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Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons*

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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 slumps and stronger turnarounds in imbalances than during normal recessions. Finally, we ask to what extent external imbalances help predict financial crises. Our overall result is that credit growth emerges as the single best predictor of financial instability. External imbalances have played an additional role, but more so in the pre-WWII era of low financialization than today.

- *Keywords:* financial instability, global imbalances, capital flows, correct classification frontier.
- *JEL codes:* C14, C52, E51, F32, F42, N10, N20

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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 2007/08. 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).

Proposals to limit imbalances feature prominently on the postcrisis 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

[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).

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.

In this paper, the focus is on the experience of selected developed economies in the long-run. This is not only motivated by data availability. There is a longer and stronger literature examining crises in emerging markets (for example, Kaminsky and Reinhart 1999). But advanced economies tend to be less plagued by the peculiar features that beset the well-studied emerging economy sample, such as institutional weaknesses and episodes of massive economic instability (hyperinflations, currency crises, etc.), a difference in key traits which could pose a serious problem for much needed long-run comparative analyses. In our view, this argues against simple pooling the data from emerging and advanced economies in a more easily assembled short/wide panel.

We therefore reach back to the economic history of the past 140 years to study the linkage between the international economy and financial instability using a long-run cross-country dataset covering 14 advanced economies. The dataset accounts for about 50 percent of global GDP over the 20th century. 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, credit, 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 advanced economies over 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 five big synchronized global crises when a significant number of countries in our sample experienced financial crises—in 1873, the early 1890s, 1907, 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 years from WWII until the mid 1970s.

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 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 (forthcoming). We find that credit trends, not external imbalances are the best predictor of financial instability. However, looking at the long-run evidence the predictive ability of the model increases somewhat if external factors are added to the regressions. But this masks important differences between the pre- and post-1945 eras. The overall result is mainly due to the pre-WWII period, when lower financialization may have permitted non-credit factors to play a larger role in the generation of financial crisis. Back then, both credit growth and capital flows contributed to financial crises, but they did so independently of each other. Financial crises back then were typically not preceded by lending booms that coincided with widening imbalances. Today, the two more often go together and crisis risks increase somewhat if credit growth accelerates and external imbalances widen. Yet overall, 140 years of crisis history show that credit growth is the dominant variable to watch from a policymaker's perspective. External imbalances do not seem to play as large a role in creating instability as credit booms. This prompts the worrisome thought that an obsession with global imbalances may—in a world of scarce political capital—unduly distract policymakers from giving due attention to mitigating credit instability via macroprudential policies, systemic risk management, and regulation and reform of the financial sector.

2 Preliminaries

In this section we discuss the new dataset and provide a summary of relevant statistical features. 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.

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. According to Maddison (2005), these countries represented a little more than 50% of global output both in the years 1900 and 2000, although this number has fluctuated considerably over time.

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 (forthcoming). 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

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.

grateful to a number of colleagues who shared their data or directed us to the appropriate sources.[2] Table 1 briefly summarizes our dataset.

With regard to the timing of financial crisis episodes in the past 140 years we are heavily indebted to many colleagues around the world who commented on a list with financial crisis dates that we sent out. This initial list was based on Schularick and A. M. Taylor (forthcoming) which in turn relied heavily on Bordo et al. (2001) as well as Reinhart and Rogoff (2009) for the pre WWII years. For the post-1960 period banking 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).

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). We therefore only look at banking crisis and excluded, for example, currency crises if they did not impact the financial sector. A table showing our definition of crisis events by country-year can be found in Table 2. In total, we identify 79 major banking crises in the 14 countries we study. We are hopeful that the crisis dates collected for this paper represent a first important step towards a consensus timing of financial crises in the past 140 years.[3]

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

[3] We wish to thank, without implicating, Daniel Waldenstroem (Stockholm), Pierre-Cyrille Hautcoeur and Angelo Riva (Paris), Jan Klovland (Oslo), Carl-Ludwig Holtfrerich (Berlin), Reinhard Spree (Munich), Margrit Grabas (Saarbrucken), Charles Tilly (Munster), Mari Oonuki (Tokyo), Tobias Straumann (Zurich),

Table 2: Crisis Dates by Country, 1870–2008

Australia	1893	1989							
Canada	1873	1907	1923						
Switzerland	1870	1910	1931	2008					
Germany	1873	1891	1901	1907	1931	2008			
Denmark	1877	1885	1902	1907	1921	1931	1987		
Spain	1883	1890	1913	1920	1924	1931	1978	2008	
France	1882	1889	1907	1930	2008				
U.K.	1873	1890	1974	1984	1991	2007			
Italy	1873	1887	1891	1907	1921	1930	1935	1990	2008
Japan	1882	1900	1904	1907	1913	1927	1992		
Netherlands	1893	1907	1921	1939	2008				
Norway	1899	1922	1931	1988					
Sweden	1878	1907	1922	1931	1991	2008			
USA	1873	1884	1893	1907	1929	1984	2007		

Sources: Schularick and A. M. Taylor (forthcoming); Bordo et al. (2001); Reinhart and Rogoff (2009); Laeven and Valencia (2008); Cecchetti et al. (2009). See text.

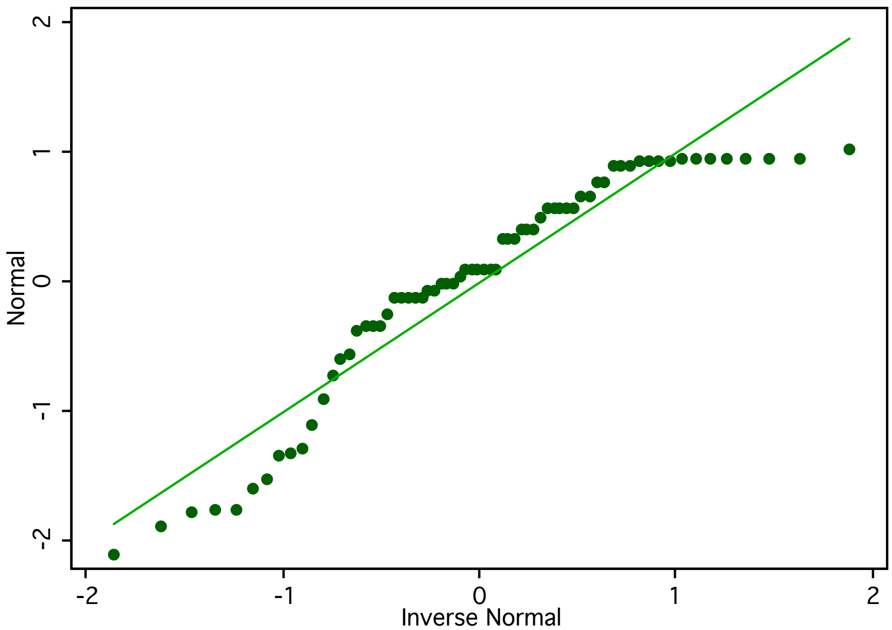
2.2 Temporal Dependence of Crisis Events

Perhaps the most natural null model characterizing the arrival of crisis events over time is the Bernouilli trial with probability p. This is a common assumption that has the implication that the duration of time between crises is distributed as a Geometric random variable. Under the alternative, crises will come in clusters, meaning that we are more likely to observe a high proportion of small durations relative to the theoretical quantiles implied by the Geometric distribution, an observation first made by Poincaré (1890). Therefore, a natural nonparametric test of dependence consists in plotting the empirical quantiles of the duration distribution against the quantiles of the Geometric distribution, for which we construct the series of spells or durations between crisis events for each country and then consolidate 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 68 completed spells averaging 25 years in duration and with a standard deviation of 23. Under the null hypothesis, the Q-Q plot will generate a graph that traces the 45° line. This is done in Figure 1.

Alternatively, one can investigate serial dependence in the duration data by calculating

Joost Jonker (Utrecht), Michael Bordo (Rutgers), Pablo Martin-Acenã (Alcalà). We asked these scholars whether they agreed that systemic banking crises took place in the given years and if any events were missing. In a few cases the question was not whether a significant crisis had occurred, but whether it should be called systemic. In such cases, we used some discretion to ensure comparability between countries. We generally coded crises if a significant part of the banking system was affected as measured by the number or the size of affected institutions.

Figure 1: 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, leaving 68 uncensored durations, based on all countries (14) for the period 1870–2008.

the autocorrelation function as suggested in Hamilton and Jordà (2002). Formally, we find that the Ljung-Box statistic cannot reject the null that the data are serially uncorrelated at any of the first 10 lags (since we only have 58 observations, it is not prudent to examine longer lag dependence). This evidence is provided in Table 3.

As a final check, we calculate the autoclassification function (ACF) proposed in Berge and Jordà (2011). The ACF consists in computing Mann-Whitney statistics for the crisis indicator variable $S_t = 1$ for crisis, 0 otherwise, using lags of S_t as scoring classifiers. Unlike the duration approach used earlier, the ACF makes full use of the original 1940 observations in the sample. The ACF can be interpreted in much the same way as a traditional autocorrelogram except that lack of dependence results in a null value of 0.5 rather than 0. Table 4 summarizes the value of the ACF for ten lags and shows that lagged information has no value for sorting current data into crisis/no-crisis events. We also broke down the ACF

Table 3: Duration Serial Correlation

Lag	Autocorrelation	Partial Autocorrelation	Ljung-Box statistic	p value
1	-0.06	-0.06	0.28	0.60
2	-0.04	-0.05	0.39	0.82
3	-0.09	-0.10	1.00	0.80
4	0.06	0.04	1.30	0.86
5	0.08	0.08	1.79	0.88
6	0.01	0.01	1.81	0.94
7	0.08	0.11	2.32	0.94
8	-0.24	-0.24	6.76	0.56
9	-0.11	-0.15	7.71	0.56
10	0.03	0.03	7.78	0.65

Notes: autocorrelation/partial autocorrelation function of the duration between crisis events for the full 1870–2008 sample across all 14 countries (58 observations total after omitting left- and right-censored spells). The Ljung-Box statistic for the joint null that the autocorrelation values for all lags up to that at which it is calculated is zero. The last column provides the p-value for this statistic.

