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Stock Markets, Banks and Economic Growth in a Context of Common Shocks and Cross-Country Dependencies

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STOCK MARKETS, BANKS AND ECONOMIC GROWTH IN A CONTEXT OF COMMON SHOCKS AND CROSS-COUNTRY DEPENDENCIES[1]

ABSTRACT

Although a great deal of research has shown how stock markets and banks may relate to economic growth, such studies ignore the role that common shocks play in the finance-growth nexus. Using panels of 54 advanced and emerging economies, and novel common factor frameworks which account for dynamics, reverse causality, observed heterogeneities, and unobserved common shocks which cause error cross-sectional dependencies across countries, we find that stock market development has positive long-term effects on economic growth, while high levels of banking development might be detrimental to overall output. These results also hold for a subsample of advanced countries; however, despite the positive and significant effect that stock market development has on growth for a subsample of emerging countries, the negative effect of bank development is as likely to be significant as insignificant in this case. Moreover, we find that ignoring the strong error cross-sectional dependencies caused by common shocks and/or assuming homogeneous coefficients may yield inconsistent estimates.

Keywords: Economic Growth, Stock Market Development, Banking Development, Cross-Section Dependence, Multifactor Error Structure.

JEL Codes: C23, G21, O16, O40

RESUMEN

Aunque un elevado número de investigaciones han demostrado que los mercados de valores y los bancos pueden influir en el crecimiento económico, dichos trabajos ignoran el papel que las perturbaciones comunes juegan en el nexo finanzas-crecimiento económico. Usando datos de panel de 54 economías avanzadas y emergentes, además de nuevas estructuras de factores comunes que se toman en consideración para estudiar la dinámica, causalidad inversa, heterogeneidades observadas y perturbaciones comunes no observadas que causan errores de dependencia de corte transversal a través de los países, se encuentra que el desarrollo de los mercados de valores tiene unos efectos positivos de largo plazo sobre el crecimiento económico, mientras que los altos niveles de desarrollo bancario podrían resultar perjudiciales para la producción global. Estos resultados también se mantienen para una submuestra de países avanzados; sin embargo, a pesar del efecto positivo y significativo que el desarrollo del mercado de valores tiene sobre el crecimiento para la submuestra

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de países emergentes, el efecto negativo del desarrollo bancario es tan probable que sea negativo como positivo en este caso. Por otro lado, se ha encontrado que el hecho de ignorar los fuerte errores de dependencia de corte transversal provocados por las perturbaciones comunes y/o asumir coeficientes homogéneos pueden generar estimaciones inconsistentes.

Palabras clave: Crecimiento económico, desarrollo del mercado de valores, desarrollo bancario, dependencia de corte transversal, estructura de errores multifactoriales

**The Appendix of this article is available in the DT 04/17.*

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ÍNDICE

1. INTRODUCTION

Ever since the pioneering empirical studies of King and Levine (1993) and Levine and Zervos (1998), a large body of research has explored the effects of the development of both banks and equity markets on economic growth. Their insights into the functioning of financial systems have influenced economic policies and sparked the academic debate about the finance-growth nexus that emerged in the aftermath of the financial crisis of 2007-08. Our research contributes to this empirical literature by discussing the effects of unobserved common shocks on the relationship between finance and output growth. As Levine and Zervos (1998) note, common shocks to real activity and both banking and stock market development may drive the results of empirical studies. To our knowledge, previous studies have not addressed this concern sufficiently. Our research therefore asks: first, whether banking and stock market development boost long-run growth when common shocks are accounted for; and second, whether neglecting common shocks affects the consistency of estimates.

Our study has three novel features: First, we employ a multifactor error structure that accounts for unobserved common micro- and macroeconomic shocks which affect the economic growth and financial development of each country in different ways and cause error cross-section dependencies, which in the context of our work are related to the cross-country financial and economic contemporaneous correlations that emerge through several channels of global financial contagion. We also allow for parameter heterogeneity to address observed cross-country characteristics. Second, we account for such panel time series properties as dynamics, reverse causality and serial correlation in errors. Third, we construct two panels of 54 advanced and emerging countries. The first panel covers banking and stock market development from 1988 to 2012. The second panel, from 1961 to 2014, only covers bank development because the data for stock market development between 1961 and 1988-89 are scarce. Still, in contrast with the first panel, it allows us to better address the above panel time series properties and reduce a possible sample bias. We also derive two subsamples for emerging and advanced countries from those panels, employ several definitions for banking and stock market development and include additional variables to check the robustness of our results.

On the basis of the above approach, we find that the functioning of stock markets may smooth the effects of common shocks, continue to efficiently allocate resources, and thus promote economic growth. On the other hand, banking development might be detrimental to long-run output growth. That may happen because when financial systems reach high levels of depth, banks become vulnerable to common shocks and therefore susceptible to malfunction. This may cause inefficiencies in credit markets which hinder resource allocation and aggregate investment spending, and consequently curtail economic growth.

These results hold for the subsample of advanced countries. For the subsample of emerging countries, however, while we do find a positive effect of stock market development on growth, the negative effect of bank development is as likely to be significant as insignificant. Our findings also suggest that financial systems structure matters for growth (e.g. Luintel et al., 2008; Demirgüç-Kunt, et al., 2012). Moreover, we find that most of the models that ignore the strong error cross-sectional dependencies caused by unobserved common shocks and/or assume homogeneous coefficients yield inconsistent estimates.

The rest of this paper is organized as follows: Section 2 reviews the existing theoretical and empirical literature which motivates our empirical approach. Section 3 presents our empirical model, estimation methodology and data. Section 4 provides our results, and Section 5 concludes.

2. Theoretical and Empirical Literature and Motivation

2.1. Previous research

Many previous empirical studies on the finance-growth nexus build on the idea that financial systems aid technological progress and promote economic development (Schumpeter, 1934). They thus focus on (i), the functions of financial intermediaries and stock markets that foster the allocation of resources and the growth of output; and, (ii), the influence of country-specific factors on the functioning of financial systems.

A review by Levine (2005) states that banks and equity markets boost output growth by: first reducing the costs of finding information on possible investments; second, strengthening corporate governance; third, facilitating the trading, hedging and pooling of cross-sectional, intertemporal and liquidity risk; fourth, mobilizing savings more efficiently; and fifth, easing transactions and encouraging specialization and technological progress. Levine (2005) nevertheless makes a distinction between the role of stock markets and banks, whose functions are independent but complementary. For instance, stock markets are better at encouraging newer and riskier ventures, and develop richer risk management tools that allow the customization of risk ameliorating instruments, whereas banks are better at establishing long-term relationships with firms, privatizing the information that they acquire and offering better intertemporal risk sharing services.

A number of other studies (Rajan and Zingales, 1998; Allen and Gale, 1999; Deidda and Fattouh, 2008; Song and Thakor, 2010) argue that financial services influence economic activity, depending on country-specific features such as the degree of economic development, technological progress, liberalization and the legal and institutional framework.

Pioneering empirical studies which take the abovementioned issues into account find that (i), at an aggregate level, there is a positive relationship between financial development and economic growth (Goldsmith, 1969; King and Levine, 1993; Levine et al., 2000; Beck et al., 2000); and (ii), at a more specific level, security markets and banks are positively and independently correlated with economic performance (Levine and Zervos, 1998), and banking and stock markets have positive effects on growth (Arestis, et al., 2001; Beck and Levine, 2004). Levine (2002) adds that distinguishing countries by their overall level of financial development, rather than their financial systems structure, helps to explain cross-country differences in long-term economic performance.

However, other studies question those conclusions. Demetriades and Hussein (1996) find that, for some observations, there may be reverse causation running from economic growth to financial development, or they have no causal relationship. Basing themselves on the observed heterogeneities in the data, Peia and Roszbach (2015) find that when financial systems reach large levels of depth, stock market development has a positive effect on economic growth while banking development does not. Still other studies, some of which account for country or region-specific characteristics, find that banking development may have a negative long-term impact on economic performance, either directly (Narayan and Narayan, 2013; Bezemer et al., 2016) or because it may reach a threshold beyond which it negatively effects growth (Shen and Lee, 2006; Arcand et al, 2015).[2] This evidence complements the results of studies that show that financial systems structure seems to matter when accounting for observed heterogeneities in the data (Luintel et al., 2008),[3] or when the link between growth and both banking and stock

[2] Other studies, which in some cases consider observed heterogeneities, find either that financial development, at an aggregate level, has a vanishing effect on growth (Rousseau and Wachtel, 2011) or that its effect is only beneficial for growth up to a certain threshold, beyond which it may be detrimental (e.g. Cecchetti and Kharroubi, 2012; Aizenman et al., 2015; Arcand et al., 2015; Ductor and Grechyna, 2015). However, the studies of Beck et al. (2014), among others, warn that this conclusion should be viewed with caution due to the difficulties of measuring financial development, distinguishing the separate effects of the functions of financial systems, or examining the degree of the quality of finance and the access to credit by enterprises and households, among others aspects.

[3] In contrast with pioneering empirical studies, Luintel et al. (2008) also show that, due to the presence of observed heterogeneities across countries, the data cannot be pooled when examining the finance-growth nexus.

market development changes with the level of economic development (Demirgüç-Kunt, et al., 2012).

Nevertheless, most of these studies do not account for the effects of unobserved common shocks on the finance-growth nexus, even though Levine and Zervos (1998) do acknowledge that common shocks may have an effect on economic growth and both banking and stock market development variables. Some recent studies (for example, Aizenman et al., 2015) admit that the link between financial development and growth is tenuous, in view of certain factors hitherto unaccounted for, such as the damaging effects of credit cycles. Another aspect that is ignored in such studies is that unobserved common shocks may cause cross-country dependencies which are heightened by global financial networks and other channels of financial contagion. Disregarding such dependencies may lead to spurious inference.

2.2. Common shocks and the finance-growth nexus

In contrast with previous research, ours is the first to analyze the finance-growth relationship by accounting for unobserved common shocks that generate cross-country correlations. In the following lines we present the theoretical arguments which describe the reactions of financial systems to shocks, and the subsequent effects on the mobilization of resources toward productive activities, the dynamics of aggregate investment and output, and the economy. In line with these arguments, we then propose a strategy for empirical research to account for shocks as common across countries and variables.

A strand of theoretical investigations shows that financial systems can smooth the impact of shocks on an economy, in a way that the functioning of banks and stock markets keeps promoting an efficient resource allocation. For instance, financial intermediaries can facilitate the intergenerational diversification of risks, such as macroeconomic shocks (Allen and Gale, 1997), and can provide long-term loans or marketed liquid assets to firms so that they can protect themselves from liquidity shocks that would prevent them from completing their projects (Holström and Tirole, 1998). Moreover, when shocks arise, equity markets effectively bankrupt distressed firms that would otherwise damage the economy (Rajan and Zingales, 2003), reduce liquidity risks by facilitating trade (Levine, 1991), and ease cross-sectional risk sharing (Allen and Gale, 1997).

Another strand of theoretical research, however, argues that financial systems can instead spread and magnify the effect of shocks on the economy and hinder the allocation of savings toward productive activities. In line with the Fisher's (1933) debt-deflation idea, Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke et al. (1999), among others, reason that, when negative shocks affect the economy, the net worth of companies may decline (that is, their liquid assets plus their collateral value) and thus increase the firms' premium on external finance (which depends inversely on the firms' net worth) and the amount of external finance required. That, in turn, may cause malfunctions of financial systems because the costs of extending credit increase and the efficiency of allocation of resources is reduced. This worsening in credit-market conditions lead to a reduction of firms' investment spending and production, generate fluctuations in real activity, and exacerbate an economic downturn. This process, known as the financial accelerator, can also be seen in credit markets used by households, where credit restrictions to households affect consumption, housing investment and aggregate output (Aoki, Proudman and Vlieghe, 2004; Iacoviello, 2005); and equity markets, due to the interaction between the profits of companies, their market capitalization and their distance-to-default (Riccetti, Russo and Gallegati, 2016).

