (2007).
$ENFORCE_c$=Mean[Rank(rule of law$_c$), Rank(debt enforcement$_c$)]. The rule of law index (0-10) is an assessment of the law and order tradition in the country produced by the country-risk rating agency *International Country Risk* (ICR) between 1982 and 1995. Debt enforcement is an index measuring the efficiency of law enforcement in a hypothetical case of an insolvent firm provided by insolvency lawyers from 88 countries (Djankov et al., 2006).
$DISCLOSE_c$=Rank(disclosure index$_c$), Disclosure index is defined in La Porta et al. (2006) measuring the disclosure requirement in securities law during equity issuance.
†, *, ** denote significance at the 95%, 97% and 99% levels.

Panel C: AR(1) coefficients of each accounting precision measures in non-overlapping consecutive periods

P	$\rho(AQ^1_{c,P}, AQ^1_{c,P-1})$		$\rho(AQ^2_{c,P}, AQ^2_{c,P-1})$		$\rho(AQ^3_{c,P}, AQ^3_{c,P-1})$		$\rho(AQ^4_{c,P}, AQ^4_{c,P-1})$		$\rho(AQ^5_{c,P}, AQ^5_{c,P-1})$		$\rho(AQ^6_{c,P}, AQ^6_{c,P-1})$	
	Spearman	Pearson	Spearman	Pearson	Spearman	Pearson	Spearman	Pearson	Spearman	Pearson	Spearman	Pearson
P=3 years	**0.453****	**0.433****	**0.533****	**0.219***	**0.416****	0.009	**0.460****	**0.346****	**0.219***	**0.277****	**0.300****	**0.392****
P=5 years	0.314	0.261	**0.378***	**0.297***	0.233	-0.028	**0.361***	-0.054	**0.368****	0.068	0.175	-0.015

$AQ^i_{c,P} = Mean_{t \in P}(AQ^i_{c,t})$. See Table III for definitions of AQ measures. AR(1)= $\rho(AQ^i_{c,P}, AQ^i_{c,P-1})$ computed over all countries.
†, *, ** denote significance at the 95%, 97% and 99% levels.

Table VI: Definitions and Descriptive Statistics of Prior Literature's Leading Indicators
[c=country, t=year]

Panel A: Definition of leading indicators

Category	Indicator (Variable name)	Definition	Measure & data source	Predicted association to crisis	
Current account	Deviation from expected real exchange rate (*XS_realEX*$_{c,t}$)	Deviation of real exchange rate from time (year) trend regression	- residual value from time trend equation estimated by each country - real exchange rate= nominal bilateral exchange rate* (IFS.00ae) [US CPI/domestic CPI] (IFS.64.ZF)	Over-valuation of local currency are linked to currency crisis	(-)
	Imports ($\Delta Imports_{c,t}$)	% change of imports	- imports (IFS.70.ZF)	Weak external sector	(+)
	Exports ($\Delta Exports_{c,t}$)	% change of exports	- exports (IFS.71.ZF)	Weak external sector	(-)
Capital account	Foreign exchange reserve ($\Delta FXreserve_{c,t}$)	% change in foreign exchange reserves	- foreign exchange reserve = Total reserve minus gold (IFS.1L.ZF)	Loss of foreign reserve is a characteristic of currency crisis; Krugman (1979)	(-)
	M2/foreign exchange reserve ($\Delta M2\_FXreserve_{c,t}$)	% change in M2/foreign exchange reserves	- M2= Quasi money (IFS.35.ZF) - foreign exchange reserve (IFS.1L.ZF)	Expansionary monetary policy and/or sharp decline in reserve is associated with a currency crisis	(+)
	Real interest rate differential (*interest_diff* $_{c,t}$)	The level of foreign and domestic interest rate differential	- foreign real interest rate = US lending interest rate – US inflation rate calculated from US CPI - domestic real interest rate = lending interest (IFS.60P.ZF) – domestic inflation rate	High world interest rate can lead to reversal of capital flow	(+)
	Short term debt/reserves ($\Delta ST\_debt_{c,t}$)	% increase in ST debt	- ST debt = debt with maturity less than 1 year (from BIS database) - foreign exchange reserve = Foreign exchange (IFS.1L.D.ZF)	Increase in ST debt are associated with currency crisis	(+)
Real sector	Industry production ($\Delta Output_{c,t}$)	% change in output	- industry production (IFS.66A.ZF)	Recessions often precede crisis	(-)
	Stock price ($\Delta Equity_{c,t}$)	% change in equity index	- equity indices (IFS.62.ZF)	Burst of asset bubble often precede currency crisis	(-)

* The nominal exchange rate between the currencies of domestic country and the US, expressed as the number of US currency units per domestic currency unit.

Table VI: Definitions and Descriptive Statistics of Prior Literature's Leading Indicators (Continued)

Domestic financial	M2 multiplier, ($\Delta M2\_multiplier_{c,t}$)	% change in M2 multiplier	- M2 multiplier = M2 / Base money - M2= Money (IFS.34.ZF) + Quasi money (IFS.35.ZF) - base money (IFS.14.ZF)	Rapid growth of credit	(+)
	Domestic credit/GDP, ($\Delta Domes\_credit_{c,t}$)	% change in domestic credit	- domestic credit (IFS.32.ZF) - GDP (IFS.99B.ZF)	Credit expands prior to crisis	(+)
	Domestic real interest rate ($Dom\_real\_interest_{c,t}$)	Domestic real interest rate	- real exchange rate = deposit interest rate (IFS.60L.ZF) – inflation - $inflation_{c,t}=[CPI_{c,t}-(CPI_{c,t-1})]/(CPI_{c,t-1})$ (IFS.64.ZF)	Higher real interest rate can signal liquidity crunch or have been increased to defend speculative attacks	(+)
	Commercial bank deposits ($\Delta comm\_deposit_{c,t}$)	% change in commercial bank deposits deflated by CPI	- commercial bank deposits = demand deposits (IFS.24.ZF) + other deposits (IFS.25.ZF) - CPI (IFS.64.ZF)	Loss of deposits occur as crisis unfolds	(-)
	Lending/deposit interest rate ($\Delta LD\_ratio_{\ c,t}$)	Level of lending to deposit ratio	- lending interest (IFS.60P.ZF) - deposit interest (IFS.60L.ZF)	Lending rates tend to rise prior to crisis due to decline in loan quality	(+)
	Excess real M1 balances ($XS\_real\_MI_{c,t}$)	Ml deflated by consumer prices less an estimated demand for money	- each country's money demand equation is estimated as a function of real GDP, domestic CPI and time (=year) - M1 = Money (IFS.35.ZF) - CPI (IFS.64.ZF) - real GDP= GDP (IFS.99B.P)	Loose monetary policy can lead to currency crisis	(+)
Global	G7 output ($G7\_GDP\_growth_t$)	% change in Changes in G7's average real GDP growth	- weighted average of G7 real GDP growth - real GDP= GDP (IFS.99B.ZF) / CPI (IFS.64.ZF)	Foreign recessions often precedes crisis	(-)
	US interest rate ($US\_real\_interest_t$)	Changes in level of US real interest rate	- real interest rate = nominal interest (IFS.60L.ZF) – inflation rate - inflation=[CPI-lag(CPI)]/(lagCPI) (IFS.64.ZF)	Increase in foreign interest associated with capital outflows	(+)
	Oil prices (Oil_price_t)	% change in oil price	- oil price (IFS.0017.AAZ)	High oil prices are associated with recessions	(+)

Notes: All leading indicator variables are measured as annual percentage changes, except (a) interest rate as changes over the previous twelve months, (b) real exchange rate as deviation from time trend, and (c) excess M1 as residuals from money demand equation. Source: International Financial Statistics (IFS) and other sources as noted.

