Accounting for Crises[#]

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Abstract

Recent analytical crises models such as Angeletos and Werning (2006), Angeletos, Hellwig, and Pavan (2006, 2007), Rey (2000), Morris and Shin (2002, 2003), and Atkenson (2000) show how public signals can coordinate crises. In all these models, when publicly disclosed fundamentals have high precision, they can coordinate speculator beliefs independent of fundamentals and precipitate currency crises. Conversely, when such fundamentals have low precision, speculator coordination fails, and realizations of fundamentals (and not self-fulfilling beliefs) are the key drivers of crises. We test this proposition on 39 currency crises from 1981 to 2005 by exploiting a key publicly disclosed fundamental driving financial markets, namely accounting data. Using well-known measures of the precision or the quality of accounting data that naturally vary across countries due to institutional factors, we find that realized accounting fundamentals are indeed much stronger in-sample predictors of crises in countries with low accounting precision. The results are robust to the inclusion of previously documented drivers of crises. By showing situations both where fundamentals work and where they don't, our setting provides strong empirical evidence on the existence of self-fulfilling beliefs.

Accounting for Crises

1. 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, 2007), Rey (2000), Atkenson (2000), and Morris and Shin (2002, 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 the public information as the key driver. If this public information is precise enough relative to speculators' private beliefs, it can coordinate multiple self-fulfilling speculator beliefs largely independent of economic fundamentals. This type of 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: prior calibration and empirical studies such as Martin and Rey (2006) and Ranciere et al. (2008), for example, have explored self-fulfilling beliefs in the context of factors such as trading costs and financial development. A big obstacle is finding a good institutionally motivated measure of the precision of public signals. This paper argues that accounting data provide such a measure 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 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 realized fundamental will have a real effect on the underlying asset's value. In the final step, this new value translates to the price.[1]

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 over a wide range. 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. Then the currency will fall, for the measure of attackers is 100%, which exceeds 30%. 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 then stand. The accurate public signal thus supports two self-fulfilling equilibria over the 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.

On the other hand, if the public signal is not very precise, 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, as all these crisis models robustly show, become the main point of coordination and thus the main driver of crises.

The crises models' authors all state that these models are especially applicable to large financial markets that feature numerous traders who collectively supply ongoing interim financing. Currency crises typically occur when investors collectively withdraw capital from the country's domestic sector and domestic financial markets (Martin and Rey 2006; Schneider and

[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).

Tornell 2004). In this paper, we test the models' key comparative static described above in a currency crisis setting 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 of the assets traded in the country's financial markets. Second, the accounting literature has extensively researched and measured 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). 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 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, accounting data, despite their institutionally interesting features, have not been carefully examined in empirical crisis prediction models.

Our setting comprises 39 currency crises in 21 countries from 1981 to 2005. Using prior literature, we construct a composite score of accounting quality for each country (based on all its firms). Angeletos and Werning (2006, Fig 1) show that the switch from uniqueness to self-fulfilling beliefs is not gradual, but occurs suddenly at a certain precision threshold. Therefore, empirically we sort the countries by our composite measure of accounting quality and nominate the sample median as the 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, corroborating our precision dichotomy. However, some interpretive caution is necessary because these graphs embody both across-country and within-country variations.

We then formally test the in-sample power of realized accounting measures to predict crises. We control for a rich list of other factors as well as country fixed effects and common cross-sectional shocks (contagion). In the overall sample, the inclusion of accounting measures significantly improves our in-sample ability to predict crisis onset one year in advance: the explanatory power increases from 0.248 to 0.284, a 14 percent increase.

More important, we show that most of this improvement comes from the subsample of countries with low accounting precision. This is precisely what the analytical models suggest. The F-statistic for the accounting measures in low precision countries is 18.8 compared to 1.8 for the high precision countries.

It is important to note that analytical models do not claim that self-fulfilling beliefs *should* precipitate crises for any specific fundamental realization in high precision countries. They can only claim that this situation is *feasible*. Therefore, an alternative explanation for the 1.8 F-statistic in the high precision countries is that the accounting data in such countries are noisy.

To test this statistical power alternative, we examine accounting data at the end of the crisis onset year. Both low precision and high precision accounting countries now show significance: the F-stats are now 24 and 9.9 respectively. So accounting data in high precision countries do appear to reflect the consequences of a crisis; they just don't have predictive power.

Finally, we explore the source of the variation in the accounting precision metrics. Prior studies suggest that this variation arises from institutional and legal factors such as law enforcement. We show that these institutional factors appear to be driving the results *through* the accounting disclosure channel. Further, accounting rules and their enforcement are not static: Angeletos et al. (2006) model and demonstrate multiplicity in settings where policy makers can change their policies in response to crises over time. This is less of an issue in our setting where the overall accounting regime and the related institutions are difficult to alter quickly (individual accounting rules may change, but we are interested in the overall accounting regime); nonetheless, we document that our results are robust to such time-varying accounting precision measures.

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 setting overcomes this objection. Finally, we show that because accounting data permits a broad array of analyses on the role of public information, it can play a useful role over and above currently used macroeconomic factors, which appear to have limited power to predict crises (Kaminsky et al. 1998, Table 1).

The rest of the paper is organized as follows. Section 2 places our research question in the context of prior literature. Section 3 describes our data and our empirical constructs. Section 4 presents the main results. Section 5 tests the robustness of our results. Section 6 concludes.

2. Background

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

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

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

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

The three endogenous variables are *Y*, the domestic GDP, *r* the domestic real interest rate (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 follows the Marshall-Lerner conditions and increases 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 ε = 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 such as loans, debt and equities that support 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 the speculators collectively coordinate and withdraw sufficient capital from a country, its currency will collapse. (Failed attacks obviously impose losses on the attackers). 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. 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* of fundamentals and speculator beliefs. This next step was undertaken by Morris and Shin (1998) who showed that, even if each speculator has an epsilon amount of private information available, each speculator becomes unsure of other speculators' private information, and the possibility of others participating in an attack. And this uncertainty is key because attackers lose money if they are in insufficient numbers. As a result, coordination for self-fulfilling beliefs will not obtain: fundamentals then remain the key driver of crises. The immediate empirical implication is that the inability of fundamentals to predict crises is a power issue.

Atkensen (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 1 of this paper for a numerical example). In particular, Atkenson (2000) pointed out that such public information could arise from trades among privately informed speculators. Angeletos and Werning (2006) and Angeletos et al. (2006, 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 positive measure range of fundamentals (they delineate this range exactly) 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 the triggers can happen 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 fundamentals and prices. Why the departure then? The key assumption in these 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' action. It is this strategic role of public information that generates information externality that leads to self-fulfilling beliefs.[2]

On the other hand, if the 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).[3] As a result crises happen only when fundamentals are weak enough for a sufficiently large mass of speculators to feel confident that they will profit in attacking the currency: fundamentals are thus the sole determinant of crises.

And why is this result so robust to endogeneity considerations? As Angeletos et al. (2006) show, the coordination game simply *recurses* to the factor that is being endogenized: agents begin to start coordinating on that factor's realization. Likewise, when the global game is played across several time periods, Angeletos et al. (2007) show that there will occur a period when the agents' common knowledge is sufficiently precise to trigger a successful coordination of beliefs irrespective of fundamental realization over a wide range. In this sense, time itself is the factor driving the coordination.

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

[2] Morris and Shin (2003), for example, show that it is when investors have very precise public information that such strategic uncertainty is maximized. The subjective density of the proportion of investors attacking turns out to be a uniform distribution when noise in public signals approaches zero (Morris and Shin, 2003, Figure 3.4).

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

crisis is triggered (Martin and Rey 2006; Schneider and Tornell 2004).[4] Consequently, if we assume that a) variation of the absolute precision of the public information across countries reflects variation of relative precision of public information (relative to private information), and b) that we can use the data to nominate the precision threshold, and c) that countries where self-fulfilling beliefs occur do experience such events at different realizations of fundamentals, 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 3 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 variance of the fundamentals and variance of the noise. Further, these measures 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. Further, in many instances, the assets (especially loans) may not be traded

[4] The crises in Martin and Rey (2006) and Schneider and Tornell (2004) occur as a result of international traders fleeing the domestic sector and domestic financial markets.

sufficiently to yield a liquid price. The U.S. mortgage crisis is a great example of a setting with considerable accounting information, speculators' beliefs about each other, but limited availability of market prices for securitized loans (Greenlaw et al., 2008). Accounting data circumvent these problems because they are inputs into the financial markets.

Despite these advantages, there has been no attempt (at least to our knowledge) to use accounting information in the context of predicting currency crisis in the early warnings literature. Studies such as Swanson et al. (2003) and Graham et al. (2000) examine the information content of financial statements *following* an event of a severe economic change.[5]

Instead, prior literature has primarily focused on macro measures to predict crises. For example, Ranciere et al. (2008) show that countries with high growth skewness are more likely to suffer crises. Yuan (2005), among others, shows that correlation across equity markets can propel crises (contagion). Schneider and Tornell (2004) link production and trade (equations (1) and (3)) and show analytically how bailout guarantees in the non-tradable sector can sustain multiple self-fulfilling beliefs.[6] Martin and Rey (2006) provide a calibrated model to show how trading costs combined with insufficient financial development can drive self-fulfilling beliefs.

We control for these macro factors with an extensive set of controls. Further, we also include country indicators to account for any across-country variations. Our regression models thus identify within-country effects. Finally, we use cross-sectionally correlated errors to account for contagion.

3. Data and Variable Definitions

3.1 Currency Crises and Financial Data

[5] For example, Swanson et al. (2003) study the value relevance of accounting figures after the 1994 Mexican currency devaluation.
[6] Their model, which relies on firm-level performance, is implicitly captured by our accounting performance data which are also obtained at the firm-level.

