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Growth Collapses[1]

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Abstract: We study episodes where economic growth decelerates to negative rates. While the majority of these episodes are of short duration, a substantial fraction last for a longer period of time than can be explained as the result of business-cycle dynamics. The duration, depth and associated output loss of these episodes differs dramatically across regions. We investigate the factors associated with the entry of countries into these episodes as well as their duration. We find that while countries fall into crises for multiple reasons, including wars, export collapses, sudden stops and political transitions, most of these variables do not help predict the duration of crises episodes. In contrast, we find that a measure of the density of a country's export product space is significantly associated with lower crisis duration. We also find that unconditional and conditional hazard rates are decreasing in time, a fact that is consistent with either strong shocks to fundamentals or with models of poverty traps.

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1. Introduction

According to the 2006 *World Development Indicators*, no developed economy attained its peak per capita GDP before 2000. By contrast, 53 percent (61 out of 116) of developing economies saw their best times before that year. Of these, more than 40% (26) saw their best peak GDP before 1980. This number is even higher in particular regions of the developing world: in Latin America, 56% (15/27) economies saw peak output before 2000, while in sub-Saharan Africa the corresponding figure is 74% (25/34).

Recessions in the developing world are much deeper and longer than in the developed world. Figure 1 presents histograms of peak-trough ratios and duration of output contractions for developing and developed countries.[2] The comparisons are striking. 87.8% of recessions in the developed world have peak/trough ratios less than 5% of peak GDP. The remaining 12.2% have peak-trough ratios between 5 and 15% of peak GDP. For developing countries, the corresponding figures are 48.3% and 25.4%, with the remaining 26.3% having contractions where the peak-trough ratio exceeds 15% of peak GDP. In terms of duration, 88.9% of recessions in developed economies last less than 4 years. In the developing world, the corresponding figure is 63.6%.

The phenomenon of deep and prolonged recessions constitutes a challenge to macroeconomic theory. At the very least, it suggest that a vision of economic fluctuations as trends around a stable and growing level of potential GDP is problematic for understanding growth in the developing world. It also suggests that understanding the causes of low frequency fluctuations may be key for accounting for differences in development performance.

Guillermo Calvo has been one of the pioneers of the study of deep recessions in developing economies. In a series of seminal papers,[3] Calvo and his coauthors have strived to achieve a complete characterization of a specific type of economic contraction: output collapses that occur in the context of sudden stops in capital flows in developing economies that are highly integrated into world financial markets. Among their most important conclusions are that these output collapses tend to be followed by rapid recoveries of output despite the lack of recoveries of either domestic or foreign credit.

Our paper goes one step further and attempts to tackle a broader question. Instead of focusing on particular types of output collapses, we ask what can be learned from studying the distribution of economic contractions across countries and over time. In other words, we investigate whether it is possible to go beyond the aggregate characterization shown in Figure 1 to a deeper understanding of the causes behind prolonged recessions. In this paper we will study both the events that coincide with the onset of crises and the determinants of the duration of crises. Among our main results, we find that a number of events – wars, export collapses, sudden stops in capital flows and high levels of inflation – coincide with the onset of crises. However, we find that the duration of crises is particularly difficult to predict. Aside from region and time-specific effects, we find that a measure of the density of a country's product space, which may capture the flexibility of the economy to adapt to external shocks, is an important predictor of crisis recovery. We also find that both conditional and unconditional hazard

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[2] The formal definition of these concepts will be introduced in section 3.

[3] Calvo, Izquierdo and Mejía (2004), Calvo, Izquierdo and Koo-Lung(2005), Calvo (2005), Calvo, Izquierdo, and Talvi (2006).

rates are declining in time, suggesting that countries have a harder time exiting crises the longer that they spend in them.

Economic Crises

Francis Galton once criticized his colleague statisticians because they "limited their inquiries to averages, and do not seem to revel in more comprehensive views." (1889, p. 62). Sir Galton could have been just as well been referring to modern growth empirics. Ever since Barro's (1989) seminal contribution, empirical work on economic growth has to a great extent been concerned with explaining differences in average growth among countries. Despite Pritchett's (1998) call to think closely about the "hills, plateaus, mountains and plains" characterizing the growth data, very little work had been carried out until recently attempting to explain the substantial differences in patterns taken by growth series with similar first and second moments.[4]

Among the notable exceptions is the work of Calvo, Izquierdo and Mejía (2004), Calvo, Izquierdo and Loo-Kung (2005) and Calvo, Izquierdo and Talvi (2006). These authors have concentrated in studying the characteristics of output collapses that are associated with "sudden stops" in capital flows in emerging market economies. They have found that some of these sudden stops – particularly those associated with systemic international capital market turmoil – are followed by rapid recoveries arising from the rapid reconstruction of credit markets.

By concentrating on a very specific form of output collapses, Calvo and his coauthors have been able to take advantages of the similarities between comparable episodes. Other works in this literature have taken a more general approach, attempting to exploit the differences arising in broader samples. Ben-David and Papell (1998), for example, study episodes of growth slowdowns, defined by statistically significant breaks in the time series trends, and find differences between the magnitude and timing of these slowdowns among developed and developing countries. Pritchett (2000), in contrast, studied declines of at least 2 percentage points in trend growth rate – without distinguishing between significant or insignificant trends. Neither of these papers make serious attempts to understand the causes behind the onset or magnitude of growth slowdowns.

Two recent papers have made a more direct attempt to understand the dynamics of growth decelerations. Cerra and Sexena (2005) study the long-run implications of economic recoveries. In essence, they show that after economic contractions GDP growth does not typically return to trend growth. Additionally, they show that the incidence of crises is an important reason for unconditional divergence in the postwar growth data.[5] Reddy and Miniou (2006) study "real income stagnations", which they define as long and sustained periods of negative growth. Their definition is perhaps the one that comes closest to ours in the literature.[6] They find that countries that suffered

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[4] An extensive literature has developed attempting to explain growth volatility. See Ramey and Ramey (1995), Imbs (2002) and Aghion and Banerjee (2004) for discussions.

[5] The definition of recoveries used by Cerran and Saxena differed from ours in that they deine a trough as any year having in which growth changes from negative to positive. In practice, this implies that they underestimate the length of "double dip" and "n-tuple dip" crises.

[6] Reddy and Minoiu also use the first "turning point" after a crisis to date the end of the crisis, being subject to the same objection made above regarding the Cerra and Saxena technique.

spells of real income stagnation were more likely to be poor, located in Latin America or Africa, undergoing armed conflict and with high dependence on primary exports.[7] The main characteristics of these and other studies dealing with long-run economic contractions are summarized in Table 1.

One common feature of all these studies is the lack of any explicit method to deal with unfinished episodes of contraction. Of the nine papers listed in Table 1, four take an explicit decision to omit or truncate the contraction episodes; two additional ones (Ben-David and Pappell, 1998 and Pritchett, 2000) adopt a methodology that is incapable of handling these breaks, thus also dropping them in practice. A sixth paper (Calvo, Izquierdo and Talvi, 2006) adopts a very restrictive definition of crises – drops in aggregate output that occur in the context of systemic capital market turmoil – with the result that recoveries are very rapid and in their main sample there are no episodes of unfinished crises. This decision comes at a cost: there is no obvious reason from growth theory why one should concentrate on aggregate instead of per capita or per worker output. The two remaining papers analyze the change in growth rates among two predetermined periods and thus do not have to deal directly with this issue. In those papers, the issue of unfinished crises is avoided at the cost choosing an arbitrary cut-off date to calculate changes in growth rates.

The issue of dealing with unfinished episodes is important because a substantial number of crisis episodes have generally not finished by the end of the period for which continuous data is available. Using the definition of crisis that we will adopt in this paper (periods of continuous negative average growth), we find that 16.07% of the events defined as crises are censored. While this number may not seem large, what is problematic is that it is asymmetrically composed of long crises episodes. Only 4.95% (18/363) of crisis episodes lasting less than 5 years are censored, while 78.5% (22/28) of those lasting more than 24 years are censored. To take a simple example of how this can affect even the most basic conclusions of research, if we had decided to drop the censored observations we would have calculated the mean duration of contractions to be 3.96 years. If we include the censored observations, we find that the mean duration is 6.05 years. Even this estimate is surely an underestimate of the expected duration of a crisis, because the real duration of censored episodes is unobserved. If we were to fit the simplest possible duration function – with an exponentially distributed hazard rate – to this data, we would estimate an expected duration of 7.21 years. Inferences about the behavior of countries during crises will thus end up being automatically biased to reflect the performance of economies that are more successful at dealing with crises.

The key contribution of this paper is to analyze the determinants of the duration of economic contractions using econometric methods that are designed explicitly to deal with censored observations. These methods, broadly grouped under the labels "duration analysis" and "survival analysis" have gained increasing prominence in modern economics primarily through their application in microeconometric settings.[8] Their key defining characteristic is the joint use of information on duration of censored and uncensored episodes in derivation of the likelihood function. Despite their obvious

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[7] Hausmann, Pritchett and Rodrik (2005), in contrast, have looked at episodes during which growth accelerates. Their main finding is that accelerations are not well explained by macroeconomic policy reforms.

[8] Two useful recent surveys are Hosmer and Lemershow (1999) and Box-Steffensmeier and Jones (2004)

appeal for the study of many macroeconomic phenomena, their application in macroeconomic analysis has been limited. The largest proportion of papers that use duration analysis in macroeconomic settings study duration dependence of business cycles in developed countries. (Mills, 2001; Bodman, 1998; Di Venuto and Layton, 2005; Diebold and Rudebusch, 1990; Mudambi and Taylor, 1991; Sichel 1991). Applications to developing countries are scant. One recent exception is Mora and Siotis (2005), who estimated a conditional duration model of recessions in a sample of 22 emerging markets. Their specification is limited by the small size of their sample and the fact that they consider only external factors.

The rest of the paper is organized as follows. Section 2 discusses our definition of crises and our data set. Section 3 takes a first look at the summary statistics of crises. Section 4 examines the factors that coincide with the onset of crises, while section 5 discusses the results of regressions to account for the duration of crises. Section 6 concludes.

2. Defining the event

For the purposes of the analysis in this paper, we define a crisis as an interval that starts with a contraction of output per worker and ends when the value immediately preceding the decline is attained again. Thus a crisis that occurs between times t and $t+j$ has by definition average growth rate equal to zero during that period and negative during the period between t and any $t+j-e$ for any $e<j$. A crisis cannot start if the country is already in crisis. In other words, if $y_t<y_{t-1}$ a crisis will start only if either (i) there is no $y_{t-j}>y_{t-1}$, or, (ii) if there is a $y_{t-j}>y_{t-1}$, there is a $y_{t-p}>y_{t-j}$ with $p<j$.

This definition is illustrated in Figure 2. This definition has several advantages for our object of study. First, it covers a selected group of growth decelerations. In particular, it covers growth decelerations where growth goes from being positive (as it must be before reaching a peak) to being negative between t and any $t+j-e$. But it doesn't cover *all* growth decelerations. In particular, we wanted to exclude the growth decelerations that one would find natural in neoclassical growth models, such as those generated by convergence to the steady state. Our definition allows us to specialize to episodes where growth decelerates to a negative rate.

Our interest in negative growth rates is related to our specialization to duration analysis. Although episodes of negative growth are a standard area of interest of macroeconomics, sustained episodes of negative growth are much harder to explain. Although it is certainly possible to account for negative growth using a neoclassical model, this requires that the economy suffer strong and sustained deteriorations in its fundamentals that are sufficiently strong to offset the effects of technical progress for periods of one or more decades. Thus long, sustained episodes of negative growth are only consistent with very large adverse changes in fundamentals or dynamics in which those fundamentals are continuously deteriorating.

In order to calculate our crisis indicator, we used GDP per person of working age – henceforth GDPW - in constant local currency units from World Bank (2006). We use working age population because it is the best widely available proxy for the size of labor force, which most closely matches the concept of labor input in growth theory. We use local currency units because we are not interested in comparisons of levels among countries and differences in PPP adjustment factors across times can be arbitrary and have unintended consequences (see Minoiu and Reddy, 2006).

Our crisis definition immediately suggests several measures of crisis intensity that we calculate and use in the rest of the analysis. These are:

(i) Duration: the number of years elapsed between the beginning and the end of the crisis.

(ii) Peak-trough ratio: the ratio between the value of GDPW immediately preceding the crisis and the lowest value it attains during the crisis, expressed as a ratio of the peak value.

(iii) Integral measure of years of lost output: this is the sum of all the gaps between peak and the GDP for each year of the crisis. More precisely, it is the integral above the output series and below a horizontal line drawn at the peak output, expressed as a fraction of peak output.

3. Collapses big and small

We start out by examining the general characteristics of crises and how they vary across regions. These summary statistics are presented in Table 2. The first striking fact that we observe is that there is a wide dispersion of crisis characteristics in the world sample. The majority of crises observed do indeed appear to be of the typical business cycle type: the median crisis duration is just two years, while the median peak-trough ration and integral measure of years lost are respectively 4% and 6% of pre-crisis GDP. These median values, however, come from a highly skewed distribution. The average duration of crises, at 6.05 years, is three times as high as the median duration, while the mean-to median ratios of the peak-trough ratio and product-years lost are respectively 2.6 and 15.9.

High dispersion of crises characteristics is also a feature of inter-regional variations. Although all regions appear to be hit by some short-lived recessions, long-lived recessions are much more prevalent in the developing world. Thus, while the mean duration of a recession in industrialized countries is only 2.52 years, in Latin America it is 6.88 years in Latin America and in Central and Eastern Europe it is 9.74 years. The median peak-to-trough ratio of a crisis, for example is six times as large in Africa and 29 times as large in Central and Eastern Europe as in the industrialized world.