Table VI: Definitions and Descriptive Statistics of Prior Literature's Leading Indicators (Continued)

[c=country, t=year]

Panel B: Descriptive statistics of leading indicators

Variables		N	Mean	Stn dev.	Min	10%	Median	90%	Max
Current Account	Over-valuation$_{c,t}$	596	0.000	595.9	-4,480†	-30.48	-0.159	31.94	3,997†
	Imports$_{c,t}$	582	0.115	0.157	-0.558	-0.057	0.112	0.292	0.991
	Exports$_{c,t}$	587	0.125	0.129	-0.216	-0.024	0.117	0.280	1.007
Capital Account	Foreign exchange reserve$_{c,t}$	619	0.191	0.509	-0.806	-0.251	0.118	0.617	4.482
	M2/foreign exchange$_{c,t}$	556	0.556	4.657	-0.757	-0.284	0.039	0.732	95.74
	Real interest rate differential$_{c,t}$	590	-0.506	6.803	-141.5	-0.074	-0.005	0.080	8.007
	Short term debt/reserves$_{c,t}$	199	0.266	0.873	-0.970	-0.485	0.040	1.183	5.461
Real sector	Industry production$_{c,t}$	476	0.045	0.060	-0.182	-0.015	0.040	0.111	0.419
	Stock prices$_{c,t}$	428	0.177	0.467	-0.470	-0.179	0.117	0.525	5.948
Domestic Financial	M2 multiplier$_{c,t}$	502	-0.009	0.255	-0.984	-0.266	0.009	0.171	1.884
	Domestic credit/GDP$_{c,t}$	556	0.008	0.145	-1.585	-0.092	0.018	0.113	0.603
	Domestic real interest rate$_{c,t}$	577	0.527	6.881	-7.961	-0.058	0.017	0.081	141.6
	Commercial bank deposits$_{c,t}$	499	0.078	0.281	-0.775	-0.043	0.062	0.197	5.521
	Lending/deposit interest rate$_{c,t}$	491	2.129	3.820	0.341	1.000	1.494	2.843	52.41
	Excess real M1 balances$_{c,t}$	576	0.000	197.0	-1,510††	-73.99	-0.026	44.924	1,477††
External	G7 output$_{t}$	619	-0.013	0.214	-0.407	-0.255	-0.020	0.268	0.557
	US interest rate$_{t}$	599	0.001	0.016	-0.020	-0.014	-0.000	0.015	0.068
	Oil prices$_{t}$	619	0.095	0.314	-0.482	-0.157	0.021	0.375	1.334

† Extreme values consist of observations from Indonesia and Mexico during periods of high inflation.

†† Extreme values are driven by EU countries that have discontinuity in M2 measures post year 1999. We repeat all our empirical tests after excluding the two variables with extreme values and find qualitatively similar results.

Table VII: Descriptive Statistics of Country Characteristics

[c=country]

Panel A: Countries with high accounting precision

Country	**Country characteristic**			**Average value of leading indicators over the sample period**							**Cost of crises**	
	# of firm years	Average inflation$_c$	AvergeΔGDP$_c$	ΔImports$_c$	ΔFXreserve$_c$	ΔSTdebt$_c$	ΔOutput$_c$	ΔEquity$_c$	ΔDomestic credit$_c$	ΔLD_ratio$_c$	Growth$_c$	Reserve loss$_c$
Denmark	2,426	0.047	0.067	0.074	0.208	0.061	0.027	0.144	0.030	2.053	0.024	-0.065
Finland	1,948	0.019	0.041	0.055	0.186	-0.195	0.027	0.070	0.011	8.746	-0.083	-0.278
Spain	1,804	0.048	0.076	0.087	0.227	0.171	0.040	0.173	0.007	2.055	-0.066	-0.206
Sweden	3,748	0.073	0.137	0.181	0.287	0.525	0.065	0.211	0.022	1.621	-0.075	0.257
Norway	2,145	0.047	0.070	0.095	0.100	0.169	0.016	0.116	0.029	0.532	-0.017	0.012
Taiwan	6,616	0.125	0.159	0.088	0.074	0.906	0.019	0.185	0.030	1.590	-	-
India	4,244	0.049	0.091	0.073	0.137	0.100	0.033	0.153	0.012	1.826	-0.015	0.796
Philippines	1,524	0.079	0.113	0.146	0.075	0.915	0.020	0.113	0.003	1.487	-0.139	-0.277
France	8,582	0.103	0.138	0.166	0.202	0.334	0.118	0.239	-0.003	1.483	-0.093	0.176
Japan	23,738	0.052	0.076	0.089	0.105	0.084	0.017	0.168	0.019	2.112	-0.068	-0.111
Mean	5677	0.064	0.097	0.105	0.160	0.307	0.038	0.157	0.016	2.350	-0.059	0.033

Notes:

$$Growth_{c,t} = \frac{1}{2}\ \%\Delta output_{c,t} + \%\Delta output_{c,t+1}\ - \frac{1}{T}\sum_{t=1}^{T} \%\Delta output_{c,t}$$

Reserve loss $_c$: Rate of annual change in foreign exchange reserves of the central bank in the fiscal year of the crisis onset.
For description of all other variables, refer to definitions in Table VI.

(Continued)

Table VII: Descriptive Statistics of Country Characteristics (Continued)

[c=country]

Panel B: Countries with low accounting precision

Country	Country characteristic			Average value of leading indicators over the sample period							Cost of crises	
	# of firm years	Average inflation$_c$	AveargeΔGDP$_c$	ΔImports$_c$	ΔFXreserve$_c$	ΔSTdebt$_c$	ΔOutput$_c$	ΔEquity$_c$	ΔDomes _credit$_c$	ΔLD_ratio$_c$	Growth$_c$	Reserve loss$_c$
Italy	4162	0.074	0.104	0.132	0.178	0.444	-	0.153	-0.010	2.366	-	0.359
Mexico	2112	0.327	0.367	0.118	0.322	0.144	0.034	0.730	-0.017	1.909	-0.089	-0.755
Thailand	5822	0.050	0.112	0.157	0.143	0.239	-	0.052	0.025	1.790	-	-0.017
Malaysia	5786	0.033	0.111	0.147	0.162	0.469	0.086	0.079	0.009	1.893	-0.151	0.000
Indonesia	2618	0.116	0.201	0.111	0.187	0.167	0.072	0.129	0.006	1.309	-0.312	0.148
Korea	6567	0.071	0.156	0.141	0.285	-0.050	0.096	0.132	0.029	1.155	-0.204	-0.407
Australia	7393	0.057	0.088	0.109	0.196	-0.008	0.022	0.112	0.031	1.713	0.023	0.012
Argentina	662	2.969	2.815	0.130	0.384	0.664	-	-	-0.020	1.546	-	0.362
Turkey	1344	0.545	0.650	0.125	0.177	0.029	0.059	-	0.025	1.026	-0.072	-0.008
Brazil	5393	4.492	3.946	0.077	0.185	0.131	0.018	-	-0.074	3.261	-0.005	0.036
Greece	2858	0.125	0.159	0.088	0.074	0.906	0.019	0.185	0.030	1.590	-	0.537
Mean	4065	0.81	0.79	0.12	0.21	0.28	0.05	0.20	0.00	1.78	-0.12	0.02

Notes:

$$Growth_{c,t} = \frac{1}{2}\left(\%\Delta output_{c,t} + \%\Delta output_{c,t+1}\right) - \frac{1}{T}\sum_{t=1}^{T}\%\Delta output_{c,t}$$

Reserve loss $_c$: Rate of annual change in foreign exchange reserves of the central bank in the fiscal year of the crisis onset.
For description of all other variables, refer to definitions in Table VI.