Since our goal is to predict in-sample crises, we limit ourselves to countries that have had crises. Given the abstractness of the analytical models, what currency crises are empirically best suited to analyze our hypotheses? Reinhart and Rogoff (2008) highlight the heterogeneity of crises by referring to Tolstoy, but then note that crises share several similarities. Likewise, Kaminiski and Reinhart (1999) also show the interconnectedness of banking and currency crises. At a basic level, though, most of these crises occur in financial markets that primarily exist to support firm activity. Our accounting data measure firm activity. We therefore use all the crises as our sample, and then conduct sensitivity analyses over specific crises subsets.

Kaminski 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 (Kaminski and Reinhart 1999, Table 2), which Caprio and Klingebiel (2005) and Kaminiski (2003) subsequently update. We define the crisis onset year as the year a crisis started in the Kaminski (2003) and Caprio and Klingebiel (2005) datasets. This procedure yields 68 crises episodes from 21 different countries as shown in Table 1.[7]

Table 1 classifies the different types of crises based on Kaminski (2003, Table 4). Table 1 shows that 78% 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 and financial information about firms thus are important drivers of these crises, making them an appropriate setting for our study.

We then 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-

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

missing values for a number of accounting variables (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 are not captured directly. It is only captured indirectly through the effect private firms have on public firms through their interactions in the product and the financial markets. However, note that public firms typically tend to be the larger firms, and can thus have a disproportionate impact on the domestic economy. Also note that Thompson Datastream defines each firm observation by the unit of equity it issues. Thus, if a firm issues equity on two different exchanges it will count as two firm observations. This makes sense from our perspective because we are using the country's domestic financial sector as the market triggering the crisis, along the line of models such as Martin and Rey (2006) and Schneider and Tornell (2004).

Our procedure yields 140,641 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 hypotheses. Collapsing the firm-years into country-years gives us 331 to 371 observations depending on the regression. Our analyses do not over-weigh country-years with more firm-year observations. These country-years include 39 crises.

Table 2 reports the onset year of each crisis in different countries, as well as the number of public firms in our sample for each country years. There is considerable variation in number of firm year observations across countries reflecting differences in level of industrialization, financial market development and perhaps data availability.

The shaded areas in Table 2 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' (Kaminsky et al 2003; Allen and Gale 2000; Yuan 2005).

3.2 Quality of Accounting Information

3.2.1 Measures of Accounting information quality

Our main prediction is that realizations of 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 based on firm level data.

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 (accruals) to construct a measure of earnings or profits. 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 larger institutional factors (over and above management idiosyncrasies) that determine firms' accounting choices are accounting rules, legal enforcement, and the legal regime (e.g., Ball et al., 2003). These factors vary across countries, yielding us an institutionally driven across-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 quality of accounting measures. We employ six commonly used measures that capture various dimensions along which accounting information reliably reflects relevant firm fundamentals. Table 3 defines in full detail the six measures we use, as well as their sources in the literature. To minimize estimation errors we aggregate each measure at a country level using the median of the firm year observations. We sign the measures so that lower values reflect higher information quality.

Our first measure of accounting information quality, 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 quality. Table 3 provides detailed definition and computation method for each measure of accounting information quality.

Our second measure AQ^2 proxies for the level of management discretion, often known as the 'smoothing' behavior (Trueman and Titman 1988; Fudenberg and Tirole 1995). 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 information quality (=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 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 4, we construct a composite measure of accounting quality 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 information quality. This is our country-based measure of the precision of the public signal.

Table 4 sorts the countries in ascending order based on the composite index with lower score reflecting higher accounting information quality. 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 1 and 3; Leuz et al. 2003, Table 2) with small difference due to different sample periods.

The models in Section 2 have a specific precision threshold at which self-fulfilling beliefs are feasible, but it is not clear how to translate those precision thresholds into the data. Table 4 therefore dichotomizes the sample at the median into countries with high and low accounting information quality.[8]

With some exceptions, such as Australia, the country classification of high and low accounting quality groups confirms findings of prior literature which suggest that institutional characteristics (La Porta et al., 1997) and enforcement of contracts (Ball et al., 2003) are related to the accounting information environment. For example, Table 4 shows high ranks for European countries such as Denmark, Spain and Norway, while developing countries like Argentina, Turkey and Brazil rank among the countries with poor information quality. The fact that some countries from common law origin are often classified in the low information quality group (i.e., Malaysia and Thailand) is consistent with Ball et al. (2003), who argue that common law

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

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 information quality and various institutional characteristics.

3.2.2 Sources of variation in accounting quality measures across countries and over time

The accounting research perspective is that accounting practice emerges in response to stewardship and valuation demands for accounting information from institutions and capital markets. Ball et at. (2003), for example, empirically link accounting quality to various institutional and legal factors.

In Table 5, we directly examine the relationship between our accounting quality measures with various proxies of legal and institutional environment from prior literature. Table 5, Panel A shows the country ranks of each institutional variables sorted by the level of accounting information quality. We use the well-known anti-director index (as defined in La Porta et al., 1998, and corrected in Djankov et al., 2008) and the creditor rights aggregate score (as defined in La Porta et al., 1997 and updated in Djankov et al., 2007) to proxy for legal environment ($LEGAL_c$) or the level of investor protection in particular. 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 a direct measure for efficiency of debt contract enforcement from Djankov et al. (2006). Finally, we examine the validity of our accounting information quality measures by examining its association with other measures of disclosure quality ($DISCLOSE_c$) collected in a completely different way (La Porta et al., 2006).

The correlations in Table 5, Panel B show that quality of accounting information is indeed positively correlated with both various measures of the quality of legal institutions and the levels of law enforcement, thus validating our accounting precision construct. Specifically, the accounting quality measures (AQ_c) show a stronger 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 of this weak correlation is additional variation in accounting quality 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 with our accounting quality measure, providing additional construct validation.

To reduce noise, 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, 2007)). As different countries makes such rule changes, temporal shifts in the cross-section of accounting quality can occur. We directly examine our measures' the time series stability by using the AR(1) correlation between the values of accounting quality measures estimated for different non-overlapping consecutive periods.

Table 5, Panel C shows the AR(1) times series correlation of each AQ measures 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 quality measures are fairly persistent ---- it is institutionally difficult to change accounting rules and enforcement quickly (unlike say interest rates). Individual accounting rules may change, but overall accounting quality 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 the main analyses with the five-year aggregation period.

3.3 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 (Kaminski et al., 1998). We adopt the leading indicators proposed in Kaminski et al. (1998, Table A4) and Edison (2003, Table 5). 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 6, Panel A provides definitions of all the 17 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. However, for indicators measuring a deviation from a trend, we do not filter the variables to represent 12 month percentage changes.[9]

The descriptive statistics of all the leading indicators are in Table 6, 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 in excess real M1 balances are driven by EU countries that have discontinuity in M2 measures following 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 qualitatively similar results.

Table 7 provides descriptive statistics for each leading indicator variable across different countries, along with additional country information, sorted by accounting quality. A comparison of the cost of crises, measured by foregone outputs as well as actual loss of reserve to defend the speculative attack (Bordo et al., 2001), indicates that countries with low accounting information quality appear to have suffered more severe crises. Countries with low quality accounting information also tend to have higher inflation and GDP growth over the sample period. Given that prior accounting literature suggests that volatile and unstable countries are more likely to have institutionally weaker accounting regimes (e.g., Ball et al., 2003), this table provides additional support for our accounting quality partition method.

3.4 Realized Accounting Fundamentals

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

Table 8 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 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.

We recognize that the list of potential accounting measures and accounting ratios useful for evaluating firm performance is very large (Ou and Penman, 1989), but the measures we choose are widely recognized as the key accounting measures of firm performance (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.

Also note that there is some overlap in the data underlying our accounting quality metrics and the data underlying realized accounting fundamentals, notwithstanding different aggregation procedures. However, our analyses have country fixed effects, so any across-country variation in the measures in Table 4 will have no impact on the results: we will assess only the within-country effect in our regressions.

3.4.1 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, in the current U.S. mortgage crisis, investment 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

[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).

materialized. Of course, the extent to which accruals systematically predict future firm 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 Hirshliefer et al. (2007) 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 (Sloan 1996; Dechow et al., 1995; Jones 1991) 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.[11]

Table 8, Panel B indicates that the mean of accruals is -0.01, similar to Sloan (1996, Table 1) 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 quality of accounting information (Section 3.2). 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 information quality is capturing 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, the implication of accruals as an accounting fundamental should only be accessed within each country.

3.4.2 Realized Accounting Signal: Operating Profitability

[11] Although it would be optimal to use a comprehensive measure of accruals that includes both operating and financing accruals, we are limited by the availability of financial statement data. In unreported tests we explore alternative definitions by using total accruals ($= \Delta TotalAsset - \Delta TotalLiability - \Delta Cash$) to test the sensitivity of our result. Our results remain qualitatively unchanged.

Operating profitability or operating earnings require little motivation. We define operating profitability as the country median of firm level net operating income scaled by the beginning total assets. Table 8, Panel B indicates that they average to a reasonable 8 percent of assets.

3.4.3 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.

3.4.4. Correlations

Table 9, Panel A presents the correlation matrix of all crises predictors, including realization of each 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 (0.34, Spearman) with domestic real interest rates. Also, the associations of the realization of our accounting signals are plausibly signed: accruals and profitability show a positive relation (0.38, Spearman). More important, there also appears to be little evidence of multicollinearity: our three realized accounting measures thus capture different dimensions of realized fundamentals.

