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Clément Mathonnat,[#] Alexandru Minea,[*] [&] and Marcel Voia[ϒ]

Abstract: Empirical studies emphasize that higher financial development (FD) amplifies the output cost of banking crises. However, no study has so far investigated the effect of FD on another key dimension of banking crises, namely their duration. Using a large sample of banking crises over the 1977-2014 period, we find that higher FD is associated with a significant increase in the duration of banking crises (DBC). This result is robust to a broad range of alternative specifications, and is unaffected by unobserved heterogeneity or endogeneity. Finally, we show that the effect of FD on DBC is subject to non-linearities, and varies across decades and with the level of economic development.

Keywords: financial development; duration of banking crises; duration models.

JEL codes: F30; G01; C41.

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I. Introduction

The duration and intensity of the subprime crisis, without equivalent since the Great Depression, brought again into the spotlight the adverse economic and social consequences of banking crises. The exceptional nature of this crisis mainly comes from the extent of speculative dynamics that took place in the financial systems of many developed countries. They partly rooted in a vast expansion of the financial sector that started in the 1980s due to financial innovations and financial liberalization (Claessens et al., 2010; Beck et al., 2016). This resulted in a sharp increase in loans and financial assets held by banks, as well as a surge in the debt levels. Instead of promoting a greater stability of the financial system, the growth of the banking sector fostered real estate market bubbles, whose burst caused massive losses for banks and triggered an unprecedented banking crisis.

Consequently, as mentioned by Beck (2012), the subprime crisis revived the debate on the benefits and risks of financial development (FD). On the one hand, through better mobilizing funds for investment, managing risk, and fostering an efficient allocation of resources, FD can have positive effects on the economy, such as promoting capital formation, productivity growth, and higher and more stable economic growth (Swamy & Dharani, 2019); this can increase the resilience of an economy to adverse shocks, and enable a faster recovery from recessions. On the other hand, a large expansion of financial systems may weaken their ability to manage information asymmetries, reduce risk, and allocate funds efficiently; this can increase banking sector's fragility and exposure to crises triggered for instance by more banks' risk-taking during the upward phase of the financial cycle, a stronger procyclicality of financial activities due to the interaction between credit supply and asset prices, and an increased sensitivity of banks to liquidity risk. From this perspective, higher FD may raise economies' sensitivity to shocks, such as banking crises, and amplify their consequences (Rajan, 2005; Demetriades, 2017).

Given these potential conflicting effects of FD, recent empirical studies explore the determinants of the cost of banking crises. Capitalizing on the role of banks' credit for the occurrence or the aftermath of banking crises (see e.g. Bekaert et al., 2011; Berkmen et al., 2012; Jorda et al., 2013, 2015, 2016a, 2016b), several studies, e.g. Boyd et al. (2005), Furceri & Zdzienicka (2012), Pesic (2012), López-Salido et al. (2017) indicate that FD is an important determinant of the output cost of banking crises, which may suggest an amplifying effect of FD on the recessive consequences of banking crises.[1]

[1] Such an amplifying effect of FD is backed-up by microeconomic evidence in Kroszner et al. (2007), who extend the work of Dell'Ariccia et al. (2008).

However, to better understand the relationship between FD and the aftermath of banking crises, it would be interesting to go one step further, and extend existing studies on the following two grounds.

First, despite banks' credit-to-GDP being the usual proxy for countries' FD (see Beck et al., 2014), a more in-depth measure should account for its multidimensional nature associated with both the size and the activity of the banking sector. Focusing on the banking sector is relevant to proxy FD from an international perspective since financial intermediaries still represent the major source of external financing in developing countries and in many developed countries, and the expansion of financial markets is closely related to an increase in market intermediation by the banking industry.[2] However, following Mathonnat & Minea (2018), it is important to go beyond a single credit measure (for example, credit-to-GDP), and account for the overall size of both assets and liabilities of banking sector's balance sheet, and also for the liquidity risk associated with an increase in the credit supply.

Second, besides output costs, banking crises are also associated with long-lasting adverse effects on the activity of both the financial sector and the real economy (Reinhart & Rogoff, 2009). Surprisingly, to our knowledge, so far no empirical analysis assessed explicitly the effect of FD on yet another key dimension of banking crises, namely their *duration*. At first sight, the duration and the cost of banking crises go hand in hand (see e.g. the Japanese crisis of the 1990's or the consequences of the subprime crisis for many western economies). Nevertheless, if we consider for instance the US Savings & Loans crisis of the 1980's, banking crises can be associated with a protracted contraction of the activity of the financial sector without resulting in a large output cost. Consequently, focusing on the duration of banking crises (DBC) might represent a complementary approach to assess the influence of FD on the recessive consequences of banking crises.

In this paper we analyze the effect of FD on the DBC, in a broad sample of 96 banking crises observed in 75 countries over the 1977-2014 period. Our results are as follows. First, using a semi-parametric mixed-proportional hazard model, we show that FD is significantly and positively associated with the DBC. Depending on the duration measure, estimations suggest that moving from the lowest to the highest FD quintile raises the length of banking crises by 4 to 6 years. Second, this result is robust when using parametric duration models, accounting for financial liberalization and stock markets development, or controlling for additional determinants of DBC, and is found not to be affected by unobserved heterogeneity,

[2] Beck et al. (2008) emphasize a strong and positive correlation between the size of the banking sector and the size of stock markets in a large database covering both developed and developing countries.

endogeneity, or outliers. Third, additional estimations outline heterogeneities in the effect of FD on the DBC: the length of banking crises significantly increases for low and high FD levels but not for intermediate levels, and it varies across decades and with the level of economic development. In an international environment still facing the consequences of the subprime crisis, our analysis contributes to the debate on the role played by the financial system in increasing financial instability and amplifying shocks, suggesting that FD mostly tends to magnify the duration of banking crises.

The paper is organized as follows. Section II reviews the literature. Sections III and IV describe the data, and the methodology. Section V presents our main results. Sections VI and VII explore the robustness of our findings. Section VIII discusses potential sources of heterogeneity in the FD-DBC relationship, and Section IX concludes the paper.

II. Literature review

We first briefly review the literature on the aftermath of banking crises, and then we discuss some theoretical mechanisms that could help understand how FD may affect the DBC.

2.1. The aftermath of banking crises

Previous studies, e.g. Reinhart & Rogoff (2009), emphasize a persistent and negative impact of banking crises on the financial sector (credit supply, or asset prices), and the real economy (consumption, investment, GDP, unemployment, or public debt). Indeed, compared to normal recessions, output losses associated with banking crises are deeper and more persistent (Bordo et al., 2001).[3] According to Jorda et al. (2013), it takes about 5 years to exit a recession triggered by a banking crisis against around 2 years for normal recessions (see also Cerra & Saxena, 2008, and Reinhart & Rogoff, 2014). Since recessions may sharply reduce capital accumulation, shrink long-term employment, and slow total factor productivity growth (Ball, 2014), the strong recessive length of banking crises may adversely impact potential output (Furceri & Mourougane, 2012).

2.2. From financial development to the duration of banking crises

Given the importance of the financial sector in explaining the consequences of banking crises (Claessens & Kose, 2013), we now investigate the link between FD and the DBC. We can *a priori* distinguish between a stabilizing and an amplifying effect.

[3] In addition, Babecky et al. (2014) underline that, compared with other financial crises (such as currency, and sovereign debt crises), banking crises entail a longer contraction of economic activity.

Regarding the *stabilizing* effect of FD, a large literature indicates that higher FD increases the supply of loanable funds, and leads to better risk management by the banking industry (e.g. Levine, 2005). Capitalizing on Beck et al. (2014)'s arguments on the financial depth-economic growth instability relationship, higher FD may increase the resilience of an economy to shocks through different channels, such as: alleviating firms' cash constraints, reducing the dependence of financial contracts on borrowers' net worth, altering the cyclical composition of investment, and promoting diversification that helps limiting risks and cyclical fluctuations. Thus, higher FD may play a counter-cyclical role by smoothing the effect of adverse shocks and enabling faster recovery from recession, which could reduce the DBC. However, for this stabilizing effect to work, banks should be able to ensure a stable allocation of the credit supply in the economy, which is not the case following the outbreak of banking crises (Mishkin, 1996). The sharp increase in information asymmetries in the financial system leads banks to reduce their risk exposure and their credit supply, magnifying the recessive impact of banking crises (Laeven, 2011).

