NBER WORKING PAPER SERIES

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Working Paper 16567
http://www.nber.org/papers/w16567

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2010

Taylor has been supported by the Center for the Evolution of the Global Economy at UC Davis and Jorda by DGCYT Grant (SEJ2007-63098-econ). Some work was completed while Taylor was a Houblon-Norman/George Fellow at the Bank of England, and later when he was a Senior Advisor at Morgan Stanley. All of this research support is gratefully acknowledged. Felix Mihram provided excellent research assistance. All errors are ours. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 16567
December 2010
JEL No. C14,C52,E51,F32,F42,N10,N20

ABSTRACT

Do external imbalances increase the risk of financial crises? In this paper, we study the experience of 14 developed countries over 140 years (1870-2008). We exploit our long-run dataset in a number of different ways. First, we apply new statistical tools to describe the temporal and spatial patterns of crises and identify five episodes of global financial instability in the past 140 years. Second, we study the macroeconomic dynamics before crises and show that credit growth tends to be elevated and natural interest rates depressed in the run-up to global financial crises. Third, we show that recessions associated with crises lead to deeper recessions and stronger turnarounds in imbalances than during normal recessions. Finally, we ask if external imbalances help predict financial crises. Our overall result is that credit growth emerges as the single best predictor of financial instability, but the correlation between lending booms and current account imbalances has grown much tighter in recent decades.

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1 Introduction

It is a great irony that crises are orphans right up to their inception, at which point they become the scions of new economic orthodoxies and a few fortune tellers. In the 2007/08 crisis some have taken issue with the Federal Reserve and a policy that kept interest rates too low in the wake of the 2001 recession (J. B. Taylor 2007, 2009).[1] Also potentially critical flaws in the reigning doctrine of inflation targeting have been pointed out with reference to its nonessential role for money and its neglect of distortions and instabilities arising from bank (or nonbank) credit channels (Borio and White 2003; Goodhart 2007; Borio, 2008; Christiano et al. 2010). Yet an influential school of thought, popular among policy makers, puts the blame less on short-term interest rates controlled by central banks, and more on international imbalances (Economic Report of the President 2009). Among others, Ben Bernanke (2009) and Mervyn King (2010) have linked the crisis to capital flows from developing into developed economies, mainly in the form of reserve accumulation by emerging markets. These reverse capital flows, the argument goes, opened up a Pandora's box of financial distortions. As foreign savings were predominantly channeled through government (or central bank) hands into Treasuries, private investors turned elsewhere to look for higher yields, which contributed to the global mis-pricing of financial risks. In the words of King (2010):

> The massive flows of capital from the new entrants into western financial markets pushed down interest rates and encouraged risk-taking on an extraordinary scale... Capital flows provided the fuel which the developed world's inadequately designed and regulated financial system then ignited to produce a firestorm that engulfed us all.

An intermediate position stresses that global imbalances and financial crises are the product of "common causes." These authors argue that the interaction of domestic and external factors prepared the ground for the boom that went bust in 2007–2009. Lax monetary policy, low real interest rates, financial innovation, and credit market distortions created a dangerous cocktail, but international factors such as exchange rates and other economic policies pursued in emerging markets also played a critical role (Obstfeld and Rogoff 2009; Obstfeld 2010; Ferguson and Schularick 2010).

[1] Also limits to liability and a short-term bonus culture have been cited as a reason for excessive risk taking (Alessandrini and Haldane 2009; Hume and Sentence 2010). Others have pointed to political incentives for excessive risk taking as part of a mistaken social policy agenda, see Calomiris (2010).

Proposals to limit imbalances feature prominently on the post-crisis policy agenda. With an eye on limiting financial fragility, Goodhart and Tsomocos (2010) have proposed taxes on capital flows to keep risky imbalances in check; others have suggested reciprocal capital account restrictions to deal with excessive reserve accumulation (Gros 2010). And as this paper was completed, the G20 announced a proposal for a system to monitor and limit current account imbalances with the support of the IMF. Yet, when it comes to the issue of financial instability, to date there is little empirical research that sheds light on the role of the global imbalances—as compared to other factors—in credit boom-bust episodes in advanced economies.[2]

In this paper we reach back to the economic history of the past 140 years to study the linkage between the international economy and financial instability. Building on a long-run cross-country dataset covering 14 advanced countries, we assess the role of external factors in financial crises. Our broad historical purview is motivated by the fact that disruptive events like economic depressions and financial crises are "rare events", at least in developed economies. Thus, sample sizes are small, and providing a detailed quantitative rendition requires that we expand our dataset across both time and space. As in recent work by Reinhart and Rogoff (2009), Barro (2009), and Almunia et al. (2009), the purpose of this paper is to go back to comparative economic history as a way to more robustly explore the link between financial crises and external imbalances.

Our empirical analysis proceeds in four steps. In the first part, we set the stage by applying new nonparametric methods to study the temporal and spatial coherence of financial crises across countries in the past 140 years. To our knowledge, this represents the first detailed attempt at analyzing these correlation patterns of financial crises in the Western world in the past century. The goal of this section is to see what, if any, empirical regularities can be detected in the frequency and distribution of financial crises across countries in the past 140 years. Our results are by and large negative. While we can identify four big synchronized global crises when a significant number of countries in our sample experienced financial crises—in 1890, 1907, 1921, 1930/31, and 2007/08—about half of all crises occur in one country only. However, it is striking from the data that no financial crises happened during the Bretton Woods years of tight financial regulation and capital controls the the years from WW2 until the mid 1970s.

[2] There is a longer and stronger literature examining these factors in emerging markers. See, for example, Kaminsky and Reinhart (1999).

In the second part, we provide descriptive statistical evidence on the behaviour of key economic and financial variables in the years leading up to national and global financial crises. The aim is to identify in what sense synchronized crises across many countries ('global crises') are different from national ('isolated') crises. Our results indicate that boom and bust dynamics have been more pronounced in the 'global' crises as measured by growth and investment dynamics. Tellingly, although both credit and money growth are strongly elevated before both types of financial crises, we find historical evidence that global crises typically occurred in an environment of particularly depressed natural interest rates. Crises are also typically preceded by somewhat larger current account deficits relative to the country's own history—a fact that we exploit later in the paper when we explore how to improve crisis prediction tools. At this stage of the paper there is in hand prima facie evidence that both domestic credit and external imbalances could play a role in financial crises.

In the third part, we focus on the economic effects of financial crises. A key contribution of this paper is that we differentiate between recessions that are preceded by a financial crises and 'normal' recessions. In other words, we ask whether financial busts lead to meaningfully different performance compared with 'normal' recessions—i.e., not compared with normal times. We also differentiate between national and global financial crises. For this more detailed analysis a consistent business cycle dating method was needed for 14 countries over 140 years. We detail our methodology in the appendix. Our key results are the following: deflationary tendencies are considerably more pronounced in crisis recessions than in normal business cycle downturns. Crisis recessions also display a strongly negative impact on loan growth, which slows down considerably more than in normal recessions. Unlike in the 19th and the first half of the 20th century, current accounts generally show a general tendency to improve in postwar recessions, but even more so in those associated with a financial crisis.

In the fourth and last empirical part, we ask whether external imbalances help predict the occurrence of financial instability in advanced economies. More specifically, we add long-run current account data as an additional 'early warning signal' into a crisis prediction framework developed in Schularick and A. M. Taylor (2009). While we find that credit trends, not external imbalances remain the best predictor of financial instability, the predictive ability of the model increases slightly if external factors are added to the regressions. In particular, in the post Bretton-Woods era the role of international capital flows (as measured by current account balances) has increased considerably and the interaction of external imbalances and credit growth gains in importance. We conclude that there is some evidence that in an era of high capital mobility elastic current accounts add to financial stability risks, but the primary warning indicator is still credit growth.

2 Preliminaries

In this section we discuss the new dataset and new methods that we will put to use.

2.1 Our Data

Our dataset covers 14 countries over the years 1870–2008. The countries included are the United States, Canada, Australia, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. At the core of the dataset are yearly data for outstanding bank loans (domestic bank credit), complemented with a narrow (M1) and broad (typically M2 or M3) monetary aggregates as well as data on nominal and real output, inflation and investment. For most variables we could rely on the dataset from Schularick and A. M. Taylor (2009). We extended this dataset using annual data on current account position and trade balances from various sources that are documented in the data appendix. With two minor exceptions (Switzerland before 1921 and Spain in the 1920s), we were able to compile long-run current account series matching the credit and real economic data series. The main sources for the current account and trade data were Jones and Obstfeld (1997), A. M. Taylor (2002), the various volumes compiled by Mitchell (2007a, b, c), as well as the IMF's International Financial Statistics (2010). We amended these using national sources wherever necessary and possible. We are grateful to a number of colleagues who shared their data or directed us to the appropriate sources.[3] Table 1 briefly summarizes our dataset.

With regard to the coding of financial crisis episodes we follow the description in Schularick and A. M. Taylor (2009), which itself relies heavily on Bordo et al. (2001) as well as Reinhart and Rogoff (2009) for the pre WWII years. For the post-1960 period detailed crisis histories can found in the databases compiled by Laeven and Valencia (2008), as well as in the evidence described by Cecchetti et al. (2009). A table showing the crisis events by country-year can be

[3] We thank: Antonio Tena Junguito (Spain); Gert den Bakker (Netherlands); Tobias Straumann (Switzerland). Felix Mihram provided excellent research assistance.

Table 1: Annual summary statistics, 1870–2008

Variable	N	mean	s.d.	min	max
Current Account/GDP	1614	-0.001	0.040	-0.182	0.196
Investment/GDP	1638	0.183	0.061	0.017	0.379
M2/GDP	1575	0.594	0.232	0.180	1.458
Loans/GDP	1521	0.484	0.402	0.016	2.504
Short term interest rate	1401	0.052	0.033	0.000	0.208
Δ log Real GDP	1715	0.021	0.036	-0.261	0.167
Δ log Money	1573	0.063	0.061	-0.180	0.662
Δ log Loans	1509	0.079	0.093	-0.470	0.693
Δ log CPI	1676	0.023	0.054	-0.218	0.331

Notes: Money denotes broad money. Loans denote total bank loans. The sample runs from 1870 to 2008. War and aftermath periods are excluded (1914–19 and 1939–47), as is the post-WW1 German hyperinflation episode (1920–25). The 14 countries in the sample are the United States, Canada, Australia, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, and the United Kingdom.

found in the appendix. In line with the previous studies, we define systemic financial crises as events during which a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or the forced merger of major financial institutions (Laeven and Valencia 2008).

2.2 Our Classification Methods

Financial crises, clinical depression and spam e-mail share common features that require specialized statistical methods. They can be characterized as binary events (one is in a financial crisis or not, one is depressed or not, an e-mail is spam or not) whose outcome may be difficult to verify even ex-post—was it a financial crisis or a simple recession, clinical depression or bipolar disorder, spam e-mail or a commercial e-mail about a product we own?

In all cases, it is desirable to have a means to predict the binary outcome but here one may not be concerned as much with a precise probability estimate about the likelihood of an outcome, as much as taking some action in response to that prediction and its quality. It is perhaps this last feature that differentiates some of the tools that we employ in this paper from the traditional discussion of binary dependent variables common in the econometrics literature. Thus some brief discussion of our techniques is called for.

Crises are events, often observed infrequently, that by nature deviate from the norm in a sizeable manner. Handling such a problem therefore requires methods that are specially flexible and for this reason the statistical design necessarily relies heavily on nonparametric methods. Let the state variable $S_t \in \{0,1\}$ be a binary indicator that is one when there is a crisis in period t, and zero otherwise. In this paper we investigate several features associated with such a variable.