Table VIII: Definitions and Descriptive Statistics of the Realized Accounting Signals
[c=country, f=firm, t=year]

Panel A: Definitions of the realized accounting signals

Accounting Signal	Description	Measure
Accruals$_{c,t}$	Country median of firm level accruals scaled by lagged total assets.	$accruals_{c,t} = Median_f\left(\frac{CurrentAccruals_{c,f,t}}{TotalAssets_{c,f,t-1}}\right)$
Profitability$_{c,t}$	Country median of firm level net operating income scaled by lagged total assets.	$profitability_{c,t} = Median_f\left(\frac{NI_{c,f,t}}{TotalAssets_{c,f,t-1}}\right)$
Volatility$_{c,t}$	Country median of firm level operating income volatility. Volatility is the standard deviation of a three year backward rolling window.	$volatility_{c,t} = Median_f\left\{\frac{\sigma_{c,f,t}(NI_{c,f,t}, NI_{c.f.t-1}, NI_{c.f.t-2})}{TotalAssets_{c,f,t-1}}\right\}$

Notes:
$CurrentAccruals_{c,f,t} = (\Delta CA_{c,f,t} - \Delta Cash_{c,f,t}) - (\Delta CL_{c,f,t} - \Delta STDebt_{c,f,,t} - \Delta TaxPayable_{c,f,t}) - Depreciation_{c,f,t}$
$NI_{c,f,t}$ = Net operating income

Panel B: Descriptive statistics of the realized accounting signals

Variables	N	Mean	Std dev.	Min	10%	Median	90%	Max
Accruals$_{c,t}$	388	-0.011	0.240	-0.278	-0.057	-0.033	0.010	3.910
Profitability$_{c,t}$	406	0.085	0.119	-0.171	0.029	0.065	0.136	1.741
Volatility$_{c,t}$	406	0.019	0.016	0.000	0.000	0.0168	0.032	7.695

Notes: Refer to Panel A for definition of realized accounting signals.

Table IX: Correlation Matrix of Crises Predictors

Panel A: Cross country correlation of crisis predictors (Spearman below diagonal, Pearson above diagonal)

	Accruals	Profitability	Volatility	Overvaluation	Imports	Exports	Foreign reserve	M2 /foreign EX	interest rate diff	ST debt/ reserves	Industry output	Stock price	M2 multiple	Dom cred. /GDP	Dom real interest	Comm deposit	Lend /dep interest	XS M1 balances
Realized accounting signals (see Table VIII)																		
$Accruals_{c,t}$		**0.62**	0.05	-0.01	-0.08	0.04	0.06	**0.67**	**-0.69**	0.02	0.04	**0.27**	**-0.18**	-0.02	**0.69**	**-0.25**	-0.05	-0.01
$Profitability_{c,t}$	**0.37**		**0.23**	-0.03	0.01	0.01	0.02	**0.31**	**-0.77**	-0.03	-0.01	**0.33**	**-0.16**	**-0.28**	**0.77**	-0.09	-0.12	-0.04
$Volatility_{c,t}$	**-0.18**	-0.03		**0.15**	-0.01	0.00	-0.08	-0.03	-0.07	0.01	**-0.17**	-0.02	-0.06	-0.09	0.07	-0.10	-0.06	0.03
Prior literature's leading indicators (see Table VI)																		
$\text{Over-valuation}_{c,t}$	**-0.27**	**-0.25**	**0.21**		-0.02	-0.03	-0.02	0.00	-0.00	0.05	-0.13	0.00	-0.03	-0.06	0.00	-0.04	0.02	-0.01
$Imports_{c,t}$	**0.20**	**0.26**	-0.04	**-0.13**		**0.46**	0.01	-0.06	0.07	**0.22**	**0.54**	0.11	0.04	**-0.23**	-0.06	-0.02	-0.05	-0.05
$Exports_{c,t}$	**0.11**	**0.21**	0.03	-0.07	**0.59**		**0.11**	0.05	0.07	0.15	**0.38**	0.08	0.09	-0.05	-0.07	0.12	-0.09	-0.00
$\text{Foreign EX reserve}_{c,t}$	**0.11**	**0.15**	-0.10	-0.09	0.02	0.07		-0.06	0.08	**-0.42**	0.05	**0.13**	-0.07	-0.06	-0.08	0.06	-0.00	-0.06
$\text{M2/foreign EX reserve}_{c,t}$	**0.21**	**0.19**	**0.13**	-0.08	0.09	0.02	**-0.70**		**-0.41**	**0.25**	-0.01	0.03	**-0.21**	0.00	**0.41**	**0.79**	-0.12	0.02
$\text{Real interest diff}_{c,t}$	0.02	-0.06	**-0.12**	-0.02	**0.10**	-0.04	0.02	-0.07		-0.01	0.10	**0.33**	**0.23**	**0.47**	**-0.90**	0.10	-0.00	-0.01
$\text{ST debt/reserves}_{c,t}$	0.04	-0.05	-0.09	-0.12	**0.17**	0.09	**-0.45**	**0.31**	0.04		0.05	-0.02	0.10	0.02	-0.03	0.07	-0.10	-0.06
$\text{Industry production}_{c,t}$	0.16	**0.25**	**-0.15**	-0.11	**0.57**	**0.44**	0.10	0.05	-0.01	-0.08		**0.17**	0.05	0.03	-0.10	**0.13**	-0.10	0.02
$\text{Stock prices}_{c,t}$	0.00	**0.31**	-0.07	0.01	**0.23**	**0.19**	**0.13**	-0.09	0.06	-0.06	**0.34**		0.09	-0.06	**-0.34**	0.05	-0.09	**-0.26**
$\text{M2 multiplier}_{c,t}$	0.11	0.06	-0.05	-0.04	0.06	0.11	-0.02	**0.11**	0.10	0.16	0.06	-0.09		**0.33**	**-0.23**	0.04	-0.10	-0.10
$\text{Domestic credit/GDP}_{c,t}$	**0.19**	0.10	**-0.15**	**-0.14**	**-0.13**	**-0.16**	**-0.13**	**0.22**	-0.04	0.09	-0.03	-0.06	**0.19**		**-0.47**	**0.60**	-0.04	0.10
$\text{Domestic real interest}_{c,t}$	-0.05	**0.12**	-0.07	-0.01	**-0.14**	0.01	-0.07	**0.15**	**-0.58**	-0.04	0.03	-0.01	0.02	**0.23**		-0.10	-0.09	0.02
$\text{Com. bank deposits}_{c,t}$	**0.15**	**0.24**	-0.09	**-0.19**	**0.16**	**0.19**	**0.12**	**0.19**	**-0.20**	0.05	**0.21**	0.10	**0.26**	**0.44**	**0.34**		**-0.14**	0.03
$\text{Lend./dep. Inter. rate}_{c,t}$	**-0.17**	**-0.39**	0.06	0.16	-0.06	**-0.11**	-0.07	**-0.21**	**-0.14**	-0.01	-0.10	-0.01	**-0.16**	**-0.18**	**-0.46**	**-0.26**		-0.01
$\text{XS real M1 balances}_{c,t}$	-0.03	-0.06	0.04	-0.06	-0.07	-0.05	-0.09	-0.03	**-0.11**	0.01	-0.04	-0.08	**-0.17**	0.02	0.09	0.03	0.03	

Refer to Table VI and Table VIII for variable definition. Bold figure denotes significance at 95% level.