This brings us to the *amplifying* effect FD may have on the DBC. The history of financial crises underlines that the procyclical dynamics of the banking sector are at the heart of the mechanisms explaining the causes and the consequences of banking crises, because the accumulation of risk relates to a self-sustaining process linking credit supply to asset prices (Kindleberger, 1978). The more the size and the activity of the banking sector increase during the upward phase of the cycle, the more the increase in indebtedness feeds a surge in asset prices. Thus, a strong expansion of the banking sector may weaken the ability of financial intermediaries to manage information asymmetries, reduce risk, and allocate funds efficiently (Beck, 2012). If asset prices collapse, they amplify the losses incurred by banks, leading to a contraction of the credit supply and a significant decrease in the private demand. In this context, banking crises have persistent recessive consequences that in turn magnify the adverse effect of the financial accelerator and debt deflation mechanisms on both the financial sector and the real economy.

When lenders suffer from information asymmetries, the financial accelerator theory (see Bernanke & Gertler, 1989; Kiyotaki & Moore, 1997; Bernanke et al, 1999; and more recently Gertler & Kiyotaki, 2011, 2012) shows that agents' financial stance creates a procyclical dynamic in the access to financing, and allows accounting for the magnitude and the persistence of shocks that negatively impact their wealth. Relatedly, the debt deflation theory (see Fisher, 1933; Minsky, 1986; and more recently Eggertsson & Krugman, 2012) suggests that higher indebtedness induces more constraints to access credit, and results in a significant drop in asset prices when the banking sector is in a crisis. Investors are forced to massively sell their assets to pay back their debts, leading to a sharp contraction in private spending that strengthens the recessive impact of the initial shock.

From this perspective, following a collapse in asset prices that significantly raises the number of defaulting borrowers, banks' wealth is adversely impacted. They experience more difficulties to finance their activity, which reinforces their financial fragility. To meet their liquidity requirement and to deleverage, banks sell a significant amount of assets, which amplifies the decline in asset prices and further weakens their balance sheet, leading to a significant credit supply contraction. The combined decline of asset prices and credit supply raises firms' and households' difficulties to obtain financing, and results in a significant contraction in aggregate demand. This leads to a decrease in production, a rise in unemployment, and a further fall in asset prices and increase in defaulting borrowers, with negative feedback effect on banks' balance sheet that results in a larger reduction in credit supply that amplifies the recessionary spiral in which the real economy is stuck. Consequently, the financial accelerator and the debt deflation theories underline the key role played by the banking sector in amplifying the recessive consequences of crises. Thus, by additionally exposing banks to shocks due to a sharp asset prices decline, a higher level of FD during the upward phase of the financial cycle could amplify the recessionary effect of banking crises, and, consequently, their duration. Hence, we derive the following testable hypothesis: the higher the FD prior to a banking crisis, the longer its recessive duration.

III. Data

To assess the effect of FD on the DBC we draw upon a dataset of 96 banking crises in 75 countries over the 1977-2014 period (see Table A in the Online Appendix (OA) for the list of countries and banking crises). Since the rise in banking crises and the deepening of financial systems in the recent decades concern both developed and developing countries, we account for the largest possible number of countries. In addition, since we lack repeated crises observations in the time dimension (only 20 countries in our sample experienced more than one banking crisis), we carry out a cross-section analysis in which the observation unit is at the crisis level.

3.1. Measurement of the duration of banking crises

The existing literature draws upon mainly two methods to measure the DBC. The first, and most popular, comes from studies on the determinants of the output cost of banking crises, and is based on a pre-crisis referential. The second is based on the dynamics of one or several variables after the outbreak of banking crises (see e.g. Angkinand, 2008, Cecchetti et al., 2009, or Wilms et al., 2018, for surveys on the measurement of the cost of banking crises).

With the first method, the DBC is measured as the time from the crisis occurrence until observed output (GDP, or its growth rate) reaches its pre-crisis level or its long-term trend. Three remarks could be made regarding this measure. First, it is sensitive to the choice of the time-window used to compute the pre-crisis benchmark; depending on the length of the window, the DBC could significantly vary and be under- or over-estimated. Second, given its exclusive focus on GDP or its growth rate, this measure ignores the dynamics of the banking sector; however, Demirgüç-Kunt et al. (2006) show that GDP growth reaches its pre-crisis level more rapidly than credit growth, suggesting that measures focusing only on GDP growth may under-estimate DBC. Third, this method omits that, after reaching their pre-crisis output level, some countries could enter a new recessive short-term spell, before actually exiting the banking crisis through a sustainable recovery, i.e. a "double dip" pattern emphasized by Reinhart & Rogoff (2014) that consists of a falling phase followed by a first short-term increase in GDP, and a new falling phase before a second increase in GDP that signals the end of the banking crisis. As such, not accounting for the persistence of the recovery following crises may under-estimate their duration.

With the second method, the DBC is mostly measured based on the dynamics of GDP growth after the occurrence of banking crises. Despite not being sensitive to the choice of a pre-crisis referential and capturing post-crisis recovery persistence, this measure omits the dynamics of the banking sector for defining the DBC.

Consequently, a more precise DBC measure should (i) account for the dynamics of both the banking sector and the real economy, (ii) not be sensitive to the choice of a pre-crisis referential, and (iii) characterize a sustainable exit from banking crises. To this end, we closely follow the strategy employed by Laeven & Valencia (2013) for building their banking crises database, and define the DBC based on the post-crises outbreak dynamics of two variables from the 2015 World Bank's *World Development Indicators* (WDI) database: (i) the growth of GDP per capita, and (ii) the growth of banks' credit to the private sector-to-GDP.

We use Laeven & Valencia's (2013) database to set the starting year of banking crises. Our first DBC measure (*Duration1*) is defined such as a banking crisis ends the year preceding the simultaneous observation of positive values for the growth of GDP per capita and the growth of banks' credit to the private sector-to-GDP. This corresponds to the measure used by Laeven & Valencia (2013), except that we do not fix a maximum length of 5 years for banking crises, since it may lead to under-estimating their duration. However, since *Duration1* takes into account only the year of immediate crisis exit, it does not consider any possible subsequent fall in GDP growth and/or credit growth. Therefore, we build a second DBC measure (*Duration2*), defined such as a banking crisis ends the year preceding the simultaneous observation of positive values during at least two consecutive years for the growth of GDP per capita and the growth of banks' credit to the private sector-to-GDP.

These two DBC measures represent two complementary approaches to assess the dynamics of both the banking sector and the real economy in the aftermath of banking crises. *Duration1* can be viewed as a "short-term" DBC measure since it only accounts for the immediate recessive duration of banking crises, without considering the sustainability of crisis exit. *Duration2* can be viewed as a more "long-term" DBC measure because, by being more restrictive on the conditions of crisis exit, it captures a possible subsequent fall and thus longer DBC. Finally, following Angkinand (2008), since some countries in our sample experienced several banking crises, we limit the maximum duration of each crisis to the year preceding the occurrence of the next banking crisis. Table A in the OA presents the values of *Duration1* and *Duration2* for the 96 banking crises in our sample.

In line with previous studies on the aftermath of banking crises (see section 2.1), banking crises are highly persistent as their duration ranges between 1 and 14 years for *Duration1* with an average of roughly 4 years, and 1 and 24 years for *Duration2* with an average of around 7 years (see Tables B1-2 in the OA). This confirms the relevance of considering two DBC measures that depict different recessive dynamics following the occurrence of banking crises.

3.2. Measurement of financial development

Following e.g. Samargandi et al. (2015) and Mathonnat & Minea (2018), we measure FD in a multidimensional way with a composite index equal to the first factor extracted from a principal component analysis (PCA) applied to a set of six variables from the *Global Financial Development Database* (GFDD) of Cihak et al. (2013) that aim to proxy the size and the activity of the banking industry. Each variable is measured the year preceding the outbreak of a banking crisis.[4] First, *Liquid liabilities* (ratio M3-to-GDP) captures the size of financial intermediaries' liabilities, and proxies for the liquidity in the economy. Second,

[4] Given the importance of the banking sector in the functioning of financial systems in both developed and developed countries and also in explaining the aftermath of banking crises, our FD measure relies on bank-based data; we discuss in the robustness analysis the influence of the stock market development.