These differences are striking, but what is even more striking is that they almost surely *underestimate* the magnitude of the differences in crisis duration both around the world median and across regions. The reason is a simple one, and will form the foundation for much of our analysis. Shorter crises are much less likely to be censored than long crises. Almost by definition, the longer a crisis is the more likely that it will be interrupted, either by the end of the sample or by an interruption in data reporting. Therefore we can never actually observe the complete duration of very long crises. It is hard to exaggerate the magnitude of this difference. In our sample, only 19 out of 387 crises (4.9%) that last less than five years are censored, while 67 of 148 crises (45.3%) lasting more than five years are censored. Take the example of

Venezuela, whose GDP per working age population was 39.4% lower in 2004 than in its peak in 1970. Even if Venezuela were to experience extremely high growth after 2004, its crisis is likely to last considerably longer than 34 years.

One possible mechanism for dealing with this problem would be to drop crises that have not ended from the sample. As discussed in our review of the literature, this is the standard choice in much of the literature that has dealt with this problem. However, it is a highly inefficient solution, as it entails throwing out a very high proportion of the crises that are most interesting for our purposes: those that are very long. Therefore we adopt the alternative solution in this paper, which is to use the estimation techniques of duration analysis (also called survival analysis in the biometric literature) which are explicitly designed to deal with censored duration times.

The essence of duration analysis is to explicitly consider unfinished crises as arising out of the same distribution as finished crises. All countries are assumed to be characterized by a (possibly time-dependent) probability of leaving a crisis at any moment of time given that they are still in the crisis state. That probability – called the *hazard rate* is affected by country-specific characteristics which can be summarized by a vector of independent variables that may include country-specific effects. The behavior over time of this rate is very interesting. If the hazard rate is increasing over time, it means that as time elapses, the probability that a country will recover to its pre-crisis GDPW level increases. This is the type of behavior that one would expect if the pre-crisis level of GDPW was an equilibrium out of which the economy was perturbed by a temporary shock. However, if we see that the longer an economy spends in a crisis the harder it is for it to get out of it – as would be implied by a declining hazard rate – this would suggest either that the economy suffered strong blows to its fundamentals – so that its steady state level of GDPW shifted downwards – or that it jumped to an inferior equilibrium.

Furthermore, in the presence of positive technological change, one would always expect that, if enough time has elapsed after the initial shock, an economy would return to its pre-crisis level of GDP even if it initially suffered an adverse shock to its fundamentals. The reason is that for a given level of fundamentals, the probability that an economy hits any level of GDPW with positive technological change must tend to 1 as time increases. Declining hazard rates over the very long run would thus be consistent not only with an initial adverse shock but rather with continuously deteriorating fundamentals as may occur because of the political system's endogenous reaction to the adverse shock.

A first intuitive way to summarize the information in our data set regarding the characteristics of crises is thus to plot the unconditional hazard functions. These hazard rate estimates are plotted in Figure 1. They are derived as smoothed kernel density estimates of the Nelson-Aalen cumulative hazard function and track the probability of exiting a crisis conditional on being in the set of countries that have not exited the crisis when *t* periods have elapsed since falling into it.

The remarkable result that emerges from Figure 3 is that hazard rates, both within regions and for the world as a whole, do not appear to be increasing. Rather, they are either flat or decreasing over time. Two distinct patterns appear to emerge. The first one is that of industrialized countries and East Asia and the Pacific, which have two humps. Within these groups, countries either get out of their crises quickly, or get out later. Even the second group, however, tend to get out of crises much earlier than those of many other regions. The rest of the regions – including the pooled world sample - have hazard rates which are generally flat or decreasing, although confidence intervals obviously become wider as one reaches higher durations. Hazard rates also tend to be much lower in non-industrial countries, reaffirming the conclusion that crises are much more likely to be of the short duration business cycle type in industrialized countries than in underdeveloped regions.

The confidence intervals drawn around the unconditional region-level hazard rates in Figure 1 are quite wide. This is simply a reflection of the fact that very long crises are sufficiently rare within each region so as to make it difficult for us to precisely estimate the hazard rate. In Figure 4 we show the result of pooling the sample of non-industrial countries and comparing it with that of industrial countries. The hazard rate for developing countries is clearly declining up at least to a period of 30 years since entry into crisis. It is also considerably lower than that of industrial countries. Whereas most industrial countries have a probability higher than 20% of leaving the crisis during each of the first few years in it, for developing countries that probability stays below 10%.

The fact that substantial interregional differences across survival functions exist can be tested systematically through several standard tests for equality of survivor functions. These tests are reported in Table 3. Column 1 shows the result of testing the null hypothesis that all regions have the same survival function. It is thus the statistical counterpart of Figure 3. Column 2 tests the null that industrial countries have the same hazard function as developing countries, forming the statistical counterpart of the comparison on Figure 2. Lastly, column 3 evaluates the null hypothesis that all groups of non-industrial countries have the same survival function. All three homogeneity hypotheses are easily rejected. The data thus indicates that there is substantial inter-regional heterogeneity in the recovery from adverse shocks.

The logical question that this analysis leads us to regards the source of these differences across regions. Is it a reflection of the fact that different regions are hot by different types of crises? Or is rather a consequence of the fact that regions differ in their capacity to react to adverse shocks? In order to answer these questions, we must understand what factors drive countries to fall into crises and what factors determine the duration of crises once you have entered into them.[9] These are the questions that we tackle in the next two sections.

4. Why do countries fall into crises?

We approach the study of the determinants of crisis occurrence through the estimation of random effects probit regressions on a panel of countries. The basic idea of this specification is to allow us to understand the potential relative triggers of a

[9] Analytically, it is important to distinguish between the causes that lead countries to fall into crises and the reasons that their recovery speeds differ. Although there could be similarities between both processes – and crises generated by large shocks may be more difficult to get out of – they may well be very different. For example, in a related analysis, Collier and Hoeffler (2004) have found that the causes that lead countries to fall into civil wars are very different from those that determine the duration of those wars.

country falling into a crisis. In essence, we investigate whether and how different possible instigators correlate with the incidence of the crisis. We look at a battery of potential causes of crises, ranging from the "usual suspects" – natural disasters, wars, sudden stops, and export collapses – to other less conventional factors.

Any exercise of this type may be subject to several types of specification bias. Simultaneity bias is one – though not necessarily the most important one – of them. Others include omitted variables, inadequacy of the linear specification, and incorrect assumptions about the error covariance structure. In the case of some potential explanatory variables – such as natural disasters - endogeneity may be less of a problem than some of these other biases. We do not make an effort to search for appropriate instruments for all of our explanatory variables because we view our exercise as a primarily exploratory attempt to investigate what factors *coincide* with the onset of crises, rather than to test tightly specified causal hypotheses. If our exercise is successful, it would help build a *typology* of crises according to the key factors that occur at the same time as the crisis.

Our baseline specification will thus be:

$$P_{it} = \Phi\left(\beta' X_{it} + \eta_i\right) \qquad (9)$$

Where P_{it} is the probability that country i falls into a crisis at time t, X_{it} is a kx1 vector of conditioning variables (generally including a constant term), η_i is a country-specific effect, β is the kx1 vector of parameters to be estimated and $\Phi(.)$ is the standard normal distribution. The random effects probit specification models η_i as following a $N(0,\sigma^2)$ distribution.

Note also that our event of interest is whether a country enters a crisis or not. According to our definition of crises, a country is obviously a candidate for entering a crisis only if it is not already in one. Therefore we exclude from the sample all country-years in which the country is in the midst of a crisis. This decision is based on the fact that these country-years contain no relevant information about the process of entering into crises.

Neoclassical growth theory views output collapses as arising out of adverse shocks that either move the steady state level of income or alter the per capita stock of physical and human capital. It is thus logical to start by looking at significant disruptions of an economy's productive framework that may either affect its capacity to convert inputs into outputs or directly affect its stock of accumulated productive assets. Several candidates come to mind. Perhaps the first two are natural disasters and wars. These tend to constitute large, generally exogenous shocks that generate significant disruptions to a society's capacity to produce. They will also commonly directly affect the capital stock. The speed of some post-war recoveries is indeed a commonly cited observation in defense of the conditional convergence hypothesis. Two other potential candidates are export collapses and sudden stops in capital flows. The latter has been well developed in the literature, particularly through the pioneering work of Guillermo Calvo. Export collapses, while much less studied, tend to crop up in the analysis of many episodes of collapse (see Hausmann and Rodríguez, 2006).

Our data for natural disasters is drawn from the International Disaster Database maintained by the Office of US Foreign Disaster Assistance (OFDA) and the Center for Research on the Epidemiology of Disasters (CRED), which has information on the physical and human damage caused by 14,877 natural disasters that occurred between 1960 and 2006. We define a substantial occurrence of natural disasters if either (i) the number of people affected by all natural disasters occurring in a given year is greater than 1% of the population, or (ii) the number of people killed by all natural disasters occurring in a given year is greater than 0,1% of the population. Our proxy for natural disasters will be an indicator variable that will be 1 if there was a substantial occurrence of natural disasters in *t, t-1* or *t-2*.

Regarding the occurrence of wars, we draw our data from Kristian Gleditsch's (2004) *Expanded War Data Set* which covers all inter and intrastate wars between and within independent states since 1816. We build an indicator variable that equals one if the country was involved in an interstate or civil war in *t, t-1, t-2* or *t-3*. We also build separate dummies for civil and interstate wars respectively. Declines in exports are measured using data on merchandise exports from World Bank (2006). We use the log difference in exports between *t* and *t-5* as our indicator of an export performance.

For the purposes of defining sudden stops in capital flows, we closely follow the definition of Calvo, Izquierdo and Mejía (2004). According to their definition, a *sudden stop* is a year-on-year decline in capital inflows containing at least one year in which the decline exceeded two standard deviations from its sample mean. The sudden stop starts when the fall exceeds one standard deviation from the sample mean and ends when it is above one standard deviation. Our measure of private capital flows comes from World Bank (2006) and consists in private debt and non-debt flows. Note that our measure differs from two other measures used by Calvo, Izquierdo and coauthors in some of their work. In particular, it differs from the *Systemic Sudden Stops* (Calvo, Izquierdo, and Talvi, 2006) measure which is given by the episodes of sudden stops that coincide with increases in the aggregate EMBI spread. Aside from the difficulty in obtaining a measure of capital market turmoil relevant for non-emerging market economies, our key reason for using the broader category is our interest in the broader phenomenon of declines in capital flows. Our measure also differs from the definition found in Calvo et al. (2006) that combines falls in capital flows with output collapses. The rationale for this is quite simple: we are attempting to understand the capacity of sudden stops to *predict* output collapses, whereas most of the work of Calvo and coauthors is concentrated on understanding the dynamics of output collapses that coincide with a decline in capital flows.[10] We shall discuss the sensitivity of our results to alternative measures of sudden stops below.

Aside from these natural candidates, we try a number of additional explanatory variables that may be associated with the onset of crises. We measure the level of a country's democracy by its score on the Polity index (Gurr et al., 2004). We also measure political transitions by the change over time in its polity index. We use a measure of the log of 1 plus the inflation rate as a proxy for macroeconomic instability. We also attempt to control for a set of additional potential explanatory variables such as years of primary, secondary and total schooling (from Barro and Lee, 2004), the rule of law (ICRG, 1999), life expectancy at birth, percent of the

[10] Another difference with our definition is that we use annual data, while Calvo and coauthors, who study the short-run dynamics of sudden stops, use monthly data.

population that is urban and number of telephone mainlines per capita (from World Bank, 2006). All of our estimates include region and decade dummies.

One additional variable of interest that we will study is the measure of the value-weighted density of the product space elaborated by Hausmann and Klinger (2006). This measure is designed to capture the sophistication of the goods that an economy could produce with its productive assets. It is built as a weighted average of the sophistication of all potential export goods, where the weights are given by the distance between these goods and the economy's present export basket. The measure of distance in the product space is calculated based on the frequency with which particular good-pairs are exported by the same country, while the measure of sophistication is given by the average income of the countries that export that good, which we call *PRODY*$_{jt}$, as originally proposed by Hausmann, Hwang and Rodrik (2005). More formally, let the proximity between two goods in the product space be given by the minimum of the conditional probabilities of exporting each one of those goods given that you are exporting the other one:

$$\varphi_{ijt} = \min\{p(x_{it} \mid x_{jt}), p(x_{jt} \mid x_{it})\} \tag{10}$$

where $p(x_{it} \mid x_{jt})$ is the probability that you have revealed comparative advantage in good i at time t given that you have revealed comparative advantage in good j at time t. Let x_{cjt} be an indicator variable that takes the value 1 if country c has a revealed comparative advantage greater than 1 in good j at time t and 0 otherwise. Then we can define a measure of the "option value" of a country's unexploited export opportunities as:

$$open\_forest_{ct} = \sum_i \sum_j \frac{\varphi_{ijt}}{\sum_i \varphi_{ijt}} (1 - x_{cjt}) x_{cit} PRODY_{jt} \tag{11}$$

open_forest thus captures the flexibility of an economy's export basket, in that it measures the value of the goods that it could be producing with the inputs that it currently devotes to its export production. *open_forest* is particularly appropriate for thinking about an economy's capacity to react to adverse export shocks. To fix ideas, suppose that an economy's exports of good i were to disappear overnight. This could happen, for example, as a result of the exhaustion of a natural resource, of the emergence of a new lower-cost supplier in international markets or as a result of the invention of a cheap substitute for that good. We know that this economy must shift resources into a new export sector. φ_{ijt} can be interpreted as our best guess of the probability that that country will shift resources into good j, and $\varphi_{ijt}(1 - x_{cjt})$ can be seen as our best guess of the probability that it will export a good j that it is not already exporting. $\varphi_{ijt}(1 - x_{cjt})PRODY_{jt}$ is the expected value (measured in terms of the sophistication of exports) from exporting that good, making *open_forest* the weighted average of that expected value over all goods that the economy currently exports. In other words, *open_forest* reflects the expected value of an economy's next best export basket if it moved out of its current basket of exports.