Table 9, Panel B presents the time series correlation of all the three accounting signals. The association of the contemporaneous and lagged accounting measure is stationary across time periods. For example, correlation between $\text{Profitability}_{c,t-2}$ and $\text{Profitability}_{c,t-1}$ (= 0.837, Spearman) is close to the correlation between $\text{Profitability}_{c,t-1}$ and $\text{Profitability}_{c,t}$ (= 0.836, 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.

4. Results

4.1 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, Rose and Wyplosz (1995), we compare the behavior of each accounting signal during the 'tranquil' periods for the same group of countries.

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.

The figures show that 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 writeoffs. 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 confidence intervals of realized accounting signals are noticeably larger in low precision countries. This relatively high uncertainty of realized accounting measures further corroborates our accounting precision dichotomy of the sample. Of course, the univariate nature of the figures necessitates caution in any inference. We now turn to a more formal analysis of the data.

4.2 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 et al., 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:

$$\begin{aligned} D\_Crisis_{c,t} &= \alpha + \sum_{i=1}^{3} \beta^i \times AccountingSignal^i_{c,t-n} + \\ &\sum_{k=1}^{18} \gamma^k \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t} \end{aligned} \tag{4}$$

Table 10 reports the results for various lead-lags in the full sample. Accounting signals two years prior have no ability to predict crises onset. However, the situation is different for a one year lead. Accounting signals are collectively significant, and their inclusion increases the explanatory power from 0.248 and 0.284, a 14 percent increase. Finally, contemporaneous accounting signals in the last column are also significant. Since the crisis has already occurred, this significance could simply reflect the toll of the crisis on firm performance.

Interestingly, Table 10 shows that many of the leading indicators also do not have statistically significant coefficients. Among the leading indicators, the real sector variables (i.e., industry production, stock price) and the capital account variables (i.e. foreign reserves, M2 balance, and short term debt) appear to be statistically significant in the predicted direction. On the other hand, coefficients of imports, domestic credit and lending/deposit rates show reverse signs.[12] This is consistent with the early warnings systems finding that even the best model has limited predictive power (Kaminsky et al., 1998 Table 1).

4.3 The Accounting Precision Dichotomy

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

$$
\begin{aligned}
D\_crisis_{c,t} = {} & \sum_{i=1}^{3} \beta_H^i \times [I_{C_H} \times AccountingSignal_{c,t-n}^i] + \\
& \sum_{i=1}^{3} \beta_L^i \times [I_{C_L} \times AccountingSignal_{c,t-n}^i] + \sum_{k=1}^{18} \gamma^k \times LeadingIndicator_{c,t-n}^k + \varepsilon_{c.t}
\end{aligned}
\tag{5}
$$

I_{C_H} (I_{C_L}) is an indicator equal to 1 when the crises is from a country with high (low) quality accounting information 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) quality information and the onset of a crisis.

Table 11 presents the result of the probit estimations. As in Table 10, accounting signals two years in advance have no power to predict crises. However, the one year prior F-tests clearly show that accounting signals have more statistical power to jointly predict crisis among countries with low information quality. In particular, the in-sample prediction power of realized accounting signals is significant for low accounting precision countries (F-stat = 18.8, p-value <

[12] This finding is consistent with other empirical research in the early warnings system literature. In particular, Edison 2003 (Table 14) finds that real interest differential, real interest rates and imports have the lowest probability of issuing a signal during the 24 month period prior to a crisis. Also these variables show the tendency to frequently issue false signals represented as a high noise-to-signal ratio (Kaminsky 1998, Table 1).

[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.

0.1%), and insignificant (F-stat = 1.88, p-value = 59.0%) 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 concurrent model in the last column of Table 11 dispels this possibility. For the concurrent model, the accounting signals appear to be jointly significant for both the high (F-stat = 9.00, p-value = 2.0%) and the low (F-state = 24.05, p-value < 0.1%) accounting quality subsample. Accounting signals in high precision countries thus appear to have the statistical power to reflect the consequence of the crises: they simply cannot predict them.

The individual coefficients of the realized accounting signals in Table 11 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 12.

We get the same result as in Table 11, 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 high precision countries. Accruals in low precision countries are negatively significant, suggesting they decline before the crises. Accruals decline if firms increase their writeoffs 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. The marginal effect (the effect of a unit change in the regressor on the probability of the crisis at the sample mean) indicates that one standard deviation drop in accruals is associated with an increase the probability of a crisis by 1 percent.

The prior-year profitability in low precision countries is significant but has the opposite sign (it does so in Table 11 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

[14] Unreported results indicate that no measure individually has any power to predict crises in both subsamples two years in advance. For the concurrent regression, some measures in both high and low precision countries achieve significance. The results basically mirror Table 11.

et al., 2008).[15] Accordingly, the cash flows coefficient is significantly positive in Table 12. But then, once the crisis hits, this boom disappears. Commensurately, the profitability in the crises years (Table 11) 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.

4.4 Institutional Factors and Time-Varying Accounting Quality

One concern with the above results is that they reflect the underlying institutions in Table 5, Panel A and not the accounting quality. This is especially true of institutions that are strongly correlated with accounting quality. In this subsection, we examine this concern directly. Table 5, Panel B shows that, of all the institutional features, legal enforcement is most strongly associated with accounting quality. We divide the sample into high and low enforcement countries and examine the predictive power of the realized accounting signals.

Table 13, 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., Acemoglu and Guerreri 2008, Martin and Rey 2006; 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).

[15] This was true at the onset of the U.S. mortgage crisis as well (Greenlaw et al. 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 13, Panel A are exactly the opposite. So the channel which does seem to be operating in Table 13, Panel A is likely the one in Table 11, namely that high enforcement countries have high precision accounting signals (Table 5, Panel B), which then fall into the purview of the analytical crisis models. Therefore, albeit indirect, Table 13, 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, 2007) show that our main prediction continues to hold in such circumstances. As discussed in Section 3.2.2, we re-sort the countries into high and low accounting quality every year, based on the accounting quality over the previous five year period. Table 13, Panel B presents the main results in Table 11 using this time-varying dichotomy. As in Table 11, the low precision countries still have stronger predictability, though the significance is somewhat attenuated. Of course, one problem is that all our accounting quality measures are noisy, and our premise is that aggregation reduces this noise. Compared to the original accounting quality measures that are aggregated over the sample horizon, we do not know how much of the variation in accounting quality across five-year periods is noise and how much reflects true variation. Recall after all that accounting rules are not like the target interest rate that can change quickly. Individual accounting rules many change, but the overall quality of reported accounting measures is likely a slow-moving institutional feature with considerable stickiness. We therefore have more confidence in our Table 11 results that computes accounting quality over long horizons.

5. Additional Analyses

5.1 Different Types of Crises

Studies such as Kaminski and Reinhart (1998) and Reinhart and Rogoff (2008) document both homogeneity and heterogeneity in 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. These crises are more a product of government monetary and macro policies than information-based speculative behavior in the corporate financing markets of equity, debt, and bank loans.

Table 14, 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 county into the first year (we are mostly dropping currency crisis that follows 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 11, we find that the predictive chi-squares of the realized fundamentals in the year before the crises are 10.01 (p-value =0.018) for the low accounting precision countries and 3.42 (p-value = 0.33) for the high precision countries. Furthermore, mirroring Table 11, both sets of countries show a significant change in fundamentals after the crises hit.

5.2 Country classification of high and low accounting quality

The switch from multiplicity to a region of uniqueness in the analytical models is not gradual, but occurs suddenly at a certain unknown threshold (Angeletos and Werning 2006, Fig1). Empirically, we have used the sample median as the precision threshold after sorting the countries by the composite index described in section 3. In this section, we examine the sensitivity of our results to alternative definitions of the precision threshold.

Table 4, Panel B shows a discrete jump in the composite index between Italy and Thailand (=10.2) and Malaysia (=13.2). We therefore redefine the countries with high accounting information quality as those with a composite index lower than Italy. Thus, Thailand and Italy are now categorized as counties with high information quality in the following analysis.

Table 14, Panel B shows the results using 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.

6. 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 (e.g. 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 settings, precise public signals can then end up coordinating traders' beliefs about each other and precipitate crises independent of realized fundamentals (e.g., Angeletos and Werning 2006, Angeletos et al. 2006, 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 can occur due to variations in legal regimes, enforcement, and accounting rules. We exploit this variation in accounting data to provide on 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.

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Table 1: Crisis onset years by different types of currency crises from years 1976 to 2005

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

Following Kaminski and Reinhart (1999), we define currency crisis as an event of a steep decrease in exchange rates and/or reserves. Crises episodes are taken directly from Kaminski and Reinhart (1999) and the banking crisis database of Caprio and Klingebiel (2005). We follow the crisis classification of Kaminski and Reinhart (2003).
* From the Caprio and Klingebiel (2005) banking crisis database.