Table 4: Autoclassification Function

Lag 1	Lag 2	Lag 3	Lag 4	Lag5	Lag 6	Lag 7	Lag 8	Lag 9	Lag 10
0.481	0.481	0.488	0.502	0.502	0.495	0.522	0.486	0.514	0.500
(0.002)	(0.002)	(0.007)	(0.012)	(0.012)	(0.010)	(0.016)	(0.007)	(0.015)	(0.012)

Notes: Values for the area under the receiver operating characteristic (ROC) curve are calculated using lags of the crisis dummy variable as scoring classifier. Under the null, the value of this statistic is 0.5. The numbers in parenthesis are standard errors. Under the null, the statistics are asymptotically normal and hence standard errors can be used in a conventional way to assess whether the value of the statistic exceeds 0.5 at conventional confidence levels.

analysis country-by-country (since each country has 139 observations using this procedure) and found similar results that are not reported here in the interest of brevity.

2.3 Spatial Dependence

Crises in our sample do not appear to be correlated over time. But advanced countries share strong trade and financial links so it is natural to ask whether crises are viral events that propagate across borders. In order to answer this question we blend some tools from network analysis (see, e.g. Watts and Strogatz, 1998) with an extension of the Berge and Jordà (2011) ACF statistic introduced earlier.

Two standard measures of a network's connectivity are the *incidence rate*, defined as $r_t = (\sum_{i=1}^{n} S_{it})/n$ where $S_{it} = 1$ if there is a crisis at time t in country i, and the *wiring ratio*, defined as the number of connected pairs (i.e. country pairs simultaneously experiencing a crisis) out of all possible pair-wise connections. Specifically, let $\eta_t = \sum_{i=1}^{n} S_{it}$ then the wiring

Table 5: Cross-Classification Function

	Lag -5	-4	-3	-2	-1	0	Lead 1	2	3	4	5
r_t	0.52	0.54	0.59**	0.56*	0.61**	0.91**	0.57**	0.52	0.62**	0.52	0.47
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
r_t^*	0.50	0.55*	0.59**	0.57**	0.61**	0.90**	0.57**	0.53	0.60**	0.52	0.48
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
w_t	0.49	0.48	0.52	0.50	0.56**	0.75**	0.54	0.50	0.51	0.49	0.47**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
w_t^*	0.49	0.48	0.52	0.50	0.56**	0.75**	0.54	0.50	0.51	0.49	0.47**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)

Notes: the statistics reported are the areas under the receiver operating characteristic (ROC) curve using the network connectivity measures as scoring classifiers. The null of no classification ability corresponds to a value of 0.5. Standard errors in parenthesis. The statistic is asymptotically normal and hence conventional confidence intervals can be constructed from the usual Gaussian critical values. r_t is the incidence rate, r_t^* is the GDP at PPP weighted incidence rate, w_t is the wiring ratio, and w_t^* is the GDP at PPP weighted wiring ratio. */** indicates significantly different from the null of no classification ability at 90/95% confidence level.

ratio is defined as

$$w_t = \frac{\eta_t(\eta_t - 1)}{n(n-1)}.$$

In addition, we consider two variations of these basic measures that allow connections to be weighed by the relative output weights (PPP adjusted) of the countries involved. Specifically:

$$r_t^* = \frac{\sum_{i=1}^n g_{it} S_{it}}{\sum_{i=1}^n g_{it}} \qquad and \qquad w_t^* = \frac{S_t G_t S_t'}{(n-1)\sum_{i=1}^n g_{it}},$$

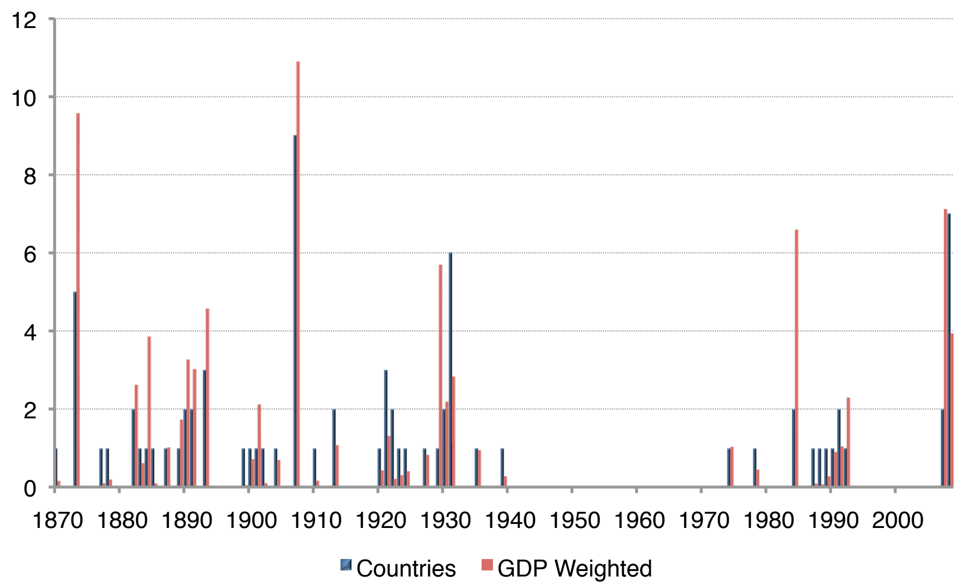
where S_t is an $n \times 1$ vector with column entries $\{S_{it}\}$ and G_t is an $n \times n$ lower triangular matrix with zeroes in the diagonal and with typical (i,j) entry given by output sums $g_{it} + g_{jt}$ for $i > j$. Notice that the denominator of w_t^* is the value of all pair-wise output weights whereas the typical entry in G_t for $i > j$ collects the output weights of two connected countries.

These two types of network connectivity measures and their leads and lags can be used to construct a natural extension of the ACF: the *cross-classification function*. That is, for any given country i with crisis indicator S_{it}, we compute the Mann-Whitney statistic obtained by using network connectivity as the scoring classifier. Figure 2 plots the un/weighted values of r_t and w_t whereas Table 5 reports the cross classification function for each network connectivity measure.

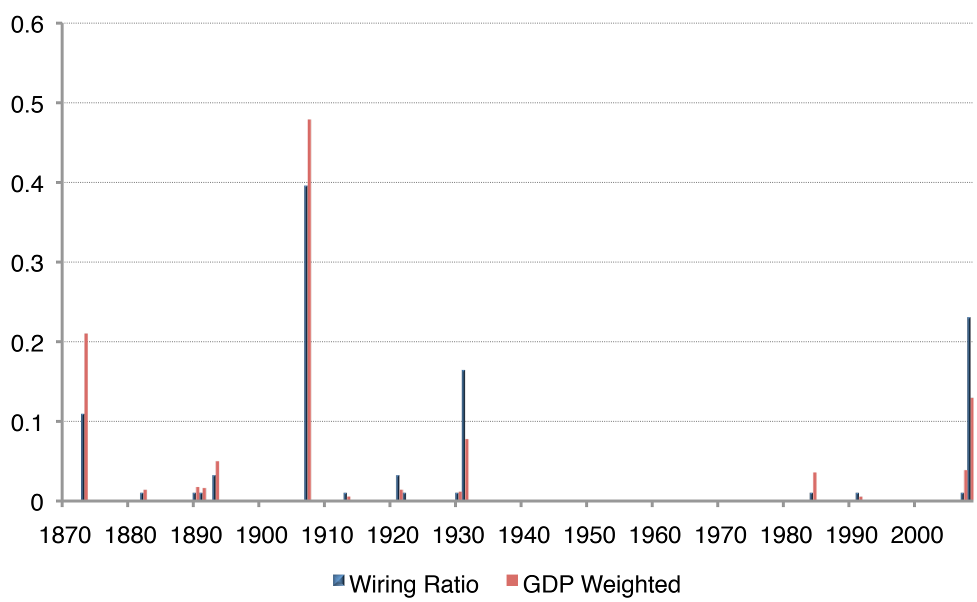
Figure 2 shows that there was a clear oasis of calm from 1945 to 1973 (the end of Bretton Woods) during which no country in our sample experienced a financial crisis. We were concerned that our previous results on lack of temporal dependence might have been

Figure 2: The Network Connectivity of Crisis Events Across Countries, 1870–2008

(a) Number of countries in crisis (out of 14 possible) and GDP-weighted equivalent



(b) Wiring ratio (which can be at most 1) and GDP-weighted equivalent



contaminated by a period that might well be considered as belonging to a different stochastic process altogether. However, we redid our analysis by dropping this period from the sample with remarkably little effect on our results (not reported here but available upon request).

Table 5 indicates that there is evidence of crisis contagion. If other countries are experiencing a crisis this or the previous year, the incidence rate suggests that there is a good chance that my country will experience a crisis as well. However, we tend to view measures based on the wiring ratio as more reliable since they avoid the self-referential nature of the incidence rate. By this metric of network connectivity, we only find evidence of concurrent contagion, with relatively weak evidence that when crises occur in several countries during the previous year, this is a good indicator that my country will experience a crisis this year. These results are also immune to dropping the 1945 to 1973 period we discussed previously.

Weighing by GDP (at PPP) has some effect on the incidence rate but less so on the wiring ratio. For example, from 1870 to 1905 there are only three instances when two countries simultaneously experienced a crisis. However, weighted by their GDP, these represented something like a crisis in 30%–40% of the GDP weighted sample. Going forward, in 1984 both the U.S. and the U.K. experienced a crisis but their combined weight (in the sample of 14 countries) at the time represented about 60% of total GDP (with Canada experiencing a crisis subsequently in 1985).