To the extent that many crises are precipitated by declines in an economy's key export sectors, we expect *open_forest* to be a good indicator of the economy's flexibility in moving to a new export basket in the face of those declines. We thus expect *open_forest* to be a significant determinant of the duration of crises. *Open_forest* may also be important in stopping crises before they materialize. The reason is that export declines in traditional sectors may occur at the same time as new sectors are moving in to absorb unused resources. The higher the productivity of the newer export sectors, the less likely that the initial export collapse will cause the economy to enter a period of negative growth. In order to test these hypotheses, we will include *open_forest* in the probit regressions of this section as well as the duration regressions of the next section.

Our baseline results are presented in Table 4. Column 1 presents the result of regressing the probability of falling into crisis on the log of real GDP per working age population and a set of continent and time dummies. The GDP term is negative, indicating that richer countries are less prone to economic crises. However, the coefficient is borderline significant (p=.075) in contrast to many of the continent dummies, which are highly significant. In column (2) we add the log change in real merchandise exports. Its coefficient is strongly significant with the expected negative sign, while the coefficient on GDP becomes insignificant. The next column adds wars, natural disasters and sudden stops. While wars and sudden stops are highly significant with the expected sign, the result on natural disasters is surprising. The coefficient is not even remotely close to statistical significance (p=.764) and furthermore has the wrong sign. This is particularly surprising since natural disasters are the one variable in the data set about whose endogeneity we are less worried. In order to confirm that its coefficient is not being distorted by the endogeneity of other explanatory variables, we reestimated the equation dropping all variables except for natural disasters, time and continent dummies.[11] This exercise (not shown in the table) still gives an insignificant, though positive, coefficient (p=.47). Column 4 adds three additional variables: inflation, political transitions, *open_forest* and the level of democracy. The first two are strongly significant, *open_forest* is borderline significant, and democracy is clearly insignificant. All have the expected sign: inflation and political change are associated with greater propensity towards crises, while *open_forest* and democracy are associated with lower crisis prevalence. Wars now drop to borderline insignificance. This appears to be more the result of reduced sample size: if we reestimate the equation of column (3) for the same number of observations as in column 4, we get a very similar coefficient as when we include the additional variables (.449, t-stat=1.7). Finally, in the last column, we drop the clearly insignificant natural disasters and democracy variables. The coefficient signs and significance tests are unaffected, with the exception of wars, which goes from borderline insignificance to borderline significance. Declines in merchandise exports, sudden stops, high inflation episodes and political transitions are strong predictors of the onset of crises, while wars and open forests have a weaker but still significant association with crisis onset.

What can we say about the global significance of these variables? There are various ways to address this question. One is by noting that the addition of the

[11] Because of the exogeneity of natural disasters, the estimate of this regression is a consistent estimate of the reduced form total effect of natural disasters on the probability of falling into crises. This is because if natural disasters are truly exogenous, any correlation between it and other potential explanatory variables must reflect causation from the former to the latter.

explanatory variables drives down the significance of the continent and time dummies. All continent dummies except for South and Central Asia are significant and positive in column (1). Since the omitted category is industrialized countries, this indicates a higher unconditional probability of falling into crises for non-industrialized countries. By column (5), those effects have disappeared – indeed, the South and Central Asia dummy has turned significantly *negative*. It thus appears that our explanatory variables account for the differences between the developing and developed worlds in the incidence of crises.[12]

A second way to address this question is by looking at some goodness of fit indicators. These are reported in the bottom two rows of Table 4. The result of this exercise is not as encouraging. The first column shows the percentage of crises that are accurately predicted by our models. Even our most satisfactory model of column 5 only predicts 6.11 % of crises adequately. This is also reflected in the pseudo-R^2 measure of McFadden (1974), which is given by:

$$R^2{}_p = 1 - \frac{\Gamma_u}{\Gamma_0} \qquad (12)$$

with Γ_u and Γ_0 respectively denoting the log-likelihood of the unrestricted model and the model with only a constant. $R^2{}_p$ hovers between .023 and .079, indicating a poor capacity of the model to predict the onset of crises.

The goodness of fit results, however, should be interpreted with caution (see Wooldridge, pp. 465-6 for a discussion). The *timing* of a crisis is likely to be a very uncertain event, and it would indeed be surprising if we were able to correctly predict it a very high number of times. Indeed, the flip side of our incapacity to adequately predict the onset of crises is that the models are very good at predicting the non-occurrence of crises. Since the entry into a crisis is a rare event (compared to staying out of the crisis), almost all prediction rules are naturally going to be very conservative. An alternative way to ask how good our model's predictive capacity is is by looking at the times that the model correctly predicts a crisis (that is, when the estimated probability exceeds 0.5) as a percentage of the total number of times it predicts a crisis. In our baseline model of column (5), this percentage is a much more reasonable 52.4%.

The economic significance of our coefficient estimates can best be interpreted by studying the marginal effect of changes in the explanatory variables on the estimated probability of a crisis. These effects are displayed in Table 5, which also shows the effect of a one standard deviation increase in each of the explanatory variables. By this metric, the largest single effect comes from inflation: a one standard deviation increase in our inflation indicator increases the probability of a crisis by 7.98%. The effect of manufacturing exports, however, is also substantial: a one standard deviation decline in the rate of growth of manufacturing exports causes an increase of 5.47 percentage points in the probability of a crisis. For indicator variables, a more natural metric is to think of the effect of the variable changing from one to zero. By this metric, a war is by far the most destructive single event, causing

[12] This result is not an artifice of simple reduction either: running the regression of column (1) for the simple in column (4) gives significantly positive continent dummies for Latin America, Africa and the MENA region.

an increase in the probability of a crisis of 13.36 percentage points. By contrast, a political transition costs 9.48 percentage points and a sudden stop costs 5.54 percentage points increase in the probability of crises.

In section 4 we showed that there were substantial interregional differences - particularly between industrial and developing regions – in the characteristics of crises. In Tables 5 and 6 we look at this issue more systematically by splitting the sample between developing economies and industrial economies. We indeed find important differences in the results in the two sub-samples. Export declines, inflation, political transitions and open forests retain their effect in the sub-sample of developing countries. Curiously, wars and sudden stops lose some significance in this exercise – but in the case of wars the effect again seems to come from the restriction of the sample. By contrast, exports, political transitions and open forests appear not to be relevant in industrial countries. Inflation retains strong significance, with a much higher absolute coefficient estimate which reflects the much smaller ranges of variation of this variable in developed economies. Wars – which in the case of developed economies are almost always interstate conflicts such as the Gulf War – are also insignificant in this sub-sample.

While these differences are certainly interesting, the evidence that the data generating process is fundamentally different across regions is not all that strong. The developed country sample is smaller so it is logical to expect broader confidence intervals. All of the variables that we found to be significant in the broader sample have the same sign in both sub-samples and in most cases – with the notable exception of the inflation rate – the coefficient estimates are strikingly similar. The similarity of these coefficient estimates suggests that the key reason for the difference in the frequency of crises across regions comes not so much from differences in the way in which these crises are generated but rather from differences in the distribution of the underlying determinants.

Another potential source of structural differences may come from the fact that very lengthy or costly crises may be generated by different causes from those that generate shorter crises Table 7 examines this hypothesis by splitting the sample between short and long crises. We split these in two dimensions: crises duration of five years (columns 1 and 2) and crisis duration of more than 75% of the last pre-crisis year's GDP (columns 3 and 4). This exercise provides some very interesting results. Regardless of whether one uses the duration or the lost output splits, one is struck by the similarity of the coefficient estimates for exports, wars, sudden stops, inflation and political transitions. There are, however, striking differences between the effects of open forests and the Latin America dummy across subsamples. These suggest that open forests and some unobserved characteristics of Latin America may not be so much a predictor of crises onset (for which its significance in the whole sample is at best weak) but rather of crisis duration. The bulk of the estimates, however, suggest that one can get thrown into short and long crises for very similar reasons. The substantial difference, therefore, may be in how one recovers from these crises.

The next three tables include a series of additional robustness tests for our baseline specification. Table 8 studies the effect of adopting alternative definitions of capital flows. One problem with the capital flows window measure (which is discussed at length in Calvo et al. (2004)) is that the decline in capital flows may be caused by an increase in export capacity. In column 1 we use a measure which combines the decline in capital stock with the condition that imports must also have declined. The coefficient on this measure, while positive, is not significantly so. This may be because the combination of these two criteria is very stringent. In column 2 we relax it by defining a sudden stop to be *any* decline in capital flows that coincides with an import decline. This measure appears to be very poorly correlated with the onset of crises (p=.523). Column 3 uses a definition based on total (as opposed to just private) capital flows, which we measure as the sum of the trade balance and the decline in reserves, combined with a decline in imports. This measure does somewhat better, attaining borderline significance (p=.091). If we make this last definition somewhat more stringent by requiring declines in total capital flows to exceed 3% of GDP and import declines to exceed 5% of initial import values, significance increases slightly (p=.051). We have carried out a substantial number of additional tests with many alternative definitions, and find that, while it is certainly possible to come up with definitions of sudden stops that are significantly associated with the onset of crisis, such a conclusion is not robust to changes in the way in which we define the event. An additional conclusion that can be drawn out of Table 8 is that the incidence of our significant explanatory variables does not change with different choices of sudden stop indicators. Changes in exports, political transitions, high inflation, wars and *open_forest* maintain their patterns of association with the onset of crises in all alternative specifications, while the coefficient on *open_forest* varies substantially across specifications.

To this moment we have assumed that the country-specific effect η_i in equation (1) is uncorrelated with the explanatory variables, giving rise to the random effects probit specification. This assumption is of course questionable, but relaxing it is problematic because of the well-known incidental parameters problem. An alternative is to use the *fixed effects logit* specification, where the coefficient vector β can be estimated with $\sqrt{n}$-consistency. This specification, however, is not without its cost. As discussed in detail by Wooldridge (2004, p. 492) it requires the conditional independence of the dependent variable given the explanatory variables. In our context, this implies assuming that the probability of a crisis is independent of the number of crises that have occurred in the past.

Table 9 shows the results of this specification. There are important changes as well as similarities with the random effects probit specification. The key similarity lies in the coefficients for merchandise exports and the capital-flow window definition of sudden stops (which retain strong statistical significance), and wars (which are significant in the broader sample and borderline significant once one adds additional controls. The effects of inflation and political transitions are preserved, although with higher p-values than under the probit specification. The striking difference, however, lies in the changes in the log of per capita GDP, which is now strongly negative and significant – indicating that richer countries have less propensity to experience crises – and *open_forest*, which is now positively – though insignificantly- related to the onset of crises.

Our last battery of robustness tests is displayed in Table 10, where we study the effect of adding additional potential explanatory variables to the probit specification. In this table, we include average years of primary, secondary and total schooling as measures of human capital's effect on propensity to fall in crises. Neither of these measures is significant (columns 1-3). Neither is a measure of institutions (the rule of law), of physical infrastructure (telephone mainlines per capita), of urbanization, or of life expectancy.

We can summarize the results of this section as follows. A number of variables appear to be associated with the onset of crises. In terms of robustness, the variable that comes out on top is the log change in merchandise exports, which has come out as significant in all the specifications in which it is included with the exception of the subsample of developed countries. In terms of economic significance, a one-standard deviation increase in inflation appears to be much more damaging than a similar increment in any other variable. Most specifications coincide in a significant effect of the capital-flows window definition of sudden stops as well as political transitions on the probability of a crisis occurring. The effects of wars, initial income and residual continent or time dummies are much more variable to specification. Particularly, while *open_forest* comes out as a significant predictor in some specifications its coefficient tends to be weak and its sign is reversed in the conditional logit specification.

5. How do countries get out of crises?

In this section we analyze the determinants of crisis duration. Most existing contributions in the literature do not deal with the problem of censoring that naturally arises in the analysis of the duration of contractionary episodes. As discussed in the introduction, the standard solution taken in the papers in the literature that address this issue is to drop or truncate those observations. Either solution is inappropriate. Dropping the observations biases the sample towards short duration episodes, while truncating them inadequately represents crises as having shorter durations than they have.

The results presented in this section deal with the problem of censored observations by adopting a duration analysis approach. Specifically, if we have n countries with $t_1 \ldots t_n$ crises duration, we concentrate on finding the estimate of the probability density function $f(t)$ with associated survival time $S(t)$ that maximizes the likelihood function:

$$L = \prod_i f(t_i)^{\delta_i} S(t_i)^{1-\delta_i} \qquad (13)$$

where δ_i is an indicator variable that takes the value 0 if the peak per worker GDP has not been reached by the last observation in the sample. Broadly speaking, there are two approaches in the literature to estimating (5). One is to specify a parametric functional form for $f(t)$ and to estimate the parameters of that form. The second one is to use a non-parametric approach to estimation of $f(t)$. The latter is commonly associated with estimation of the Cox proportional hazards model. Although the nonparametric approach is more flexible, it can lead to more imprecise estimates of the hazard function than a correctly specified parametric form. We will present versions of both models in this section.

Another key issue has to do with how to handle country level heterogeneity in this framework. For analogous reasons to those of panel data estimation with binary dependent variables, fixed effects estimators are not consistent for duration models (Andersen, Klein and Zhang, 1999). Two alternative approaches exist. One is to assume that countries have differing propensities to experiencing crises. These propensities – called *frailties*– are analogous to the random effects of panel data models. An alternative approach is to use the fact that in the presence of repeated events, the Cox proportional hazards model, parameter estimates converge to a value that can be interpreted meaningfully, but the estimated covariance matrix is inappropriate for hypothesis testing (Lin and Wei, 1989, Struthers and Kalbfleisch, 1984). *Variance-corrected* models modify the covariance matrix of the Cox model in order to be able to carry out appropriate tests.