A natural place to start is by asking whether one can detect such events in advance using information from variables dated prior to the onset of the crisis. For this purpose, there exist well known parametric models for binary dependent variables. Instead, we begin by thinking about the decision problem faced by the policymaker. Suppose $\widehat{y}_t \in (-\infty, \infty)$ is a scoring classifier such that for a given threshold c, then $\widehat{y}_t > c$ is a signal taken to predict that $S_t = 1$ and $\widehat{y}_t \leq c$ corresponds to $S_t = 0$ instead. Notice that $\widehat{y}_t$ could be a probability prediction from a typical binary model (such as a probit, logit, etc.); a linear probability model; a factor model; etc. For the time being, it is not important to be specific as the framework we discuss is quite general. There are four outcomes facing the policy maker, summarized in the following table:

		Prediction	
		Negative	Positive
Outcome	Negative	$TN(c) = P(\widehat{y}_t < c \mid S_t = 0)$	$FP(c) = P(\widehat{y}_t > c \mid S_t = 0)$
	Positive	$FN(c) = P(\widehat{y}_t < c \mid S_t = 1)$	$TP(c) = P(\widehat{y}_t > c \mid S_t = 1)$

where $TN(c)$ and $TP(c)$ refer to the correct classification rates of non-crisis ("negatives") and crisis ("positives") respectively; $FN(c)$ and $FP(c)$ refer to the incorrect classification rates of negatives and positives respectively; and clearly $TN(c) + FP(c) = 1$ and $FN(c) + TP(c) = 1$.[4]

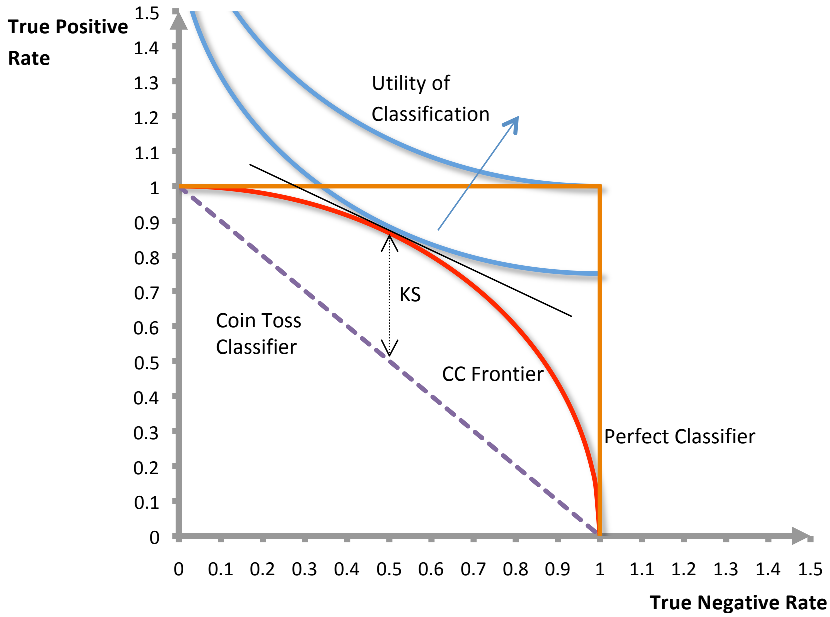
A policymaker's actions will be determined by balancing the costs and benefits associated with his decisions and by the accuracy of the scoring classifier. Consider the first of these two considerations. If π denotes the unconditional probability of a crisis and U_{ij} for $i \in \{n,p\}$ and $j \in \{N,P\}$ is the utility associated with each of the four states defined by the (*classifier, outcome*) pair, then the utility of classification

$$\begin{aligned} U(c) &= U_{pP}TP(c)\pi + U_{nP}(1 - TP(c))\pi + \\ &\quad U_{pN}(1 - TN(c))(1 - \pi) + U_{nN}TN(c)(1 - \pi) \end{aligned} \qquad (1)$$

is clearly seen to depend on c.

[4] Customarily, $TP(c)$, the true positive rate, is called *sensitivity* and $TN(c)$, the true negative rate, is called *specificity*.

Figure 1: The Correct Classification Frontier



Varying c will naturally change the true and false positive rates of classification (and, hence, utility). For example, if c is very large, then $TP(c) \to 1$ but $FN(c) \to 1$ as well. On the other hand, if c is very low, then $TN(c) \to 1$ but $FP(c) \to 1$. For economists, a natural way to summarize the classification ability of $\widehat{y}_t$ and these trade-offs is to construct a production possibilities frontier that plots the maximal combinations of $TP(c)$ and $TN(c)$ for different values of $c \in (-\infty, \infty)$. Jordà and A. M. Taylor (2010) call this curve the *correct classification frontier* (CCF), a concept closely related to the receiver operating characteristics (ROC) curve in statistics.

The CCF lives in the unit square $[0, 1] \times [0, 1]$, where a perfect classifier is one for which $TP(c) = 1$ for any $TN(c)$ and corresponds to the north and east sides of the unit square (see Figure 1). An uninformative classifier on the other hand, is one where $TP(c) = 1 - TN(c)\ \forall c$ and corresponds to the north-west/south-east "coin-toss" diagonal. Therefore the closer the CCF is to the north-east corner, the better the scoring classifier $\widehat{y}_t$. Jordà and A. M. Taylor (2010) also show how to construct a utility-weighted variant of the correct classification frontier, denoted CCF* (and to conduct inference on that object) in a manner consistent with equation (1).

The next step is to find the optimal operating point, which is determined by the tangent of the policymaker's utility function (1) with the CCF. However, in general policy trade-offs are unknown to the econometrician and thus it is necessary to construct summary measures of classification accuracy that, as much as possible, accommodate a wide range of scenarios.

Traditionally, one such measure is the Kolmogorov-Smirnov statistic defined as:

$$KS = \max_{c} 2 \left| \left(\frac{TN(c) + TP(c)}{2} \right) - \frac{1}{2} \right| \tag{2}$$

which is based on the distance between the maximum of the average correct classification rates attainable and 1/2, the average correct classification rate for a coin-toss. Notice that $KS \in [0, 1]$, with 0 meaning no classification ability and 1 meaning perfect classification ability. Inference on KS is relatively simple, although it involves some nonstandard distributions. [5]

However, the KS statistic refers to a specific value of c that may or may not be relevant for the decisions encapsulated by expression (1). This is especially true when the payoffs U_{ij} are not symmetric and/or the distribution of outcomes is particularly skewed, both likely features in our data. In response to these difficulties, another commonly used statistic is the area under the CCF or AUC. It is easy to see that for a coin-toss the AUC = 0.5 (the area under the north-west/south-east diagonal in the unit-square) whereas for a perfect classifier, AUC = 1, most applications in practice falling somewhere in-between. Inference on AUC is very simple, since its distribution is asymptotically Normal. [6]

[5] If T_k for $k = N, P$ denotes the total number of observations in a sample $t = 1, ..., T$ for which $S_t = 0, 1$ respectively, such that $T_P/T_N \to \lambda > 0$ with $T = T_N + T_P$, then correct classification rates can be computed as:

$$\widehat{TN}(c) = \frac{\sum_{i=1}^{T_N} I(\widehat{y}_t \leq c)}{T_N}; \widehat{TP}(c) = \frac{\sum_{j=1}^{T_P} I(\widehat{y}_t > c)}{T_P}.$$

where the indices i, j indicate observations in t such that $S_t = 0, 1$ respectively; and $I(.)$ is the indicator function that takes the value of 1 when the argument is true, 0 otherwise. Then, it can be shown that under standard regularity conditions:

$$\sqrt{\frac{T_N T_P}{T}} \widehat{KS} \to \sup_{\tau} |B(\tau)|$$

where $B(\tau)$ is a Brownian-bridge, that is, $B(\tau) = W(\tau) - \tau W(1)$ with $W(\tau)$ a Wiener process (see, e.g. Conover, 1999 for an explanation of this result).

[6] Let u denote the values of $\widehat{y}$ for which $S = 1$ and let v denote the values of $\widehat{y}$ for which $S = 0$. Then, a simple, nonparametric estimate of the AUC is

$$\widehat{AUC} = \frac{1}{T_N T_P} \sum_{i=1}^{T_N} \sum_{j=1}^{T_P} \left\{ I(u_j > v_i) + \frac{1}{2} I(u_j = v_i) \right\}.$$

The AUC can be interpreted as $P(v < u)$ (see Green and Swets, 1996) and if $T_P/T_N \to \lambda > 0$ as $T \to \infty$, under standard regularity conditions Hsieh and Turnbull (1996) show that

$$\sqrt{T}(\widehat{AUC} - P(v < u)) \to N(0, \sigma^2) \tag{3}$$

where the formula for σ^2 can be found in Jordà and A. M. Taylor (2010). The asymptotic normality result makes this statistic particularly convenient since hypothesis tests can be constructed using the Wald principle.

3 Summary Measures of Spatial and Temporal Dependence: Are Crises Random Events?

A central question for a policymaker is to determine whether crises are random events that are no more predictable than the outcome of a coin toss. Under this null, there is little that the policymaker can do. Under the alternative, the onus is on the policymaker to come up with "early warning systems," and state-contingent responses; and this in turn creates a need for the development of macroeconomic models whose dynamics could explain the formation of such extreme events, how best to avoid them, and how best to respond to their onset.

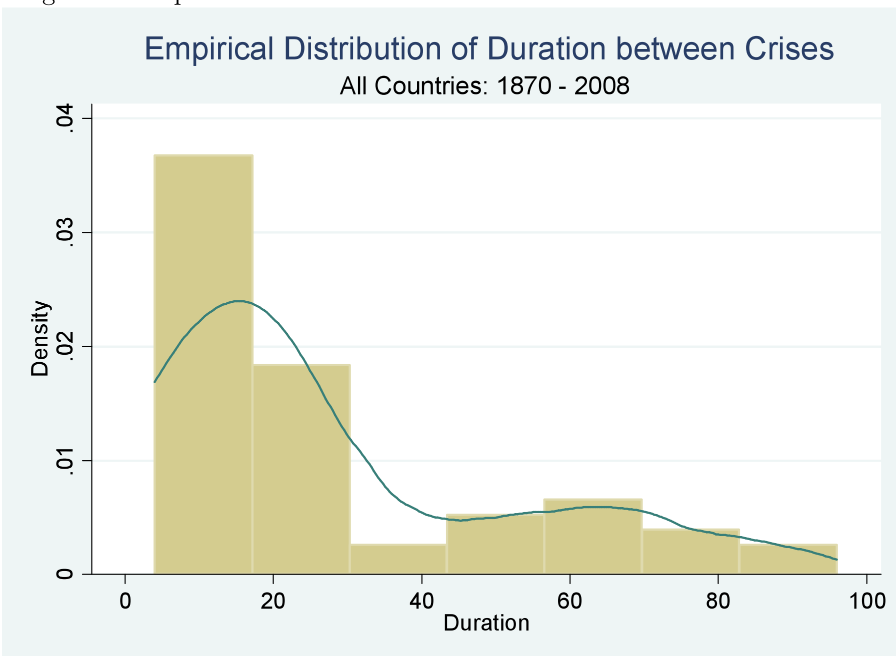
In this section we consider several nonparametric methods to assess some aspects of this null. One area of immediate interest is whether there is any serial correlation or temporal dependence in the binary crisis data. Another is whether there is any systematic spatial dependence. To foreshadow out results in this section, we find no evidence of serial correlation in the crisis data pattern, but we do find moderately strong evidence of some spatial dependence. Thus, in the case of the big global crises, if other countries are having a crisis there is a good chance that your country is having, or is about to have, a crisis too.

3.1 Duration Analysis

In the simplest of views we can think of crises as a Bernoulli trial with probability p. Under this null, the duration between crisis events is distributed as a Geometric random variable. Under the alternative, crises come in clusters, meaning that we are likely to observe a high proportion of small durations relative to the theoretical quantiles implied by the Geometric distribution, thus generating overdispersion. If one further assumes that the arrival of crises is independent across countries, then, under the null, it is valid to pool observations across countries into a single sample.

We begin by constructing the series of spells or durations between crisis events for each country and consolidating these observations across countries to generate one long series. During this process, we drop left- and right-censored durations that occur at the beginning and end of each individual country's sample. This resulted in 58 complete spells and the histogram and kernel density estimate for these data are displayed in Figure 2, with a mean duration between crises of 28 years and a standard deviation of 24. We remark that during the period 1940–1973 no country experienced a crisis and therefore it is natural to consider whether this oasis of calm represents a

Figure 2: Empirical distribution of the duration between crises across all countries, 1870–2008



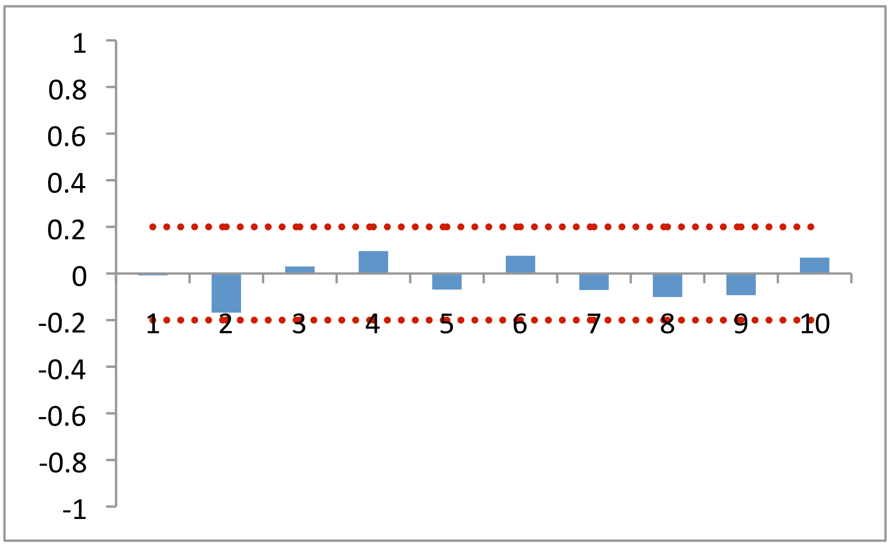
Notes: mean duration is 28 years, standard deviation is 24 years. Left-censored observations at the beginning of each countryÕs sample are deleted, leaving 58 complete durations. Right censored observations at the end of each countryÕs sample are also deleted (but since most countries experienced a crisis in either 2007 or 2008, these coincide with the end of the sample in any event).

break in the stochastic process describing our data. Omitting this period, the sample is reduced further to 44 completed spells with the average duration between crises dropping to 15 years with a standard deviation of 8. However, the histogram and kernel density estimates have the same overall shape and are not reported for brevity.