Finally, the bottom panel of Figure 2, which displays the un/weighted wiring ratio, clearly shows that there are at least four events where several countries experienced a crisis simultaneously. These are: 1873, 1890/93, 1907, 1930/31, and 2007/08. The 1873 crisis affected five countries representing about 68% of group GDP. The 1890/93 crises also affected five countries but represented a larger proportion of group GDP at 91%. 1907, tangled 9 countries representing 78% of group GDP. The well known 1930/1 period also engulfed 9 countries representing a similar percentage of group GDP at 78%. Such a wide-spread event also characterizes the recent 2007/8 global financial crisis, which ensnared 9 countries representing about 79% of group GDP. In what follows and given the breadth of scope of the events, we allow the data to possibly treat these 'global crisis' events differently than isolated 'national crisis' events the rest of the sample.

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 involving four or more economies. Therefore, serial correlation is not a concern, but spatial dependence might be. Finally, these results remain largely unchanged whether one includes or excludes the seemingly long period of calm between 1945 and 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.

3 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 crash of 1873, the Baring-related panic of the early 1890s, the U.S.-centered international crisis of 1907 that led to the establishment of the Federal Reserve; 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 crisis 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 1873, 1890, 1907, 1930/1 and 2007/08) and an *national crisis sample*, which includes the remaining isolated, country-specific crises. We use the terms "global crisis" and "national crisis" to refer to these two kinds of crisis episodes.

We summarize the behavior of key macroeconomic variables for the four years leading into a crisis and the crisis itself. 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, credit growth, and asset prices; and the external environment captured by trends in current account balances. Figures 3 to 6 display the behavior of GDP and inflation, followed by interest rates, as well as other 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 five global crises (1873, 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. Things are slightly different in the prologue to global financial crises. Here we find that growth rates tend to be a 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. In short, there is nothing in our data that suggests that higher inflation helps 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 adjusted for real growth rates) 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. The global crises of 1873, 1890, 1907, 1930/31 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. Figure 5 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 Figure 6, 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. National crises are associated

