Credit Reversals

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Abstract

This paper studies episodes in which aggregate bank credit contracts alongside expanding economic activity—*credit reversals*. Using data for 179 countries during 1960–2017, the paper finds that reversals are a relatively common phenomenon--on average, they occur every five years. By comparison, banking crises take place every eight years on average. Credit reversals and banking crises also appear related to each other: reversals become more likely in the aftermath of banking crises, while the likelihood of crises drops following reversals. Reversals are shown to be very costly in terms of foregone economic activity—about two-thirds of the costs of banking crises, after taking into account their relative frequencies.

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I. INTRODUCTION

The early phases of the COVID pandemic in 2020 prompted a quick relaxation of prudential regulations. Across the globe, government officials deployed an arsenal of policies to support banks' lending capacity, including the issuance of government guarantees on bank credit, releasing countercyclical bank capital buffers, and postponing the introduction of accounting standards on expected credit losses. In parallel, monetary policy rates were cut and many central banks implemented large scale asset purchase programs and other liquidity facilities to support the flow of credit to the economy. These policies tried to achieve a delicate balance between two conflicting goals: averting a contraction in bank credit while preserving bank capital buffers to maintain financial stability.

The view that banking crises are costly in terms of output foregone is supported by a large amount of research (see for example Romer and Romer, 2017 and Laeven, 2011). Yet, the cyclical dynamics of bank credit and the costs of supply-side contractions in bank credit are yet not well understood. A relatively new strand of literature has looked at the characterization of credit and financial cycles (Terrones, Kose, and Claessens, 2008) with attention focused on the analysis of the so-called *credit booms* and their relationship with the incidence of banking crises.[1] While a definition of credit booms has to be widely accepted, most papers have used the evolution of the credit-to-GDP gap (CYGAP), typically measured by the deviations of the credit-to-GDP ratio from its HP-filtered trend (Drehman *et al*., 2010; 2011).[2]

A related object of study, also flawed by the lack of a widely accepted definition, is the notion of *credit crunches*. In loose terms, a credit crunch is a significant contraction in the supply of bank loans, holding constant both the risk-free real interest rate and the quality of potential borrowers (Bernanke and Lown, 1991). Yet, operationalizing this concept has proven difficult because credit supply and demand tend to be pro-cyclical. In practice, researchers have measured credit crunches by focusing on the lower quantiles of the credit growth distribution using diverse criteria.

This paper looks at a related class of events, henceforth labeled *credit reversals*: episodes where a contraction in bank credit happens alongside expanding economic activity. This identifies periods when a contraction in credit can be most surely attributed to supply-driven factors. In fact, since credit demand is unlikely to drop with expanding economic activity, the definition provides a conservative filter to identify supply-side contractions in bank credit.

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[1] Studies show that credit booms are relatively frequent. Furthermore, credit booms appear necessary, but not sufficient conditions for banking crises: while most crises are preceded by credit booms, only about one-third of the credit booms end in banking crises. See for example: Demirguc-Kunt and Detragiache, 1998; Gourinchas *et al*., 2001; Tornell and Westermann, 2002; Mendoza and Terrones, 2008; Jorda et al., 2011; Schularick et al., 2012; Bossay et al., 2016; Borio and Lowe, 2002a; Borio and Drehman, 2009; and Gorton and Ordoñez, 2016.

[2] Alternatively, some papers have focused on the *size* of the credit gap, typically measured as deviations of the log of credit from its trend (for example, Mendoza and Terrones, 2008; Gorton and Ordoñez, 2016).

The definition of reversals parallels the events studied in Calvo, Izquierdo and Talvi (2006) and Abiad, Dell'Ariccia, and Li (2011). Yet, their analyses focus on episodes of negative credit growth in the aftermath of adverse economic events (i.e., after a recession, sudden stop, or output collapse). In contrast, the definition used in this paper is unconditional and thus covers a broader class of events.

This paper makes two main contributions to the analysis of the bank credit dynamics and its relationship with economic activity. First, it studies the relationship between credit reversals and banking crises and, in turn, between these two types of events and the shape of credit cycles—defined by the evolution of CYGAP ratios. In addition, it provides estimates of the economic costs associated with the presence of credit reversals, comparing them with those attributable to banking crises.

The analysis uses country-level data at the yearly frequency, covering 179 countries during 1960–2017. This is the most comprehensive dataset exploited to date. We favor the use of yearly data as credit risk tends to evolve slowly over time and the buildup of systemic macro-financial imbalances takes several years. Throughout the analysis, we break the data in two groups: industrial countries on one side and developing and emerging market countries (henceforth *developing*) on the other, searching for differences across countries with dissimilar levels of financial development.

The paper presents several findings. First, credit reversals are not uncommon: they occur about once every five years. They are also more prevalent in developing countries. By comparison, banking crises occur once every eight years, and are equally likely across developing and industrial countries. In terms of timing, banking crises and credit reversals tend to happen in distinct phases of the CYGAP cycles. Crises tend to occur when the CYGAP is positive, while reversals are clustered in the negative phase. In fact, the likelihood of observing credit reversals doubles from 12 percent in the positive phase to 26 percent in the negative. Banking crises and credit reversals appear also related to each other: reversals become more likely in the aftermath of banking crises, while the likelihood of crises drops following credit reversals.

By comparing cycles with- and without-reversals and taking the later as controls, the paper finds significant differences in the characteristics of CYGAP dynamics. Cycles with reversals display sharper and more protracted collapses of credit during their negative phase than their respective control groups. Surprisingly, parallel exercises comparing cycles with- and without-credit reversals suggest that credit reversals are even more constraining than banking crises in terms of their impact on credit availability. In fact, the economic costs of credit reversals, measured by the output differentials vis-à-vis cycles with no reversals, appear substantial—at about one-half of the estimated costs of crises and up to two-thirds after factoring in their relative frequencies. We also find that, in terms of output foregone, banking crises are more costly in industrial than in developing countries, a result that is in line with the findings of Bordo et al. (2001), Hoggart, Reis, and Saporta (2002), Cerra and Saxena (2008), Laeven and Valencia (2018).

While arguably compelling, the use of cycles without reversals/crises as controls, does not establish a causal relationship running from our target events to economic activity. Thus, our findings provide at most only suggestive evidence on the causal impact of credit reversals and baking crises on real outcomes. Yet, in relative terms, the economic costs of reversals vis-a-vis crises are likely more robust, as there are no clear reasons to expect differential endogeneity problems between reversals and crises.

As a by-product, the paper studies key characteristics of CYGAP cycles and reports several patterns. As it turns out, the shape of the cycle during the positive phase in terms of duration, amplitude and implied changes in credit-to-GDP ratios, appears systematically related to the shape of the subsequent negative phase. More sizable and long-lasting CYGAP during the positive phase lead to deeper and longer negative gaps. As a result, larger increases in credit-to-GDP ratios during the positive gap episodes are associated with sharper subsequent declines. Yet, we find no systematic relationship with the subsequent rates of credit growth or GDP growth, taken individually.

The rest of the paper is organized as follows. Section 2 discusses the operational definitions of credit reversals and banking crises. Section 3 describes the methodology and data. Section 4 explores for patterns in the co-movement of bank credit and economic activity, using the credit cycle as a reference to frame the time dimension. Section 5 explores the relationship between reversals and crises and, in turn, between these two and the shape of the credit cycle. Section 6 presents estimates of the economic costs of reversals and crises in terms of output differentials between cycles with—and without—reversals and crises, using the latter as controls. Section 7 concludes.

II. Credit reversals and Banking Crises

Before starting, we define two proxies of supply-driven, negative dynamics in credit markets. First, as mentioned before, we define *credit reversal* as an episode when credit contracts alongside expanding economic activity. This metric is intended to isolate events where a decline in credit is most likely driven by supply-side factors. As argued above, if credit demand does not fall with expanding economic activity, this definition should provide a stringent filter to identify episodes of contractions in credit supply. Since the identification of the episodes is data-driven, it avoids the potential researcher-induced bias of more traditional event analysis techniques used to identify distress in credit markets. More importantly, it identifies events that are less catastrophic—and therefore more common—than financial crises.

It is important to note that the definition of credit reversals relates to the concepts of *Phoenix miracles* proposed by Calvo, Izquierdo and Talvi (2006) and *creditless recoveries* studied in Abiad, Dell'Ariccia, and Li (2011). However, these two later concepts focus on episodes of negative credit growth in the aftermath of an economic downturn (a recession, sudden stop or output collapse). The definition proposed in this paper is less restrictive and therefore encompasses a wider class of objects. It is also important to note that we identify credit reversals with a binary variable, but a natural and richer alternative is to use the actual data to measure their relative intensity. This is left for future research.

The second proxy focuses on events where the capacity of the banking system to provide credit and normal financial intermediation is impaired at the systemic level. In our baseline exercises, we use the operational definition and dating of *banking crises* proposed by Laeven and Valencia (2017). According to that, a banking crisis is an event that meets two conditions: (i) significant signs of distress in the banking system (bank runs, losses in the banking system, and/or bank liquidations), and (ii) significant banking policy intervention measures in response to large losses in the banking system. In robustness checks, we also use the Reinhart-Rogoff (2009) banking crises database, which identifies a banking crisis by the occurrence of two types of events: (i) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions, and (ii) if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions), that marks the start of a string of similar outcomes for other financial institutions. It is important to note that, in terms of coverage, the Laeven and Valencia (2017) database spans 160 countries, between 1970–2017, while the Rogoff-Reinhart (2009) database covers 70 countries during 1800–2010. We extend the later to 2017 to match our macro dataset.