In addition to spreading shocks, financial systems may cause shocks of their own. For instance, Schularick and Taylor (2012) detect this when the leverage of financial systems becomes excessive, and take it as predictor of a coming financial crisis, an idea which is based on, among others, Minsky (1977) and Kindleberger (1978), who state that the formation of endogenous lending booms produces future economic instability.

Shocks also generate dependencies in financial systems, generally through several sources of contagion. Kaminsky et al. (2003), who characterize cross-country dependencies as adverse chain reactions among economies, argue that they (i) materialize via currency markets, the leverage of financial institutions, capital flows, international trade, and surprise announcements; and (ii), are associated with financial and economic instability.

The financial crisis of 2007-08 is an example of how dependencies can emerge in financial networks, which are a crucial source of contagion because they (i) interact with other sources of contagion and amplify their effects; and (ii), magnify the impact of shocks through bankruptcy costs, in the case of a default cascade, and liquidation costs and liquidity hoarding in a funding run (Glasserman and Young, 2016).[4] Although the

[4] Several works show how financial networks may spread the impact of adverse shocks and augment dependencies. For example, Allen and Gale (2000) and Acemoglu et al. (2015) find that the degree of connectivity of financial networks and the size and number of shocks may determine the extent to which such networks facilitate contagion and initiate a cascade of failures. Moreover, Elliot et al. (2014) observe that, in the face of intermediate shocks, this contagion causes cascades that occur in waves of dependencies (i.e. some initial failures are enough to cause a second wave of failures, which in turn cause a third and so forth), especially in networks that have intermediate levels of diversification (the number of counterparts per financial organization) and integration (the dependence on counterparts). In fact, there is evidence that cascading effects, occurring through a chain of long-term interbank loans, can spread through the global economy (Hale et al., 2016). Kodres and Pritzker (2002) and Pavlova and Rigobon (2008), among other works, also find that, in networks of asset markets, the effect of shocks is

real consequences of dependencies in financial networks have not yet been investigated, Glasserman and Young (2016) state that the impairment of contractual obligations in financial networks, as a results of the effects of exogenous shocks, may have negative repercussions on the economy, such as the generation of economic losses, lower availability of credit for funding new investments projects, liquidation of existing investments to meet short-term obligations, larger administrative and legal costs, delays in making payments, markdowns in the valuation of assets, and deteriorating conditions of households balance sheets which lead to reductions on consumption and underutilization of productive capacity in the economy.

While the studies we have just mentioned support our research, we believe there is a need to explain the relationship between shocks, the functioning of financial systems and the dynamics of output in a rigorous empirical way. Towards that end, we formulate the following two questions for empirical investigation: First, whether banking and stock market development foster long-run growth by taking common shocks into account; and second, whether neglecting such common shocks affects the consistency of estimates.

We model shocks using a multifactor error structure, so that they are unobserved and common to all economies, have an impact on both financial development and economic growth which differs across economies, and generate error cross-sectional dependencies, which, according to our approach, are related to the cross-country financial and economic dependencies that emerge through global financial networks and other channels of financial contagion. We also address country-specific features through heterogeneous coefficients.[5] By employing this empirical approach we expect that, if there is a link between finance and growth when unobserved common shocks arise, then the impact of financial variables on economic growth is positive so long as the functioning of banks and equity markets smooth (though do not necessarily eliminate) the effect of common shocks and keep allocating resources towards productive activities and thus foster growth. However, if the effect is negative, unobserved common factors might cause malfunctions in banks and stock markets which hinder the efficient allocation of resources towards productive activities, hamper aggregate investment spending, and consequently curtail economic growth.

Table 1 provides a summary of other factors that may explain such negative effect (particularly a possible detrimental impact of banking

amplified through informational contagion, which may produce informational cascades.

5 There is only one study, by Gantman and Dabós (2013), which has analyzed some of the empirical aspects that we study here to examine the finance-growth nexus. However, it does not address all the theoretical concerns which our study does, and ignores such empirical issues as dynamics, reverse causality, and strong/weak error cross-section dependence.

development on growth), and that were generally ignored in the past but have been addressed by some recent studies (e.g. Arcand et al., 2015).[6]

TABLE 1

Summary of additional factors that explain a negative effect of financial development on economic growth

Studies	Factors
Tobin (1984), Philippon and Reshef (2013), Cecchetti and Kharroubi (2015)	An extraction of excessively high informational rents that causes suboptimal allocation of talents toward the financial sector and generates diminishing social returns
Galor and Zeira (1993)	Credit market imperfections which at high levels of inequality obstruct the accumulation of human capital which enhances output growth
Jappelli and Pagano (1994)	A reduction on credit restrictions on households which leads to suboptimal low savings rates by households
Rajan (2006)	Excessive deregulation that may exacerbate financial cycles
Adrian and Shin (2010), Gennaioli et al. (2012)	Financial innovation and the birth of the shadow baking system
Beck et al. (2012), Bezemer et al. (2016)	The shifting of credit from enterprise ventures to households which may reduce investment in productive ventures
Farhi and Tirole (2012)	An implicit government insurance and the expectation of rescue operations for distressed institutions
Schularick and Taylor (2012)	The shrinkage of liquid safe assets that might serve as a buffer against economic stress
Aizenman et al. (2015)	Lower quality of credit which no longer boosts economic growth when financial systems reach a certain depth
Ductor and Grechyna (2015)	Rapid growth in private credit that is not accompanied by growth in real output

3. Empirical Methodology and Data

3.1. Empirical Specification

Since the main objective of our empirical analysis is to estimate the long-term effects of financial development (explained by banks and

[6] Although this effect may coincide with the negative long-run estimates that are obtained in studies about thresholds in the finance-growth nexus, our empirical approach offers a different interpretation of this result because we address the existence of observed and unobserved heterogeneities in the data.

stock market development) on growth for all the countries that we study here, we apply the following standard linear regression model for the relationship between growth and financial development, where we address the differences in the long-term effects across countries by accounting for observed and unobserved heterogeneity:

$$Y_{it} = \alpha_i + \beta_i^B B_{it} + \beta_i^S S_{it} + u_{it}, \quad u_{it} = \boldsymbol{\gamma}_i' \boldsymbol{f}_t + e_{it} \tag{1}$$

$$\boldsymbol{X}_{it} = \boldsymbol{\Gamma}_i' \boldsymbol{f}_t + \boldsymbol{v}_{it} \tag{2}$$

In equation (1), Y_{it} is economic growth, B_{it} is the log of banking development, S_{it} is the log of stock market development, and α_i is an intercept. These variables, their respective coefficients and the intercept constitute the observable part of our framework and are specific to country i at time t for $i = 1, \dots, N$ and $t = 1, \dots, T$.[7]

In line with some studies of panel time series,[8] equation (1) specifies that economic growth is not only determined by financial development, but also by a set of unobserved common factors. Thus, the term u_{it} has a multifactor error structure, where $\boldsymbol{f}_t$ is the $mX1$ vector of unobserved common factors, $\boldsymbol{\gamma}_i'$ is a $1Xm$ vector of factor loadings, and e_{it} are the idiosyncratic errors, which, according to Chudik et al. (2011, 2017), might themselves be weakly cross-correlated and serially correlated, and be uncorrelated with the factors. Equation (2) includes a $2X1$ vector of financial development variables, $\boldsymbol{X}_{it} = (B_{it}, S_{it})'$, and assumes that these variables are also driven by the above unobserved common factors, $\boldsymbol{f}_t$, where $\boldsymbol{\Gamma}_i'$ is the $2Xm$ matrix of factor loadings, and $\boldsymbol{v}_{it}$ is the $2X1$ vector of the idiosyncratic components of $\boldsymbol{X}_{it}$ which are assumed to be distributed independently of e_{it}.

In our framework, unobserved common factors are sources of error cross-section dependence and drive all variables in a fashion that differs across countries. Thus, we can characterize the differing impact of these factors as follows:

$$u_{it} = \sum_{l=1}^{m_{fs}} \gamma_{il}^s f_{lt}^s + \sum_{l=1}^{m_{fw}} \gamma_{il}^w f_{lt}^w + e_{it} \tag{3}$$

In line with Chudik et al. (2011), the common factor structure is then described by a combination of a limited number (m_{fs}) of strong factors, f_{lt}^s, which may be possibly correlated with the regressors of the basic model, and a number (m_{fw}) of weak, semi-weak and semi-strong factors, f_{lt}^w, which might be infinite and affect a subset of countries in the sample. Examples of strong factors/shocks are structural changes, the stance of global financial cycle (Chudik et al., 2017), changes in U.S.

[7] This framework allows for heterogeneous coefficients; that is, ones that are fixed but differ across countries, as stated by Pesaran and Smith (1995).

[8] For a review, see Chudik and Pesaran (2015b).

interest rates, and commodity price shocks (Cavalcanti et al., 2015), while weak, semi-weak and semi-strong factors might be due to local spillovers produced by industrial activity, domestic consumption, geographical proximity, R&D investment (Eberhardt et al., 2013), house prices (Holly et al., 2010), or climate and agricultural productivity (Eberhardt and Vollrath, 2016).

Allowing for possible error cross-section dependence caused by unobserved common factors is central to this study, because it enables us to account for the recent financial crisis and its consequences, such as the worldwide transmission of financial vulnerabilities and the slowdown in global economic growth. The financial crisis likewise may have had different effects in different countries, with a stronger effect on the smaller national economies than on the larger ones (Chudik et al., 2017).

3.2. Empirical implementation

Our estimation strategy follows Eberhardt and Teal (2013), Eberhardt and Presbitero (2015), and Chudik et al. (2017), by implementing different regression models that have different assumptions about parameters, the error term, and dynamics. The results are then compared to yield conclusions about the consistency of the estimates, and the sign and the magnitude of the long-term effects of bank and stock market development on growth.

3.2.1. Static models

First, we estimate the coefficients of the static panel time series version of the model proposed by Beck and Levine (2004), for the data from 1988 to 2012:

$$Y_{it} = \alpha_i + \beta_i^B B_{it} + \beta_i^S S_{it} + u_{it} \tag{4}$$

We assume, first, that the parameters are homogeneous, and that errors are cross-sectionally independent (i.e. cross-country dependencies that arise through global financial sources of contagion and are caused by the combined effect of unobserved common shocks, are not regarded). Here, we implement such estimators as the pooled OLS (POLS) augmented with year dummies, two-way fixed effects (2FE) augmented with year and country dummies, and first differences (FD) augmented with year dummies. We then allow for heterogeneous parameters (i.e. we address observed country-specific conditions) and use the Mean Group (MG) estimator proposed by Pesaran and Smith (1995).

However, the assumption of error cross-section independence might be misleading because the exposure of countries to common shocks might affect financial systems and growth. If these shocks are ignored, while they are correlated in fact with the financial development regressors, we may derive biased and inconsistent estimates (Phillips and Sul, 2007; Sarafidis and Wansbeek, 2012). Thus, to allow for cross-sectionally dependent errors, we propose the following model:

$$Y_{it} = \alpha_i + \beta_i^B B_{it} + \beta_i^S S_{it} + \psi_i^Y \bar{Y}_t + \psi_i^B \bar{B}_t + \psi_i^S \bar{S}_t + e_{it} \quad (5)$$

where $\bar{Y}_t$, $\bar{B}_t$ and $\bar{S}_t$ are the cross-section averages of the GDP growth, log of bank development, and log of security market development, respectively. Following Pesaran (2006), these cross-section averages are used as proxies for the unobserved common factors of the equation (1).[9] To estimate the coefficients of this model, we follow two approaches: first, the Common Correlated Effects Pooled estimator (CCEP) of Pesaran (2006), where coefficients are restricted so as to be homogeneous and common country dummies are included; and second, the Common Correlated Effects MG (CCEMG) of Pesaran (2006), where we allow for heterogeneous slopes and unobserved heterogeneities.[10]

Given the limited data available for the stock market development variable and other regressors, we find it convenient to use the CCE approach, because the predetermined weights of the averages usually lead to a better small sample performance than do others that deal with error cross-section dependencies (Chudik and Pesaran, 2015b).[11]

3.2.2. Dynamic models

We also pay attention to the estimates of the long-run effects of the development of stock markets and banks on output, using (i), the autoregressive distributed lag (ARDL) framework in an error correction model (ECM); and (ii), the distributed lag (DL) model. These models are intended to be a dynamic representation of (4) to deal with several time series properties that the above static models cannot handle. We employ these dynamic models for the two panel data sets in question.