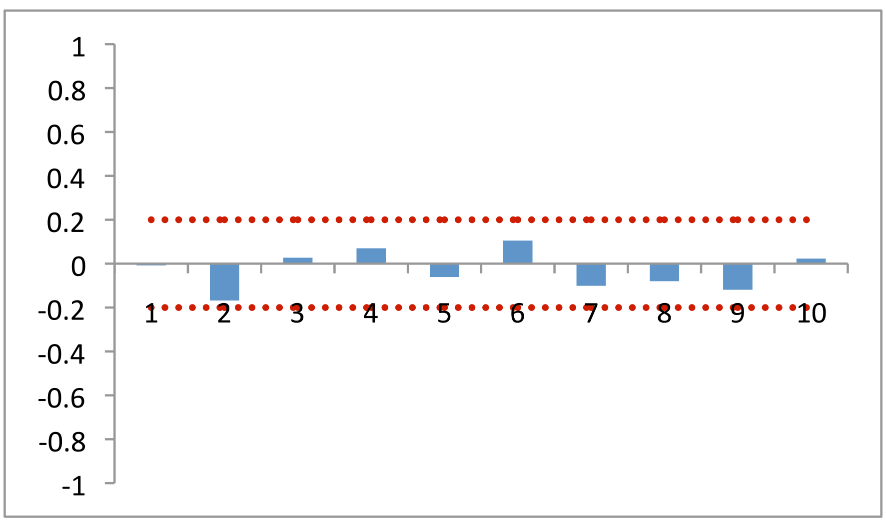
Hamilton and Jordà (2002) construct a dynamic model for just such discrete-duration data, the autoregressive conditional hazard (or ACH) model and propose using simple autocorrelation and partial autocorrelation functions (ACF and PACF, respectively) to diagnose the serial correlation properties of the data. This is done in Figure 3, which reveals no evidence of serial correlation in the data. Ljung-Box statistics fail to reject the null that the data are serially uncorrelated at any lag between 1 and 10. Furthermore, omitting the 1940–1973 period does not change these results in the least, which at first blush may seem surprising. Part of the explanation is that the truncation results in dropping the longest spell for each country (14 in total so that we go from 58 to 44 observations) but these observations are not influential in explaining the dynamics of the data.

Figure 3: Correlogram of the Duration between Crises, All Countries 1870–2008

(a) Autocorrelation Function



(b)Partial Autocorrelation Function



Notes: The Ljung-Box statistic cannot reject the null that the duration data are serially uncorrelated at any lag between1 and 10. The duration data are constructed with all countries over 1870–2008 and dropping any left censored observations (which occur at the beginning of the sample for each country) and right censored observations (which occur at the end).

Another possible manifestation of clustering over time would result in an empirical distribution of the data that is overdispersed (see Hamilton and Jordà, 2002 for an explanation of this phenomenon). Therefore, an alternative first-pass nonparametric diagnostic of temporal clustering of crisis events is a Q-Q plot.

Specifically, let n denote the 14 countries in our sample, each a time series with T observations. Let $S_{it} \in \{0, 1\}$ be a binary crisis variable for $i = 1, ..., 14$ and $t = 1, ..., T$. Then the maximum likelihood estimate of p, the parameter of the Bernoulli/Geometric null distribution, is simply:

$$\widehat{p} = \frac{\sum_{i=1}^{n} \sum_{t=1}^{T} S_{it}}{nT}$$

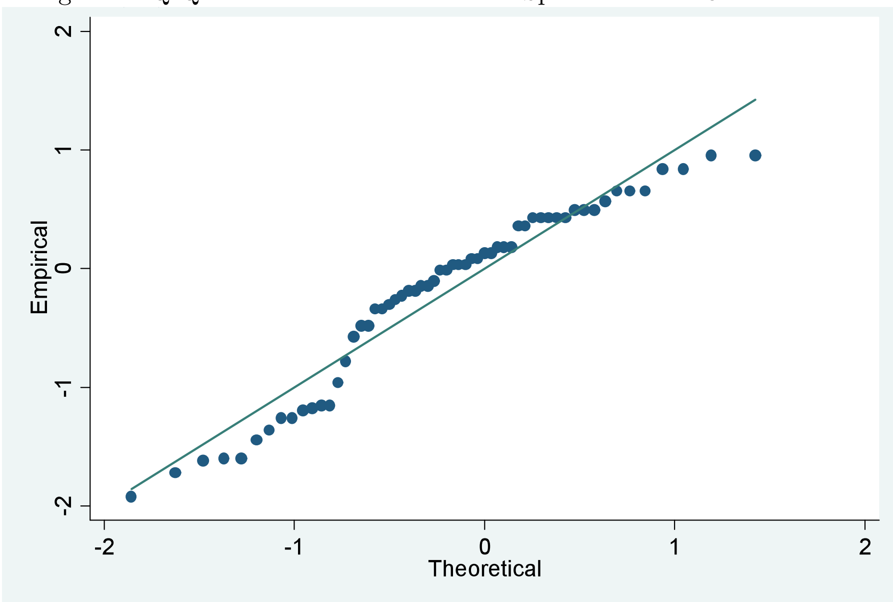
If the data are well represented by the Bernoulli/Geometric assumption, then a plot of the theoretical quantiles for this distribution against the empirical quantiles of the duration distribution (the Q-Q plot) will generate a graph that traces the 45^0 line. However, if there is any sort of clustering, across time, then, specially in the lower quantiles, there will be easily identifiable differences between both distributions.

The Q-Q plot is displayed in Figure 4 and shows that the data do not exhibit over-dispersion with respect to the null of a Geometric distribution. A similar plot is obtained when omitting the 1940-1973 period. Thus far, the evidence points strongly against there being duration dependence in the data that could be exploited to improve forecasting ability of crisis events. The next section refines this analysis further with some recently introduced tools and examines whether crises tend to come in country clusters.

3.2 Autoclassification and Cross-Classification Analysis

Even before examining the classification ability of any candidate explanatory variable (e.g., macroeconomic time series), perhaps the simplest scoring classifier one could consider are the lagged values of the crisis indicator variable S_{it}. In a typical time series, the autocorrelation function is a simple statistic that visually displays the serial correlation patterns of a variable with its past values and where a white noise is the natural null model. Berge and Jordà (2010) introduce an equivalent concept for classification problems that they dub the *autoclassification function* (ACF) based on the area under the CCF. The results of the previous section do not suggest that there is duration dependence but here dependence is assessed differently and in a manner that exploits

Figure 4: Q-Q Plot of the Distribution of Spells between Crisis Events across All Countries



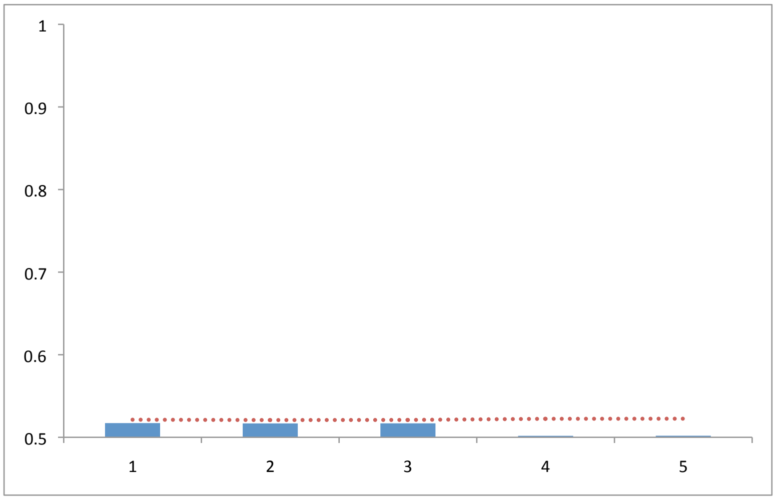
Notes: Under the assumption that crisis events occur randomly in time with a Bernouilli distribution, the duration between crises is a random variable with a Geometric distribution. The Q-Q plot compares the theoretical and empirical quantiles of this duration random variable. Time dependence in the arrival of crises tends to manifest itself with excess dispersion and the clustering of crises which would generate distortions in the lower quantiles with respect to the theoretical distribution. Left and right censored durations are omitted from the sample, which is based on all countries (14) for the period 1870–2008.

the full sample of 1,940 observations rather than with data on the 58 spells between crisis events examined above.

The ACF displays the AUC values when $\widehat{y}_{it} = S_{t-k}$ for $k = 1, ..., q$. Evidently, for $k = 0$ we get perfect classification and the AUC is trivially seen to equal 1. On the other hand, if the arrival of a crisis at time $t - k$ has no impact on the likelihood of a crisis at time t, then its AUC $= 0.5$ (rather than 0, as would be the case when computing a traditional autocorrelation). Together with the large-sample results in expression (3), the ACF provides a formal nonparametric method to examine whether the arrival of crises over time is random. The plot of the ACF for the combined sample of 14 countries in our sample is provided in Figure 5 and shows that even by this metric, there is still no evidence of time-dependence in the arrival of crises. The reported AUC values are statistically indistinguishable from the null value of AUC $= 0.5$.[7]

[7] Moreover, unlike the duration analysis of the previous section, the ACF can be computed on a country by country basis (Jordà and A. M. Taylor, 2010 discuss why, unlike other statistics, the AUC statistic is robust to situations where the unconditional probability of observing an event is low, such as in our application). The results of the per-country ACFs mirror that of the combined ACF displayed in Figure 5 and are not reported here for brevity.

Figure 5: Autoclassification Function for all countries, 1870–2008



Notes: The autoclassification function displays the area under the correct classification frontier for the problem of predicting whether there will be a crisis in period t given information on whether there was a crisis in a previous period (here from 1 to 5 years). A value of 0.5 indicates no classification ability, and a value of 1 indicates perfect classification ability. The 95% confidence upper band is displayed as the dotted line.

However, policymakers also worry about possible contagion from crises occurring in other countries—is there a similarly convenient, nonparametric statistic that could evaluate such a feature? We provide an answer to this question by blending the classification tools introduced above, with tools from network analysis (see, e.g. Watts and Strogatz, 1998). In particular, we consider two standard measures of network connectivity. The simplest one computes the *incidence rate* of crises across countries at time t, that is, $r_t = \frac{1}{n}\sum_{i=1}^{n} S_{it}$. However, it is also common to assess a network's connectivity by measuring the *wiring-ratio*. The wiring ratio is similar in flavor to a "majority voting rule," a tool commonly used in pattern recognition problems (see, e.g. Hastie, Tibshirani, and Friedman, 2009), and has increasing marginal effects as the network's connectivity increases, as we shall see. Specifically, the wiring ratio, w_t, can be computed as the number of connected pairs (i.e., country pairs simultaneously experiencing a crisis) out of all the possible pair-wise connections of a fully connected network.[8]

[8] That is, if n is the number of nodes in the network (the number of countries in our case), there are $n(n-1)/2$ possible pair-wise connections (with 14 countries this number is 91). Suppose that at time t, 7 out of the 14 countries experience a crisis. In that case there would be $7(7-1)/2 = 21$ pair-wise connections for a wiring ratio $w_t = 21/91 = 0.24$. Compare this number to $r_t = 0.5$ and then it becomes clear that, whereas the relation between r_t and the number of countries experiencing a crisis simultaneously is linear, the relation with respect to w_t is concave so that the marginal effect of an additional country experiencing a crisis is low when only one other country is experiencing a crisis, but it becomes very high when many countries experience a crisis at the same time.

These two network connectivity measures, r_t and w_t, and their leads and lags can be used to construct what we will call, a cross-classification function, a parallel concept to a cross-correlation function. Specifically, for country i with crisis indicator S_{it}, compute the AUC based on setting $\widehat{y}_t = r_{t-k}$ and $\widehat{y}_t = w_{t-k}$ for $k = 0, \pm 1, \pm 2, ..., \pm q$. The top panels of Figures 6 (for r_t) and 7 (for w_t) display the cross-classification patterns for each country in the sample whereas the bottom panels of the figures display the time series for r_t and w_t, respectively.