Bank assets (ratio of deposit bank assets-to-GDP) measures the size of financial intermediaries' assets, and assesses the importance of commercial banks for savings allocation and risk-taking before banking crises. Third, *Bank deposits* (ratio of bank deposits-to-GDP) captures banking sector's capacity to mobilize available savings. Fourth, *Bank ratio* (ratio of commercial bank assets, to the sum of commercial bank assets and the central bank assets) measures the relative size of commercial banks in savings' allocation compared to the central bank. Fifth, *Credits* (ratio of credits to the private sector by banks-to-GDP) captures the activity of financial intermediaries in their crucial task of channelling savings towards investment; this way, we also proxy the effect of credit-risk, and as such capture the procyclical dynamic of the credit supply during the upward phase of the financial cycle. Sixth, *Credits/Deposits* (ratio of credits to the private sector by banks-to-deposits) measures the intermediation capacity of the banking sector, and also the risk-taking behaviour of financial intermediaries leading to an increase in the liquidity risk triggered by a bank panic.[5]

Using a PCA to compute a composite FD index is especially relevant in our case because, except for *Credits/Deposits*, the variables we use to proxy FD are strongly correlated (see Table B3 in the OA). Thus, a PCA allows not only to extract a large proportion of the variability shared by these variables but also to avoid multicollinearity issues in our econometric analysis. The PCA (see Table B4 in the OA) reveals that most of variables' variance (70%) is accounted by the first factor. Except *Credits/Deposits*, and, to a lesser extent, *Bank ratio*, each variable is strongly correlated with the first factor, and few of their remaining variance is unexplained by it. This confirms the relevance of using the composite *FDindex* to proxy the overall level of FD before banking crises.[6]

3.3. A first look at the FD-DBC relationship

To get a preliminary view on the link between FD and DBC, we perform a non-parametric estimate of the survival probability of banking crises using the Kaplan-Meier estimator. Figure 1 reports the unconditional survival functions for *Duration1* and *Duration2* when the *FDindex* is above and below its median value (-0.32). Figure 1a shows that *Duration1* for the *FDindex* above its median is longer in almost all cases, which might support the hypothesis of an amplifying effect of FD on the DBC. However, Figure 1b with *Duration2* confirms this result only for banking crises lasting at most 10 years. Since *Duration2* accounts for possible

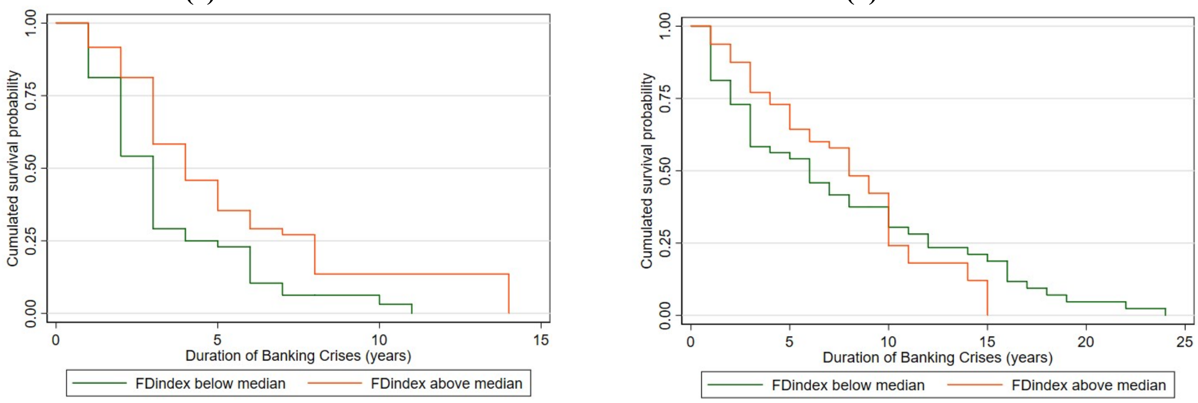
[5] Table B2 in the OA reports descriptive statistics for these variables.

[6] By using the *FDindex* our goal is not to identify the precise components of FD that influence DBC, but rather to determine if a global and synthetic measure of FD before banking crises may explain their length (Table B2 in the OA report descriptive statistics for the *FDindex*).

subsequent recessive falls, it seems that countries with higher FD are less subject to long banking crises, suggesting a potential heterogeneity in the effect of FD on the DBC. Nevertheless, banking crises lasting more than 10 years with *Duration2* are mainly observed in Sub-Saharan countries with weak macroeconomic and institutional environment that may equally explain the high persistence of banking crises in this region.

Figure 1. Kaplan-Meier survival functions for the DBC according to FDindex

(a) *Duration1* **(b) *Duration2***



To formally check these results, we perform an equality test of the two distributions (EoD). Since the Kolmogorov-Smirnov statistics for *Duration1* (*Duration2*) equals 0.38 (0.31), and the associated p-value equals 0.00 (0.02), we reject the null hypothesis of equality, meaning that on average the DBC is significantly longer for an *FDindex* above its median. To assess more in-depth how the *FDindex* affects the distribution of the DBC, we look at stochastic dominance tests (SDT). Let $Y_{i,t}$ be the survival probabilities of the comparison group, where i is a banking crisis at time t, and let its distribution be $F_t(y) \equiv \Pr[Y_{i,t} \leq y]$. Analogously, let $Y_{i,s}$ be the outcome variable of interest for crisis i at time s, with its corresponding distribution $F_s(y) \equiv \Pr[Y_{i,s} \leq y]$. Furthermore, let $D_1^{[t]}(y) = F_t(y)$, and we define higher orders o, such as $D_o^{[t]}(y) = \int_0^y D_{o-1}^{[t]}(x)dx$.[7] According to SDT in Table B5 in the OA, countries with higher pre-crisis FD experienced longer banking crises, measured by *Duration1* (this is confirmed by second-order dominance test, while the first-order is barely rejected). In addition, for *Duration2* we find a dominance path at order three. Therefore, SDT tend to support the hypothesis of an amplifying effect of FD on the DBC for both *Duration1* and *Duration2*, and this effect seems stronger for *Duration1*. Capitalizing on these preliminary findings, we carry out in the following a more detailed econometric analysis.

[7] Appendix E in the OA details the EoD and SDT.

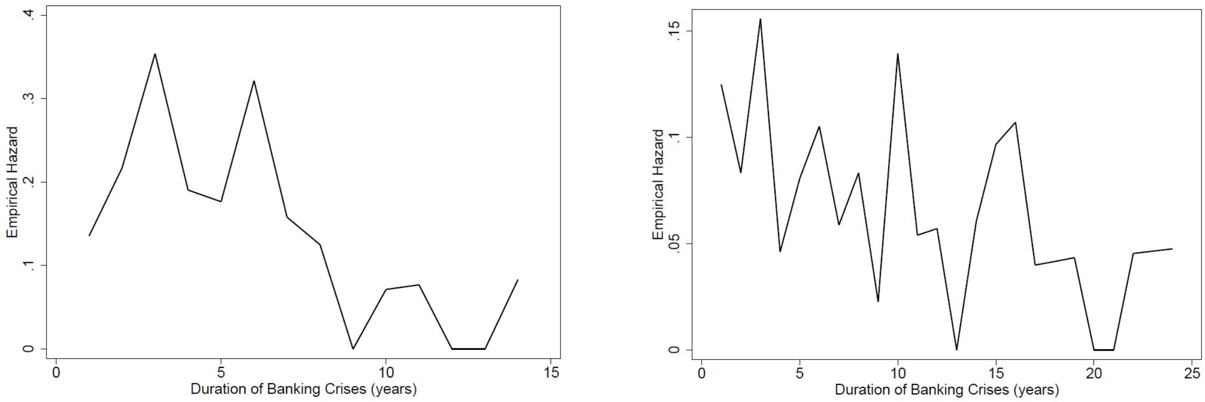
IV. Methodology

4.1. Hazard models

To estimate the relationship between FD and the DBC, we draw upon the semi-parametric mixed proportional hazard model (MPH) coined by Cox (1972). Compared to parametric duration models, the MPH has the advantage of imposing no assumption on the distribution of the baseline hazard rate. This is especially relevant in our context given the complexity of the empirical hazard rates of the DBC (i.e. the probability of exiting banking crisis over time) depicted in Figure 2. In addition, many banking crises in our sample have the same duration, making it difficult to isolate the ending probability of each of them; to break these ties, we employ Efron's (1977) method and use probability weights on the number of banking crises that ended at the preceding period. Moreover, 20 among the 75 countries in our sample experienced several banking crises over the 1977-2014 period, sometimes at close intervals; since the banking crises occurring in the same country may be correlated, we compute a variance-covariance matrix of estimated coefficient robust to within-country correlation following Lin & Wei (1989). Finally, we consider the binary variable *Multiple crises* equal to 1 if the banking crisis *j* occurs in country *i* that experienced several banking crises over the 1977-2014 period (and to 0 otherwise) among our control variables.

Figure 2. Estimated empirical hazard of DBC

(a) *Duration1* **(b) *Duration2***



4.2. Model specification

We estimate the effect of FD on the DBC using the following MPH model

$$h_j(t) = h_0(t)\exp\left(\alpha\, FD_{jt} + \beta\, X_{jt}\right), \tag{1}$$

with $j = \overline{1,N}$ the number of banking crises, $t = \overline{1,T}$ the DBC, $h_j(t)$ the hazard rate of banking crisis j, $h_0(t)$ the baseline hazard identical for all banking crises j, *FDindex* the composite FD measure, and X a vector of DBC determinants. In addition, we include regional dummies to control for unobserved heterogeneity at the regional level (based on World Bank's classification, the six regions are: Eastern and Pacific Asia, Central and Eastern Europe & Central Asia, Northern Africa & Middle East, Sub-Saharan Africa, Latin America & Caribbean, and Western Europe & North America).