Before proceeding to the statistical tests, we start out by looking at the characteristics of crises according to the events associated with them. The summary statistics associated with these different types of crises, as well as their associated unconditional hazard functions, are shown respectively in Table 11 and Figure 5. If different types of crises correspond to different types of shocks, then we would expect that the patterns of recoveries associated with different crises would also differ. In particular, this would be true if we believe that some crises triggers have non-permanent effects on the determinants of steady state income. As we have discussed previously, in this case hazard functions should be clearly increasing. This is precisely the feature that Calvo and coauthors have argued characterizes some sudden stops of capital flows. Similarly, to the extent that the *level* of democracy appears to be irrelevant for crisis onset, political regime transitions should have a transitory effect on the level of income: they should create havoc during the time of the transition, but after they occur one would not expect there to be a permanent effect.

What is interesting about Figure 3 is that it shows that declining hazard rates appear to characterize many different types of crises. Indeed, all splits appear to be characterized by the same overall pattern: a short initial period of increasing hazard rates, and a much longer period of strongly declining rates. The relative magnitudes are also similar across characteristics. The one striking difference is *open_forest*. Countries with very high open forests have crises of much lower duration and consequently display a higher probability of exiting the crisis at any one moment. Recall that of the variables that we have used to carry out the splits, *open_forest* (along with natural disasters) was not robustly associated with the onset of crises. This figure suggests that it may be directly associated with crisis duration

This hypothesis can be tested more systematically by looking at the effect of these factors in duration regressions. We do this in the rest of the section. We start out by looking at the most common parametric duration model, which is the Weibull distribution. Essentially, we estimate the hazard rate for country *i* as a function of a baseline hazard and the covariates:

$$h_i\,(t \mid X) = h_{0t} v_i \exp(\beta X) \qquad (14)$$

where $h_{0t}=pt^{p-1}$. The parameter p characterizes the shape of the Weibull distribution, with $p<1$ corresponding to a decreasing hazard function. The ν_i are the country-level frailty terms which are assumed to follow a Gamma distribution. Estimates are displayed in Table 12.

Colum (1) shows the effect of simply running a regression of duration on log of per worker GDP. The hazard specification is presented, so that a positive coefficient implies that increasing the variable in question leads to a higher probability of leaving the crisis. The first surprising result is that income by itself does not appear to have an effect on duration. Rather, as column (2) shows, it is other region-specific characteristics, aside from income differences, that are driving the key differences between crises duration across countries. In column (3) we introduce *open_forest* into the regression. We find that it is very strongly correlated with crisis duration. A one-standard deviation increase in *open_forest* implies an increase of 86.8% in the probability of leaving the crisis (exp(.557)*sd(*open_forest)*). Column (4) introduces controls for the level of democracy and sudden stops. The democracy control can be taken as a naïve test of Rodrik's (1997) hypothesis that countries with better institutions for conflict management have an easier time adjusting to negative shocks. Framed this way, the hypothesis does not get strong support in our data: the effect of democracy is not significantly related with the probability of leaving the crisis, though the coefficient estimate is positive. However, Rodrik's hypothesis is somewhat more nuanced – see the additional results in Table 13. Calvo and coauthors have suggested that the recoveries associated with some types of sudden stops may be associated with faster recoveries. The estimates in column (4) show that this is not the case for collapses in capital flows generally speaking.

The next columns of Table 12 introduce other potential determinants of crisis duration. The first logical candidates for this are the different determinants that we used in the probit analysis of the previous sections. If *how* you fall into the crisis matters for post-crisis behavior, then we should expect crisis durations to differ significantly for crises that were initiated by different events. We have already seen in Figure 3 that there is little indication of this being the case in unconditional hazard rates by group, but we now verify this within the framework of the parametric Weibull specification. In effect, the estimates in column 4 show that different factors that were significantly associated with the onset of crises are not associated with crisis duration. This is the case of wars, inflation, and political transitions – as well as of natural disasters, which did not prove significant in the probit analyses.

One may expect that both open forests and democracy may make the society more capable of responding to particular types of shocks rather than uniformly increasing the probability of exiting all types of crises. *Open_forest*, for example, should have a positive effect on an economy's capacity to adapt to export collapses, while democracy may make societies more capable of adapting to external shocks such as sudden stops. The last two columns of Table 12 evaluate these hypotheses, and find little support. Neither an interaction between open forests and changes in exports nor the interaction term between democracy and the two external shock indicators (changes in exports and sudden stops) are significant. This may of course reflect the relative coarseness of these multiplicative terms to capture complex nonlinearities.

Table 13 tests a battery of additional possible correlates of crisis duration. These include an alternative indicator of non-systemic sudden stops in column 1 (the same one in column 4 of Table 8, which captures large decreases in total capital flows that coincide with substantial import declines), an indicator of trade policy in (column 2), a measure of human capital (total years of schooling – column 3), a measure of financial deepening (liquid liabilities in GDP, column 4), a general measure of openness (trade/GDP ratio, column 5), and a measure of social modernization (life expectancy, column 6). We also try two measures of the idea that institutions may have an effect on crisis duration. The first one introduces an interaction between our indicator of democracy and the terms of trade shock, thus capturing the idea that democracies are better able to adapt to adverse terms of trade shocks. This effect is insignificant. Another specification uses the interaction between the Gini index and one minus a scaled democracy variable. This is closest to Rodrik's (1997) precise specification. It gets tentative support in the data, with a borderline significant negative coefficient. In one last specification we include the regressors of columns 1-7 together (column 9). None of these terms are significant, while the *open_forest* indicator remains strongly significant.

In the next table we adopt as our baseline specification a regression including time and region dummies, *open_forest* and the log of initial GDP, and we evaluate whether the strength of the coefficient on open forests is at all dependent on the parametric specification of the hazard function. We use four alternative parameterizations: the exponential, the Gompertz, the log-logistic and the log-normal. In reading Table 14, it is important to bear in mind that the last two specifications do not accept a hazard rate interpretation and are thus reported in accelerated-failure time modes, so that the dependent variable is the duration of the crisis. Thus a positive effect in the hazard representation is analogous to a negative effect in the accelerated-failure time representation. That is, in fact, what we find: open forest has a positive, significant effect in the hazard rate representations and a negative, significant effect in the failure time representations. The result that *open_forest* decreases the time necessary to escape a crisis is robust to the parameterization adopted.

Figure 6 displays the conditional hazard rates that emerge from the five parametric specifications that we have estimated (with the controls of Table 13). These are the estimated hazard rates for an observation with the expected random effect ν_i =1. In contrast to the unconditional hazard rates of Figure 2-5, they are not affected by the changing composition of the population and reflect the estimated probability that a particular country will exit the crisis. For comparison purposes, we also report the unconditional hazard rate of a Cox model without shared frailties. Except for the exponential form, which is constrained to be constant, all our estimates of the hazard rates again give declining functions in time.

In the next two tables we turn towards estimation in the framework of a variance-corrected Cox proportional hazards model. In particular, we specialize to the conditional risk-set model of Prentice, Williams, and Peterson (1981, hence forth PWP). The basic idea of the PWP model is to stratify by event number, so that the conditional risk set for experiencing crisis *k* is the number of countries that have experienced *k-1* crises in the past. The model is stratified by number of crises in order to obtain the corrected variance estimates. Tables 15 and 16 repeat the estimation exercises of Tables 12 and 13 using the PWP specification. The results are broadly similar. *Open_forest* is almost always significant, with the only exception being the last column of Table 15, which has a very small number of observations (here it has a borderline p value of .116 with 60 observations). None of the other potential covariates emerge as significant.

As we have argued above, declining hazard rates may indicate the presence of multiple equilibria – with negative shocks leading countries to shift to inferior equilibria – or adverse permanent productivity shocks. A valid question to ask at this stage is whether there is evidence that this phenomenon is due to changes in fundamentals. One way to tackle this question is by asking whether the "triggers" which appear to have sent the economy into the crisis have returned to pre-crisis levels at the time periods during which we are observing declining hazard rates. Figure 5 presents one such exercise. In it we calculate the average paths for countries with crisis duration greater than or equal to ten years for five of the variables that we have found to be significantly associated with the onset of crises: wars, exports, capital flows, inflation, and political transitions. The evidence is mixed, and thus interesting. By the 10th year of the crisis, the fraction of countries in the midst of a war has returned to pre-crisis levels. The number of countries undergoing political transitions has also declined, though not to pre-crises levels. Capital flows have actually *gone up* in comparison to their pre-crises levels. This is interesting not only because it suggests that the decline in capital flows is not the cause for declining hazard rates but also because it is suggestive that the marginal product of capital in equilibrium has not gone down. On the other hand, we find that the average inflation levels has gone up while the share of exports in GDP has gone down during the crisis. Both of these are consistent with the hypothesis that the economy enters some type of economic tailspin both in its export capacity and in the quality of its macroeconomic policy during prolonged crises.

There are several ways in which we can interpret the strength of the *open_forest* variable. At a general level, *open_forest* is an indicator of an economy's flexibility. It measures the possibilities that an economy has of moving to the production of other goods, weighted by the sophistication of these goods. It thus combines a hypothesis that flexibility is important with the hypothesis that countries develop by producing rich-country goods, as suggested by Hausmann and Rodrik (2003). In Table 17 we use a measure of open forests that does not weigh goods by their *PRODY*, thus implicitly assigning goods equal value. The absolute value of the coefficient and its significance are very similar to those obtained by *open_forest*. When both variables are introduced in the regression (not shown) neither of them is significant at 5%, suggesting that they are too collinear to distinguish between the alternative hypotheses they represent. To the extent that pure density is a simpler explanation, Occam's razor would suggest sticking with it. Column 2 looks at other potential measures of flexibility. One is a Herfindahl index of export concentration. The idea is that countries with more concentrated export sectors will have a harder time reacting to adverse shocks as it will be more difficult for other industries to expand. It is possible that *open_forest* is simply capturing the effects of having a diversified export structure. The result shown in columns 2-4 are surprising: export concentration seems to be associated with a *higher*, not lower, probability of exiting the crisis. A similar fact appears to be true about the log of population, another measure of the size of the economy and of its possible flexibility (column 3). In any case, the coefficient on open forests is robust to the inclusion of these alternative indicators of flexibility, as well as of land area (column 4). In column 5 we present an additional robustness test, which is to control for the magnitude of the initial crisis by introducing measures of the magnitude of the initial shock. In particular, we control for initial and lagged GDP growth, initial and lagged export growth and the initial terms of trade shock. Since some of these measures will be correlated with the dependent variable by definition, we do not use this set of controls more broadly in this paper. *Open_forest* is robust to the inclusion of these controls.

6. Concluding Comments

This paper has analyzed episodes during which economic growth decelerates to negative rates in a sample of 180 developing and developed economies. We identify 535 episodes of output contractions. The distribution of these episodes is highly skewed: while the median duration is 2 years, more than a quarter of them last more than 7 years and roughly 14% last more at least 15 years. Developing countries are much more likely to experience prolonged contractions than industrial countries.

We have studied the factors that coincide with the onset of these crises. In terms of statistical significance, we find that the change in exports is the variable most strongly associated with the probability of suffering a crisis – at least in developing countries. A one standard deviation decrease in the growth rate of merchandise exports implies a 5.47 percentage point increase in the probability of a crisis. In terms of economic significance, a one-standard deviation increase in inflation appears to be slightly more damaging, though the coefficient is somewhat less precisely estimated. Wars, sudden stops and political transitions also tend to coincide with the onset of crises.

The duration of crisis is somewhat more difficult to predict. Surprisingly, the variables that we find to be significantly associated with the probability of a crisis occurring do not appear to be related to crisis duration. The main variable that we find to be robustly associated with crisis duration – aside from continent and decade effects - is a measure of the density-weighted value of a country's alternative export basket suggested by Hausmann and Klinger (2006). We take this measure to be an indicator of the flexibility of an economy's productive apparatus to adapt to external shocks. This intuition is confirmed by case studies of collapse episodes in developing countries that emphasize the role that poor performance in the non-traditional export sector plays in deepening growth collapses[13].

Our results leave open several avenues for future analysis. On the one hand, it would be desirable to refine the predictive capacity of the duration model. One possible avenue for doing this would be to adopt a model of time-varying covariates. We have shied away from that alternative because we find it easier to believe in the exogeneity of changes that took place before the onset of the crisis than we would in changes that occur during the crisis. Another avenue is to explore the possible channels through which *open_forest* is correlated with crisis duration. Our first tentative attempts to get at this issue failed to find a significant interaction between export collapses and *open_forest*. Several explanations could account for this fact. *Open_forest* may be a more general measure of the economy's adaptability to several types of productivity shocks, a multiplicative interaction may be too coarse to capture generalized nonlinearities, or *open_forest* may be proxying for some unmeasured country specific effect. Further research could help discern among these potential competing hypotheses.

[13] See, for example, Hausmann and Rodríguez (2006) on Venezuela and Auty (2001) on Saudi Arabia.

We also find that decreasing conditional and unconditional hazard rates are a pervasive characteristic of our estimation. While this is not necessarily surprising for unconditional rates, as it may be a consequence of the changing composition of the population, it is definitely counterintuitive when these hazard rates are conditioned on estimated country frailties and covariates. Even though decreasing hazard rates can be accounted for within a neoclassical model as a result of substantial, permanent shocks to output, the depth and duration of some recessions in this sample appear hard to explain. To take just one example, there is widespread agreement among many observers of the Bolivian economy that its institutional, political and macroeconomic framework was more solid at the beginning of this century than in the mid-seventies.[14] However, GDP per working age person was 14.9% lower in 2004 than it was in 1978 despite the fact that world productivity surely increased during this period. Further investigation of the characteristics of recessions may allow us to find ways to disentangle between alternative interpretations of this type of phenomenon.