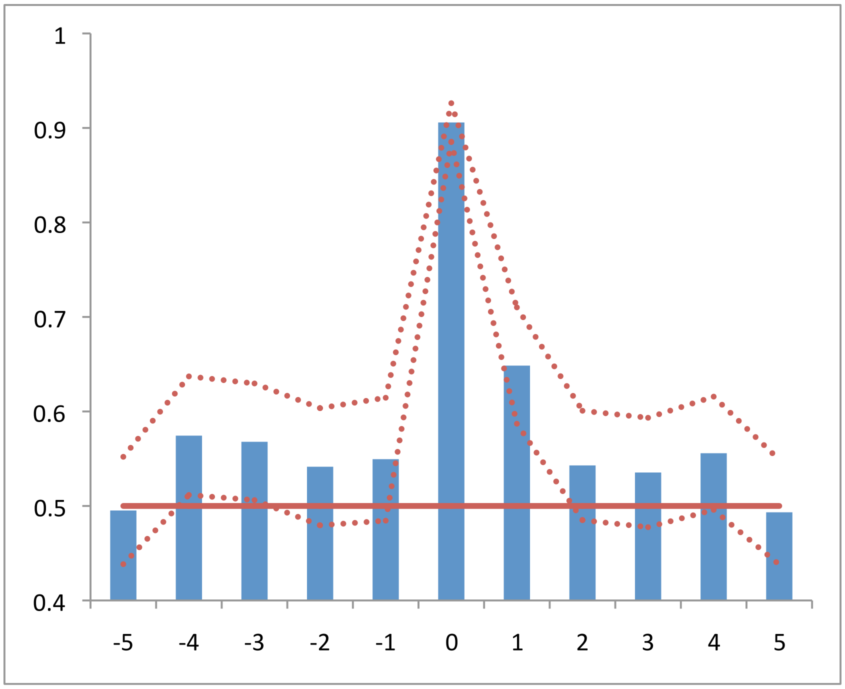
The top panels of Figures 6 and 7 put these features in more formal context. When a crisis occurs in several other countries, the likelihood that another country will also experience a crisis is high, as shown by the high and statistically significant AUC value at $k = 0$. But how about the power of a cluster of countries experiencing a crisis for the purposes of predicting whether a crisis will occur in later another country? This is evaluated using the AUC values displayed to the right-hand side of $k = 0$, and they indicate that there is *some* classification ability when such a cluster is observed the previous year, but probably not thereafter: the AUC values under either measure are statistically different from 0.5 for the first lag $k = 1$, but not by a wide margin. In the opposite direction, that is looking at classification ability of past events, there is not much evidence of a relation between countries experiencing crises simultaneously. There results survive largely unchanged if one were to drop the period 1945 to 1973.

We begin by remarking on the differences between the latter: the incidence rate and wiring ratio measures. Notice that when only one country experiences a crisis, the incidence rate is 1/14 but the wiring ratio is 0 so that the wiring ratio is a better measure for the purposes of computing cross classification ability since it avoids some of the self-referential nature of the incidence rate. Moreover, even when the wiring ratio is non-zero, its value will be relatively low when only a few countries experience a crisis simultaneously, thus highlighting those episodes when many countries experienced a crisis at the same time. In fact, our sample contains only five episodes in which four or more countries experienced a crisis in the same year: 1890(5), 1907 (5), 1921 (4), 1931 (6) and 2008 (7). The bottom panel of Figure 7 helps visualize the oasis of calm between 1945 to 1973.

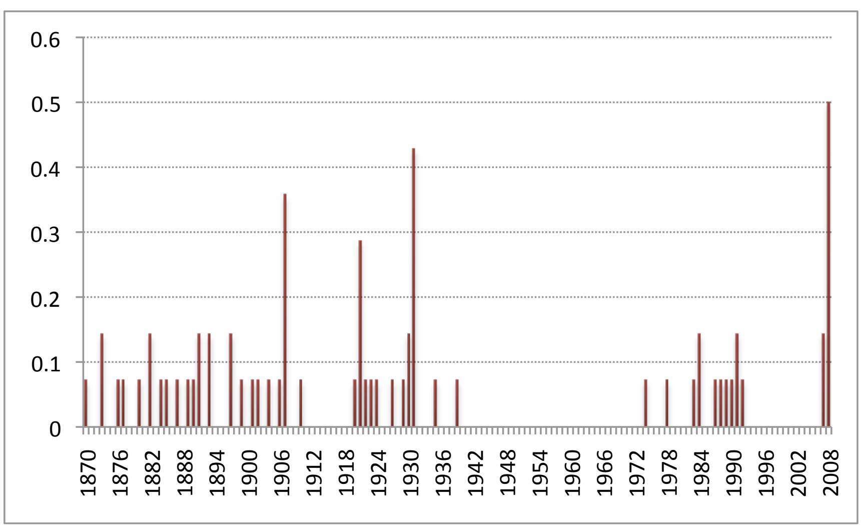
The lessons from the analysis in this section can be summarized as follows: (a) the likelihood of a crisis does not seem to be influenced by the time elapsed since the last crisis experienced; (b) about half of the crises in our sample (31 out of 71) occurred in only one country, nine episodes involved two countries, and there were four episodes involving four, five, six and seven countries, that is about one third of the crises (22) was experienced simultaneously in a cluster of countries

Figure 6: The Crossclassification Function for all Countries, 1870–2008 using the Incidence Ratio

(a) The Crossclassification Function



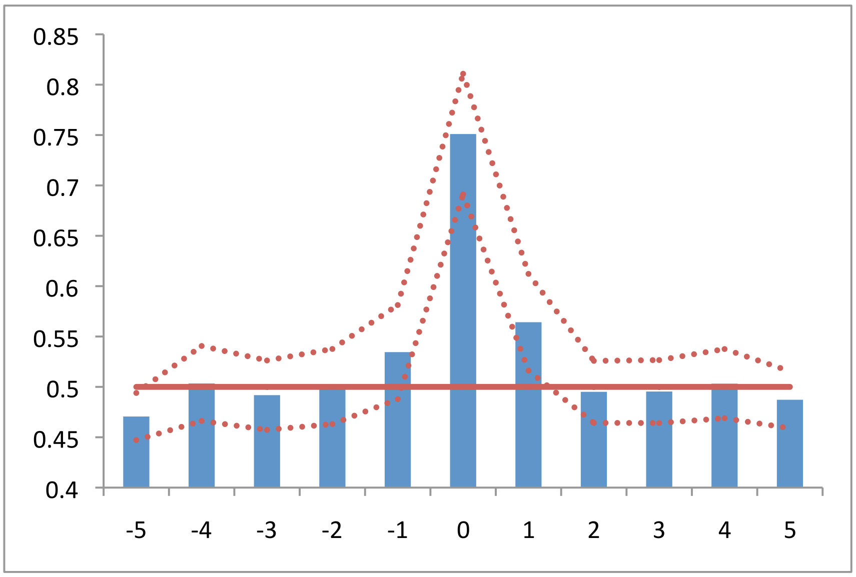
(b) Time Series of the Incidence Ratio



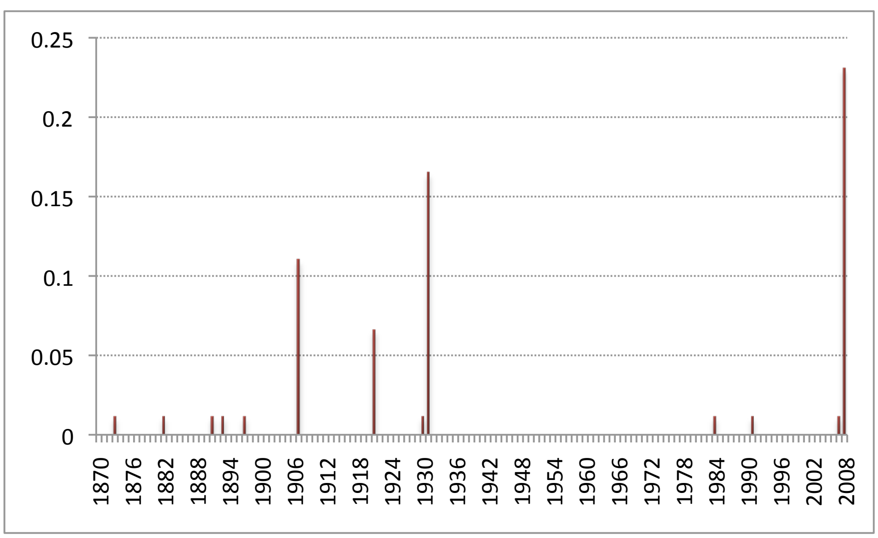
Notes: In panel (a), each bar represents the area under the correct classification frontier associated with predicting crises with leads and lags (up to 5) of the overall incidence rate of a crisis across countries. The dotted lines are 95% confidence bands.

Figure 7: The Crossclassification Function for all Countries, 1870–2008 using the Wiring Ratio

(a) The Crossclassification Function



(b) Time Series of the Wiring Ratio



involving four or more economies. Therefore, serial correlation is not a concern, but spatial dependence might be. Finally, these results remain largely unchanged to whether one includes or excludes the seemingly long period of calm between 1945 to 1973. Building on these results, the next section explores whether information about the macroeconomic outlook of countries can be used to detect a crisis in the future.

4 Pre-Crisis Dynamics: Isolated vs. Common Crises

We begin our empirical analysis informally by compiling a number of stylized facts regarding the international dimensions of financial crises. We start by looking more closely at the pre-crisis dynamics, differentiating between 'isolated' financial crises and clustered financial crises. Subsequently, we will also turn to the macroeconomic effects of financial crises. In 140 years of modern macroeconomic history, we identify five episodes in which a significant portion of countries simultaneously experienced a crisis: the Baring-related panic of 1890, the U.S.-centered international crisis of 1907 that led to the establishment of the Federal Reserve; the European post-war crises in 1921; the banking panics at the beginning of the Great Depression in 1930/31; and the global financial crisis associated with the Great Recession of 2007/08. The remaining events are mostly single country crises (almost half the sample) with a few episodes that involved two or three countries at most. For this reason, we break down the analysis into a *global crisis sample* (which includes the international crisis episodes of 1890, 1907, 1921, 1930/1 and 2007/08) and an *national crisis sample*, which includes the remaining isolated, contry-specific crises. We use the terms "global crisis" and "national crisis" to refer to these partitions of the crisis episodes.

We summarize the behavior of key macroeconomic variables for the four years leading into a crisis and the crisis itself. Unfortunately, we cannot perform this analysis for the 1921 crisis as the preceding years coincide with the final years of World War One and its aftermath, a period heavily distorted by the effects of disarmament and the return to a peacetime economy. We focus initially on the prologue to financial crises. This is partly motivated by the fact that the aftermath of the Great Recession is still unfolding and so the data are not in yet. We are also concerned that a thorough analysis of the aftermath of financial crises necessitates distinguishing between normal recessions and recessions that coincide with financial crises—which makes for a more complex analysis. We return to this point below. On the more practical side, we adjust our data for country-specific level and trend effects, to provide a common basis over which to aggregate the experiences of countries with diverse economic systems and histories. Therefore, our transformed data are best interpreted as deviations from a steady-state (so, e.g., a negative datum for inflation refers to a demeaned/detrended level and does not necessarily indicate outright deflation).

We investigate three specific aspects of economic performance preceding a financial crisis: the macroeconomic basics including output growth and inflation; the role of financial factors such as interest rates and credit growth; and the external environment captured by trends in current account balances. Figures 8–11 display the behavior of GDP and inflation, followed by interest rates, financial and external variables. In all figures, for comparison purposes, the left panel shows the average behavior (detrended and relative to country averages) of the variables in the prologue to national financial crises, while the right panel is for the four global crises (1890, 1907, 1930/31, 2007/08) in our long-run sample.

Growth and inflation dynamics reveal some interesting insights. With regard to growth, we see that national financial crises are typically not preceded by a period of higher growth. Questions about the net real effects of financial boom and bust as discussed, for example, in Ranciere et al. (2008), do not seem to arise for our sample as economic activity hardly accelerates before crises. There is little evidence that growth is significantly faster in the run-up to national financial crises. However, things are slightly different in the prologue to global financial crises. Here we find that growth rates are elevated before the crisis and collapse stronger in the year of financial turmoil (although the latter finding is likely to be driven by the 1930/31 collapse). Interesting differences are also evident with regard to price dynamics. For our (predominantly developed) country sample, there is scant evidence that normal financial crises are preceded by higher inflation. But in international crises, inflation undershoots significantly relative to country averages. There is nothing in our data that suggests that inflation trends help detect growing financial vulnerability.