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[9] These averages are employed to pool past and current views of the information on markets contained in the variables of the model.

[10] In the models where we assume parameter homogeneity we obtain White heteroskedastic-robust standard errors. Meanwhile, in the case of specifications where we allow for heterogeneous slopes, our estimates follow Hamilton (1992) by employing weights based on the absolute residuals to mitigate the impact of outliers on the average estimate. For these models we also construct nonparametric standard errors following Pesaran and Smith (1995) and Pesaran (2006) (the latter for specifications where cross-section averages are modeled).

[11] Other advantages of the CCE estimator are that it allows for nonstationary factors; the augmentation with averages also provides consistent estimates in the presence of structural breaks and serial correlation in errors; and it does not require prior knowledge of the number of unobserved common factors or that the variables of the model and factors be cointegrated (Pesaran, 2006; Kapetanios et al., 2011; Pesaran and Tosetti, 2011; Westerlund and Urbain, 2015).

Let us say that we have the following ARDL model:

$$Y_{it} = \alpha_i + \gamma_{i1} Y_{i,t-1} + \beta_{i0}^B B_{it} + \beta_{i0}^S S_{it} + \beta_{i1}^B B_{i,t-1} + \beta_{i1}^S S_{i,t-1} + u_{it} \quad (6)$$

which we can represent as an ECM, as follows:

$$\Delta Y_{it} = \alpha_i + \lambda_i (Y_{i,t-1} - \theta_i^B B_{i,t-1} - \theta_i^S S_{i,t-1}) + \beta_{i0}^B \Delta B_{it} + \beta_{i0}^S \Delta S_{it} + u_{it} \quad (7)$$

where $\lambda_i = -(1-\gamma_{i1})$, $\theta_i^B = \frac{\beta_{i0}^B + \beta_{i1}^B}{1-\gamma_{i1}}$, $\theta_i^S = \frac{\beta_{i0}^S + \beta_{i1}^S}{1-\gamma_{i1}}$, $\Delta Y_{it} = Y_{it} - Y_{i,t-1}$, $\Delta B_{it} = B_{it} - B_{i,t-1}$, and $\Delta S_{it} = S_{it} - S_{i,t-1}$. Here λ_i is the speed of convergence of the economy to its long-run equilibrium, and $Y_{i,t-1} - \theta_i^B B_{i,t-1} - \theta_i^S S_{i,t-1}$ yields the cointegrating relationship of the ECM system.[12] We employ the ECM representation because we can (i), distinguish the short- from the long-term effects;[13] (ii), analyze the speed of convergence towards the long-term equilibrium of steady state; and (iii), study cointegration through a statistical analysis of the error correction term. We include only one lag of the dependent and independent variables, given the restricted time series data for stock markets.

According to Pesaran and Smith (1995) and Pesaran and Shin (1999), compared to the static specifications, the ARDL model allows for (i), dynamics; and (ii), feedback effects of lagged GDP growth on the financial development covariates, in a way that allows us to address a possible reverse causality.[14] However, since we only include one lag for the variables, the ARDL model has a limitation because, as Chudik et al. (2017) note, sufficiently long lags are necessary to fully address reverse causality and derive consistent ARDL estimates. Still, we can compare the results of these models with those obtained from the static and DL models to arrive at some conclusions about the long-run effects of both banking and stock market development on growth. However, further research will be needed to tackle this concern.

We also consider the ARDL model which uses the banking development variable as the only proxy for financial development between 1961 and 2014, since the data for this regressor are available for those years. As

[12] So long as $\lambda_i \neq 0$, the economies in the panel return to the long-run path after a shock. In this case, we have cointegration between the variables of the model and the processes in $Y_{i,t-1} - \theta_i^B B_{i,t-1} - \theta_i^S S_{i,t-1}$. As reported by Eberhardt and Presbitero (2015), the long-run is defined as an econometric concept, rather than a macroeconomic definition, and it refers to the range of years in the sample. In addition, we compute standard errors of the ARDL system in an ECM representation, employing the Delta method.

[13] In order to ease comparison with the results of the static models, we only report the long-term coefficients of the ARDL models. Short-run estimates are available on request.

[14] The ARDL model can also be used to estimate long-run effects even in the presence of I(0) or I(1) variables, or regardless if they are endogenous or exogenous.

in Chudik et al. (2017), we can include up to three lags for the dependent and independent variables in the ARDL system,[15] and we can thus properly account for endogeneity and the short-term dynamics from which the long-term coefficients are derived. For this model, we use the POLS, 2FE, and MG estimators.

We employ the distributed lag (DL) model, allowing for coefficient heterogeneity as an alternative approach to the dynamic models. It can be derived from (6) as follows:

$$Y_{it} = \delta_i + \ddot{\theta}_i^B B_{it} + \ddot{\theta}_i^S S_{it} + \eta_{i1}^B \Delta B_{it} + \eta_{i1}^S \Delta S_{it} + \ddot{u}_{it} \quad (8)$$

where $\delta_i = A(L)^{-1}\alpha_i$, $\ddot{\theta}_i^B = A(L)^{-1}(\beta_{i0}^B + \beta_{i1}^B)$, $\ddot{\theta}_i^S = A(L)^{-1}(\beta_{i0}^S + \beta_{i1}^S)$, $\eta_{i1}^B = -A(L)^{-1}\beta_{i1}^B$, $\eta_{i1}^S = -A(L)^{-1}\beta_{i1}^S$, $\ddot{u}_{it} = A(L)^{-1}u_{it}$, and $A(L) = 1 - \gamma_{i1}L$. In contrast with the ARDL, this model has a better small sample performance and only requires the selection of a truncation lag order; however, as Chudik et al. (2016) note, this approach produces consistent estimates so long as feedback effects from the lagged values of the dependent variable on the regressors are assumed to be absent. Given the short time series available for stock market development between 1988 and 2012, we only include one lag for the independent variable. Alternatively, we include three lags for the bank development variable for the panel between 1961 and 2014.[16] For the DL model we use the MG estimator.

Although the above dynamic specifications deal with slope heterogeneity, dynamics, and endogeneity, they do not model common shocks and the error cross-section dependencies they cause. Therefore, we also analyze models that account for this with the use of a dynamic version of (5). To examine the role of observed and unobserved heterogeneity, reverse causality, and dynamics, we employ the following Cross-Sectional (CS) ARDL, which is based on Chudik and Pesaran (2015a), for the panel from 1988 to 2012:

$$\begin{aligned} Y_{it} = {} & \alpha_i + \gamma_{i1} Y_{it-1} + \beta_{i0}^B B_{it} + \beta_{i0}^S S_{it} + \beta_{i1}^B B_{it-1} + \beta_{i1}^S S_{it-1} \\ & + \sum_{l=0}^{3} (\psi_{il}^Y \bar{Y}_{it-l} + \psi_{il}^B \bar{B}_{it-l} + \psi_{il}^S \bar{S}_{it-l}) + e_{it} \end{aligned} \quad (9)$$

[15] We also run ARDL regressions and choose the number of lags in line with the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). We therefore conclude that including three lags of the dependent and independent variable is appropriate. We reach the same conclusion for the number of lags of the independent variable of DL models.

[16] For both panels, we assume that the lags of the ARDL and DL models are the same across variables and countries because, as stated in Chudik et al. (2017), this helps to reduce the adverse effects of the selection of data which may be subject to the use of lag order selection procedures, such as the Akaike or Schwarz criteria. We thus leave the specific dynamics of a particular country for future studies and focus on the long-term average estimates of the sample.

In contrast with the traditional ARDL approach, we augment the CS-ARDL model with three lags for the cross-sectional averages of the dependent and independent variables to capture the dynamic effect of unobservable common factors, while allowing for slope heterogeneity and weakly exogenous regressors.[17] We determine the lags for the cross-sectional averages independently of the number of lags for the variables in (9) and according to the rule of thumb $T^{1/3}$ (Chudik and Pesaran, 2015a), which in our case is made to approach three (i.e. $l = 0{,}1{,}2$ and 3). This model can be represented as an ECM, as follows:

$$\Delta Y_{it} = \alpha_i + \lambda_i(Y_{it-1} - \theta_i^B B_{it-1} - \theta_i^S S_{it-1}) + \beta_{i0}^B \Delta B_{it} + \beta_{i0}^S \Delta S_{it} + \sum_{l=0}^{3} (\psi_{il}^Y \bar{Y}_{it-l} + \psi_{il}^B \bar{B}_{it-l} + \psi_{il}^S \bar{S}_{it-l}) + e_{it} \quad (10)$$

Following Chudik et al. (2017), we also employ the cross-sectional DL model for the panel between 1988 and 2012 as an alternative approach to estimating the long-run effects while accounting for common shocks.[18] Thus, from (7), and assuming that $\psi_{il}^Y = 0$ for $l = 1{,}2$ and 3, we obtain:

$$Y_{it} = \delta_i + \ddot{\theta}_i^B B_{it} + \ddot{\theta}_i^S S_{it} + \eta_{i1}^B \Delta B_{it} + \eta_{i1}^S \Delta S_{it} + \pi_{i0}^Y \bar{Y}_{it} + \sum_{l=0}^{3} (\pi_{il}^B \bar{B}_{it-l} + \pi_{il}^S \bar{S}_{it-l}) + \ddot{e}_{it} \quad (11)$$

where $\ddot{e}_{it} = A(L)^{-1} e_{it}$, $\pi_{i0}^Y = A(L)^{-1} \psi_{i0}^Y$, $\pi_{il}^B = A(L)^{-1} \psi_{il}^B$ and $\pi_{il}^S = A(L)^{-1} \psi_{il}^S$ for $l = 0{,}1{,}2$ and 3. For the CS-ARDL and CS-DL models, we use the dynamic CCEMG estimator. We also use versions of these models for the panel between 1961 and 2014, where we include up to three lags for the output growth and bank development variables, and for cross-sectional averages.

Although we extensively use the ARDL and the DL models and their cross-sectional versions, we recognize that they have some drawbacks. The ARDL models may suffer from a large sampling uncertainty due to the limited time dimension of our samples. Furthermore, when we employ a time frame between 1988 and 2012, these models may not accurately capture the feedback effects running from output growth to the financial development variables since we only include one lagged value of the variables. Although we try to mitigate these problems for the estimates of banking development by expanding the sample of this

17 As stated in Eberhardt and Presbitero (2015), the standard instrumentation employed in the empirical frameworks that are based on Arellano and Bond (1991) and Blundell and Bond (1998) might not be appropriate for the empirical frameworks in our study, since it is not possible to obtain valid instruments due to the presence of unobserved common factors, slope heterogeneity, cointegration and other time series elements.

18 According to Chudik et al. (2016), the CS-DL model is robust to breaks in the errors and residual serial correlation, and to the possibility of unit roots in some or all of the regressors and/or factors.

variable to a time frame from 1961 to 2014; we are not able to implement this strategy for the estimates of stock market development in the absence of data for this variable before 1988-89. Nevertheless, as Chudik et al. (2017) point out, the ARDL and the DL frameworks are complementary when dealing with several econometric aspects and obtain robust estimates. We also use the static CCEMG models to complement the results of dynamic specifications because they yield a satisfactory performance for relatively small values of T and N.