III. METHODOLOGY

The paper looks at the relative dynamics of bank credit and economic activity throughout credit cycles, using event studies techniques (Gourinchas *et al*. 2001; Mendoza and Terrones, 2008; 2012). In the analysis, we use credit cycles as the reference frame to study the relationship between credit reversals and banking crises, and their effects on credit cycles and economic activity. Since there is not a widely accepted operational definition of credit cycles and to facilitate the comparison with previous studies, we restrict ourselves to cycles defined by the evolution of the CYGAP, while acknowledging several important caveats.[3] Specifically, we measure the CYGAP by detrending the ratio of credit-to-GDP with a two-sided HP filter with smoothing parameter λ=100 to account for the yearly frequency of the data (Mendoza and Terrones, 2008), and carry out robustness checks using a higher λ, as suggested by the BIS (2002b).[4]

After computing the set of credit cycles based on the CYGAP we carry out three types of exercises. First, we explore if the evolution of credit and GDP during the positive phase of the CYGAP cycle are systematically related with their subsequent cyclical dynamics, Specifically, we focus on the duration of the positive and negative phases, the pace of credit

[3] Using the CYGAP has some important and well-acknowledged shortcomings. First, it assumes that bank credit and GDP share a common trend, which is unlikely to hold during the period studied due to financial development and the associated deepening of credit markets. In addition, the CYGAP also depends on how the trend is determined, which imposes the frequency, duration, and amplitude of the resulting cycles.

[4] Credit cycles have lower frequency than business cycles (Drehmann *et al.*, 2012), which would imply using a larger λ. For example, the Bank of International Settlements uses 400,000 for quarterly data (Borio and Lowe, 2002b) which would be equivalent to using 1,600 for annual data. We carried out a robustness check using 1,600 with similar qualitative results. It is also worth noting that some papers apply a backward-looking, one-sided HP filter, attempting to mimic the availability of data in real time to the policymaker (Gourinchas *et al.* 2001). While this approach is attractive, it comes at the cost of underestimating the presence of credit booms and busts and exacerbating end-of-sample bias in the filtering process. Since we are not attempting to build a model to be used in real time, we exploit all the available data by applying a two-sided filter.

growth and GDP growth, and the implied changes in the credit-to-GDP ratios. Alongside, we study the extent of co-movement between credit growth and GDP growth throughout the credit cycles. Second, we study the relationship between credit reversals and banking crises, focusing on their relative timing and likelihood, conditional on the realization of the other. Finally, we explore the effect of credit reversals and banking crises on the credit cycle and on economic activity, providing an estimation of their costs in terms of output forgone.

A. Data

Our focus on bank credit follows the bank lending channel literature (Bernanke and Gertler, 1995; Kashyap and Stein 2000), which proposes that credit and market financing are imperfect substitutes. The paper exploits yearly data for 179 countries during 1960–2017, which is all the data available from the International Financial Statistics (IFS). The yearly frequency avoids seasonal and high frequency patterns that are uninteresting for our purposes. Also, the yearly frequency allows us to capture the eventual build-up of slow-moving but persistent macro-financial imbalances, which are critical from the systemic stability perspective. Credit is measured by domestic bank credit to the private sector (IFS line 22d), which excludes cross-border lending, and thus allows us to focus on the cyclical behavior of resident banks. Credit series are converted to real terms by using the GDP deflator, which is arguably more adequate (than the CPI) to capture the underlying structure of the credit portfolios.

IV. KEY FEATURES OF SHORT-TERM CREDIT-TO-GDP DYNAMICS

In this section we provide an overview of the key features of short-term dynamics of the CREDIT-TO-GDP ratio. To do so, after HP-filtering the data, we identify the years marking the start and end of positive and negative CYGAP as well as the local maxima and minima corresponding to each cyclical phase. Following Claessens, Kose and Terrones (2011) we measure the following distances to characterize the credit cycles:

- *Positive Duration*: the number of years with an uninterrupted positive CYGAP.
- *Negative Duration*: the number of years with uninterrupted negative CYGAP.
- *Amplitude*: the difference between the maximum and the minimum CYGAP in each cycle.
- *Downturn Duration*: the number of years between the peak CYGAP and its subsequent minimum.
- *Upturn Duration*: the number of years between the minimum CYGAP and its subsequent peak.
- *Deepening*: the cumulative change in CREDIT-TO-GDP ratios during positive and negative CYGAP phases.

- *Speed*: the average compounded yearly growth rate of real credit during positive and negative CYGAP phases.

Summary statistics of the resulting metrics are presented in Table 1. A total of 371 entire cycles are captured, plus some additional incomplete episodes at the start and end of the sampled period. On average, the entire cycle lasts about ten years, equally split between the positive and negative gaps, albeit it is convenient to stress that the duration and symmetry between ups and downs occurs by construction.

Overall, credit-to-GDP ratios increase by about nine percentage points during positive gap episodes and drop by about two percentage points during the negative gaps, with industrial countries displaying a stronger deepening during the positive phase and more resilience during the negative. Contrary to our priors, average credit growth remains positive in both phases. Thus, negative gaps tend to reflect periods where GDP growth is relatively more dynamic than credit growth. The extreme gaps average 15 percent and –18 percent and tend to be wider in developing countries. The likelihood of observing a credit reversal during the negative phase is about 22 percent, almost two times higher than during positive gaps. These facts suggest that the degree of co-movement between credit and the CYGAP may not be that strong. This is explored in the next session.

A. How do credit and GDP co-move throughout the Credit Cycle?

A cursory look at the co-movement between credit growth and GDP growth is presented in Figure 1. While the correlation is positive and statistically significant, as expected, its value is rather small (0.32), and close to zero during episodes of negative credit growth (0.09). Their directional co-movement is positive and driven by subset of years in which both GDP and credit expand. A comparison between the first and second quadrants provides casual evidence that credit reversals are associated with substantially lower GDP growth rates. However, there is a non-trivial amount of mass in the second and fourth quadrants. In fact, negative credit growth is observed in about one-quarter (23.4 percent) of the years in which economic activity expands, while positive credit growth is observed in about half (47.9 percent) of the years with contracting activity (Table 2).

Next, we assess the directional co-movement between credit and GDP growth with the concordance index proposed by Harding and Pagan (2002). Specifically, the concordance index for variables x and y over period t=1,…,T, is defined as:

$$Concordance_{x,y} = \frac{1}{T}\sum_{t}[(D_{x,t} \times D_{y,t}) + (1 - D_{x,t}) \times (1 - D_{y,t})]$$

Where:

$D_{x,t}$ ={1 if the growth of variable x in period t is positive, and 0 otherwise}

$D_{y,t}$ ={1 if the growth of variable y in period t is positive, and 0 otherwise}

Accordingly, the index measures the proportion of the time where the two variables move in the same direction. It ranges from zero (lack of concordance) to one (perfect concordance), and is 0.5 for two unrelated series. The average concordance between credit growth and GDP growth is moderate (0.68 for developing countries and 0.73 for industrial countries), which is in line with the findings reported in Claessens, Kose and Terrones (2011) using a smaller dataset. Furthermore, concordance is almost exclusively driven by the periods of positive co-movement, as reflected by the small distance between overall and positive concordance (Figure 2). Over time, there is a slight downward trend in concordance in industrial countries, and a sharp drop in the aftermath of the 2008–09 crisis which may reflect a credit glut in bank balance sheets and the rapid development of shadow banking.

Lastly, we explore the behavior of credit growth and GDP growth conditional on the CYGAP (Table 3). While average credit growth remains positive during the two phases, it is considerably more volatile than GDP growth, particularly in developing countries. During the positive CYGAP phases, the average pace of credit growth is three to five times faster than GDP growth. In turn, during negative CYGAP episodes, the contractions of credit in a single year can be dramatic.

B. A Closer Look at Credit-to-GDP Dynamics

Is the shape of the positive phase of CYGAP cycles systematically related with the shape of the subsequent negative phase? To answer this question, we collapse the time dimension of the data into the set of individual cycles. Our goal is to assess whether the key characteristics of the positive CYGAP episodes are associated with the features of their subsequent negative gap phases. Specifically, we are interested in assessing if the duration and amplitude of the CYGAPs, and the speed of credit growth and GDP growth during the positive gap episodes are systematically related to the dynamics of the subsequent negative gaps. We expect that more robust and protracted credit dynamics during the positive gap phase of the cycle would lead to deeper and more protracted slowdown of credit during the negative phase. To this end, we run a series of bi-variate regressions of selected characteristics of the negative gap phase on corresponding characteristics of the precedent positive phase, taken as explanatory variables.

The results support our priors (Table 4). More sizable and long-lasting CYGAPs during the positive phase lead to deeper and longer negative gaps, and to lower credit and GDP growth during the subsequent negative phase. Similarly, larger increases in the credit-to-GDP ratio during the positive gap episodes lead to sharper subsequent declines in the credit-to-GDP ratio. Interestingly, there is no systematic relationship with the subsequent rates of credit growth or GDP growth, which suggests that both variables tend to move in opposite directions during the negative phase. Lastly and contrary to expectations, more dynamic credit growth and GDP growth during the positive gap episodes tend to exert a dampening effect on their subsequent dynamics during the negative phase.