Table 2: Crisis onset years and number of public firms from years 1976 to 2005

	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	6				8	
1985		17		4	7	17	2			12	4
1986		32		4	10	24	15			21	21
1987	2	44		5	13	70	42			61	34
1988	6	152	15	36	39	467	45			324	74
1989	7	236	99	96	77	566	45			348	332
1990	7	274	113	125	91	633	50	6	3	359	1355
1991	7	287	111	127	91	683	59	6	11	370	1722
1992	16	293	148	134	91	705	99	34	87	374	1876
1993	21	305	151	137	90	748	154	140	95	370	1910
1994	26	307	162	143	93	768	178	159	102	364	1961
1995	30	336	197	143	94	776	184	178	107	389	2035
1996	28	435	253	141	94	820	184	264	148	397	2094
1997	37	498	256	171	117	1028	240	289	156	438	2143
1998	39	534	278	175	132	1173	268	306	162	505	2202
1999	49	611	319	167	131	1279	286	313	164	550	2847
2000	60	811	571	154	127	1343	350	317	193	590	2865
2001	66	1213	561	145	135	1362	386	358	262	613	2985
2002	68	1956	541	140	133	1316	400	419	283	603	3215
2003	68	2056	529	137	129	1294	382	444	287	597	3223
2004	64	2228	541	124	133	1275	389	517	285	610	3303
2005	61	2518	548	118	134	1274	395	582	287	603	3360
Total # of firm-years	662	15161	5393	2426	1967	17635	4153	4332	2632	8508	39561
# of crisis years (sum of shaded cells)	6	1	7	2	3	1	1	1	5	1	1

(Continued)

Table 2: Crisis onset years and number of public firms from years 1976 to 2005 (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								
1984		3		1			1			
1985		5	11	7		2	5			
1986	1	7	11	13		3	5			
1987	1	10	16	17		8	9			
1988	14	35	43	68		54	13		4	2
1989	77	44	52	84	5	71	90	6	8	10
1990	110	51	54	99	5	76	118	6	21	18
1991	103	56	53	99	10	86	150	6	42	21
1992	104	107	83	98	36	89	154	29	141	24
1993	115	136	98	92	46	92	160	32	231	28
1994	169	139	122	103	52	92	166	49	301	40
1995	201	157	134	99	57	93	177	121	319	38
1996	226	235	133	100	82	97	190	214	347	41
1997	268	268	143	169	87	119	189	236	373	53
1998	308	305	151	176	88	116	241	250	386	73
1999	392	310	189	159	103	117	275	253	376	89
2000	663	343	196	130	114	116	269	399	376	111
2001	682	549	203	132	153	119	273	507	518	131
2002	746	672	204	128	166	114	265	1116	533	140
2003	828	710	200	133	177	113	255	1201	586	169
2004	851	794	195	145	174	117	263	1264	632	179
2005	860	863	187	145	178	110	281	1264	640	177
Total # of firm-years	6719	5800	2478	2197	1533	1804	3549	6953	5834	1344
Total # of crisis years (sum of shaded cells)	1	2	3	6	4	5	4	1	7	3

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 1.

Table 3: Individual countries' measure of accounting information quality
[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)	$AQ^6_{c,t} = Median_f\left(\frac{\lvert TotalAccurals\rvert_{c,f,t}}{\lvert CFO\rvert_{c,f,t}}\right)$
$AQ^i_{c,t,P}$ *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	$AQ^i_c = Mean_t\left(AQ^i_{c,t}\right)$

Note: Each measure is defined such that *lower* value represents *higher* information quality.
Variable definitions:

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

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

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

Table 4: Countries' average accounting information quality from 1981 to 2005
[c=country]

Panel A: Countries with high quality accounting information

Country	# of years	# of firm years	**Average accounting information quality 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 $i = 1..6$
Denmark	21	2,426	0.051	0.908	-0.049	0.557	0.039	0.634	6.0
Spain	21	1,804	0.050	0.934	-0.037	0.448	0.059	0.660	6.7
Norway	22	2,197	0.061	0.636	-0.050	0.551	0.048	2.331	7.5
Taiwan	17	6,953	0.048	0.945	-0.038	0.557	0.039	0.670	7.5
Sweden	23	3,549	0.052	0.827	-0.033	0.470	0.072	0.789	8.0
Finland	22	1,967	0.015	0.917	-0.050	0.684	0.059	0.790	8.7
Mexico	21	2,478	0.047	0.821	-0.033	0.374	0.217	1.460	9.0
India	16	4,332	0.051	0.761	-0.019	0.451	0.090	0.828	9.0
France	25	17,635	0.065	0.921	-0.038	0.523	0.061	0.669	9.3
Philippines	17	1,533	0.047	0.848	-0.029	0.507	0.074	0.976	9.7
Japan	21	39,561	0.100	0.975	-0.029	0.500	0.027	0.666	9.8

Variable definitions are in Table 3. Sample is described in Table 2.

(Continued)

Table 4: Countries' average accounting information quality from 1981 to 2005 (Continued)
[c=country]

Panel B: Countries with low quality accounting information

Country	# of years	# of firm years	**Average accounting information quality 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
Thailand	18	5,834	0.058	0.806	-0.030	0.572	0.070	0.833	10.0
Italy	23	8,508	0.055	0.909	-0.049	0.646	0.060	0.943	10.2
Malaysia	23	5,800	0.083	0.918	-0.013	0.563	0.053	1.054	13.2
Indonesia	16	2,632	0.349	0.979	-0.033	0.629	0.007	0.978	13.2
Korea	20	6,719	0.103	0.945	-0.028	0.615	0.059	0.985	14.2
Australia	25	15,161	0.085	0.815	-0.019	0.858	0.068	3.126	14.8
Greece	21	4,153	0.071	0.849	-0.003	0.620	0.122	1.078	15.0
Argentina	19	662	0.067	0.524	0.326	0.982	2.468	6.238	16.2
Turkey	18	1,344	0.182	0.779	0.064	0.670	0.443	2.010	16.2
Brazil	18	5,393	0.306	0.840	-0.021	0.660	3.511	4.499	17.0

Variable definitions are in Table 3. Sample is described in Table 2.

Table 5: Stability of accounting information quality across different legal institutions and over time

[c=country]

Panel A: Country rankings of quality of legal institutions by accounting information quality

Country	Accounting quality	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 information quality									
Denmark	**6**	Code (S)	7	1	**4**	1	9	**5**	**11**
Spain	**6.7**	Code (F)	1	5	**3**	10	8	**9**	**15**
Norway	**7.5**	Code (G)	12	5	**9**	1	4	**2.5**	**11**
Taiwan	**7.5**	Code (S)	16	5	**11**	8	2	**5**	**5**
Sweden	**8**	Code (S)	12	14	**13**	1	7	**4**	**11**
Finland	**8.7**	Code (S)	12	14	**13**	1	3	**2**	**15**
Mexico	**9**	Code (F)	16	20	**18**	15	10	**12.5**	**11**
India	**9**	Common (U)	1	5	**3**	19	.	**19**	**1**
France	**9.3**	Code (F)	12	20	**16**	6	12	**9**	**5**
Philippines	**9.7**	Code (F)	7	14	**11**	21	18	**19.5**	**4**
Japan	**9.8**	Code (G)	5	5	**5**	6	1	**3.5**	**5**
Countries with low accounting information quality									
Thailand	**10**	Code (F)	7	5	**6**	13	11	**12**	**1**
Italy	**10.2**	Code (F)	19	5	**12**	9	15	**12**	**10**
Malaysia	**13.2**	Common(U)	1	1	**1**	11	14	**12.5**	**1**
Indonesia	**13.2**	Code (F)	7	5	**6**	20	17	**18.5**	**15**
Korea, Rep.	**14.2**	Code (S)	5	1	**3**	15	5	**10**	**5**
Australia	**14.8**	Code (S)	7	1	**4**	1	6	**3.5**	**5**
Greece	**15**	Code (S)	19	14	**17**	14	13	**13.5**	**20**
Argentina	**16.2**	Code (F)	19	14	**17**	15	16	**15.5**	**15**
Turkey	**16.2**	Code (G)	16	5	**11**	18	20	**19**	**15**
Brazil	**17**	Code (S)	1	14	**8**	12	19	**15.5**	**21**

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

Table 5: Stability of accounting information quality across different legal institutions and over time (Continued)
[c= country, P= Length of non-overlapping consecutive periods over which stability is measured]

Panel B: Correlation of accounting information quality and legal institutions

	AQ_c	$LEGAL_c$	$ENFORCE_c$	$DISCLOSE_c$
AQ_c	1	0.0674	**0.5045***	0.2260
$LEGAL_c$		1	0.0573	0.4091
$ENFORCE_c$			1	0.0651
$DISCLOSE_c$				1

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 between the values of each accounting quality measures over 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	**0.6835****	**0.6806****	**0.6531****	**0.3933****	**0.5369****	**0.5938****	**0.6230****	**0.4903****	**0.4425****	**0.6424****	**0.5839****	**0.6353****
P=5 years	**0.5489****	**0.5459****	**0.6066****	0.1319	**0.5311****	**0.6473****	**0.4995****	**0.3606****	0.0830	0.0179	0.2528	0.1280

$AQ^i_{c,P} = Mean_{t\in P}(AQ^i_{c,t})$. See Table 3 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 6: 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 6: 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	(+)

Source: International Financial Statistics (IFS) and other sources as noted. All leading indicator variables are measured as annual percentage changes, except (a) interest rate as 12 month level change, (b) real exchange rate as deviation from time trend, and (c) excess M1 as residuals from money demand equation.