3.3. Data

In line with the conventional approach, we measure (i) economic performance with the constant GDP growth; (ii) the log of bank development using the natural logarithm of the ratio of domestic credit to private sector by banks to GDP; and (iii), the log of stock market development with the natural logarithm of the ratio of market capitalization of listed companies to GDP. In some cases, we use alternative variables for GDP growth (such as the constant GDP per capita growth), banking development (such as the log of liquid liabilities to GDP and the log of the bank lending-deposit spread, the latter is used for the panel between 1988 and 2012 only because it has short time series data), and stock market development (such as the log of the ratio of the total value of traded stocks to GDP and the log turnover ratio of traded stocks).

We also add other regressors to check the robustness of our results. These variables include inflation, human capital, the ratio of trade to GDP, the ratio between general government final consumption expenditure and GDP, the ratio of gross fixed capital formation to GDP (all these variables are in logarithms), population growth, a banking crisis dummy (1=banking crisis, 0=none), a term for the interaction between the dummy of banking crisis and the log of the ratio of domestic credit to private sector by banks to GDP, and a term for the interaction between the dummy of banking crisis and the log of the ratio of market capitalization of listed companies to GDP. The variables which are computed by using the banking crisis dummy are employed for the regressions from 1988 to 2012, due to the limited time series. We further include the ratio of the total (domestic plus external) gross (central and/or general) government debt to GDP because high levels of public debt may (i), trigger banking crises and therefore harm long-run economic growth (Reinhart and Rogoff, 2009, 2010, 2011; Eberhardt and Presbitero, 2015; Chudik et al., 2017); and (ii), worsen the effects of private sector deleveraging when entering a financial crisis recession, which is a problem that may be accompanied by a prolonged period of sub-par economic performance (Jordà et al., 2016).[19] See section A2

[19] However, as documented in some studies which are reviewed by Eberhardt and Presbitero (2015), our measurement of public debt does not take into account (i) that a high proportion of foreign currency-denominated debt may generate financial instability; (ii), net debt; and (iii), that countries can borrow at different maturities and contractual forms.

from the online supplement for a brief description of the definitions and sources of the data for these variables.

To provide estimates of the above models, we use two different unbalanced panel data sets with $N_{min} = 20$ and $T_{min} = 20$ annual observations across all countries and time periods:[20] the first panel is from 1988 to 2012, and the second from 1961 to 2014. Due to the scarcity of data for the three abovementioned measurements of stock market development for the panel between 1961 and 2014, we only use bank development to measure of financial development. The sample is made up of 25 advanced economies and 29 emerging economies for a total of 54.[21] For some of our specifications we split the panel between advanced and emerging economies. Table 2 presents descriptive statistics for the variables in levels.[22]

TABLE 2

Descriptive Statistics, Variables in Levels

	From 1988 to 2012				From 1961 to 2014			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
GDP growth	3.42	3.55	-14.36	19.74	3.93	3.93	-31.88	23.39
Log domestic credit to private sector by banks/GDP	-0.66	0.77	-3.41	1.13	-0.94	0.79	-3.95	1.13
Log inflation	2.05	1.14	-2.79	8.68	2.26	1.18	-2.79	8.68
Log trade/GDP	-0.46	0.59	-2.02	1.48	-0.63	0.68	-2.99	1.48
Population growth	1.42	1.15	-6.34	7.98	1.66	1.32	-6.34	12.99
Log general government final consumption expenditure/GDP	-1.89	0.35	-3.51	-1.15	-1.93	0.35	-3.51	-0.83
Log gross fixed capital formation/GDP	-1.52	0.25	-2.73	-0.79	-1.51	0.25	-2.73	-0.77
Log total (domestic plus external) gross (central and/or general) government debt/GDP	-0.71	0.65	-3.21	0.86	-0.99	0.76	-4.63	1.04
Log human capital	0.92	0.22	0.12	1.28	0.79	0.28	0.05	1.28
Per capita GDP growth	2.16	3.50	-16.51	17.07	2.45	3.83	-30.86	20.10
Log liquid liabilities/GDP	-0.53	0.63	-2.67	1.38	-0.72	0.62	-2.74	1.38
Log bank lending-deposit spread	1.44	0.64	-1.62	4.36	1.42	0.65	-1.62	4.36
Banking crisis dummy	0.11	0.31	0	1	0.06	0.25	0	1
Log market capitalization of listed companies/GDP	-1.04	1.05	-5.86	1.51	-	-	-	-
Log total value of stocks traded/GDP	-2.42	2.04	-10.01	1.46	-	-	-	-
Log turnover ratio of stocks traded	-1.30	1.44	-6.53	1.60	-	-	-	-

Notes: These descriptive statistics refer to the sample of N = 54 countries from (i) 1988 to 2012, and (ii) 1961 to 2014.

Fig. 1 shows the evolution of the average ratio of bank credit to GDP, and its correlation with average GDP growth (both in percentage) for the full sample and for the subsamples of advanced and emerging countries. The chart on the upper left shows that the average bank credit has a

[20] We exclude several emerging and developing economies due to the lack of data for many of our variables.

[21] Countries are classified as advanced or emerging economies in accordance with *World Economic Outlook (2015), Adjusting to lower commodity prices.*

[22] The list of countries, the time coverage per variable and country, the descriptive statistics on growth rates and the number of total observations per variable can be found in Tables D1-D7 in the online supplement.

positive evolution for all samples, and that private deleveraging has occurred in recent years, particularly in advanced countries.[23] The other three plots show a negative relation between the average GDP growth and the average ratio of bank credit, for all samples. Moreover, they suggest that high levels of average banking credit might be associated with low or negative levels of average GDP growth in the case of the full sample, and that this might be explained by advanced countries. These levels coincide with those in the last two decades, as shown on the plot of the upper left.

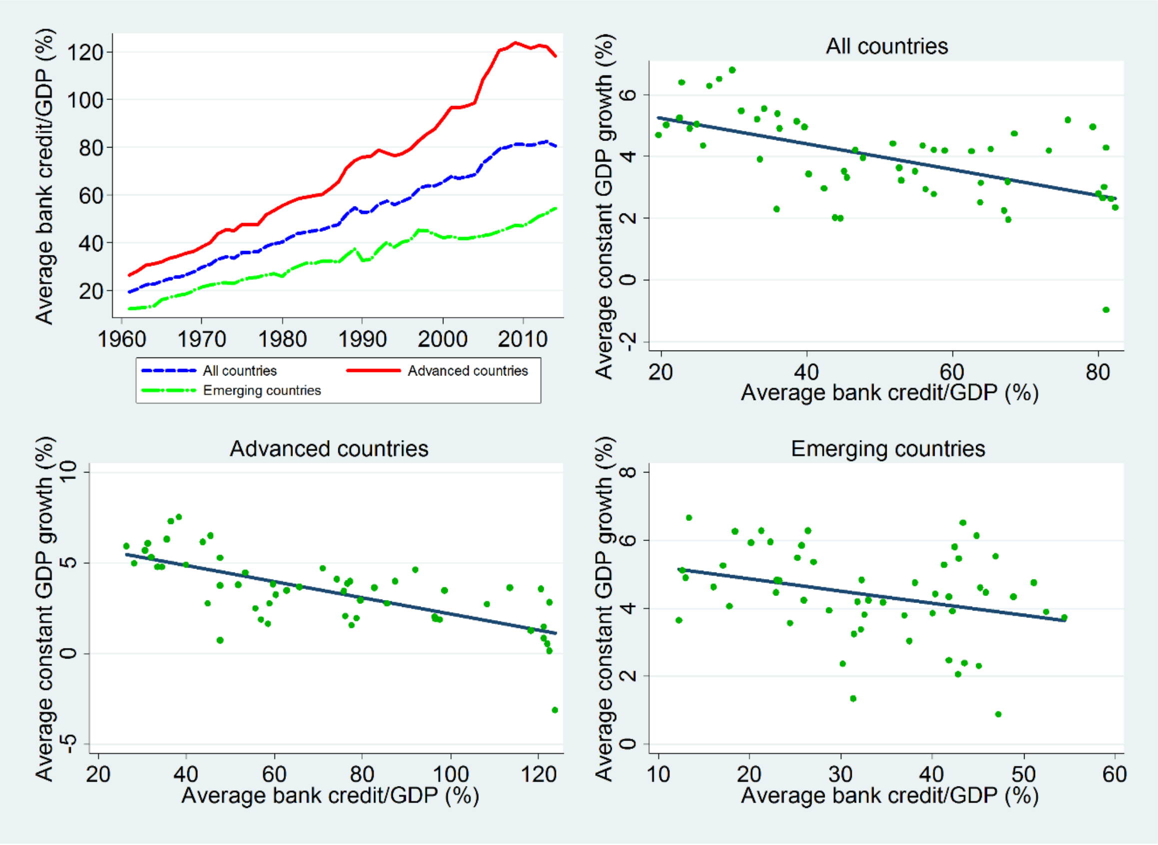

Fig. 1. The upper left chart presents the average private credit by banks as a share of GDP (in percentages), for the time period between 1961 and 2014, the sample of all countries, and the subsamples of advanced and emerging economies. The other three graphs present the correlation of the average constant GDP growth with the average ratio of bank credit to GDP (both in percentages) for each year between 1961 and 2014, and for the three samples. We overlay a linear fit which predicts the average constant GDP growth from the average ratio of bank credit to GDP.

Fig. 2 presents the long-term characteristics of the average market capitalization of listed companies as a share of GDP, and illustrates its correlation with average GDP growth (both in percentages). The plots

[23] The box plots in Fig. A4 in the online supplement coincide with this illustration.

show data for all abovementioned samples, and indicate that, for all of these samples, average market capitalization has followed a positive trend over time, despite of an abrupt contraction during the recent financial crisis,[24] and that it is positively correlated with GDP growth.

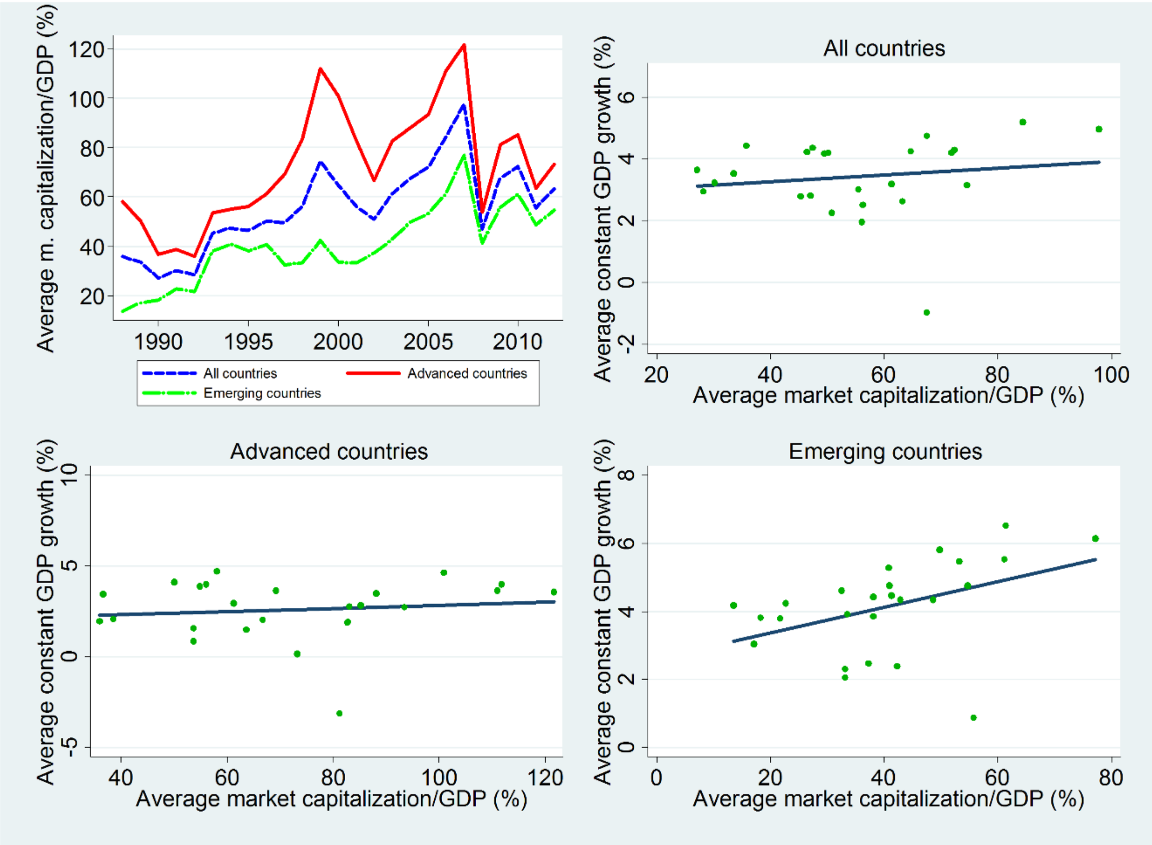

Fig. 2. The upper left chart presents the average market capitalization of listed companies as a share of GDP (in percentages), for the time period between 1988 and 2012, the sample of all countries, and the subsamples of advanced and emerging economies. The other three graphs present the correlation of the average constant GDP growth with the average ratio of market capitalization of listed companies to GDP (both in percentage) for each year between 1961 and 2014, and for the three samples. We overlay a linear fit which predicts the average constant GDP growth from the average ratio of market capitalization of listed companies to GDP.

