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Abstract

The existing weight of evidence suggests that financial structure (the classification of a financial system as *bank-based* versus *market-based*) is irrelevant for economic growth. This contradicts the common belief that the institutional structure of a financial system matters. We re-examine this issue using a novel dataset covering 69 countries over 1989-2011 in a Bayesian framework. Our results are conformable to the belief - a *market-based* system is relevant - with sizable economic effects for the high-income but not for the middle-and-low-income countries. Our findings provide a counterexample to the weight of evidence. We also identify a regime shift in 2008.

JEL Classification: G0; O4; O16
Keywords: Financial Structure; Economic Growth; Cointegration; Bayesian Model Averaging; Structural Breaks.

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1. Introduction

It is widely presumed that the institutional structure of a financial system is important. This is why the role of financial structure on corporate governance and economic growth has been debated over centuries. According to Allen and Gale (2001), this debate dates back to the early 18th century South Sea Bubble of the UK and the Mississippi Bubble of France, which prompted discussions about corporate governance and financial stability, hence the debate on *bank-based* versus *market-based* financial systems. Subsequently, Gerschenkron (1962) and Goldsmith (1969) elaborated on the potential role of financial structure on economic growth. Ever since, an extensive body of literature has evolved on this issue culminating in *bank-based*, *market-based*, *financial services*, *law-and-finance* and *reputation-and-relationships* views.

The financial structure of a country is a blend of financial institutions, instruments, markets and the rules governing the financial system and contracts. However, in the development finance literature, the financial structure is defined by the relative weight (size and activities) of intermediaries and capital market in the country's financial sector. A financial system is defined as *bank-based* if the relative share (size and/or activities) of intermediaries is bigger than the capital market; the system is termed *market-based* if the share of capital market is bigger. Although the forms and roles of financial intermediaries and capital markets may differ markedly across countries, nonetheless this classification of *bank*- and *market-based* financial systems, widely used in the literature, does represent different financial structures, albeit in a narrow and highly aggregated sense. In Section 3 we outline the standard measures of financial structures.

The *bank-based* view argues that intermediaries are superior to financial markets in fostering resource allocation and economic growth. This view emphasizes, among others things, the relationship banking (the long term lender-borrower relationship) and banks' ability to alleviate asymmetric information and adverse selection. Banks' *ex post* monitoring of investments is seen to reduce moral hazards and banks are also perceived to address agency problems and short-termism (Stiglitz, 1985). Moreover, banks are the sole source of external finance for small and medium enterprises (SMEs) which have no access to capital markets. [1]

In contrast, the *market-based* view perceives capital markets as superior to intermediaries in fostering corporate governance, resource allocation and economic growth. The basic argument is that large, liquid and well-functioning markets facilitate risk management and risk reductions through diversification. Capital markets are also superior to banks in funding new ideas (projects), research and development (R&D) and venture capital (Allen and Gale, 1999), which are vital in raising productivity and competitiveness.

The *financial services* view, on the other hand, stresses both banks and capital markets, arguing that they provide complementary financial services. In any case, the dichotomy between *bank-* and *market-based* financial systems is not mutually exclusive. The financial systems designated as *market-based* (e.g., UK and US) do have global banks and those designated as *bank-based* (e.g., Germany and Japan) also have sizable and well-functioning capital markets. Intermediaries often play pivotal roles in financial markets as issuers and buyers of securities and hence are key market infrastructures. Likewise, capital markets play an important role in raising capital through new issues and provide a platform for secondary trading which ensures liquidity. Therefore, according to the *financial services* view, what matters for productivity and growth is the provision and effective delivery of financial services by the financial system (inclusive of intermediaries and markets).