V. Credit Reversals, Banking Crises and the CYGAP

We now study the relationship between credit reversals and banking crises, by estimating the likelihood of each of these events in the years around the realization of the other. First, we construct a window centered on the occurrence of banking crises and compute the probabilities of observing credit reversals five years before and five years after (i.e., considering the average cycle duration).[5] Then, we construct a window centered on the occurrence of credit reversals and do a symmetrically reverse analysis.

The results suggest that credit reversals are more likely to occur after banking crises (Figure 3). For industrial countries for example, the likelihood of observing a credit reversal conditional on the occurrence of a previous banking crisis increases from about 8 percent to 35 percent. For developing countries, the corresponding probabilities increase from 15 to 25 percent. In contrast, banking crises tend to precede credit reversals in both groups of countries, and their likelihood drops after the credit reversals (Figure 4). Interestingly, the likelihood of banking crises tends to increase in the years leading to the credit reversal, suggesting that the latter could reflect a defense mechanism by banks to curb the buildup of excessive credit risk.

Next, we study the likelihood of banking crises and credit reversals within the phases of the CYGAP cycles. As a first pass, we compare the unconditional probabilities of crises and reversals versus their conditional pairs, in the positive and negative phases of the CYGAP cycles (Table 5). In line with the findings of Reinhart and Rogoff (2013), banking crises seem equally likely to happen across industrial and developing countries (roughly once every eight years). Credit reversals are relatively more frequent, particularly in developing countries (where they occur about once every five years). Looking at the conditional probabilities, banking crises are more likely to happen when the CYGAP is positive, a result mostly driven by the subsample of industrial countries. This fact is consistent with the view that crises are credit booms gone bad (Schularick and Taylor, 2012). In contrast, credit reversals are two times more likely to happen during negative CYGAPS, and the differences between developing and industrial countries seem unremarkable.

What is the incidence of banking crises and credit reversals within the CYGAP cycles? Basel regulations on countercyclical bank capital buffers advocate for the use of the CYGAP as a reference metric for their implementation. This policy rests on the view that banking crises tend to happen at a relatively late stage in the positive phase of the CYGAP cycles, in the aftermath of rapid credit growth episodes. To test this view, we track the evolution of the yearly probabilities of banking crises and credit reversals within the cycles, using a ten-year window centered on the year when the CYGAP shifts from positive to negative.[6] Surprisingly, the yearly probabilities of banking crises in developing countries are rather flat throughout the entire reference window (Figure 5). In sharp contrast, in industrial countries the likelihood of crises peaks early in the CYGAP cycle, four years before the CYGAP turns negative. These results suggest that the CYGAP may provide insufficient lead time for the buildup of bank capital buffers, posing questions on its adequacy as reference trigger for countercyclical capital buffers. In turn, the likelihood of credit reversals within cycles

[5] Robustness checks with seven-year windows (14-year cycles) produced similar results.

[6] The length of the window reflects the average duration of CYGAP cycles. Similar results were obtained using a 14-year window.

follows a different pattern (Figure 6). It bottoms up early in the positive phase of the CYGAP cycle and increases monotonically afterward, peaking when the CYGAP becomes negative.

What is the impact of credit reversals and banking crises on the shape of CYGAP cycles? To answer this question, we split the data in two groups: cycles with the presence of crises or reversals versus cycles with no crises/reversals, which we use as controls. Then, we compare the characteristics of the negative phase of the CYGAP across these two groups using the metrics described earlier. To facilitate the comparison, we run OLS regressions of cycle characteristics on a set of dummy variables that equal one for the cycles with crises/reversals. As before, we also split the sample across industrial and developing countries by using interacting dummies. Granted, these regressions do not establish causality and are only intended to facilitate the comparison across cycles.

Not surprisingly, cycles with crises display a sharper collapse of credit growth during the negative CYGAP phase and are also more protracted, deeper and wider than those of the control group (Table 6, panel A). Across country groups, the differences between industrial and developing countries are not statistically significant, except for the amplitude and range of the CYGAP, which indicates a more severe collapse in developing countries. The results are also significant form the economic perspective. For example, the negative phase of the credit cycles with banking crises is on average 1.7 years longer than the control group, with a differential drop in credit-to-GDP ratios of 5 percentage points.

The results for reversals are qualitatively similar, but the differences vis-à-vis the control group somewhat less prominent than those obtained for crises, except for the contraction in credit growth, which is almost two-times higher (Table 6, panel B). Also, the change in credit-to-GDP ratios associated with reversals compares in magnitude with the results of the crises. Thus, in terms of the impact on credit availability, credit reversals seem more constraining than crises, raising questions on their relative costs in terms of economic activity. Across country groups, it is remarkable that the duration of the negative phase is even longer for industrial countries, while the difference in the amplitude and range of their cycles vis-à-vis their control group remains narrower. In all, this suggests that reversals in industrial countries have a less severe, but more protracted, impact on credit dynamics.

As a complementary exercise, we use the frequencies of reversals/crises within cycles as a proxy for their intensity and rerun the regressions by replacing the dummies with these frequencies (Table 6, panels C and D). Clearly, the negative phase of cycles with a higher incidence of banking crises tends to be longer and wider than cycles with no crises. Credit growth is also substantially slower in cycles with banking crises, leading to lower credit-to-GDP ratios. Reversals are also associated with deeper, faster and wider drops in credit-to-GDP ratios relative to their control group and, surprisingly, the contraction in credit and credit-to-GDP ratios relative to the control group is also more severe than the corresponding results associated with the banking crises.

Besides statistical significance, virtually all the estimated coefficients are economically meaningful. To illustrate, we compute the effect of a one-standard deviation increase in the probabilities of reversals/crises on the cyclical characteristics of the negative phase (Table 7). So, for example, a 16-percentage point increase in the frequencies of banking crises (one stadard deviation) leads to a –0.5 percentage point change in credit-to-GDP ratios during the negative CYGAP phase in developing countries and –0.9 in industrial, vis-à-vis their control groups. The same shock would lead to an increase in the duration of the negative phase of the CYGAP by about four months in developing countries (0.328 years) and two months in industrial. Surprisingly, the effects of credit reversals surpass those of banking crises across most variables. This picture suggests that credit reversals have large effects on economic activity. We explore this further in the next session.

VI. The Economic Costs of Credit reversals and Banking Crises

To provide a first approximation at the costs of reversals and crises we take the sets of CYGAP-based cycles used in the previous session and split the data in two groups, differentiating between cycles with reversals/crises from cycles with no reversals/crises, which we use as controls. As before, we establish a ten-year window centered on the years when the CYGAP turns negative. Using this reference window, we track the evolution of economic activity within cycles by computing the average output gaps and the average GDP growth for each group.

Our focus is the estimation of the economic costs of credit reversals. A large body of literature has focused the economic costs of banking crises. Across the literature, the estimated costs of banking crises appear significant, with a relatively wide dispersion, ranging in most cases between 4–15 percent of GDP (Table 8). Unfortunately, the comparability of the results is hampered by different crises definitions and dating, methodological approaches, and sample coverage. In many cases, the validity of results is also limited by the use of relatively small samples (typically less than 21 countries).

We try to control for differences in methodology by applying the same approach to the estimation of credit reversals and banking crises. Thus, while our paper presents average cost estimates, emphasis in the interpretation is placed on the *relative* costs of reversals and crises, which we deem more robust to potential methodological flaws (such as endogeneity and omitted variables bias).

The relative dynamics of the output gap and GDP growth across cycles with, and without, banking crises, are plotted in Figure 7. Clearly, the output gap, computed as the percent deviation of (the log of) GDP relative to its HP-filtered trend, displays wider swings in cycles with banking crises. The pattern is qualitatively similar across industrial and developing countries, albeit the later seem to quickly close the gap differentials. As for GDP growth, the set of cycles with banking crises overperform their control group early in the window but display a substantially lower pace afterwards, and the differences remain protracted, especially in industrial countries. This result is consistent with several papers that report larger economic costs of banking crises in industrial countries (for example, Bordo *et al*., 2001; Cerra and Saxena, 2008; Laeven and Valencia, 2018). The parallel comparison for the case of credit reversals is presented in Figure 8. The magnitudes of the GDP growth differentials are comparable with those obtained for the case of banking crises but appear substantially more persistent in developing countries.

Using these results, we come up with an estimation of the costs of banking crises and credit reversals. To do so, we accumulate GDP growth for up to six years after the CYGAP turns negative and take the difference between cycles with- and without-crises. The starting point is guided by the fact that the output gap differential is close to zero. Yet, we acknowledge that this choice is rather arbitrary (we try to account for this below, by looking at the relative economic performances across the entire cycles). More importantly, this methodology assumes that crises and reversals are exogenous to economic performance which, as discussed previously, is unlikely. Under more plausible assumptions, if the likelihood of reversals/crises is endogenous and inversely related to the pace of economic activity, the estimated costs of reversals/crises presented here would be upward biased, thus providing a conservative estimate of the associated costs.

The results (Table 9), indicate that banking crises have large and protracted costs in terms of forgone economic activity, which is consistent with Cerra and Saxena (2008). In developing countries, however, the median costs are significantly smaller than the mean (and in fact close to zero), suggesting that the mean is influenced by a smaller number of cases with very large output losses. In other words, the positive skewness of the distribution suggests that most developing countries tend to rebound quickly after banking crises. In contrast, the estimated costs for industrial countries are larger, of the order of 11 percentage points in terms of foregone output seven years after the start of the negative CYGAP.