Fig. 3 presents histograms of the log of the ratio of private credit by banks to GDP, and overlays fractional polynomial lines (with a 95% confidence interval) for GDP growth against the log of the ratio of private credit by banks to GDP. It includes information for all samples and the two time periods we study here. It clearly shows potential nonlinearities between both variables, as confirmed by recent studies (with thresholds between 60% and 90% for the sample of all countries, and both time frames), and strengthens the conclusions we obtain from Fig. 1, in that high levels of bank credit might be associated with lower

[24] See Fig. A5 from the online supplement for similar evidence.

or negative levels of GDP growth, particularly for the full sample and the subsample of advanced economies. However, there is no graphical evidence for similar nonlinearities across the samples. In fact, Fig. A1 and Fig. A2 from the online supplement show that there are observed heterogeneities in nonlinearities for nine advanced and emerging countries and both time periods.

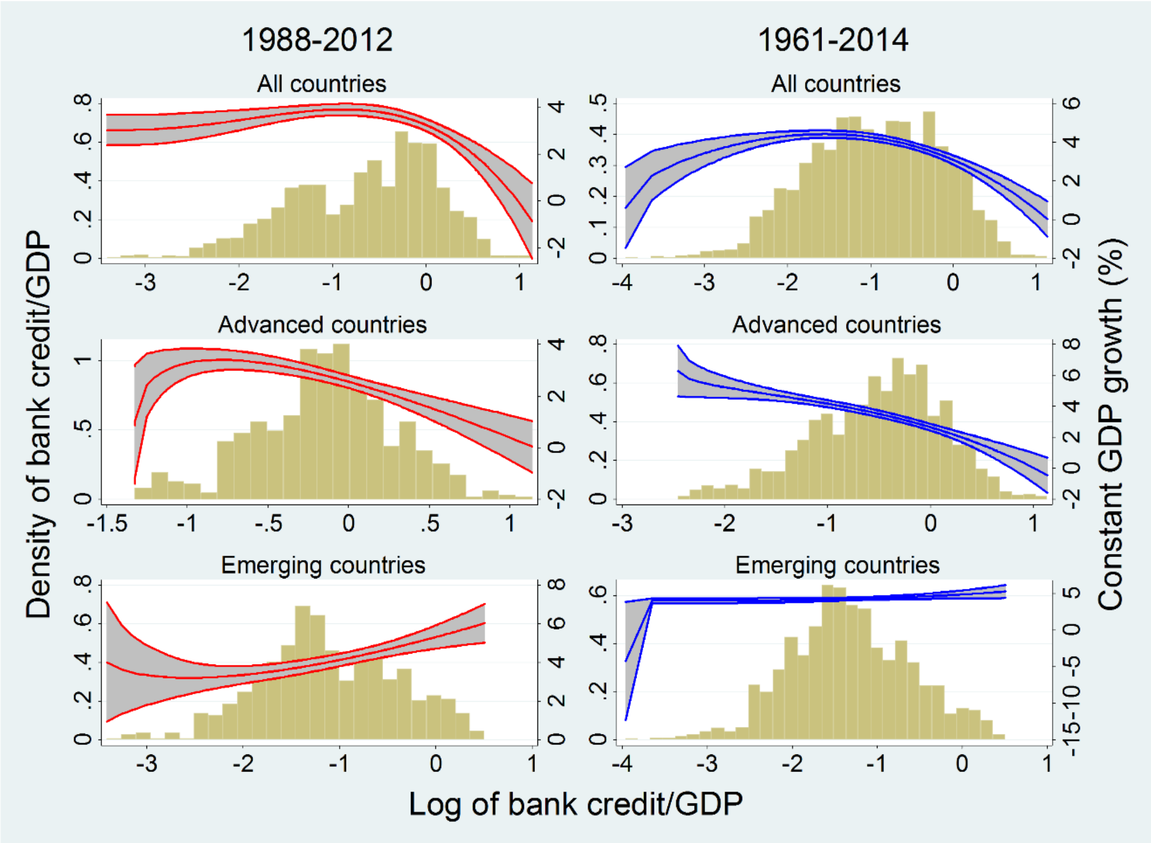

Fig. 3. It presents histograms of the log of the ratio of private credit by banks to GDP, and overlays fractional polynomial lines (with a 95% confidence interval) for GDP growth against the log of the ratio of private credit by banks to GDP. On the left side, plots are for a time frame from 1988 to 2012, and on the right side for a time period between 1961 and 2014. The first row of the graphs corresponds to the full sample, while the second and the third represent data for advanced and emerging economies, respectively.

The above shows that, although it might be reasonable to analyze nonlinearities in the finance-growth nexus, it should be done by addressing these heterogeneities and those which are produced by unobserved common shocks, otherwise empirical analysis might be misleading. We do not study such heterogeneous nonlinearities here because it would require large time-series data for our main financial development variables to obtain consistent estimates for the full sample and for each country.[25] Thus, we leave the estimation of heterogeneous

[25] Ours is not the first study to mention such data constraints, particularly for the proxy variables of stock market development (see Arcand et al., 2015).

tipping points for further research. Fig. 4 illustrates a similar analysis for GDP growth and the log of the ratio of market capitalization of listed companies to GDP. It shows that there are no thresholds beyond which larger levels of market capitalization are associated with a smaller growth of GDP, but this feature is not identical across samples and the abovementioned nine countries (see Fig. A3 from the online supplement).

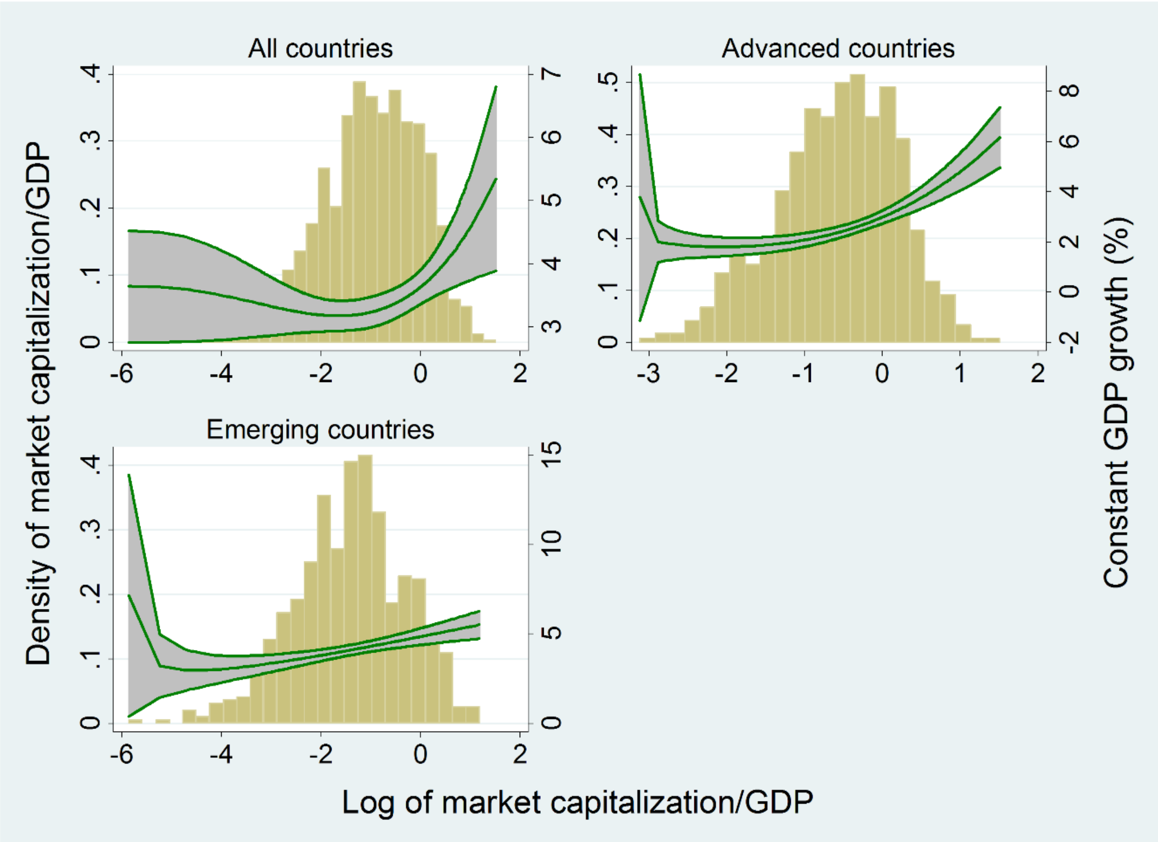

Fig. 4. It presents histograms of the log of the ratio of market capitalization of listed companies to GDP, and overlays fractional polynomial lines (with a 95% confidence interval) for GDP growth against the log of the ratio of market capitalization of listed companies to GDP. Plots are for a time frame from 1988 to 2012. The first row of graphs (from the left to the right) present data for the full sample and for advanced countries, respectively; while the plot in the second row presents data for emerging economies.

This causes important problems for estimating country-specific, and even average, thresholds effects (Chudik et al., 2017); and since stock markets and banks provide complementary services (as stated in Section 2.1.), we believe that both financial development variables should have enough time series data for estimating of threshold effects.

4. Results

4.1. Cross-Section Dependence and Unit Root Tests

To study the extent of the cross-section dependence of errors caused by unobserved common shocks, we use the cross-section dependence (CD) test of Pesaran (2004, 2015) as in Chudik et al. (2017) and Eberhardt and Vollrath (2016). The implicit null hypothesis of the CD test, which is based on the average pair-wise error correlations and tested at a 5% level of significance, is a weak cross-section dependence of errors, and the alternative is a strong error cross-section dependence. [26][27] In line with Chudik et al. (2017), a rejection of the null implies that such a strong error cross-section dependence might be due to unobserved common factors/shocks which are omitted or not properly accounted for. In this case, the estimates might be seriously biased and inconsistent. We also employ this test to examine the cross-section correlations of variables for the two panel data sets (the results are in Tables C9-C10 from the online supplement). We find that all the series are strongly cross-sectionally dependent in both panels, except for the one for liquid liabilities, which is weakly cross-sectionally dependent.