A related strand of literature is the *law-and-finance* view. Legal scholars (e.g., Reynolds and Flores, 1989) classify the genesis of commercial legal systems of different countries into three main legal families, namely, the English Common Law, the French Civil Law and the German Civil Law. This school argues that the protection of outside investors against expropriations by insiders is fundamental for sound corporate governance and financial development to foster the finance-growth nexus. This view, therefore, emphasizes the legal provisions – laws governing contract, company, securities, bankruptcy, takeover, competition etc. – and their enforcement quality. [2]

One exception to the *law-and-finance* view, however, is Allen et al. (2005). They show that China rates poorly vis-à-vis legal provisions and enforcement mechanisms, quality of government, corruption in government, and institutions and investor protection, compared to other emerging countries, including those in La Porta et al. (1998). Yet the Chinese economy is growing rapidly, mainly fueled by the growth of small private sector family firms (enterprises).

According to Allen et al. (2005), the Chinese growth experience is an important "counterexample" to the extant findings of the law-finance-and-growth literature. They argue that Confucian beliefs have led to high social trusts in China, enabling the development of alternative financing and governance mechanisms based on *reputation-and-relationships*.

The theoretical controversy, as Langfield and Pagano (2016, p. 62) neatly put it, "….has not established a clear-cut prediction regarding the superiority of *bank-based* or *market-based* finance in promoting the efficient allocation of funding, and thus on economic performances". Hence, the battle is fought on empirical grounds. Historically, this debate is empirically scrutinized by taking the US and UK as the standard-bearers of *market-based* financial systems versus Japan and Germany as the stalwarts of *bank-based* systems. As stated elsewhere (e.g., Goldsmith, 1969; Beck and Levine, 2002), the problem with this type of empirical scrutiny is that both pairs of countries are developed economies and they exhibit similar long-run growth rates. Therefore, when countries with *bank-based* (Germany and Japan) and *market-based* (the UK and US) financial systems achieve similar levels of development and growth rates, then little can be dispensed on the role of their differing financial structures.

This narrow empirical focus – i.e., the comparative study of the UK and US versus the German and the Japanese financial systems – in evaluating the role of financial structure on corporate governance and economic growth has taken a significant turn over the last two decades or so. A voluminous work by Beck, Demirgüç-Kunt, Levine, Maksimovic and their collaborators – culminating in several influential journal articles and book volumes – examines the role of financial development and financial structure on (i) long-run economic growth, (ii) industrial growth and (iii) the creation of new firms by analyzing cross-country, cross-country-and-cross-industry and firm-level data in panel and/or cross-sectional frameworks (some of the major references are cited in footnote 1). They consistently report that financial structure (the classification of the financial system as *bank-based* versus *market-based*) is immaterial (insignificant) for economic growth, industrial growth and the creation of new firms across a large array of sample countries. Instead, they find that the level of overall financial development – an aggregate measure of capital market and intermediaries which proxies the *financial services* view – is significant. Hence, they conclude that their findings are supportive of the *financial services* view which emphasizes the role of financial services offered by the financial system collectively (Merton and Bodie, 1995; Levine, 2002). The time series study of Luintel et al.

(2008), which examines the role of financial structure and financial development utilizing similar measures and specifications but addressing the non-stationarity in the data, does find evidence of financial structure significantly explaining economic growth, but these types of study are relatively sparse.

The *law-and-finance* view is extensively scrutinized by Djankov, La Porta, Lopez-de-Silanes, Shleifer, Vishny and their collaborators who have produced a large body of influential literature (references in footnote 2). They consistently report that the highest protection for outside investors is provided by the common law countries followed by the German civil law countries; the French civil law countries provide the least protection. They report that common law countries have (i) bigger stock markets relative to their GDP, (ii) more listed firms per millions of people, (iii) more Initial Public Offerings (IPOs) relative to GDP and (iv) less concentrated ownership, compared to the French civil law countries. Their results confirm that investors' protection enables financial sector development which in turn stimulates the real economy. Hence, their policy prescription is to focus on better laws and enforcement mechanisms, which contributes to the development of the financial sector and hence the finance-growth nexus.