Based on Cecchetti et al. (2009) and Wilms et al. (2018), we consider in the vector X three sets of potential DBC determinants. *Pre-crisis* proxies for macroeconomic, financial (including credit growth and credit boom variables) and institutional conditions preceding banking crises, and we distinguish between pre-crisis *internal* and *external conditions*. *Crisis* contains measures of the severity of banking crises (e.g. if they are systemic, or associated with the occurrence of currency and/or sovereign debt crises). *Post-crisis* refers to economic policies implemented to fight banking crises (*internal conditions*), and international macroeconomic and financial conditions during each crisis (*external conditions*).[8]

Among the 32 potential DBC determinants in vector X,[9] we select the most relevant ones for our baseline estimations using a two-step procedure. First, using a MPH model with regional dummies, but without the *FDindex*, each control variable was regressed on the hazard rate associated with *Duration1*; retained variables were those significant at least at 10%, leading to 16 variables. Second, using a *stepwise* selection procedure, we estimated a MPH model where all 16 variables are jointly regressed on *Duration1*. We conserved those significant at least at 10% for our baseline estimations, leading to 8 variables belonging to our three sets of DBC determinants, namely: *Regional banking*, *Log gdppc*, *FDI*, *Systemic crises*, *Subprime crises*, *World banking post*, *World GDP growth post* and *IMF program*. Finally, to ensure the comparability of our results for the two DBC measures, we also use this set of variables with *Duration2*, all the more given that the same two-step procedure leads to the selection of a close set of control variables.

V. Main Results

5.1 Diagnostic tests, and control variables

Table 1 presents the estimations based on the MPH model. To check their validity, we ran two tests. First, the Grambsch & Therneau (1994) test, based on Schoenfeld's residuals, confirms that the key proportional hazard hypothesis needed to obtain unbiased estimates is verified for

[8] We abstract from *Post-crisis* variables accounting for macroeconomic and financial domestic conditions in the aftermath of banking crises to avoid a potential simultaneity bias with the DBC.
[9] Definitions, sources, and descriptive statistics are reported in Table B6-7 in the OA.

the specific effect of the *FDindex* (*PH test FDindex*) and for the average effect of all covariates (*PH test global*). Second, the concordance C-test of Harrell et al. (1982), which measures the closeness between predicted and observed DBC, reveals a high explanatory power of our model, since the rate of good DBC predictions is above 90%.

Regarding control variables, reported coefficients are hazard ratios showing the effect of each variable in terms of proportional change of the ratio between the hazard rate and the baseline hazard rate: a coefficient significantly above (below) 1 indicates an increase (decrease) in the exit probability of banking crises. Focusing on *Duration1*, the effect of all control variables is significant, except for GDP per capita (*Log gdppc*; see Reinhart & Rogoff, 2013, for a possible explanation). Five variables are associated with a decrease in the probability of exiting banking crises: longer banking crises are those that are systemic (*Systemic crises*) and related to the subprime crisis (*Subprime crises*), and those followed by a higher world GDP growth rate (*World GDP growth post)*, a larger number of banking crises worldwide (*World banking post)*, and the presence of IMF programs *(IMF program*). On the contrary, two variables are associated with an increase in the probability of exiting banking crises, namely when preceded by more banking crises in the same region (*Regional banking*), and by higher foreign direct investment inflows (*FDI*).[10]

5.2 FD and the DBC

Table 1 shows that a pre-crisis increase in FD is associated with a significant increase in the DBC, irrespective of its measure. The stability of *FDindex* coefficients, both for *Duration1* and *Duration2*, and for different sets of control variables, suggests that the size of the potential bias coming from selection on unobservables is fairly weak (Altonji et al., 2005). The magnitude of the estimated effect is also important: a one-unit increase in the *FDindex*, corresponding to roughly one standard deviation, decreases the probability of exiting banking crises by about 65%. Corroborating estimations performed on *Duration1*, which indicate that higher FD increases the DBC in the short-term, similar findings arise when considering a more long-term perspective on the DBC using *Duration2*.

These results confirm our hypothesis of an amplifying effect of FD on the DBC. In line with the analysis carried out in section 2, a possible interpretation could be that an increase in the pre-crisis size and activity of the banking sector, by strengthening the pro-

[10] Results are comparable for *Duration2*, except for the absence of significance of Systemic crises and Regional banking, and for the change in the sign of the effect of FDI.

cyclicality of the financial sector-real economy relationship, might expose banks to shocks, and thus increase the recessive length of banking crises.

Table 1. Financial development and the duration of banking crises

	Duration1				Duration2			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
FDindex	0.362***	0.294***	0.321***	0.312***	0.385***	0.325***	0.340***	0.335***
	[0.116]	[0.118]	[0.133]	[0.116]	[0.119]	[0.0893]	[0.0948]	[0.119]
Regional banking (t-1)		1.393***	1.417***	1.532***		1.072	1.082	1.112
		[0.168]	[0.163]	[0.138]		[0.183]	[0.192]	[0.171]
Log gdppc (t-1)		0.870	0.869	0.766		1.456	1.469	1.143
		[0.245]	[0.252]	[0.207]		[0.387]	[0.393]	[0.272]
FDI (t-1)		1.034***	1.038***	1.043***		0.960**	0.964*	0.957**
		[0.00937]	[0.00913]	[0.00878]		[0.0197]	[0.0197]	[0.0174]
Systemic crises			0.581**	0.526*			0.779	1.304
			[0.160]	[0.185]			[0.318]	[0.794]
Subprime crises			0.509	0.0710***			0.702	0.187***
			[0.242]	[0.0380]			[0.444]	[0.103]
World GDP growth post				0.501***				0.471**
				[0.109]				[0.142]
World banking post				0.918***				0.936***
				[0.00976]				[0.00869]
IMF program				0.611***				0.571***
				[0.0954]				[0.0825]
Regional dummies	Yes							
Crises/Countries	96/75	94/73	94/73	94/73	96/75	94/73	94/73	94/73
Log likelihood	-300.65	-285.16	-283.35	-239.75	-258.00	-247.00	-246.69	-191.95
AIC	615.31	590.32	590.69	509.51	530.01	514.00	517.39	413.90
BIC	633.26	615.75	621.21	547.66	547.96	539.43	547.91	452.05
Wald stat	27.36	36.93	39.68	201.75	39.15	43.41	42.85	150.87
Wald p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PH test global				0.20				0.65
PH test FDindex				0.43				0.67
C-stat				0.91				0.91

Note: coefficients displayed are hazard ratios. Robust standard errors according to the Lin & Wei (1989) method are reported in brackets. Efron (1977) method is used for tied failures. Wald stat and Wald p-value refer to a Wald test of joint significance of covariates. PH test global and PH test FDindex denote a proportional hazard test based on Schoenfeld's residuals for all covariates and for the *FDindex*, respectively. C-stat is the concordance specification test of Harrell et al. (1982). ***p<0.01, **p<0.05, *p<0.1.

5.3. Predicted DBC

We now assess the effect of FD on the predicted DBC. Since predicted DBC are obtained by inverting the estimated hazard, we resort to parametric duration models that allow the estimated hazard to be invertible. Based on the AIC and BIC information criteria, we selected the Weibull-distribution duration model for *Duration1* and the Gompertz-distribution duration model for *Duration2*. Table 2 indicates a sizeable difference between the DBC predicted on the basis of *Duration1* (4.8 years) compared to *Duration2* (8.0 years), confirming that these two variables capture two different DBC dimensions (a short- and a long-term perspective, respectively).

Then, to quantify the effect of a large change in FD on the DBC, we predict the average DBC as a function of the median value of observations located in the first and the last quintile of the *FDindex*. Table 2 shows that an important increase in FD, from -0.99 (lowest 20% of *FDindex* observations) to 1.61 (highest 20% of *FDindex* observations), increases the DBC by roughly 6 years for *Duration1* and 4 years for *Duration2*. As such, a rise in FD has a stronger negative effect on the probability of immediate exit from banking crises (*Duration1*). In reference to our previous discussion, this result may suggest that higher FD could amplify the recessive effect of the financial accelerator and debt deflation mechanisms following the outbreak of banking crises, maintaining the economy in a long-lasting recession.

Table 2. Predicted banking crises duration

	Duration1: Weibull	Duration2: Gompertz
	(1)	(2)
Mean predicted DBC	4.79	7.96
Lowest 20% of FDindex	2.67	6.72
Highest 20% of FDindex	8.61	10.50
Controls/Regional dummies	Yes/Yes	
Crises/Countries	94/73	
Log likelihood	-22.37	-46.09
AIC/BIC	78.75/121.98	126.18/169.42
Wald-stat/p-value	157.97/0.00	147.18/0.00

Note: mean predicted DBC according to the median values of the lowest 20% (-0.99) and highest 20% (1.61) *FDindex* observations. Wald-stat and its p-value refer to a Wald test of joint significance of covariates. Within-country correlations of banking crises accounted with the Lin & Wei (1989) method.

