Growth-and-Risk Trade-off *

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Abstract

We study the effects of credit over the business cycle, distinguishing between expansions and contractions. We find that there is a growth and risk trade-off in the pace of credit growth over the business cycle. While rapid credit growth tends to be followed by deeper recessions, we also find that credit growth has a positive impact on the duration of expansions. This poses a trade-off for the policymaker: Limiting the buildup of financial risk to avoid a deep recession can negatively affect the cumulation of economic growth during the expansion. We show that intermediate levels of credit growth maximize long-term growth while limiting volatility. Macroprudential policies should be used to manage this growth and risk trade-off, striking a balance between allowing expansions to last longer and avoiding deep recessions.
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Non-technical summary

Deep recessions tend to be preceded by episodes of rapid growth in bank credit to the private sector. The post-crisis regulatory reform agenda has focused on managing these downside risks associated with the buildup of financial imbalances, including through the introduction of countercyclical capital regulation. While the benefits of such policies are clear, given the large social costs associated with financial crises and deep recessions, there has been less emphasis on the potential costs of achieving these stability objectives. This is surprising given that a large body of literature prior to the recent crisis has established that financial deepening contributes positively to long-run economic growth. This suggests that there is a trade-off in the growth and financial stability nexus. This paper combines these two strands of the literature by analyzing the effects of bank credit over the business cycle, distinguishing between expansion and contractions. We confirm results in the existing literature showing that episodes of rapid credit growth tend to be followed by deeper recessions. However, we also find that credit growth lengthens the duration of expansions. This poses a tradeo-ff: restraining credit growth to avoid deep recessions can negatively affect the accumulation of economic growth during the expansion. Empirically, we show that intermediate levels of credit growth strike a healthy balance between stimulating longer expansions and avoiding deeper recessions. When we distinguish between household and corporate credit, we find that our results are primarily driven by household credit but we do not find statistical dependence on the influence of house prices. We also consider the influence of macroprudential policy over and above its potential impact on the evolution of credit itself, and find that expansions tend to be longer when macroprudential policy is in place, even though the effect of credit dominates. Taken together, our results indicate that the emphasis on recessions in the literature on the real effects of financial conditions is somewhat misplaced. The dynamics of financial conditions during expansion periods is equally important.

1 Introduction

There is broad consensus that episodes of rapid growth in credit tend to precede recessions and financial crises (Kaminsky and Reinhart (1999); Schularick and Taylor (2012); Gourinchas and Obstfeld (2012); Claessens et al. (2011b); and Mian et al. (2017)).[1] Moreover, there is ample evidence that credit crunches tend to be associated with deeper recessions and slower recoveries (Jorda et al. (2013); Claessens et al. (2011a,b,c)). More recently, Adrian et al. (2019) considered the effect of financial conditions not only on the expected intensity of recessions but also on the risk associated with recession periods. They show that deteriorating financial conditions are associated with a decrease in the mean of GDP growth and also with an increase in volatility. However, they find that upside risks to GDP growth are low even when there is an improvement in financial conditions, indicating a highly non-linear effect of financial conditions on the mean and the volatility of GDP growth.

This focus on the downside risks associated with financial imbalances can also be found in the post-crisis macroprudential approach to regulation. According to the FSB-IMF-BIS (2011), the objective of macroprudential policy is to "limit systemic or system-wide financial risk, thereby limiting the incidence of disruptions in the provision of key financial services that can have serious consequences for the real economy". The argument is that macroprudential policies should be implemented because they affect intermediate variables related to financial distress, and that financial distress has a direct impact on the volatility of GDP growth and the depth of recessions. Indeed, if credit expansions primarily downside risks and have limited upside risks, then one should fully exploit macroprudential policy to tame the credit cycle. The theoretical underpinnings for such interventions have been formulated in models with financial frictions that incorporate externalities in leverage choice, such as fire sales or aggregate demand spillovers in the presence of an effective lower bound on interest rates (e.g., Lorenzoni (2008); Farhi and Werning (2016)). Empirical work supports the view that macroprudential policies are effective in limiting credit growth, even though there are limits to such policies due to leakages and regulatory perimeters (e.g., Cerutti et al. (2017); Galati and Moessner (2017)).

While the benefits of such policies are clear, given the large deadweight losses associated with financial crises and deep recessions, there has been less emphasis on the potential costs of achieving these stability objectives. This is surprising given that a large body of literature prior to the recent crisis had established that financial deepening is positively associated with long-run economic growth (King and Levine, 1993; Jayaratne and Strahan, 1996; Levine, 2005), even though more recent literature has shown that the growth-enhancing effects of credit taper off at high levels of financial deepening (Aghion et al. 2005; Rousseau and Wachtel, 2011). Moreover, there is evidence that expansions without credit, or "creditless recoveries", result in below-average growth (Abiad et al. (2011)). This suggests that there is a trade-off in the growth and financial stability nexus.

In this paper, we combine these two strands of the literature by analyzing the effects of credit over the business cycle, distinguishing between expansions and contractions. We show that there is a growth-and-risk trade-off associated with the pace of credit growth. While we confirm results in the existing literature showing that rapid credit growth tends to be followed by deeper recessions, we are the first to find that credit growth has a direct positive impact on the duration of expansions. This poses a trade-off for the policymaker: Limiting the buildup

[1] In complementary work, Lopez-Salido et al. (2017) find that exuberant credit market sentiment, as measured by a combination of narrow credit spreads and a high share of junk bond issuances relative to historical norms, is followed by lower economic growth.

of financial risk by restraining credit growth in order to avoid a deep financial crisis-induced recession can negatively affect the cumulation of economic growth during the expansion. We show that for policymakers who trade off the mean and variance of growth, intermediate levels of credit growth maximize long-term growth while limiting volatility. Macroprudential policies could then be used to manage this trade-off, striking a balance between longer expansions and deeper recessions.

The positive effect of credit growth during expansions operates by lengthening the duration of expansions, not the average growth rate during expansions. The existing literature on finance and growth has focused exclusively on growth rates. To the best of own knowledge, we are the first to draw attention to the importance of duration in the finance and growth literature nexus.

When we distinguish between household and corporate credit, we find that our results are primarily driven by household credit but we do not find statistical dependence on the influence of house prices. We also consider the influence of macroprudential policy over and above its potential impact on credit itself, and find that expansions tend to be longer when macroprudential policy is in place, even though the effect of credit dominates.

The trade-off we consider is reminiscent of Ranciere et al. (2008) who show that economies with occasional credit busts associated with crises grow faster on average. A key difference with our paper is that we consider credit dynamics over the business cycle, distinguishing between expansions and recessions. Our paper also relates to research showing that not all credit booms end up in crises (e.g., Dell'Ariccia et al., 2012; Gorton and Ordonez, 2018). Our finding that there are both upside and downside risks to credit growth is similar in spirit to these papers.

The rest of the paper is structured as follows. Section 2 introduces the characteristics of business cycles, presents the data, and offers a preliminary analysis of the link between credit and the business cycle for a broad sample of OECD countries. Sections 3 and 4 study the effect of credit on recessions and expansions, respectively. Section 5 connects these two pieces of analysis by describing credit dynamics over the business cycle, providing a simulation of the total effect of credit over the business cycle, and assessing the growth-and-risk trade-offs of credit. Section 6 considers several extensions of our main analysis, including the role of different types of credit, the impact of house prices, and the effect of macroprudential policy. Section 7 concludes. Appendixes add a detailed description of the data, and extension that endogenizes the path of credit during expansions and several robustness checks relating to our main analysis, covering the influence of outliers and alternative measures of credit dynamics.

2 Setting the stage and description of data

Economic growth is not a continuous phenomenon. Business cycles are not uniform; some are short, lasting for a few months, while others last for several years. A simplified description of these intuitive ideas is displayed in Figure 1 where we try to mimic the pattern of a standard concatenation of expansion and recession periods.

In order to analyze the effect of credit on growth, we have to study its influence in each phase of the economic cycle. Although, as mentioned before, the literature has focused on the analysis of the effects of an excess of credit on the intensity of the recession, we must also consider the right-hand side of the growth distribution, the expansion, which is, after all, the main driver of economic growth. To do this, we will start by carrying out a preliminary analysis of the characteristics of both cyclical phases in a large sample of OECD countries, in order to subsequently incorporate the effect of credit.

2.1 Business cycle characteristics

We take business cycles, in the spirit of Burns and Mitchell (1946), to be the short-term periodic but irregular, up-and-down movements in GDP, the most comprehensive measure of overall economic activity. This approach to business cycles implies that we consider two phases, the expansion and recession phases. According to this framework, GDP usally grows until it reaches its (local) maximum and a contraction phase begins as GDP starts to decline. After some time of negative growth, GDP reaches its (local) mimimum, and an expansion begins as GDP growth rates become positive.

We estimate the specific business cycle turning point chronologies by applying the Harding and Pagan (2002) non-parametric dating procedure, which extends the seminal Bry and Boschan (1971) monthly dating to a quarterly frequency. This algorithm consists of a set of filters and rules, based on moving averages of the data with different windows, that isolates the local minima and maxima in the log levels of the national series of seasonally-adjusted GDP, subject to constraints on both the length and amplitude of expansion and contraction periods.[2]

Having established the turning points, we compute the characteristics of the expansion and recession phases of country i ($i = 1, ..., N$), related with their length, depth and shape, and define the duration (D^R), amplitude (A^R), and cumulation (C^R) for recessions and, analogously, the duration (D^E), amplitude (A^E), and cumulation (C^E) for expansions.

The first feature is *duration.* For the j-th recession of a particular country i, duration refers to the time spent between the j-th peak (P_{ij}) and the following trough (T_{ij}). So, the duration for the recession is computed as $D^R_{ij} = T_{ij} - P_{ij}$. For an expansion, the duration is defined as the time spent between the j-th trough (T_{ij}) and the following peak (P_{ij}), $D^E_{ij} = P_{ij} - T_{ij}$.

The second feature is the *amplitude.* If $y_{P_{ij}}$ and $y_{T_{ij}}$ are the log levels of GDP at the j-th peak and the j-th trough, respectively, the amplitude of the recession (expansion) is defined as $A^R_{ij} = y_{T_{ij}} - y_{P_{ij}} (A^E_{ij} = y_{P_{ij}} - y_{T_{ij}})$. Multiplied by 100, the amplitude represents the percentage of total loss (gain) of the downturn (upturn) in terms of GDP.

The third characteristic of a cyclical phase, *cumulation*, measures the severity of the recession (expansion) through the cumulative falls (increases) in economic activity within the downturn (upturn). It could be intuitively considered as the wealth destroyed (created) during the recessionary (expansionary) period. Harding and Pagan (2002) propose computing cumulation as $C^R_{ij} = -\left(\sum_{h=1}^{D^R_{ij}} \left|y_{P_{ij}+h} - y_{P_{ij}}\right| - 0.5A^R_{ij}\right)$, where the term $0.5A_{ij}$ removes the bias due to the approximation of a triangle by a sum of rectangles. In this work, this measure is calculated by approaching, with numerical methods, the integral of the area described by the evolution of the log level of GDP between $y_{P_{ij}}$ and $y_{T_{ij}}$, $C^R_{ij} = \int_{P_{ij}}^{T_{ij}} y dy$. In the same fashion, the cumulation of an expansion is $C^E_{ij} = \int_{T_{ij}}^{P_{ij}} y dy$, with the approximation of $C^E_{ij} = -\left(\sum_{h=1}^{D^E_{ij}} \left|y_{P_{ij}+h} - y_{P_{ij}}\right| - 0.5A^E_{ij}\right)$.

These three characteristics are represented in the stylized business cycle graph shown in Figure 1.

2.2 Data

We use a broad sample of OECD and non-OECD economies to compute business cycle characteristics and their relationship with the credit-to-GDP ratio. To represent the rhythm of economic

[2] The chronology of turning points obtained with our database is the same taking logarithms or not of the series of GDP levels. However, to correctly compute the business cycle characteristics it is necessary to take logarithms.

growth, we use the quarterly GDP. [3] We use all available data. The number of countries is 53, and the sample period is 1947Q1 to 2018Q2, although the starting date varies by country depending on data availability. [4] The source is the OECD (*https : //stats.oecd.org/*) Quarterly National Accounts, for most countries, and otherwise the Federal Reserve Bank of St. Louis (*https : //fred.stlouisfed.org/*). We denote this variable as $Y_{t,i}$ for each country i at time t, being $y_{t,i} = ()log(Yt,i) - log(Y_{t-1,i}) * 100$ its growth rate. Appendix 1 lists the countries included in the sample with their respective sample periods.

The credit-to-GDP ratio can be found on the website of the Bank for International Settlements (*https : //www.bis.org/statistics/c$_g$aps.htm*) for a total of 44 countries. The variable selected is credit-to-GDP ratio (actual data), named in the database as "Credit from All sectors to Private non-financial sector" at a quarterly frequency. We denote this variable as $cr_{t,i}$ for each country i at time t.

We estimate the chronology and characteristics of business cycles applying the previous framework to our database. The results are presented in Table 1. We find a total of 244 recessions and 285 expansions[5]. The recessions have an average duration of 4.42 quarters, an amplitude of -4.38%, and a cumulation of -14.63%. For expansions, the figures are 25.82 quarters (duration) , 27.51% (amplitude), and 646.08% (cumulation).

2.3 Some preliminary issues: a panel approach

Before starting with the full analysis of the effect of credit on the economic cycle, we adopt the standard approach taken in most papers that dynamically link credit and growth in a large sample of countries. We estimate a panel with fixed effects that relates economic growth, $y_{t,i}$ with the variation (i.e., the change) in the level of credit-to-GDP ratio in the previous period and some control variables, $\Delta cr_{t-1,i}$. Table 2 displays the results of this first approach. Firstly, we find that the overall effect is negative and significant when we consider the whole sample. This result appears at odds with the literature on financial deepening, which tends to find a positive relationship (e.g., King and Levine (1993) and Levine (2005), among others). However, Rousseau and Wachtel (2011) claim this relation changed in the early 90s. According to these authors, excessive financial deepening in general, and too rapid a growth of credit in particular, might have led to growth-inhibiting financial crises. These conflicting results point to a non-linear relation between credit and growth. To consider the most straightforward of possible non-linearities, we separate the sample into periods of expansion and recession, observing that the negative effect of credit only occurs in recession periods. This result is robust to controlling for lagged GDP growth as an explanatory variable and is consistent with the results in the literature showing that rapid credit growth is a strong predictor of the occurrence and depth of recessions (e.g. Schularick and Taylor (2012); Gourinchas and Obstfeld (2012); Claessens et al. (2011b); and Mian et al. (2017)).

Now that the relation between credit and growth in recessions has been established, we investigate whether the intra-recession variation or the variation across recessions is the main driver of our results. The question is whether it is credit variation during the recession periods that drives the performance of the economy during the recession or whether it is the initial conditions that matter. Some descriptive statistics clarify what is the main driver of the results. On average, the

[3]We use estimates of seasonally-adjusted GDP in terms of volume, with an expenditure approach and in national currency.

[4]The US has the largest sample that runs from 1947Q1 to 2018Q2; the smallest samples start in 1995Q1.

[5]Samples do not usually finish at the end of the cycle. We have incomplete cycles at the end of the sample which explains why we do not have exactly the same number of expansions and recessions.

standard deviation of credit-to-GDP ratio within recessions is 2.36. The standard deviation of credit-to-GDP across recessions is 30 times bigger, 66.26. Therefore, the relation between credit and growth during recessions is mainly due to the initial conditions across recessions rather than variation within a recession period.

3 The role of credit in recessions

In this section, we analyze the influence of initial credit conditions on the characteristics of recessions. Following the literature, we use the credit-to-GDP ratio (CR) as proxy for credit conditions (e.g., Jorda et al. 2013; Dell'Ariccia et al. 2012). In this paper, we analyze the most common transformations of this variable. Our baseline variable is the variation in CR in the two years prior to the beginning of the recession period, ΔCR_{t-1}, computed as $CR_{t-1} - CR_{t-9}$, with t the beginning of the recession period based on quarterly data. In subsection 6.2, we consider real credit growth as alternative proxy for credit conditions. We refrain from using credit-to-GDP gap measures because of the well-documented problems of using the Hodrick and Prescott filter on macroeconomic variables, especially for the case of credit-to-GDP (Hamilton (2018)).[6]

3.1 Quantile regression model of credit and recessions

We start by studying the effect of ΔCR_{t-1} on the characteristics of recessions. As ΔCR_{t-1} is one of the key intermediate objectives of macroprudential policy, we can assess the possible gains that a control of credit booms produces on the severity of crises.