Table 1: Summary of existing literature

Paper	Time series	Countries	Data-base	Freq	Breaks	GDP used	Taxonomy	Crisis that did not end
Ben-David and Papell (1998)	1955-1993 / 1950-1993	74	PENN 5.5	Annual	One or zero breaks, depending on significance.	Real per capita PPP	Slowdown (if Δ^{-} growth but growth > 0). Meltdown (if growth < 0)	Method does not apply; in practice they are ommitted
Rodrik (1999)	1960-1989	110	WDI	15 years	One and the same for all countries in 1975	Real per capita growth, PPP	Collapse	Not pertinent
Ali and Elbadewi (1999)	1965-1996	62 Developing countries	WDI	10 - 21 years	One and the same for all countries (1965-1974) - (1975-1996)	Real per capita GDP growth	Collapse	Not pertinent
Pritchett (2000)	1960 - 1992 (some until 1985)	111	PENN 5.6	-	One or zero breaks, depending on significance.	Real GDP, PPP 1985	Plateau, Mountain, Hill, Plains	Method does not apply; in practice they are ommitted
Cerra and Sexena (2005)	1960-2001/ 1960-2000 Unbalanced panel	192 / 154	WDI / PENN 6.1	Annual	Not breaks, but events of crisis	Real GDP growth	Recessions	Omit
Cespedes and de Gregorio 2005	Data 1980-2004 (But Y trend built since 1960)	71	WDI/IMF WEO	Annual	Not breaks, but events of crisis	Real GDP	Product contraction episode or recession	Omit
Reddy and Minoiu 2006	1960-2001	119	WDI	Annual	Not breaks, but events of crisis	Moving average (1/3{(t-1)+(t)+ (t+1)} of Per capita GDP, constant LCU	Real Income stagnation.	Truncate
Blyde , Daude and Fernandez Arias (2006)	1960-2003	71	PENN 5.6	Annual	Not breaks, but events of crisis	Real PPP	Collapse	Omit
Calvo, Izquierdo and Talvi (2006)	1980-2003	31 (Emerging markets covered by EMBI)	WDI/ IMF WEO	Annual	Not breaks, but events of crisis	Real GDP	Episode of Output Contraction	No cases in main sample

[14] See Sachs and Morales (1992), Jimenez Zamora, Candia, and Mercado Lora (2005).

Table 2: Summary Statistics of Crises by Region								
	Number of Observations	Mean	Standard Deviation	Minimum	25th percentile	Median	75th percentile	Maximum
Duration of Crisis								
Africa	151	8.14	10.09	1	1	3	13	43
Asia	42	4.79	5.71	1	1	2	7	24
Central and Eastern Europe	34	9.74	6.38	1	1	12.5	15	19
East Asia and Pacific	46	3.78	4.23	1	1	2	5	20
Industrialized	90	2.52	2.88	1	1	2	3	19
Latin America and Caribbean	109	6.88	8.92	1	1	3	7	34
Middle East and North Africa	63	5.13	7.56	1	1	2	4	27
Total	535	6.05	8.02	1	1	2	7	43
Peak to Through								
Africa	151	0.13	0.16	0.00	0.02	0.06	0.19	0.95
Asia	42	0.08	0.12	0.00	0.02	0.04	0.08	0.52
Central and Eastern Europe	34	0.29	0.24	0.00	0.06	0.29	0.45	0.77
East Asia and Pacific	46	0.08	0.08	0.00	0.02	0.05	0.11	0.35
Industrialized	90	0.02	0.03	0.00	0.01	0.01	0.03	0.13
Latin America and Caribbean	109	0.10	0.13	0.00	0.01	0.05	0.15	0.62
Middle East and North Africa	63	0.12	0.20	0.00	0.01	0.04	0.12	0.91
Total	535	0.11	0.16	0.00	0.01	0.04	0.13	0.95
Product-Years lost (Integral)								
Africa	151	1.42	2.94	0.00	0.02	0.10	0.93	16.40
Asia	42	0.51	1.16	0.00	0.02	0.07	0.26	5.51
Central and Eastern Europe	34	2.71	2.81	0.00	0.06	2.15	4.03	9.79
East Asia and Pacific	46	0.31	0.54	0.00	0.02	0.07	0.26	2.46
Industrialized	90	0.07	0.16	0.00	0.01	0.02	0.06	1.16
Latin America and Caribbean	109	1.05	2.35	0.00	0.01	0.06	0.62	13.78
Middle East and North Africa	63	1.16	2.88	0.00	0.01	0.06	0.20	12.73
Total	535	1.00	2.36	0.00	0.01	0.06	0.44	16.40

Table 3: Tests for Equality of Survivor Functions			
	All regions	Industrialized vs. Non-Industrialized	Only Non-Industrialized
Log-rank	54.49***	33.78***	21.31***
Cox	38.24***	20.78***	16.72***
Wilcoxon	37.36***	20.05***	17.84***
Tarone-Ware	45.38***	25.95***	19.82***
Peto-Peto	43.76***	24.58***	19.72***

Table 4: Random Effects Probit Regressions, All Countries
Dependent Variable: Probability of Falling into a Crisis

	(1)	(2)	(3)	(4)	(5)
Log GDP per Working Age Person	**-0.017**	-0.007	-0.001	0.000	-0.004
	(1.78)*	(0.66)	(0.06)	(0.01)	(0.17)
Latin America	**0.473**	**0.495**	**0.551**	0.215	0.223
	(5.2)***	(5.34)***	(4.82)***	(1.15)	(1.26)
Africa	**0.565**	**0.488**	**0.430**	-0.001	0.024
	(6.69)***	(5.72)***	(4.17)***	(0.01)	(0.1)
South and Central Asia	0.157	0.041	-0.109	**-0.385**	**-0.381**
	(1.41)	(0.35)	(0.74)	(1.83)*	(1.98)**
East Asia and Pacific	**0.188**	0.160	0.162	-0.169	-0.175
	(1.71)*	(1.47)	(1.17)	(0.82)	(0.91)
Central and Eastern Europe	**0.274**	-0.058	0.079	-0.132	-0.190
	(2.19)**	(0.3)	(0.34)	(0.32)	(0.48)
Middle East and North Africa	**0.475**	**0.515**	**0.432**	0.122	0.108
	(4.38)***	(4.73)***	(3.39)***	(0.54)	(0.54)
1960s	-0.088				
	(1.02)				
1970s	-0.050	**0.184**	**0.287**	0.482	
	(0.6)	(1.86)*	(2.23)**	(1.43)	
1980s	0.096	**0.279**	**0.297**	0.519	0.031
	(1.17)	(2.68)***	(2.63)***	(1.61)	(0.22)
2000s	**-0.208**	-0.052			-0.484
	(1.98)**	(0.42)			(1.45)
1990s		0.112	0.107	0.391	-0.096
		(1.05)	(0.91)	(1.22)	(0.67)
Log Change in Real Merchandise Exports		**-0.266**	**-0.430**	**-0.422**	**-0.410**
		(4.03)***	(4.85)***	(3)***	(2.94)***
War			0.732	0.415	**0.467**
			(3.66)***	(1.56)	(1.81)*
Natural Disaster			**-0.037**	**0.063**	
			(0.3)	(0.37)	
Sudden Stop			**0.167**	**0.240**	**0.229**
			(2.19)**	(2.36)**	(2.27)**
Log of Inflation				**1.017**	**1.020**
				(3.31)***	(3.35)***
Change in Polity Indicator				**0.312**	**0.362**
				(2.45)**	(2.92)***
Open Forest				**-0.144**	**-0.158**
				(1.69)*	(1.89)*
Democracy				-0.002	
				(0.18)	
Constant	**-1.173**	**-1.301**	**-1.366**	0.370	1.068
	(11.46)***	(10.82)***	(9.37)***	(0.29)	(0.9)
ln(sigma^2 u)	-4.424	-14.999	-15.000	-15.000	-15.000
	(4.03)***	(0.02)	(0.03)	(0.03)	(0.03)
Observations	3344	2785	1872	1054	1062
Countries	187	169	145	83	83
Percent crises predicted	0.0%	0.0%	1.6%	5.1%	6.1%
Pseudo-R^2	2.3%	3.8%	5.5%	7.4%	7.9%

Table 5: Marginal Effects of Explanatory Variables, Baseline Estimation			
	dp/dx	**sd(x)**	**(dp/dx)*sd(x)**
Continuous variables			
Log of per worker GDP	-0.0009	3.4652	-0.0030
Log change in manufacturing exports	-0.0960	0.5699	-0.0547
Lof(1+Inflation)	0.2385	0.3347	0.0798
Open Forest	-0.0369	0.9898	-0.0366
Indicator variables			
War	0.1336	0.1337	0.0179
Sudden Stops	0.0554	0.4374	0.0242
Political Transitions	0.0948	0.4416	0.0419
Latin America	0.0564	0.3864	0.0218
Africa	0.0057	0.4273	0.0024
Asia	-0.0764	0.2587	-0.0198
East Asia and Pacific	-0.0381	0.3307	-0.0126
Central and Eastern Europe	-0.0402	0.3307	-0.0133
Middle East and North Africa	0.0264	0.2948	0.0078
1980s	0.0072	0.4163	0.0030
1990s	-0.0221	0.4163	-0.0092
2000s	-0.0881	0.3150	-0.0278

Table 6: Random Effects Probit Regressions, Industrialized Countries
Dependent Variable: Probability of Falling into a Crisis

	(1)	(2)	(3)	(4)	(5)
Log GDP per Working Age Person	0.040	0.043	0.044	0.065	0.066
	(1.29)	(1.32)	(1.1)	(1.03)	(1.05)
Log Change in Real Merchandise Exports		0.039	-0.038	-0.409	-0.372
		(0.18)	(0.12)	(0.92)	(0.84)
War			**0.775**	0.789	0.725
			(1.83)*	(1.41)	(1.35)
Natural Disaster			-5.670	-5.403	
			(0)	(0)	
Sudden Stop			**0.356**	**0.393**	**0.390**
			(2.44)**	(2.04)**	(2.04)**
1980s			-0.061	0.016	0.025
			(0.26)	(0.05)	(0.09)
1990s			-0.367	0.290	0.260
			(1.6)	(0.9)	(0.81)
2000s			-0.390	-5.149	-4.993
			(1.35)	(0)	(0)
Log of Inflation				**11.554**	**10.982**
				(4.01)***	(4.03)***
Political Transitions				0.315	0.158
				(0.53)	(0.28)
Open Forest				-0.124	-0.089
				(0.38)	(0.27)
Democracy (Polity Index)				0.316	
				(0.77)	
Constant	**-1.550**	**-1.558**	**-1.405**	-3.873	-1.220
	(7.69)***	(6.82)***	(4.11)***	(0.64)	(0.26)
log(sigma^2 u)	-17.125	-17.125	-16.000	-15.000	-15.125
	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)
Observations	934	816	577	368	368
Countries	25	25	25	19	19
Percent crises predicted	0.0%	0.0%	2.5%	5.3%	6.6%
Pseudo-R^2	1.4%	3.4%	5.7%	7.3%	7.7%

Table 7: Random Effects Probit Regressions by intensity of crisis

Dependent Variable: Probability of Falling into a Crisis	(1) Duration<5 years	(2) Duration>5 years	(3) Integral<0.75 GDP-years	(4) Integral>0.75 output years
Log GDP per Working Age Person	0.015	-0.030	0.010	-0.046
	(0.58)	(0.93)	(0.41)	(1.2)
Log Change in Real Merchandise Exports	**-0.295**	**-0.477**	**-0.379**	**-0.425**
	(1.9)*	(2.25)**	(2.49)**	(1.84)*
War	0.431	0.400	0.347	0.614
	(1.5)	(1.04)	(1.2)	(1.51)
Sudden Stop	**0.192**	0.189	**0.221**	0.118
	(1.73)*	(1.14)	(2.08)**	(0.61)
Log of Inflation	**0.806**	**0.972**	**0.897**	**0.897**
	(2.44)**	(2.25)**	(2.79)***	(1.9)*
Political Transitions	**0.320**	**0.421**	**0.305**	**0.442**
	(2.27)**	(2.32)**	(2.29)**	(2.09)**
Open Forest	-0.043	**-0.394**	-0.004	**-0.498**
	(0.43)	(3.36)***	(0.04)	(3.83)***
Latin America	-0.045	**0.742**	0.142	**0.874**
	(0.21)	(2.47)**	(0.73)	(2.06)**
Africa	0.027	0.138	0.168	0.207
	(0.1)	(0.36)	(0.63)	(0.42)
South and Central Asia	**-0.368**	-0.179	-0.262	-0.375
	(1.75)*	(0.49)	(1.32)	(0.66)
East Asia and Pacific	-0.297	0.253	-0.176	0.454
	(1.38)	(0.73)	(0.87)	(0.97)
Central and Eastern Europe	-0.316	0.425	-0.401	1.100
	(0.72)	(0.67)	(0.91)	(1.58)
Middle East and North Africa	0.160	0.167	0.203	0.216
	(0.75)	(0.45)	(0.98)	(0.43)
1970s	0.419			
	(1.25)			
1980s	0.333	0.224	-0.064	0.284
	(1.04)	(1.01)	(0.42)	(1.16)
1990s	0.207	0.092	-0.101	-0.272
	(0.65)	(0.39)	(0.68)	(0.9)
2000s		-5.143	-0.461	-4.943
		(0)	(1.37)	(0)
Constant	-1.071	**3.288**	-1.182	**4.522**
	(0.72)	(1.97)**	(0.86)	(2.42)**
lnsig2u	-14.999	-15.000	-15.000	-15.000
	(0.01)	(0.03)	(0.02)	(0.03)
Observations	1004	933	1023	921
Countries	81	83	81	83
Percent crises predicted	0.8%	2.0%	1.4%	2.6%
Pseudo-R^2	4.7%	20.4%	5.0%	26.8%

Table 8: Random Effects Probit Regressions, Alternative Sudden Stop Definitions
Dependent Variable: Probability of Falling into a Crisis