Table 6: 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 7: Descriptive statistics of country characteristics
[c=country]

Panel A: Countries with high quality accounting information

Country	**Country characteristic**		**Average value of leading indicators over the sample period**								**Cost of crises**	
	# of firm years	Average $inflation_c$	$Avearge\Delta GDP_c$	$\Delta Imports_c$	$\Delta FXreserve_c$	$\Delta STdebt_c$	$\Delta Output_c$	$\Delta Equity_c$	ΔDomestic $credit_c$	ΔLD_ratio_c	$Growth_c$	Reserve $loss_c$
Denmark	2426	0.047	0.067	0.074	0.208	0.061	0.027	0.144	0.030	2.053	0.024	-0.065
Finland	1967	0.019	0.041	0.055	0.186	-0.195	0.027	0.070	0.011	8.746	-0.083	-0.278
France	17,635	0.103	0.138	0.166	0.202	0.334	0.118	0.239	-0.003	1.483	-0.093	0.176
India	4332	0.049	0.091	0.073	0.137	0.100	0.033	0.153	0.012	1.826	-0.015	0.796
Japan	39561	0.052	0.076	0.089	0.105	0.084	0.017	0.168	0.019	2.112	-0.068	-0.111
Mexico	2478	0.327	0.367	0.118	0.322	0.144	0.034	0.730	-0.017	1.909	-0.089	-0.755
Norway	2197	0.047	0.070	0.095	0.100	0.169	0.016	0.116	0.029	0.532	-0.017	0.012
Philippines	1533	0.079	0.113	0.146	0.075	0.915	0.020	0.113	0.003	1.487	-0.139	-0.277
Spain	1804	0.048	0.076	0.087	0.227	0.171	0.040	0.173	0.007	2.055	-0.066	-0.206
Sweden	3549	0.073	0.137	0.181	0.287	0.525	0.065	0.211	0.022	1.621	-0.075	0.257
Mean		0.084	0.118	0.108	0.185	0.231	0.038	0.207	0.011	2.502	-0.062	-0.045

Variable definitions:

$Growth_{c,t} = \frac{1}{2}\left(\%\Delta output_{c,t} + \%\Delta output_{c,t+1}\right) - \frac{1}{T}\sum_{t=1}^{T}\%\Delta output_{c,t}$ (Source: International Financial Statistics item 66A.ZF)

Reserve loss $_c$: 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 6.

(Continued)

Table 7: Descriptive statistics of country characteristics (Continued)

[c=country]

Panel B: Countries with low quality accounting information

Country	Country characteristic		Average value of leading indicators over the sample period								Cost of crises	
	# of firm years	Average $inflation_c$	AverageΔGDP_c	$\Delta Imports_c$	$\Delta FXreserve_c$	$\Delta STdebt_c$	$\Delta Output_c$	$\Delta Equity_c$	$\Delta Domes\_credit_c$	ΔLD_ratio_c	$Growth_c$	Reserve $loss_c$
Argentina	662	2.969	2.815	0.130	0.384	0.664	-	-	-0.020	1.546	-	0.362
Australia	15,161	0.057	0.088	0.109	0.196	-0.008	0.022	0.112	0.031	1.713	0.023	0.012
Brazil	5,393	4.492	3.946	0.077	0.185	0.131	0.018	-	-0.074	3.261	-0.005	0.036
Greece	4,153	0.125	0.159	0.088	0.074	0.906	0.019	0.185	0.030	1.590	-	0.537
Indonesia	2,632	0.116	0.201	0.111	0.187	0.167	0.072	0.129	0.006	1.309	-0.312	0.148
Italy	8,508	0.074	0.104	0.132	0.178	0.444	-	0.153	-0.010	2.366	-	0.359
Korea	6,719	0.071	0.156	0.141	0.285	-0.050	0.096	0.132	0.029	1.155	-0.204	-0.407
Malaysia	5,800	0.033	0.111	0.147	0.162	0.469	0.086	0.079	0.009	1.893	-0.151	0.000
Thailand	5,834	0.050	0.112	0.157	0.143	0.239	-	0.052	0.025	1.790	-	-0.017
Turkey	1,344	0.545	0.650	0.125	0.177	0.029	0.059	-	0.025	1.026	-0.072	-0.008
Mean		0.794	0.842	0.121	0.197	0.302	0.059	0.122	0.006	1.696	-0.12	0.10

Variable definitions:

$$Growth_{c,t} = \frac{1}{2}\left(\%\Delta output_{c,t} + \%\Delta output_{c,t+1}\right) - \frac{1}{T}\sum_{t=1}^{T}\%\Delta output_{c,t}$$ (Source : International Financial Statistics item 66A.ZF)

Reserve loss $_c$: 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 6.

Table 8: 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.	$volatility_{c,t} = Median_f\left\{\frac{\sigma_{c,f,t}(NI_{c,f,t}, NI_{c.f.t-1}, NI_{c.f.t-2})}{TotalAssets_{c,f,t-1}}\right\}$

Variable definitions:

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

$NI_{c,f,t}$ = 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

Table 9: Correlation matrix of crises predictors from 1981 to 2005

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 8)																		
$Accruals_{c,t}$	1	**0.62**	0.06	0.0	-0.08	0.04	0.06	**0.67**	**-0.69**	0.04	0.06	0.03	**-0.18**	-0.02	**0.69**	**-0.25**	-0.06	0.01
$Profitability_{c,t}$	**0.38**	1	**0.23**	0.0	0.01	0.01	0.02	**0.31**	**-0.77**	-0.03	-0.02	**0.27**	**-0.16**	**-0.28**	**0.77**	-0.09	**-0.12**	-0.03
$Volatility_{c,t}$	**-0.16**	-0.05	1	**0.15**	-0.02	0.00	-0.07	-0.03	-0.07	0.00	**-0.16**	-0.02	-0.06	-0.09	0.07	-0.10	-0.05	0.03
Prior literature's leading indicators (see Table 6)																		
$Over\text{-}valuation_{c,t}$	**-0.27**	**-0.25**	0.20	1	-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
$Imports_{c,t}$	**0.18**	**0.25**	-0.05	**-0.13**	1	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
$Exports_{c,t}$	**0.10**	**0.19**	0.02	-0.07	**0.59**	1	**0.11**	0.05	0.07	0.15	**0.38**	**0.08**	0.09	-0.05	-0.07	0.12	-0.09	0.00
Foreign EX $reserve_{c,t}$	0.10	**0.16**	-0.07	-0.09	0.02	0.07	1	-0.06	0.08	**-0.42**	0.05	0.13	-0.07	-0.06	-0.08	0.06	0.00	-0.06
M2/foreign EX $reserve_{c,t}$	**0.20**	**0.18**	0.11	-0.08	0.09	0.02	-0.70	1	**-0.41**	**0.25**	-0.01	0.03	**-0.21**	0.00	**0.41**	**0.79**	-0.12	0.02
Real interest $diff_{c,t}$	0.01	-0.05	**-0.13**	-0.02	0.10	-0.04	0.02	-0.07	1	-0.01	0.10	**0.33**	**0.23**	**0.47**	**-1.00**	0.10	0.00	-0.01
ST $debt/reserves_{c,t}$	0.04	-0.05	-0.10	-0.12	0.17	0.09	-0.45	**0.31**	0.04	1	0.05	-0.02	0.10	0.02	-0.03	0.07	-0.10	-0.06
Industry $production_{c,t}$	**0.18**	**0.24**	**-0.15**	-0.11	**0.57**	**0.44**	0.10	0.05	-0.01	-0.08	1	0.17	0.05	0.03	-0.10	0.13	-0.10	0.02
Stock $prices_{c,t}$	0.01	**0.31**	-0.06	0.01	**0.23**	**0.19**	0.13	-0.09	0.06	-0.06	**0.34**	1	0.09	-0.06	**-0.34**	0.05	-0.09	**-0.26**
M2 $multiplier_{c,t}$	0.08	0.05	-0.06	-0.04	0.06	0.11	-0.02	0.11	0.10	0.16	0.06	-0.09	1	**0.33**	**-0.23**	0.04	-0.10	-0.10
Domestic $credit/GDP_{c,t}$	**0.18**	0.09	**-0.15**	**-0.14**	**-0.13**	**-0.16**	-0.13	**0.22**	-0.04	0.09	-0.03	-0.06	**0.19**	1	**-0.47**	**0.60**	-0.04	0.10
Domestic real $interest_{c,t}$	-0.03	0.11	-0.08	-0.01	**-0.14**	0.01	-0.07	**0.15**	**-0.58**	-0.04	0.03	-0.01	0.02	**0.23**	1	-0.10	-0.09	0.02
Com. bank $deposits_{c,t}$	**0.16**	**0.23**	-0.07	**-0.19**	**0.16**	**0.19**	0.12	**0.19**	**-0.20**	0.05	**0.21**	0.10	**0.26**	**0.44**	**0.34**	1	**-0.14**	0.03
Lend./dep. Inter. $rate_{c,t}$	**-0.16**	**-0.37**	0.08	**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**	1	-0.01
XS real M1 $balances_{c,t}$	0.00	-0.05	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	1

The sample is described in Tables 1 and Table 2. Refer to Table 6 and Table 8 for variable definition. Bold figure denotes significance at 95% level.

Table 9: Correlation matrix of crises predictors from 1981 to 2005 (Continued)

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

	$Accruals_{c,t-2}$	$Accruals_{c,t-1}$	$Accruals_{c,t}$	$Profitability_{c,t-2}$	$Profitability_{c,t-1}$	$Profitability_{c,t}$	$Volatility_{c,t-2}$	$Volatility_{c,t-1}$	$Volatility_{c,t}$
$Accruals_{c,t-2}$	1	**0.491**	0.092	**0.626**	0.035	0.026	0.067	0.028	0.003
$Accruals_{c,t-1}$	**0.512**	1	**0.492**	**0.497**	**0.624**	0.035	0.003	0.060	0.025
$Accruals_{c,t}$	**0.404**	**0.509**	1	**0.228**	**0.496**	**0.622**	0.002	-0.001	0.057
$Profitability_{c,t-2}$	**0.414**	**0.440**	**0.379**	1	**0.335**	**0.313**	**0.270**	**0.170**	**0.137**
$Profitability_{c,t-1}$	**0.360**	**0.405**	**0.415**	**0.837**	1	**0.340**	**0.131**	**0.244**	**0.157**
$Profitability_{c,t}$	**0.254**	**0.334**	**0.381**	**0.674**	**0.836**	1	**0.226**	**0.115**	**0.230**
$Volatility_{c,t-2}$	**-0.160**	**-0.147**	-0.107	-0.043	-0.025	0.048	**1**	**0.752**	**0.525**
$Volatility_{c,t-1}$	-0.103	**-0.163**	**-0.145**	-0.005	-0.048	-0.020	**0.621**	**1**	**0.746**
$Volatility_{c,t}$	-0.076	-0.108	**-0.157**	-0.012	-0.015	-0.047	**0.443**	**0.648**	**1**

The sample is described in Table 1 and Table 2. Refer to Table 8 for definitions of accounting signals. Bold figure denotes significance at 95% level.