Figure 3: GDP and Inflation

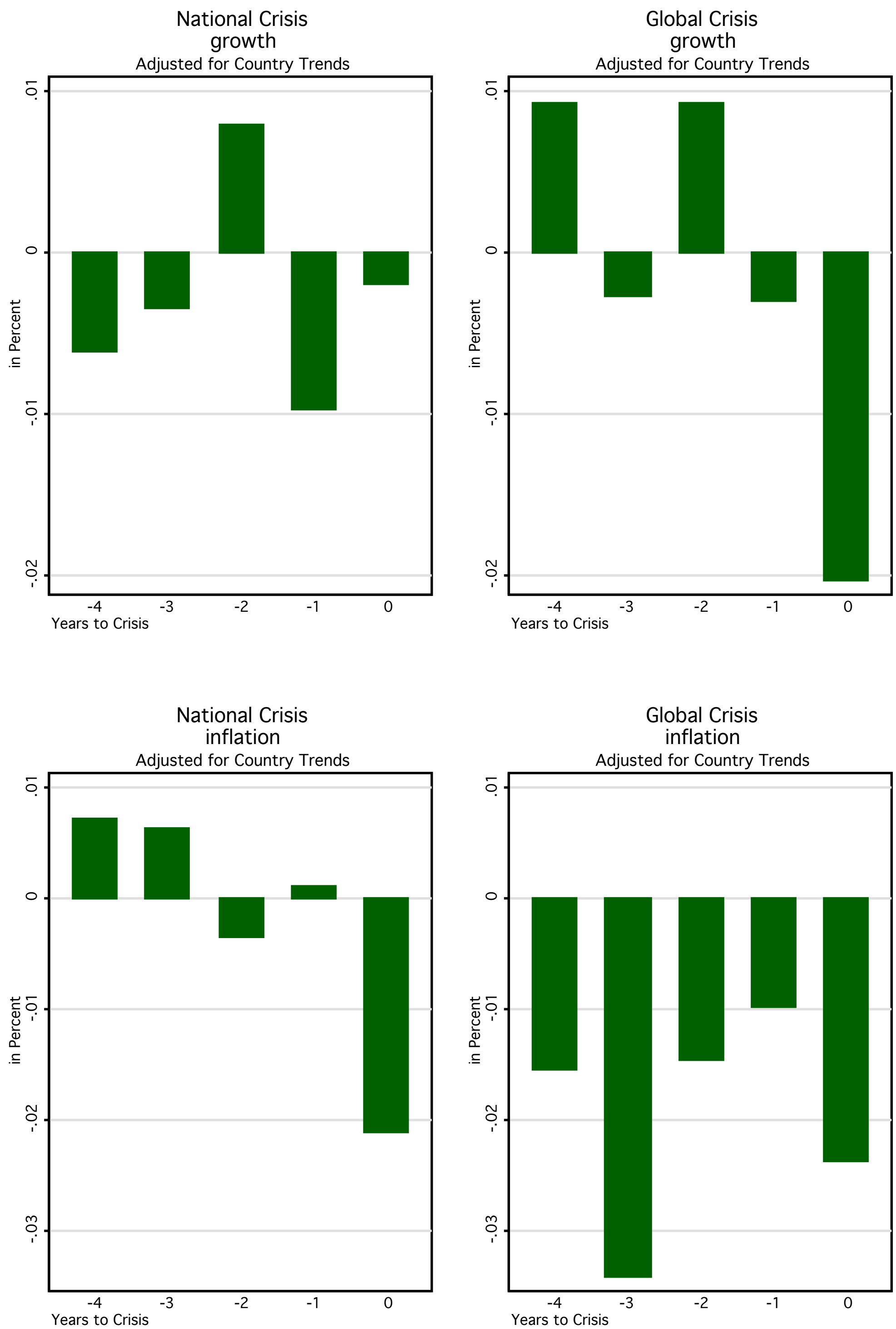


Figure 4: "Natural" and Real Interest Rates

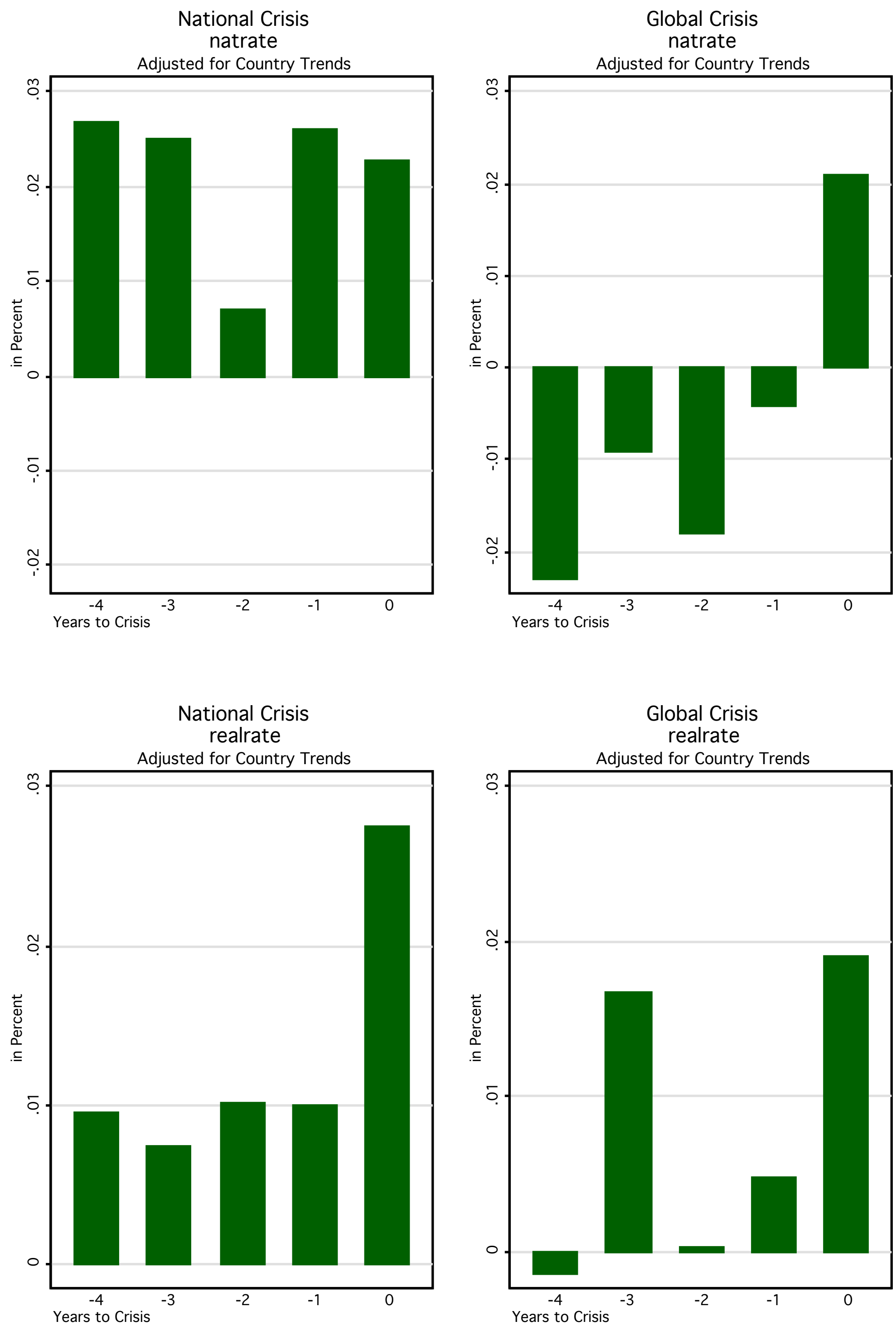


Figure 5: Loans and Credit to GDP Ratio

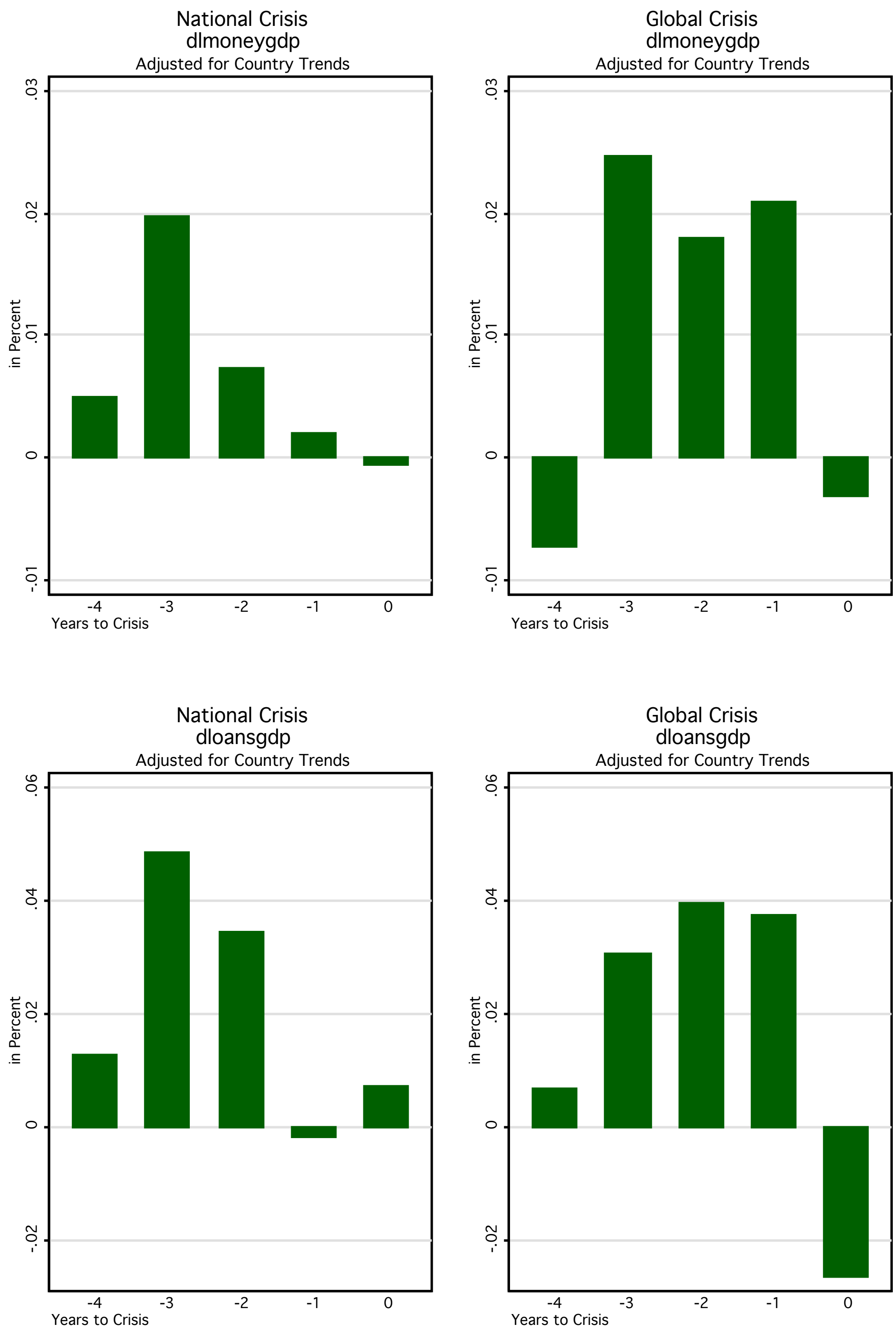


Figure 6: Current Account and Change in Current Account to GDP Ratio

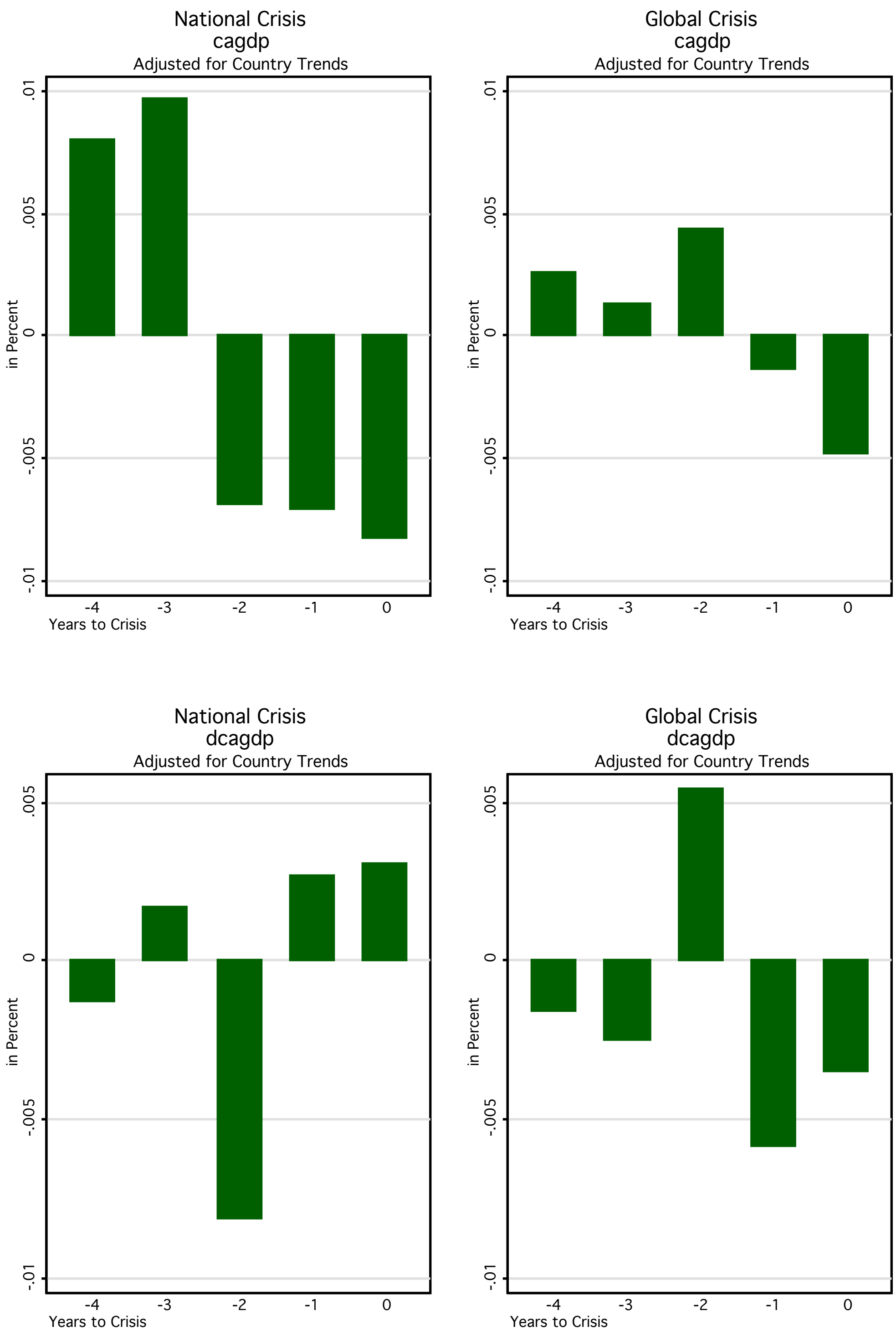


Table 6: Effects Before Financial Crises

Log level effect, 4 years before crises versus non-crisis trend, 1870–2008†	Local crises	Global crises	Difference
Number of crisis episodes	43	35	
Log real GDP	-0.038***	-0.009	0.0287**
	(0.012)	(0.133)	(0.017)
Log real investment	-0.029	0.0166	0.046
	(0.052)	(0.055)	(0.072)
Log loans/GDP	0.0974***	0.117***	0.0198
	(0.0314)	(0.032)	(0.043)
Log money/GDP	0.0529**	0.071***	0.0174
	(0.022)	(0.028)	(0.031)
Log inflation	0.023	-0.057***	-0.079***
	(0.017)	(0.018)	(0.024)
Log Current account/GDP (level)	-0.0203	-0.002	0.018
	(0.0123)	(0.126)	(0.017)
Log Current account/GDP (change)	-0.008	-0.008	0.0001
	(0.007)	(0.007)	(0.010)
Real short term interest rate, CPI-based (level)	0.006	0.004	-0.001
	(0.004)	(0.004)	(0.006)
Short term interest rate, adjusted for GDP growth (level)	0.023***	-0.014***	-0.037***
	(0.004)	(0.004)	(0.006)
Real equity prices (change)	-0.016	0.133	0.149
	(0.091)	(0.094)	(0.126)

† Excluding war and aftermath years: 1914–19 and 1939–47.

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

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, possibly because both surplus and deficit countries are affected.

Table 6 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, both credit and money growth are strongly elevated before national and global financial crises. Second, 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. In light of the evidence from 140 years of modern economic history, global financial crises different in that they combine strong credit growth with an environment of low interest rates (relative to real growth) and tame inflation.

4 Postcrisis 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 7 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

Table 7: Business Cycle Peaks

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

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 (177 observations);

(b) recessions cum national (isolated) financial crises (31 observations);

(c) recessions cum global (common) financial crises (36 observations).

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 postcrisis dynamics (yet). We are thus left with only the first two groups (normal v. national crisis recessions) for the postwar period.

In the results shown in Figures 7 to 9, 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.