We also carry out panel unit root tests, as in Eberhardt et al. (2013) and Eberhardt and Teal (2013), to investigate the stationarity of the variables and residuals of the static models. We employ (i), the first-generation panel unit root test of Maddala and Wu (1999) (for variables only); and (ii), the second-generation panel unit root test of Pesaran (2007) (for variables and residuals).[28] The null hypothesis of these tests is that all the series are nonstationary and it is tested at a 5% level of significance. We examine these two tests by performing Dickey Fuller (DF) regressions, including (i) a zero to three lags augmentation for the

[26] More specifically, in line with the exponent of cross-sectional dependence, α, introduced in Bailey et al. (2016), the null hypothesis refers to the case when $0 \leq \alpha < 1/2$, which corresponds to different degrees of weak cross-sectional dependence, in contrast with the case when $1/2 < \alpha \leq 1$, which refers to different degrees of strong cross-sectional dependence.

[27] According to Chudik et al. (2017), even though the properties of the CD test for dynamic panels that include lagged dependent and independent variables have not yet been investigated, the CD test continues to be valid in the presence of these types of variables.

[28] We only use the Pesaran (2007) unit root test to examine the stationarity of residuals, since it accounts for the effect of unobserved common shocks; still, when we employ the Maddala and Wu (1999) unit root test we obtain similar results. Moreover, Pesaran et al. (2013) show that the Pesaran (2007) unit root test is exposed to size distortions if there is more than common factor. Therefore, we suggest that further research should focus on addressing this concern.

panel from 1988 to 2012; and (ii), a zero to four lags augmentation for the panel from 1961 to 2014.[29]

From our results (found in Tables C1-C8 from the online supplement), we infer that, for the panel between 1988 and 2012, all variables in levels may be integrated of order 1 (I(1)), except for log inflation, which might be I(0), and log human capital, which is neither I(0) nor I(1). In this panel, we do not employ these variables for static models since cointegration in this case requires all variables to be I(1);[30] we nevertheless employ the log of inflation in dynamic models. Moreover, the results for the panel between 1961 and 2014 suggest that all the variables are I(1), except for log inflation, GDP growth, GDP per capita growth, and the log human capital, all of which are I(0).

In the results we also provide the Root Mean Squared Error (RMSE), the number of country-time observations (NXT), and the number of countries (N) per regression.[31]

4.2. Long-run effects of banking and stock market development on growth from 1988 to 2012

4.2.1. Estimates of the basic static and dynamic models

Table 3 presents the results of the pooled panel estimators (POLS, 2FE, FD), and the CCEP, MG, and CCEMG estimators, according to the static specifications (4) and (5). Overall, the development of stock markets has positive, long-term statistical effects on economic growth. The effect of banking development, on the other hand, is negative and statistically significant. Turning to the diagnostics, the Pesaran (2007) unit root test suggests that the 2FE and CCEP models yield nonstationary residuals. Furthermore, the CD test shows that the MG estimator suffers from strong residual cross-section dependence. Due to these problems, we infer that the 2FE, CCEP and MG models may be misspecified, while the estimates of the POLS, FD and CCEMG specifications are consistent.

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29 We determine the lag length for each panel by analyzing DF regressions and following information criteria such as the AIC or BIC. In addition, DF regressions of the Pesaran (2007) unit root test are augmented with cross-section averages to account for cross-sectional dependence.

30 See Engle and Granger (1987) and Breitung and Pesaran (2008).

31 We carry out our empirical analysis by employing the Stata commands written by Markus Eberhardt, such as the xtcd, xtmg and multipurt.

TABLE 3

Static models according to the basic specification

	POLS (1)	*2FE* (2)	*FD* (3)	*CCEP* (4)	*MG* (5)	*CCEMG* (6)
B	-0.667***	-1.284***	-2.474**	-2.115***	-4.122***	-3.780***
	(0.171)	(0.353)	(1.200)	(0.571)	(0.769)	(0.855)
S	0.480***	1.547***	1.073**	1.977***	1.855***	2.170***
	(0.133)	(0.223)	(0.427)	(0.316)	(0.232)	(0.279)
CD-test statistic	0.06	-0.41	-0.39	0.20	38.15	-0.07
CD-test p-value	0.95	0.68	0.69	0.84	0.00	0.94
Order of Integration	I(0)	I(1)	I(0)	I(1)	I(0)	I(0)
RMSE	3.24	2.77	3.39	2.53	2.63	2.09
NXT	1313	1313	1259	1313	1313	1313
N	54	54	54	54	54	54

Notes: GDP growth is the dependent variable. Log domestic credit to private sector by banks to GDP (B) and log market capitalization of listed companies to GDP (S) are the independent variables. The estimates of the intercept term are omitted. Standard errors are given in parentheses. Results are reported for a period of time from 1988 to 2012. Estimators: (1) POLS: Pooled OLS, augmented with T-1 year dummies; (2) 2FE: Two-way fixed effects, augmented with T-1 year dummies and N-1 country dummies; (3) FD: First Differences, augmented with T-2 year dummies; (4) CCEP: Pooled Pesaran (2006), augmented with common country dummies and cross-section averages; (5) MG: Mean Group Pesaran and Smith (1995); (6) CCEMG: Common Correlated Effects MG Pesaran (2006), augmented with cross-section averages. White heteroskedasticity-robust standard errors are reported for models (1)-(4). For models (5)-(6) we report (i), the estimates of the outlier-robust mean of parameter coefficients across groups following Hamilton (1992); and (ii), nonparametric standard errors according to Pesaran and Smith (1995) and Pesaran (2006) (the latter only for (6)). Levels of significance are represented by * 10%, ** 5% and *** 1%. Diagnostics: (evaluated at the 5% level of significance, full results of the following tests are available on request): 1) CD test: The Pesaran (2004, 2015) test, for which Ho: Weak cross-section dependence of the residuals (the test statistic as well as the p-value for each model are reported). 2) CIPS test: The Pesaran (2007) test evaluates the order of integration of the residuals where I(0): stationary, I(1): nonstationary. We include an augmentation of up to 3 lags in the Dickey Fuller regressions employed. The root mean squared error (RMSE), NXT number of country-time observations and N number of countries are also included.

The estimates of the dynamic models in Table 4 are statistically significant and agree with those presented in Table 3 in terms of the sign of the effect of the financial development variables on GDP growth. Moreover, a long-term cointegration is achieved at the 1% level in the ARDL models. While the estimates of the POLS, 2FE, CS-ARDL and CS-DL are consistent, the results of the MG and DL-MG models are seriously biased and inconsistent, due to strong residual cross-section dependence. Results from Tables A1 and A2 from the online supplement show that when modelling bank and stock market development separately by employing all of the above estimators, the level of significance and sign of the estimates coincide with those of the abovementioned results.[32][33] As can be seen, some of the pooled static and dynamic models provide consistent estimates even when unobserved common factors are ignored. However, further estimates, in particular those in section 4.3., suggest that we cannot fully rely on pooled specifications because they ignore potential observed country-specific features and error cross-section dependencies, and may therefore yield inconsistent estimates.

TABLE 4

Dynamic models according to the basic specification

	POLS (1)	*2FE* (2)	*MG* (3)	*DLMG* (4)	*CS-ARDL* (5)	*CS-DLMG* (6)
B	-1.013***	-1.930***	-3.905***	-4.317***	-4.679***	-4.871***
	(0.268)	(0.441)	(0.844)	(0.794)	(1.568)	(1.638)
S	0.592***	1.757***	2.642***	2.583***	3.078***	3.244***
	(0.196)	(0.299)	(0.333)	(0.323)	(0.724)	(0.621)
Cointegration coefficient	-0.569***	-0.816***	-0.944***		-1.261***	
	(0.042)	(0.048)	(0.039)		(0.073)	
CD-test statistic	-0.42	-0.76	30.07	30.23	-1.92	-1.59
CD-test p-value	0.67	0.44	0.00	0.00	0.05	0.11
RMSE	2.86	2.64	2.21	2.30	0.82	1.25
NXT	1259	1259	1259	1259	1133	1167
N	54	54	54	54	52	54

Notes: GDP growth is the dependent variable. Log domestic credit to private sector by banks to GDP (B) and log market capitalization of listed companies to GDP (S) are the independent variables. The estimates of the intercept term are omitted. Standard errors are given in parentheses. Results are reported for a period of time from 1988 to 2012. Long run estimates of dynamic models and cointegration coefficients of ARDL models are reported. Estimators: (1) POLS: Dynamic autoregressive distributed lagged (ARDL) Pooled OLS, augmented with T-2 year dummies; (2) 2FE: Dynamic ARDL Two-way fixed effects, augmented with T-2 year dummies and N-1 country dummies; (3) MG: Dynamic ARDL Mean Group Pesaran and Smith (1995); (4) DLMG: Distributed lagged DL Mean Group; (5) CS-ARDL: Dynamic cross-sectional ARDL Chudik and Pesaran (2015a), augmented with three lags of the cross-sectional averages of the dependent and independent variables; (6) CS-DLMG: Cross-sectional DL Chudik et al. (2016) Mean Group, augmented with three lags of the cross-sectional averages of the independent variables. Models (1), (2), (3) and (5) are represented by a Error Correction Model (ECM) and are augmented with one lag of the dependent and independent variables. Standard errors of ARDL models are computed via the Delta method. Models (4) and (6) are augmented with one lag of the independent variables. White heteroskedasticity-robust standard errors are reported for models (1) and (2). For models (3)-(6) we report (i), the estimates of the outlier-robust mean of parameter coefficients across groups following Hamilton (1992); and (ii), nonparametric standard errors according to Pesaran and Smith (1995) and Pesaran (2006) (the latter only for (5) and (6)). Levels of significance are represented by * 10%, ** 5% and *** 1%. Diagnostics: See Table 3, except for the CIPS test.

[32] For a brief description of the results from the online supplement that complement the findings that we present here, see section A1.

[33] We obtain similar findings when we model bank development separately and use data from 1988 to 2014.

There are two possible implications of the results in the above paragraphs, particularly those from models that consider observed and unobserved heterogeneities. First, the functioning of stock markets may smooth the effects of unobserved common factors and therefore promote an efficient allocation of resources which spurs economic growth across countries. This coincides with studies which show that stock markets reduce the exposure of an economy to a downturn (e.g. Easterly et al., 2000).

Second, banking development may be detrimental to long-term growth. This might be because, when financial systems reach high levels of depth, the unobserved common shocks which produce dependencies across countries may trigger malfunctions in banking systems that hinder the allocation of resources toward productive activities, which, in turn, may discourage aggregate investment spending and therefore hamper economic growth. These assertions are supported by Tables A34-A36 and Tables B27-B30 from the online supplement which suggest that stock market development may promote long-term investment in fixed assets, while banking development may not.

Our findings also complement studies that suggest that (i) endogenous lending booms cause economic instability (Minsky, 1977; Kindleberger, 1978; Schularick and Taylor, 2012); and (ii), banking crises generate large output losses and tend to be followed by serious recessions and slow recoveries (Laeven and Valencia, 2010; Jordà et al., 2013).

4.2.2. Results for advanced and emerging economies and robustness checks

Table 5 presents the results of static and dynamic heterogeneous models that account for unobserved common factors and employ two different subsamples, one for advanced countries and the other for developing countries.[34] However, the cross-sectional averages for advanced economies are only based on these countries plus China, since the models that include cross-sectional averages based on the whole sample are misspecified due to strong residual cross-sectional dependence (see for example Table A9 from the online supplement),[35] whereas the cross-sectional averages for emerging economies are computed on the basis of the full sample.[36]

[34] Tables A5-A8 from the online supplement show the estimates of the models which assume cross-sectionally independent errors. Although, the sign and level of significance of these estimates agree with the findings that we present here, some of them are inconsistent due to strong cross-section dependence and/or non-stationarity in residuals.