Table IX: Correlation Matrix of Crises Predictors from 1981 to 2005 (Continued)

Panel B: Time series correlation of accounting signals (Spearman below diagonal, Pearson above diagonal)

	$Accruals_{c,t-2}$	$Accruals_{c,t-1}$	$Accruals_{c,t}$	$Profitability_{c,t-2}$	$Profitability_{c,t-1}$	$Profitability_{c,t}$	$Volatility_{c,t-2}$	$Volatility_{c,t-1}$	$Volatility_{c,t}$
$Accruals_{c,t-2}$		**0.492**	0.092	**-0.929**	**-0.626**	-0.079	**0.628**	**0.037**	0.028
$Accruals_{c,t-1}$	**0.564**		**0.492**	**-0.330**	**-0.928**	**-0.626**	**0.499**	**0.626**	0.038
$Accruals_{c,t}$	**0.451**	**0.560**		0.025	**-0.330**	**-0.928**	**0.230**	**0.498**	**0.624**
$Profitability_{c,t-2}$	**-0.217**	0.018	0.066		**0.510**	0.033	-0.328	0.131	0.147
$Profitability_{c,t-1}$	-0.012	**-0.224**	0.007	**0.549**		**0.510**	**-0.477**	**-0.325**	0.132
$Profitability_{c,t}$	-0.009	-0.030	**-0.240**	**0.464**	**0.559**		-0.070	**-0.473**	**-0.321**
$Volatility_{c,t-2}$	**0.401**	**0.428**	**0.366**	**0.570**	**0.424**	**0.321**		**0.336**	**0.313**
$Volatility_{c,t-1}$	**0.336**	**0.391**	**0.404**	**0.545**	**0.573**	**0.435**	**0.831**		**0.341**
$Volatility_{c,t}$	**0.236**	**0.312**	**0.369**	**0.500**	**0.553**	**0.581**	**0.666**	**0.831**	

The sample is described in Table I and Table II. Refer to Table VIII for definitions of accounting signals. Bold figure denotes significance at 95% level.

Table X: Multivariate Analysis of Crisis Prediction Using Realized Accounting Signals
[c=country; t=year]

Model (see Table I for crises onset years):

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{3} \beta^{i} \times AccountingSignal^{i}_{c,t-n} + \sum_{k=1}^{18} \gamma^{k} \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

		Predictive [-n =-2]		*Predictive* [-n =-1]		*Concurrent* [-n =0]	
		$\frac{dF}{dX}$	(z- stat)	$\frac{dF}{dX}$	(z- stat)	$\frac{dF}{dX}$	(z- stat)
Table VIII's Realized accounting signals (= β^{i})							
Accruals$_{c,t}$	-	-0.0948	(-0.88)	**-0.2090*****	(-3.57)	**0.2470*****	(4.24)
Profitability$_{c,t}$	-	-0.1231	(-0.75)	**0.4980****	(2.86)	**-0.5846****	(-3.10)
Volatility$_{c,t}$	+	1.6267	(1.92)	-1.3254	(-1.37)	**3.4562*****	(4.08)
F- test [Prob > χ^2**] :**		χ^2 (3) =3.84 [0.279]		**χ^2 (3)=17.97 [<0.001]**		**χ^2(3)=29.59 [<0.001]**	
Table VI's prior literature's leading indicators and time trend (= γ^{k})							
Over-valuation$_{c,t}$	-	**-0.0006****	(-2.59)	**-0.0003***	(-2.49)	**-0.0000***	(-2.28)
Imports$_{c,t}$	+	-0.1084	(-1.09)	0.0000	(0.00)	**-0.3416****	(-3.15)
Exports$_{c,t}$	-	**0.3471***	(2.55)	-0.1311	(-1.04)	0.1756	(1.44)
Foreign exchange reserve$_{c,t}$	-	0.0256	(0.62)	0.0007	(0.02)	**-0.1203****	(-3.01)
M2/foreign exchange$_{c,t}$ reserve$_{c,t}$	+	-0.0107	(-1.83)	0.0140	(1.81)	**0.0208*****	(3.53)
Real interest rate differential$_{c,t}$	+	-0.0607	(-0.23)	**-0.5530***	(-2.08)	-0.1168	(-0.81)
Short term debt/reserves$_{c,t}$	+	0.0088	(0.41)	-0.0121	(-0.51)	**0.0429***	(2.40)
Industry production$_{c,t}$	-	0.2173	(0.89)	-0.6776	(-1.76)	**-0.6979***	(-2.46)
Stock prices$_{c,t}$	-	-0.1145	(-1.31)	-0.1019	(-1.11)	**-0.1811****	(-2.68)
M2 multiplier$_{c,t}$	+	-0.0747	(-1.01)	-0.1283	(-1.49)	0.0514	(0.95)
Domestic credit/GDP$_{c,t}$	+	**0.2467***	(2.48)	0.2059	(1.71)	**-0.3535****	(-2.65)
Domestic real interest rate$_{c,t}$	+	-0.0551	(-0.21)	**-0.5564***	(-2.10)	-0.1209	(-0.84)
Commercial bank deposits$_{c,t}$	-	0.1282	(0.78)	**-0.4644****	(-3.00)	0.2306	(1.33)
Lending/deposit interest rate$_{c,t}$	+	-0.0356	(-1.76)	**-0.0452***	(-2.34)	-0.0220	(-1.95)
Excess real M1 balances$_{c,t}$	+	**0.0001***	(2.43)	**0.0002****	(2.65)	**0.0001****	(2.64)
G7 output$_{t}$	-	-0.0960	(-1.08)	-0.1243	(-1.72)	0.0501	(0.99)
US interest rate$_{t}$	+	2.3744	(1.61)	2.0254	(0.85)	1.3749	(0.85)
Oil prices$_{t}$	+	0.1136	(1.53)	0.0988	(1.25)	-0.0024	(-0.04)
Year$_{t}$		**-0.0099***	(-2.55)	-0.0018	(-0.48)	**-0.0128*****	(-4.47)
Country Fixed Effects		**Yes**		**Yes**		**Yes**	
Standard Error clustering on year		**Yes**		**Yes**		**Yes**	
# country years		331		351		371	
Mc Fadden's R^2		**0.281**		**0.283**		**0.459**	
Mc Fadden's R^2 (excluding accounting signals)		**0.245**		**0.245**		**0.377**	

Notes:

$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of currency crises. See Table I and Table II for crisis onset years. Refer to Table VI and Table VIII for the definitions of leading indicator variables and accounting signals. Reported coefficients represent the marginal effect averaged over all observations.

McFadden's $R^2 = 1 - \frac{\ln \hat{L}}{\ln \hat{L}_0}$,where $\hat{L}$ is the likelihood from the estimated model and $\hat{L}_0$ is the likelihood from a model containing only a constant.

†, *, ** denote significance at the 95%, 97% and 99% levels.

Table XI
Crisis Prediction Using Realized Accounting Signals: The Accounting Precision Dichotomy
[c=country, t=year]

Model (see Table I for crises onset years):

$$D\_crisis_{c,t} = \sum_{i=1}^{3} \beta_H^i \times [I_{C_H} \times AccountingSignal^i_{c,t-n}] + \sum_{i=1}^{3} \beta_L^i \times [I_{C_L} \times AccountingSignal^i_{c,t-n}] + \sum_{k=1}^{18} \gamma^k \times LeadingIndicator^k_{c,t-n} + \varepsilon_{c.t}$$

$D\_crisis_{c,t}$ = 1 in a crisis onset year (see Table I), 0 otherwise.

$I_{C_H} = 1$: if country has high accounting precision, 0 otherwise.