We estimate the following regression:

$$X_{ij}^{R} = \alpha + \beta \Delta CR_{t-1,ij} \tag{1}$$

where $X_{ij}^{R} = D_{ij}^{R}, A_{ij}^{R}, C_{ij}^{R}$ are the characteristics of the recessions for country i and recession j, and $\Delta CR_{t-1,ij}$ is the variation in credit-to-GDP ratio in the two years prior to the starting point of the recession for country i and recession j. The results are presented in the top panel of Table 3. We observe a positive coefficient in the case of duration and a negative one in the case of amplitude and cumulation.[7] Therefore, greater credit growth is associated with longer duration and greater severity of recessions. When focusing on cumulation, which combines amplitude and duration and therefore best summarizes the severity of recessions, we find that higher levels of credit imply a greater loss of wealth during recession periods.

However, even though the results in the top panel of Table 3 show a significant effect on credit and recession characteristics, Figure 2 suggests that the nature of this relation is non-linear. The figure displays the box-plot of cumulation for each of the 4 quartiles of the variation in the credit-to-GDP ratio in the last two years before the recession. As can be seen in the figure, being in the first quartile of the distribution of $\Delta CR_{t-1,ij}$ implies lower levels of cumulation (in absolute value) in the following recession, but also less uncertainty about the developments of

[6] We also use the series in levels, CR_{t-1} as in Gourinchas and Obsfeld (2011) and Kaminsky and Reinhart (1999). In this case, the variable CR_{t-1} represents the level of credit-to-GDP in the quarter prior to the beginning of the recession period. Results are very similar and are available upon request to the authors.

[7] Note that amplitude and cumulation have negative values in recession periods. The parameter β is significant for duration, amplitude and cumulation when we use a robust estimation of the errors (HAC method) to prevent heteroscedasticity and outlier effects. The outliers can be clearly identified, especially in the figure of cumulation, and correspond to the crises in Argentina (1998Q3-2002Q1) and Greece (2007Q3-2013Q4).

the next recession periods. On the other hand, high levels of $\Delta CR_{t-1,ij}$ are associated not only with higher losses during recessions on average, but with the possibility of having an extreme recession period.

To further explore this idea, and to use a parsimonious representation that could illustrate the nature of the non-linear relation between $\Delta CR_{t-1,ij}$ and the associated cumulation of the recession period, we divide the sample of $\Delta CR_{t-1,ij}$ by quartiles. For each quartile we identify the corresponding recessions. Then, for each of these four groups, we take the cumulation values of the related recessions and estimate their distribution as a mixture of two normal distributions. A mixture of normal distributions is a parsimonious way of representing a rich amount of density functions.[8]

Consequently, to obtain a richer picture of the conditional relationship between the severity of recessions and the credit-to-GDP ratio variation, we rely on quantile regressions. As mentioned before, in order to summarize the results in one statistic, the analysis will be carried out only for the cumulation, C_{ij}^{R}, since this is the characteristic that best summarizes the intensity of the recession. We estimate the following model for the conditional quantile τ associated with the response of the corresponding credit measure in recession j of country i:

$$Q_{C_{ij}^{R}}\left(\tau|\Delta CR_{t-1,ij}\right) = \alpha_{\tau} + \Delta CR'_{t-1,ij}\beta\left(\tau\right);\ i = 1, ..., N;\ j = 1, ..., J^{R}, \tag{2}$$

where $(C_{ij}^{R},\ \Delta CR_{t-1,ij})$ denote the values of the dependent and independent variables, respectively.

Following Koenker and Basset (1978), the parameters for each quartile τ can be estimated solving this minimization problem:

$$\begin{aligned}\widehat{\beta}\left(\tau\right) = \min_{a,\beta}[& \sum_{ij\in(ij:C_{ij}^{R}\geq\alpha-\Delta CR_{t-1,ij}\beta)} \tau\left|Cij^{R} - \alpha - \Delta CR_{t-1,ij}\beta\right| + \\ & \sum_{ij\in(ij:C_{ij}^{R}<\alpha-\Delta CR_{t-1,ij}\beta)} (1-\tau)\left|C_{ij}^{R} - \alpha - \Delta CR_{t-1,ij}\beta\right|]\end{aligned} \tag{3}$$

Figure 3 presents a summary of the quantile regression results. The figure plots the quantile regression estimates $\widehat{\beta}\left(\tau\right)$ for each quantile. They can be interpreted as the impact of a change in the exogenous variable (the measure of the variation in credit-to-GDP) on the cumulation of a recession. On the horizontal axis are the ten quantiles that we consider, τ, and the vertical scale indicates the estimated effect of credit on cumulation. Each blue point represents the estimated value of $\widehat{\beta}\left(\tau\right)$ and the red points and their dotted lines the 90% pointwise confidence intervals estimated by bootstrap techniques.

The interpretation of the figure is as follows. For the smallest quartile of cumulation (referring to the biggest recessions because the cumulation is negative) the coefficient that relates these recessions with the $\Delta CR_{t-1,ij}$ is much bigger (in absolute value) and has a bigger variance. In contrast, the coefficient that relates these recessions with $\Delta CR_{t-1,ij}$ when the recession periods are small is very close to 0. Therefore, the results that we obtain from the linear specification are basically driven by credit-to-GDP in the worst recessions, being almost non-significant in most other cases.

From the previous evidence we can obtain a clear insight. The worst recessions are associated with higher dependence on $\Delta CR_{t-1,ij}$. Given the magnitude of these worst recessions, the

[8] Actually, a t-distribution as the one estimated in Adrian et al. (2019) can be approximated by a mixture of normals; see Koop (2003).

previous level of $\Delta CR_{t-1,ij}$ should be really high. Variation in credit-to-GDP is harmless up to a certain level. When that level is very high, the future recession could become an extreme one.

We assume that each group is characterized by a univariate Gaussian density, parameterized by its mean μ_k and its variance σ_k, which are collected in vector θ_k. The probability density function of the mixture model is

$$f\left(C_{ij}^{R}|\theta_k\right)=\sum_{k=1}^{K}\eta_k N\left(\mu_k,\sigma_k\right), \tag{4}$$

where $i=1,\ldots,N$, and η_k are the mixing proportions or weights and represent the proportion of observations from each cluster, with $\eta_k \geq 0$, and $\eta_1+\ldots+\eta_K=1$. The observations are labeled through an unobservable latent variable s that allows us to identify the mixture component each observation has been generated from: if $s_i=k$, then the observation i of the characteristic (cumulation) belongs to cluster k. In our case, we consider $K=2$.

The estimation of the parameters in the vector $\theta=(\theta_1,\ldots,\theta_K)$, the mixing proportions $\eta=(\eta_1,\ldots,\eta_K)$, and the inference on s, are calculated through a Markov Chain Monte Carlo (MCMC) method. The algorithm also gives the number of observations assigned to each density and their within-group mean and variance.

The final estimation results are summarized in Table 4 for the two mixtures of each quartile. As can be seen in the table, for quartile 1 two different normals describe the distribution of the cumulation. With an 80% probability, the recession will imply a loss in wealth of 3% of GDP (the red area in Figure 1) and, consequently, with a 20% probability, the recession represents a loss in wealth of 20% of GDP. When we increase the quartile of credit, the means of the distributions do not change much, but the probability of the "tamed" recession decreases to 65%. In the third quartile, the deep recession is characterized by a loss of 73%, but also the mild recession doubles the loss of the mild recession of the first quartile. Finally, the fourth quartile shows that with a probability of 90% the economy faces a bad recession with a 15% GDP loss in wealth and there is almost a 10% probability of an extremely bad recession period. Figure 4 graphically illustrates these mixtures.

Taken together, it is very clear from the evidence presented above that high values of credit imply deeper and potentially extreme recession periods. This evidence justifies the attempt to control the evolution of credit using macroprudential policies, because these policies, by their impact on credit, have a direct impact on the final objective of any economic policy of stimulating stability in the economy and, by avoiding deep recessions, promoting higher and stable growth. Next we analyze whether there is a cost to limiting credit during expansion periods.

4 The role of credit in expansions

First, it is important to point out that, when analyzing the role of credit in business cycles, most studies focus on recessions and marginalize expansions. The consequence is that the positive effects of credit in good times are ignored. However, these positive effects also matter. In fact, they matter more than the effects of credit during recessions because economies are in expansion for longer periods than they are in recession.

As a matter of fact, the literature on finance and growth clearly states that expansions need credit. Economic growth needs credit as a fuel, as stated in Gertler and Karadi (2011), Gertler and Kiyotaki (2010) and many others. This fact has been clearly documented in the literature, and expansions which do not rely on credit, the so-called creditless recoveries, are characterized by an average growth of about a third lower than standard expansions, as shown by Abiad et al. (2011). Thus, expansions cannot be ignored when attempting to understand the effect of credit on business cycles. Indeed, the effect of credit on expansions should be carefully analyzed.

In order to analyze the role of credit in expansions, we start by applying the same analysis to periods of expansions as that carried out for recession periods. As with recessions, we estimate the following regression:

$$X_{ij}^E = \alpha + \beta \Delta CR_{t-1,ij} \tag{5}$$

where $X_{ij}^E = D_{ij}^E, A_{ij}^E, C_{ij}^E$ are the characteristics of the expansions for country i and expansion j, and $\Delta CR_{t-1,ij}$ is the variation of credit-to-GDP ratio in the two years prior to the starting point of the expansion for country i expansion j. The main findings can be summarized as follows. The characteristics of expansions are not related to the initial conditions of the credit variables at the beginning of the expansion periods.[9] Similar results are obtained with quantile regressions. The parameters are close to zero and are not significant in any percentile.[10]

The measures previously used for recessions are not suitable for expansions since, due to their longer duration, the initial conditions of expansions are not important. Therefore, in this case we need a measure that is updated as the expansion progresses. Obviously if we use, for example, the variation in credit-to-GDP during the expansion period, this measure would clearly be endogenous to the characteristics of the expansion because it will be specifically related to the duration. In order to avoid this problem, we use credit intensity, defined as the variation in the credit-to-GDP ratio during the expansion, but normalized by the duration of the expansion. This measure relates with the one proposed by Jorda et al. (2011).[11] The estimated regression in this case is the same as in equation 5, except that we substitute $\Delta CR_{t-1,ij}$ with ΔCRI_{ij}, where ΔCRI_{ij} is the credit intensity in country i expansion j.

The results are displayed in the second panel of Table 3. As can be seen in the table, ΔCRI_{ij} matters for the duration, amplitude and cumulation of the expansions, especially for the duration. However, when analyzing possible non-linearities, the same type of approach that we took for the recessions does not provide statistical differences across quantiles. It is necessary, therefore, to adopt a different approach to analyze the role of credit in expansions and test for possible non-linearities.

In the case of recessions, we use cumulation as the reference measure because it reflects the intensity of the recession. It combines the changing duration of recessions and the effect of the changes in the growth rate of GDP in every period of the recession conditional on the initial credit-to-GDP. However, for expansions, quarterly growth rates do not change much as a function of the initial credit-to-GDP, as reflected in Table 2. This is consistent with the consensus in the literature that credit is primarily important for growth rates during recession periods. Therefore, the difference across expansions reflected in Table 3 should come from somewhere else.

If the quarterly growth rate of GDP is not closely related to credit and all business cycle features are related to this variable, the only possible answer is that the magnitudes are affected through the effect of credit on the duration of expansions. If duration is affected, amplitude is affected because amplitude can be calculated as the average growth rate of GDP times duration. Cumulation can be approximated by the area of the triangle between duration and amplitude

[9] The details of the results are not presented but are available from the authors upon request.

[10] As in the case of recessions, we repeat the analysis for the levels of credit-to-GDP. The results are similar.

[11] Jorda et al. (2011) propose credit intensity as the growth rate of credit-to-GDP related to its mean. The correlation of our measure with theirs is higher than 0.7. We prefer our measure in order to avoid taking growth rates of ratios. Furthermore, it simplifies the interpretation of credit intensity.

(one half of duration times amplitude). Then, in every expansion, we can approximate cumulation C^E as follows:

$$C^E = 1/2 * \overline{Y}^E * (D^E)^2 \tag{6}$$

where $\overline{Y}$ is the average growth rate of GDP and D is the duration. Therefore, credit affects duration and through this effect it is related to all the other business cycle features.

Given that we have seen that credit affects the duration of expansion, we propose survival models as a way to measure the role of credit in the characteristics of expansions. This approach also has a clear advantage over the methodology commonly used when analyzing the relationship between credit and the economic cycle, namely the logit regression (e.g., Gourinchas and Obsfeld (2012) and Jorda et al. (2011), among many others). Survival models are able to distinguish between the effect of the passage of time and that of the covariate of interest preventing that the relationship between credit and economic cycle may be a direct consequence of the temporary accumulation of credit during the expansion (see Gadea and Perez-Quiros, 2015).

This survival methodology has been used extensively in biological and medical applications and, to a lesser extent, in engineering and quality control. Although its use in economics is less common, we think it is the most appropriate approach to study the duration of expansions and their relationship with other environmental variables, such as credit. Making an analogy with a medical application, we will treat the expansions as possible patients with a certain life expectancy, representing the expected duration of the expansion, and a risk of death, representing the risk of going into recession. We can define the survival function as:

$$S(t) = Pr(T > t) \tag{7}$$

where t is time, T is a random variable denoting the time of death (recession), and Pr stands for probability. We can also define the lifetime distribution function as the complement of the survival function:

$$F(t) = Pr(T \leq t) = 1 - S(t). \tag{8}$$

Another relevant function is the hazard function. This hazard function, $\lambda(t)$, is defined as the event rate at time t conditional on survival until time t or later.[12] Suppose that an item has survived for a time t and we desire to calculate the probability that it will not survive for an additional time dt:

$$\lambda(t) = \lim_{dt \to 0} \frac{\Pr(t \leq T < t + dt)}{dt.S(t)} = \frac{S'(t)}{S(t)} \tag{9}$$

We compute the cumulative lifetime, survival and hazard functions using the Kaplan-Meier method.[13] The results are displayed in Figure 5, for $F(t)$ and $\lambda(t)$.

The first question that arises from looking at these figures is whether the probability of staying in expansion is duration dependent. This is not a new question in the literature (see, for example, Sichel (1991), Diebold and Rudebush (1996), Diebold et al. (1992) or Zuehlke (2003)). However, these papers only concentrate on the US. We take advantage of our dataset that comprises more than 200 expansions, providing us with the statistical power to analyze the role of credit as a determinant of the duration of expansion periods. In order to answer this question, we have adjusted two of the most popular functions in the survival literature, the exponential and the Weibull functions:

$$\begin{aligned} \text{Exponential: } S(t) &= exp(-\lambda t) \\ \text{Weibull: } S(t) &= exp[-(\lambda t)^\gamma] \end{aligned} \tag{10}$$

[12] We can also define the cumulative hazard function $\Lambda(t)$ and note that it is easy to go from the survival to the hazard function and viceversa: $\Lambda(t) = -\log(S(t))$ and $S(t) = exp(-\Lambda(t))$.

[13] The alternative Nelson-Aalen method provides similar results.

The hazard function of the exponential distribution is constant and equal to λ. In the case of the Weibull, the hazard function depends on t. Figure 6 presents the graphical analysis of these two survival specifications. This graphical analysis suggests that the Weibull provides a better fit to the data of the duration of the expansions than the exponential. This result is confirmed when we estimate the two functions. The key to testing for the time dependence of the hazard function is the significance of parameter γ. The estimated parameter for the Weibull function is 1.247, with a confidence interval of [1.141, 1.362]. The scale parameter, λ, is very similar in both distributions but the Weibull has a significant shape parameter, higher than 1, which implies that the risk is increasing, as opposed to being constant as it is in the exponential distribution. This means that, as the expansion progresses, the risk of going into recession increases.

4.1 Duration model of credit and expansions

In this section, we consider the link between variation in credit and the duration of expansions through the lens of a duration model: the Cox proportional hazard regression model. This model, introduced by Cox (1972) and Cox and Oakes (1984), allows us to assess the influence of different covariates on the failure time.[14] The general hazard model has the following expression:

$$\lambda(t|X) = \lambda_0(t)exp(\beta' X) \tag{11}$$

where $\lambda_0(t)$ is the baseline hazard function, β' is a vector of regression coefficients and X a vector of covariates that, in their simplest form, are time-fixed.

One important characteristic of this approach is that it is not necessary to make any assumption about the baseline hazard distribution and, in the absence of time-variant variables, we can compute the hazard ratio, which is constant:

$$\widehat{HR} = \frac{\lambda_0(t)\exp(\beta' X)}{\lambda_0(t)} = \exp(\beta' X) \tag{12}$$

In a Cox regression related to the hazard function, a positive coefficient indicates a worse prognosis and a negative coefficient indicates a protective effect of the variable with which it is associated. The hazard ratio associated with a predictor variable is given by the exponent of its coefficient. The hazard ratio may also be thought of as the relative event rate. The interpretation of the hazard ratio depends on the measurement scale of the predictor variable in question because it provides the risk of an individual who has received treatment in comparison with another who has not. Then, expansions are treated in a compact manner, following the medical simile, as if each of them were a patient. The credit, or treatment received, is measured as the intensity of credit during the completed expansion, defined as the variation in the credit-to-GDP ratio from the beginning to the end of the expansion normalized by its duration. None of the observations is treated as censored because we consider that, in all of them, the event of interest has occurred, namely, the end of the expansion with the arrival of a recession[15].