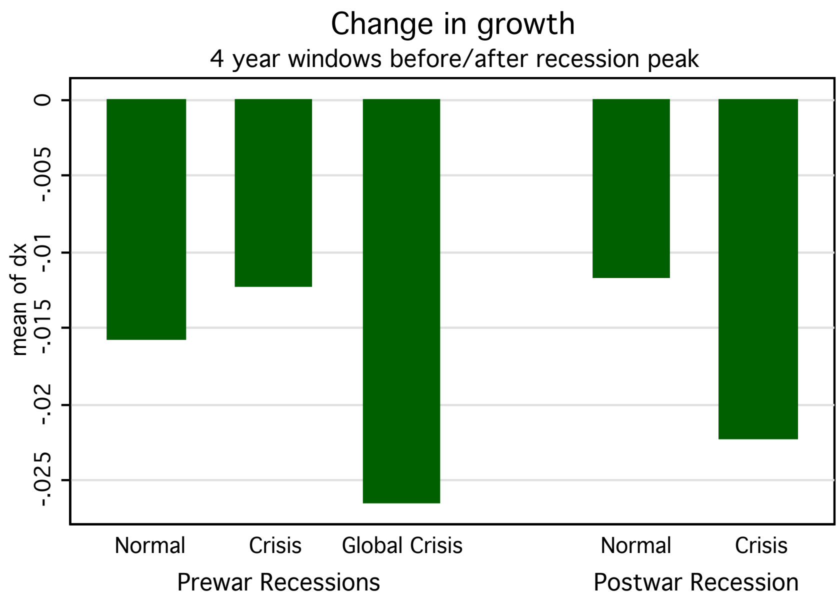
Starting with growth and inflation, we obtain a relatively clear picture that is in line with previous research (Schularick and A. M. Taylor forthcoming). Recessions that align with financial crises are about twice as costly than normal ones. But this result only holds after WWII, not before. Recessions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

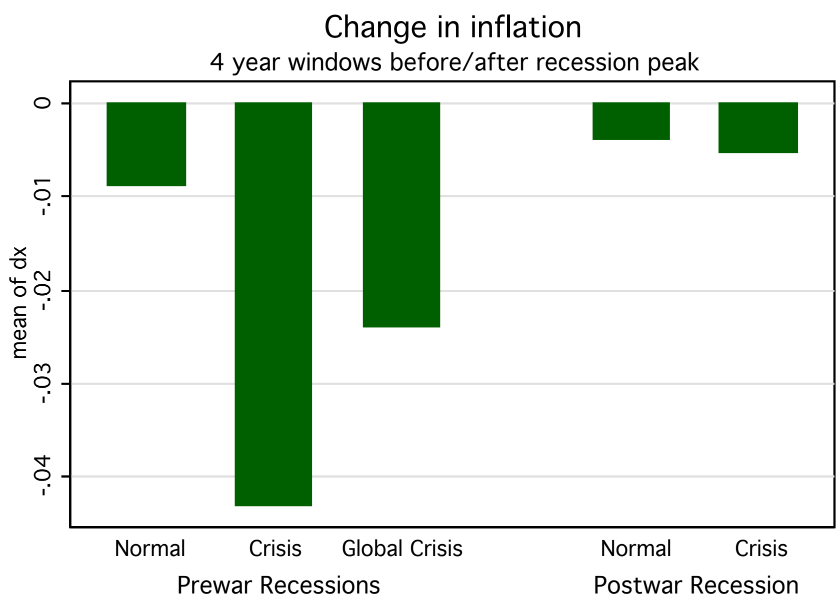
We next turn to the behavior of credit growth in recessions. Both the pre- and postwar data show a clear slowdown in loan growth in recessions (but relative to GDP it remains positive pre-WWII). This reversal of loan growth, however, is considerably more pronounced in crisis recessions. The rate at which loans contracted was about 4 times larger 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 four 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 post-1945. 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

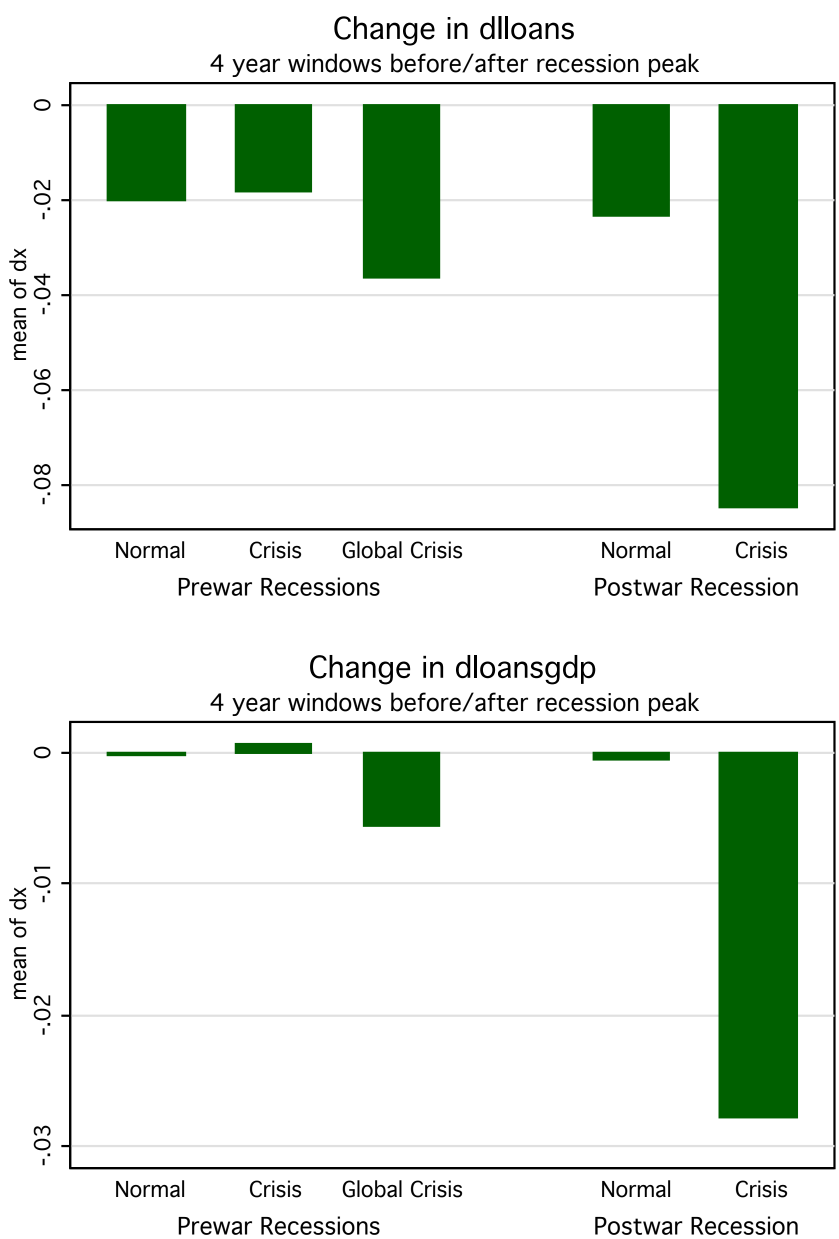
Figure 7: Growth and Inflation





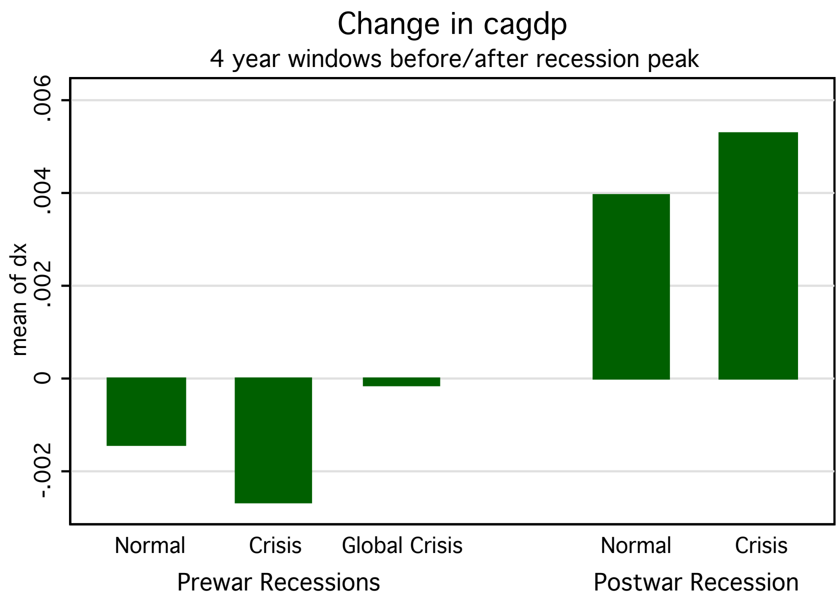
Note: 177 normal recessions, 31 recessions cum local crises, 36 recessions cum global crises.

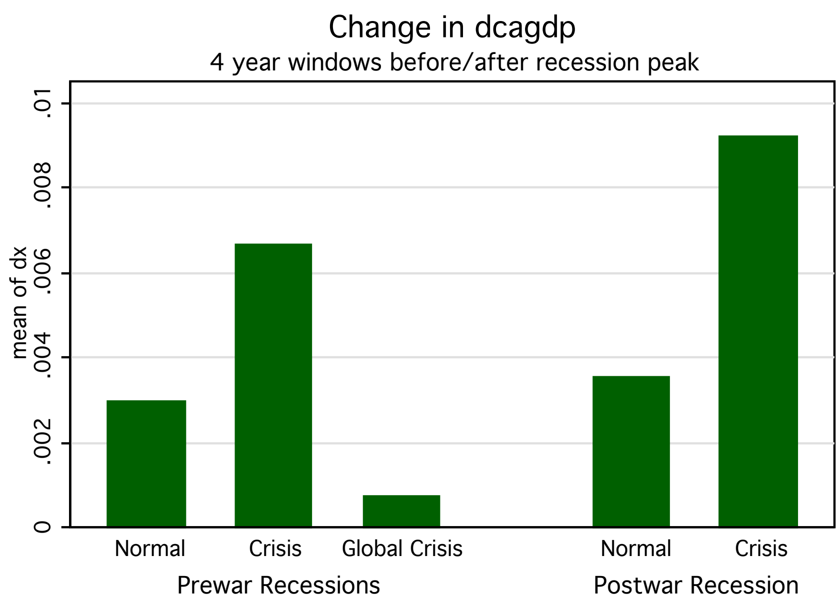
Figure 8: Loan growth and loans to GDP



Note: 177 normal recessions, 31 recessions cum local crises, 36 recessions cum global crises.

Figure 9: Current account and change in current account





Note: 177 normal recessions, 31 recessions cum local crises, 36 recessions cum global crises.

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.

5 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 (forthcoming) 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?