$I_{C_L} = 1$: if country has low accounting precision, 0 otherwise.

		sign	*Predictive* [-n =-2] $\frac{dF}{dX}$	(z-stat)	*Predictive* [-n =-1] $\frac{dF}{dX}$	(z-stat)	*Concurrent* [-n = 0] $\frac{dF}{dX}$	(z-stat)	*Aftermath* [- n = +1] $\frac{dF}{dX}$	(z-stat)
Table VIII's Realized accounting signals (= β^i)										
Accruals$_{c,t}$	β_H^1	-	0.627	(0.92)	0.215	(0.26)	0.014	(0.02)	**-0.994****	(-3.29)
	β_L^1	-	-0.162	(-0.55)	**-0.206*****	(-3.50)	**0.241*****	(4.05)	0.241	(0.55)
Profitability$_{c,t}$	β_H^2	-	0.192	(0.33)	-0.497	(-0.74)	**-1.770***	(-1.96)	**-1.908****	(-3.18)
	β_L^2	-	-0.160	(-0.79)	**0.455***	(2.42)	**-0.567*****	(-3.30)	**-0.758*****	(-3.45)
Volatility$_{c,t}$	β_H^3	+	1.577	(0.51)	-1.925	(-0.74)	2.189	(0.93)	4.186	(1.82)
	β_L^3	+	1.741	(1.89)	-1.625	(-1.62)	**3.012*****	(3.53)	**4.428*****	(3.74)
F- test of β_H^i s [Prob > χ^2]**:**			χ^2(3) = 1.18 [0.758]		χ^2(3) = 1.31 [0.726]		χ^2(3) = 6.17 [0.104]		**χ^2(3) = 26.62 [<0.001]**	
F- test of β_L^i s [Prob > χ^2]**:**			χ^2(3) = 3.71 [0.295]		**χ^2(3) =14.17 [0.003]**		**χ^2(3)=29.82 [<0.001]**		**χ^2(3) = 17.67 [<0.001]**	

(Continued)

Table XI (Continued)
Crisis prediction using realized accounting signals: The accounting precision dichotomy

		Predictive [-n = -2]		*Predictive* [-n = -1]		*Concurrent* [-n = 0]		*Aftermath* [- n = +1]	
Table VI's prior literature's leading indicators and time trend (= γ^k)									
Over-valuation$_{c,t}$	-	**-0.001***	(-2.46)	**-0.000****	(-2.60)	**-0.000***	(-2.11)	-0.000	(-1.48)
Imports$_{c,t}$	+	-0.112	(-1.01)	-0.031	(-0.38)	**-0.332*****	(-3.33)	0.006	(0.06)
Exports$_{c,t}$	-	**0.372****	(2.97)	-0.105	(-0.87)	0.181	(1.52)	**0.428****	(3.21)
Foreign exchange reserve$_{c,t}$	-	0.028	(0.69)	-0.008	(-0.20)	**-0.121****	(-2.99)	**0.065****	(2.83)
M2/foreign exchange$_{c,t}$ reserve$_{c,t}$	+	**-0.011***	(-1.97)	0.013	(1.81)	**0.020*****	(3.71)	**0.022****	(2.80)
Real interest rate differential$_{c,t}$	+	-0.068	(-0.27)	-0.508	(-1.93)	-0.095	(-0.73)	0.160	(0.87)
Short term debt/reserves$_{c,t}$	+	0.008	(0.34)	-0.014	(-0.61)	**0.041***	(2.21)	-0.023	(-0.53)
Industry production$_{c,t}$	-	0.244	(1.03)	-0.610	(-1.56)	**-0.693****	(-2.72)	**-0.619***	(-1.98)
Stock prices$_{c,t}$	-	-0.122	(-1.32)	-0.085	(-0.92)	**-0.174***	(-2.53)	-0.062	(-1.07)
M2 multiplier$_{c,t}$	+	-0.077	(-1.11)	-0.119	(-1.32)	0.044	(0.79)	0.012	(0.19)
Domestic credit/GDP$_{c,t}$	+	**0.229***	(2.07)	0.174	(1.72)	**-0.344****	(-2.82)	-0.151	(-1.40)
Domestic real interest rate$_{c,t}$	+	-0.062	(-0.24)	-0.511	(-1.95)	-0.099	(-0.76)	0.142	(0.79)
Commercial bank deposits$_{c,t}$	-	0.173	(0.96)	**-0.433*****	(-3.35)	0.212	(1.28)	-0.115	(-1.02)
Lending/deposit interest rate$_{c,t}$	+	-0.035	(-1.76)	**-0.044***	(-2.26)	-0.020	(-1.75)	-0.008	(-0.79)
Excess real M1 balances$_{c,t}$	+	**0.000***	(2.45)	**0.000***	(2.25)	**0.000***	(2.23)	-0.000	(-0.83)
G7 output$_t$	-	-0.091	(-1.03)	-0.126	(-1.75)	0.043	(0.90)	-0.017	(-0.25)
US interest rate$_t$	+	1.983	(1.34)	2.023	(0.88)	1.805	(1.10)	0.046	(0.03)
Oil prices$_t$	+	0.103	(1.34)	0.107	(1.40)	0.015	(0.26)	-0.049	(-0.56)
Year$_t$		**-0.009***	(-2.21)	-0.002	(-0.57)	**-0.013*****	(-4.76)	**-0.008***	(-2.12)
Country Fixed Effects		**Yes**		**Yes**		**Yes**		**Yes**	
Standard Error clustering on year		**Yes**		**Yes**		**Yes**		**Yes**	
# of country years		331		351		371		371	

Notes:
$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of currency crises. See Table I and Table II for crisis onset years. Refer to Table VI and Table VIII for definitions of the leading indicator variables and accounting signals. Reported coefficients represent the marginal effect averaged over all observations. †, *, ** denote significance at the 95%, 97% and 99% levels.

Table XII: Crisis Prediction Using Individual Accounting Signals

[c=country, t=year]

Model:

$$D\_crisis_{c,t} = \beta_H \times [I_{C_H} \times AccountingSignal^{i}_{c,t-1}] + \beta_L \times [I_{C_L} \times AccountingSignal^{i}_{c,t-1}] +$$

$$\sum_{k=1}^{18} \gamma^k \times LeadingIndicator^{k}_{c,t-1} + \varepsilon_{c.t}$$

$D\_crisis_{c,t}$ = 1 in a crisis onset year (see Table I), 0 otherwise.

$I_{C_H} = 1$: if country has high accounting precision , 0 otherwise.

$I_{C_L} = 1$: if country has low accounting precision, 0 otherwise.

		(1)		(2)		(3)		(4)	
	sign	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)
Table VIII's Realized accounting signals (= β^i)									
Accruals$_{c,t}$	β^1_H -	0.8843	(1.23)						
	β^1_L -	**-0.1471***	**(-2.09)**						
Profitability$_{c,t}$	β^2_H -			-0.3614	(-0.58)				
	β^2_L -			**0.3329****	**(2.65)**				
Volatility$_{c,t}$	β^3_H +					-3.5250	(-1.30)		
	β^3_L +					0.2408	(0.26)		
CFO$_{c,t}$	β^4_H -							-0.1036	(-0.24)
	β^4_L -							0.1850	(1.79)
Leading indicators from Table VI and time trend		**Included**		**Included**		**Included**		**Included**	
Country Fixed Effects		**Yes**		**Yes**		**Yes**		**Yes**	
Standard Error clustering on year		**Yes**		**Yes**		**Yes**		**Yes**	

Notes:

$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of currency crises. See Table I and Table II for crisis onset years. Refer to Table VI and Table VIII for the definitions of the accounting signals and leading indicator variables. CFO is cash flow from operations and is computed as $CFO_{c,t} = Median_f \left(\frac{CFO_{c,f,t}}{TotalAssets_{c,f,t-1}} \right)$. Reported coefficients represent the marginal effect averaged over all observations.