Table 10: Crisis prediction with multivariate analysis of realized accounting signals from 1981 to 2005

[c=country; t=year]

Model (see Table 1 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]	
	sign	$\frac{dF}{d\overline{\overline{X}}}$	(z- stat)	$\frac{dF}{d\overline{\overline{X}}}$	(z- stat)	$\frac{dF}{d\overline{\overline{X}}}$	(z- stat)
Table 8's Realized accounting signals (= $\hat{\beta}^i$)							
Accruals$_{c,t}$	-	-0.015	(-0.98)	**-0.057****	(-3.95)	**0.051****	(4.75)
Profitability$_{c,t}$	-	-0.031	(-0.86)	**0.136****	(2.67)	**-0.113****	(-2.64)
Volatility$_{c,t}$	+	0.277	(1.51)	-0.361	(-1.14)	**0.797****	(4.04)
F- test [Prob > χ^2**] :**		χ^2(3) = 4.18 [0.243]		**χ^2(3) = 20.95 [<0.001]**		**χ^2(3)=10.46 [<0.001]**	
Table 6's prior literature's leading indicators and time trend (= $\hat{\gamma}^k$)							
Over-valuation$_{c,t}$	-	**0.000****	(-2.45)	**0.000****	(-2.86)	**0.000****	(-2.44)
Imports$_{c,t}$	+	-0.020	(-1.08)	0.000	(0.00)	**-0.071****	(-3.01)
Exports$_{c,t}$	-	**0.063****	(2.68)	-0.036	(-1.05)	0.037	(1.34)
Foreign exchange reserve$_{c,t}$	-	0.004	(0.59)	0.000	(0.02)	**-0.025****	(-3.21)
M2/foreign exchange$_{c,t}$ reserve$_{c,t}$	+	-0.002	(-1.56)	**0.004**†	(1.88)	**0.004****	(3.12)
Real interest rate differential$_{c,t}$	+	-0.010	(-0.22)	**-0.151***	(-2.33)	-0.028	(-0.88)
Short term debt/reserves$_{c,t}$	+	0.001	(0.38)	-0.003	(-0.51)	**0.009****	(2.46)
Industry production$_{c,t}$	-	0.038	(0.86)	**-0.183**†	(-1.85)	**-0.147****	(-2.75)
Stock prices$_{c,t}$	-	-0.020	(-1.23)	-0.028	(-1.12)	**-0.037****	(-3.01)
M2 multiplier$_{c,t}$	+	-0.013	(-0.98)	-0.035	(-1.47)	0.012	(1.05)
Domestic credit/GDP$_{c,t}$	+	**0.042****	(2.62)	0.056	(1.85)	**-0.071****	(-2.70)
Domestic real interest rate$_{c,t}$	+	-0.009	(-0.20)	**-0.152****	(-2.35)	-0.029	(-0.91)
Commercial bank deposits$_{c,t}$	-	0.023	(0.77)	**-0.126****	(-3.52)	0.049	(1.43)
Lending/deposit interest rate$_{c,t}$	+	**-0.006**†	(-1.80)	**-0.012****	(-2.51)	**-0.005***	(-2.14)
Excess real M1 balances$_{c,t}$	+	**0.000****	(2.47)	**0.000****	(2.65)	**0.000****	(-3.12)
G7 output$_{t}$	-	-0.018	(-1.13)	**-0.034**†	(-1.73)	0.011	(0.99)
US interest rate$_{t}$	+	**0.433**†	(1.66)	0.559	(0.88)	0.269	(0.81)
Oil prices$_{t}$	+	0.020	(1.49)	0.027	(1.27)	-0.002	(-0.13)
Year$_{t}$		**-0.002****	(-2.77)	0.001	(-0.46)	**-0.003****	(-4.18)
Country Fixed Effects		**Yes**		**Yes**		**Yes**	
Standard Error clustering on year		**Yes**		**Yes**		**Yes**	
# country years		331		351		371	
Pseudo R^2		**28.3%**		**28.4%**		**46.1%**	
Pseudo R^2 (excluding accounting signals)		**24.7%**		**24.8%**		**37.7%**	

$PseudoR^2 = 1 - \frac{\ln \hat{L}}{\ln L_0}$, where $\hat{L}$ is the likelihood from the estimated model and $\hat{L}_0$ is the likelihood from a model containing only a constant. $D\_Crisis_{c,t}$ is an indicator variable indicating the onset of currency crises. See Table 1 and Table 2 for crisis onset years. The model is estimated with all data pooled across countries. We include country fixed effects and correct the standard errors for cross-sectional correlation by clustering on year. Refer to Table 6 and Table 8 for the definitions of leading indicator variables and accounting signals.

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

Table 11: Crisis prediction of accounting signals for high vs. low accounting quality sub-sample from 1981 to 2005
[c=country, t=year]

Model (see Table 1 for crises onset years):

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

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

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

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

			Predictive [-n =-2]		*Predictive* [-n =-1]		*Concurrent* [-n =0]	
		sign	$\frac{dF}{d\overline{X}}$	(z-stat)	$\frac{dF}{d\overline{X}}$	(z-stat)	$\frac{dF}{d\overline{X}}$	(z-stat)
Table 8's Realized accounting signals (= $\hat{\beta}^i$)								
$\text{Accruals}_{c,t}$	β_H^1	-	0.071	(-0.56)	0.151	(0.60)	0.100	(0.82)
	β_L^1	-	-0.016	(-0.90)	**-0.055****	(-3.93)	**0.040****	(3.40)
$\text{Profitability}_{c,t}$	β_H^2	-	0.076	(0.66)	-0.288	(-0.17)	**-0.508****	(-2.85)
	β_L^2	-	-0.037	(-0.89)	**0.138****	(2.67)	**-0.074****	(-2.95)
$\text{Volatility}_{c,t}$	β_H^3	+	0.189	(0.34)	-0.857	(-1.11)	0.058	(0.13)
	β_L^3	+	0.314	(1.49)	-0.257	(-0.75)	**0.666****	(4.64)
F- test of β_H^i s [Prob > χ^2]**:**			χ^2(3) =0.91 [0.82]		χ^2(3) =1.88 [0.59]		**χ^2(3) =9.97 [0.02]**	
F- test of β_L^i s [Prob > χ^2]**:**			χ^2(3) =3.75 [0.29]		**χ^2(3) =18.8 [<0.001]**		**χ^2(3)=24.05 [<0.001]**	

(Continued)

Table 11: Crisis prediction of accounting signals for high vs. low accounting quality sub-sample from 1981 to 2005 (Continued)

		Predictive [-n = -2]		*Predictive* [-n = -1]		*Concurrent* [-n = 0]	
Table 6's prior literature's leading indicators and time trend $(=\hat{\gamma}^k)$							
Over-valuation$_{c,t}$	-	**0.000***	(-2.42)	**0.000****	(-2.78)	**-0.000****	(-2.73)
Imports$_{c,t}$	+	-0.020	(-1.03)	-0.002	(-0.07)	**-0.059****	(-3.54)
Exports$_{c,t}$	-	**0.066****	(3.18)	-0.022	(-0.70)	0.039	(1.97)
Foreign exchange reserve$_{c,t}$	-	0.005	(0.71)	0.000	(-0.02)	**-0.020****	(-2.89)
M2/foreign exchange$_{c,t}$ reserve$_{c,t}$	+	-0.002	(-1.50)	0.003	(1.75)	**0.003****	(3.46)
Real interest rate differential$_{c,t}$	+	-0.010	(-0.23)	**-0.137***	(-2.14)	-0.010	(-0.45)
Short term debt/reserves$_{c,t}$	+	0.001	(0.34)	-0.004	(-0.73)	**0.007***	(2.26)
Industry production$_{c,t}$	-	0.035	(0.80)	-0.137	(-1.49)	**-0.095****	(-2.58)
Stock prices$_{c,t}$	-	-0.022	(-1.33)	-0.023	(-1.02)	**-0.025****	(-2.61)
M2 multiplier$_{c,t}$	+	-0.014	(-1.10)	-0.031	(-1.38)	0.008	(0.85)
Domestic credit/GDP$_{c,t}$	+	0.040	(2.23)	0.048	(1.91)	**-0.058****	(-3.26)
Domestic real interest rate$_{c,t}$	+	-0.009	(-0.20)	**-0.138***	(-2.16)	**-0.011**	(-0.47)
Commercial bank deposits$_{c,t}$	-	0.027	(0.88)	**-0.105****	(-3.43)	**0.052***	(2.35)
Lending/deposit interest rate$_{c,t}$	+	-0.006	(-1.79)	**-0.012****	(-2.53)	-0.003	(-1.63)
Excess real M1 balances$_{c,t}$	+	**0.000***	(2.48)	**0.000***	(2.27)	0.000	(1.95)
G7 output$_{t}$	-	-0.016	(-1.11)	-0.032	(-1.72)	0.007	(0.87)
US interest rate$_{t}$	+	0.351	(1.42)	0.504	(0.88)	0.232	(0.96)
Oil prices$_{t}$	+	0.017	(1.27)	0.029	(1.52)	0.003	(0.31)
Year$_{t}$		**0.001***	(-2.33)	0.000	(-0.26)	**-0.002** *	(-3.81)
Country Fixed Effects		**Yes**		**Yes**		**Yes**	
Standard Error clustering on year		**Yes**		**Yes**		**Yes**	
# of country years		331		351		371	

$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of currency crises. See Table 1 and Table 2 for crisis onset years. The model is estimated with all data pooled across countries. We include country fixed effects and correct the standard errors for cross-sectional correlation by clustering on year. Refer to Table 6 and Table 8 for definitions of the leading indicator variables and accounting signals. †, *, ** denote significance at the 95%, 97% and 99% levels.