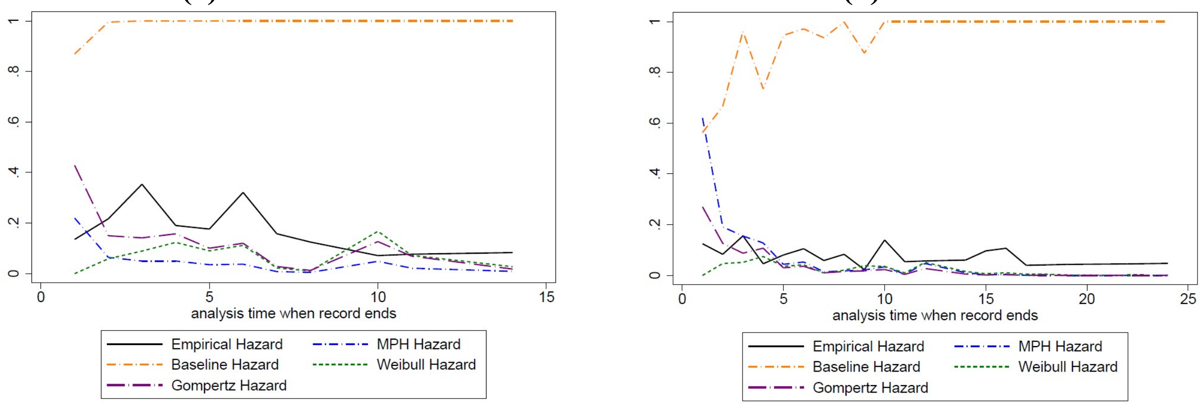
VI. Robustness: method

6.1. MPH performance compared to alternative estimation methods

Considering the MPH as our baseline model, Figure 3 reports the empirical hazard (the continuous line), together with the estimated MPH hazard and the baseline hazard. Despite that the MPH fits the data rather well (see section 5.1), its estimated baseline hazard is relatively flat (particularly for *Duration1*), suggesting that alternative methods might improve our estimations. Thus, we report on the same charts the estimated hazard rates from different parametric models for our two DBC measures. Intuitively, Figure 3 suggests that the Weibull model (for *Duration1*) and the Gompertz model (for *Duration2*) may outperform the MPH.

Figure 3. Performance of the MPH compared to parametric duration models

(a) *Duration1* **(b) *Duration2***



Starting from this observation, we implement Vuong (1989)'s test for discriminating between rival non-nested models. Vuong's test allows selecting a model over another if its average log-likelihood is significantly greater than the one of the rival model. Formally, comparing distributions H_{MPH} (the Cox model) and H_P (with P the Weibull and Gompertz parametric models for *Duration1* and *Duration2*, respectively), there are three possible outcomes: (i) the two distributions are equal; (ii) MPH outperforms P if the value of the test is large and positive; and (iii) MPH is worse than P if the value of the test is large and negative.[11] The calculated Vuong's statistic equals -14.98, and is statistically significant. This high negative value indicates that the Weibull model is closer to the true specification than the MPH model for *Duration1*, confirming the graphical intuition. Comparable results were found for *Duration2*: Vuong's statistic equals -6.64 and is statistically significant, suggesting that the Gompertz model is better than the MPH model.

Consequently, we evaluate the robustness of our baseline results when re-estimating columns (1d)-(2d) of Table 1 using the Weibull and Gompertz parametric duration models.[12] Columns (1a)-(2a) in Table 3 confirm that a pre-crisis increase in FD is associated with longer banking crises regardless of the parametric model used, and the magnitude of the effect is consistent with the MPH model.[13] Therefore, our analysis of the FD-DBC relationship focuses on the MPH model, as it avoids using different models for our two DBC measures.

Table 3. Parametric duration models estimates, and unobserved heterogeneity

	Duration 1: Weibull		**Duration 2: Gompertz**	
	(1a)	(1b)	(2a)	(2b)
FDindex	0.264*** [0.106]	0.264*** [0.088]	0.361*** [0.131]	0.361*** [0.118]
Regional dummies	Yes	Yes	Yes	Yes
Shared frailty (country)	No	Yes	No	Yes
Crises/Countries	94/73			
Log pseudo-likelihood	-22.37	-22.37	-46.09	-46.09
AIC/BIC	78.75/121.98	80.75/126.53	126.18/169.42	128.18/173.96
Wald-stat/p-value	157.97/0.00		147.18/0.00	
LR-stat/p-value		168.22/0.00		138.88/0.00
LR test frailty p-value		1.00		0.50

Note: coefficients displayed are hazard ratios. In columns (1a)-(2a) robust standard errors reported in brackets are computed according to the Lin & Wei (1989) method, and Wald stat and Wald p-value refer to a Wald test of joint significance of covariates. In columns (1b)-(2b) we account for shared frailty at the country-level with gamma distribution, LR stat and LR p-value refer to a likelihood ratio test of joint significance of covariates, and LR test frailty p-value corresponds to a likelihood ratio test of country-unobserved heterogeneity. ***p<0.01, **p<0.05, *p<0.1.

[11] Compared to Cox's test that may reject both models, i.e. an "absolute" test against the data, Vuong's test allows selecting the closest model to the true specification even if both models could be far from it, i.e. a "relative" test against the data, and of each model against each other (see Appendix E in the OA for details).

[12] Since the Weibull and Gompertz parametric duration models allow a proportional hazard formulation, their estimated coefficients are directly comparable to those coming from the MPH model.

[13] Our baseline results are also robust to the use of the main alternative parametric duration models based on exponential, log-normal, log-logistic, and gamma distributions (results are available upon request).

6.2. Unobserved heterogeneity, and endogeneity

The flat baseline hazard estimated with the MPH model (see Figure 3) may suggest either the presence of unobserved heterogeneity, or a strong DBC persistence. In our sample, unobserved heterogeneity may arise, for instance, from differences between countries regarding the extent of concentration of their banking sector, or the quality of the regulation of their financial system. Unfortunately, the use of existing data on banking sector concentration (e.g. World Bank's *Global Financial Development Database*) and on financial system regulation (e.g. Lee & Lu, 2015) would dramatically reduce the size of our sample. An alternative strategy to check if unobserved heterogeneity affects our results consists of re-estimating columns (1d)-(2d) of Table 1 using shared frailty at the country level. However, since we could not obtain convergent estimates with the MPH model, these estimations were realized with the Weibull and Gompertz parametric duration models. Results in Table 3 show that the likelihood ratio test (*LR test frailty p-value*) systematically accepts the null hypothesis of absence of country-unobserved heterogeneity. Therefore, estimations in columns (1b)-(2b) are very close to those associated with the Weibull and the Gompertz models without shared frailty, and confirm that FD significantly increases the DBC with a magnitude close to that in the MPH model. Thus, our baseline results are not affected by country-unobserved heterogeneity and the flat baseline hazard estimated with the MPH model reflects strong DBC persistence, in line with our discussion in section 2.

Finally, we perform a test to detect potential endogeneity. Drawing upon Huynh et al. (2010), we implement a split sample test to assess the presence of correlation between observables and unobservables in our sample. This test consists of the following five steps: (i) we randomly split the sample of crises in two equal parts; (ii) we estimate the duration model on the first sample based on covariates $x^{(1)}$, and retrieve the estimated coefficients $\hat{\beta}^{(1)}$; (iii) using $\hat{\beta}^{(1)}$ and second-sample covariates $x^{(2)}$, we create predicted durations, based on which we compute the difference between actual and predicted transformed durations: $\log\left(t^{(2*)}\right) = \log\left(t^{(2)}\right) - x'^{(2)}\hat{\beta}^{(1)}$; (iv) this new outcome variable is regressed against second sample covariates $x^{(2)}$, namely: $\log\left(t^{(2*)}\right) = -x'^{(2)}\hat{\beta}^{(2)} + \log\left(u^{(2)}\right)$; (v) finally, we construct a $\chi^2(m)$ test, with m the number of variables, in which the null hypothesis of no bias is $H_0 : \beta^{(2)} = 0$ (see Appendix E in the OA for details). The results of the split sample test show that irrespective of the type of randomization used (i.e. on crises and, alternatively, on countries, see Table C in the OA), the estimated coefficients of the *FDindex* are not significant, and this is also the case for almost all control variables (except for *Log gdppc* and *FDI* with *Duration1*). Consequently, our estimations of the FD-DBC relationship do not seem to suffer from endogeneity coming from correlation between observables and unobservables in our sample.

VII. Robustness: alternative FD measures, outliers, and control variables

In complement to the previous section, we explore the robustness of our main results to alternative FD measures, the presence of outliers, and additional control variables.