†, *, ** denote significance at the 95%, 97% and 99% levels.

Table XIII: Institutional Factors and Endogenous Policy Effects

[c=country; t=year]

Model:

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{3} \beta_H^i \times [I_{C_H} \times AccountingSignal_{c,t-n}^i] + \sum_{i=1}^{3} \beta_L^i \times [I_{C_L} \times AccountingSignal_{c,t-n}^i]$$

$$+ \sum_{k=1}^{18} \gamma^k \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

$I_{C_H} = 1$: if country rank of law enforcement is below the sample median, 0 otherwise.

$I_{C_L} = 1$: if country rank of law enforcement exceeds the sample median, 0 otherwise.

(Note: lower rank indicates higher quality. See Table V, Panel A.)

Panel A: Crises prediction using accounting signals in high and low enforcement countries

			Predictive [-n =-1]		*Concurrent* [-n =0]		*Aftermath* [- n = +1]	
		Sign	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)
Table VIII's Realized Accounting Signals (= β^i)								
Accruals$_{c,t}$	β_H^1	-	-0.045	(-0.07)	-0.219	(-0.31)	**-1.209***	(-2.49)
	β_L^1	-	**-0.207*****	(-3.73)	**0.246*****	(3.65)	**0.839***	(1.96)
Profitability$_{c,t}$	β_H^2	-	0.530	(0.90)	-0.367	(-0.61)	**-0.856***	(-2.04)
	β_L^2	-	**0.461****	(2.94)	**-0.517****	(-2.77)	**-0.809****	(-2.59)
Volatility$_{c,t}$	β_H^3	+	-2.858	(-1.41)	-0.322	(-0.16)	2.742	(1.58)
	β_L^3	+	-1.317	(-1.58)	**2.614*****	(3.43)	**4.210*****	(3.99)
F- test of β_H^i s [Prob >χ^2]:			χ^2(3) = 3.81 [0.283]		χ^2(3) = 0.38 [0.945]		**χ^2(3) = 9.05 [0.028]**	
F- test of β_L^i s [Prob > χ^2]:			**χ^2(3) = 19.88 [0.002]**		**χ^2(3) = 22.83 [<0.001]**		**χ^2(3) = 19.96 [<0.001]**	
Leading indicators from Table VI and time trend			**Included**		**Included**		**Included**	
Country Fixed Effects			**Yes**		**Yes**		**Yes**	
Standard Error clustering on year			**Yes**		**Yes**		**Yes**	
# country years			351		371		371	

Notes:

$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of a crises. See Table I and Table II for crisis onset years. Refer to Table VI and Table VIII for the definitions of the accounting signals and leading indicator variables. Reported coefficients represent the marginal effect averaged over all observations.

†, *, ** denote significance at the 95%, 97% and 99% levels.

Table XIII: Institutional Factors and Endogenous Policy Effects (Continued)
[c=country; t=year, P=non-overlapping period over which accounting precision is measured]

Model:

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{3} \beta_H^i \times [I_{c,H,P,t} \times AccountingSignal_{c,t-n}^i] + \sum_{i=1}^{3} \beta_L^i \times [I_{c,L,P,t} \times AccountingSignal_{c,t-n}^i]$$
$$+ \sum_{k=1}^{18} \gamma^k \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

$I_{c,H,P,t} = 1$ if $Mean_i\{Rank_c(AQ_{c,P=5,t}^i)\}$ is below the corresponding period's sample median($t \in P$)
$I_{c,L,P,t} = 1$ if $Mean_i\{Rank_c(AQ_{c,P=5,t}^i)\}$ exceeds the corresponding period sample median($t \in P$), else 0.
Note that lower rank indicates higher accounting precision. See Table V, Panel C.

Panel B: Crises prediction using time-varying measures of accounting precision (measured across 5-year non-overlapping periods)

			Predictive [-n =-1]		*Concurrent* [-n =0]		*Aftermath* [- n = +1]	
		Sign	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)
Table VIII's Realized accounting signals (= β^i)								
Accruals$_{c,t}$	β_H^1	-	0.215	(0.26)	0.014	(0.02)	**-0.994****	(-3.29)
	β_L^1	-	**-0.206*****	(-3.50)	**0.241*****	(4.05)	0.241	(0.55)
Profitability$_{c,t}$	β_H^2	-	-0.497	(-0.74)	**-1.770***	(-1.96)	**-1.908****	(-3.18)
	β_L^2	-	**0.455***	(2.42)	**-0.567*****	(-3.30)	**-0.758*****	(-3.45)
Volatility$_{c,t}$	β_H^3	+	-1.925	(-0.74)	2.189	(0.93)	4.186	(1.82)
	β_L^3	+	-1.625	(-1.62)	**3.012*****	(3.53)	**4.428*****	(3.74)
F- test of β_H^i s [Prob >χ^2]:			χ^2(3) = 1.31 [0.726]		χ^2(3) = 6.17 [0.103]		**χ^2(3) = 26.62 [<0.001]**	
F- test of β_L^i s [Prob > χ^2]:			**χ^2(3) = 14.17 [0.003]**		**χ^2(3) = 29.82 [<0.001]**		**χ^2(3) = 17.67 [<0.001]**	
Leading indicators from Table VI and time trend			**Included**		**Included**		**Included**	
Country Fixed Effects			**Yes**		**Yes**		**Yes**	
Standard Error clustering on year			**Yes**		**Yes**		**Yes**	
# country years			351		371		371	

Notes:
$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of a crises. See Table I and Table II for crisis onset years. Refer to Table VI and Table VIII for definitions of the accounting signals and leading indicator variables. Reported coefficients represent the marginal effect averaged over all observations.
†, *, ** denote significance at 95%, 97% and 99% levels.

Table XIV: Sensitivity Analysis

[c=country; t=year]

Model:

$$D\_BCrisis_{c,t} = \alpha + \sum_{i=1}^{3} \beta_H^i \times [I_{C_H} \times AccountingSignal^i_{c,t-n}] + \sum_{i=1}^{3} \beta_L^i \times [I_{C_L} \times AccountingSignal^i_{c,t-n}]$$

$$+ \sum_{k=1}^{18} \gamma^k \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

$I_{C_H} = 1$: if the country has high accounting precision, 0 otherwise

$I_{C_L} = 1$: if the country has low accounting precision, 0 otherwise.

Panel A: Crises prediction of 32 banking crises

		Predictive [-n =-1]		*Concurrent* [-n =0]		*Aftermath* [- n = +1]	
	Sign	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)
Table VIII's Realized accounting signals (= β^i)							
Accruals$_{c,t}$	β_H^1 -	0.192	(0.32)	-0.231	(-0.41)	-0.881	(-1.87)
	β_L^1 -	**-0.166*****	(-3.54)	**0.322*****	(4.20)	**1.092***	(2.27)
Profitability$_{c,t}$	β_H^2 -	0.424	(0.73)	-0.095	(-0.18)	-0.775	(-1.85)
	β_L^2 -	**0.489*****	(3.36)	-0.340	(-1.80)	**-0.831****	(-2.75)
Volatility$_{c,t}$	β_H^3 +	-2.239	(-1.12)	0.989	(0.60)	3.298	(1.74)
	β_L^3 +	**-1.676***	(-2.17)	1.657	(1.85)	**3.694*****	(3.62)
F- test of β_H^i s [Prob $>\chi^2$]:		χ^2(3) = 3.32 [0.345]		χ^2(3) = 0.59 [0.899]		**χ^2(3) = 7.25 [0.064]**	
F- test of β_L^i s [Prob $>\chi^2$]:		**χ^2(3) = 17.99 [<0.001]**		**χ^2(3) =28.71 [<0.001]**		**χ^2(3) = 18.81 [0.003]**	
Leading indicators from Table VI and time trend		**Included**		**Included**		**Included**	
Country Fixed Effects		**Yes**		**Yes**		**Yes**	
Standard Error clustering		**Yes**		**Yes**		**Yes**	
# country years		351		371		371	

Notes:

$D\_BCrisis_{c,t}$ is an indicator variable indicating the onset of banking crises (Financial excess and Sovereign debt in Table I). See Table 1 and Table II for crisis onset years. Refer to Table VI and Table VIII for definitions of the accounting signals and leading indicator variables. Reported coefficients represent the marginal effect averaged over all observations.