5.1 Empirical Strategy

Financial 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. Recall the state variable $S_t \in \{0, 1\}$ is a binary indicator that is one when there is a crisis in period t, and zero otherwise. It is always desirable to have a means to predict the binary outcome, but in addition one may be concerned about taking some policy action in response to that prediction given 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 a brief and preliminary discussion of our techniques is called for.

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]

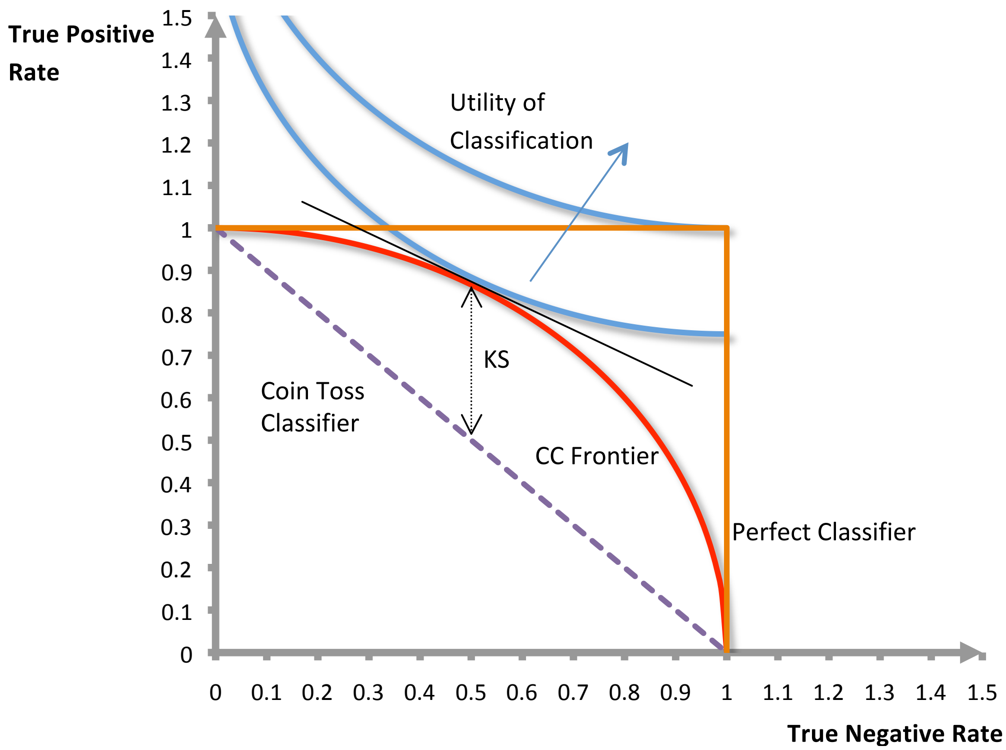
Varying c will naturally change the true and false positive rates of classification (and, hence, utility). For example, if c is very large, then $TP(c) \to 1$ but $FN(c) \to 1$ as well. On the other hand, if c is very low, then $TN(c) \to 1$ but $FP(c) \to 1$. For economists, a natural way to summarize the classification ability of $\widehat{y}_t$ and these trade-offs is to construct a production possibilities frontier that plots the 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 characteristic (ROC) curve in statistics, which is displayed in Figure 10.

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. 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 $\widehat{y}_t$.

The next step would be to find the optimal operating point, which is determined by the tangent of the policymaker's utility function with the CCF. However, in general policy

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

Figure 10: The Correct Classification Frontier



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. A 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, with most applications in practice falling somewhere in-between. Inference on AUC is very simple, since its distribution is asymptotically normal.[5] In addition, the AUC is a statistic particularly well suited to scoring

[5] 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

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

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

$$\sqrt{T}(\widehat{AUC} - P(v < u)) \to N(0, \sigma^2) \tag{1}$$

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.

classification of events that are observed seldom in the sample. Crises occur in less than 4% of our sample so a model that always predicts "no crisis" will be correct 96% of the time, a seemingly good result. In contrast, the AUC weighs the correct classification rates of both crisis and non-crisis events, thus providing a more complete picture.

5.2 Results

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

$$\log \frac{P[S_{it} = 0|X_{it}]}{P[S_{it} = 1|X_{it}]} = b_{0i} + b_1(L)X_{it} + e_{it} \tag{2}$$

where L is the lag operator. We will elect to summarize the information about lagged trends in macroeconomic variables 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. We also subject this specification to several perturbations that take the form of including additional control variables in the vector X as described above.

Table 8 shows the results of our baseline estimations. We start by replicating the results from Schularick and A. M. Taylor (forthcoming) using a model with country fixed effects and introducing the change in credit over GDP as the sole explanatory variable. The key result is 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 0.662, 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 horseraces. Widening imbalances are also a significant predictor of financial crises, albeit the fit, as measured by the pseudo r-squared, is 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 0.626. Note that we restricted the analysis to an identical sample of 1441 common observations for credit and current account data. 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 and large positive. Both the credit and the current account remain significant, and also the AUC (0.690) of the combined model is a higher than in the pure credit model (0.662). While credit remains a key variable to watch for the policy maker, adding the external balance improves predictive power by some margin. The next step is to interact credit growth and current account balances. However, this does not lead to meaningful

Table 8: Crisis Prediction

	1	2	3	4	5	6	7
Change in Loans/GDP	30.80***		29.68***	28.44***	29.31***	28.16***	28.15***
	(6.436)		(6.427)	(6.900)	(6.942)	(7.011)	(6.902)
Change in CA/GDP		-51.13***	-42.93***	-30.88*	-31.35**	-32.20*	-33.31**
		(13.53)	(12.51)	(15.87)	(15.24)	(16.54)	(16.04)
Loans/GDP x CA/GDP				-641.4	-660.2	-607.3	-629.6
				(571.1)	(595.5)	(605.3)	(578.7)
GDP per capita growth					-19.03***		
					(5.330)		
Investment growth						0.140	
						(2.282)	
Inflation							-1.580
							(4.103)
Observations	1,441	1,441	1,441	1,441	1,441	1,403	1,430
Pseudo R^2	0.0494	0.0239	0.0654	0.0673	0.0849	0.0668	0.0673
Pseudolikelihood	-237.1	-243.5	-233.1	-232.7	-228.3	-228.4	-232.2
Test for country effects = 0	5.131	1.445	3.973	3.374	4.807	3.089	3.425
p value	0.0235	0.229	0.0462	0.0662	0.0283	0.0788	0.0642
AUC	0.662	0.626	0.690	0.692	0.730	0.691	0.691
Standard error	0.0358	0.0348	0.0338	0.0338	0.0329	0.0339	0.0331

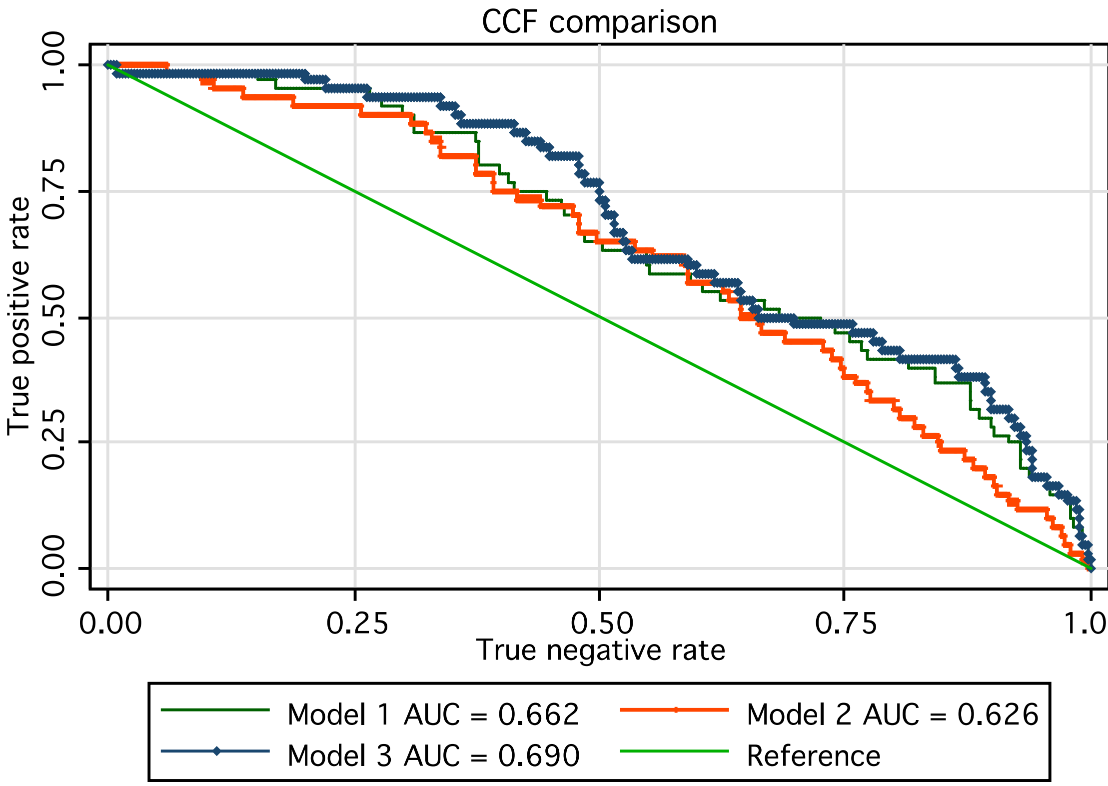
Notes: ***/**/* denotes significance at the 99% / 95% / 90% level. Standard errors in parentheses. Constant terms not shown.

improvements in fit or predictive ability as can be seen from regression 4. Credit booms fueled by capital inflows do not seem to be more risky than others.

The CCF comparison is graphically shown in Figure 11. We compare the pure credit with the current account model and a model containing both credit growth and the current account. It can be easily seen that the predictive ability of a pure current account model is weaker than that of the credit model. Adding the current account (model 3) leads to overall gains in forecasting performance. In brief, looking back at the past 140 years, surges in capital inflows clearly help predict financial crises to some extent.