The model is semi-parametric, because the parameters of the baseline hazard function are

[14] In unreported results we find that results are qualitatively unaltered when using an accelerated failure of time (AFT) model instead of a Cox regression model

[15] This non-censoring procedure considers the last part of the sample which, in most of the countries, includes the recovery after the Great Recession, a period of enormous interest for the analysis. The decision not to censor this part is based on an experiment showing that extending the last period for a relevant number of quarters, there are no significant changes.

not considered and the estimation method is partial likelihood.[16] The results of the estimation of our compact model in Table 5 show that credit intensity has a positive effect on the duration of expansions because the estimated β' is negative. More specifically, the probability of entering into recession is 20% lower for each additional unit of credit recorded in an expansion. This table also shows some validation tests and, more importantly, the test for the proportional hazard assumption which is not able to reject the null hypothesis that the reduction in the hazard is not a function of time.[17] This is an important characteristic of this type of model because we can separate the effect of time itself, through the baseline hazard function, from the influence of other covariates. This is an advantage with respect to logistic regression models, where the predictive effect of the credit on the probability of entering into recession can be confused with its simple cumulative effect over time.

Following the recession analysis, we also consider the possibility of a non-linear relation between credit and duration (further and beyond the non-linearity already implicit in the survival model) and divide the sample of expansions into four groups according to the quartiles of credit intensity. Then, we estimate Cox regressions where the interaction of the credit measure with a dummy variable representing each quartile is included as an additional regressor. Specifically, we estimate four models:

$$\lambda(t|\Delta CRI_{ij}) = \lambda(t)exp(\beta_0' * \Delta CRI_{ij} + \beta_1' \Delta CRI_{ij} * Dummy_s) \quad (13)$$

where $Dummy_s$ is a dummy variable that takes the value of 1 if the ΔCRI_{ij} belongs to the quartile s.

Table 6 shows the main results. In the first quartile, the estimated coefficients are $\beta_0' = -0.13$ and $\beta_1' = -0.14$. Given that the average credit intensity in this quartile is -0.89, the total effect of the interaction between the coefficient and the average credit implies a 28% increase in the probability of ending the expansion with respect to the baseline probability. From this analysis it is clear that creditless expansions tend to be shorter on average. The results for the second quartile imply that the probability is close to the baseline model. The results for the third quartile imply a massive reduction in the probability of ending the expansion. Specifically, the probability yields more than a 40% decrease. Finally, the results of the fourth quartile put these probabilities back to close to the baseline model. These results are in line with the idea that the influence of credit can disappear at high levels of credit.

Even though normalizing by duration diminishes the endogeneity problem, additional endogeneity of the credit intensity measure is addressed in Appendix 2 where we repeat the results of this section by dividing each expansion into a number of one-year periods and using as an explanatory variable the variation in credit-to-GDP in each of these periods which is predetermined when calculating the probability of dying the last day of the quarter. Our main results are qualitatively unaltered using this alternative approach.

4.2 The expected remaining duration

Next we consider the effect of credit at different levels of expected remaining duration of the expansion. To this end, we compute the Mean Remaining Lifetime (MRL) function, which is

[16] Cox (1972) demonstrated that although partial likelihood is not, in general, a likelihood in the sense of being proportional to the probability of an observed dataset, nonetheless it can be treated as a likelihood for the purposes of asymptotic inference.

[17] We have carried out a detailed study of other types of residuals: Cox-Snell residuals, to check the goodness-of-fit of the model; Martingale residuals, to study the functional form of a covariate; Score residuals, to detect the influence of individual observations on the parameters; and Deviance residuals, to detect the influence of individual observations on the model. All these analyses confirm the robustness of the estimated model.

defined as follows for each t:

$$MRL(t) = E[T - t|T > t] = \int_0^\infty \frac{S(x+t)}{S(t)} dx \text{ for } S(t) > 0 \text{ and } 0 \text{ if } S(t) = 0 \tag{14}$$

To evaluate the effect of credit on the MRL by quartile of credit intensity, we first estimate the baseline model without credit and then we estimate the model with the credit intensity and the quartile dummy variables. Figure 7 displays the results. We obtain basically no difference between the model without credit and the model with credit, when we evaluate the model at the mean value of credit intensity. However, when we evaluate the model at the mean level of each quartile, we obtain important differences by quartile of credit intensity in the extended model that includes the credit intensity and the quartile dummy variables. For example, if the expansion is in its fifth year and credit intensity is at a relatively low level in its first quartile, the expected duration of the expansion is less than 15 quarters. In contrast, if credit intensity is in the third quartile of the distribution, the expected value of the expansion is more than 30 quarters.

The conclusion from the analysis in this section is clear: credit has a positive effect by increasing the expected duration of the expansion. This relationship between credit and duration is not monotonic. After a certain threshold credit decreases expected duration.[18]

5 The role of credit over the business cycle

We have seen how credit affects expansions and recessions. For expansions, we have seen that credit affects their duration. For recessions, we have seen how credit affects their depth. There is a clear trade-off between the "positive" effect of credit in the economy on the duration of expansions and the "negative" effect on the depth of recessions. More credit, up to a point, implies longer expansions, but this comes at the cost of deeper recession periods.

In this section, we will analyze the effects of credit over the business cycle, combining its effects during expansions and recessions. Before passing to the simulation exercise that will bring together the features of both recession and expansion periods, we first present some summary statistics that provide the intuition for the results we find. Table 7 presents for every quartile of the credit intensity of the expansion periods the features of the corresponding expansion and the consecutive recession. As can be seen in Table 7, when credit intensity in an expansion is in the first quartile, the expected duration for expansions is only 15.42 quarters. The expected duration increases for each quartile up until the third, and decreases in the fourth. The same happens with the other features of the expansions. Amplitude and cumulation decrease in the fourth quartile. However, for recessions, the magnitude of the features increases monotonically (in absolute value) for all four quartiles. It is then very clear that the fourth quartile should be avoided. It has worse expansion features and worse recession features compared to the third quartile. With respect to the other three quartiles, the third quartile has the most attractive properties. Compared to the first and second quartile, the recession features are marginally worse in the third quartile but the expansion features sharply improve.

We now address this issue in the context of our proposed specification. In order to combine these positive and negative features we propose a simulation exercise that, for different levels of credit in the economy allows us to characterize the features of each economy. If we start

[18] The conclusions of computing the MRL with the extended model that allows the credit to vary during expansion are similar (see Appendix 2).

in an expansion period, we assume four levels of average credit in each quartile of the credit distribution$(X_{1,}X_{2,}X_{3,}X_4)$.[19] These levels of credit imply a different survival function:

$$S(t) = S(0)exp(\beta' X_i) \quad i = 1 \text{ to } 4 \tag{15}$$

The difference between this function and equation (11) is the assumption about the baseline hazard distribution. In equation (11), there was no need to specify a baseline function. However, that involved a difficulty in carrying out the simulations because the estimation was only done in discrete time and within the range of observations of the sample.[20] To solve this problem we proceed as follows.

First, we fit a Weibull distribution to the duration sample and collect the parameters, $\widehat{S(0)}$.[21]

Second, for each of the four levels of credit, "X_i", we generate a survival function $S_i(t)$ from a Survival Weibull distribution that takes into account the effect of credit in each quartile (as in equation (15)) where we use the estimated parameters in the Cox regression and the average credit in each quartile.

Third, we need to transform the survival function $S_i(t)$ into a realization of a duration for a given simulation "j", of the quartile "i" . In order to do that, as we know, the survival function provides a set of probabilities of "dying" in every time period. Therefore, we draw random realizations of a uniform distribution. When the "t" realization is above the "dying" probability of the survival function $S_i i(t)$, the expansion is over and it has lasted "t" periods. We name this scalar $d_{j,i}$ referring to duration of iteration j for a level of credit in the mean of the quartile i.

Fourth, for each draw of duration, $d_{j,i}$, we randomly generate $d_{j,i}$ observations from the empirical distribution of the growth rate of GDP for each credit quartile. These distributions depart from normal behavior and we take into account this departure by using the skewness and the kurtosis of each credit quartile.[22]

The following step for each simulated expansion is to mimic the following recession. We assume that cumulation follows a mixture of two normal distributions for each group of economies, whose probability has been estimated in the previous section. For each iteration, we randomly draw a uniform distribution to know which of the two normals we should use to draw an observation. This observation represents cumulation loss of recession "j" for the level of credit "i". The separation of cumulation between duration and the quarterly growth rate is made assuming that the duration is constant across recessions, because, unlike expansions, most of the dispersion across recessions is due to the dispersion of growth rates (i.e., duration is close

[19]These four levels of credit correspond to four different values of credit intensity during the expansion periods. The four values of credit intensity that we propose reflect the average quarterly variation in credit-to-GDP ratio in each of the four quartiles.

[20]The estimation of the survival function requires an estimate of the baseline hazard. The baseline hazard is usually considered as an arbitrary function that can be estimated in a second step conditioned on the estimation of the parametric part. The Nelson-Aalen-Breslow, Efron or Kalbfleish-Prentice are among the most common of various methods (see, for example, Lee and Wang, 2003). The evidence obtained previously allows us, however, to use a parametric version of the baseline hazard function based on the Weibull distribution.

[21]Another possibility is to use a type of hazard-based duration model, such as the discrete-time Weibull models, which directly incorporate the survival function and can be used in continuous time. Furthermore, as mentioned previously, an interesting alternative are the AFT models. The main difference between the AFT models versus the Cox proportional risk is that they offer a more intuitive interpretation of the parameters and, more importantly for the purpose of the simulations, they allow making predictions in continuous time due to their parametric expression. This characteristic of the AFT models allows us to overcome one of the main weaknesses of the Cox model, which only allows us to replicate the discrete observations of the sample. The results of applying these approaches are analogous and are available upon request from the authors.

[22]The results are very similar using the same figures for the mean, variance, skewness and kurtosis for the four quartiles.

to constant across recessions). Knowing both duration and cumulation, we can easily compute the average of the growth rate during each recessions.

We then add the corresponding recession to the simulated expansion. The process is repeated concatenating expansions and recessions until we reach a sample size of 300, equivalent to 75 years. We repeat this exercise 10,000 times, generating 10,000 economies of 300 observations. Finally, we calculate several outcomes such as average growth rate, standard deviation of growth rate, average growth in expansions, average growth in recessions, and frequency of recessions.

The simulation exercise shows that growth needs credit. Expansions without credit growth are the worst. A reasonable growth of credit encourages the duration of the expansions and, therefore, the long-term growth of the economy. But an excess of credit has two negative consequences. The first is a slowdown in the expansion, reducing its duration, and the second is an increase in the probability of causing more severe recessions.

Results for the simulation exercise are summarized in Figure 8. We find that the highest average growth corresponds to the second and third quartile (0.63 and 0.65 respectively) and the lowest to the fourth quartile (0.12). The first quartile presents a growth rate of 0.55. The third quartile is the one that presents the lowest frequency of recessions, a higher duration of expansions and the highest cumulation. The first quartile presents the lowest standard deviation, but with low growth and short expansions. The worst quartile is unquestionably the fourth which has the lowest growth and highest volatility. The second and third quartiles are very similar. The only major difference lies in the accumulation of wealth. The longer expansions of the third quartile make the economy grow steadily for a long period of time which maximizes the integral under the curve of the expansions.

Taken together, the results imply that moderate levels of credit growth strike the right balance between fostering longer expansions and avoiding deep recessions. A robustness analysis covering the effect of outliers leads to similar conclusions and the results are shown in the first section of Appendix 3.[23]

Finally, even though most academic papers use credit-to GDP as the relevant variable to analyze the evolution of credit, some others (e.g. Cechetti and Kharroubi, 2018) use real credit growth. This is also a relevant variable in policy discussions. In order to check the robustness of our results to this alternative measure, we repeat the whole exercise using this variable. Results are robust and are displayed in the second section of Appendix 3.

5.1 Going normative: Defining optimal intervals

The previous analysis has defined as optimal being in the second-to-third quartile of credit for maximizing growth. However, quartiles are defined using slightly different variables. For expansions we use credit intensity, which refers to the average credit during the expansion period. For recessions, we use variation in credit-to-GDP in the last two years prior to the recession. This variable could also be expressed on average figures by diving by 8 quarters ΔCR_{t-1}, but this average refers to a different period of time: not the whole period of expansion, but just its ending. Even though there is a close relation between these two measures (high credit intensity correlates closely with high credit variation in the last two years of expansion, with a correlation

[23]An attractive exercise is to compare our GDP-at-risk trade-off results with the GDP-at-risk of Adrian et al. (2019). For this we have carried out two experiments. First, we generate 10,000 economies with the features of the growth-at-risk trade-offs and we check that Adrian et al. (2019) have no power to detect the subtle feature of the duration of expansion periods dependent on credit that we propose. For the second, we generate 10,000 economies with the growth at risk features and we conclude that they are compatible with the depth of recessions as a function of credit to GDP before the recession periods.

coefficient of 0.83), there are small differences that one should take into account. As can be seen in Figure 9, the cutting points for the first, second and third quartiles of credit intensity are slightly different than for these quartiles for the average variation in credit-to-GDP in the last two years.

At any given point in time, the policymaker only observes the variation in credit-to-GDP but does not know if it is the end of the expansion period or not. We learned from the previous analysis that the first quartile for credit intensity should be avoided because of its consequences for growth during the expansion period. We know that any variation in credit-to-GDP that falls below that threshold contributes to decreasing the expected duration of expansion and should therefore be avoided. This variation in credit-to-GDP is, in quarterly terms, -0.23. Therefore, in annual terms, any variation below approximately -1% should be considered suboptimal.

Using the same argument, getting into deep recession territory (fourth quartile of variation in credit-to-GDP in the last two years of expansion) or excessive credit in expansions (fourth quartile of credit intensity) should also be avoided. The lower of these two thresholds is a 0.77 quarterly variation. This figure implies that annual variations in credit to GDP of more than 3% should also be considered dangerous.

As an illustration of these intervals, Figure 10 presents the evolution of annual variation in credit-to-GDP for the Euro area and the US with the non-dangerous variation bands. As can be seen, in both economic areas the periods outside the bands coincide with well-known periods of financial distress. In particular, during the run-up to the 2007-08 global financial crisis, the credit variable moves outside the comfort zone in both economic regions.

6 Extensions

6.1 Splitting credit in Household and Non-Financial Corporations

In this section, we extend the previous analysis distinguishing between two different types of credit, household and non-financial corporations. Research by Main, Sufi and Verner (2017) suggests that increases in household indebtedness tend to be followed by particularly deep recessions.

With respect to recession periods, we therefore repeat the exercise displayed in Table 4 for the aggregate credit for each of the two types of credit, credit to households (household credit) and credit to non-financial corporations (corporate credit). The results for each type of credit are displayed in Table 8 and Table 9. As can be seen in the tables the results are similar to the ones found for aggregate credit. Higher levels of each type of credit are associated with deeper recessions. For both types of credit, the fourth quartile of variation in credit is followed by the deepest recessions.

For expansions, we enlarge the specification in equation 13 as follows:

$$\begin{aligned}\lambda(t|\Delta CRIH_{ij}, \Delta CRINFC_{ij}) = \lambda(t)exp(&\beta'_{0H} * \Delta CRIH_{ij} + \beta'_{0NFC} * \Delta CRINFC_{ij} + \\ &\beta'_{1H}\Delta CRIH_{ij} * Dummy_s + \beta'_{1NFC}\Delta CRINFC_{ij} * Dummy_s)\end{aligned} \tag{16}$$

where the dummies are assigned according to the total credit quarters, $\Delta CRIH$ is household credit intensity and $\Delta CRINFC$ is corporate credit intensity.

The results are displayed in Figure 11. The quartiles are divided according to the total amount of credit and the upper graph in Figure 11 represents the total effect of the two variables evaluated in the mean of each quartile. For example, for the first quartile, it represents

$\lambda(t/\Delta CRIH_{Mean1}, \Delta CRINFC_{Mean1})$, where $\Delta CRIH_{Mean1}$ represents the level of household credit intensity in the first quartile of total credit intensity, and $\Delta CRINFC_{Mean1}$ represents the level of corporate credit intensity in the first quartile of total credit intensity. As in the case of total credit-to-GDP, the third quartile seems to be the one in which the probability of "dying" is minimized, which implies longer expansions.

In the next two panels the results of the first panel are divided by coefficients and average level. The coefficient of the Cox regression associated with credit to households is largest in the third quartile, showing that in this quartile, credit to households has the strongest effect on maintaining the expansion period. The biggest coefficient associated with credit to non-financial corporations is in the first quartile, so it is at low levels of credit that increases in credit have the biggest impact on the duration of the expansion. The lower panel shows the behavior of both types of credit in each quartile and highlights that creditless recoveries in the first quartile are mainly driven by low levels of credit to non-financial corporations.