†, *, ** denote significance at 95%, 97% and 99% levels.

Table XIV: Sensitivity Analysis (Continued)

[c=country; t=year]

Model:

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{3} \beta_H^i \times [I_{C_H} \times AccountingSignal_{c,t-n}^i] + \sum_{i=1}^{3} \beta_L^i \times [I_{C_L} \times AccountingSignal_{c,t-n}^i]$$

$$+ \sum_{k=1}^{18} \gamma^k \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

$I_{C_H} = 1$: if the country has high accounting precision, 0 otherwise.

$I_{C_L} = 1$: if the country has low accounting precision, 0 otherwise.

Panel B: Crises prediction with alternative classification of high and low accounting precision countries

			(1)		(2)		(3)	
			Predictive [-n =-1]		*Predictive* [-n =-1]		*Predictive* [-n =-1]	
		Sign	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)
Table VIII's Realized accounting signals (= β^i)								
Accruals$_{c,t}$	β_H^1	-	0.786	(0.81)	1.295	(1.07)	0.453	(0.38)
	β_L^1	-	**-0.209*****	(-3.47)	**-0.226*****	(-3.40)	**-0.260*****	(-3.78)
Profitability$_{c,t}$	β_H^2	-	-0.399	(-0.61)	-0.344	(-0.49)	-0.019	(-0.02)
	β_L^2	-	**0.434***	(2.34)	**0.485****	(2.74)	**0.615****	(2.66)
Volatility$_{c,t}$	β_H^3	+	-1.529	(-0.59)	-1.012	(-0.43)	-2.231	(-0.83)
	β_L^3	+	-1.675	(-1.62)	-1.496	(-1.49)	-1.772	(-1.38)
F- test of β_H^i s [Prob > χ^2]**:**			$\chi^2(3)$ = 1.62 [0.655]		$\chi^2(3)$ = 1.77 [0.622]		$\chi^2(3)$ =0.97 [0.808]	
F- test of β_L^i s [Prob > χ^2]**:**			**$\chi^2(3)$ = 13.40 [0.004]**		**$\chi^2(3)$ =13.82[<0.001]**		**$\chi^2(3)$ =16.25 [0.001]**	
Countries that change accounting precision categories from Table V			**Italy, Mexico**		**Italy, Mexico, France, Japan**			
Countries dropped from Table V							**Italy, Mexico, France, Japan**	
Leading indicators from Table VI and time trend			**Included**		**Included**		**Included**	
Country Fixed Effects			**Yes**		**Yes**		**Yes**	
Standard Error clustering on year			**Yes**		**Yes**		**Yes**	
# country years			351		351		275	

Notes:

$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of a crises. See Table I and Table II for crisis onset years. Refer to Table VI and Table VIII for definitions of the accounting signals and leading indicator variables. Model (1) defines the precision threshold as the sample *mean* of the composite country index (see Table IV). Model (2) defines precision threshold using $Mean_i[rank_c(AQ_c^1), rank_c(AQ_c^2), rank_c(AQ_c^3)]$ as the composite index. Model (3) drops the four countries that are closest to the precision threshold. Reported coefficients represent the marginal effect averaged over all observations.

†, *, ** denote significance at 95%, 97% and 99% level.

Table XIV: Sensitivity Analysis (Continued)

[c=country; t=year]

Model:

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{3} \beta_H^i \times [I_{C_H} \times AccountingSignal_{c,t-n}^i] + \sum_{i=1}^{3} \beta_L^i \times [I_{C_L} \times AccountingSignal_{c,t-n}^i]$$

$$+ \sum_{k=1}^{18} \gamma^k \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

$I_{C_H} = 1$: if the country has high accounting precision, 0 otherwise.

$I_{C_L} = 1$: if the country has low accounting precision, 0 otherwise.

Panel C: Crises prediction using realized accounting signals in the tradable sector

			Predictive [-n =-1]		*Concurrent* [-n =0]		*Aftermath* [- n = +1]	
		Sign	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)	$\frac{dF}{dX}$	(z-stat)
Table VIII's Realized accounting signals (= β^i)								
Accruals$_{c,t}$	β_H^1	-	-0.291	(-0.39)	0.580	(0.85)	**-0.832***	(-2.17)
	β_L^1	-	**-0.585***	(-2.38)	-0.052	(-1.00)	0.256	(0.61)
Profitability$_{c,t}$	β_H^2	-	-1.302	(-1.69)	**-2.325****	(-2.60)	**-1.343***	(-2.28)
	β_L^2	-	0.360	(1.45)	**-1.255*****	(-5.51)	**-0.722****	(-3.07)
Volatility$_{c,t}$	β_H^3	+	-2.788	(-1.18)	2.564	(1.18)	4.299	(1.87)
	β_L^3	+	-1.714	(-1.70)	**3.025*****	(3.93)	**4.314*****	(3.85)
F- test of β_H^i s [Prob > χ^2]:			χ^2(3) = 4.40 [0.221]		**χ^2(3) = 9.01 [0.029]**		**χ^2(3) = 13.08 [0.004]**	
F- test of β_L^i s [Prob > χ^2]:			**χ^2(3) = 12.73 [0.005]**		**χ^2(3) =49.23 [<0.001]**		**χ^2(3) = 18.01 [<0.001]**	
Leading indicators from Table VI and time trend			**Included**		**Included**		**Included**	
Country Fixed Effects			**Yes**		**Yes**		**Yes**	
Standard Error clustering			**Yes**		**Yes**		**Yes**	
# country years			351		368		368	

Notes: Following Tornell and Westermann (2005), tradable sector is defined as all sectors excluding wholesale, retail trade, utilities, and transportation industries (ICB classification code: 2350, 5370, 5750, 7530, and 7570). $D\_Crisis_{c,t}$ is an indicator variable indicating the onset of currency crises. Refer to Table V for specific countries included in high versus low accounting precision groups. Refer to Table VI and Table VIII for definitions of the leading indicator variables and accounting signals. Reported coefficients are average marginal effects, the mean marginal effect evaluated at each observation.

†, *, ** denote significance at 95%, 97% and 99% level.