7.1. Alternatives FD measures

First, as previously emphasized, the bilateral correlation between the variable *Credits/Deposits* and the other five FD variables is relatively low. Consequently, we compute the *FDindex2* as the first factor coming from a PCA based on all FD variables except *Credits/Deposits*. Second, measuring the *FDindex* the year before banking crises outbreak may lead to an overestimation of FD, because it relates to the pre-crisis upward phase of the financial cycle that may be associated with speculative bubbles. Thus, we compute the *FDindex3* based on the average values of all FD variables during the three years before the occurrence of banking crises (results of the PCA used to compute *FDindex2* and *FDindex3* are available upon request). Estimations in Table 4 show that accounting for alternative FD measures leaves our main results unchanged, in both significance and magnitude.

7.2. Outliers

To deal with the potential influence of DBC outliers, we remove banking crises of 14 (22 and 24) years for *Duration1* (*Duration2*), i.e. the longest crises in our sample. Moreover, we account for potential FD outliers by applying the *dfbeta* statistics to the *FDindex*. Finally, we look at outliers for all the explanatory variables included in our baseline model using the likelihood displacement test.[14] As shown by Table 4, dropping these potential outliers does not alter the significance of the effect of the *FDindex* on our two DBC measures.[15]

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[14] The *dfbeta* statistic equals the difference between the estimated coefficient of the *FDindex* on the full sample and those obtained when removing each observation sequentially; the larger the difference, the more an observation can be considered as an outlier. The likelihood displacement test assesses the aggregate change in estimated likelihood following the sequential removal of observations; the higher the gap between the likelihood for the full sample and the one obtained by removing a given observation, the more this observation could be considered as an outlier (details are available upon request).

[15] Comparable conclusions arise when we further drop DBC outliers, namely all DBC above 9 years (3 observations) for *Duration1* and above 16 years (5 observations) for *Duration2*; and also when we do not

Table 4. Alternative FD measures, and outliers

	FDindex2		FDindex3		DBC outliers		FDindex outliers		Overall outliers	
	Durat.1	**Durat.2**	**Durat.1**	**Durat.2**	**Durat.1**	**Durat.2**	**Durat.1**	**Durat.2**	**Durat.1**	**Durat.2**
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
FDindex	0.326***	0.346***	0.383***	0.380***	0.360***	0.335***	0.312***	0.335***	0.224***	0.277***
	[0.113]	[0.120]	[0.118]	[0.138]	[0.0997]	[0.119]	[0.116]	[0.119]	[0.083]	[0.103]
Controls/Reg. dum.	Yes/Yes									
Crises/Countries	92/72	92/72	93/72	93/72	93/72	94/73	94/73	94/73	93/72	93/73
Log likelihood	-235.88	-188.18	-237.80	-191.34	-235.78	-191.95	-239.75	-191.95	-235.92	-184.72
AIC	501.75	406.37	505.61	412.69	501.56	413.9	509.51	413.9	501.83	399.44
BIC	539.58	444.19	543.59	450.68	539.55	452.05	547.66	452.05	539.82	437.43
Wald stat	195.84	153.9	197.55	152.15	202.22	150.87	201.75	150.87	196.66	129.38
Wald p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PH test (global)	0.21	0.66	0.09	0.53	0.56	0.65	0.20	0.65	0.06	0.80
PH test (FDindex)	0.47	0.77	0.33	0.9	0.13	0.67	0.43	0.67	0.32	0.82
C-stat	0.91	0.91	0.90	0.91	0.91	0.91	0.91	0.91	0.91	0.92

Note: coefficients displayed are hazard ratios. Robust standard errors according to the Lin & Wei (1989) method are reported in brackets. Efron (1977) method is used for tied failures. AIC and BIC are respectively Akaike and Bayesian information criteria. Wald stat and Wald p-value refer to a Wald test of joint significance of covariates. PH test global and FDindex denote a proportional hazard test based on Schoenfeld's residuals for all covariates and for the *FDindex*, respectively. C-stat is the concordance specification test of Harrell et al. (1982). ***p<0.01, **p<0.05, *p<0.1.

7.3. Additional control variables

First, we account for two additional characteristics of financial systems that may be correlated with both our bank-based measure of FD and the DBC, namely the degree of financial liberalization and the level of stock market development. Highly-liberalized financial systems are associated with a strong competition between financial institutions that may increase risk-taking (Amess & Demetriades, 2010). This leads to a rapid growth in both credit and asset prices during the upward phase of the financial cycle (Kaminsky & Reinhart, 1999), with a subsequent rise in financial fragility that may trigger banking crises. Besides, in financial systems with developed stock markets, agents' wealth is more sensitive to asset prices fluctuations (Rajan, 2005; IMF, 2006). This influences the access conditions to credit and may strengthen the recessive impact of banking crises due to greater instability in the credit supply and broad deleveraging operations. As such, it would not be the size and the activity of the banking system *per se* that would increase the DBC, but rather the fact that financial systems with a more developed banking sector are also those with higher financial liberalization and stock markets development.

We account for the pre-crisis internal and external dimensions of financial liberalization policies using the *Financial liberalization* variable, corresponding to the financial liberalization index of Abiad et al. (2008), and the *Financial openness* variable that is the updated *de jure* measure of capital account openness from Chinn & Ito (2006) (see

truncate the DBC until the beginning of the next crisis for the three countries concerned with this issue in our sample, namely Argentina, Brazil, and Cameroon (results are available upon request).

Bekaert et al, 2005, 2011; Bekaert et al., 2016). Stock market development is captured through the composite index *SMindex*, which corresponds to the first factor derived from a PCA applied to the pre-crisis values of three variables coming from the World Bank's GFDD database: *Capitalization* (stock market capitalization-to-GDP), *Liquidity* (stock market total value traded-to-GDP), and *Turnover ratio* (*Liquidity/Capitalization*).[16] As shown by Table D3 in the OA, financial liberalization and stock market development variables are not significant (except *Financial openness* for *Duration1*), while for all specifications the *FDindex* is still significantly and positively associated with the DBC.[17] This suggests that our baseline results are not driven by correlations between our bank-based measure of FD and these two additional features of financial systems.[18]

Second, we sequentially introduce all the variables that were not included in our baseline MPH model (see section 4.2). Irrespective of the considered variable, higher FD still significantly increases DBC, with a magnitude comparable with our baseline findings (see Tables D4a-d in the OA). Therefore, since we account for either the pre-crisis growth of banks' credit or the credit boom, our baseline results are not driven by an important surge in the growth of credit supply before the outbreak of banking crises: more developed financial systems represent an independent and significant factor contributing to longer banking crises due to e.g. higher sensitivity to shocks and the amplification of their recessive consequences.[19]

VIII. Heterogeneity in the effect of FD on DBC

In this section, we look at potential nonlinearities in the FD-DBC relationship, and at possible heterogeneities related to the time period, and the level of economic development.

8.1. Nonlinearities

Recent studies highlight a non-linear effect of FD on economic growth (Law & Singh, 2014) or on the occurrence of banking crises (Mathonnat & Minea, 2018). Here, we look for a

[16] Definitions and descriptive statistics of these variables are reported in Tables D1-2 in the OA, and the results from the PCA used to compute the *SMindex* are available upon request.

[17] Although the effect of the *FDindex* is of higher magnitude when using the *SMindex*, this is mainly driven by losing roughly half of observations following its introduction (as shown by columns (1d)-(2d) in Table D3 in the OA, where we re-estimate our baseline MPH model using exclusively the available *SMindex* observations).

[18] We report comparable findings when we account for the seven sub-indicators used for the computation of the financial liberalization index (*Financial lib.*, from Abiad et al., 2008) to capture the regulatory environment of countries' financial system (results are available upon request).

[19] Our results are also robust when accounting, using data from Laeven and Valencia (2013), more in-depth for the different containment and resolution policies implemented by the central bank and the Treasury to fight the adverse consequences of banking crises (results are available upon request).

potential non-linear effect of FD on the DBC. Indeed, above a certain size threshold, the banking sector benefits from a better management of information asymmetries and more risk diversification (Levine, 2005), which may increase the resilience of financial intermediaries to banking crises. However, higher FD may equally be associated with less productive and more speculative credit allocation (Beck, 2012), making the banking system less resilient following crises. To deal with this issue in a non-linear model such as the MPH, we split the increasingly-ordered *FDindex* in quartiles (for instance, *FDindexQ1* equals the *FDindex* for observations in the first FD quartile, and 0 otherwise). According to columns (1a)-(2a) in Table 5, the DBC significantly increases only for low (*FDindexQ1*) and high (*FDindexQ4*) FD levels, but not for intermediate levels (*FDindexQ2* and *FDindexQ3*). These results amend our baseline findings, and suggest that both previous arguments on the potential non-linear relationship between FD and the DBC might hold.