	(1)	(2)	(3)	(4)
Log GDP per Working Age Person	-0.002	-0.002	-0.017	-0.013
	(0.1)	(0.11)	(0.72)	(0.57)
Log Change in Real Merchandise Exports	**-0.401**	**-0.390**	**-0.338**	**-0.350**
	(2.88)***	(2.78)***	(2.2)**	(2.29)**
War	**0.456**	**0.457**	**0.535**	**0.562**
	(1.76)*	(1.76)*	(1.96)*	(2.06)**
Sudden Stop 1	0.122			
	(1.07)			
Log of Inflation	**1.029**	**1.030**	**1.030**	**0.992**
	(3.39)***	(3.4)***	(3.3)***	(3.18)***
Political Transitions	**0.359**	**0.351**	**0.360**	**0.360**
	(2.9)***	(2.83)***	(2.77)***	(2.77)***
Open Forest	**-0.156**	**-0.159**	**-0.186**	**-0.185**
	(1.86)*	(1.9)*	(2.13)**	(2.11)**
Latin America	0.199	0.190	0.150	0.144
	(1.13)	(1.08)	(0.82)	(0.79)
Africa	0.025	0.021	-0.069	-0.088
	(0.1)	(0.09)	(0.28)	(0.36)
South and Central Asia	**-0.382**	**-0.389**	**-0.384**	**-0.395**
	(1.99)**	(2.02)**	(1.98)**	(2.04)**
East Asia and Pacific	-0.157	-0.148	-0.160	-0.184
	(0.82)	(0.78)	(0.82)	(0.94)
Central and Eastern Europe	-0.235	-0.259	-0.160	-0.152
	(0.59)	(0.65)	(0.46)	(0.44)
Middle East and North Africa	0.091	0.076	0.069	0.042
	(0.46)	(0.38)	(0.34)	(0.21)
1970s	0.464	0.451		0.593
	(1.4)	(1.36)		(1.64)
1980s	0.483	0.467	0.030	**0.617**
	(1.52)	(1.47)	(0.2)	(1.77)*
1990s	0.364	0.349	-0.122	0.486
	(1.14)	(1.1)	(0.81)	(1.39)
Sudden Stop 2		0.062		
		(0.64)		
Sudden Stop 3			**0.174**	
			(1.69)*	
2000s			-0.568	
			(1.57)	
Sudden Stop 4				**0.226**
				(1.95)*
Constant	0.626	0.684	1.538	0.968
	(0.5)	(0.54)	(1.25)	(0.74)
lnsig2u	-15.000	-15.000	-15.125	-15.000
	(0.03)	(0.03)	(0.04)	(0.04)
Observations	1061	1061	1004	1002
Countries	83	83	83	83
Percent crises predicted	0.0611	0.0556	0.0599	0.0539
Pseudo-R^2	0.0759	0.0752	0.0839	0.0846

Table 9: Fixed Effects Logit Specification
Dependent Variable: Probability of Falling into a Crisis

Log GDP per Working Age Person	**-1.158**	**-1.308**	**-2.398**	**-3.792**	**-3.807**
	(3.83)***	(3.25)***	(3.63)***	(3.7)***	(3.71)***
Log Change in Real Merchandise Exports		**-0.452**	**-0.892**	**-1.277**	**-1.273**
		(3.21)***	(4.53)***	(4.13)***	(4.11)***
War			**1.073**	**0.839**	**0.842**
			(2.93)***	(1.72)*	(1.72)*
Natural Disaster			0.101	0.208	
			(0.4)	(0.6)	
Sudden Stop			**0.396**	**0.528**	**0.528**
			(2.58)***	(2.55)**	(2.55)**
Log of Inflation				**1.293**	**1.291**
				(1.88)*	(1.88)*
Change in Polity Indicator				**0.457**	**0.451**
				(1.79)*	(1.77)*
Openforest				0.339	0.343
				(0.79)	(0.8)
1960s	**-1.156**				
	(3.62)***	(3.08)***	(2.05)**		
1980s	-0.111	**1.220**	-0.210	**0.579**	**0.587**
	(0.64)	(4.54)***	(0.7)	(1.98)**	(2)**
1990s		**1.248**	-0.059	**1.103**	**1.118**
		(3.82)***	(0.23)	(2.7)***	(2.74)***
2000s	**-0.454**	**1.061**		0.643	0.656
	(2.01)**	(2.74)***		(0.83)	(0.84)
Observations	3273	2673	1766	986	986
Countries	180	149	125	75	75
Percent crises predicted	1.50%	1.80%	0.60%	2.24%	2.24%
Pseudo-R^2	1.30%	2.40%	5.25%	8.69%	8.69%

Table 10: Random Effects Probit

Dependent Variable: Probability of Falling into a Crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP per Working Age Persor	-0.005	-0.006	-0.005	-0.017	0.000	-0.005	0.010	0.023
	(0.23)	(0.28)	(0.22)	(0.6)	(0.01)	(0.24)	(0.27)	(0.48)
Log Change in Real Merchandise	**-0.507**	**-0.507**	**-0.510**	**-0.429**	**-0.420**	**-0.416**	**-0.477**	**-0.869**
	(3.06)***	(3.05)***	(3.07)***	(2.04)**	(2.88)***	(2.97)***	(2.03)**	(2.36)**
War	**0.764**	**0.764**	**0.764**	**0.655**	**0.472**	**0.474**	**0.922**	**0.990**
	(2.78)***	(2.78)***	(2.78)***	(2.03)**	(1.82)*	(1.83)*	(2.18)**	(2.14)**
Sudden Stop	**0.261**	**0.263**	**0.262**	**0.277**	**0.206**	**0.226**	**0.445**	**0.666**
	(2.44)**	(2.46)**	(2.45)**	(2.06)**	(2)**	(2.24)**	(2.94)***	(3.35)*
Log of Inflation	**1.185**	**1.132**	**1.155**	**0.806**	**0.974**	**0.974**	**1.137**	**0.987**
	(3.71)***	(3.59)***	(3.66)***	(2.2)**	(3.18)***	(3.13)***	(2.3)**	(1.68)*
Change in Polity Indicator	**0.298**	**0.304**	**0.299**	**0.543**	**0.331**	**0.370**	0.035	-0.112
	(2.14)**	(2.18)**	(2.15)**	(3.2)***	(2.58)**	(2.97)***	(0.15)	(0.29)
Openforest	-0.092	-0.106	-0.094	-0.039	-0.120	**-0.177**	**-0.378**	-0.261
	(0.89)	(1.03)	(0.91)	(0.28)	(1.37)	(2.01)**	(2.29)**	(0.92)
Years of Primary Schooling	-0.039							0.010
	(0.83)							(0.02)
Latin America	0.203	0.215	0.190	**0.655**	0.119	0.229	-0.005	0.256
	(1.04)	(1)	(0.92)	(2.25)**	(0.51)	(1.29)	(0.02)	(0.41)
Africa	-0.187	-0.139	-0.191	0.233	-0.147	0.087	**-1.002**	-1.150
	(0.63)	(0.45)	(0.62)	(0.57)	(0.51)	(0.34)	(1.89)*	(1)
South and Central Asia	**-0.448**	-0.389	**-0.447**	-0.310	**-0.534**	-0.300	**-0.834**	-0.326
	(1.94)*	(1.63)	(1.83)*	(0.99)	(2.02)**	(1.33)	(2.02)**	(0.52)
East Asia and Pacific	-0.152	-0.148	-0.171	-0.114	-0.288	-0.145	-0.340	-0.320
	(0.75)	(0.67)	(0.8)	(0.45)	(1.2)	(0.74)	(1.04)	(0.67)
Central and Eastern Europe	-0.024	-0.116	-0.092	-0.070	-0.334	-0.147	-0.062	-0.346
	(0.05)	(0.26)	(0.21)	(0.16)	(0.78)	(0.37)	(0.14)	(0.45)
Middle East and North Africa	-0.125	-0.104	-0.128	0.435	0.032	0.109	0.118	0.140
	(0.53)	(0.43)	(0.54)	(1.51)	(0.13)	(0.54)	(0.33)	(0.23)
1980s	-0.007	-0.013	-0.008	0.140	0.058	0.026	0.651	0.041
	(0.05)	(0.09)	(0.05)	(1)	(0.4)	(0.19)	(1.18)	(0.18)
1990s	-0.145	-0.156	-0.142		-0.028	-0.111	0.484	
	(0.94)	(1)	(0.91)		(0.18)	(0.77)	(0.89)	
Years of Secondary Schooling		-0.019						-0.104
		(0.26)						(0.2)
Total Years of Schooling			-0.020					-0.006
			(0.66)					(0.01)
?????????				0.049				**0.303**
				(0.67)				(1.87)*
Telephone mainlines (per 1,000 p					-0.001			-0.002
					(0.96)			(1.24)
2000s					-0.390	-0.499		
					(1.13)	(1.49)		
Urban population (% of total)- WD						0.002		**0.018**
						(0.67)		(1.88)*
Life expectancy at birth, total (yea							-0.019	-0.035
							(1.07)	(0.9)
1970s							0.566	
							(0.96)	
Constant	0.380	0.457	0.384	-0.970	0.688	1.205	**4.979**	3.142
	(0.27)	(0.32)	(0.27)	(0.49)	(0.57)	(1.01)	(2.16)**	(0.72)
N	951	951	951	672	1037	1062	522	369
N_g	74	74	74	61	80	83	77	50
Percent crises predicted	7%	7%	7%	7%	5%	6%	7%	6%
Pseudo-R^2	8%	8%	8%	10%	8%	8%	11%	13%

Table 11: Characteristics of Crises by Coinciding Initial Events	Number of Observations		Duration	Peak to Trough Ratio	Lost Years of GDP	OLS Trend Growth (end to end+5)
	Max	Min				
Substantial Change in Merchandise Exports	95	56	6.51	11.6%	0.98	1.1%
Wars	32	21	6.53	16.5%	1.50	2.1%
Natural Disasters	51	33	7.51	13.0%	1.30	1.0%
High Inflation	62	49	6.60	10.2%	0.97	1.7%
Political Transition	118	84	6.69	11.0%	1.04	1.7%
Sudden Stop	109	71	5.83	8.8%	0.86	1.6%
High Openforest (>14)	75	66	3.08	4.6%	0.23	2.3%

Table 12: Duration Regressions, Weibull Specification with Frailty Dependent Variable: Years in crisis. Representation, Hazard rate with Region and Decade dummies (not shown)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per Working Age Person	0.024	0.030	0.056	0.057	0.046	0.049	0.055
	(1.2)	(1.4)	(1.21)	(1.15)	(0.75)	(1.07)	(1.1)
Openforest			**0.533**	**0.558**	**0.712**	**0.438**	**0.494**
			(3.61)***	(3.13)***	(3.36)***	(2.49)**	(2.36)**
Democracy (Polity Index)				0.031	0.028		**0.032**
				(1.48)	(1.07)		(1.35)
Sudden Stop				-0.092	-0.223		
				(0.45)	(1)		
Log Change in Real Merchandise Exports					0.287	**-1.648**	**-1.345**
					(0.83)	(0.64)	(0.38)
War					-0.584		
					(1.11)		
Natural Disaster					0.055		
					(0.14)		
Log of Inflation					-0.262		
					(0.4)		
Change in Polity Indicator					**-0.186**		
					(0.65)		
Change in Exports*Open Forest						**0.136**	0.104
						(0.66)	(0.38)
Polity*Change in Merchandise Exports							-0.003
							(0.06)
Polity*Sudden Stops							**-0.003**
							(0.12)
Constant	**-1.679**	**-0.796**	**-8.117**	**-8.982**	**-10.640**	**-6.859**	**-8.138**
	(11.74)***	(2.64)***	(3.89)***	(3.63)***	(3.3)***	(2.81)***	(2.82)***
N	535	535	233	191	175	230	191

Table 13: Weibull Specification, Alternative Controls

Dependent Variable: Years in crisis Representation - Hazard	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log GDP per Working Age Person	0.055	**0.114**	**0.090**	0.044	0.062	0.005	0.048	**0.098**	0.226
	(1.05)	(2)**	(1.78)*	(0.94)	(1.26)	(0.07)	(0.96)	(1.78)*	(1.64)
Openforest	**0.517**	**0.547**	**0.564**	**0.572**	**0.633**	**0.631**	**0.537**	**0.547**	**1.119**
	(2.96)***	(2.98)***	(2.99)***	(3.49)***	(4)***	(2.43)**	(3.25)***	(2.73)***	(2.42)**
Sudden Stop 4	-0.067								
	(0.31)								
Latin America	**-1.512**	**-1.356**	**-1.251**	**-1.268**	**-1.293**	**-1.263**	**-1.265**	**-0.995**	**-1.464**
	(3.72)***	(3.52)***	(3.16)***	(3.48)***	(3.45)***	(1.79)*	(3.39)***	(2.30)**	(1.71)*
Africa	-0.766	-0.513	-0.449	**-0.777**	-0.419	-0.465	-0.672	0.086	-2.440
	(1.51)	(1)	(0.8)	(1.78)*	(0.91)	(0.29)	(1.46)	-0.14	(1.54)
South and Central Asia	-0.071	-0.211	0.054	-0.004	-0.190	-1.148	-0.080	-0.138	-1.729
	(0.13)	(0.41)	(0.09)	(0.01)	(0.36)	(1.13)	(0.17)	-0.23	(1.35)
East Asia and Pacific	-0.276	-0.687	-0.135	-0.275	-0.444	-0.313	-0.288	-0.094	-1.580
	(0.54)	(1.34)	(0.32)	(0.62)	(0.89)	(0.45)	(0.64)	-0.17	(1.35)
Central and Eastern Europe	**-1.922**	**-2.183**	-1.009	-1.052	**-1.648**	**-1.744**	-0.857	**-1.189**	**-2.741**
	(2.62)***	(2.39)**	(1.32)	(1.28)	(2.55)**	(2.4)**	(1.13)	(2.01)**	(1.97)**
Middle East and North Africa	-0.301	0.072	-0.163	-0.143	-0.215	-1.093	-0.151	0.459	-1.459
	(0.63)	(0.15)	(0.33)	(0.32)	(0.47)	(1.48)	(0.34)	-0.83	(0.98)
1970s	**-1.293**		**0.513**		-0.612	-0.273	0.429		
	(1.73)*		(1.7)*		(0.95)	(0.18)	(1.48)		
1980s	**-1.803**	**-0.874**	**-0.436**	**-0.749**	**-1.453**	-1.415	-0.378	**-0.603**	-0.676
	(2.57)**	(3.42)***	(1.73)*	(2.59)***	(2.46)**	(0.95)	(1.59)	(2.09)**	(1.49)
1990s	**-1.451**	**-0.531**		-0.433	**-1.148**	-1.053		-0.478	-0.311
	(2.03)**	(1.92)*		(1.32)	(1.91)*	(0.74)		-1.55	(0.57)
2000s		0.443		0.986				0.397	
		(0.39)		(1.18)				-0.48	
Tariff Rate		6.008							14.763
		(0.78)							(0.36)
Total Years of Schooling			**0.034**						-0.104
			(0.53)						(1.04)
Liquid Liabilities/GDP				0.001					0.008
				(0.2)					(0.86)
Openness					**0.002**				0.006
					(0.81)				(0.65)
Life expectancy at birth, total (years)-						**-0.022**			-0.036
						(0.43)			(0.38)
Polity * TOT							**0.209**		**0.012**
							(0.67)		(0.01)
Gini*(1-Democracy)								**-0.017**	
								(1.79)*	
Constant	-6.940	**-8.733**	**-9.588**	**-8.719**	**-9.140**	-7.288	**-8.651**	**-8.745**	**-15.104**
	(2.65)***	(3.33)***	(3.6)***	(3.86)***	(3.72)***	(1.59)	(3.57)***	(3.11)***	(2.68)***
N	190	177	179	191	224	100	183	182	60