Figure 1: Timeline of Recent Crises Models

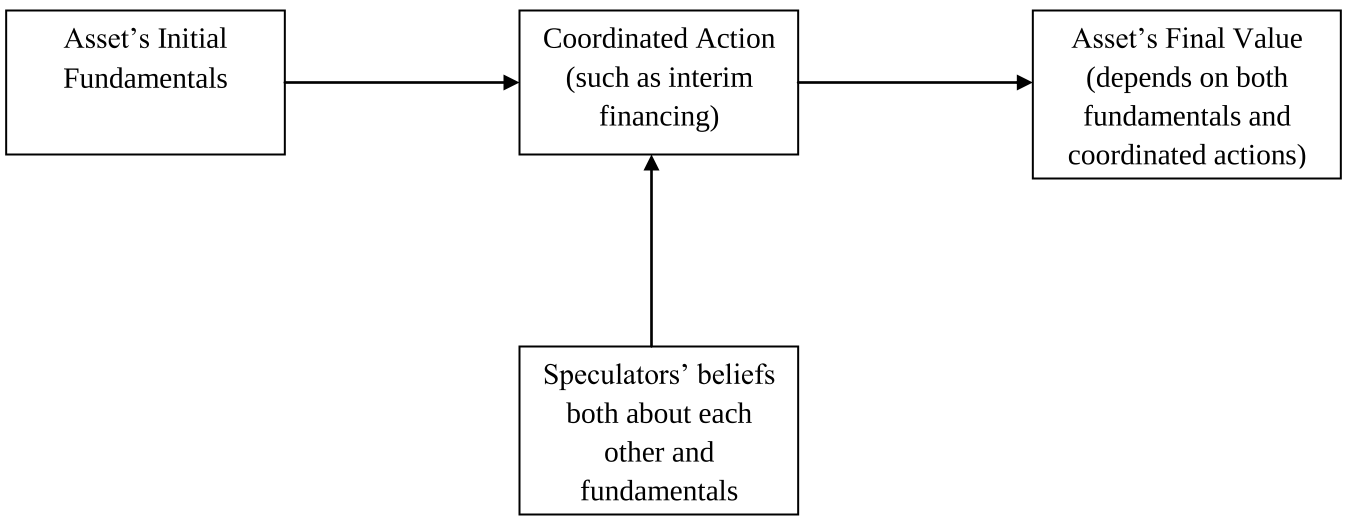
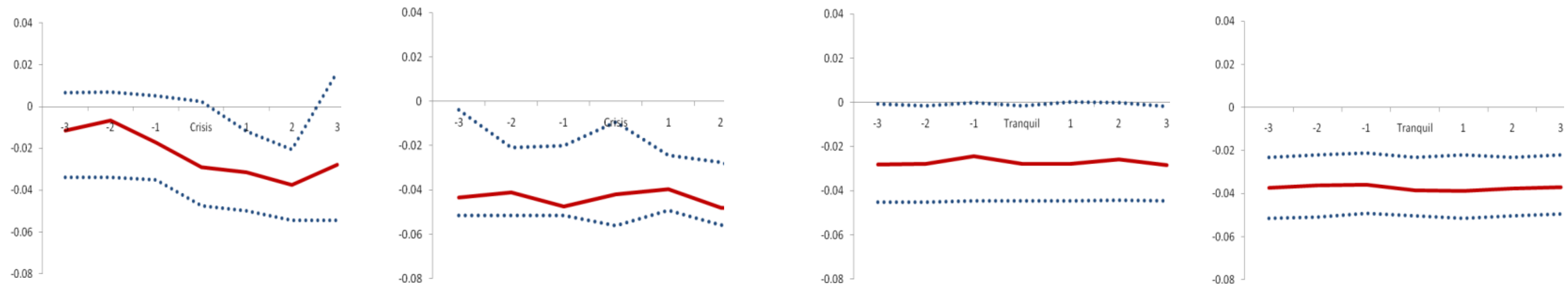


Figure 2: Realized Accounting Signals Before and After 39 Crises Episodes

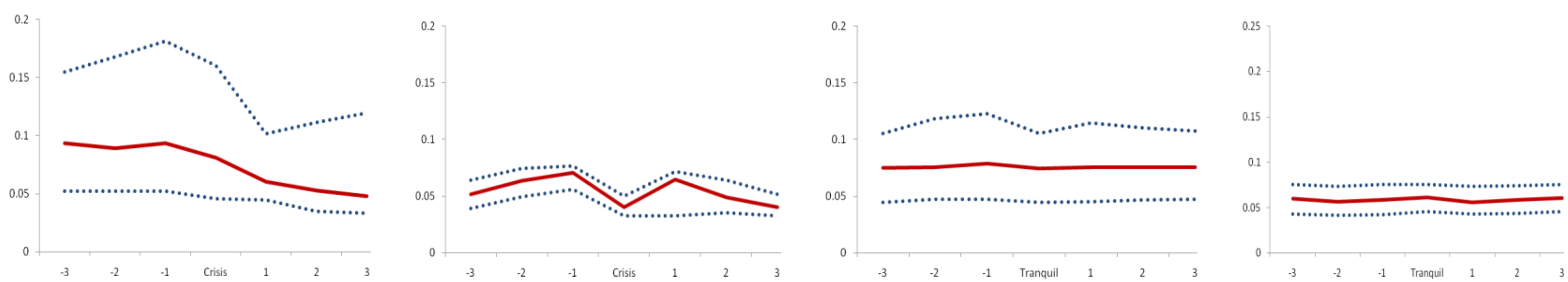
[c=country; t=year]

Panel A: Accruals$_{c,t}$



Crisis years -Countries with low accounting precision | Crisis years -Countries with high accounting precision | Tranquil years -Countries with low accounting precision | Tranquil years -Countries with high accounting precision

Panel B: Profitability$_{c,t}$

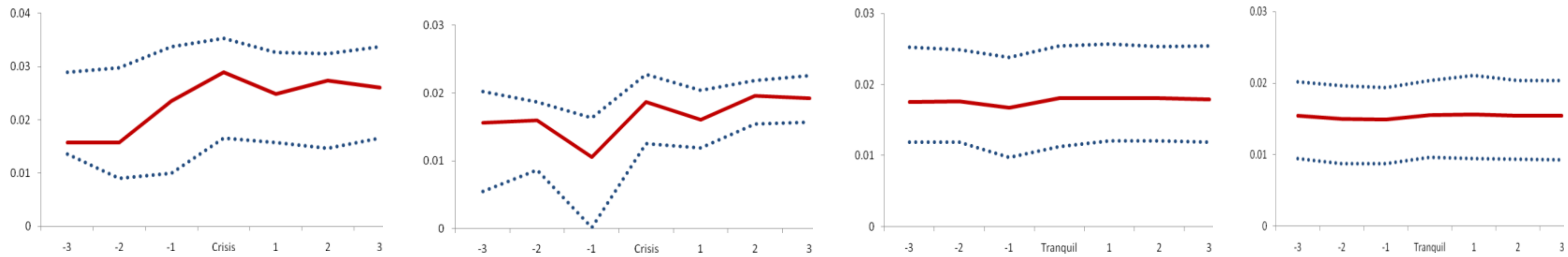


Crisis years - Countries with low accounting precision | Crisis years -Countries with high accounting precision | Tranquil years -Countries with low accounting precision | Tranquil years -Countries with high accounting precision

Figure 2: Realized Accounting Signals Before and After 39 Crises Episodes (Continued)

[c=country; t=year]

Panel C: Volatility$_{c,t}$



Crisis years - Countries with low accounting precision	Crisis years -Countries with high accounting precision	Tranquil years -Countries with low accounting precision	Tranquil years -Countries with high accounting precision

Notes: See Table I and Table II for crises onset year and Table VIII for definitions of each accounting signal. Low and high accounting precision countries are defined in Table IV. 'Tranquil' years are all years that are not within 24 months before and after an onset of a currency crisis. The horizontal axes represents the number of years before and after a crisis (or tranquil) year. The vertical axes represent the level of realized accounting signals. The solid line represents the country median of realized accounting signals before and after the crises (or tranquil) years. The bands represent the upper and lower 25% quartiles of the realized accounting signals.