Consistent with our previous findings, the costs of credit reversals are also protracted and, in terms of magnitude, comparable with those of banking crises. It is important to stress that we are applying the same methodology to estimate the costs of crises and reversals. Thus, their relative orders of magnitude should stand as a robust indicator, provided that the reference window is suitable for both types of events, which is not necessarily the case. Furthermore, as discussed before, crises and reversals tend to come together, so their costs may get entangled. To account for this, we apply a second approach by computing two sets of panel regressions:

$$GDP\ Growth_{i,t} = \alpha_i + \beta BC_{i,t} + \gamma CC_{i,t} + \delta BC_{i,t}CC_{i,t} + \varepsilon_{i,t} \qquad [1]$$

and

$$GDP\ Growth_{i,t} = \alpha_i + \beta PBC_{i,t} + \gamma PCC_{i,t} + \delta PBC_{i,t}PCC_{i,t} + \varepsilon_{i,t} \qquad [2]$$

Where GDP growth stands for yearly GDP growth; *BC* is a dummy variable that equals one for credit-to-GDP cycles that contained banking crises and zero otherwise; and *CC* is a dummy variable that equals one for credit-to-GDP cycles that contained banking crises and zero otherwise; *PBC* is the frequency of years with banking crises in the credit-to-GDP cycles; and *PCC* is the frequency of years with credit reversals in the credit-to-GDP cycles. The sub-indexes *i* and *t* denote countries and time, respectively. Is it worth emphasizing that the explanatory variables do not vary within cycles. Therefore, their coefficients in regression [1] capture the differences in average GDP growth between the entire cycles with- and without- crises and reversals. In turn, the coefficients of the frequencies in regression [2] provide information on the effects of prevalence of banking crises and credit reversals on economic activity. A priory, we expect all the coefficients to be negative.

The results of equation [1] indicate that both banking crises and credit reversals have a substantial negative impact on economic activity, particularly in industrial countries (Table 10). As for crises, the estimated drop in GDP growth (versus the control group) is 1.3 percent *per year* during the entire credit-to-GDP episodes. As the cycles last about ten years, the cumulative GDP differential stands at about 14 percentage points (=1.013^10–1). This result is broadly consistent with our previous calculations, since the later were based on the differences during the negative phase of the cycle only. In fact, using the five-year average duration of the negative phase, the implied cumulative drop in GDP growth stands at around 7 percent (=1.013^10–1), which is comparable with the previous results. By comparison, the result is in the lower range of the estimations obtained by Hoggart, Reis and Saporta (2002) and seems slightly smaller than the averages reported in Laeven and Valencia (2018).

Fundamentally, these results suggest that credit reversals have substantial economic costs, at about half of those associated with banking crises. Moreover, since reversals are more frequent than crises, their economic costs over time are even more substantial. To provide a broad estimation using the relative frequencies of reversals (about one every 7.6 years) and crises (about one every 5.1 years), the overall cost of reversals over time come to represent about two-thirds of those associated with banking crises ($0.69 = \frac{0.006}{0.013} \times \frac{7.6}{5.1}$). These results provide strong support to macro-prudential policies that try to prevent supply-driven contractions in bank credit.

We now turn to regression [2], which conveys information on the sensitivity of the costs in response to a one percentage point increase in the frequency of crises and reversals (Table 11). The results are robust and consistent with the previous discussion. For brevity, it is worth highlighting only the similar magnitude of the coefficients associated with banking crises and credit reversals, and their large economic significance. For example, a one percentage point increase in the frequency of credit reversals leads to a drop of GDP growth of about 1.9 percentage point per year. Moreover, the estimated losses are larger for industrial countries, which is surprising considering their deeper money and capital markets and the availability of alternative financing sources to firms.

VII. Concluding Remarks

The literature on the time dimension of systemic risk lacks consensus on the characterization and measurement of its fundamental building blocks. Operational definitions of basic objects such as *credit booms* and *credit crunches* are not yet universally accepted. As a result, comparing across studies remains difficult. In this paper we propose a definition of credit reversals based on the relative behavior of aggregate bank credit and economic activity. The definition is clean and stringent. As such, it excludes episodes where a supply-side contraction in bank credit may occur concurrently with a contraction in credit demand.

Our methodology is based on event studies. It uses credit cycles, measured by the deviations of credit-to-GDP ratios from their HP-filtered trends, as the reference framework to collapse the time dimension. While this reference is endogenous to be behavior of credit and economic activity, it is still useful to analyze their relative dynamics. We acknowledge that the measurement of credit cycles using HP-filtered credit-to-GDP series is somewhat arbitrary. Our choice aims at facilitating the comparison with other papers and reflects its widespread use in financial sector surveillance and macro-prudential policies (i.e., countercyclical capital buffers).

The analysis uncovers robust connections between credit reversals, banking crises, and credit cycles and opens some avenues for future research. First, there is a large amount of work on the role of credit booms on the likelihood of subsequent financial crises. A parallel literature could focus on credit reversals. The results presented here suggest that credit reversals could reduce the likelihood of financial crises but falls short of establishing a causal relationship.

Second, the fact that banking crises tend to occur early in the positive CYGAP phases of the credit cycles, raises questions on the adequacy of credit-to-GDP ratios as a metric to guide the implementation of countercyclical capital buffers. This paper suggests a rather loose connection between credit and GDP along the cycles based on CYGAP levels. Further research is needed on alternative metrics to track the evolution of macro-financial risks and anchor macroprudential policies.

Finally, the economic costs of credit reversals appear significant, at about one-half of those obtained for banking crises and up to two-thirds when considering their relative frequencies. The impact of reversals and crises on economic activity seem larger in industrial than in developing countries, which may partly reflect the deeper banking and financial systems of the former but is also puzzling given the wider availability of financing sources to firms. Moreover, following a crisis, the rebound in economic activity in developing countries tends to be faster than in industrial. This may be due to systematic differences on the dampening role of FX rate depreciation and the supporting role of external demand (i.e., banking crises in industrial countries may have lager global effects on economic activity). Exploring the validity of these hypotheses is left for future work.

These results do not imply a causal relationship running from reversals/crises to economic growth due to possible endogeneity or omitted variables. Under the plausible hypothesis that reversals/crises are more likely under sluggish economic growth, these cost estimates are likely to be upward biased, offering conservative estimates.

VIII. References

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Table 1. Selected Statistics of the Credit-to-GDP Cycle 1/

		Total	Duration Positive	Duration Negative	Change Credit-GDP Positive	Change Credit-GDP Negative	Credit Growth Positive	Credit Growth Negative	GDP Growth Positive	GDP Growth Negative	Maximum Gap Positive	Maximum Gap Negative	Prob. Credit Crunch Positive	Prob. Credit Crunch Negative
Developing	Mean	10.3	5.0	5.2	0.069	-0.029	0.103	0.020	0.036	0.046	0.168	-0.198	0.119	0.219
Industrial	Mean	11.2	5.1	6.0	0.141	0.001	0.076	0.040	0.031	0.039	0.119	-0.115	0.104	0.210
Total Sample	Mean	10.6	5.0	5.4	0.089	-0.021	0.096	0.025	0.034	0.044	0.155	-0.176	0.115	0.217
Developing	Median	10.0	5.0	5.0	0.051	-0.017	0.096	0.027	0.036	0.040	0.146	-0.160	0.000	0.143
Industrial	Median	11.0	5.0	5.0	0.093	0.006	0.064	0.041	0.023	0.036	0.094	-0.082	0.000	0.101
Total Sample	Median	10.0	5.0	5.0	0.062	-0.013	0.088	0.032	0.032	0.039	0.133	-0.138	0.000	0.143
Developing	Std. Dev.	3.2	2.1	2.1	0.079	0.092	0.088	0.094	0.039	0.041	0.288	0.197	0.158	0.260
Industrial	Std. Dev.	3.3	1.8	2.5	0.166	0.245	0.057	0.053	0.039	0.024	0.135	0.110	0.146	0.273
Total Sample	Std. Dev.	3.2	2.0	2.3	0.114	0.151	0.082	0.085	0.039	0.037	0.257	0.182	0.155	0.263
Developing	Percentile 80	13	7	7	0.121	0.032	0.151	0.082	0.061	0.065	0.316	-0.058	0.250	0.400
Industrial	Percentile 80	14	7	8.5	0.249	0.101	0.118	0.084	0.052	0.056	0.200	-0.036	0.250	0.400
Total Sample	Percentile 80	13	7	7	0.145	0.041	0.145	0.083	0.058	0.061	0.280	-0.048	0.250	0.400
Developing	Percentile 20	7	3	3	0.015	-0.086	0.042	-0.049	0.011	0.022	0.038	-0.310	0.000	0.000
Industrial	Percentile 20	8	3	4	0.038	-0.097	0.027	-0.003	0.006	0.019	0.030	-0.172	0.000	0.000
Total Sample	Percentile 20	8	3	3	0.020	-0.087	0.036	-0.032	0.009	0.021	0.035	-0.269	0.000	0.000
Developing	No. Obs.	268	293	288	293	288	293	288	293	288	377	377	377	419
Industrial	No. Obs.	103	111	110	111	110	111	110	111	110	137	137	137	146
Total Sample	No. Obs.	371	404	398	404	398	404	398	404	398	514	514	514	565

1/ Credit Cycle defined by the Credit-to-GDP Gap versus HP Trend using a smoothing parameter lambda=100.

This table presents selected sumary statistics of the credit-to-GDP cycle. The sample is split by developing and industrial countries.