The behavior of interest rates is perhaps the most interesting of all the variables under consideration here. Looking at both the 'natural' rate (short-term market interest rates less real economic growth) and (ex post) real interest rates (adjusted for current inflation) we find that in the prelude to the big international crises the natural rate was considerably lower than its trend for an extended period. No such conspicuous behavior is apparent in the case of real interest rates. If anything, in the run-up to international financial crises, CPI-adjusted nominal rates were slightly higher than during normal times. In other words, the global crises of 1890, 1907, 1930/31

Figure 8: GDP and Inflation

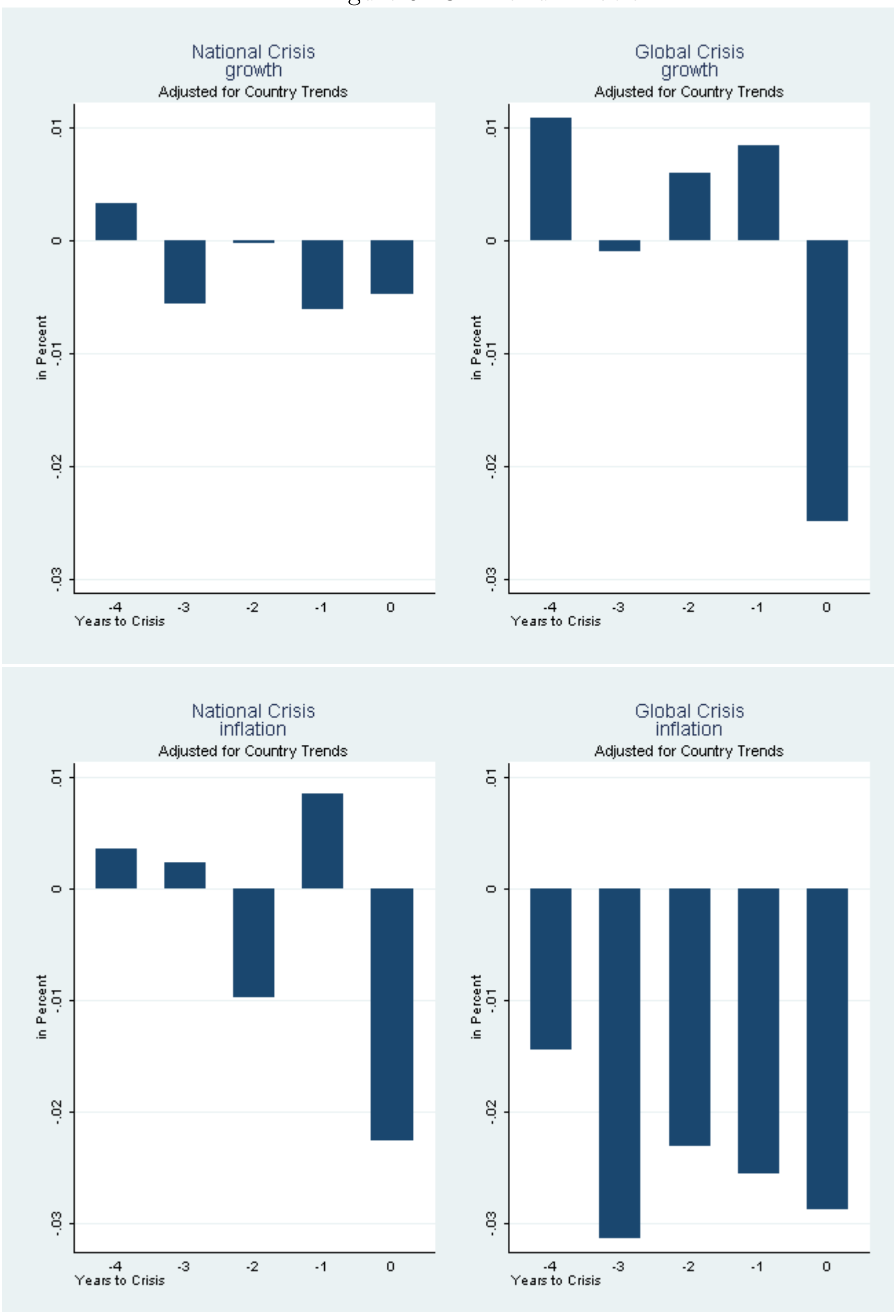


Figure 9: “Natural” and Real Interest Rates

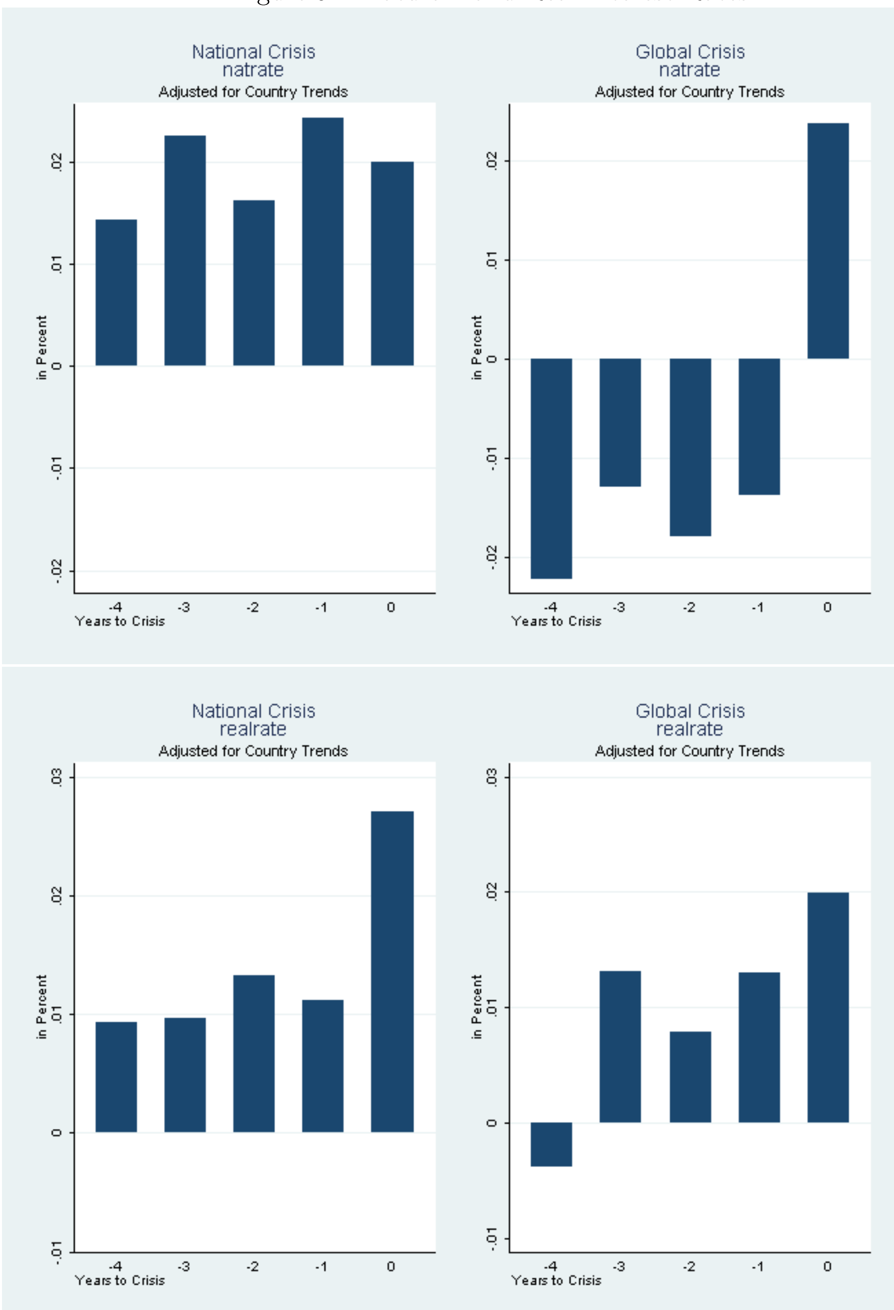


Figure 10: Loans and Credit to GDP Ratio

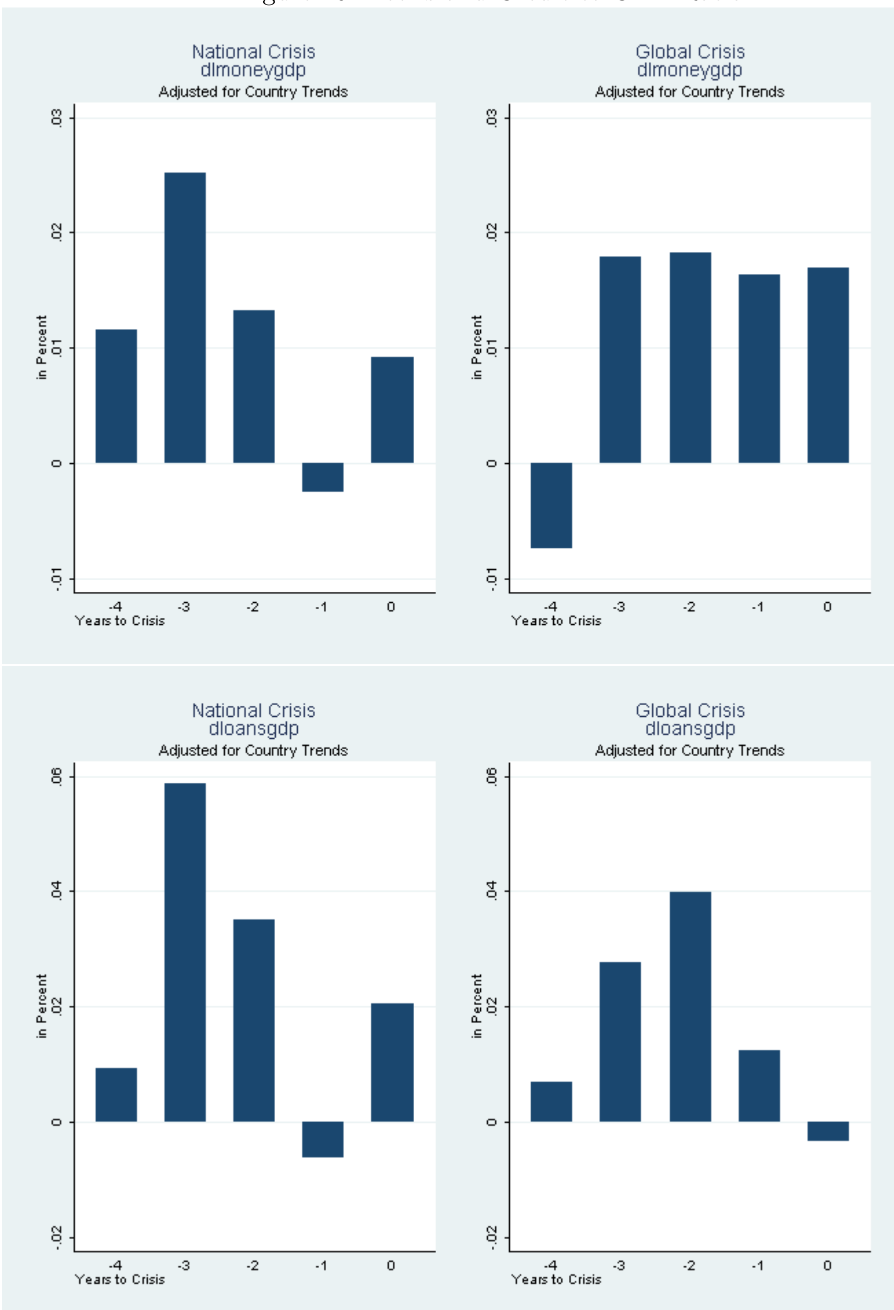
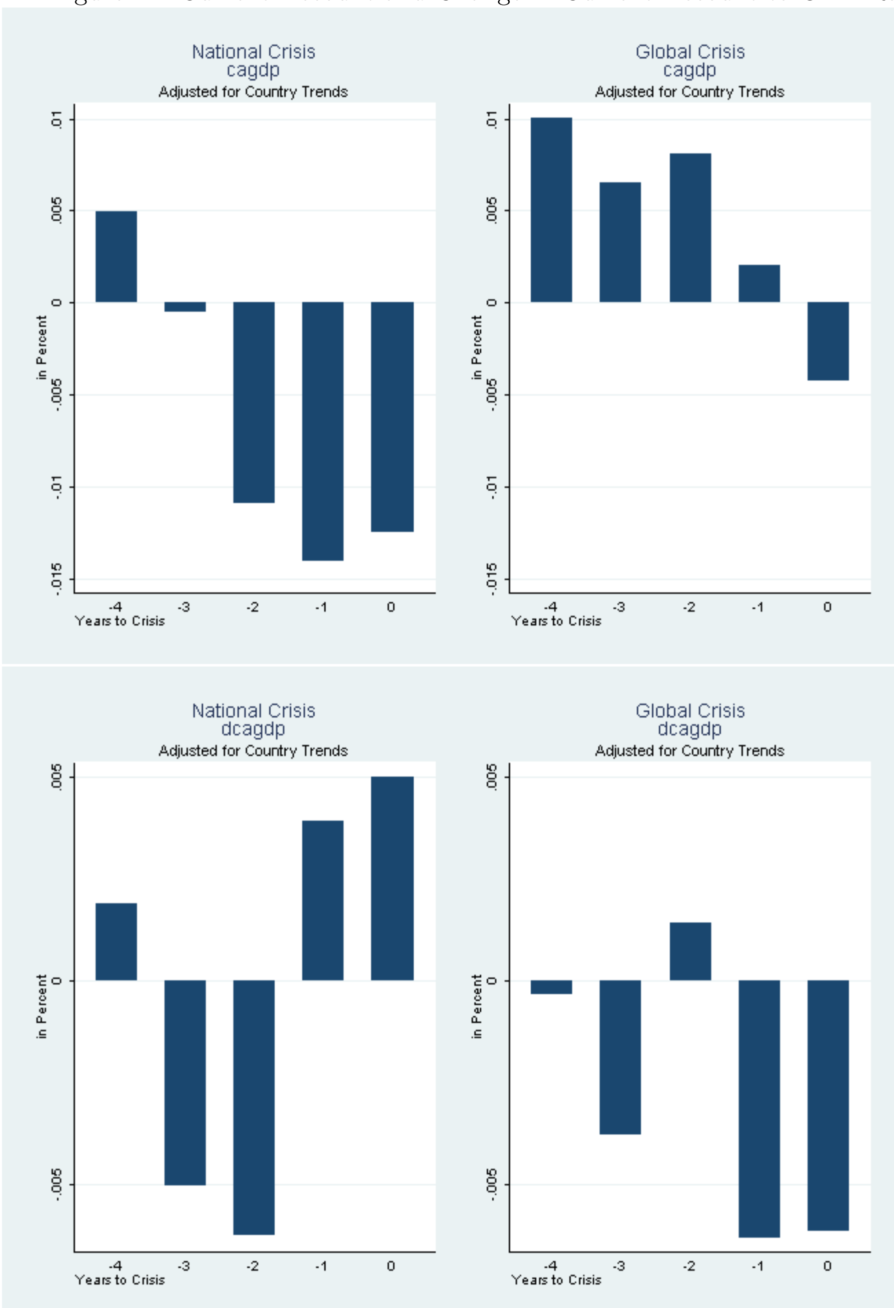


Figure 11: Current Account and Change in Current Account to GDP Ratio



and 2007/08 were different in the sense that they were preceded by periods in which interest rates were unusually low relative to the real growth rate of the economy. It is not impossible that central banks could have misread the absence of inflationary pressures and kept short-term interest rates too low, akin to the model discussed in Christiano et al. (2010).