35 We follow Chudik and Pesaran (2015b) for the construction of cross-sectional averages in unbalanced panels. We therefore assume that for advanced countries we account for error cross-section dependencies from these countries and China.

36 Due to the different way in which cross-sectional averages are constructed for advanced and emerging economies, we believe that the results for these

TABLE 5

Static and dynamic CCEMG models for advanced and emerging countries

	Advanced countries			*Emerging countries*		
	CCEMG	*CS-ARDL*	*CS-DLMG*	*CCEMG*	*CS-ARDL*	*CS-DLMG*
	(1)	(2)	(3)	(4)	(5)	(6)
B	-3.815***	-4.278	-3.249*	-3.308***	-6.077***	-6.485***
	(1.283)	(3.207)	(1.818)	(1.142)	(1.751)	(1.901)
S	1.507***	1.238	2.101***	2.017***	3.955***	4.749***
	(0.572)	(1.059)	(0.708)	(0.383)	(1.020)	(1.090)
Cointegration coefficient		-1.259***			-1.370***	
		(0.100)			(0.091)	
CD-test statistic	0.27	0.06	0.91	-2.04	-0.22	-1.79
CD-test p-value	0.79	0.95	0.36	0.04	0.82	0.07
Order of Integration	I(0)			I(0)		
RMSE	1.44	0.60	0.77	2.50	0.99	1.53
NXT	608	502	536	705	631	631
N	25	23	25	29	29	29

Notes: GDP growth is the dependent variable. Log domestic credit to private sector by banks to GDP (B) and log market capitalization of listed companies to GDP (S) are the independent variables. The estimates of the intercept term are omitted. Long run estimates of dynamic models and cointegration coefficients of ARDL models are reported. Standard errors of ARDL specifications are computed via the Delta method. Standard errors are given in parentheses. Results are reported for a period of time from 1988 to 2012. Estimators: (1) and (4) CCEMG: Common Correlated Effects MG Pesaran (2006), augmented with cross-section averages; (2) and (5) CS-ARDL: Dynamic cross-sectional ARDL Chudik and Pesaran (2015a) represented by a Error Correction Model (ECM), augmented with one lag of the dependent and independent variables and three lags of the cross-sectional averages of the dependent and independent variables; (3) and (6) CS-DLMG: Cross-sectional DL Chudik et al. (2016) Mean Group, augmented with one lag of the independent variable and three lags of the cross-sectional averages of the independent variables. For advanced countries we compute the cross-section averages based only on advanced countries plus China, while for emerging economies we use cross-section averages based on the full sample. For these models we report (i), the estimates of the outlier-robust mean of parameter coefficients across groups following Hamilton (1992); and (ii), nonparametric standard errors according to Pesaran and Smith (1995) and Pesaran (2006). Levels of significance are represented by * 10%, ** 5% and *** 1%. Diagnostics: See Table 3.

We find that two of the three models for advanced economies yield significant and consistent coefficients and their signs agree with the findings for the full sample. This is also the case for the dynamic models of the sample of emerging economies, although the magnitude of the slopes is greater than that of advanced countries. The results also suggest that there is cointegration of variables at the 1% level for the CS-ARDL model. Accordingly, the conclusions of the previous section may apply to the results of these two subsamples for the period of

subsamples should be interpreted and contrasted with utmost caution whenever the effect of shocks is modeled.

1988-2012; however, as we will see in the following section, this may not be the case for the coefficients of bank development in the emerging economies between 1961 and 2014, because they become insignificant.

TABLE 6

Static CCEMG models including additional regressors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
B	-3.910***	-3.638***	-4.379***	-4.617***	-3.305***	-3.992***	-4.976***
	(1.103)	(0.949)	(0.945)	(1.146)	(0.943)	(0.986)	(0.834)
S	1.767***	1.465***	1.541***	1.822***	1.687***	1.875***	1.763***
	(0.255)	(0.302)	(0.279)	(0.322)	(0.305)	(0.344)	(0.332)
TR	2.847*						
	(1.458)						
GCE		-7.733***					
		(2.383)					
GFK			6.718***				
			(1.273)				
GD				-2.415***			
				(0.736)			
PG					-0.273		
					(0.571)		
BC						-0.713	-0.442
						(0.485)	(0.292)
BxBC						-0.348	
						(0.277)	
SxBC							0.114
							(0.225)
CD-test statistic	0.56	0.64	0.91	0.81	1.84	1.93	2.80
CD-test p-value	0.57	0.52	0.36	0.41	0.06	0.05	0.00
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	1.89	1.89	1.88	1.84	1.93	1.79	1.71
NXT	1313	1309	1309	1294	1313	1264	1208
N	54	54	54	54	54	54	54

Notes: GDP growth is the dependent variable. Log domestic credit to private sector by banks to GDP (B) and log market capitalization of listed companies to GDP (S) are the main independent variables. We include additional regressors such as the log trade to GDP (TR), log general government final consumption expenditure to GDP (GCE), log gross fixed capital formation to GDP (GFK), log total (domestic plus external) gross (central and/or general) government debt to GDP (GD), population growth (PG), a banking crisis dummy (1=banking crisis, 0=none) (BC), the interaction between the dummy of banking crisis and the log domestic credit to private sector by banks to GDP (BxBC), and the interaction between the dummy of banking crisis and log market capitalization of listed companies to GDP (SxBC). The estimates of the intercept term are omitted. Standard errors are given in parentheses. Results are reported for a period of time from 1988 to 2012, except for those models which include banking crisis dummies where the time frame is from 1988-2011. We use the Common Correlated Effects MG Pesaran (2006) estimator augmented with cross-section averages of the dependent and independent variables. Here we report (i), the estimates of the outlier-robust mean of parameter coefficients across groups following Hamilton (1992); and (ii), nonparametric standard errors according to Pesaran and Smith (1995) and Pesaran (2006). Levels of significance are represented by * 10%, ** 5% and *** 1%. Diagnostics: See Table 3.

Table 6 presents a version of the model (5) which includes additional regressors for robustness checks. The models that include banking crisis dummies cover the period from 1988 to 2011. Given the lack of time series data, we only include one additional variable at a time. In columns (5) and (6), following Shen and Lee (2006), we include a dummy for banking crisis and a term for the interaction between this variable and the financial development regressors. The results coincide with those from previous tables, even when gross government debt is included, whose effect is negative and significant.[37] Only the model in column (6) is misspecified due to strong residual cross-sectional correlation.[38]

Results in Table 7 include alternative proxy variables for banking and stock market development and economic growth. Models that include the log of the turnover ratio of stocks traded run from 1989 to 2012. Although the model that includes the log bank lending-deposit spread (SP_{it}) is misspecified because it suffers from nonstationary residuals, the implementation of these alternative variables does not affect the sign and significance of the financial development estimates that we find above; hence, the aforementioned conclusions about the impact of these variables on growth also hold here.[39] Furthermore, basing ourselves on these and previous results, we also infer that, at the levels of financial development and the samples we are considering here, financial systems structure may matter for economic activity in the sense that market based systems might be better than bank-based systems at promoting long-run economic growth.

37 See Tables A33-A34 from the online supplement for evidence from dynamic models when gross government debt is included as an additional regressor.

38 These results hold for other specifications and for the subsamples of advanced and emerging countries. See Tables A10-A14 of the online supplement.

39 Additional results in Tables A16-A32 in the online supplement support our conclusions.

TABLE 7

Static CCEMG models including other proxy variables for economic growth, banking sector development and stock market development

	STV (1)	*MTR* (2)	*YP* (3)	*LL* (4)	*SP* (5)
Banking sector development	-4.096***	-3.998***	-3.943***	-4.141***	-0.567
	(0.794)	(0.811)	(0.853)	(0.828)	(0.584)
Stock market development	1.302***	0.548**	2.219***	1.998***	1.483***
	(0.189)	(0.251)	(0.287)	(0.304)	(0.568)
CD-test statistic	0.47	1.31	-0.09	0.05	-0.75
CD-test p-value	0.63	0.19	0.92	0.95	0.45
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(1)
RMSE	2.02	1.99	2.10	2.13	2.15
NXT	1309	1257	1313	1261	615
N	54	54	54	52	26

Notes: In contrast with previous tables, in models (1) and (2) the log total value of stocks traded to GDP (STV) and the log turnover ratio of stocks traded (MTR) respectively are used as proxies of stock market development. Meanwhile, model (3) includes per capita GDP growth as a proxy of economic growth (YP). Following Shen and Lee (2006), models (4) and (5) include log liquid liabilities to GDP (LL) and log bank lending-deposit spread (SP) respectively as proxies of the financial depth of the banking industry. The estimates of the intercept term are omitted. Standard errors are given in parentheses. Results are reported for a period of time from 1988 to 2012, except for those models which include the log of the turnover ratio of stocks traded where the time frame is from 1989-2012. We use the Common Correlated Effects MG Pesaran (2006) estimator augmented with cross-section averages of the dependent and independent variables. Here we report (i), the estimates of the outlier-robust mean of parameter coefficients across groups following Hamilton (1992); and (ii), nonparametric standard errors according to Pesaran and Smith (1995) and Pesaran (2006). Levels of significance are represented by * 10%, ** 5% and *** 1%. Diagnostics: See Table 3.

4.3. Long-run effects of banking development on economic growth from 1961 to 2014

The results in Table 8 show the estimates for the full sample of the CS-ARDL and CS-DLMG models by including the banking development variable as the only proxy for financial development, and two additional variables for robustness checks, such as the log of the ratio of final general government consumption expenditure to GDP (GCE_{it}) and the log of inflation ($INFL_{it}$).[40] These models include up to 3 lags of variables and

[40] Tables B1-B27 from the online supplement show the additional results of models which (i) include other regressors for robustness checks and other proxy variables for financial development and economic growth; (ii), employ

cross-sectional averages. Once again, the long-run effects of banking development might be detrimental for output growth.[41] The variables of the CS-ARDL models are cointegrated at the 1% level. The CD test shows that all dynamic models successfully deal with residual cross-section dependence.

TABLE 8

Dynamic CCEMG models for banking development and growth from 1961-2014, including general government final consumption expenditure to GDP and inflation as additional regressors

	CS-ARDL			*CS-DLMG*		
	1 lag	*2 lags*	*3 lags*	*1 lag*	*2 lags*	*3 lags*
	(1)	(2)	(3)	(4)	(5)	(6)
B	-1.762***	-1.663**	-1.696*	-1.973***	-1.647*	-1.844*
	(0.663)	(0.816)	(0.971)	(0.702)	(0.893)	(1.037)
GCE	-6.301***	-7.622***	-7.149***	-6.709***	-5.866***	-6.853***
	(1.549)	(1.782)	(2.572)	(1.659)	(1.893)	(2.363)
INFL	-1.053***	-1.163***	-1.191***	-0.791***	-1.207***	-0.894**
	(0.223)	(0.271)	(0.425)	(0.196)	(0.255)	(0.359)
Cointegration coefficient	-0.994***	-1.139***	-1.136***			
	(0.032)	(0.064)	(0.088)			
CD-test statistic	-0.15	1.66	-0.14	-0.57	0.44	-0.09
CD-test p-value	0.87	0.09	0.88	0.56	0.66	0.92
RMSE	1.73	1.51	1.33	1.91	1.74	1.61
NXT	2431	2334	2193	2463	2419	2327
N	53	50	46	54	53	50

Notes: GDP growth is the dependent variable. Log domestic credit to private sector by banks to GDP (B) is the main independent variable. Log general government final consumption expenditure to GDP (GCE) and log inflation (INFL) are included as additional regressors. The estimates of the intercept term are omitted. Standard errors are given in parentheses. Long run estimates of dynamic models and cointegration coefficients of ARDL models are reported. Standard errors of ARDL specifications are computed via the Delta method. Estimators: (1)-(3) CS-ARDL: Dynamic cross-sectional ARDL Chudik and Pesaran (2015a) represented by a Error Correction Model (ECM), augmented with one, two and three lags of the dependent and independent variables and three lags of the cross-sectional averages of the dependent and independent variables; (4)-(6) CS-DLMG: Cross-sectional DL Chudik et al. (2016) Mean Group, augmented with one, two and three lags of the independent variables and three lags of the cross-sectional averages of the independent variables. For all models we report (i), the estimates of the outlier-robust mean of parameter coefficients across groups following Hamilton (1992); and (ii), nonparametric standard errors according to Pesaran and Smith (1995) and Pesaran (2006). Levels of significance are represented by * 10%, ** 5% and *** 1%. Diagnostics: See Table 3, except for the CIPS test.