Table 2. Frequencies of Credit Growth and GDP Growth, 1960–2017

	Credit Growth								
	All Sample			Developing			Industrial		
	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total
Negative GDP Growth									
No. Obs.	557	513	1,070	456	401	857	101	112	213
Row Percent	52.06	47.94	100	53.21	46.79	100	47.42	52.58	100
Column Percent	27.52	9.66	14.59	28.08	10.16	15.38	25.25	8.24	12.1
Positive GDP Growth									
No. Obs.	1467	4,795	6,262	1168	3,547	4,715	299	1248	1547
Row Percent	23.43	76.57	100	24.77	75.23	100	19.33	80.67	100
Column Percent	72.48	90.34	85.41	71.92	89.84	84.62	74.75	91.76	87.9
Total									
No. Obs.	2,024	5,308	7,332	1,624	3,948	5,572	400	1,360	1,760
Row Percent	27.61	72.39	100	29.15	70.85	100	22.73	77.27	100
Column Percent	100	100	100	100	100	100	100	100	100

This table presents the frequencies of credit growth and GDP growth. The sample is split by episodes of positive and negative growth in the variables, and by industrial versus developing countries.

Table 3. Summary Statistics of Credit Growth and GDP Growth Conditional on the Phases of Credit-to-GDP Cycles, 1960–2017

	Mean		Median		10 Percentile		90 Percentile		No. Obs.	
	Credit	GDP	Credit	GDP	Credit	GDP	Credit	GDP	Credit	GDP
Developing										
Negative Gap	0.051	0.045	0.042	0.044	-0.169	-0.009	0.259	0.095	2997	2997
Positive Gap	0.143	0.037	0.093	0.039	-0.051	-0.021	0.340	0.091	2688	2688
Industrial										
Negative Gap	0.050	0.040	0.048	0.037	-0.051	0.005	0.147	0.084	937	937
Positive Gap	0.086	0.030	0.058	0.028	-0.026	-0.016	0.207	0.077	861	861
Total Sample										
Negative Gap	0.051	0.044	0.045	0.042	-0.144	-0.004	0.231	0.094	3934	3934
Positive Gap	0.129	0.035	0.083	0.036	-0.043	-0.020	0.309	0.089	3549	3549

This table presents summary statistics of credit growth and GDP growth during positive and negative gaps of the Credit-to-GDP cycle.

Table 4. Bivariate OLS Regressions of Cyclical Parameters of Credit-to-GDP Cycles, 1960–2017

	Negative Phase of Credit to GDP Gap					
	Min Gap	Duration	Change Credit to GDP	Speed Credit GDP	Yearly credit growth	Yearly GDP growth
Positive Phase of Credit to GDP Gap						
Max Gap	-0.161***	1.449***	-0.010	-0.009***	-0.030***	0.006
	[0.028]	[0.251]	[0.011]	[0.003]	[0.010]	[0.005]
Duration	-0.002	0.329***	-0.004**	-0.001	0.000	-0.001
	[0.004]	[0.039]	[0.002]	[0.000]	[0.002]	[0.001]
Change Credit to GDP	0.198*	1.492	-0.215***	-0.089***	0.057	-0.004
	[0.103]	[1.022]	[0.043]	[0.011]	[0.040]	[0.022]
Speed Credit GDP	0.562*	-7.987***	-0.551***	-0.292***	0.075	0.045
	[0.302]	[2.656]	[0.112]	[0.027]	[0.105]	[0.058]
Yearly credit growth	-0.045	-0.865**	0.034*	-0.003	-0.026	0.047***
	[0.048]	[0.408]	[0.017]	[0.004]	[0.016]	[0.009]
Yearly GDP growth	0.400**	-3.023*	0.104	0.031*	0.158**	0.090**
	[0.202]	[1.772]	[0.076]	[0.019]	[0.070]	[0.038]

This table presents the results of bivariate OLS regressions of key parameters of the credit-to-GDP cycle during negative gap episodes (the variables in the columns) as a function of the corresponding parameters during the previous positive phase of the cycle (the variables in the rows). The regressions include a constant (not reported).

Table 5. Probabilities of Banking Crises and Credit Reversals Conditional on the Credit-to-GDP Gap, 1960–2017

	No. Crises and Reversals		No. Observations		Probabilities	
	Banking Crises	Credit Reversals	Banking Crises	Credit Reversals	Banking Crises	Credit Reversals
Developing						
Total	288	1184	2216	5824	0.130	0.203
Positive Gap	152	342	1060	2763	0.143	0.124
Negative Gap	136	842	1156	3061	0.118	0.275
Industrial						
Total	132	305	970	1836	0.136	0.166
Positive Gap	90	94	448	880	0.201	0.107
Negative Gap	42	211	522	956	0.080	0.221
Total Sample						
Total	420	1489	3186	7660	0.132	0.194
Positive Gap	242	436	1508	3643	0.160	0.120
Negative Gap	178	1053	1678	4017	0.106	0.262

This table presents the conditional probabilities of banking crises conditional on the credit-to-GDP gap. Credit Reversals are defined as episodes where there is a simultaneous ocurrence of negative credit growth and positive GDP growth.

Table 6. OLS Regressions of Selected Credit Cycle Characteristics on the Presence of Banking Crises and Credit Reversals, 1960–2017

	[1]	[2]	[3]	[4]	[5]	[6]
	Duration of Negative Phase	Change of Credit to GDP in Negative Phase	Speed of Change in Credit to GDP Ratio in Negative Phase	Yearly Credit Growth in Negative Phase	Amplitude of Cycle	Minimum Credit to GDP Gap
A. Explanatory: Dummy Banking Crises						
Cycles with Banking Crises	1.745***	-0.050***	-0.015***	-0.031**	-0.204***	-0.080**
	[0.284]	[0.013]	[0.004]	[0.014]	[0.055]	[0.034]
Cycles with Banking Crises x Industrial	0.160	0.017	0.005	0.039*	0.221**	0.110**
	[0.460]	[0.021]	[0.007]	[0.023]	[0.089]	[0.056]
Constant	3.435***	-0.012***	-0.008***	0.011**	-0.278***	-0.135***
	[0.087]	[0.004]	[0.001]	[0.004]	[0.016]	[0.010]
Observations	938	938	938	938	1046	1046
R-squared	0.059	0.018	0.015	0.005	0.013	0.006
B. Explanatory: Dummy Credit Reversals						
Cycles with Credit Reversals	1.053***	-0.042***	-0.008***	-0.056***	-0.156***	-0.058***
	[0.178]	[0.008]	[0.003]	[0.009]	[0.032]	[0.020]
Cycles with Credit Reversals x Industrial	1.007***	-0.014	-0.006	0.030**	0.112**	0.056*
	[0.248]	[0.011]	[0.004]	[0.012]	[0.047]	[0.030]
Constant	2.833***	0.012*	-0.004*	0.043***	-0.210***	-0.111***
	[0.142]	[0.006]	[0.002]	[0.007]	[0.024]	[0.015]
Observations	938	938	938	938	1,046	1,046
R-squared	0.069	0.035	0.015	0.043	0.024	0.009
C. Explanatory: Frequency Banking Crises						
Frequency of Banking Crisis in Cycle	1.095*	-0.049	-0.023**	-0.069***	-0.402***	-0.161***
	[0.586]	[0.033]	[0.011]	[0.023]	[0.054]	[0.028]
Freq. Banking Crisis x Industrial	0.947	-0.047	0.003	0.085*	0.424***	0.176***
	[1.126]	[0.063]	[0.022]	[0.044]	[0.106]	[0.055]
Constant	3.645***	-0.023***	-0.013***	0.006	-0.236***	-0.097***
	[0.139]	[0.008]	[0.003]	[0.005]	[0.012]	[0.006]
Observations	455	455	455	455	522	522
R-squared	0.015	0.01	0.011	0.021	0.097	0.061
D. Explanatory: Frequency Credit Reversals						
Frequency of Credit Reversal in Cycle	-0.013	-0.157***	-0.037***	-0.216***	-0.281***	-0.099*
	[0.496]	[0.021]	[0.007]	[0.023]	[0.088]	[0.055]
Freq. Credit Reversal x Industrial	2.736***	-0.206***	-0.043***	0.085**	0.292*	0.158
	[0.837]	[0.036]	[0.012]	[0.039]	[0.156]	[0.098]
Constant	3.589***	0.019***	-0.002	0.047***	-0.253***	-0.127***
	[0.122]	[0.005]	[0.002]	[0.006]	[0.021]	[0.013]
Observations	938	938	938	938	1,046	1,046
R-squared	0.012	0.119	0.053	0.085	0.011	0.004

Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

This table presents a set of OLS regressions of selected characteristics of credit cycles, presented in the columns, on four groups of explanatory variables. The regressions displayed in panel A use a dummy variable that equals one for cycles with the presence of banking crises and zero otherwise. The regressions in panel B use a dummy variable that equals one for cycles with the presence of credit reversals and zero otherwise. Panels C and D present parallel regressions using the within-cycle frequencies of banking crises and credit reversals as a proxy for their intensity.