Taken together, we find that both household and corporate credit contribute to wealth creation by lengthening the duration of expansions, up to a point. Our main results are primarily driven by credit to households.

6.2 Interacting credit and house prices

Recent research has shown that credit booms associated with house price increases tend to be followed by deeper recessions (Mian and Sufi (2014), Jorda et al.(2016)). Next, we consider to what extent our results depend on the influence of house prices. We obtained data on residential property prices from the BIS property price database, available from https://www.bis.org/statistics/pp.htm. As in the previous extension, we first present the mixture of normals analysis for each of the quartiles of the housing prices on the cumulation of recessions. The results are displayed in Table 10. In this case, even though the results follow the same general pattern as the results for total credit, they are more similar across the different quantiles. For expansions, the specification is the following:

$$\begin{aligned}\lambda(t|\Delta CRI_{ij}, \Delta HP_{ij}) = \lambda(t)exp(&\beta'_{0C} * \Delta CRI_{ij} + \beta'_{0HP} * \Delta HP_{ij} + \\ &\beta'_{1C}\Delta CRI_{ij} * Dummy_s + \beta'_{1HP}\Delta HP_{ij} * Dummy_s)\end{aligned} \tag{17}$$

where ΔHP is the average quarterly variation of house prices during each expansion.

Looking at Figure 12, in the top panel, we can see that, even controlling for housing prices, the third quartile is the one that maximizes the expected duration. In the middle and lower panel we decompose the total effect into the effect of the coefficients and the average level. With respect to the coefficients, as can be seen in the middle panel, an increase in house prices decreases the probability of a turning point equally across quartiles. However, credit coefficients change dramatically from the third to the fourth quartile. During the third quartile, when house prices increase more than the variation in credit-to-GDP as reflected in the lower panel, an increase in credit will substantially increase the probability of staying in expansion (coefficient close to -1). However, in the fourth quartile, when credit is increasing at a higher rate than house prices, an additional increase in credit decreases the probability of staying in the expansion state.

Taken together, the results show that our main result is robust to controlling for house prices. When credit intensity is in its third quartile, credit has the most beneficial impact on the duration of the expansion. This benefit arises despite strong house price growth in this quartile, and does not come at the cost of deeper recessions. Moreover, house price growth lengthens expansions and this effect does not significantly depend on the variation in credit intensity.

6.3 Interacting credit and macroprudential policies

Next we consider whether our results are altered when controlling for the influence of macroprudential policies. After all, these policies are intended to reduce the buildup of systemic risk associated with excessive credit growth and other financial imbalances. To this end, we combine our measure of credit with a measure of macroprudential policies. We use the macroprudential policy index developed by Cerutti et al. (2017)[24] which contains an increasing number of macroprudential policies in place for a large number of countries over the period 2000 to 2015. The number of cyclical periods is drastically reduced to 72 for expansions and 64 for recessions because of the shorter sample period in the macroprudential database. In this case, it is difficult to divide the results by quartiles and we specify the following categories:

Group 1: Low credit growth ($\Delta CR_{t-1,ij} < median(\Delta CR_{t-1,ij})$)

Group 2: High credit growth($\Delta CR_{t-1,ij} > median(\Delta CR_{t-1,ij})$) and low level of macroprudential policies $MP_{ij} < Median(MP_{ij})$

Group 3: High credit growth($\Delta CR_{t-1,ij} > median(\Delta CR_{t-1,ij})$) and high level of macroprudential policies $MP_{ij} > Median(MP_{ij})$

MP represents the aggregate level of the macroprudential policy index as defined in Cerutti et al. (2017). This index is increasing in regulatory intensity, with a higher score denoting a tighter macroprudential policy stance.

Table 11 displays the results for the recession periods. As can be seen in the tables, Group 1 has a 65% probability of a really mild recession, and a 34% probability of a bad recession. The probability of a mild recession decreases to 54% for Group 2, but the recession is worse than for Group 1. The recession characteristics of Group 3 are comparable to those of Group 2. However, we should clarify that that the estimated coefficients represent the effects of macroprudential policies on cumulation of recessions over and above the effect that these policies could have on cumulation by controlling credit. If macroprudential policies are effective in managing variation in credit, as documented in the literature, then we will observe less variation in credit-to-GDP in the data when macroprudential policies are in place.

The main difference between the three groups comes in the expansion periods. We create the same three groups based on the credit intensity in each expansion and the level of macroprudential policies.

$$\lambda(t|\Delta CRI_{ij}, MP_{ij}) = \lambda(t)exp(\beta_1' * \Delta CRI_{ij} * Dummy_g) \tag{18}$$

where $Dummy_g$=1,2,3 depending on whether the expansion j in country i, according to its level of credit intensity and macroprudential policies, belongs to each of the groups previously defined.

The results are plotted in Figure 13 (upper panel). As can be seen in the figure, when credit is low (group 1), an increase in credit substantially decreases the probability of leaving the expansion, (β_1' is negative with a large absolute value). Credit is very much needed for an expansion to last. However, when credit is high and macroprudential policy low (group 2), the results show that β_2' is positive. In this case, more credit implies a higher probability of a turning point in the cycle.

When credit is high and macroprudential policy is high (group 3), β_3' is negative. In this case, more credit is good for the economy, but not as much as when credit is low (group 1) (i.e., β_1' is more negative than β_3').

[24]Updated on the IMF website: https://www.imf.org/en/Publications/WP/Issues/2016/12/31/The-Use-and-Effectiveness-of-Macroprudential-Policies-New-Evidence-42791.

However, this analysis based on three different groups does not have much power, given the reduction in the number of cycles that are left in the sample once we include macroprudential policies. We therefore complement the previous evidence with a model that does not include different dummy variables, but simply includes the macroprudential policy variable alongside credit in a standard duration model.

$$\lambda(t|\Delta CRI_{ij}, MP_{ij}) = \lambda(t)exp(\beta'_{0C} * \Delta CRI_{ij} + \beta'_{0MP} * MP_{ij}) \tag{19}$$

The coefficients are displayed in Figure 13. Credit dominates the effect, but higher levels of macroprudential policies also reduce the probability of the expansion period coming to an end.

Taken together, these results indicate that macroprudential policy can have a positive effect on the cumulation of wealth by lengthening the expansion period. This effect is over and above its potential direct impact on credit, and the effect of credit dominates.

7 Conclusions

Expansions are more important than recessions when computing the total gains of a full business cycle. Economies are in expansion most of the time and the gains from these periods outweigh the size of the losses sustained in recession periods. Therefore, understanding the role of credit in expansions is key to assessing the overall impact of credit dynamics on the real economy.

We show that there is an optimal level of credit that maximizes the length of expansions with relatively small recession losses. Expansions without credit growth are the worst. A reasonable increase in credit encourages the duration of expansions and therefore the long-term growth of the economy. But an excess of credit has two negative consequences. The first is a slowdown in the expansion, reducing its duration, and the second is an increase in the probability of causing more severe recessions. Macroprudential policy could be used to manage this growth-and-risk trade-off.

More generally, our results indicate that the emphasis on recessions in the literature on the real effects of financial conditions is somewhat misplaced. We offer new insights regarding that the dynamics during expansion periods are equally important. More research is needed to assess this growth-and-risk trade-off from a normative perspective.

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Tables

Duration	Amplitude	Cumulation
EXPANSIONS		
25.82	27.51	646.08
RECESSIONS		
4.42	-4.38	-14.63

Note: The table shows the average for all recessions and expansions of all the countries in the sample. *Duration* is presented in quarters and *amplitude*, and *cumulation* in percentage of GDP.

Table 1: Characteristics of business cycles

	Variation in credit in t-1					
	without a lag of GDP growth			with a lag of GDP growth		
	All phases	Expansions	Recessions	All phases	Expansions	Recessions
$y_{t-1,i}$	–	–	–	0.1761 (0.000)	-0.0072 (0.620)	-0.0124 (0.776)
$\Delta cr_{t-1,i}$	-1.3486 (0.019)	0.4389 (0.444)	-4.3237 (0.006)	-1.5672 (0.006)	0.4350 (0.451)	-4.4199 (0.006)

Note: A fixed-effect panel data has been estimated; p-values in brackets. $y_{t-1,i}$ represents the GDP growth of country i in time $t-1$ and $\Delta cr_{t-1,i}$ the variation in credit-to-GDP ratio of country i in period $t-1$.

Table 2: Panel estimation

RECESSIONS			
variables/characteristics	duration	amplitude	cumulation
constant	3.9430	-0.0341	-0.1040
	(19.5191)	(-10.9968)	(-4.9614)
$\Delta CR_{t-1,ij}$	0.0514	-0.0007	-0.0040
	(1.8893)	(-2.8875)	(-1.6978)
EXPANSIONS			
variables/characteristics	duration	amplitude	cumulation
constant	22.7571	0.2094	4.2224
	(16.9427)	(11.6695)	(6.5448)
ΔCRI_{ij}	2.7473	0.0308	1.1241
	(3.0060)	(2.7637)	(2.9152)

Note: For recessions the measure of credit, $\Delta CR_{t-1,ij}$, is the variation in credit-to-GDP ratio in the two previous years; for expansion we use the intensity of credit ΔCRI_{ij}, measure as the variation in credit-to-GDP during the expansion normalized by its duration. The sub-indices i and j denote country and recession/expansion, respectively. *Duration* is presented in quarters and *amplitude* and *cumulation* in per-unit terms.

Table 3: OLS estimation of regressions

	QUARTILE 1		QUARTILE 2		QUARTILE 3		QUARTILE 4	
	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2
μ	-0.0300	-0.2001	-0.0223	-0.1730	-0.0574	-0.7309	-0.1558	-4.4595
σ	0.0005	0.0034	0.0003	0.0100	0.0029	0.4952	0.0256	0.0618
prob.	0.8062	0.1938	0.6492	0.3508	0.8153	0.1847	0.9078	0.0922

Note: This table shows the result of estimating a mixture of two normal distributions for the cumulation within each quartile of credit, measured as the variation in the last two years before the recession. *Cumulation* is expressed in per-unit terms.

Table 4: Mixture of distributions by quartiles (Recessions)

Estimates				
	Coeff	Exp(Coeff)	z-statistic	p-value
CRI_{ij}	-0.201	0.811	-2.687	0.007
Validation of the model				
		test	s.e./p-value	
Concordance		0.582	0.023	
Likelihood ratio test		7.100	0.008	
Wald test		7.220	0.007	
Score (logrank) test		6.930	0.008	
Test the Proportional Hazards Assumption of a Cox Regression				
		rho	χ^2	p-value
KM		-0.052	0.764	0.382
Identity		-0.0285	0.227	0.634

Note: This table displays the estimated coefficients and their p-values in a Cox regression where expansions are considered in their compact form. Concordance is a ranking measure and represents the probability of concordance between the predicted and the observed survival (its standard error is reported). The likelihood test, the Wald test and the Score test confirm the goodness of the fit of the model (p-values in brackets). Specifically, the null hypothesis of the score or log-rank test is that there is no difference between the populations in the probability of an event (here the end of expansionist phase) at any time point. The hypothesis of proportional risks is tested by correlating the corresponding scaled Schoenfeld residuals with an adequate transformation of time (based either on the Kaplan-Meier estimate of the survival function or on one's own identity).

Table 5: Cox regression estimates

Variable	Coeff	Exp(coeff)	Credit average	Credit effect	p-value
CRI_{ij}	-0.13	0.76	-0.89	1.28	0.28
$CRI_{ij} * qr1$	-0.14	-	-	-	0.49
CRI_{ij}	-0.20	1.16	0.06	1.01	0.01
$CRI_{ij} * qr2$	0.35	-	-	-	0.67
CRI_{ij}	-0.17	0.39	0.55	0.59	0.02
$CRI_{ij} * qr3$	-0.77	-	-	-	0.01
CRI_{ij}	-0.34	0.94	1.55	0.92	0.00
$CRI_{ij} * qr4$	0.28	-	-	-	0.05

Note: This table displays the estimated coefficients and their p-values in a Cox regression where expansions are considered in their compact form. This specification disentangles the effect of credit intensity considering also its interaction with a dummy variable that represents its position in the distribution divided in four quartiles. The effect of credit is computed as $e^{\sum \widehat{\beta CRI}(q)}$ where CRI is the mean of credit intensity in each quartile q. Values above (below) one indicate a negative (positive) effect of credit on the hazard function.

Table 6: Cox regression with quartiles (compact expansions)

Characteristics/quartiles	Q1	Q2	Q3	Q4
Duration expansion	15.4200	20.1200	31.1200	27.1800
Duration recession	3.7273	3.9778	4.4390	5.1739
Amplitude expansion	0.1349	0.1872	0.2893	0.2651
Amplitude recession	-0.0307	-0.0325	-0.0390	-0.0552
Cumulation expansion	2.0002	3.0422	7.1335	6.1422
Cumulation recession	-0.0770	-0.0800	-0.1465	-0.2286

Note: This table presents for each quartile of credit intensity the characteristics of expansions and subsequent recession periods. *Duration* is presented in quarters and *amplitude* and *cumulation* in per-unit terms.

Table 7: Summary of business cycle characteristics by quartiles of credit intensity

	QUARTILE 1		QUARTILE 2		QUARTILE 3		QUARTILE 4	
	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2
μ	-0.0245	-0.1934	-0.0821	-2.3647	-0.0342	-0.2996	-0.1158	-4.4692
σ	0.0004	0.0022	0.0064	0.0150	0.0013	0.0273	0.0128	0.0316
prob.	0.7870	0.2130	0.8664	0.1336	0.6194	0.3806	0.8693	0.1307

Note: See Table 4.

Table 8: Mixture of distributions by quartiles (Household credit) for recessions

	QUARTILE 1		QUARTILE 2		QUARTILE 3		QUARTILE 4	
	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2
μ	-0.0308	-0.1957	-0.0270	-0.1879	-0.0481	-1.4741	-0.1416	-4.4654
σ	0.0005	0.0031	0.0005	0.0126	0.0040	0.5563	0.0259	0.0625
prob.	0.8025	0.1975	0.6824	0.3176	0.8214	0.1786	0.8601	0.1399

Note: See Table 4.

Table 9: Mixture of distributions by quartiles (Corporate credit) for recessions

	QUARTILE 1		QUARTILE 2		QUARTILE 3		QUARTILE 4	
	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2
μ	-0.0247	-0.2185	-0.0258	-0.1765	-0.0321	-0.2181	-0.0696	-0.3389
σ	0.0004	0.0019	0.0003	0.0134	0.0009	0.0157	0.0037	0.0203
prob.	0.7815	0.2185	0.7023	0.2977	0.7161	0.2839	0.5724	0.4276

Note: See Table 4.

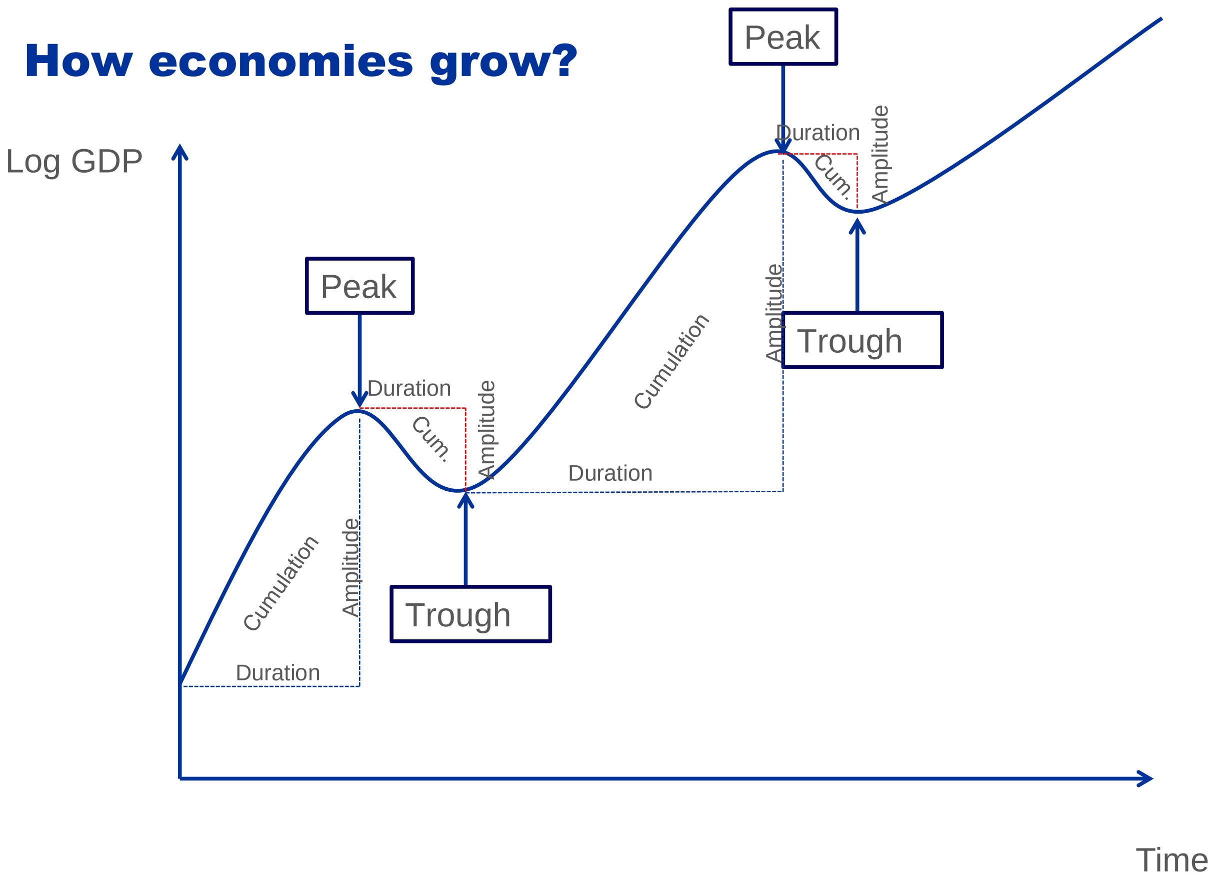
Table 10: Mixture of distributions by quartiles (House prices) for recessions

	GROUP 1		GROUP 2		GROUP 3	
	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2
μ	-0.0339	-0.2199	-0.0647	-0.2513	-0.0761	-0.2351
σ	0.0009	0.0170	0.0039	0.0099	0.0026	0.0039
prob.	0.6540	0.3460	0.5466	0.4534	0.5974	0.4026

Notes: This table shows the result of estimating a mixture of two normal distributions for the cumulation within each group. GROUP 1 includes recessions with low credit-to-GDP ratio in the two previous years; GROUP 2 with high credit and low average level of macroprudential polices in the two previous years and, finally, GROUP 3 collects recessions with high levels of credit and macroprudential policies. *Cumulation* is expressed in per-unit terms.