The next two figures complete our description of financial variables. The first figure shows broad money over GDP, the second panel bank credit over GDP. We have also run a comparable analysis using proxies for banks' funding leverage (loans over money) with similar results. Both national and global crises are preceded by an expansion in money and credit. But the expansion of bank loans is more pronounced, suggesting that credit, not money is the key variable.

What about external imbalances? The behavior of these is summarized in the next figure, with the top panel displaying the current account to GDP ratio in levels and the bottom panel displaying the change of the current account to GDP ratio. Both crisis types are clearly associated with some deterioration of current account balances in the run-up to the crisis. But beyond that we find little evidence that big international crises such as the one we recently went through can be identified by glaringly abnormal current account trends.

Table 2 summarizes the historical evidence by looking at the cumulative effects before financial crises by comparing the global and national crisis samples in the years leading to the financial instability episode. Several results deserve comment. First, boom and bust dynamics seem to be more pronounced in big international crises as measured by growth and investment dynamics. Second, both credit and money growth are strongly elevated before national and global financial crises. Third, national crises are preceded by larger current account deficits relative to the country's own history. Lastly, we find historical evidence that the global crises occurred in an environment of depressed natural rates (i.e. when measured by the difference between nominal short term rates and real growth). In other words, international crises have tended to happen after non-inflationary real booms. However, no such misalignment is apparent if real interest rates are calculated using current inflation real interest rates. Prices were relatively static in the run-up to normal and common crises. In light of the evidence from 140 years of modern economic history, the big international crises are different in that they combine strong credit growth with an environment of low real interest rate (relative to real growth) and tame inflation. External imbalances could play an additional role, but at a first glance they appear secondary to the role played by credit growth and interest rates.

Table 2: Effects before financial crises

Log level effect, 4 years before crises, and versus non-crisis trend, for:	National crisis	Global crisis	Difference
Log real GDP	-0.028**	0.005	0.033*
	0.012	0.015	0.018
Log real investment	0.014	0.050	0.036
	0.052	0.061	0.076
Change in bank loans/GDP	0.101***	0.086**	-0.014
	0.032	0.034	0.044
Change in M2/GDP	0.070***	0.057**	-0.013
	0.022	0.025	0.032
Inflation	0.020	-0.081***	-0.101***
	0.017	0.020	0.026
CA/GDP	-0.033**	0.004	0.037**
	0.012	0.014	0.018
Change of CA/GDP	-0.008	-0.012	-0.004
	0.007	0.008	0.011
Short term interest rate – current inflation	0.008*	0.007	-0.001
	0.004	0.005	0.006
Short term interest rate – real GDP growth	0.022***	-0.017***	-0.039***
	0.004	0.005	0.006

Notes: ***/**/* denotes significance at the 99% / 95% / 90% level. Standard errors in parentheses.

5 Post-Crisis Dynamics

Turning to the behavior of key macroeconomic variables in the aftermath of financial crises, we are interested in the question of how disruptions in financial intermediation lead to real economic outcomes that are different from the normal behavior of these variables over the business cycle. Financial crises often go hand in hand with recessions. But it would be clearly wrong to attribute all of the output decline in recessions to the financial crisis. During 'normal' recessions, output also declines and inflation rates fall. In order to isolate a 'true' real economic effect we therefore should not compare the aftermath of financial crises with normal business cycle expansions. Rather, we should compare apples with apples and test whether recessions that occur in the wake of financial crises are deeper than 'normal' recessions. As an additional question, we can ask whether recessions that are associated with the big-4 international financial crises show different dynamics.

While conceptually clear, the empirical implementation is difficult. First, a consistent business cycle chronology is needed for all the 14 countries in our sample. This will enable us to identify recessions that coincide with financial crises and normal recessions. Second, the exercise is further complicated by the uncertainty surrounding the timing of financial crises for individual countries. One could for instance argue that the crisis of 2007/08 commenced in 2007 in the US and the UK, but reached other countries only in 2008. Such timing issues make it difficult to align crisis dates and recession dates. We therefore opted for an intermediate strategy. In a first step, we compiled a consistent business cycle history for the 14 countries in our sample by relying on the data provided in Barro and Ursua (2008). We coded a business cycle peak whenever GDP per capita in any given year was lower than in the preceding year. In a second step we made some manual adjustments (documented in the appendix) to the resulting series. Manual adjustments were only made when GDP recovered somewhat after a recession but failed to recover to the prerecession level and fell again the following year. We treated such short-term rebounds as part of the same recessionary episode and not as independent business cycles. Table 3 shows the resulting business cycle peak dates for the countries in our sample. The third step was to align the business cycle chronology with the financial crisis chronology.

Our aim is to examine the difference between recessions that coincide with financial crises and normal recessions. We therefore aligned all variables of interest on the business cycle peak year. In other words, whenever a financial crisis occurred in the year of, before, or after the business cycle peak, we code this observation as a 'crisis recession', and all others as 'normal recessions' (including instances when a financial crisis happened late in the course of the recession). Additionally, we also differentiate between isolated financial crises and international financial crises. This results in three different groups across which we compare the behavior of key macroeconomic variables in recessions:

(a) normal recessions;

(b) recessions cum national (isolated) financial crises;

(c) recessions cum global (common) financial crises.

However, there is only one global crisis in the post-1945 period—that of 2007/08. The aftermath of this crisis is still unfolding, so we cannot study the post-crisis dynamics (yet). We are thus left with only the first two groups (normal v. national crisis recessions) for the postwar period.

Table 3: Business Cycle Peaks

Business Cycle Peaks 1870-2008												
Australia	1875	1878	1885	1889	1891	1896	1900	1910	1926	1938	1943	
	1951	1961	1973	1981	1989							
Canada	1871	1877	1884	1888	1891	1894	1903	1907	1913	1917	1928	
	1944	1953	1956	1981	1989	2007						
Switzerland	1871	1875	1880	1886	1890	1893	1899	1906	1912	1916	1920	
	1929	1933	1939	1947	1957	1974	1981	1990	2001	2008		
Germany	1874	1879	1890	1898	1905	1908	1913	1916	1922	1929	1943	
	1966	1974	1980	1992	2001	2008						
Denmark	1876	1880	1883	1887	1911	1914	1920	1923	1931	1939	1944	
	1950	1962	1973	1979	1987	1992	2007					
Spain	1873	1877	1883	1892	1901	1909	1913	1916	1925	1929	1935	
	1940	1944	1947	1952	1958	1974	1978	1992	2007	2008		
France	1874	1882	1892	1896	1900	1905	1909	1912	1920	1926	1929	
	1937	1940	1943	1974	1992	2007	2008					
Great Britain	1875	1883	1889	1896	1899	1907	1918	1925	1929	1943	1951	
	1957	1973	1979	1990	2007							
Italy	1874	1883	1887	1891	1918	1929	1939	1942	1974	1992	2002	
	2007											
Japan	1875	1880	1887	1890	1895	1898	1901	1907	1913	1919	1925	
	1929	1940	1943	1973	1992	1997	2001	2007				
Netherlands	1873	1877	1889	1899	1902	1906	1913	1929	1937	1940	1957	
	1974	1980	2001	2008								
Norway	1876	1885	1897	1902	1916	1920	1930	1939	1941	1957	1981	
	1987	2008										
Sweden	1873	1876	1879	1885	1888	1890	1899	1907	1913	1916	1920	
	1924	1930	1939	1976	1980	1990	2007					
United States	1873	1882	1887	1892	1895	1901	1906	1909	1913	1918	1926	
	1929	1937	1944	1948	1953	1957	1969	1973	1979	1990	2000	2007

In the following charts, we contrast the behavior of key macroeconomic variables in the years $T+1$ to $T+4$ after the business cycle peak with the three final years of the expansion, i.e. $T-3$ to T, where the peak is in year t. Looking at the mean change in normal recessions, crisis recessions, and international crisis recessions, we aim to quantify the effects of disruptions in financial intermediation. As before, we focus the analysis on three key areas: growth and inflation; credit growth; external balances.

Starting with growth and inflation, we obtain a relatively clear picture that is in line with previous research (Schularick and A. M. Taylor 2009). Recessions that align with financial crises are about 1/3 more costly than normal ones. But this result only holds after WWII, not before.

Recessions accompanied by global crises stand out as the most costly ones, but this (prewar) result is strongly influenced by the Great Depression. Price trends display a similar pattern postwar. Inflation slows down in recessions, but more so in downswings that happen after financial crises.

We next turn to the behavior of credit growth in recessions. Both the pre- and postwar data show a clear slowdown in loan growth in recessions (but relative to GDP it remains positive pre-WWII). This reversal of loan growth, however, is considerably more pronounced in crisis recessions. Loan growth was about 4 times weaker in crisis recessions than in normal recessions after 1945. Before WWII, the slowdown in bank lending was only about twice as pronounced as in normal downturns. This finding is confirmed when we look at the growth rate of loans over GDP. In normal recessions, both pre-1945 and post-1945, the growth rate of loans over GDP hardly slowed down at all relative to the pre-peak trend. However, in financial crisis recessions pre and postwar, but in particular in recent decades, the growth rate of bank loans over GDP contracts meaningfully.

Last but not least, we ask how external balances fare in the various recession categories. The first insight we uncover is that the pre-WWII fixed exchange rate dynamics differ markedly from the post Bretton Woods experience. In gold standard times, the current account level tended to deteriorate both in normal recessions and crisis recessions. Only for the three global crises we find that the current account improved in the recession. However, in the postwar era recessions were consistently associated with improving current account positions. The same dichotomy applies to normal v. crisis recessions in the two eras. Since the end of the Bretton Woods regime, crisis recessions are associated with current account reversals even more strongly than normal recessions. Before 1945 no such trend is apparent.

Summing up, we find conspicuously different post crisis dynamics before and after WWII. The growth slowdown is more pronounced in the past decades. Inflation, however, slows down less than pre-WWII possibly reflecting more active central bank policies to avoid deflation. Yet we find little evidence that these policies have also succeeded in reducing output costs. Deflationary tendencies are much more pronounced in crisis recessions than in normal business cycle downturns. Crisis recessions also display a strongly negative impact on loan growth, possibly accounting for the slower growth experience than in normal recessions. Unlike in the 19th and the first half of the 20th century, current accounts generally have a tendency to improve in postwar recessions, even more so in those associated with financial crisis.