Table 14: Duration Regressions, Alternative Specifications				
Dependent Variable: Years in crisis	(1)	(2)	(3)	(4)
Dsitribution	Exponential	Gompertz	Cox	Log-normal
Representation	Hazard	Hazard	Hazard	AFT
Log GDP per Working Age Person	0.054	0.040	-0.064	**-0.082**
	(1.22)	(1.26)	(1.54)	(1.79)*
Openforest	**0.516**	**0.393**	**-0.328**	**-0.282**
	(3.7)***	(3.75)***	(2.45)**	(1.94)*
Latin America	**-1.231**	**-0.913**	**0.548**	**0.549**
	(3.54)***	(3.52)***	(1.73)*	(1.68)*
Africa	-0.605	-0.449	0.156	0.230
	(1.43)	(1.55)	(0.38)	(0.53)
South and Central Asia	-0.311	-0.365	-0.214	-0.262
	(0.65)	(1.13)	(0.52)	(0.65)
East Asia and Pacific	-0.065	-0.089	-0.201	-0.145
	(0.16)	(0.3)	(0.54)	(0.41)
Central and Eastern Europe	**-1.456**	**-1.057**	**0.836**	0.904
	(2.74)***	(2.57)**	(1.72)*	(1.61)
Middle East and North Africa	-0.227	-0.069	-0.154	-0.291
	(0.54)	(0.24)	(0.43)	(0.78)
1980s	**-0.790**	**-0.436**	**0.799**	**0.887**
	(3.35)***	(2.15)**	(4.04)***	(4.53)***
1990s	**-0.525**	-0.271	**0.639**	**0.723**
	(2.06)**	(1.2)	(2.95)***	(3.42)***
2000s	0.657	0.917	0.033	0.122
	(1.06)	(1.61)	(0.06)	(0.25)
Constant	**-7.893**	**-6.240**	**5.234**	**4.549**
	(4)***	(4.24)***	(2.8)***	(2.23)**
N	233	233	233	233

Table 15: Duration Regressions, PWP Stratified Cox Model Dependent Variable: Years in crisis Representation, Hazard	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per Working Age Person	0.019	0.018	0.036	0.038	0.031	0.032	0.036
	(1.51)	(1.32)	(1.38)	(1.21)	(0.89)	(1.17)	(1.12)
Latin America		**-0.797**	**-0.864**	**-0.601**	-0.445	**-0.895**	**-0.610**
		(5.11)***	(3.54)***	(2.14)**	(1.55)	(3.59)***	(2.09)**
Africa		**-0.979**	**-0.492**	0.022	0.236	**-0.565**	-0.008
		(6.38)***	(1.73)*	(0.05)	(0.47)	(1.93)*	(0.02)
South and Central Asia		**-0.548**	-0.243	-0.081	-0.018	-0.258	-0.092
		(3.13)***	(0.71)	(0.23)	(0.05)	(0.76)	(0.26)
East Asia and Pacific		**-0.376**	-0.036	-0.071	0.068	-0.075	-0.067
		(1.84)*	(0.16)	(0.24)	(0.23)	(0.32)	(0.22)
Central and Eastern Europe		**-1.083**	**-0.764**	-0.334	-0.384	**-0.587**	-0.282
		(4.25)***	(2.72)***	(1.13)	(1.03)	(1.83)*	(0.83)
Middle East and North Africa		**-0.473**	-0.171	0.368	0.445	-0.174	0.341
		(2.36)**	(0.68)	(1.08)	(1.16)	(0.68)	(0.98)
1960s		**0.866**					
		(3.32)***					
1970s		0.329			-0.484		
		(1.26)			(1.13)		
1980s		0.124	-0.315	-0.211	-0.645	-0.318	-0.226
		(0.5)	(1.62)	(0.9)	(1.57)	(1.46)	(0.89)
1990s		0.091	-0.347	-0.178	-0.641	-0.315	-0.184
		(0.38)	(1.59)	(0.76)	(1.54)	(1.35)	(0.74)
2000s			**0.841**	0.554		**0.840**	0.529
			(2.44)**	(1.58)		(2.38)**	(1.39)
Open Forest			**0.353**	**0.341**	**0.377**	**0.281**	**0.311**
			(3.21)***	(2.5)**	(2.64)***	(2.09)**	(1.92)*
Democracy (Polity)				0.022	0.027		0.020
				(1.59)	(1.51)		(1.24)
Sudden Stop				-0.016	-0.059		-0.039
				(0.09)	(0.32)		(0.18)
Log Change in Real Merchandise Exports					0.097	-1.266	-1.018
					(0.27)	(0.58)	(0.35)
War					-0.008		
					(0.02)		
Natural Disaster					0.148		
					(0.47)		
Log of Inflation					-0.279		
					(0.4)		
Change in Polity Indicator					-0.067		
					(0.28)		
Change in Exports*Open Forest						0.098	0.080
						(0.58)	(0.35)
Polity*Change in Merchandise Exports							-0.006
							(0.19)
Polity*Sudden Stops							0.007
							(0.32)
N	535	535	233	191	175	230	191
Pseudo-R2	0.1%	2.2%	4.3%	4.2%	4.4%	3.9%	4.2%

Table 16: PWP Stratified Cox Model, Alternative Controls Dependent Variable: Years in crisis Representation, Hazard	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP per Working Age Person	0.020	**0.068**	0.051	0.026	0.040	0.039	0.029	0.215
	(0.51)	(0.07)	(0.14)	(0.40)	(0.17)	(0.47)	(0.41)	(0.12)
Openforest	**0.369**	**0.371**	**0.371**	**0.332**	**0.415**	**0.794**	**0.389**	0.940
	(2.74)***	(2.69)***	(2.15)**	(2.47)**	(3.63)***	(3.53)***	(2.64)***	(1.57)
Sudden Stop 4	-0.064							
	(0.39)							
Latin America	**-1.015**	**-0.951**	**-0.812**	**-0.811**	**-0.921**	**-1.332**	**-0.801**	-1.634
	(3.41)***	(3.38)***	(2.79)***	(3.05)***	(3.65)***	(2.42)**	(2.82)***	(1.6)
Africa	-0.491	-0.421	-0.360	**-0.535**	-0.412	-1.505	-0.430	**-3.318**
	(1.45)	(1.17)	(0.89)	(1.68)*	(1.4)	(1.26)	(1.25)	(1.87)*
South and Central Asia	-0.166	-0.271	-0.139	0.029	-0.198	**-1.581**	-0.134	**-2.671**
	(0.48)	(0.67)	(0.34)	(0.08)	(0.56)	(2.32)**	(0.38)	(1.86)*
East Asia and Pacific	-0.202	**-0.525**	-0.043	-0.224	-0.286	-0.299	-0.161	-1.901
	(0.75)	(1.71)*	(0.15)	(0.9)	(1.1)	(0.63)	(0.57)	(1.31)
Central and Eastern Europe	**-1.179**	**-1.163**	**-0.453**	**-0.577**	**-0.850**	**-0.931**	-0.347	**-2.539**
	(2.99)***	(2.27)**	(1.79)*	(2.2)**	(2.23)**	(2.05)**	(1.5)	(2.21)**
Middle East and North Africa	-0.168	0.016	-0.054	-0.050	-0.192	-0.770	0.005	-1.435
	(0.51)	(0.06)	(0.14)	(0.16)	(0.77)	(0.97)	(0.02)	(1.01)
1970s	**-1.212**		0.329		**-0.821**	-0.935	0.269	
	(2.76)***		(1.17)		(2.23)**	(1.11)	(1.11)	
1980s	**-1.301**	**-0.444**	-0.139	-0.308	**-1.169**	**-1.759**	-0.137	-0.678
	(3.7)***	(2.11)**	(0.57)	(1.41)	(3.52)***	(2.42)**	(0.64)	(1.18)
1990s	**-1.173**	-0.368		-0.195	**-1.184**	**-1.469**		-0.466
	(3.02)***	(1.39)		(0.65)	(3.19)***	(2.11)**		(0.7)
2000s		0.259		**0.936**				
		(0.59)		(2.07)**				
Tariff Rate		6.978						15.316
		(1.32)						(0.42)
Total Years of Schooling			**0.014**					-0.142
			(0.3)					(1.7)*
Liquid Liabilities/GDP				0.002				0.006
				(0.91)				(0.79)
Openness					**0.002**			0.003
					(1.15)			(0.44)
Life expectancy at birth, total (years)-						**-0.075**		-0.082
						(1.77)*		(0.78)
Interaction between Polity and Terms of							**0.086**	0.456
							(0.32)	(0.5)
N	190	177	179	191	224	100	183	60
Pseudo-R2	5%	5%	5%	5%	5%	8%	5%	12%

Table 17: Alternative Hypotheses	(1)	(2)	(3)	(4)	(5)
Log GDP per Working Age Person	0.056	0.057	0.056	0.057	0.28
	(1.22)	(1.25)	(1.18)	(1.16)	(3.25)***
Open Forest					0.856
					(2.58)***
Open Forest (Density Only)	0.581	0.935	1.25	1.264	
	(3.71)***	(3.68)***	(4.22)***	(4.03)***	
Herfindahl		2.017	2.531	2.657	
		(1.81)*	(2.21)**	(2.21)**	
Log of Population			-0.199	-0.203	
			(2.30)**	(2.05)**	
Area (sq, km)				0.009	
				(0.13)	
Growth in Terms of Trade at t=1					7.254
					(4.38)***
Growth in GDP at t=1					27.922
					(4.48)***
Growth in Merchandise Exports at t=1					-0.882
					(0.88)
Growth in GDP at t=0					9.648
					(1.43)
Growth in Merchandise Exports at t=0					2.39
					(2.35)**
Constant	-2.708	-4.833	-3.232	-3.285	-14.82
	(2.53)**	(2.98)***	(1.84)*	(1.79)*	(2.97)***
Latin America	-1.245	-1.315	-1.347	-1.361	-0.502
	(3.37)***	(3.54)***	(3.55)***	(3.51)***	(0.79)
Africa	-0.593	-0.702	-0.371	-0.404	-0.063
	(1.34)	(1.58)	(0.77)	(0.79)	(0.07)
South and Central Asia	-0.268	-0.266	0.254	0.26	-0.978
	(0.53)	(0.54)	(0.45)	(0.44)	(1.28)
East Asia and Pacific	-0.04	-0.042	-0.046	-0.048	0.824
	(0.09)	(0.10)	(0.10)	(0.11)	(1.15)
Central and Eastern Europe	-1.48	-1.457	-1.384	-1.327	-2.823
	(2.62)***	(2.59)***	(2.38)**	(2.18)**	(2.87)***
Middle East and North Africa	-0.19	-0.407	-0.371	-0.396	0.862
	(0.42)	(0.89)	(0.79)	(0.82)	(1.18)
1970s	-0.789	-0.791	-0.788	-0.781	0.124
	(1.26)	(1.28)	(1.28)	(1.26)	(0.14)
1980s	-1.568	-1.523	-1.561	-1.571	-0.442
	(2.69)***	(2.61)***	(2.66)***	(2.67)***	(0.54)
1990s	-1.259	-1.169	-1.135	-1.131	-0.158
	(2.11)**	(1.96)*	(1.89)*	(1.88)*	(0.19)
Observations	233	233	233	229	130
Number of groups	102	102	102	99	62

Absolute value of z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1: Comparison of crisis characteristics