Table 7. Estimated Impact of an Increase in the Frequency of Banking Crises and Credit Reversals on Selected Cycle Characteristics, 1960–2017

	Duration of Negative Phase	Change of Credit to GDP in Negative Phase	Speed of Change in Credit to GDP Ratio in Negative Phase	Yearly Credit Growth in Negative Phase	Yearly GDP Growth in Negative Phase	Amplitude of Cycle	Minimum Credit to GDP Gap
Banking Crises							
Developing Countries							
Reg. Coefficient	1.095	-0.049	-0.023	-0.069	-0.00	-0.402	-0.161
St. Dev. Banking Crises	0.157	0.157	0.157	0.157	0.157	0.157	0.157
Estimated Impact	0.171	-0.008	-0.004	-0.011	0.000	-0.063	-0.025
Industrial Countries							
Reg. Coefficient	2.042	-0.089	-0.020	0.016	-0.020	0.022	0.015
St. Dev. Banking Crises	0.161	0.161	0.161	0.161	0.161	0.161	0.161
Estimated Impact	0.328	-0.014	-0.003	0.003	-0.003	0.004	0.002
Credit Reversals							
Developing Countries							
Reg. Coefficient	-0.013	-0.157	-0.037	-0.216	-0.018	-0.281	-0.099
St. Dev. Credit Reversals	0.190	0.190	0.190	0.190	0.190	0.190	0.190
Estimated Impact	-0.002	-0.030	-0.007	-0.041	-0.003	-0.053	-0.019
Industrial Countries							
Reg. Coefficient	2.717	-0.357	-0.037	-0.136	-0.018	0.009	0.051
St. Dev. Credit Reversals	0.187	0.187	0.187	0.187	0.187	0.187	0.187
Estimated Impact	0.509	-0.067	-0.007	-0.025	-0.003	0.002	0.010

This Table presents the impact of a one-standard deviation increase in the frequency of banking crises and credit reversals on selected characteristics of the negative phase of credit cycles, presented in the columns. The impact is measured in terms of differencial effects vs. cycles without crises/reversals. The frequencies of crises and reversals are computed by dividing the number of years with crises/reversals within cycles over the total number of years in the corresponding cycles. The calculations use the results of the OLS regressions presented in Table 7.

Table 8. Estimated Costs of Banking Crises, Summary Results

Paper	Sample	Average Drop in GDP (Percent)	Average Duration (Years)	Differencial Effects between Industrial and Developing Countries	Comments
Reinhart and Rogoff (2009)	18 countries; 1899-2007	9.3	1.9 years	Not studied	
Bordo et al. (2001)	21 countries, 1973-1997	6.2-7.0	3.1	Larger impact on industrial countries	
Schularick and Taylor (2012)	14 countries, 1870-2008	4.1-7.9	5 years	Not studied	
Jorda, Schularick, and Taylor (2013)	14 countries, 1870-2008	4	4 years	Not studied	Compare across recessions with and without banking crises
Cerra and Saxena (2008)	190 countries, 1960-2001	7.5	10 years	Larger and more protracted impact on high income countries	
Laeven and Valencia (2018)	160 countries, 1970-2017	35 (industrial countries); 13.8 (low- and middle-income countries)	More than 8 years	Higher and more persistent output losses in industrial countries; very assymetric distribution of costs among low- and middle-income countries	
Claessens, Kose and Terrones (2008, 2010)	21 OECD countries, 1960-2007	Median: 2.2; Mean: 9.4-21.9	Median: 1.2 years; Mean: 1.5-1.7 years	Not studied	
Hoggart, Reis, and Saporta (2002)	47 countries, 1977-1998	Industrial: 13.2-20.7; Medium and Low Income countries: 13.9-15.0	Industrial: 4.1; Medium and Low Income countries: 3.3	Output losses in industrial countries larger than in emerging market countries	
Romer and Romer (2017)	24 OECD countries, 1967-2012	4-6	3.5-5 years	Not studied	Wide variation in the estimated costs across countries. The exclusion of a few outliers has a large effect on the average estimated costs.

This table presents summary results of papers that focus on the estimation of economic costs of banking crises.

Table 9. Costs of Banking Crises and Credit Reversals
Cumulative GDP Growth Differential, 1960–2017

	Banking Crises		Credit Reversals	
	Mean	Median	Mean	Median
Developing Countries				
Year 0	0.0000	0.0000	0.0000	0.0000
Year 1	-0.0189	-0.0085	-0.0018	-0.0094
Year 2	-0.0224	-0.0069	-0.0143	-0.0221
Year 3	-0.0194	-0.0001	-0.0241	-0.0443
Year 4	-0.0018	0.0173	-0.0332	-0.0612
Year 5	-0.0176	0.0097	-0.0590	-0.0982
Year 6	-0.0503	0.0023	-0.0547	-0.1072
Industrial Countries				
Year 0	0.0000	0.0000	0.0000	0.0000
Year 1	-0.0167	-0.0132	-0.0181	-0.0113
Year 2	-0.0395	-0.0343	-0.0293	-0.0262
Year 3	-0.0650	-0.0553	-0.0392	-0.0417
Year 4	-0.0776	-0.0725	-0.0639	-0.0615
Year 5	-0.0897	-0.0869	-0.0876	-0.0816
Year 6	-0.1010	-0.1057	-0.0984	-0.0953

This table presents the estimated costs of banking crises and credit reversals in industrial and developing countries. The costs are computed as the difference in cumulative GDP growth between credit cycles with and without the presence of banking crises (or credit reversals). The starting point (Year 0) is the year when the credit-to-GDP gap turns negative.

Table 10. Fixed-Effect Regressions of GDP Growth on Banking Crises and Credit Reversals, 1960–2017

	[1] All Sample	[2] All Sample	[3] Developing	[4] Industrial
Dummy for Cycles with Banking Crises (DBC)	-0.013**	-0.013*	-0.012	-0.013***
	[0.005]	[0.007]	[0.010]	[0.004]
Dummy for Cycles with Credit Reversals (DCC)	-0.006***	-0.006**	-0.004	-0.011**
	[0.002]	[0.002]	[0.003]	[0.004]
DBC x DCC	0.004	0.004	0.005	0.004
	[0.006]	[0.008]	[0.011]	[0.005]
Constant	0.045***	0.045***	0.045***	0.044***
	[0.002]	[0.002]	[0.002]	[0.003]
Observations	7205	7205	5465	1740
R-squared	0.004	0.004	0.002	0.027
Number of countries	177	177	139	38
Sigma_u	0.020	0.020	0.020	0.018
Sigma_e	0.059	0.059	0.065	0.039
Rho	0.103	0.103	0.091	0.171
Average obs per group	40.7	40.7	39.3	45.8
Min obs per group	2	2	2	15
Max obs per group	57	57	57	57
Robust errors	No	Yes	Yes	Yes

Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.0

This table presents the results of fixed effect regressions of yearly GDP growth on a set of dummy variables that serve to split the sample into credit-to-GDP cycles with banking crises and credit reversals from cycles without the incidence of these events.

Table 11. Fixed-Effect Regressions of GDP Growth on the Frequency of Banking Crises and Credit Reversals, 1960–2017

	[1] All Sample	[2] All Sample	[3] Developing	[4] Industrial
Frequency of Banking Crisis in Cycle (PBC) 1/	-0.021***	-0.021*	-0.021	-0.028***
	[0.008]	[0.011]	[0.015]	[0.009]
Frequency of Credit Reversal in Cycle (PCC) 1/	-0.019***	-0.019***	-0.014**	-0.033**
	[0.005]	[0.005]	[0.006]	[0.014]
PBC x PCC	0.025	0.025	0.035	0.038
	[0.031]	[0.037]	[0.054]	[0.039]
Constant	0.044***	0.044***	0.045***	0.041***
	[0.001]	[0.001]	[0.001]	[0.002]
Observations	7205	7205	5465	1740
R-squared	0.004	0.004	0.002	0.023
Number of countries	177	177	139	38
Sigma_u	0.020	0.020	0.020	0.017
Sigma_e	0.059	0.059	0.065	0.039
Rho	0.103	0.103	0.091	0.162
Average obs per group	40.7	40.7	39.3	45.8
Min obs per group	2	2	2	15
Max obs per group	57	57	57	57
Robust errors	No	Yes	Yes	Yes

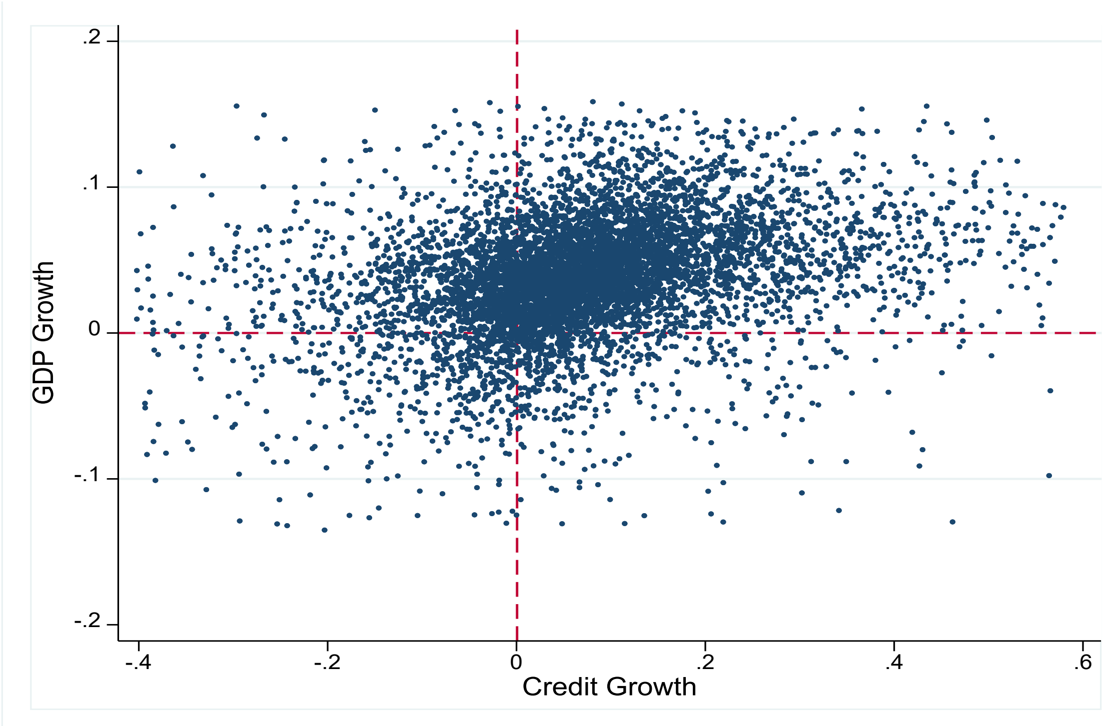
Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.0

1/ Frequency is the proportion of years with banking crises or credit reversals within cycles.