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. Only GDP growth is statistically significant. Its inclusion leads to a further increase in the AUC to above 0.7. But none of these additions lead to a meaningfully different interpretation: credit growth is unaffected and dominates as the single most important factor, but the current account also has a role to play. This being said, the significance of the current account variable falls slightly in some specifications and is generally lower than the significance level of the credit variable. The historical evidence suggests that excessive credit

Figure 11: Predictive Ability Testing



growth is the dominant factor, but surges in capital inflows clearly help predict financial crises to some extent.

However, an objection to these findings could be that the global capital flow regime and the global financial order have changed substantially over time years rendering long-term comparisons problematic. In particular, the transition to floating exchange rates and capital mobility in the past four decades has brought about a new 'elasticity' of current account balances, and the rapid increase in the activity of the financial sector has also made credit much more abundant. It is therefore possible that the dynamics of credit, capital flows and crises have changed accordingly. Taking this hypothesis seriously, we look closer at the pre-1940 and post-1945 subsamples. Have the relationships meaningfully changed over time?

At first sight, Table 9 displays the familiar picture of credit growth dominated crisis histories. Significance, fit and predictive ability of the credit model are generally high. Yet under the surface a number of slight changes can be identified. On its own, the current account was a better predictor of financial stability in the pre-1940 period than in the post WWII era. Adding capital flows to a pure credit model yields highly significant coefficient estimates and improves predictive ability before 1940. But the current account matters on its own, not mainly through the interaction with loan growth. The interaction term is insignificant and also has the 'wrong' sign. After 1945, however, the current account on its own becomes less and less important. As an additional regressor it turns insignificant at standard significance levels, and loans growth is clearly dominating the regressions. But a different trend emerges with respect to the interaction between credit growth and the current account. In the post WWII years, the interaction term between credit growth and current account gains in significance, both statistically and economically. High loan growth rates, coupled with widening imbalances are clearly problematic. Not only is the coefficient estimate much stronger than before, it now also comes closer to standard statistical significance levels. There exist also clear signs of a growing collinearity between credit growth and current account trends, in particular in recent decades: 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, suggesting that higher loan growth went increasingly hand in hand with widening imbalances.

Summarizing these results, we find a stronger correlation between current account deficits and financial crises pre-1940 than post-1945, and at the same time a growing importance of the interaction between credit growth and capital flows in the postwar period. Oddly, in the contemporary era when observers are so obsessed with imbalances, we find little causal role for them, whereas in the pre-WWII era they had played such a key role. Why is this? We conjecture that this finding is related to the shifts in finance seen over the long run, or then versus now. In the prewar era, banks in advanced economies could not or would not lever up as shown by Schularick and A. M. Taylor (forthcoming). International capital flows were predominantly market-based and cross-border borrowing by banks played only a minor role. Capital inflow booms occurred from time to time and led to boom and bust cycles in the real economy and in financial markets that affected the financial sector and contributed to financial crises. Both bank lending and capital inflows could lead to financial instability, but they operated by and large independent of each other through separate channels.

In contrast, in recent decades and especially post-1975, banking systems have not only grown much bigger relative to the size of the economy. They have also become more important intermediaries of capital inflows and the crisis dynamics have shifted markedly. The correlation between credit growth and external deficits has picked up in recent years. Also the interaction between the two gained in significance in the generation of financial crises. Credit growth and imbalances interact more strongly than before to generate episodes of financial instability. They have more and more become two sides of the same coin. However,

Table 9: Crisis Prediction: Pre-1940 versus Post-1975 Sample

	1	2	3	4	5	6	7	8
	<1940	<1940	<1940	<1940	>1945	>1945	>1945	>1945
Change in Loans/GDP	29.49***		28.92***	28.60***	44.20***		42.99***	40.15***
	(7.420)		(7.500)	(7.905)	(12.38)		(11.91)	(12.67)
Change in CA/GDP		-48.41***	-41.11***	-35.72**		-46.22*	-31.81	17.99
		(14.88)	(12.86)	(13.88)		(23.71)	(22.78)	(42.44)
Loans/GDPxCA/GDP				-317.8				-2,110
				(364.1)				(1,752)
Observations	634	634	634	634	807	807	807	807
Pseudo R^2	0.0413	0.0264	0.0612	0.0620	0.108	0.0185	0.114	0.126
Pseudolikelihood	-143.1	-145.3	-140.1	-140.0	-83.62	-91.97	-82.98	-81.87
Test for country effects = 0	2.780	0.353	1.902	1.838	3.042	1.235	2.663	1.392
p value	0.0954	0.552	0.168	0.175	0.0811	0.266	0.103	0.238
AUC	0.647	0.613	0.680	0.683	0.760	0.644	0.773	0.763
Standard error	0.0408	0.0403	0.0385	0.0383	0.0650	0.0648	0.0624	0.0645

Notes: ***/**/* denotes significance at the 99% / 95% / 90% level. Standard errors in parentheses. Constant terms not shown.

while lending booms that go hand in hand with widening imbalances should raise particular concerns, the key warning signal clearly comes from the credit side.

In the last step of our empirical analysis we ask what role asset prices play in the generation of financial crises, on their own or in combination with external imbalances. Both the 2007/08 crisis and the Great Depression were preceded by large increases in asset prices. Does the inclusion of asset prices lead to meaningfully different results from those that we have reported above? Unfortunately, long run comparative data on house prices are not available for a wide country sample. As a rough proxy, we therefore had to work with equity price data collected from a selection of historical sources, as detailed in the data appendix.

The results are reported in Table 10. We first add equity prices as an additional regressor to the baseline credit and current account model. In a second step, we interact asset prices and the current account to test whether foreign financed asset price booms increase crisis risks. But including asset prices does not lead to meaningfully different results with regard to the importance of credit growth and external imbalances. The credit variable remains highly significant throughout. By contrast, equity prices remain insignificant and do not add explanatory power or predictive ability. However, the interaction term of asset prices with current account imbalances enters the equation significantly in some regressions, but the gain in predictive ability is negligible. While these results lend some limited support to the notion that external imbalances and asset prices interact in the generation of financial crises, more detailed research is needed to appropriately assess what role they can play in

Table 10: Crisis Prediction: Role of Asset Prices

	1	2	3	4	5	6
	all years	all years	<1940	<1940	>1945	>1945
Change in Loans/GDP	31.53***	31.24***	29.79***	28.62***	41.53***	42.17***
	(7.518)	(7.533)	(8.638)	(8.306)	(12.65)	(12.73)
Change in CA/GDP	-43.43***	-39.54***	-45.01***	-43.30***	-32.77	-31.64
	(12.99)	(12.16)	(13.61)	(12.76)	(22.54)	(23.59)
Change in real stock prices	0.562	1.035	1.773	2.514	1.153	1.183
	(1.485)	(1.465)	(2.489)	(2.191)	(2.450)	(2.617)
Change in real stock prices		168.2*		127.7		143.9
x change in CA/GDP		(96.38)		(91.32)		(272.1)
Observations	1,258	1,258	451	451	807	807
Pseudo R^2	0.0780	0.0820	0.0766	0.0800	0.116	0.117
Pseudolikelihood	-185.0	-184.2	-94.37	-94.02	-82.85	-82.71
Test for country effects = 0	3.746	3.536	1.667	1.478	2.597	2.630
p value	0.0529	0.0601	0.197	0.224	0.107	0.105
AUC	0.708	0.707	0.707	0.705	0.769	0.773
Standard error	0.0392	0.0394	0.0449	0.0461	0.0640	0.0624

Notes: ***/**/* denotes significance at the 99% / 95% / 90% level. Standard errors in parentheses. Constant terms not shown.

crisis prediction. Across our estimations, credit growth clearly dominates as a predictive variable and appears the key variable to watch for policymakers.

Summing up, our analysis provides some limited support for the idea that widening imbalances have historically contributed to financial instability. Looking at the entire 140 year period, current accounts seem to add some predictive ability to our crisis regressions. But one needs to look closer under surface in order to identify the different pre- and postwar dynamics. The significance of the current account is predominantly based on the pre-1940 crisis episodes. During this period, credit booms and capital flow bonanzas were indicators of impending financial crises, but they operated by and large independent of each other. Lending booms financed by foreign inflows were not more problematic than others. In the postwar period, the current account on its own is a less accurate predictor of financial instability. But at the same time capital flows correlate much closer with credit growth than before. From a policy perspective, our results do not support an exclusive focus on imbalances as a causal factor in financial crises. The most reliable signal that financial stability risks are growing typically comes from excessive loan growth. In the light of our results, regulation of the financial sector, including its role in intermediating foreign capital inflows, should remain the primary target for regulation.

6 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 analyze 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 five clusters of big international crises are discernible: 1873, 1890/3 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 unusually low in the run-up to the four global crises, while real interest rates and inflation did not exhibit a meaningful deviation from trend.

In the third part, we studied postcrisis 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 part of this paper asks whether widening external imbalances are a signal for policy makers that financial instability risks are building. We find that, from a policymaker's perspective, credit growth generates the best predictive signals of financial instability. We find little evidence that asset prices play an equally important role. The inclusion of external imbalances improves the predictive ability overall, but this is mainly due to the pre-1940 period. During this period capital inflow booms and credit cycles increased the risk of financial crises, but they operated by and large independent of each other. Post-1945, the correlation of credit growth and current accounts has grown tighter. Clearly, in a globalized economy with free capital mobility credit cycles and capital flows have the potential to reinforce each other more strongly than before. But the data clearly suggest that excessive credit growth poses the key stability risk. It is one policy makers should not ignore.

Appendix 1: Data Sources

All data come from Schularick and A. M. Taylor (forthcoming), except for current accounts and equity prices. Historical equity prices come from the Global Financial Database, with the following exceptions:

USA: Robert Shiller (2000), Irrational Exuberance, Princeton University Press. 2009 updates from http://www.econ.yale.edu/ shiller/data.htm

Sweden: Waldenstroem, Daniel, Swedish stock prices and returns and bond yields, 1856-2006, forthcoming in R. Edvinsson, T. Jacobsson and D. Waldenstroem, Historical Monetary and Financial Statistics for Sweden, Volume 2, Sveriges Riksbank.