Table 12: Crisis prediction of individual accounting signals for high vs. low accounting quality sub-sample from 1981 to 2005
[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 1), 0 otherwise.

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

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

		sign	(1)		(2)		(3)		(4)	
			$\frac{dF}{d\bar{X}}$	(z-stat)	$\frac{dF}{d\bar{X}}$	(z-stat)	$\frac{dF}{d\bar{X}}$	(z-stat)	$\frac{dF}{d\bar{X}}$	(z-stat)
Table 8's Realized accounting signals (= $\hat{\beta}^i$)										
Accruals$_{c,t}$	β^1_H	-	0.215	(0.84)						
	β^1_L	-	**-0.043**[*]	(-2.17)						
Profitability$_{c,t}$	β^2_H	-			-0.213	(-0.86)				
	β^2_L	-			**0.145**[†]	(2.04)				
Volatility$_{c,t}$	β^3_H	+					-0.994	(-1.15)		
	β^3_L	+					0.013	(0.03)		
CFO$_{c,t}$	β^4_H	-							-0.069	(-0.45)
	β^4_L	-							**0.053**[†]	(1.74)
Leading indicators from Table 6 and time trend			**Included**		**Included**		**Included**		**Included**	
Country Fixed Effects			**Yes**		**Yes**		**Yes**		**Yes**	
Standard Error clustering on year			**Yes**		**Yes**		**Yes**		**Yes**	

$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of currency crises. See Table 1 and Table 2 for crisis onset years. The model is estimated with all data pooled across countries. We include country fixed effects and correct the standard errors for cross-sectional correlation by clustering on year. Refer to Table 6 and Table 8 for the definitions of the accounting signals and leading indicator variables. CFO is cash flow from operations and is computed as $CFO_{c,t} = Median_f\left(\frac{CFO_{c,f,t}}{TotalAssets_{c,f,t-1}}\right)$

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

Table 13: 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 5, Panel A.)

Panel A: <u>Crises and law enforcement from 1981 to 2005</u>

			Predictive [-n =-1]		*Concurrent* [-n =0]	
		Sign	$\frac{dF}{d\overline{X}}$	(z-stat)	$\frac{dF}{d\overline{X}}$	(z-stat)
Table 8's Realized accounting signals (= $\hat{\beta}^i$)						
Accruals$_{c,t}$	β_H^1	-	-0.079	(-0.78)	0.064	(1.45)
	β_L^1	-	**-0.006****	(-2.84)	**0.010****	(3.97)
Profitability$_{c,t}$	β_H^2	-	0.122	(0.68)	**-1.555**†	(-1.79)
	β_L^2	-	**0.144****	(3.10)	**-0.105****	(-3.39)
Volatility$_{c,t}$	β_H^3	+	**-1.297**†	(-1.70)	**0.708**†	(1.80)
	β_L^3	+	-0.219	(-0.66)	**0.663****	(3.94)
F- test of β_H^is [Prob > χ^2]:			χ^2(3) = 4.45 [0.216]		**χ^2(3) = 14.81 [0.002]**	
F- test of β_L^is [Prob > χ^2]:			**χ^2(3) = 20.04 [<0.001]**		**χ^2(3) = 26.53 [<0.001]**	
Leading indicators from Table 6 and time trend			**Yes**		**Yes**	
Country Fixed Effects			**Yes**		**Yes**	
Standard Error clustering on year			**Yes**		**Yes**	
# country years			351		371	

$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of a crises. See Table 1 and Table 2 for crisis onset years. The model is estimated with all data pooled across countries. We include country fixed effects and correct the standard errors for cross-sectional correlation by clustering on year. Refer to Table 6 and Table 8 for the definitions of the accounting signals and leading indicator variables. †, *, ** denote significance at the 95%, 97% and 99% levels.

Table 13: Institutional Factors and Endogenous Policy Effects (Continued)
[c=country; t=year, P=non-overlapping period over which accounting quality is measured]

Model:

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

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

Panel B: Crises prediction for the time-varying (across 5-year non-overlapping periods) high vs. low accounting quality sub-samples from 1981 to 2005

			Predictive [-n =-2]		*Predictive* [-n =-1]		*Concurrent* [-n =0]	
		Sign	$\frac{dF}{d\overline{X}}$	(z-stat)	$\frac{dF}{d\overline{X}}$	(z-stat)	$\frac{dF}{d\overline{X}}$	(z-stat)
Table 8's Realized accounting signals (= $\hat{\beta}^i$)								
Accruals$_{c,t}$	β_H^1	-	0.1666	(1.80)	-0.1875	(-1.11)	0.0282	(0.28)
	β_L^1	-	-0.0005	(-0.14)	-0.0068	(-0.98)	**0.0145****	(2.59)
Profitability$_{c,t}$	β_H^2	-	-0.2211	(-1.53)	0.0464	(0.19)	**-0.2541***	(-1.72)
	β_L^2	-	-0.0352	(-0.74)	**0.2302***	(2.50)	**-0.4234***	(-2.53)
Volatility$_{c,t}$	β_H^3	+	0.3371	(0.79)	0.2760	(0.35)	**1.3298****	(3.02)
	β_L^3	+	0.2533	(0.96)	**-1.1279**†	(-1.85)	**0.6725***	(2.18)
F- test of β_H^i s [Prob > χ^2]**:**			χ^2(3) = 3.62 [0.305]		χ^2(3) = 1.59 [0.661]		**χ^2(3) = 10.28 [0.016]**	
F- test of β_L^i s [Prob > χ^2]**:**			χ^2(3) = 1.13 [0.769]		**χ^2(3) = 6.41 [0.093]**		**χ^2(3) = 9.93 [0.019]**	
Leading indicators from Table 6 and time trend			**Yes**		**Yes**		**Yes**	
Country Fixed Effects			**Yes**		**Yes**		**Yes**	
Standard Error clustering on year			**Yes**		**Yes**		**Yes**	
# country years			349		369		389	

$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of a crises. See Table 1 and Table 2 for crisis onset years. The model is estimated with all data pooled across countries. We include country fixed effects and correct the standard errors for cross-sectional correlation by clustering on year. Refer to Table 6 and Table 8 for definitions of the accounting signals and leading indicator variables. †, *, ** denote significance at 95%, 97% and 99% levels.

Table 14: 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 quality accounting information , 0 otherwise

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

Panel A: Crises prediction of 32 banking crises from 1981 to 2005

			Predictive [-n =-2]		*Predictive* [-n =-1]		*Concurrent* [-n =0]	
		Sign	$\frac{dF}{d\overline{X}}$	(z-stat)	$\frac{dF}{d\overline{X}}$	(z-stat)	$\frac{dF}{d\overline{X}}$	(z-stat)
Table 8's Realized accounting signals (= $\hat{\beta}^i$)								
Accruals$_{c,t}$	β_H^1	-	0.060	(0.53)	0.256	(1.19)	0.070	(0.58)
	β_L^1	-	-0.014	(-0.85)	**-0.038****	(-3.87)	**0.555****	(3.59)
Profitability$_{c,t}$	β_H^2	-	0.015	(0.14)	-0.348	(-1.36)	**-0.438***	(-2.44)
	β_L^2	-	-0.025	(-0.62)	**0.126****	(3.01)	**-0.070***	(-2.46)
Volatility$_{c,t}$	β_H^3	+	0.186	(0.26)	-0.788	(-1.32)	0.263	(0.62)
	β_L^3	+	0.221	(1.12)	-0.272	(-0.90)	**0.557****	(3.20)
F- test of β_H^i s [Prob > χ^2]**:**			χ^2 (3) = 0.38 [0.94]		χ^2 (3) = 4.39 [0.22]		**χ^2 (3) = 9.60 [0.02]**	
F- test of β_L^i s [Prob > χ^2]**:**			χ^2 (3) = 2.86 [0.41]		**χ^2 (3) = 17.36 [<0.001]**		**χ^2 (3) = 19.65 [<0.001]**	
Leading indicators from Table 6 and time trend			**Yes**		**Yes**		**Yes**	
Country Fixed Effects			**Yes**		**Yes**		**Yes**	
Standard Error clustering on year			**Yes**		**Yes**		**Yes**	
# country years			331		351		371	

$D\_BCrisis_{c,t}$ is an indicator variable indicating the onset of banking crises (Financial excess and Sovereign debt in Table1). See Table 1 and Table 2 for crisis onset years. The model is estimated with all data pooled across countries. We include country fixed effects and correct the standard errors for cross-sectional correlation by clustering on year. Refer to Table 6 and Table 8 for definitions of the accounting signals and leading indicator variables. †, *, ** denote significance at 95%, 97% and 99% levels.

Table 14: 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 quality accounting information, 0 otherwise.