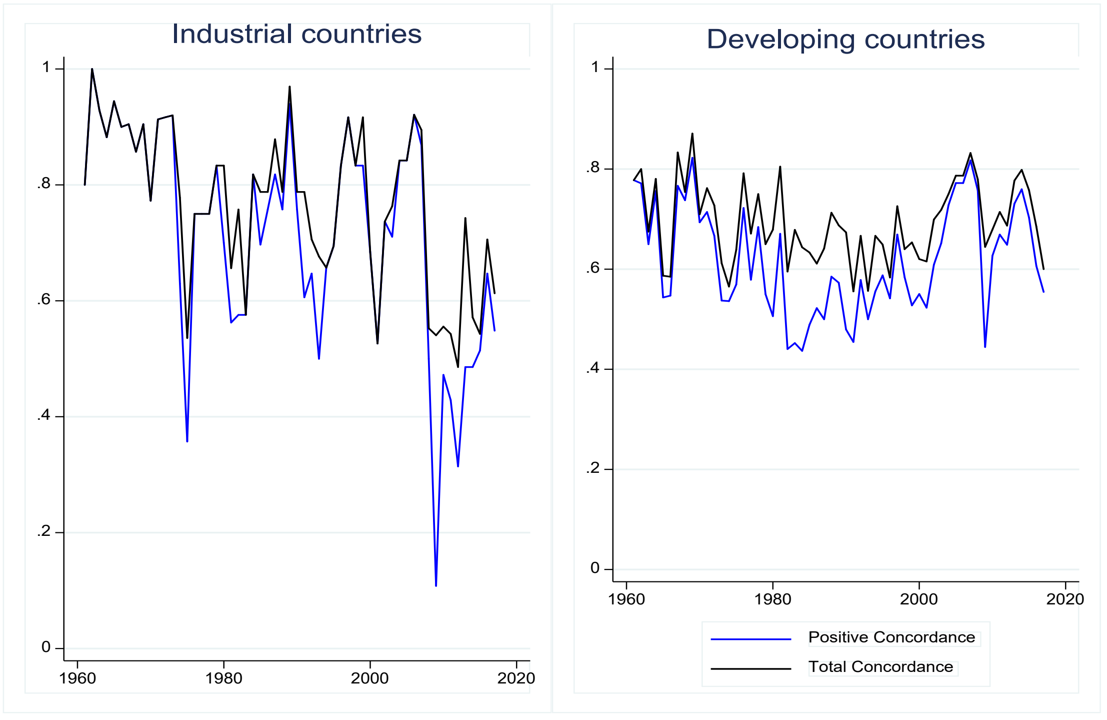
This table presents the results of fixed effect regressions of yearly GDP growth on the frequencies of banking crises and credit reversals within credit-to-GDP cycles.

Figure 1. Bank Credit and Economic Activity
Yearly growth rates, in percent, 1960–2017



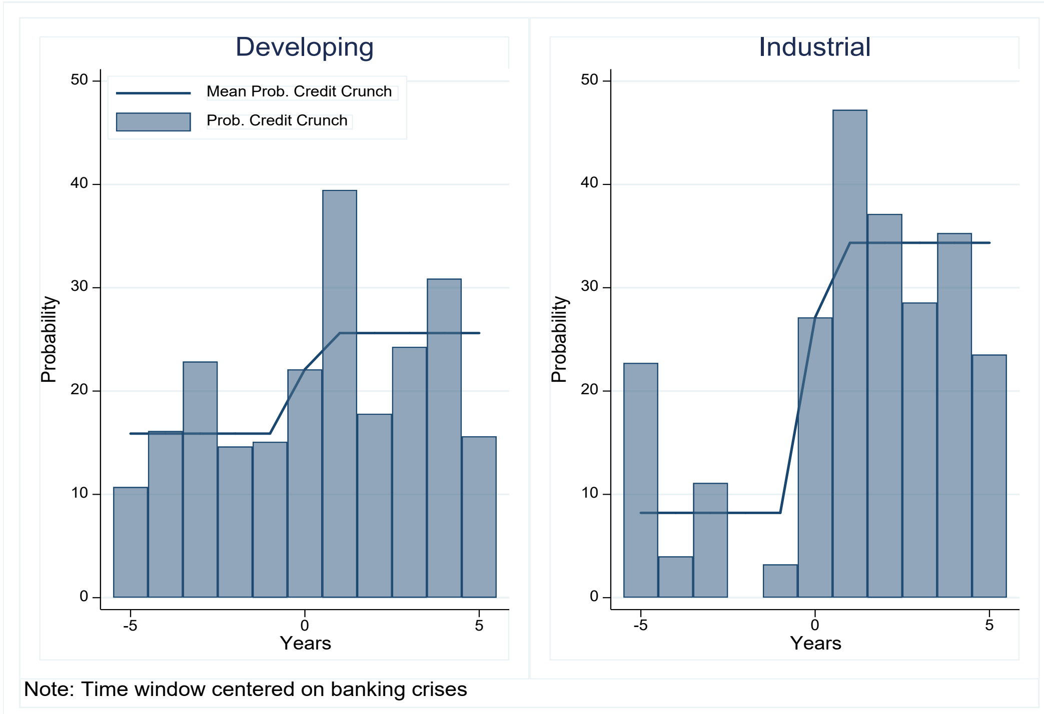
This figure plots the yearly growth rates of GDP and credit (both in real terms using the GDP deflator).

Figure 2. Evolution of Concordance between Credit and GDP Growth, 1960–2017



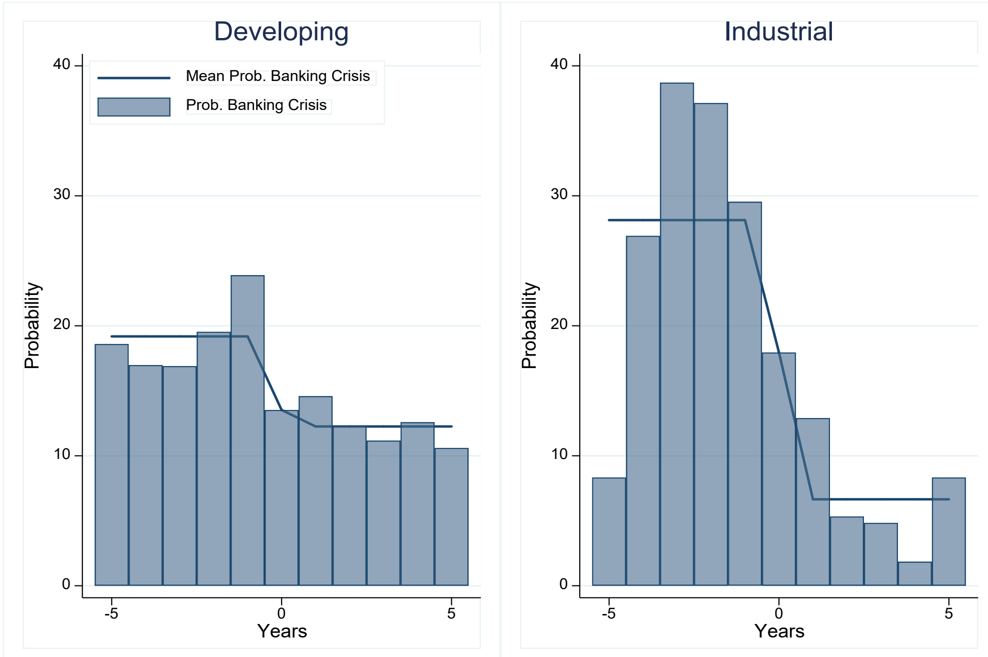
This figure shows the evolution of concordance between credit growth and GDP growth across developing and industrial countries.

Figure 3. Probabilities of Credit Reversals around Banking Crises, 1960–2017



This figure presents the yearly probabilities of banking crises around the ocurrence of banking crises. The ten-year window is centered at the start of the banking crises according to the Reinhard-Rogoff (2009) definition.