Netherlands: Tweehonderd jaar statistiek in tijdreeksen, 1800-1999, University of Groningen and Centraal Bureau voor de Statistiek, Voorburg/Heerlrn 2001, Table 10. Data made available by Peter Koujdis (Barcelona).

France: new series made available by Pierre-Cyrille Hautcoeur, Paris.

Italy: Da Pozzo M. and Felloni G., La Borsa Valori di Genova nel secolo XIX, Torino, ILTE, 1963, Tab. LXVII, p. 499; and Parodi S., Il mercato finanziario genovese dal 1895 al 1914, unpublished mater thesis (tesi di laurea), University of Genoa, 1966, Tab XLV, p. 238. Data made available by Angelo Riva (Paris).

Norway: Klovland, J.T.(2004). "Historical stock price indices in Norway 1914-2001", 329-348, Chapter 8 in Eitrheim, Ø., J.T. Klovland and J.F. Qvigstad (eds.), Historical Monetary Statistics for Norway 1819-2003, Norges Bank Occasional Papers no. 35, Oslo, 2004

Current account data, unless otherwise stated, come from the following three sources:

(i) J/O: Jones and Obstfeld data set (http://www.nber.org/databases/jones-obstfeld/).

(ii) Mitchell: Mitchell, Brian R. (2007abc).

(iii) 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

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

References

Almunia, Miguel, Agustí Bénétrix, Barry Eichengreen, Kevin H. O'Rourke, and Gisela Rua. 2010. From Great Depression to Great Credit Crisis: Similarities, Differences and Lessons. *Economic Policy* April 2010: 219265.

Authers, John. 2010. Book extract: The Fearful Rise of Markets. *The Financial Times* May 21, 2010.

Bakker, Age, and Bryan Chapple. 2002. Advanced Country Experiences with Capital Account Liberalization. Occasional Paper 214, Washington, D.C.: International Monetary Fund.

Barro, Robert J. 2009. Rare Disasters, Asset Prices, and Welfare Costs. *American Economic Review* 99(1):243–64.

Berge, Travis J. and Òscar Jordà 2011. Evaluating the Classification of Economic Activity into Expansions and Recessions. *American Economic Journal: Macroeconomics*, forthcoming.

Bernanke, Ben S. 2005. The Global Saving Glut and the US Current Account Deficit. Homer Jones Lecture, St. Louis, Missouri, April 15.

Bernanke, Ben S. 2007. Global Imbalances: Recent Developments and Prospects. Bundesbank Lecture, Berlin, September 11.

Bernanke, Ben S. 2009. Four questions about the financial crisis. Chairman of the Board of Governors of the US Federal Reserve System, Speech at the Morehouse College, Atlanta, Georgia, April 14.

Bordo, Michael, Barry Eichengreen, Daniela Klingebiel, and Maria Soledad Martinez-Peria. 2001. Is the crisis problem growing more severe? *Economic Policy* 16(32):51–82.

Borio, Claudio. 2008. The financial turmoil of 2007–? A preliminary assessment and some policy considerations. BIS Working Papers no. 251.

Borio, Claudio, and William R. White. 2003. Whither Monetary and Financial Stability: The Implications of Evolving Policy Regimes. Proceedings, Federal Reserve Bank of Kansas City, pp. 131–211.

Cerra, Valerie, and Sweta C. Saxena. 2008. Growth Dynamics: The Myth of Economic Recovery. *American Economic Review* 98(1):439–457.

Chernyshoff, Natalia, David S. Jacks, and Alan M. Taylor. 2009. Stuck on Gold: Real Exchange Rate Volatility and the Rise and Fall of the Gold Standard, 1875-1939. *Journal of International Economics* 77:195–205.

Christiano, Lawrence J., Roberto Motto,and Massimo Rostagno, 2010. Financial factors in economic fluctuations. European Central Bank Working Paper Series 1192.

Conover, W. J. 1999. *Practical Nonparametric Statistics.* 3rd edition. New York: John Wiley and Sons.

Diebold, Francis X., and Roberto S. Mariano. 1995. Comparing Predictive Accuracy. *Journal of Business and Economic Statistics* 13(3):253–63.

Dooley, Michael, David Folkerts-Landau and Peter Garber. 2009. Bretton Woods II Still Defines the International Monetary System. Deutsche Bank Global Markets Research, February 11.

Economic Report of the President. 2009. Washington D.C., January 2009.

Ferguson, Niall, and Moritz Schularick. 2010. The End of Chimerica. *International Finance* forthcoming.

Giacomini, Raffaella, and Halbert White. 2006. Tests of Conditional Predictive Ability. *Econometrica* 74(6):1545–78.

Goodhart, Charles, and Dimitrios Tsomocos, 2010. How to restore current account imbalances in a symmetric way. Column, September 24, 2010, http://www.eurointelligence.com

Gros, Daniel, 2010. How to Level the Capital Playing Field in the Game with China. CEPS Commentary, October 8, 2010.

Hume, Michael, and Andrew Sentance. 2009. The Global Credit Boom: Challenges for Macroeconomics and Policy. *Journal of International Money and Finance* 28(8):1426–1461.

Hunt, Chris. 2008. Financial Turmoil and Global Imbalances—The End of Bretton Woods II. *Reserve Bank of New Zealand Bulletin* 71(3).

International Financial Statistics. 2010. International Monetary Fund.

Jordà, Òscar, and Alan M. Taylor. 2009. The Carry Trade and Fundamentals: Nothing to Fear but FEER itself. NBER Working Papers no. 15518.

Jordà, Òscar, and Alan M. Taylor. 2010. Performance Evaluation for Zero Net-Investment Strategies. University of California, Davis. Unpublished.

Kaminsky, Graciela L., and Carmen M. Reinhart, 1999. The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. *American Economic Review* 89(3):473–500.

Kaminsky, Graciela L., Carmen M. Reinhart, and Carlos A.Végh. 2004. When It Rains, It Pours: Procyclical Capital Flows and Policies. In Mark Gertler and Kenneth S. Rogoff, eds.NBER Macroeconomics Annual 2004. Cambridge, Mass: MIT Press, 11–53

Khandani, Amir E., Adlar J. Kim, and Andrew W. Lo. 2010. Consumer Credit Risk Models via Machine-Learning Algorithms. Massachusetts Institute of Technology, Sloan School of Management and Laboratory for Financial Engineering. Unpublished.

King, Mervyn. 2010. Governor of the Bank of England, Speech at the University of Exeter. January 19.

Laeven, Luc, and Fabian Valencia. 2008. Systemic Banking Crises: A New Database. IMF Working Paper 08/224, November.

Lusted, Lee B. 1960. Logical Analysis in Roentgen Diagnosis. *Radiology* 74:178–93.

Mason, Ian B. 1982. A Model for the Assessment of Weather Forecasts. *Australian Meterological Society* 30:291–303.

Mitchell, Brian R. 2007a. *International Historical Statistics: Europe 1750–2005.* Palgrave Macmillan.

Mitchell, Brian R. 2007b. *International Historical Statistics: the Americas 1750–2005.* Palgrave Macmillan

Mitchell, Brian R. 2007c. *International Historical Statistics: Africa, Asia and Oceania 1750–2005.* Palgrave Macmillan

Obstfeld, Maurice. 2010. The immoderate world economy. *Journal of International Money and Finance* 29:603–614.

Obstfeld, Maurice, and Alan M. Taylor. 2004. *Global Capital Markets: Integration, Crisis, and Growth.* Cambridge: Cambridge University Press.

Obstfeld, Maurice, Jay C. Shambaugh, and Alan M. Taylor. 2009. Financial Instability, Reserves, and Central Bank Swap Lines in the Panic of 2008. NBER Working Paper 14826.

Peirce, Charles S. 1884. The Numerical Measure of the Success of Predictions. *Science* 4:453–454.

Pepe, Margaret S. 2003. *The Statistical Evaluation of Medical Tests for Classification and Prediction.* Oxford: Oxford University Press.

Peterson, W. Wesley, and Theodore G. Birdsall. 1953. The Theory of Signal Detectability: Part I. The General Theory. Electronic Defense Group, Technical Report 13, June 1953. Available from EECS Systems Office, University of Michigan.

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

Rancire, Romain, Aaron Tornell and Frank Westermann, 2008. "Systemic Crises and Growth," *The Quarterly Journal of Economics* 123(1): 359-406.

Reinhart, Vincent, and Carmen Reinhart. 2008. Capital Flow Bonanzas: An Encompassing View of the Past and Present. CEPR Discussion Paper no. 6996.

Reinhart, Carmen M., and Kenneth S. Rogoff. 2009. *This Time is Different: Eight Centuries of Financial Folly.* Princeton, N.J.: Princeton University Press.

Schularick, Moritz, and Alan M. Taylor. Forthcoming. Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008. *American Economic Review.*

Silvennoinen, Annastiina, Timo Teräsvirta, and Changli He. 2008. Unconditional Skewness from Asymmetry in the Conditional Mean and Variance. Department of Economic Statistics, Stockholm School of Economics. Unpublished.

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

Spackman, Kent A. 1989. Signal Detection Theory: Valuable Tools for Evaluating Inductive Learning. In *Proceedings of the Sixth International Workshop on Machine Learning.* Morgan Kaufman, San Mateo, Calif., 160–63.

Swets, John A. 1973. The Relative Operating Characterstic in Psychology. *Science* 182:990–1000.

Taylor, Alan M. 2002. A Century of Current Account Dynamics. *Journal of International Money and Finance* 21:725–748.

Taylor, John B. 2007. Housing and Monetary Policy. NBER Working Paper 13682.

Taylor, John B. 2009. *Getting Off Track.* Stanford: Hoover Institution Press.

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.

West, Kenneth D. 1996. Asymptotic Inference about Predictive Ability. *Econometrica* 64(5):1067–84.

White, William R. 2006. Is Price Stability Enough? BIS Working Papers, No. 205, April.

Youden, W. J. 1950. Index for Rating Diagnostic Tests. *Cancer* 3:32–35.