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

Panel B: Crises prediction from 1981 to 2005 with alternative classification for Italy and Thailand

			Predictive [-n =-2]		*Predictive* [-n =-1]		*Concurrent* [-n =0]	
		Sign	$\frac{dF}{d\overline{X}}$	(z-stat)	$\frac{dF}{d\overline{X}}$	(z-stat)	$\frac{dF}{d\overline{X}}$	(z-stat)
Table 8's Realized accounting signals (= $\hat{\beta}^i$)								
Accruals$_{c,t}$	β_H^1	-	-0.012	(-0.10)	0.079	(0.44)	0.102	(0.96)
	β_L^1	-	-0.015	(-1.05)	**-0.045****	(-4.13)	**0.038****	(3.54)
Profitability$_{c,t}$	β_H^2	-	-0.135	(-1.19)	**-0.393**†	(-1.74)	**-0.491****	(-3.22)
	β_L^2	-	-0.022	(-0.64)	**0.152****	(3.34)	**-0.069***	(-2.44)
Volatility$_{c,t}$	β_H^3	+	0.228	(0.51)	-0.070	(-0.13)	0.491	(1.17)
	β_L^3	+	0.233	(1.09)	**-0.557**†	(-1.77)	**0.553****	(4.11)
F- test of β_H^i s [Prob > χ^2]**:**			χ^2 (3) = 3.95 [0.267]		χ^2 (3) = 5.46 [0.140]		**χ^2 (3) = 14.52 [0.002]**	
F- test of β_L^i s [Prob > χ^2]**:**			χ^2 (3) = 3.95 [0.267]		**χ^2 (3) = 27.74 [<0.001]**		**χ^2 (3) = 21.67 [0.001]**	
Leading indicators from Table 6 and time trend			**Yes**		**Yes**		**Yes**	
Country Fixed Effects			**Yes**		**Yes**		**Yes**	
Standard Error clustering on year			**Yes**		**Yes**		**Yes**	
# country years			331		351		371	

$D\_Crisis_{c,t}$ is an indicator variable indicating the onset of a crises. See Table 1 and Table 2 for crisis onset years. The model is estimated with all data pooled across countries. We include country fixed effects and correct the standard errors for cross-sectional correlation by clustering on year. Refer to Table 6 and Table 8 for definitions of the accounting signals and leading indicator variables. †, *, ** denote significance at 95%, 97% and 99% levels

Figure 1: Timeline of recent crises models

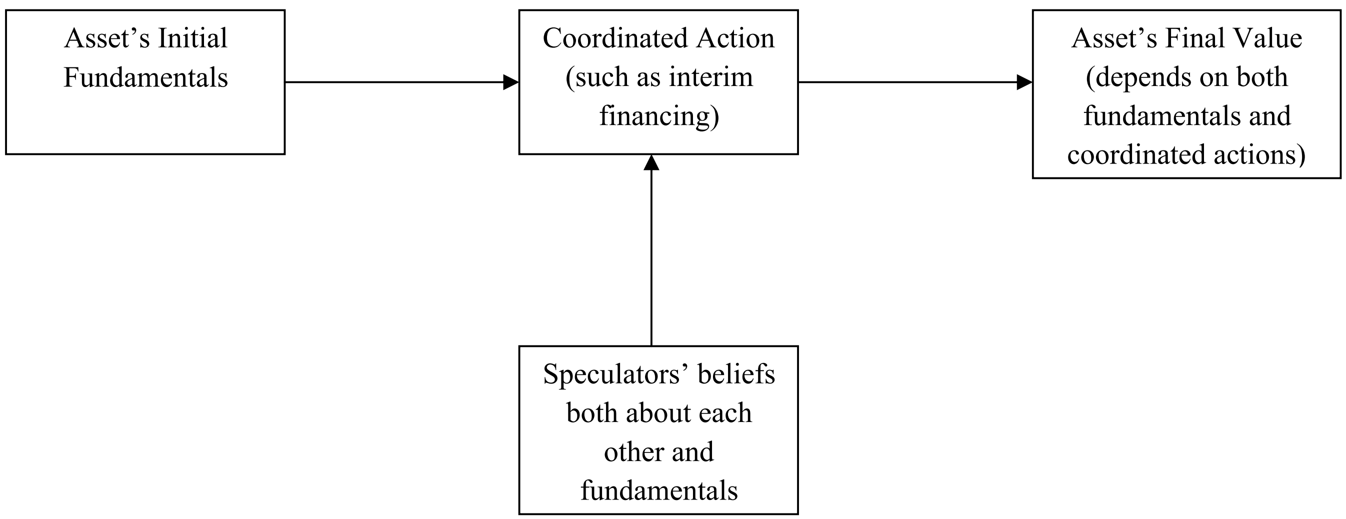
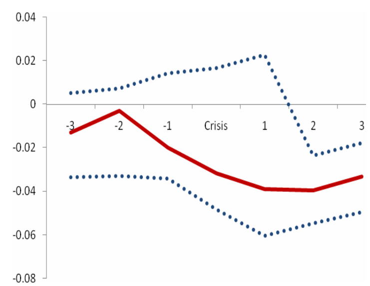


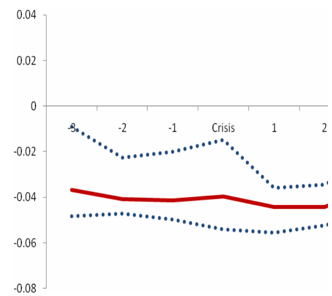
Figure 2: Realized accounting signals before and after 39 crises episodes from 1981 to 2005

[c=country; t=year]

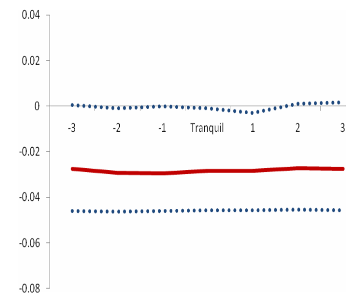
Panel A: Accruals$_{c,t}$



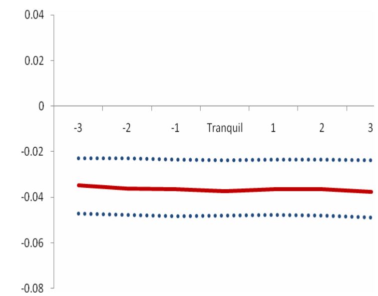
Crisis years
-Countries with low information quality



Crisis years
-Countries with high information quality

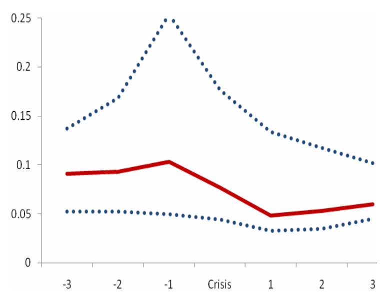


Tranquil years
-Countries with low information quality

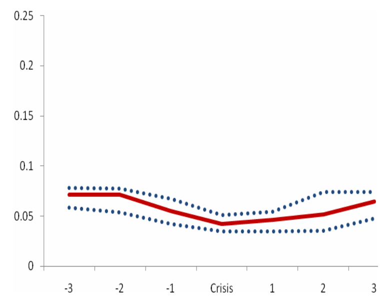


Tranquil years
-Countries with high information quality

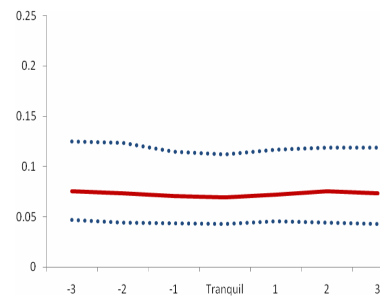
Panel B: Profitability$_{c,t}$



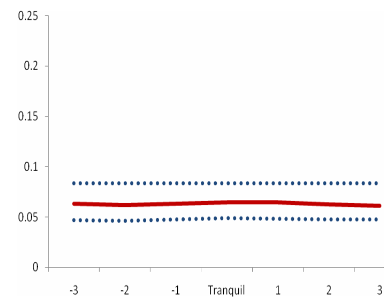
Crisis years
- Countries with low information quality



Crisis years
-Countries with high information quality



Tranquil years
-Countries with low information quality

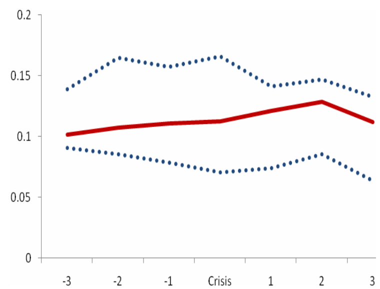


Tranquil years
-Countries with high information quality

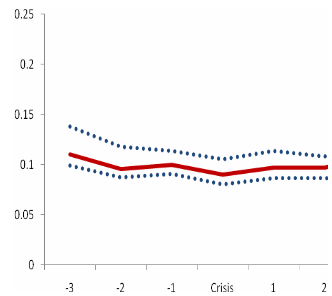
Figure 2: Realized accounting signals before and after 39 crises episodes of 21 countries (Continued)

[c=country; t=year]

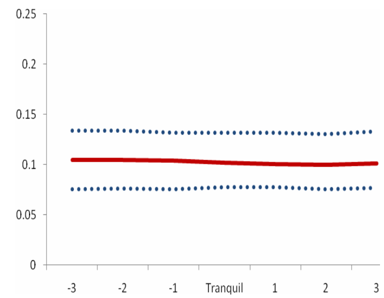
Panel C: Volatility$_{c,t}$



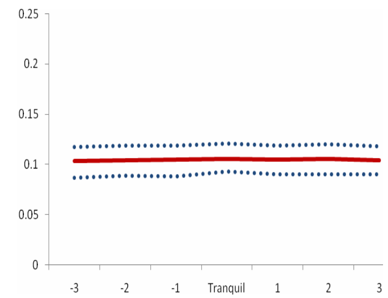
Crisis years
-Countries with low information quality



Crisis years
-Countries with high information quality



Tranquil years
-Countries with low information quality



Tranquil years
-Countries with high information quality

See Table 1 and Table 2 for crises onset year and Table 8 for definitions of each accounting signal. Low and high accounting information quality countries are defined in Table 4. ‘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.