Figure 12: Growth and Inflation

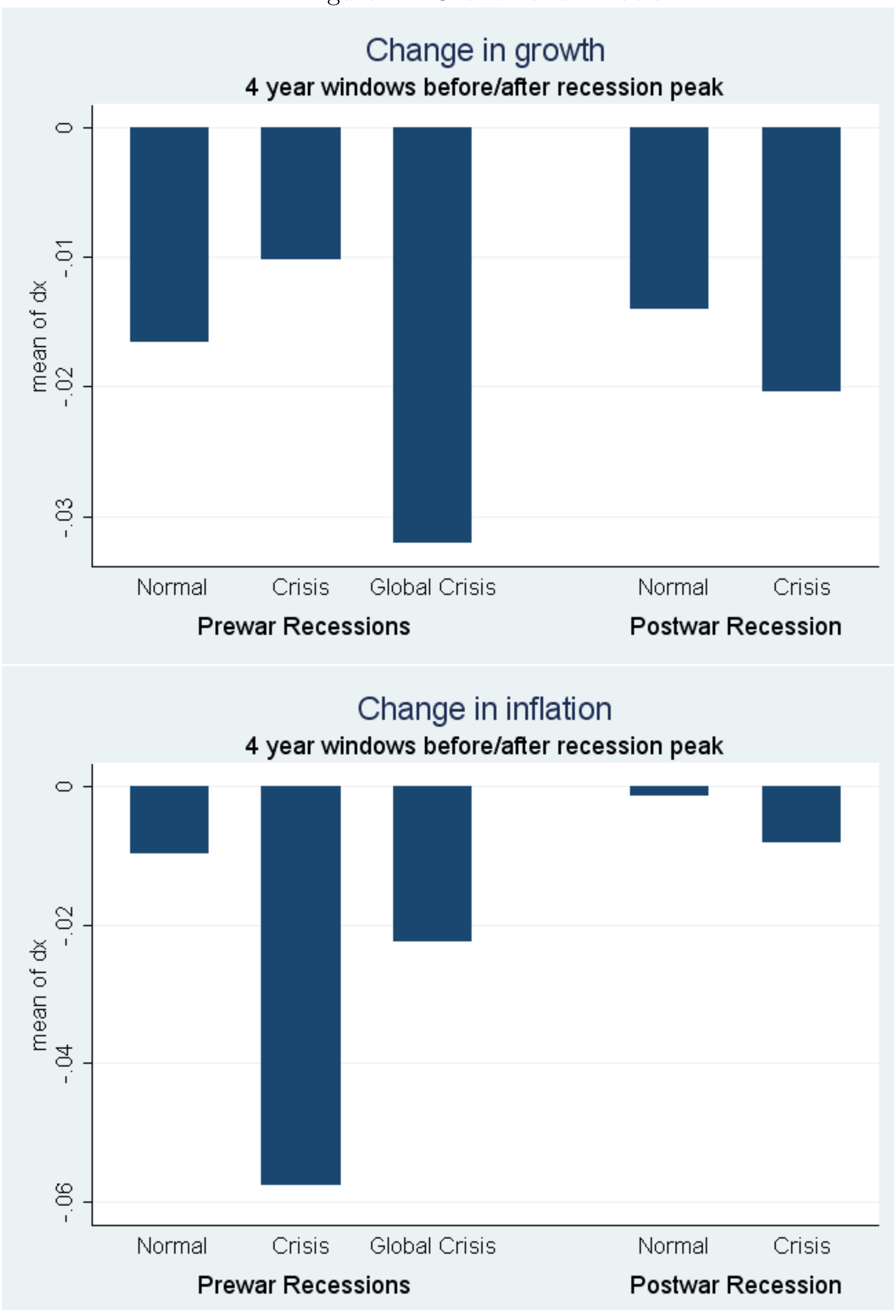


Figure 13: Loan growth and loans to GDP

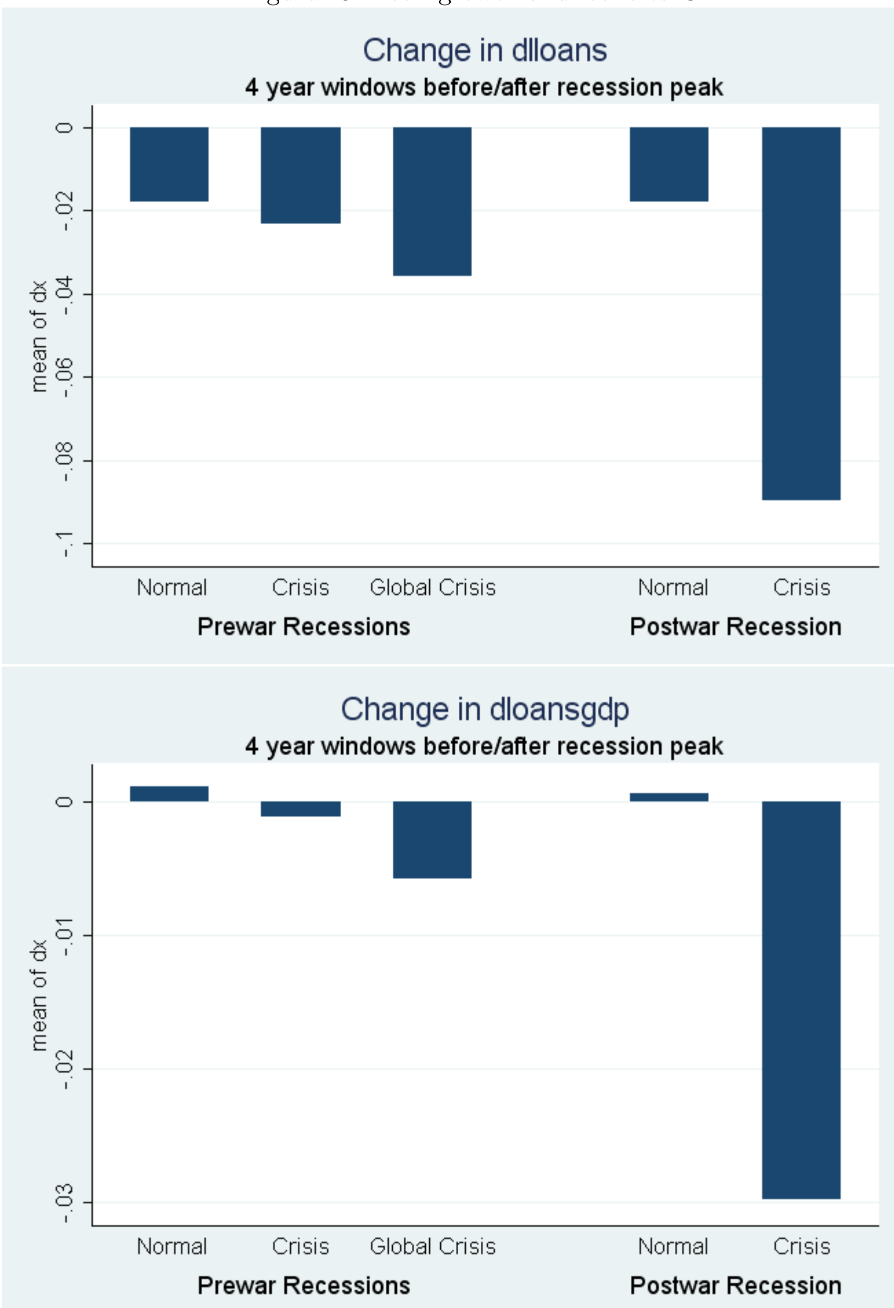
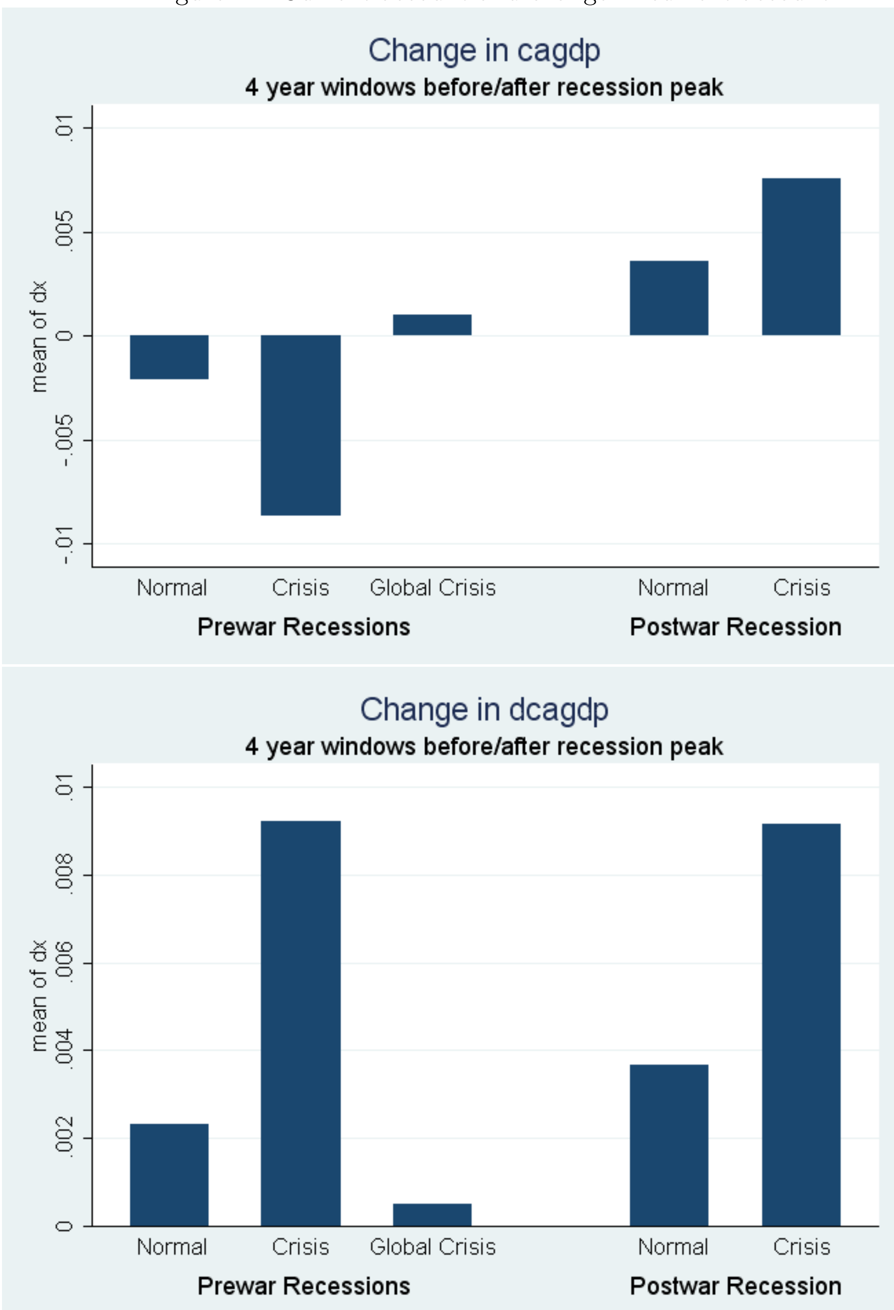


Figure 14: Current account and change in current account



6 Crisis Prediction: Do Current Account Imbalances Help Predict Financial Crises?

Are external imbalances an important causal factor of financial crises? The idea is certainly attractive. The global financial turmoil of 2007/08 occurred after a period of major imbalances in the global economy, marked by large deficits in a number of countries, first and foremost in the US. These countries at the recipient end of global capital flows also witnessed major asset price booms and were the home of the financial turmoil that engulfed the global economy. Prominent commentators have linked the recent crisis to external imbalance. To some extent, these issues are open to empirical investigation. This is what we attempt to do in the last part of our analysis. A large literature exists on boom and bust cycles in capital flows to emerging economies which are thought to increase macroeconomic vulnerabilities (Kaminsky et al. 2004). Similar studies for industrial countries are harder to come by. In the following, we ask whether the current account, alongside other economic fundamentals, contains information about the likelihood of a future financial crisis. We build on the crisis prediction framework presented in Schularick and A. M. Taylor (2009) who stressed the role of credit growth in generating financial instability on a country level. For this study, we have collected accompanying long run series for current account balances for the 1870-2008 period. This allows us to answer a number of pertinent questions: Does the historical record show that widening imbalances play a role in financial crisis? Should widening imbalances raise concerns for policy makers? And finally, what is the interaction of capital flows and credit growth in the origins of financial disruptions?

Using our long-run annual dataset for 14 countries, we start from a probabilistic model of a financial crisis event occurring in country i, in year t, as a function of lagged macroeconomic fundamentals, including current account imbalances, in year t,

$$\text{logit}(p_{it}) = b_{0i} + b_1(L)X_{it} + e_{it} \tag{4}$$

where $\text{logit}(p) = \ln(p/(1-p))$ is the log of the odds ratio and L is the lag operator. We are summarizing the information about lagged trends in macroeconomics using a 5-year moving average term which allows us to introduce interaction terms between imbalances and credit trends in the course of the analysis. The error term e_{it} is assumed to be well behaved. We also subject this

Table 4

Table 4: Crisis Prediction

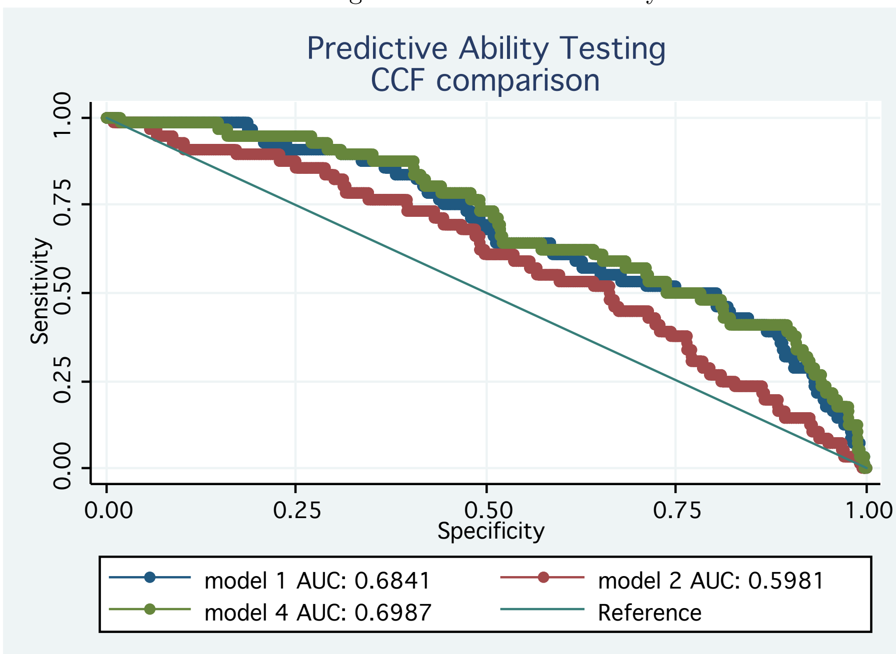
Logit country fixed effects	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Loans/GDP	32.61***		32.21***	31.55***	31.92***	31.65***	31.29***
(5-year mov. av.)	(6.301)		(6.315)	(6.534)	(6.542)	(6.647)	(6.574)
Change in CA/GDP		-29.05**	-24.77*	-11.39	-11.98	-7.754	-12.30
(5-year mov. av.)		(13.39)	(13.69)	(20.18)	(19.03)	(22.10)	(20.41)
(d.Loans/GDP)x(d.CA/GDP)				-524.6	-463.2	-482.2	-524.3
(5-year mov. av.)				(557.7)	(546.3)	(571.7)	(580.6)
GDP pc growth					-11.86**		
					(5.329)		
Real investment growth						2.383	
						(2.298)	
Inflation							-0.810
							(4.409)
Constant	-4.33***	-3.60***	-4.28***	-4.24***	-4.07***	-4.27***	-4.21***
	(0.383)	(0.297)	(0.372)	(0.371)	(0.375)	(0.378)	(0.383)
Observations	1,593	1,593	1,593	1,593	1,593	1,549	1,582
Pseudo R2	0.0564	0.0107	0.0627	0.0647	0.0720	0.0653	0.0644
Pseudolikelihood	-228.8	-239.9	-227.3	-226.8	-225.0	-222.1	-226.5
Test for country effects = 0	4.102	1.168	3.430	2.990	3.668	2.617	2.957
p value	0.0428	0.280	0.0640	0.0838	0.0555	0.106	0.0855
AUC	0.684	0.598	0.695	0.699	0.719	0.697	0.697

Notes: ***/**/* denotes significance at the 99% / 95% / 90% level. Standard errors in parentheses.

specification to several perturbations that take the form of including additional control variables in the vector X as described above.