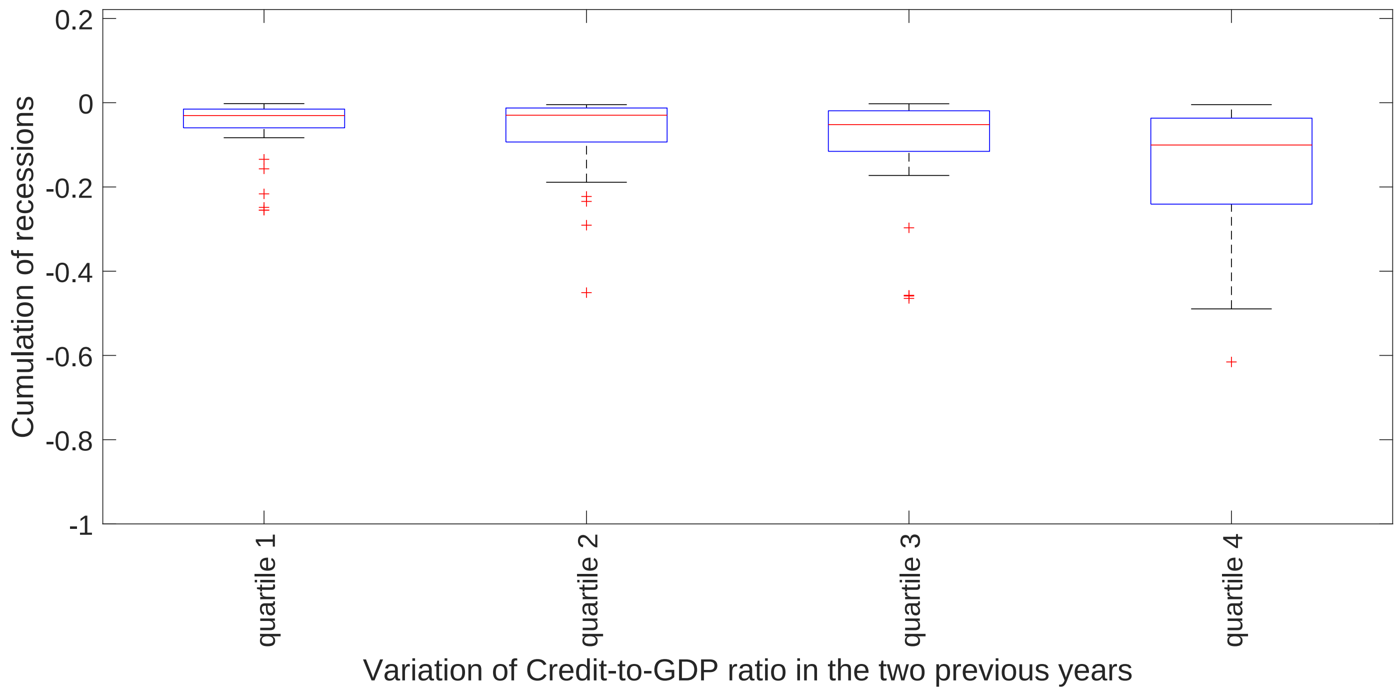
Table 11: Mixture of distributions by quartiles (macroprudential policies) for recessions

Figures



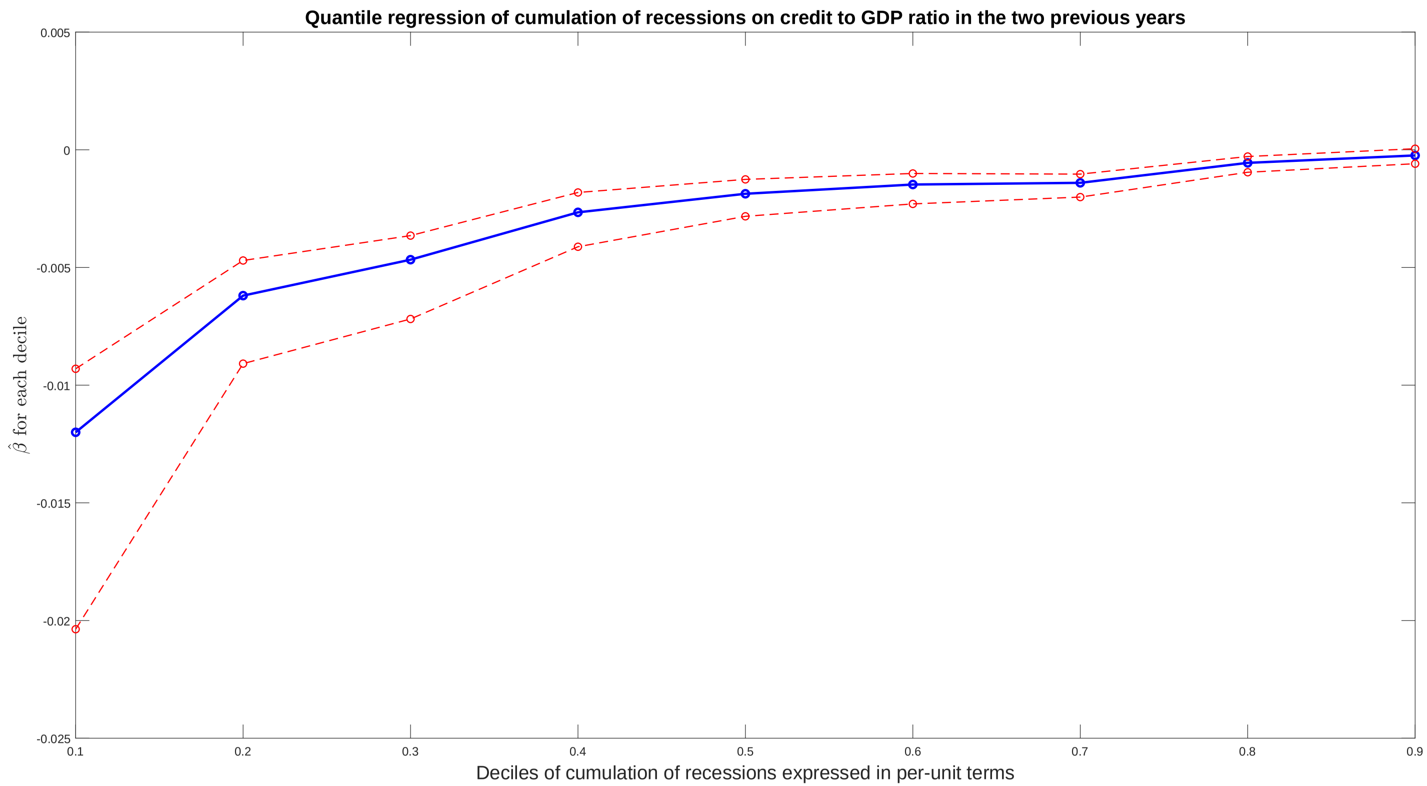
Note: The figure shows a scheme that concatenates two expansions and two recessions together with the total effect on the economy.

Figure 1: Scheme of the business cycle



Note: To improve visibility, the two main outliers (Argentina, 1998Q3-2002Q1 and Greece, 2007Q3-2013Q4) have been excluded in the graph. *Cumulation* expressed in per-unit terms.

Figure 2: Boxplots of cumulation of the four quartiles according to the variation in credit-to-GDP ratio in the previous two years



Note: The blue line represents the $\hat{\beta}$ coefficients for each decile; the dotted lines display the bootstrap confidence intervals at 5% level.

Figure 3: Quantile regression of the cumulation recessions on the variation in credit-to-GDP ratio in the previous two years

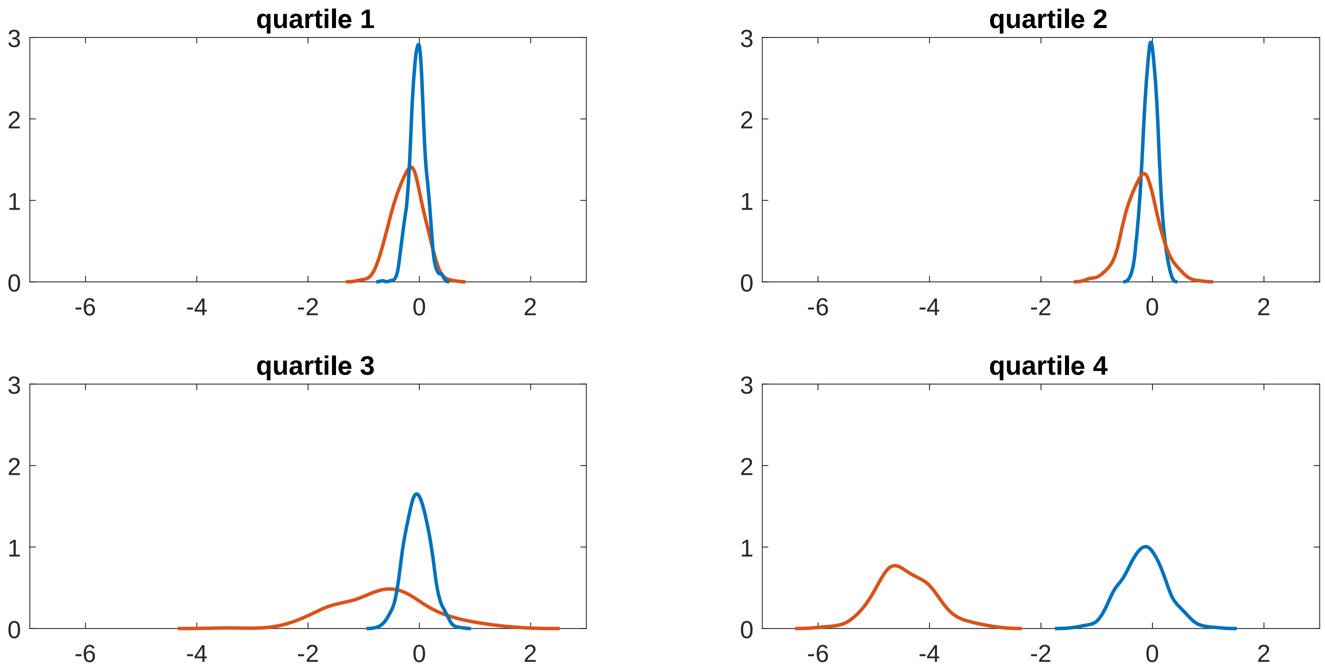
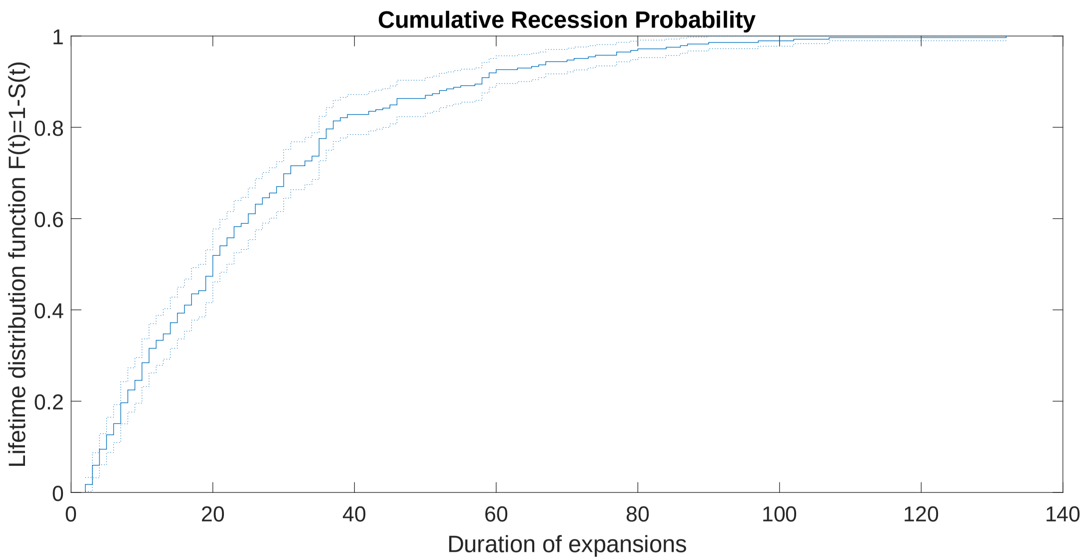
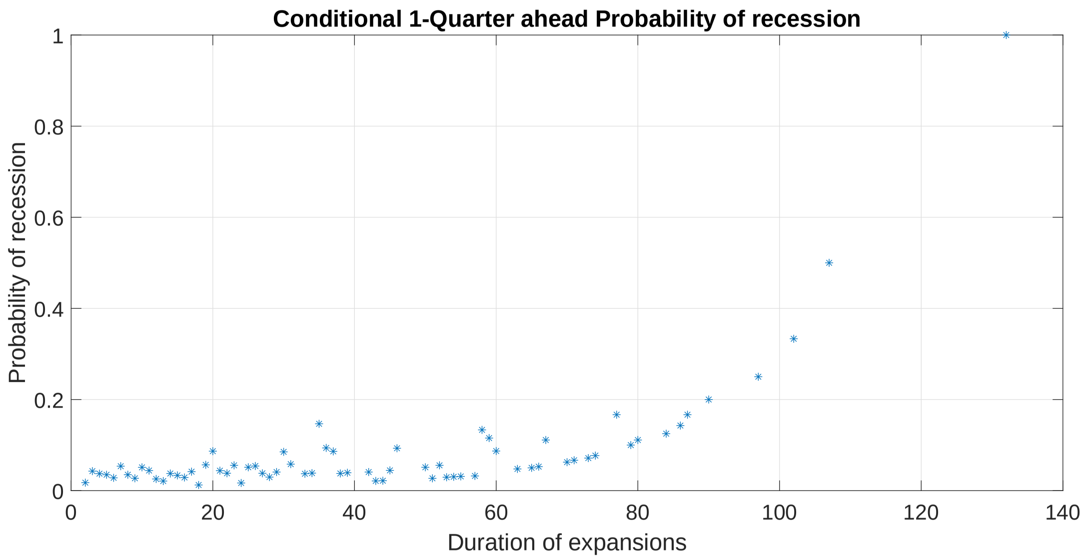


Figure 4: Mixture of normal distributions in the quartiles of cumulation of recessions according to the variation in credit-to-GDP ratio in the two previous years



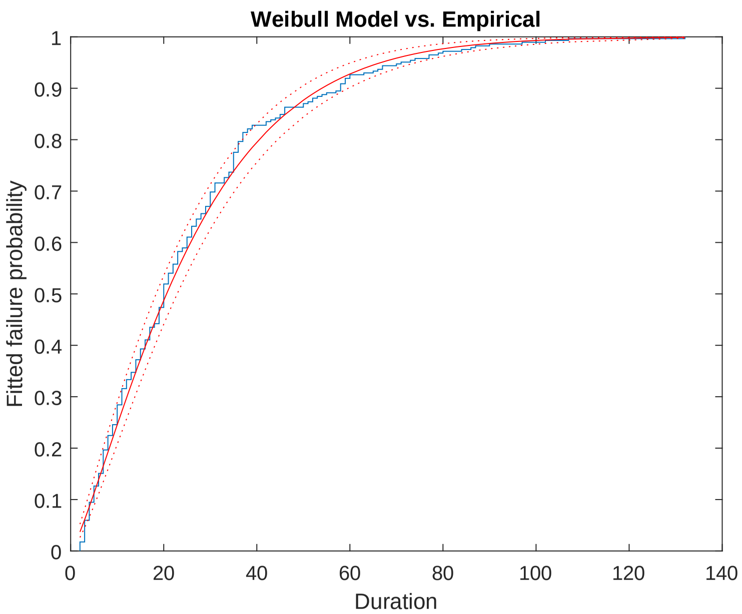
(a) Cumulative lifetime function for duration of expansion



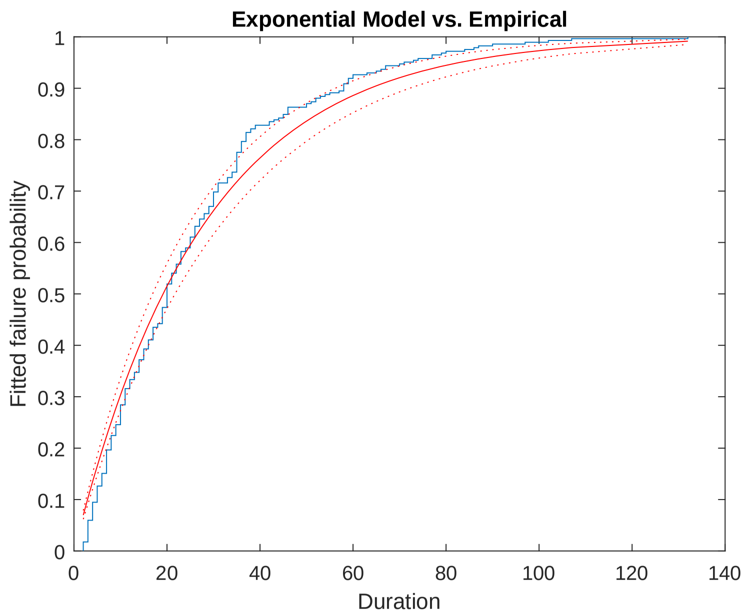
(b) Hazard function for duration of expansions

Note: The blue line in the top graph represents the Kaplan-Meier estimate of the empirial cumulative distribution function for durations; the dotted lines its confidence intervals at 5% level.