Table 9 shows that the estimates for the subsample of advanced countries coincide with those of the full sample in the sense that the

subsamples of emerging and advanced countries (in addition to the models that we present in Tables 9-10); and (iii), use other estimators. Overall, these results support the findings of this section.

[41] Our results also hold for some specifications from 1961 to 2007.

coefficients of banking development are negative, significant and consistent; the cointegration of variables in the CS-ARDL models is achieved at 1%; and all the dynamic models deal with residual cross-section correlation. By contrast, Table 10 shows that, for emerging economies, the estimates for banking development are negative and consistent, but insignificant. These findings contradict those from the 1988-2012 panel, where the estimates of banking development are significant, either when this variable is modeled along with stock market development, or when it is regarded as the only financial development variable. This may indicate that the negative effect of bank development on growth is mainly limited to advanced countries.

TABLE 9

Dynamic CCEMG models for banking development and growth from 1961-2014 for advanced countries, including general government final consumption expenditure to GDP and inflation as additional regressors

	CS-ARDL			*CS-DLMG*		
	1 lag (1)	*2 lags* (2)	*3 lags* (3)	*1 lag* (4)	*2 lags* (5)	*3 lags* (6)
B	-1.228**	-2.286***	-3.503***	-1.363**	-1.631**	-2.033**
	(0.569)	(0.848)	(0.965)	(0.634)	(0.665)	(0.945)
GCE	-5.688***	-5.449**	-4.940**	-5.340***	-6.508***	-5.969**
	(1.601)	(2.382)	(2.224)	(1.441)	(1.756)	(2.385)
INFL	-1.081***	-1.116***	-1.303***	-1.216***	-1.156***	-0.989**
	(0.271)	(0.310)	(0.454)	(0.229)	(0.316)	(0.479)
Cointegration coefficient	-1.080***	-1.101***	-1.164***			
	(0.039)	(0.084)	80.112)			
CD-test statistic	-0.81	-0.37	-1.96	-1.54	-1.7	-2.17
CD-test p-value	0.41	0.71	0.05	0.12	0.09	0.03
RMSE	1.21	1.06	0.99	1.34	1.23	1.17
NXT	1186	1179	1112	1190	1184	1178
N	25	25	23	25	25	25

Notes: In contrast with Table 8, we implement cross-section averages based only on advanced countries plus China. For additional details see Table 8. For diagnostics see Table 3, except for the CIPS test.

TABLE 10

Dynamic CCEMG models for banking development and growth from 1961-2014 for emerging countries, including general government final consumption expenditure to GDP and inflation as additional regressors

	CS-ARDL			*CS-DLMG*		
	1 lag (1)	*2 lags* (2)	*3 lags* (3)	*1 lag* (4)	*2 lags* (5)	*3 lags* (6)
B	-1.338	-0.576	0.228	-2.069*	-1.293	-0.543
	(1.046)	(1.386)	(1.151)	(1.099)	(1.502)	(1.729)
GCE	-3.458	-3.936	0.750	-3.167	-2.324	-3.871
	(2.435)	(2.554)	(3.696)	(2.741)	(3.171)	(3.883)
INFL	-1.107**	-1.566***	-1.356**	-0.708*	-1.395***	-0.808
	(0.452)	(0.471)	(0.638)	(0.367)	(0.505)	(0.662)
Cointegration coefficient	-0.989***	-1.174***	-1.317***			
	(0.046)	(0.101)	(0.155)			
CD-test statistic	-1.34	-1.01	-0.60	-1.34	-1.42	-1.36
CD-test p-value	0.18	0.31	0.54	0.18	0.15	0.17
RMSE	2.08	1.85	1.60	2.29	2.10	1.94
NXT	1245	1155	1081	1273	1235	1149
N	28	25	23	29	28	25

Notes: In contrast with Table 9, we implement cross-section averages based on the full sample. For additional details see Table 8. For diagnostics see Table 3 except, for the CIPS test.

Tables A3-A4 from the online supplement present the estimates of dynamic models by including bank development as the only independent variable to verify whether pooling and/or assuming error cross-sectional independence for this sample yields consistent estimates. The results suggest that the coefficient of bank development is negative and significant. However, all pooled and cross-sectionally independent MG specifications suffer from strong residual cross-sectional dependence. By contrast, only one of all the CCEMG models indicates this problem. These results coincide with those of the pooled and error cross-sectionally independent MG dynamic specifications where other regressors are modeled, and which are reported in Table 11 and Tables B16-B20 from the online supplement.[42] Therefore, in contrast with what happens with smaller panel time series, the CD test tends to reject the weak residual cross-section dependence of all pooled estimators when they have more dynamics, and therefore address reverse causality in a more accurate manner and reduce a possible small sample bias. These findings suggest that pooling observations and/or disregarding error cross-sectional dependencies may be susceptible to incorrect inference

[42] We find similar results for the subsamples of advanced and emerging countries, or when we employ several robustness checks.

because it may ignore substantial observed and unobserved heterogeneities in the data.

TABLE 11

Dynamic pooled and MG models for banking development and growth from 1961-2014, including general government final consumption expenditure to GDP and inflation as additional regressors

	POLS			*2FE*			*MG*			*DLMG*		
	1 lag	*2 lags*	*3 lags*	*1 lag*	*2 lags*	*3 lags*	*1 lag*	*2 lags*	*3 lags*	*1 lag*	*2 lags*	*3 lags*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
B	-0.127	-0.222	-0.367	-0.596**	-0.749**	-0.879**	-1.444***	-1.521***	-1.739***	-1.360***	-1.564***	-1.736***
	(0.208)	(0.241)	(0.281)	(0.285)	(0.308)	(0.342)	(0.424)	(0.451)	(0.480)	(0.437)	(0.475)	(0.452)
GCE	-2.016***	-2.172***	-2.220***	-3.172***	-3.276***	-3.352***	-5.744***	-5.941***	-6.008***	-5.417***	-5.868***	-6.095***
	(0.357)	(0.397)	(0.473)	(0.698)	(0.723)	(0.843)	(1.237)	(1.418)	(1.527)	(1.153)	(1.287)	(1.392)
INFL	-0.145	-0.248	-0.231	-0.395**	-0.529***	-0.495**	-0.502***	-0.534***	-0.337**	-0.449***	-0.473***	-0.410**
	(0.161)	(0.189)	(0.229)	(0.160)	(0.178)	(0.209)	(0.117)	(0.136)	(0.165)	(0.121)	(0.127)	(0.159)
Cointegration coefficient	-0.609***	-0.535***	-0.447***	-0.734***	-0.712***	-0.647***	-0.891***	-0.894***	-0.908***			
	(0.032)	(0.034)	(0.034)	(0.033)	(0.037)	(0.040)	(0.023)	(0.035)	(0.050)			
CD-test statistic	-2.53	-2.23	-2.35	-2.77	-2.45	-2.50	17.08	17.69	15.20	18.01	18.78	18.00
CD-test p-value	0.01	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
RMSE	3.13	3.09	3.05	3.01	2.99	2.98	2.54	2.33	2.18	2.60	2.43	2.31
NXT	2517	2463	2409	2517	2463	2409	2517	2463	2409	2525	2473	2421
N	54	54	54	54	54	54	54	54	54	54	54	54

Notes: GDP growth is the dependent variable. Log domestic credit to private sector by banks to GDP (B), log general government final consumption expenditure to GDP (GCE), and log inflation (INFL) are the independent variables. The estimates of the intercept term are omitted. Standard errors are given in parentheses. Results are reported for a period of time from 1961 to 2014. Long run estimates of dynamic models and cointegration coefficients of ARDL models are reported. Estimators: (1)-(3) POLS: Dynamic autoregressive distributed lagged (ARDL) Pooled OLS, augmented with T-2 year dummies; (4)-(6) 2FE: Dynamic ARDL Two-way fixed effects, augmented with T-2 year dummies and N-1 country dummies; (7)-(9) MG: Dynamic ARDL Mean Group Pesaran and Smith (1995); (10)-(12) DLMG: Distributed lagged DL Mean Group. Models (1)-(9) are represented by a Error Correction Model (ECM) and are augmented with one, two and three lags of the dependent and independent variables. Standard errors of ARDL models are computed via the Delta method. Models (10)-(12) are augmented with one, two and three lags of the independent variables. White heteroskedasticity-robust standard errors are reported for models (1)-(6). For models (7)-(12) we report (i), the estimates of the outlier-robust mean of parameter coefficients across groups following Hamilton (1992); and (ii), nonparametric standard errors according to Pesaran and Smith (1995). Levels of significance are represented by * 10%, ** 5% and *** 1%. Diagnostics: See Table 3, except for the CIPS test.

5. Conclusion

This article analyzes the long-term effects of banking and stock market performance on economic growth in unbalanced macro panels. Our paper offers three innovations for the study of this subject: First, we employ models that allow for parameter heterogeneity to consider country-specific features. We extend this notion of heterogeneity to the unobserved determinants of the variables, such as common shocks, to account for error cross-section dependence in a multifactor error structure. Second, we address several time series features, such as dynamics, serial correlation in errors and reverse causality, to determine the long-term equilibrium of variables. We also use static models to deal with a possible sampling uncertainty. Third, we employ two panels of 54 advanced and emerging countries: the first includes banking and stock market development variables from 1988 to 2012, while the second only covers banking development from 1961 to 2014. We further examine one subsample for advanced countries and another for emerging countries. We check the robustness of our results by including additional regressors, or employing different proxies for our main variables.

For the full sample we find (i), a significant negative long-run relationship between banking development and GDP growth; and (ii), a significant positive effect of stock market development on economic activity. The results for the subsample of advanced countries agree with these findings; however, there is no convincing evidence that this is the case for emerging economies, where despite a positive and significant effect of stock market development on growth, the negative effect of bank development is as likely to be significant as insignificant. Moreover, we find that disregarding strong error cross-sectional dependencies caused by common factors and/or assuming homogeneous slopes may be susceptible to incorrect inference.

Our findings, however, may be subject to an important limitation: although banks and stock markets promote financial development insofar as they reduce transaction costs and facilitate access to information, our definitions of financial development may not sufficiently capture these aspects (Levine, 2005). Furthermore, our proxy variables for banking development may not account for the quality of intermediation or the extent to which non-financial enterprises and households use credit services (Beck et al., 2012, 2014). While these issues prevent us from accurately linking theory and measurement, we can still draw the following conclusions and policy implications from our empirical analysis: First, financial systems structure may matter for economic activity across countries because market based systems might be better than bank-based systems at boosting long-term growth; second, further studies should take country-specific aspects and common shocks into account to examine the components of financial development that generate the effects that we find in our study, otherwise empirical analysis may be inconsistent, as we demonstrate here.

Third, if policy makers adopt growth-enhancing measures that are associated with fostering the financial functioning of equity markets and improving the intermediating functions of the banking system and, therefore, the quality of credit, this should be done by implementing financial contingency strategies that first, hedge against unexpected macro and microeconomic common shocks, which are propagated through global financial networks and other channels of contagion, and generate cross-country dependencies; and second, adjust to the evolution of financial interconnected systems and the specific economic conditions of each country.

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