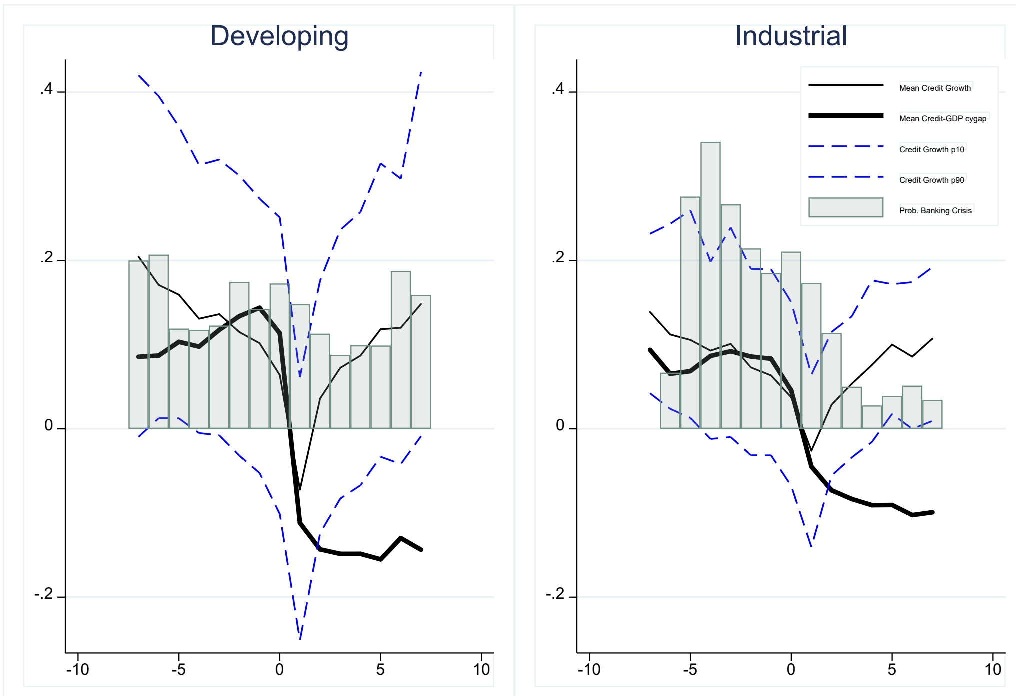
Figure 4. Probabilities of Banking Crises Around Credit Reversals, 1960–2017



Note: Time window centered on credit reversals

This figure presents the yearly probabilities of banking crises around the ocurrence of credit reversals. The ten-year window is centered at the start of the credit reversal.

Figure 5. Probabilities of Banking Crises Conditional on the Credit-to-GDP Gap
1960–2017



Note: Time window centered when the Credit-to-GDP gap goes from positive to negative

Figure 6. Probabilities of Credit Reversals Conditional on the Credit-to-GDP Gap
1960–2017

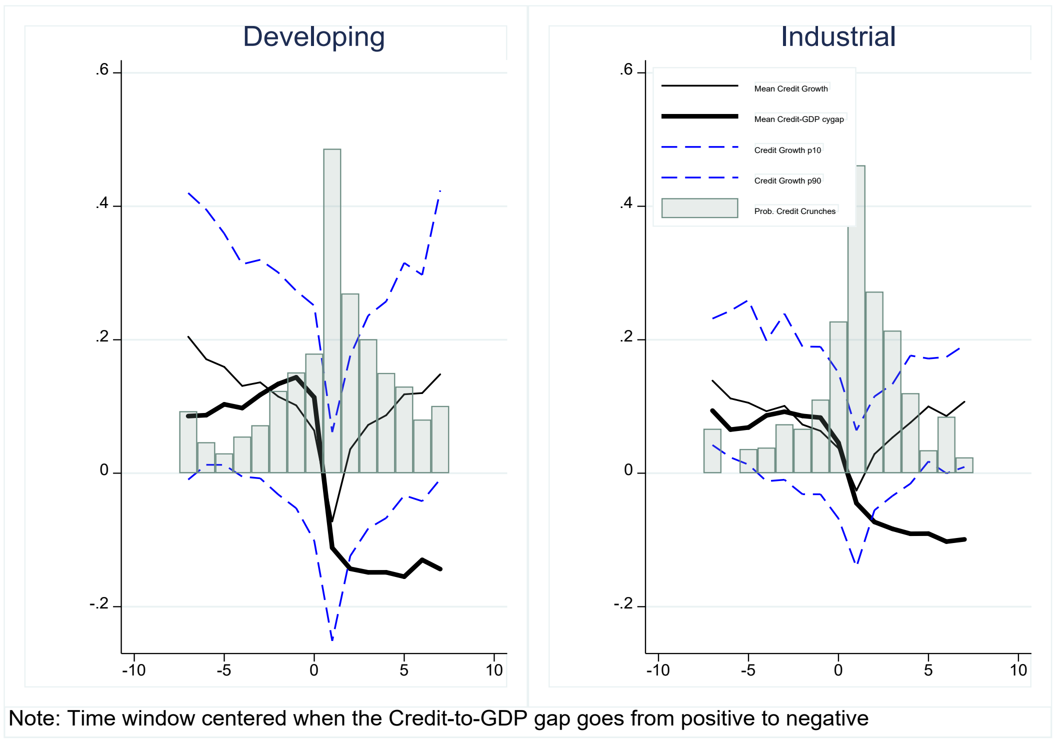
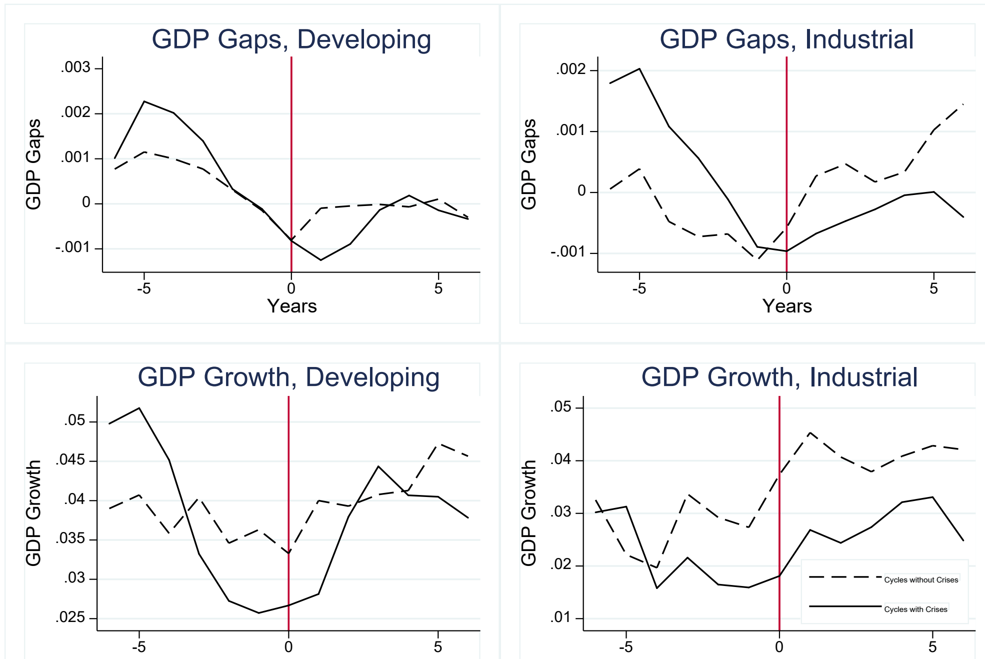
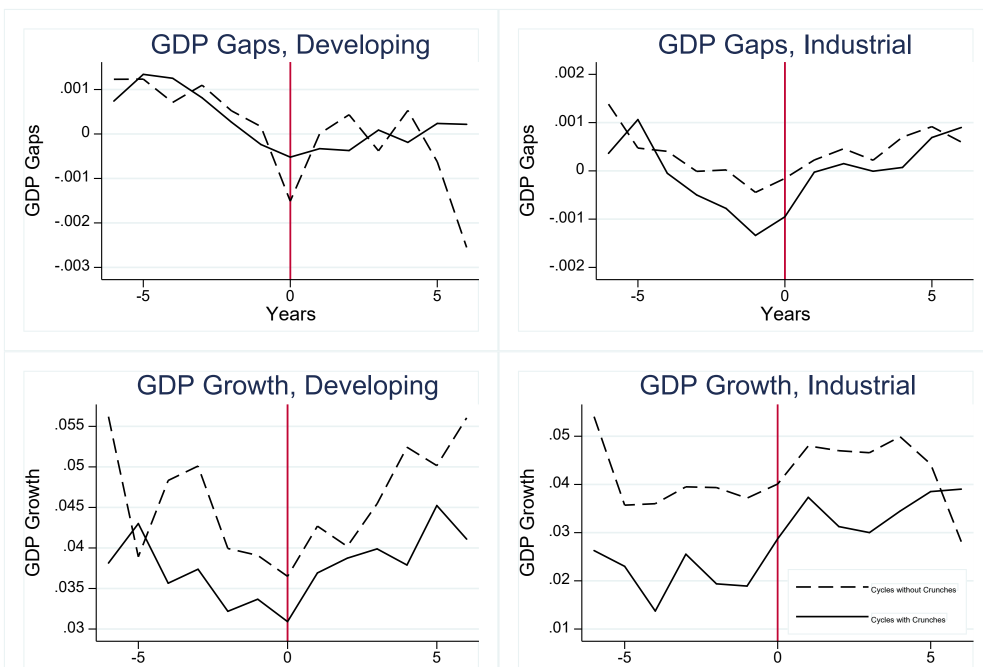


Figure 7. GDP Dynamics Conditional on Banking Crises, 1960–2017



Note: Window centered when the Credit-to-GDP Gaps goes from positive to negative

Figure 8. GDP Dynamics Conditional on Credit Reversals, 1960–2017



Note: Window centered when the Credit-to-GDP Gaps goes from positive to negative