Figure 5: Survival analysis of expansions



(a) Weibull



(b) Exponential

Note: The figure represents in blue the empirical cumulative distribution function for durations and in red two theoretical distributions with their confidence intervals at 5% level: Weibull on the left and Exponential on the right.

Figure 6: Functions for duration of expansions

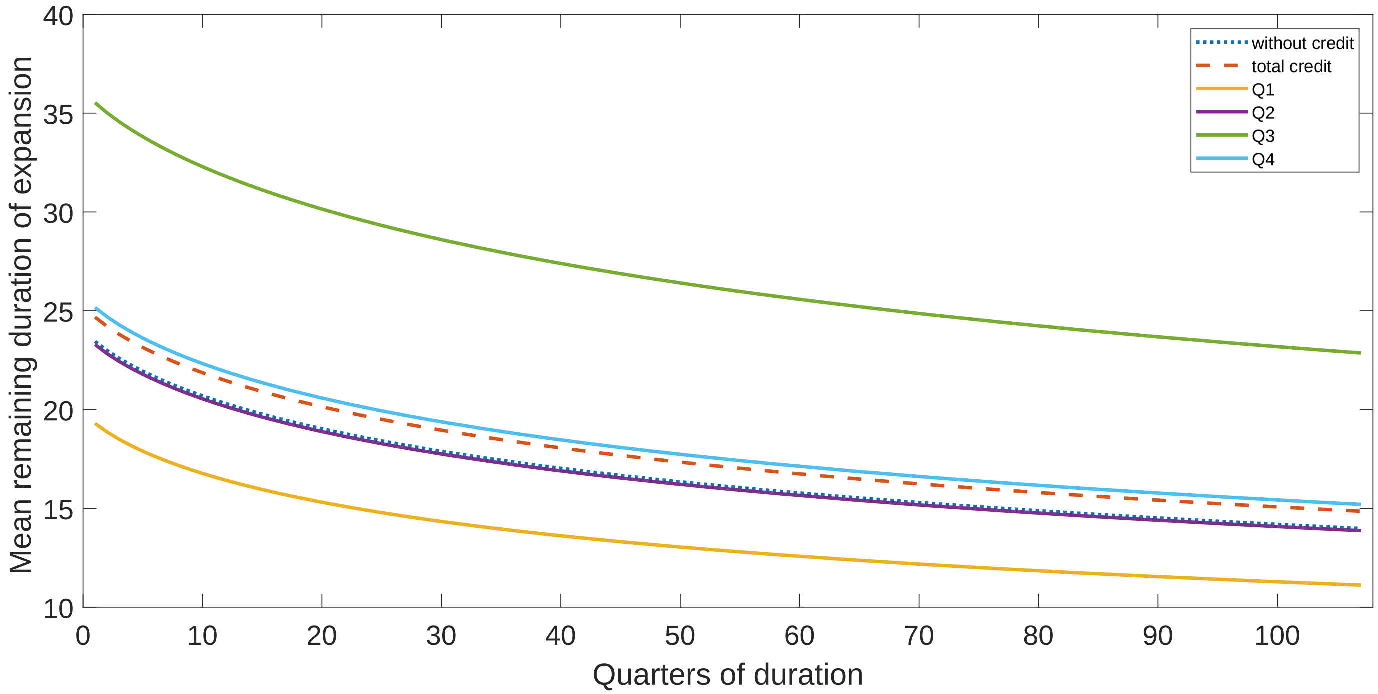


Figure 7: Effect of credit intensity on mean remaining duration of expansion

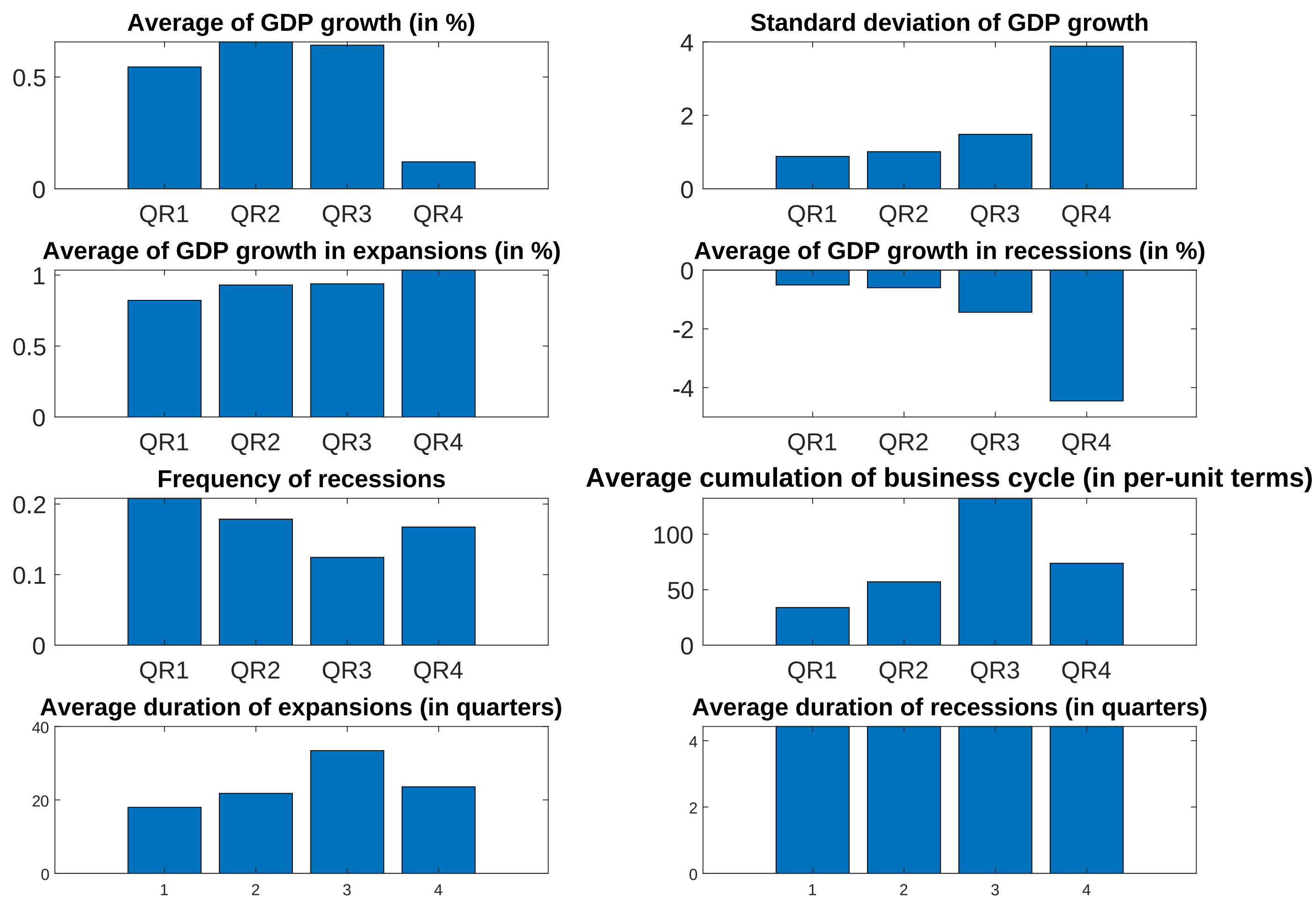
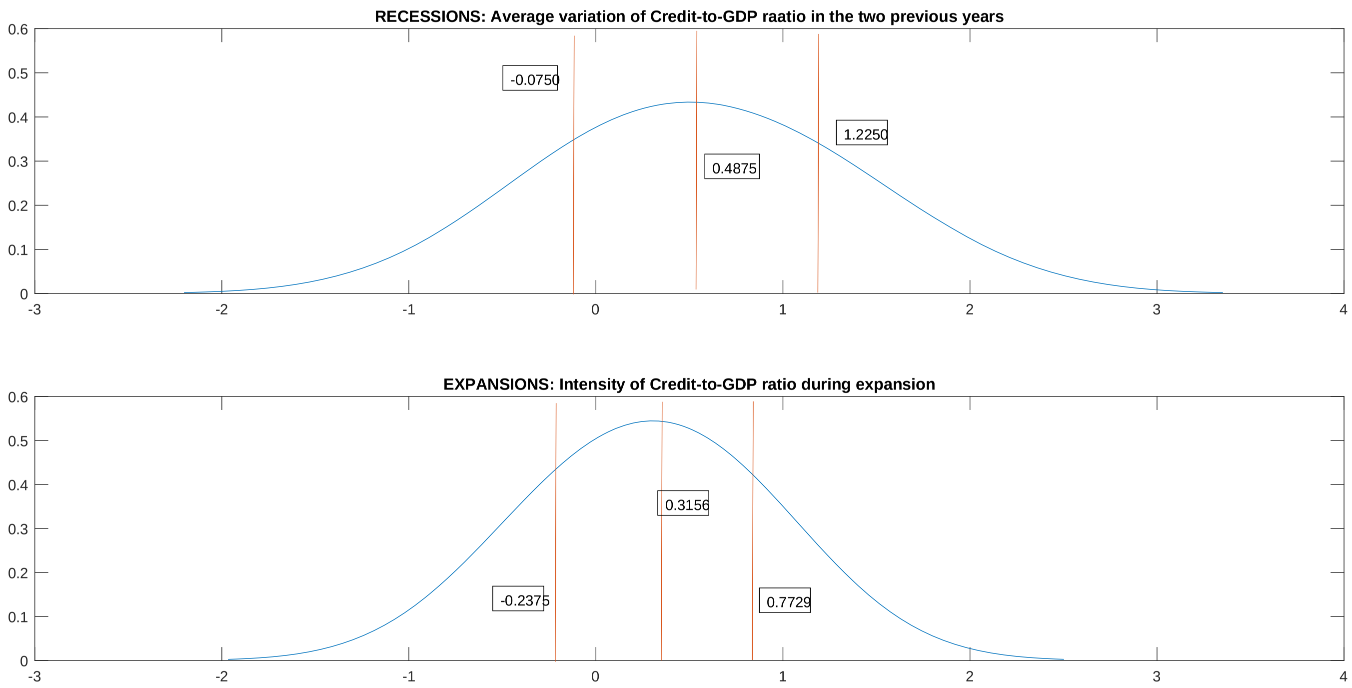
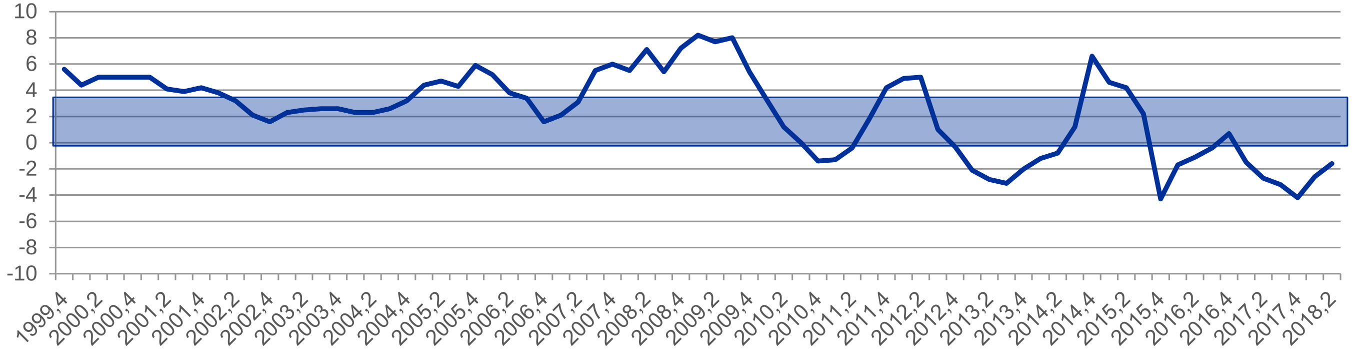


Figure 8: Simulation experiment over the business cycle (Cox regression model)

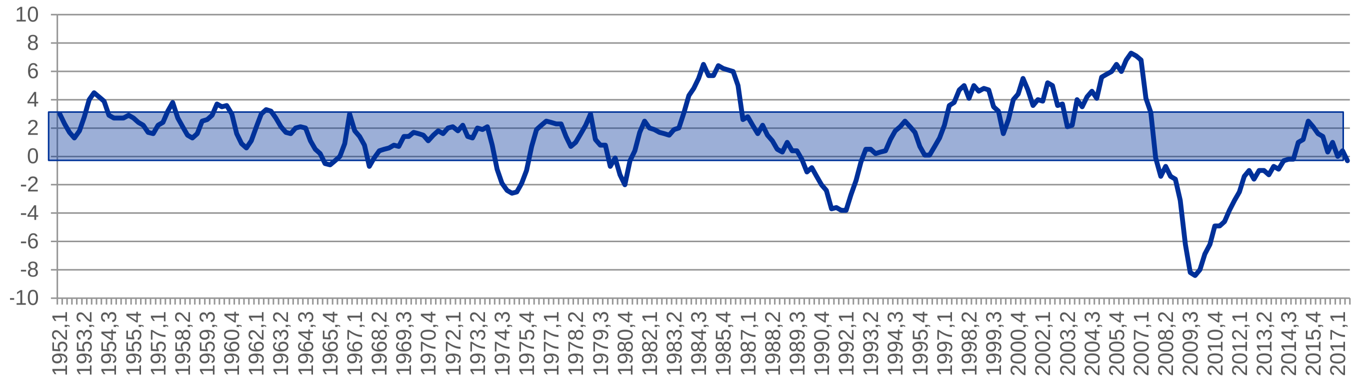


Note: The top chart presents the density function of $\Delta CR_{t-1}/8$. The bottom chart presents the density function of ΔCRI. The read line shows the cutpoints corresponding to the first, second and third quantile of each distribution.