Table 5. Accounting for heterogeneity in the FD-DBC relationship

	Duration1				**Duration2**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
FDindexQ1	0.422*				0.338**			
	[0.186]				[0.176]			
FDindexQ2	0.82				0.58			
	[0.524]				[0.549]			
FDindexQ3	0.554				1.198			
	[0.624]				[1.680]			
FDindexQ4	0.277**				0.367**			
	[0.159]				[0.143]			
FDindex 1980s		0.290***				0.339**		
		[0.134]				[0.165]		
FDindex 1990s		0.353***				0.304***		
		[0.133]				[0.0990]		
FDindex 2000s		0.175***				0.346*		
		[0.101]				[0.201]		
FDindex DC			0.473**				0.429*	
			[0.159]				[0.193]	
FDindex DV				0.207**				0.250
				[0.150]				[0.240]
Controls/Reg. dummies	Yes							
Crises/Countries	94/73	93/73	70/52	24/21	94/73	93/73	70/52	24/21
Log likelihood	-239.01	-234.41	-183.76	-18.9	-191.41	-237.11	-148.24	-9.61
AIC	514.02	502.82	385.52	55.8	418.82	508.22	314.48	35.22
BIC	559.8	545.87	405.76	66.4	464.6	551.27	334.72	44.65
Wald stat	211.63	210.53	127.87	158.09	186.95	56.66	144.26	2800.1
Wald p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PH test (global)	0.11	0.04	0.01	0.29	0.70	0.00	0.56	1.00
PH test (FDindex)			0.62	0.99			0.28	0.39
C-stat	0.28	0.91	0.89	0.96	0.91	0.77	0.90	0.96

Note: coefficients displayed are hazard ratios. Robust standard errors according to the Lin & Wei (1989) method are reported in brackets. Efron (1977) method is used for tied failures. AIC and BIC are respectively Akaike and Bayesian information criteria. Wald stat and Wald p-value refer to a Wald test of joint significance of covariates. PH test global and FDindex denote a proportional hazard test based on Schoenfeld's residuals for all covariates and for the *FDindex*, respectively. C-stat is the concordance specification test of Harrell et al. (1982). ***p<0.01, **p<0.05, *p<0.1.

8.2. The time period

During the period covered by our sample (1977-2014), financial systems experienced substantial transformations in their size and structure, for example due to financial innovations and financial liberalization policies. To explore potential temporal heterogeneities in the effect of FD on the DBC, we split the *FDindex* by differentiating between three periods: the 1980s (1977-1989), the 1990s (1990-1999), and the 2000s (2000-2014). Results in columns (1b)-(2b) of Table 5 show that, regardless of the period considered, the *FDindex* is significantly associated with an increase in the DBC. Furthermore, the estimated effect of FD on the DBC is larger in the last period (2000s) when using *Duration1*, while fairly stable across periods for *Duration2*. In light of the recent history of several developed countries having been struck by the subprime crisis, the strong deepening of the banking sector during the first-half of the 2000's may have amplified the recessive consequences of banking crises, maintaining the economy in a longer recessive state without short-term economic recovery.

8.3. The level of economic development

Despite the non-significance of GDP per capita (*Log gdppc*) in our baseline regressions, several arguments may advocate for potential differences in the FD-DBC relationship between developed (DV) and developing (DC) countries. On the one hand, DC are characterized by higher agents' dependence on the banking sector to obtain external financing due to less developed capital markets (Levine, 2005), less effective regulation and supervision of the financial sector (Demirguc-Kunt & Detragiache, 2005), a rapid and late implementation of financial liberalization policies in a weak institutional context (Reinhart & Rogoff, 2009), and a greater pro-cyclicality in the access to foreign financing (Eichengreen et al., 2003). These features may magnify the effect of FD on the DBC in DC. On the other hand, financial systems in DV are larger, more complex, and more interconnected (Rajan, 2005), and are characterized by stronger interdependence between financial markets and financial intermediaries (Laeven, 2011). This may increase systemic risk and credit supply instability, and thus amplify the recessionary impact of banking crises. Based on World Bank's classification, we divide our sample into DV and DC, and re-estimate our baseline MPH model. Estimations in columns (1c)-(1d) of Table 5 suggest that higher FD is associated with longer crises in both DV and DC. Depending on the considered measure of the DBC, both previous explanations can hold, since the effect of FD on the DBC is somewhat stronger for DV (DC) for *Duration1* (*Duration2*).

IX. Conclusion

Several empirical studies highlight a significant role of FD in amplifying the output cost of banking crises. However, no study has so far investigated the effect of FD on another key dimension of banking crises, namely their duration. Using a large sample of 96 banking crises in 75 countries over the 1977-2014 period, the goal of this paper was to assess the relationship between FD and the DBC. Estimations showed that higher FD significantly increases the DBC. This result is robust to a broad range of alternative specifications, and is not affected by unobserved heterogeneity or endogeneity. Additional estimations suggested that the effect of FD on the DBC is subject to non-linearities, and varies across decades and with the level of economic development.

Our findings may contribute to the current debate on the consequences of banking crises, since they show that, beyond its amplifying effect on the output cost of banking crises, a higher FD can also increase the duration of banking crises. A possible interpretation is that an increase in the pre-crisis level of FD, by strengthening the pro-cyclicality of the financial sector-real economy relationship, might additionally expose banks to shocks, and, as a result, amplify the recessive length of banking crises. Therefore, our findings suggest that larger financial systems might not act as a countercyclical factor in times of crisis but, on the contrary, could play a key role in the amplification of shocks.

Over the last decades many developed and developing countries experienced a significant deepening of their financial system that went hand in hand with a higher exposure to banking crises. Our analysis highlights the strong interdependence between these two factors in the form of periods of financial instability associated with a contraction of the real economy resulting from a higher level of financial development. Given the potential negative consequences for political and social stability or economic growth, regulations that aim at limiting the pro-cyclicality of the financial sector during the upward phase of the cycle, through more constraints on the size and the activity of the banking sector, may potentially reduce the adverse effects of banking crises on the real economy and the financial system.

We see several directions for future work. First, close to our analysis, it would be interesting to investigate the relationship between FD and the duration of other types of financial crises. Second, one may look at dimensions of FD that may limit the DBC, like the access to and the efficiency of the banking system and financial markets, or study the extent to which various policies—and particularly trade policies, see Falvey et al. (2012)—could be used to reduce the duration of FD-driven banking crises. Finally, provided that higher-frequency macroeconomic data become available, a valuable contribution would consist of observing the international spread of risk through the financial system, all the more if such data could be coupled with more disaggregated data allowing accounting for the transmission channels and the response to various policymakers' regulations.

References

A. Abiad, E. Detragiache & T. Tressel (2008). A New Database of Financial Reforms, IMF wp 266.

A. Angkinand (2008). Output loss and recovery from banking and currency crises: estimation issues, *manuscript*.

J. Altonji, T. Elder & C. Taber (2005). Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools, *Journal of Political Economy* 113, 151-184.

K. Amess & P. Demetriades (2010). Financial Liberalisation and the South Korean Financial Crisis: An Analysis of Expert Opinion, *World Economy* 33, 212-238.

J. Babecky, T. Havranek, J. Mateju, M. Rusnak, K. Smidkova & B. Vasicek (2014). Banking, debt, and currency crises in developed countries: Stylized facts and early warning indicators, *Journal of Financial Stability* 15, 1-17.

L.M. Ball (2014). Long-Term Damage from the Great Recession in OECD Countries, NBER wp 20185.

T. Beck, E. Feyen, A. Ize & F. Moizeszowicz (2008). Benchmarking Financial Development, World Bank Policy Research wp 4638.

T. Beck (2012). The Role of Finance in Economic Development: Benefits, Risks, and Politics, in Dennis Muller (eds.): *Oxford Handbook of Capitalism*.

T. Beck, T. Chen, C. Lin & F.M. Song (2016). Financial innovation: The bright and the dark sides, *Journal of Banking and Finance* 72, 28-51.

T. Beck, H. Degryse & C. Kneer (2014). Is more finance better? Disentangling intermediation and size effects of financial systems, *Journal of Financial Stability* 10, 50-64.

G. Bekaert, C. Harvey & C. Lundblad (2005). Does financial liberalization spur growth?, *Journal of Financial Economics* 77, 3-55.

G. Bekaert, C. Harvey & C. Lundblad (2011). Financial Openness and Productivity, *World Development* 39, 1-19.

G. Bekaert, C. Harvey, A. Kiguel & X. Wang (2016). Globalization and Asset Returns, *Annual Review of Financial Economics* 8, 221-288.

S. Berkmen, G. Gelos, R. Rennhack & J. Walsh (2012). The global financial crisis: Explaining cross-country differences in the output impact, *Journal of International Money and Finance* 31, 42-59.