Table 4 shows the results of our baseline estimations. We start by replicating the results from Schularick and A. M. Taylor (2009) using a logit model with country fixed effects and introducing the change in credit over GDP as the sole explanatory variable. Our key finding is again that a high rate of credit extension over the previous five years is indicative of an increasing risk of a financial crisis. Credit growth over GDP is highly significant, and the AUC test for predictive ability of the model yields a solid (in-sample) number of 0.68, outperforming a simple coin toss (AUC $= 0.5$) by a good margin. In regression 2, we let the change in the current account balance over GDP enter the horserace. Widening imbalances are also a significant predictor of financial crises, albeit the significance level is slightly lower and the fit much poorer. Equally important, the predictive ability of the current account model is somewhat worse than that of the credit model. The AUC falls to about 0.6. Note that we restricted the analysis to an identical sample of 1593 common observations for credit and current account data.

Figure 15: Predictive Ability



In a next step, we include both variables to see if additional predictive power results from credit and current account trends. The result is by an large negative. The credit variable remains highly significant and while the current account remains marginally significant, the AUC of the combined model is only a small notch higher than in the pure credit model. From this perspective, credit emerges as the variable to watch for the policy maker, not the external balance. A similar insight emerges from regression 4 in which we additionally interact credit growth and changes in the current account. Predictive ability rises only marginally indicating that credit booms fueled by capital flows are not much different from normal credit booms. The CCF comparison is graphically shown in the following figure. It can be easily seen that the predictive ability of a pure current account model is significantly weaker than that of the credit model. Including the current account and the interaction term (model 4) leads only to very small gains in forecasting performance.

Regressions 5, 6 and 7 add, additional economic control variables. First, a five year moving average of real GDP growth; second, real investment growth; third, we add inflation trends. None of these additions leads to meaningfully different results: credit dominates as the single most important factor and a more complex model improves predictive ability only slightly. Overall, we find only limited evidence that current account deficits have played a major role in generating financial crises in the past 140 years. In the quest for financial stability, the historical evidence would suggest that mechanism to restrict credit growth have better chances of success.

However, an objection to these findings could be that the global capital flow regime has changed substantially in the past 35 years rendering long-term comparisons problematic. The transition to floating exchange rates and capital mobility after the demise of the Bretton Woods system has brought about a new 'elasticity' of current account balances. It is possible that the dynamics of credit, capital flows and crises have changed accordingly. Taking this hypothesis seriously, we look closer at the post-1945 and post-1975 subsamples. Have the relationships meaningfully changed in the past decades?

At first sight, table 5 displays the familiar picture of credit growth dominated crisis histories. Significance, fit and predictive ability are far superior. Yet under the surface a slight change can be discerned. In the post-1975 period, the interaction term between credit growth and current account approaches statistical significance. Also the coefficient is much bigger than for the sample as a whole. There are also signs of a growing collinearity between credit growth and current account trends: the correlation between credit growth and current account changes was low and insignificant before 1975. But it has picked up strongly in the past decades, both in magnitude and significance. The correlation of current account changes and loan growth is -0.15 and highly significant after 1975, suggesting that higher loan growth went increasingly hand in hand with widening imbalances.

Summing up, our analysis provides only limited support for the idea that widening imbalances have historically been a key factor in financial crises. Simply put, in the past 140 years financial crises, driven by excessive loan growth, occurred by and large independent of current account imbalances. In the past three decades, the interaction between credit growth and external imbalances has grown. We find that the correlation between credit growth - in the light of our regressions the key indicator to watch from a financial stability perspective—and widening external deficits has picked up considerably in recent decades. This points to a potential shift in the crises dynamics and an increasingly complex picture where domestic credit growth and capital flows are much closer to being two sides of the same coin than before. But it is too early to draw policy conclusion with great confidence. The current global economic order, combining floating exchange rates with capital mobility, has no historical precedent which makes direct comparisons difficult.

Table 5: Crisis Prediction: Post-1945/1975 Sample

Logit country fixed effects	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	post-45	post-45	post-45	post-45	post-75	post-75	post-75	post-75
Change in Loans/GDP	42.11***		41.32***	38.91***	34.94***		33.05***	29.93**
(5-year mov. av.)	(11.68)		(11.27)	(11.64)	(11.61)		(11.08)	(11.85)
Change in CA/GDP		-38.82	-26.35	42.02		-61.52	-40.24	22.73
(5-year mov. av.)		(25.04)	(22.51)	(47.64)		(39.67)	(36.90)	(55.18)
(D.Loans/GDP)x(D.CA/GDP)				-2,266				-2,306
(5-year mov. av.)				(1,588)				(1,885)
Constant	-5.21***	-3.94***	-5.14***	-4.98***	-4.55***	-3.44***	-4.46***	-4.32***
	(0.829)	(0.482)	(0.792)	(0.784)	(0.829)	(0.511)	(0.792)	(0.775)
Observations	809	809	809	809	462	462	462	462
Pseudo R2	0.0969	0.0112	0.101	0.116	0.0816	0.0208	0.0890	0.104
Pseudolikelihood	-87.96	-96.31	-87.52	-86.13	-75.64	-80.65	-75.03	-73.81
Test for country effects=0	1.940	0.553	1.735	0.779	1.732	0.558	1.525	0.751
p value	0.164	0.457	0.188	0.377	0.188	0.455	0.217	0.386
AUC	0.744	0.617	0.750	0.678	0.718	0.631	0.727	0.718

Notes: ***/**/* denotes significance at the 99% / 95% / 90% level. Standard errors in parentheses.

7 Conclusion

140 years of lessons regarding financial crises and external imbalances are not easily summarized. The picture we have encountered is a complex one. Our analysis of the historical relationship between financial crises and external imbalances has proceeded in four steps. First, we have applied a number of new statistical tools to analyse the temporal and spatial patterns of financial crises in the past 140 years. Our key finding here was that such patterns are not easily identified. Looking only at the incidence of crises across space and time, we cannot reject the notion that crises occur by and large randomly. Yet four (five, if the European postwar crises of 1921 are included) cluster of big international crises are discernible: 1890, 1907, 1930/31 and 2007/08.

In the second part, we looked in greater detail at the pre-crisis dynamics of various macroeconomic indicators. Three findings stand out. Loan growth is clearly elevated both before national ('isolated') and also before global crises. The current account deteriorates in the run-up to normal crises, but the evidence is inconclusive in global crises, possibly because both surplus and deficit countries get embroiled in the crisis. A key finding is that the natural interest rate was strongly suppressed in the run-up to the four global crises in the sample while real interest rates and inflation did not exhibit a meaningful deviation from trend.

In the third part, we studied post-crisis macroeconomic dynamics with greater granularity than before. We distinguished between recessions with and without financial crisis, and recessions following global economic crises. We find that recessions that are associated with financial crises are more costly than normal recessions, while recessions after global crises are particularly hard. While the Great Depression experience has a strong impact on this result, taken together these results add further evidence to the expectation that the recovery from the Great Recession will be sluggish. Regarding current account dynamics, we find that current accounts tend to improve more strongly in crisis recessions than in normal recession in the post-1945 world economy.

The final prediction part of this paper addressed the question whether widening external imbalances are a signal for policy makers that financial instability risks are building. Our overall result is that, from a policy-maker's perspective, credit growth—not the current account—generates the best predictive signals of impeding financial instability. However, the relation between credit growth and current accounts has grown much tighter in recent decades. In a globalized economy with free capital mobility credit cycles and capital flows have the potential to reinforce each other more strongly then before. The historical data clearly suggest that high rates of credit growth coupled with widening imbalances pose stability risks that policy makers should not ignore.

8 Appendix 1: Data Sources

All data come from Schularick and A. M. Taylor (2009), except for current accounts and trade balances. Unless otherwise stated, the additional data come from the following three sources

- J/O: Jones and Obstfeld data set; retrievable at: `http://www.nber.org/databases/jones-obstfeld/`
- Mitchell: Mitchell, Brian R. (2007abc).
- IFS: International Financial Statistics. 2010. International Monetary Fund.

Australia:

1870–1945 J/O
1946–1959 Mitchell
1960–2008 IFS

Canada:

1870–1945 J/O
1948–2009 IFS

Switzerland:

1921–1939 Kellenberg, Eduard (1939–1942): Kapitalexport und Zahlungsbilanz; Bern: A. Francke; Bd. I: S. 155, 245, 307; Bd. II: S. 87, 244f, 364f.
1948–1976 Mitchell
1977–2009 IFS

Germany:

1872–1938 J/O
1948–1973 Mitchell
1974–2009 IFS

Denmark:

1874–1945 J/O
1946–1974 Mitchell
1975–2009 IFS

Spain:

1870–1913 Prados De La Escosura, Leandro. 2010. Spain's international position 1850 -1913. *Journal of Iberian and Latin American Economic History* 20(1):173–215.

1931–1974 Tena Junguito, Antonio. 2007. New series of the Spanish foreign sector, 1850–2000. Working Papers in Economic History WP 07-14, Universidad Carlos III de Madrid.

1975–2009 IFS

France:

1870–1945 J/O
1948–1974 Mitchell
1975–2009 IFS

Great Britain:

1870–1945 J/O
1946–1969 Mitchell
1970–2009 IFS

Italy:

1870–1945 J/O
1946–1969 Mitchell
1970–2009 IFS

Japan:

1870–1944 J/O
1948–1976 Mitchell
1977–2009 IFS

Netherlands:

1870–1913 Smits, Horlings, van Zanden. 2000. Dutch GNP and its components, 1800–1913. GGDC Research Memorandum No.5, University of Groningen.

1921–1939 Statistics Netherlands, National accounts of the Netherlands (various issues), provided by Gert den Bakker (CBS Netherland)

1948–1966 Mitchell
1967–2009 IFS

Norway:

1870–1939 J/O
1946–1974 Mitchell
1975–2009 IFS

Sweden:

1870–1945 J/O
1946–1969 Mitchell
1970–2009 IFS

United States:

1870–1945 J/O
1946–1969 Mitchell
1970–2009 IFS

9 Appendix 2: Business Cycle Dating

We identify business cycle peaks using real GDP per capita. If output per capita growth was negative in any given year, we coded the preceding year as the business cycle peak. We then adjusted the resulting series for short term rebounds within recessions. These are cases when output rebounded but failed to recover the pre-recession level and fell again in the following year. We treated such short-term rebounds as part of the same recessionary episode and not as independent business cycles. Some minor adjustments were also made when country histories and other data sources suggested a slightly different chronology. For example, some differences may arise when accepted chronologies are built on higher-frequency (quarterly/monthly) data, in contrast to our annual data. In such cases, we moved the peak year by a maximum of one year to align our chronology with the accepted country histories.

D: Deleted peaks A: Added peaks

Australia: D: 1881, 1892, 1904, 1913, 1916, 1929, 1956, 1976 A: 1891

Canada D: 1874, 1882, 1920, 1931, 1947 A:1884

Switzerland D: 1878, 1881, 1902, 1951, 1994 A:1880

Germany D: 1875, 1931, 1928 A: 1874, 1929

Denmark D: 1870, 1917

Spain D: 1886, 1889, 1895, 1904, 1932

France D: 1872, 1875, 1878, 1885, 1916, 1933 A: 1874

UK D: 1871, 1878, 1892, 1902, 1938, 1946

Italy D: 1870, 1897, 1923, 1932

Japan D: 1883, 1904, 1922, 1933 A: 1992

Netherlands D: 1870, 1892, 1916, 1932, 1943

Norway D: 1881, 1893, 1923, 1942 A: 1941

Sweden D: 1883, 1886, 1904 A: 1885, 1888

USA D: 1916, 1919, 1932 A: 1918

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