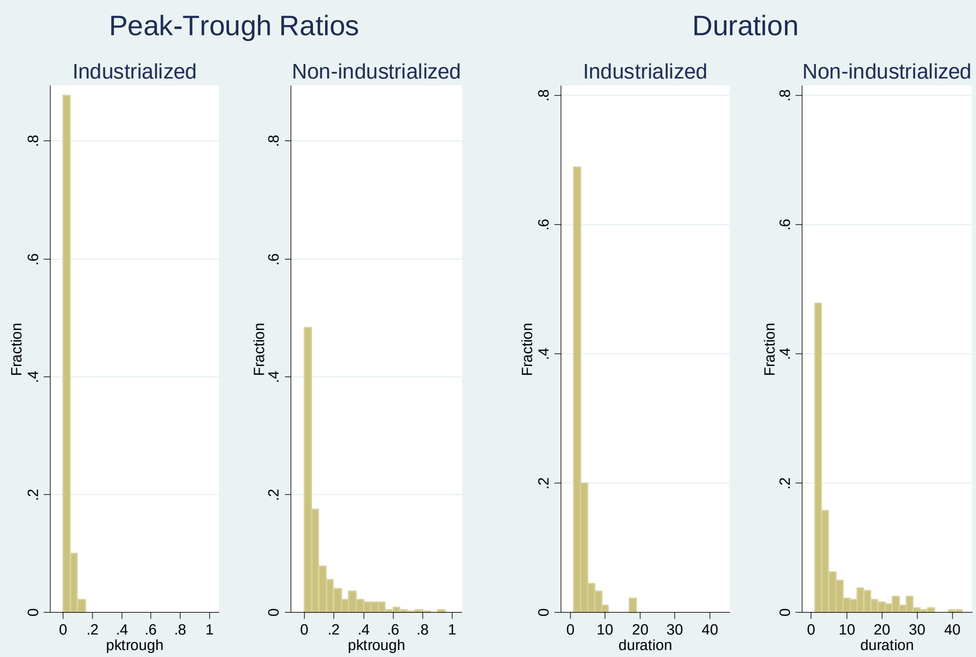
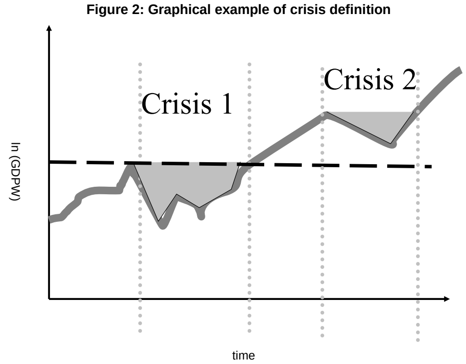


Figure 2: Graphical example of crisis definition



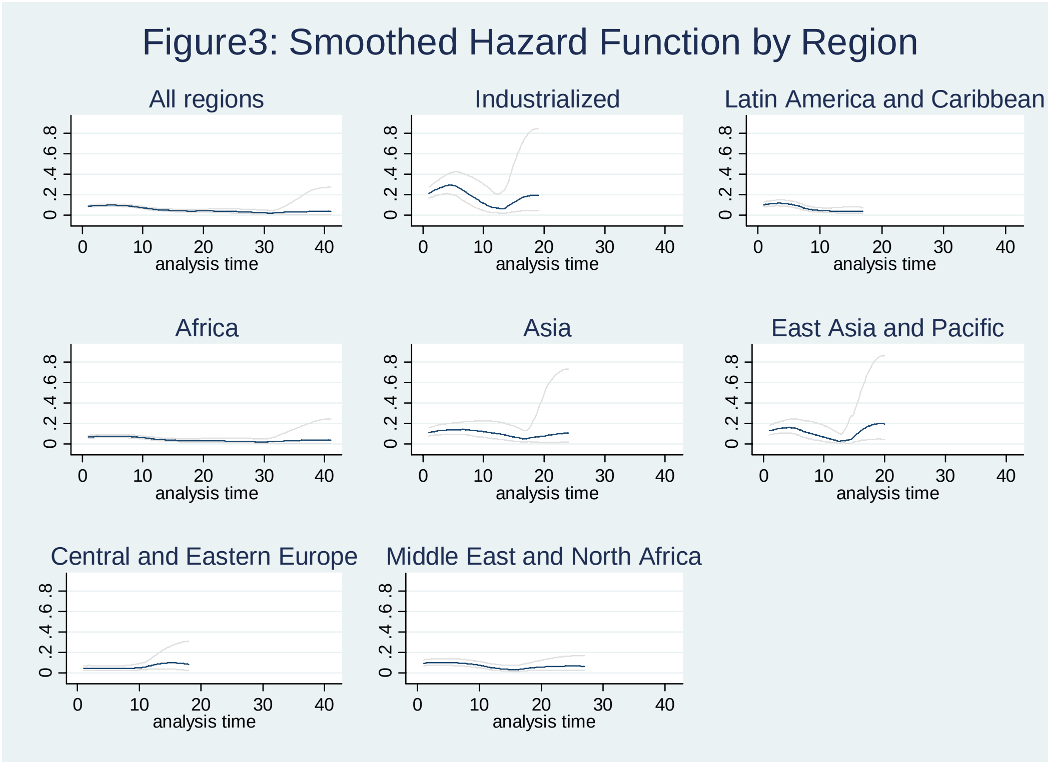


Figure3: Smoothed Hazard Function by Region
All regions
Industrialized
Latin America and Caribbean
Africa
Asia
East Asia and Pacific
Central and Eastern Europe
Middle East and North Africa
0 .2 .4 .6 .8
0 10 20 30 40
analysis time

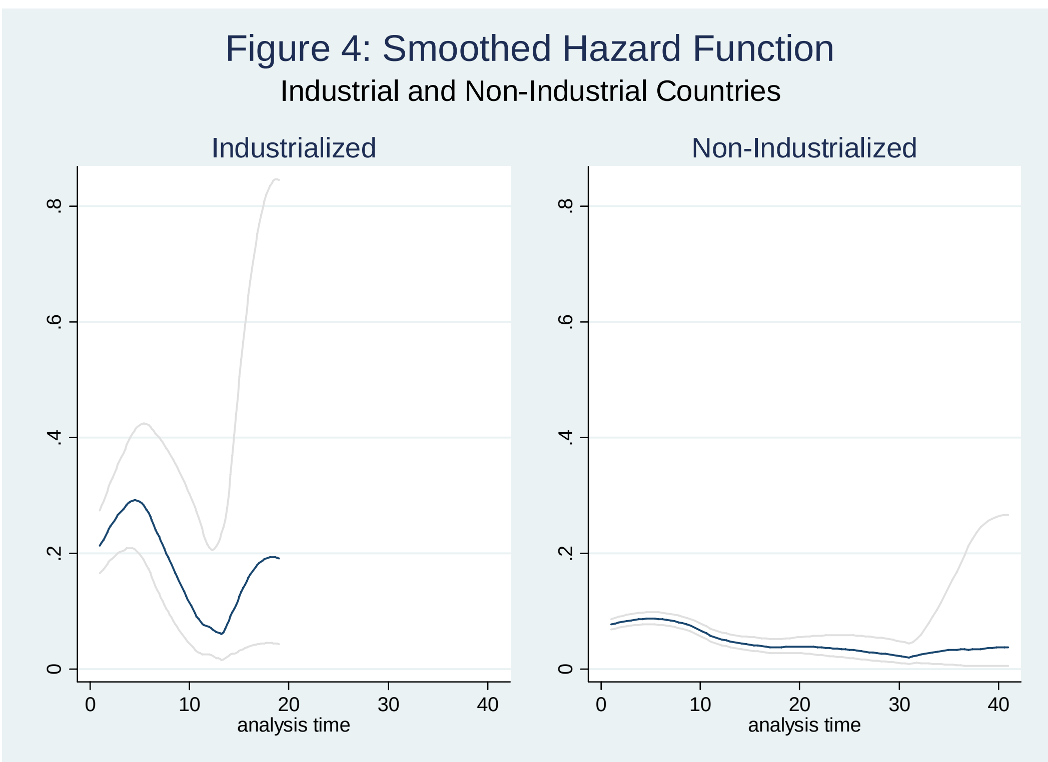


Figure 4: Smoothed Hazard Function
Industrial and Non-Industrial Countries
Industrialized
Non-Industrialized
0 .2 .4 .6 .8
0 10 20 30 40
analysis time

Figure 5: Hazard Function by Type of Crisis

Alternative Specifications

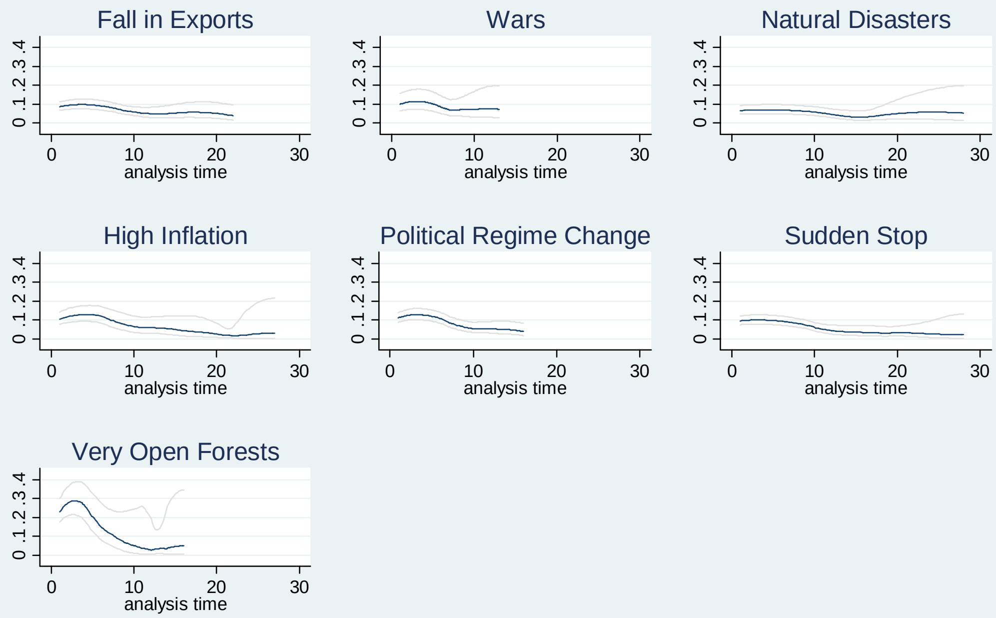


Figure 6: Conditional Hazard Function

Alternative Specifications

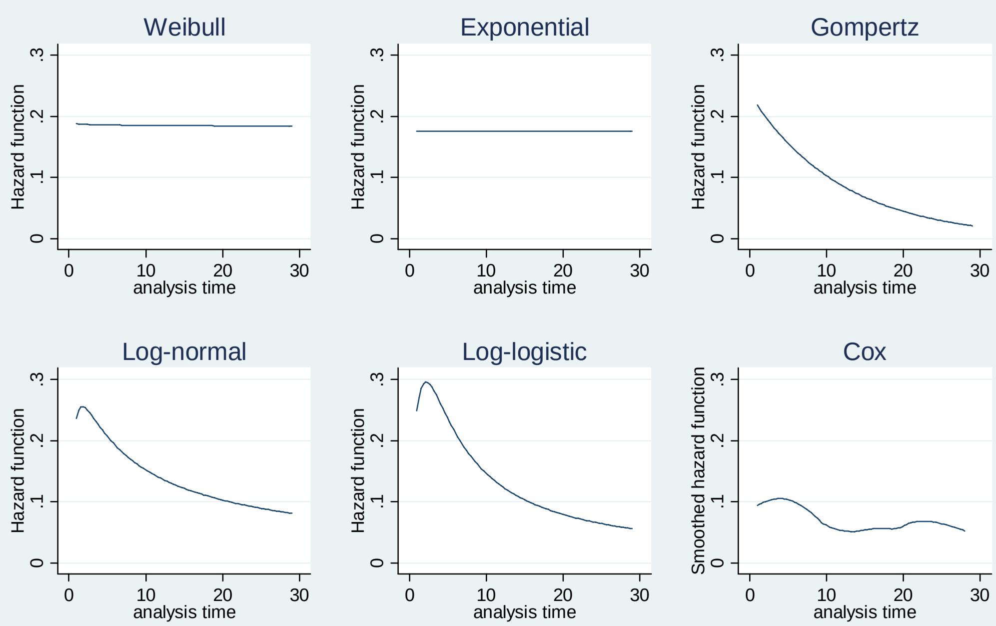
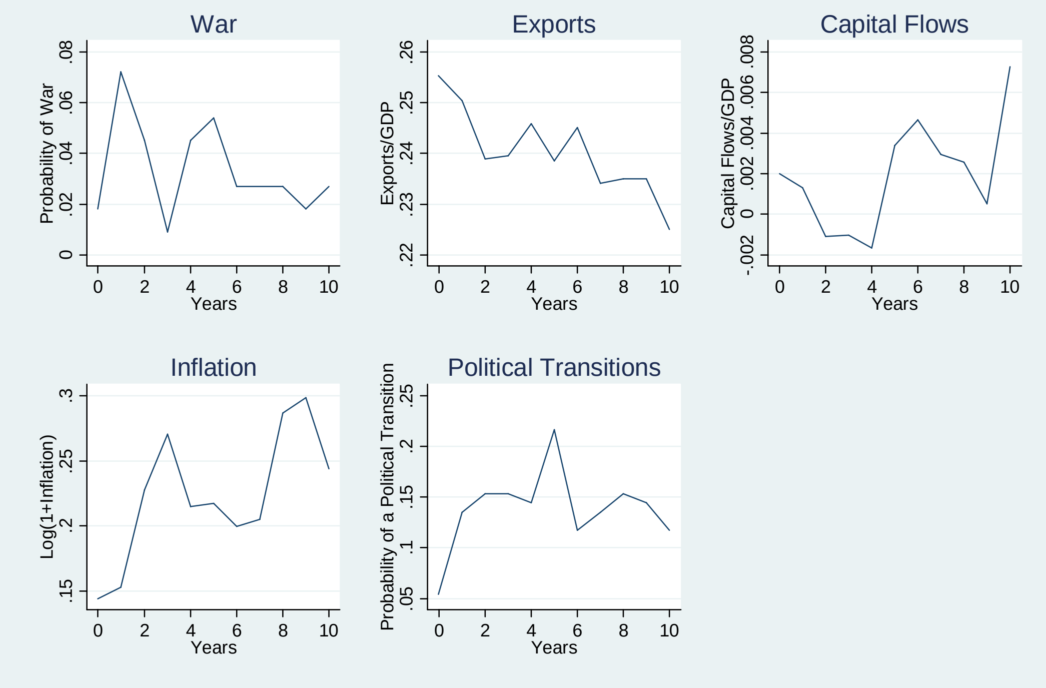


Figure 7: Evolution of covariates during crises



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