B. Bernanke & M. Gertler (1989). Agency Costs, Net Worth, and Business Fluctuations, *American Economic Review* 79, 14-31.

B. Bernanke, M. Gertler & S. Gilchrist (1999). The financial accelerator in a Quantitative Business Cycle Framework, in J. Taylor (eds.): *Handbook of Macroeconomics* 1. Amsterdam: North-Holland, 1341-1393.

M. Bordo, B. Eichengreen, D. Klingebiel, M. Soledad Martinez-Peria & A. Rose (2001). Is the Crisis Problem Growing More Severe?, *Economic Policy* 16, 53-82.

J. Boyd, S. Kwak & B. Smith (2005). The real output losses associated with modern banking crises, *Journal of Money, Credit and Banking* 37, 977-999.

S. Cecchetti, M. Kohler & C. Upper (2009). Financial crises and economic activity, NBER wp 15379.

V. Cerra & S.C. Saxena (2008). Growth Dynamics: The Myth of Economic Recovery, *American Economic Review* 98, 439-457.

M. Chinn & H. Ito (2006). What Matters for Financial Development? Capital Controls, Institutions, and Interactions, *Journal of Development Economics* 81, 163-192.
M. Cihak, A. Demirgüç-Kunt, E. Feyen & R. Levine (2013). Financial Development in 205 Economies, 1960-2010, NBER wp 18946.
S. Claessens, G. Dell'Ariccia, D. Igan & L. Laeven (2010). Lessons and Policy Implications from the Global Financial Crisis, IMF wp 44.
S. Claessens & M.A. Kose (2013). Financial Crises: Explanations, Types, and Implications, IMF wp 28.
D. Cox (1972). Regression models and life-tables (with discussion), *Journal of the Royal Statistical Society* 30, 187-220.
R. Davidson & J.-Y. Duclos (2000). Statistical inference for stochastic dominance and for the measurement of poverty and inequality, *Econometrica* 68, 1435-1464.
G. Dell'Ariccia, E. Detragiache & R. Rajan (2008). The real effect of banking crises, *Journal of Financial Intermediation* 17, 89-112.
P. Demetriades (2017). *A Diary of the Euro Crisis in Cyprus: Lessons for Bank Recovery and Resolution*. Palgrave Macmillan.
A. Demirgüç-Kunt & E. Detragiache (2005). Cross-Country Empirical Studies of Systemic Banking Distress: A Survey, *National Institute Economic Review* 192, 68-83.
A. Demirgüç-Kunt, E. Detragiache & P. Gupta (2006). Inside the crisis: An empirical analysis of banking systems in distress, *Journal of International Money and Finance* 25, 702-718.
B. Efron (1977). The efficiency of Cox's likelihood function for censored data, *Journal of the American Statistical Association* 72, 557-565.
G. Eggertsson & P. Krugman (2012). Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach, *Quarterly Journal of Economics* 127, 1469-1513.
B. Eichengreen, R. Hausmann & U. Panizza (2003). Currency Mismatches, Debt Intolerance and Original Sin: Why They Are Not the Same and Why it Matters, NBER wp 10036.
R. Falvey, N. Foster & D. Greenaway (2012). Trade Liberalization, Economic Crises, and Growth, *World Development* 40, 2177-2193.
I. Fisher (1933). Debt Deflation, *Econometrica* 1, 337-357.
D. Furceri & A. Mourougane (2012). The effects of financial crises on potential output: New empirical evidence from OECD countries, *Journal of Macroeconomics* 34, 822-832.
D. Furceri & A. Zdzienicka (2012). Banking Crises and Short and Medium Term Output Losses in Emerging and Developing Countries: The Role of Structural and Policy Variables, *World Development* 40, 2369-2378.
M. Gertler & N. Kiyotaki (2011). Financial intermediation and credit policy in business cycle analysis, *Handbook of Monetary Economics* 3, 547-599, Amsterdam: Elsevier.
M. Gertler & N. Kiyotaki (2012). Banking, Liquidity, and Bank Runs in an Infinite Horizon Economy, *American Economic Review* 105, 2011-2043.
P. Grambsch & T. Therneau (1994). Proportional hazards tests and diagnostics based on weighted residuals, *Biometrika* 81, 515-526.
F. Harrell Jr., R. Califf, D. Pryor, K. Lee & R. Rosati (1982). Evaluating the yield of medical tests, *Journal of the American Medical Association* 247, 2543-2546.
M. Hutchison (2003). A cure worse than the disease? Currency crises and the output costs of IMF-supported stabilization programs, in M. Dooley & J. Frankel, (eds.) *Managing Currency Crises in Emerging Markets*. Chicago: University of Chicago Press.
K. Huynh, R. Petrunia & M. Voia (2010). The Impact of Initial Financial State on Firm Duration Across Entry Cohorts, *Journal of Industrial Economics* 58, 661-689.

International Monetary Fund (2006). How do financial systems affect economic cycles?, *World Economic Outlook*, September.
O. Jorda, M. Schularick & A. Taylor (2013). When Credit Bites Back, *Journal of Money, Credit, and Banking* 45, 3-28.
O. Jorda, M. Schularick & A. Taylor (2015). Leveraged Bubbles, *Journal of Monetary Economics* 76, S1-S20.
O. Jorda, M. Schularick & A. Taylor (2016a). Sovereigns versus Banks: Credit, Crises, and Consequences, *Journal of the European Economic Association* 14, 45-79.
O. Jorda, M. Schularick & A. Taylor (2016b). The Great Mortgaging: Housing Finance, Crises and Business Cycles, *Economic Policy* 31, 107-152.
G. Kaminsky & C. Reinhart (1999). The Twin Crises: The Causes of Banking and Balance-of-Payments Problems, *American Economic Review* 89, 473-500.
C. Kindleberger (1978). *Manias, Panics, and Crashes: A History of Financial Crises*, New York: Palgrave Macmillan.
N. Kiyotaki & J. Moore (1997). Credit Cycles, *Journal of Political Economy* 105, 211-248.
R. Kroszner, L. Laeven & D. Klingebiel (2007). Banking crises, financial dependence and growth, *Journal of Financial Economics* 84, 187-228.
L. Laeven (2011). Banking Crises: A Review, *Annual Review of Financial Economics* 3, 17-40.
L. Laeven & F. Valencia (2013). Systemic Banking Crises Database, *IMF Economic Review* 61, 225-270.
S. Law & N. Singh (2014). Does too much finance harm economic growth?, *Journal of Banking and Finance* 41, 36-44.
K. Lee & W. Lu (2015). Do bank regulation and supervision matter? International evidence from the recent financial crisis, *Journal of Financial Economic Policy* 7, 275-288.
R. Levine (2005). Finance and Growth: Theory and Evidence, in P. Aghion & S.N. Durlauf (eds.), *Handbook of Economic Growth* 1, 865-910, Amsterdam: Elsevier.
D. Lin & L. Wei (1989). The robust inference for Cox proportional hazards model, *Journal of the American Statistical Association* 84, 1074-1078.
D. López-Salido, J. Stein & E. Zakrajšek (2017). Credit-Market Sentiment and the Business Cycle, *Quarterly Journal of Economics* 132, 1373-1426.
C. Mathonnat & A. Minea (2018). Financial development and the occurrence of banking crises, *Journal of Banking and Finance* 96, 344-354.
H. Minsky (1986). *Stabilizing an Unstable Economy*, New Haven, CN: Yale University Press.
F. Mishkin (1996). Understanding Financial Crises: A Developing Country Perspective, IMF wp 5600.
V. Pesic (2012). The Real Effects of Financial Crises: Evidence from an International Perspective, *American International Journal of Contemporary Research* 2, 55-65.
R. Rajan (2005). Has Financial Development Made The World Riskier?, NBER wp 11728.
C. Reinhart & K. Rogoff (2009). *This time is different. Eight centuries of financial folly*, Princeton University Press: Princeton and Oxford.
C. Reinhart & K. Rogoff (2013). Banking crises: An equal opportunity menace, *Journal of Banking and Finance* 37, 4557-4573.
C. Reinhart & K. Rogoff (2014). Recovery from Financial Crises: Evidence from 100 Episodes, IMF wp 19823.
N. Samargandi, J. Firdmuc & S. Ghosh (2015). Is the Relationship Between Financial Development and Economic Growth Monotonic? Evidence from a Sample of Middle-Income Countries, *World Development* 68, 66-81.

V. Swamy & M. Dharani (2019). Thresholds of financial development in the Euro area, *World Economy*, early view.
Q. Vuong (1989). Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses, *Econometrica* 57, 307-333.
P. Wilms, J. Swank & J. de Haan (2018). Determinants of the real impact of banking crises: A review and new evidence, *The North American Journal of Economics and Finance* 43, 54-70.