Figure 9: Optimal level of credit



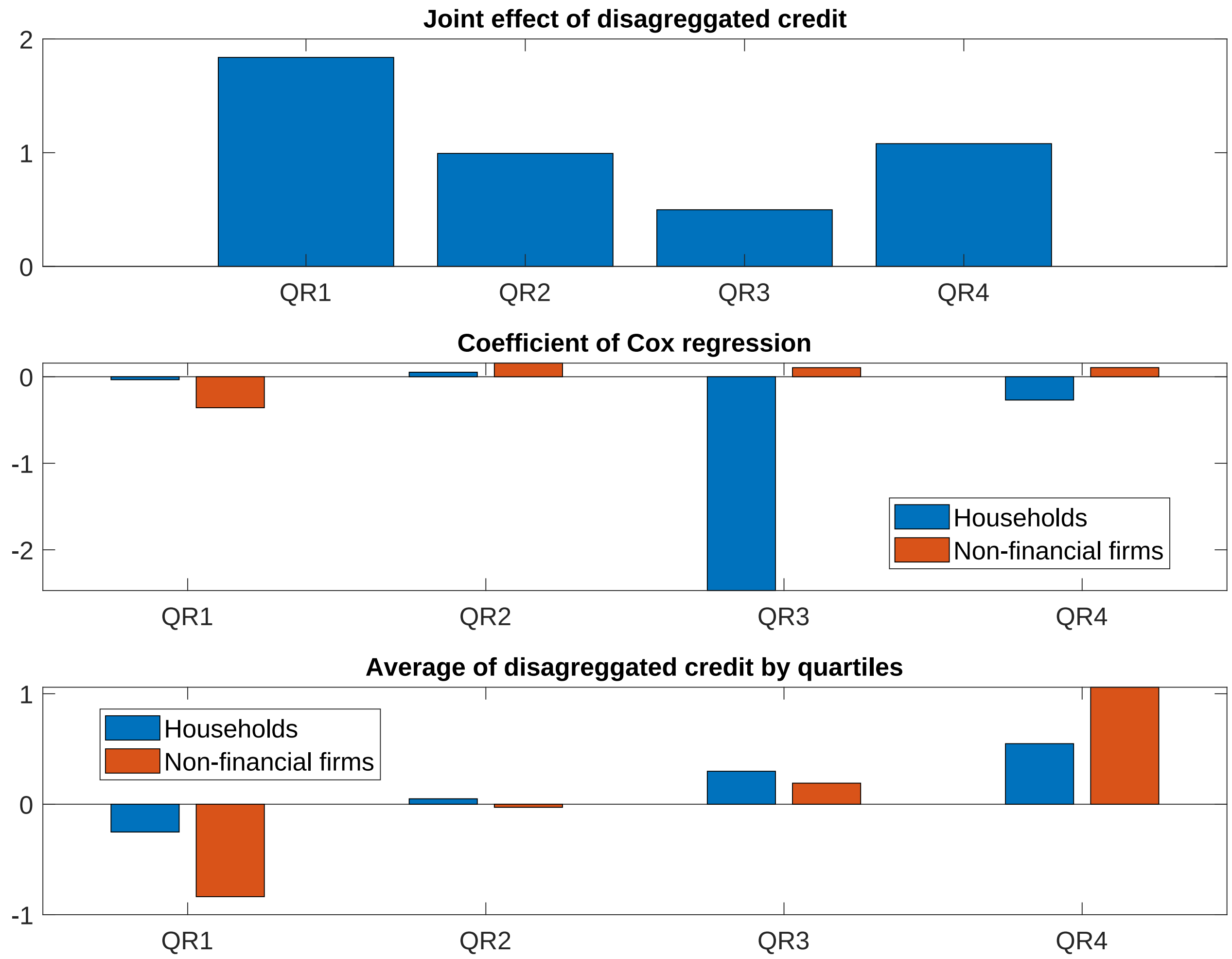
(a) Euro area



(b) US

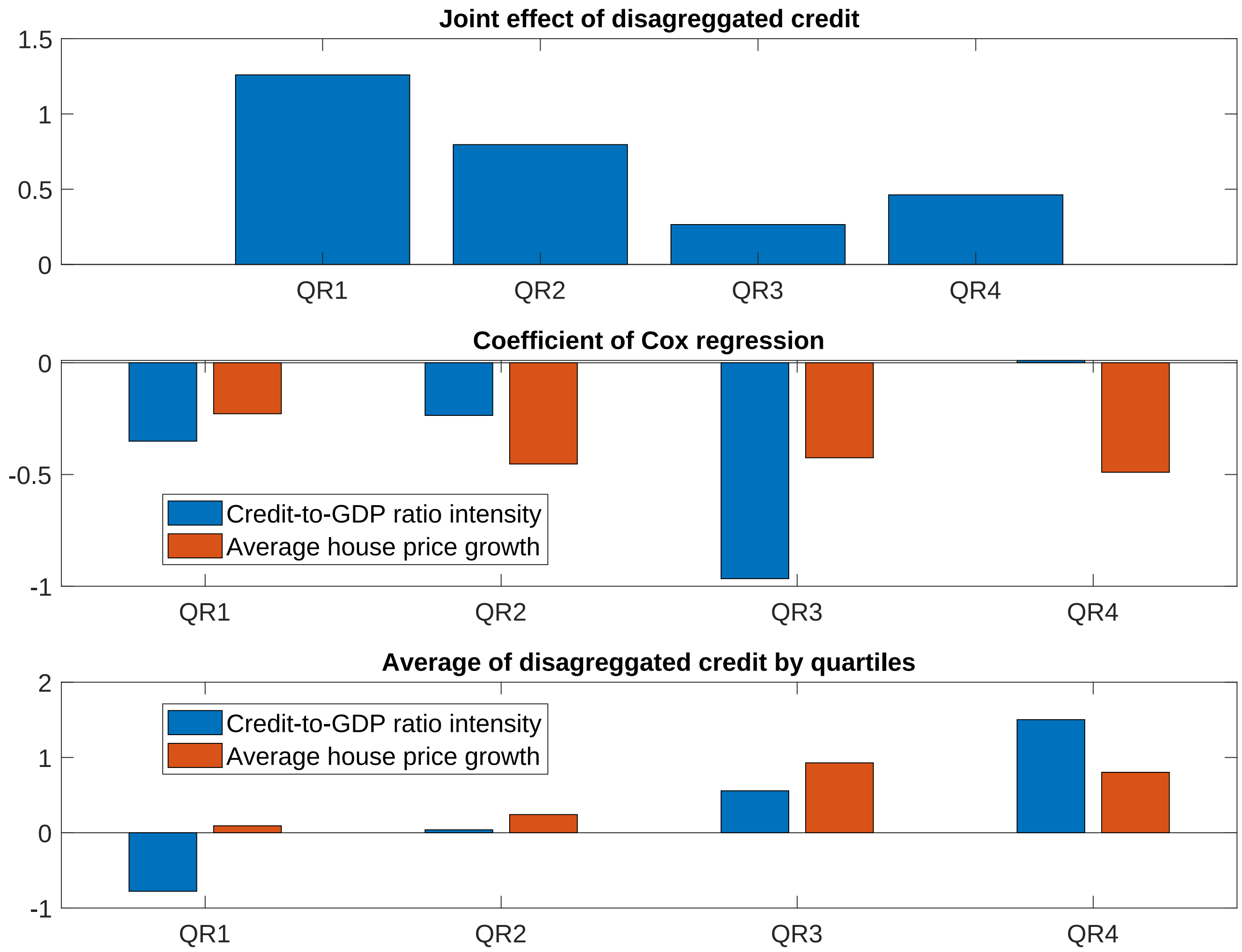
Note: The plot presents the annual change of credit-to-GDP in every quarter. The bands represent the levels of the annual variation associated to being in the second or third quantity of the distribution of $DeltaCR_{t-1}$ or ΔCRI.

Figure 10: Variation in credit-to-GDP



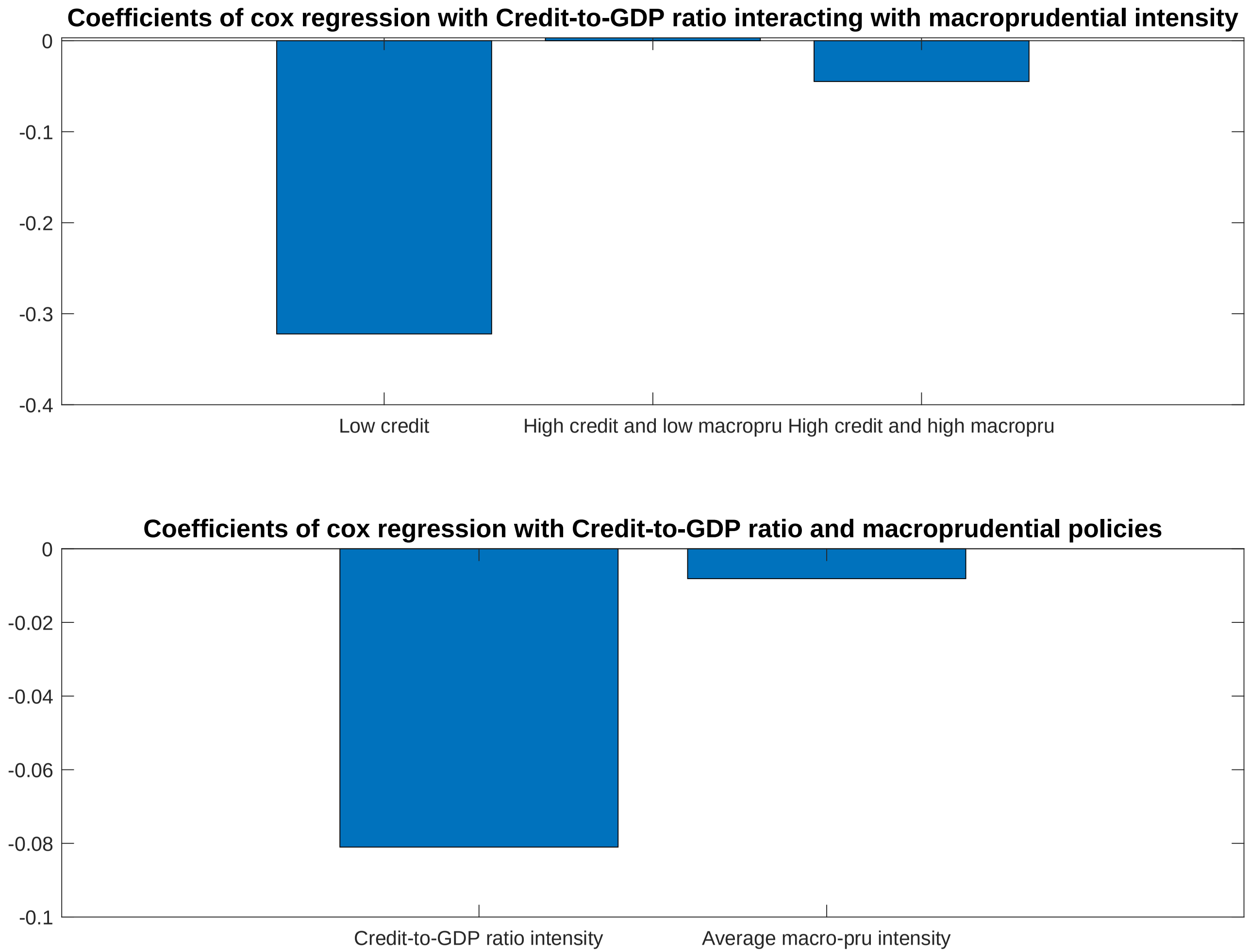
Note: The upper graph summarizes the total effect of each component of credit (households and non-financial firms) on duration of expansions. In the middle and lower graphs we decompose the total effect into the effect of the coefficients and the average level.

Figure 11: Results of splitting credit for expansions



Note: The upper graph summarizes the total effect of credit intensity and house prices on duration of expansions. In the middle and lower graphs we decompose the total effect into the effect of the coefficients and the average level.

Figure 12: Results of interacting credit with house prices for expansions



Note: The upper graph presents the effect of each group of credit defined according to its level of intensity and macroprudential policies on durations of expansions. The lower graph displays the effect of total credit intensity controlling by macroprudential policies.

Figure 13: Results of interacting credit with macroprudential policies for expansions

Appendix 1: Data

Country	Sample
Albania	Q1 2009 - Q1 2018
Argentina	Q1 1993 - Q2 2018
Australia	Q1 1960 - Q2 2018
Austria	Q1 1960 - Q2 2018
Belgium	Q1 1960 - Q2 2018
Brazil	Q1 1996 - Q2 2018
Bulgaria	Q1 1995 - Q1 2018
Canada	Q1 1960 - Q2 2018
Chile	Q1 1995 - Q2 2018
Colombia	Q1 2000 - Q2 2018
Costa Rica	Q1 1991 - Q2 2018
Croatia	Q1 2000 - Q2 2018
Cyprus	Q1 1995 - Q1 2018
Czech Republic	Q1 1994 - Q2 2018
Denmark	Q1 1960 - Q2 2018
Estonia	Q1 1995 - Q2 2018
Finland	Q1 1960 - Q2 2018
France	Q1 1950 - Q2 2018
Germany	Q1 1960 - Q2 2018
Greece	Q1 1960 - Q2 2018
Hungary	Q1 1995 - Q2 2018
Iceland	Q1 1960 - Q2 2018
India	Q2 1996 - Q2 2018
Indonesia	Q1 1990 - Q2 2018
Ireland	Q1 1960 - Q2 2018
Israel	Q1 1995 - Q2 2018
Italy	Q1 1960 - Q2 2018
Japan	Q1 1960 - Q2 2018
Korea	Q1 1960 - Q2 2018
Latvia	Q1 1995 - Q2 2018
Lithuania	Q1 1995 - Q2 2018
Luxembourg	Q1 1960 - Q1 2018
Macedonia	Q1 2000 - Q2 2018
Malta	Q1 2000 - Q2 2018
Mexico	Q1 1960 - Q2 2018
Netherlands	Q1 1960 - Q2 2018
New Zealand	Q1 1960 - Q2 2018
Norway	Q1 1960 - Q2 2018
Poland	Q1 1995 - Q2 2018
Portugal	Q1 1960 - Q2 2018
Romania	Q1 1995 - Q2 2018
Russia	Q1 1995 - Q2 2018
Saudi Arabia	Q1 2010 - Q1 2018
Serbia	Q1 1995 - Q2 2018
Slovak Republic	Q1 1993 - Q2 2018
Slovenia	Q1 1995 - Q2 2018
South Africa	Q1 1960 - Q2 2018
Spain	Q1 1960 - Q2 2018
Sweden	Q1 1960 - Q2 2018
Switzerland	Q1 1960 - Q2 2018
Turkey	Q1 1960 - Q2 2018
United Kingdom	Q1 1955 - Q2 2018
United States	Q1 1947 - Q2 2018

Sources: OECD (*https://stats.oecd.org/*) Quarterly National Accounts, for most countries, and otherwise the Federal Reserve Bank of St. Louis (*https://fred.stlouisfed.org/*).

Table A1: GDP Data - OECD Statistics

Country	Sample
Argentina	Q1 1984 - Q4 2018
Austria	Q4 1960 - Q4 2018
Australia	Q2 1960 - Q4 2018
Belgium	Q4 1970 - Q4 2018
Brazil	Q1 1996 - Q4 2018
Canada	Q4 1955 - Q4 2018
Switzerland	Q4 1960 - Q4 2018
Chile	Q1 1983 - Q4 2018
Colombia	Q4 1996 - Q4 2018
Czech Republic	Q1 1993 - Q4 2018
Germany	Q4 1960 - Q4 2018
Denmark	Q4 1966 - Q4 2018
Spain	Q1 1970 - Q4 2018
Finland	Q4 1970 - Q4 2018
France	Q4 1969 - Q4 2018
United Kingdom	Q1 1963 - Q4 2018
Greece	Q4 1970 - Q4 2018
Hungary	Q4 1970 - Q4 2018
Indonesia	Q1 1976 - Q4 2018
Ireland	Q2 1971 - Q4 2018
Israel	Q4 1990 - Q4 2018
India	Q2 1951 - Q4 2018
Italy	Q4 1960 - Q4 2018
Japan	Q4 1964 - Q4 2018
Korea	Q4 1962 - Q4 2018
Luxembourg	Q1 1999 - Q4 2018
Mexico	Q4 1980 - Q4 2018
Netherlands	Q1 1961 - Q4 2018
Norway	Q4 1960 - Q4 2018
New Zealand	Q4 1960 - Q4 2018
Poland	Q1 1992 - Q4 2018
Portugal	Q4 1960 - Q4 2018
Russia	Q2 1995 - Q4 2018
Saudi Arabia	Q1 1993 - Q4 2018
Sweden	Q1 1961 - Q4 2018
Singapore	Q4 1970 - Q4 2018
Turkey	Q1 1951 - Q4 2018
United States	Q1 1951 - Q4 2018
South Africa	Q1 1965 - Q4 2018

Source: Bank for International Settlements ($https://www.bis.org/statistics/c_gaps.htm$) for a total of 44 countries. The variable selected is credit-to-GDP ratio (actual data), named in the database as "Credit from All sectors to Private non-financial sector" at a quarterly frequency.

Table A2: Credit Data - BIS Credit Statistics

Appendix 2: Extended Cox regression model

In this Appendix we analyze in further detail the evolution of the expansions throughout their duration, considering that the covariate variable, credit, changes over time during the follow-up period. So, credit becomes an internal covariate that is generated by the expansions under study and it is observed as long as the subject survives or is uncensored. To deal with this approach, we have built a new database generating sub-expansions of each expansion, taking them from year to year (4 quarters) and producing a sequence of censored and uncensored data.

This basic model can be extended to allow time-varying covariates (see Therneau and Grambsch (2000)) for this and other extensions of the Cox model):

$$\lambda(t|\Delta CRI_{t,ij}) = \lambda(t)exp(\beta_0' * \Delta CRI_{t,ij} + \beta_1' \Delta CRI_{t,ij} * Dummy_s) \tag{20}$$

where credit intensity is defined in a different way than in Section 4 because, in this case, $\Delta CRI_{t,ij}$ refers to credit intensity during year t, country i, expansion j, predetermined when calculating the probability of dying the last day of the quarter. Consequently, dummies variables are defined differently that in Section 4. $Dummy_{t,s}$, is now a dummy variable that takes value 1 if the intensity of year t, country i, expansion j belongs to the quartile s. Note that the value of $Dummy_s$ changes over time as the expansion progresses correcting the possible endogeneity.

As can be seen, we have split out each expansion into sub-expansions year by year, and we have computed the intensity of credit in each of them. All subsamples except the last one are treated as censored data. The results of estimating equation 20 are displayed in Table A3 and show several nuances with respect to previous results. In the first quartile, the final effect of the credit to the survival of the expansion is negative but of less intensity than in the compact model. For the second quartile, the effect is very similar. In the third quartile, the effect is also positive although slightly less intense than in the baseline model and, finally, we find a significant negative effect in the fourth quartile.[25]

Finally, Figure A1 displays the Mean Remaining Lifetime with the extended sample. The dummies that identify the credit intensity quartiles have been calculated taking into account all the in-sample information.[26] Bypassing the irregularities of the beginning due to the small number of observations, the evolution is similar to that obtained with the compact sample and, again, the third quartile offers the best survival results.

[25] The exercise has been repeated eliminating those live expansions at the end of the sample obtaining very similar results.

[26] Furthermore, they have been computed from the live expansions at each moment of time t, approaching an experiment in real time and obtaining similar conclusions about the third quartile.

Intensity in the sub-expansion					
Variable	Coeff	Exp(coeff)	Credit average	Credit effect	p-value
credit	0.03	0.91	-1.29	1.13	0.38
credit*qr1	-0.13	-	-	-	0.03
credit	-0.02	0.79	0.09	0.98	0.51
credit*qr2	-0.21	-	-	-	0.73
credt	-0.02	0.63	0.76	0.70	0.65
credit*qr3	-0.45	-	-	-	0.04
credit	-0.10	1.04	2.27	1.10	0.01
credit*qr4	0.14	-	-	-	0.01

Notes: This table displays the estimates coefficients and their p-values in a Cox regression where expansions are considered in their expanded form. This specification disentangles the effect of credit intensity considering also its interaction a dummy variable that represents its position in the distribution divided in four quartiles. The effect of credit is computed as $e^{\sum \widehat{\beta}\overline{z}(i)}$ is the mean of credit intensity in each quartile. Values above (below) one indicate a negative (positive) effect of the credit on the hazard function.

Table A3: Cox regression with quartiles (extended expansions)

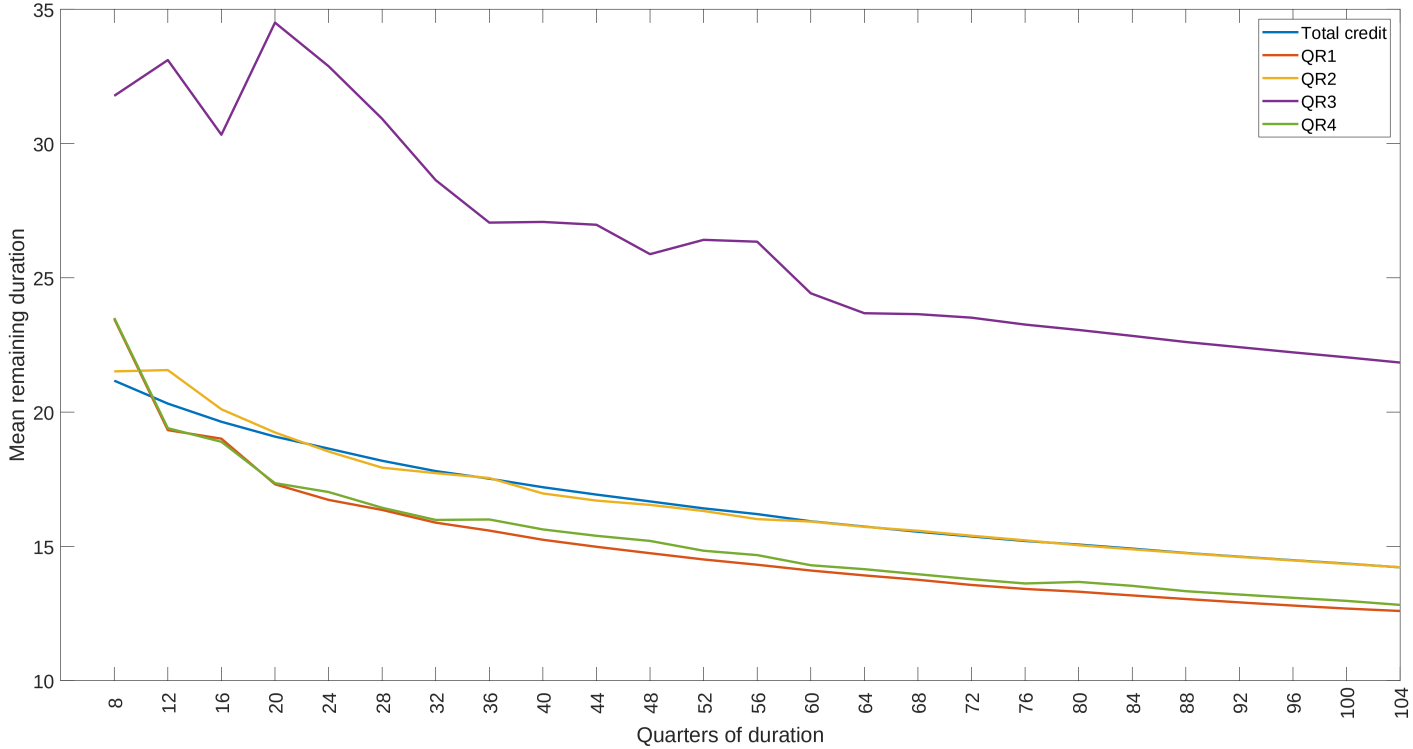


Figure A1: Effect of Time-variant Credit Intensity on Mean Remaining Duration

Appendix 3: Robustness analysis

In this section we consider several robustness checks of our main analysis: the influence of outliers and alternative measures of credit imbalances.

Controlling outliers

We test whether our results are biased by the influence of some outliers observed in the recessions in the sample.[27] We have replicated the calculations after removing these atypical recessions. The findings are summarized in Table A4 and Figure A2. In the first, we observe that the behavior of the fourth quartile has clearly changed although the key results remain unchanged. The huge tail on the right has disappeared but the proportion of very bad recessions has increased with respect to the third quartile. In others words, a slight probability of finding terrible recessions has been substituted by an substantial probability of finding extremely bad recessions. The effects of this finding on the whole business cycle are displayed in Figure A2 which reproduces the simulations considering the new results relating to recessions.[28] In this figure, we confirm that the third quartile offers the best results in terms of average growth rate, high cumulation, less volatility and the lowest frequency of recessions.

[27] These outliers appear in Argentina and Greece.

[28] Results are qualitatively unaltered when using AFT parameters instead of Cox-regression parameters.

	QUARTILE 1		QUARTILE 2		QUARTILE 3		QUARTILE 4	
	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2
μ	-0.0304	-0.2018	-0.0228	-0.1723	-0.0549	-0.3863	-0.0627	-0.2985
σ	0.0005	0.0032	0.0003	0.0099	0.0025	0.0107	0.0028	0.0215
prob.	0.8050	0.1950	0.6492	0.3508	0.8308	0.1692	0.5769	0.4231

Note: See Table 4.

Table A4: Mixture of distributions by quartiles (recessions without outliers)

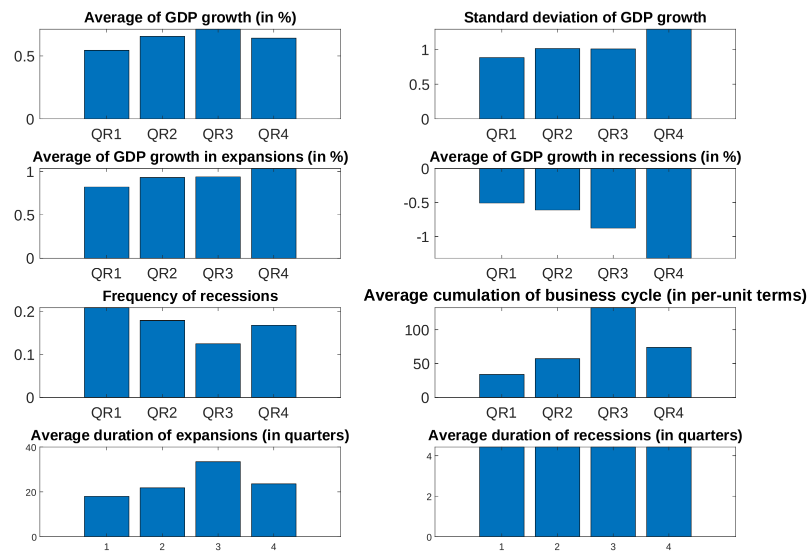


Figure A2: Simulation experiment without recession outliers (Cox regression)

Real credit growth

As mention in the main text some papers use real credit growth as the main variable to analyze the evolution of credit (e.g., Cechetti and Kharroubi, 2018). In order to check the robustness of our results to this alternative measure of credit we repeat the whole exercise using average real credit growth during expansions (as a substitute for credit intensity) and average real credit growth in the two years before the recessions (as a substitute for variation in credit-to-GDP in the last two years of expansions).[29] Results are displayed in Tables A5-A8 and Figure A3. Table A5 corresponds with the top panel of Table 3, Table A6 with Table 4, Table A7 with the bottom panel of Table 3, Table A8 with Table 6 and, finally, Figure A3 with Figure 8. As can be seen in the tables, even though the number of observations is reduced, from 200 expansions-recessions when using credit to GDP to 175/155 when using real credit growth, the results are nevertheless robust. The third quartile continues to be the most desirable quartile to maximize the expected growth rate. The negative effect on the cumulation of wealth of being in the fourth quartile that we find with credit-to-GDP measures is still maintained because the expansions of the third quartile of average real credit growth are longer than those of the fourth quartile. With regard to recessions, we find in the fourth quantile the most intense cumulative loss of GDP, although the effect is less pronounced than with the credit-to-GDP ratio. We consider the results based on credit-to-GDP to be more relevant because the number of observations diminishes when using real credit growth, the variability of this variable is much bigger than the relatively smooth credit-to-GDP, and the majority of academic papers consider credit-to-GDP as the most relevant variable.

[29] In this case we use the sample excluding outliers because the sample is smaller and the outliers seriously distort the results.

Real credit growth in the previous two years			
variables/characteristics	duration	amplitude	cumulation
constant	3.7798	-0.0256	-0.0650
	(17.6471)	(-9.4442)	(-7.1733)
$\Delta RCR_{t-1,ij}$	0.0227	-0.0008	-0.0021
	(2.0354)	(-4.5402)	(-4.1779)

Note: The measure of credit, $\Delta RCR_{t-1,ij}$, is the average real credit growth in the two previous years. The sub-indices i and j denote country and recession, respectively. *Duration* is presented in quarters and *amplitude* and *cumulation* in per-unit terms.

Table A5: Estimation of ols regressions (recessions)

	QUARTILE 1		QUARTILE 2		QUARTILE 3		QUARTILE 4	
	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2	Mixture 1	Mixture 2
μ	-0.0279	-0.2029	-0.0290	-0.2081	-0.0668	-0.3970	-0.0761	-0.2826
σ	0.0005	0.0045	0.0006	0.0141	0.0035	0.0101	0.0045	0.0232
prob.	0.7691	0.2309	0.7671	0.2329	0.7865	0.2135	0.6388	0.3612

Note: See Table 4.

Table A6: Mixture of distributions by quartiles

Average of real credit growth during expansions			
variables/characteristics	duration	amplitude	cumulation
constant	20.0565	0.1442	2.4419
	(13.2591)	(6.8141)	(3.3949)
$\Delta RCRI_{ij}$	2.5750	0.0494	1.4217
	(4.3547)	(3.8782)	(2.6038)

Note: $\Delta RCRI_{ij}$ is the average real credit growth during expansions. The sub-indices i and j denote country and expansion, respectively. *Duration* is presented in quarters and *amplitude* and *cumulation* in per-unit terms.

Table A7: Estimation of ols regressions (expansions)

Variable	Coeff	Exp(coeff)	Credit average	Credif effect	p-value
credit	-0.13	0.68	-0.48	1.21	0.01
credit*qr1	-0.26	-	-	-	0.08
credit	-0.17	0.62	0.78	0.69	0.00
credit*qr2	-0.31	-	-	-	0.13
credt	-0.15	0.71	1.75	0.54	0.00
credit*qr3	-0.19	-	-	-	0.05
credit	-0.37	0.87	4.51	0.54	0.00
credit*qr4	0.24	-	-	-	0.00

Note: See Table 6.

Table A8: Cox regression with quartiles

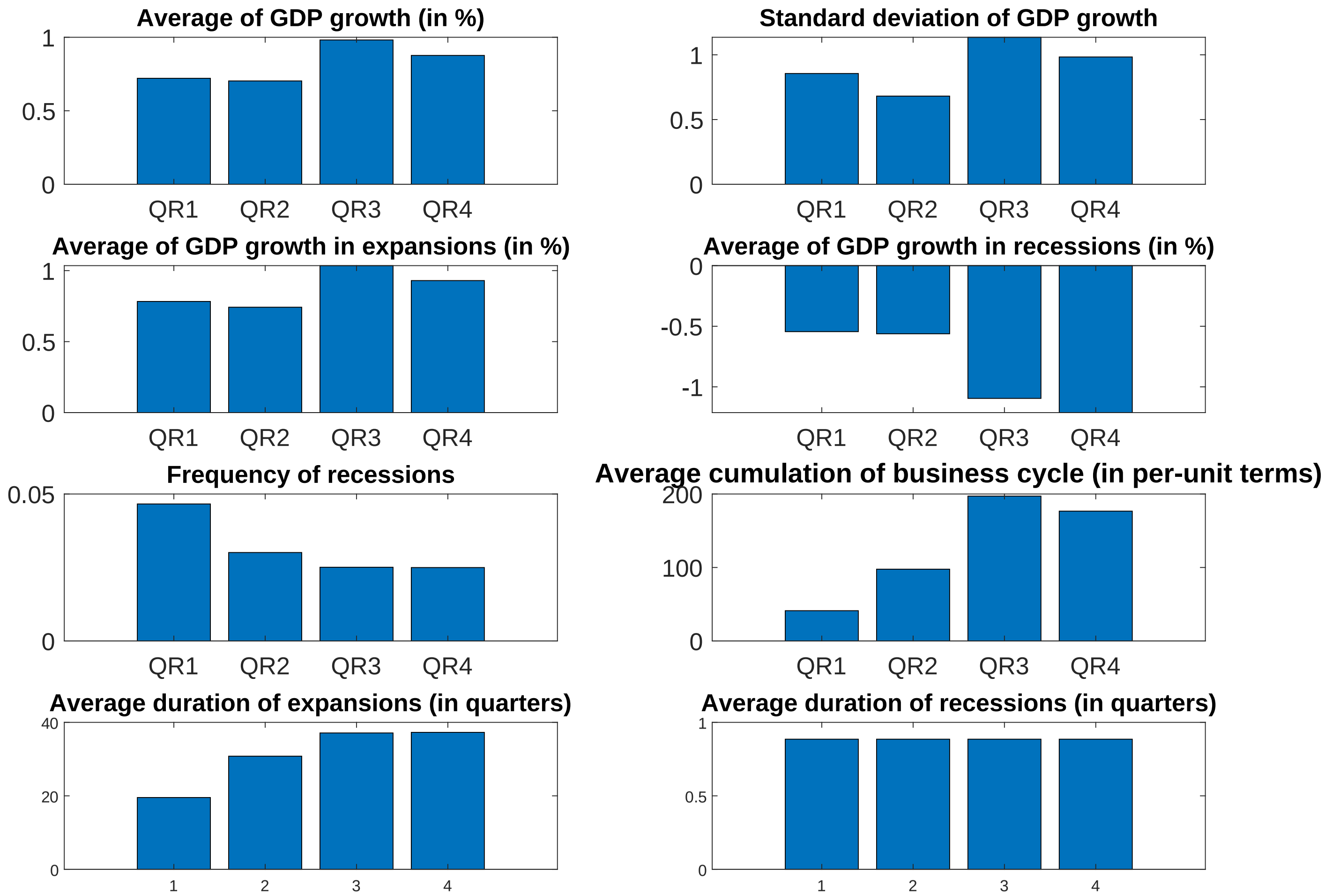


Figure A3: Simulation experiment with real credit growth (Cox regression)