Some exceptions notwithstanding, the weight of evidence has been that financial structure is not significant in explaining economic growth. This refutes the wide presumption that the institutional structure of a financial system matters. These findings also pose an important policy dilemma vis-à-vis the institutional structure of a country's financial system. In this context, we reinvestigate this contentious issue of the irrelevance of financial structure vis-à-vis economic growth by (i) utilizing a recently released novel dataset and (ii) proposing some advances in econometric (investigation) methodology. For any multicountry empirical study, which encompasses a large number of countries, the quality and consistency of data is vital for the reliability of its results. Indeed, Čihák, Demirgüç-Kunt, Feyen and Levine (2013; hereafter CDFL, 2013) have recently made available a thoroughly revised and updated dataset on financial development and structure for a large number of countries which we utilize.[3] They state that "All indicators have been recalculated for the entire time period to ensure higher quality and consistency over time." When we compile and compare the different measures of financial development and structures based on this new dataset with those used in the previous literature (e.g., Levine, 2002) we find striking differences in these measures across countries (see Section

3). We analyze a full panel of 69 countries, along with separate panels of 33 high-income and 36 middle-and-low-income countries. This dataset spans 1989-2011 and covers the recent financial crisis. The global financial crisis of 2008, which has led to a prolonged recession, has been a wake-up call to both bankers and policy makers. In this context, an interesting issue would be to examine whether the global financial crisis has impacted structural shift in the relationship between financial development, structure and economic growth. We also investigate this issue.

Methodologically, we extend the panel dynamic ordinary least squares (DOLS) estimator (Stock and Watson, 1993; Kao and Chiang, 2000) to a Bayesian framework. Our extension allows for multiple breaks in unknown locations. To our knowledge, almost all empirical literature (definitely all those cited above) on this issue is based on the frequentist approach. The Bayesian approach is shown to be a powerful method to estimate models with an unknown number of structural breaks (e.g. Pesaran et al., 2006), which squares nicely with investigating the episodes of structural breaks or regime shifts in the relationship. The clear advantages are that: (i) we obtain credible parameter (e.g. cointegrating vectors) estimates and confidence intervals that are robust to the presence of breaks, (ii) the use of a transition equation implies that we have a prior for the parameters after the break that is centered on the parameters before the break which improves efficiency, and (iii) it enables us to deal with the large number of possible break locations that arise when the number of breaks is unknown.[4] We thus hope to extend the econometric methodology and take the empirical literature on the link between financial development, structure and economic growth in a new direction.

Our study complements some of the recent studies in this field. In an interesting paper, Langfield and Pagano (2016) show that the European financial system has become more *bank-based* since the mid-1990s which has increased systemic risk intensity at the bank-level and adversely affected economic growth. They also report that banking crises and stock market crises tend to amplify these adverse effects on systemic risk and growth, and more so in the *bank-based* financial systems. They focus on the role of disproportionately large banks in the run up to the financial crisis and its propagation, whereas we focus on re-examining the weight of evidence on the irrelevance of financial structure – which has hitherto directly contradicted the widely held belief that financial structure should matter for growth – in the light of new data and methods. Further, Langfield and Pagano analyze 20 countries whereas we analyze a much larger sample (69 countries). Gambacorta et al. (2014) also report different yet non-monotonic effects of intermediaries (bank credit to GDP ratio) and markets (stock market turnover to GDP ratio) on economic growth. Again, our country coverage, data, specification and empirical approach are different from theirs. Finally, Arcand et al. (2015) report that the effect of financial depth on economic growth is an inverted U-shape. They estimate credit thresholds of 80% - 100% of GDP beyond which financial depth is found to be inversely related to economic growth. These are interesting findings in their own right, yet the focus is on the effects of financial depth (measured by total credit or bank credit to GDP ratios) on economic growth, whereas we focus on the issue of financial structure, development and growth. Our paper complements these recent studies by documenting further new results vis-à-vis the nexus between financial development, structure and economic growth.

A brief preview of our results is in order. We find a long-run equilibrating (cointegrating) relationship between the variables that tie real income levels to financial development and structure. We find that financial structure matters for the group of high-income countries; all assessed structure measures contribute positively and significantly to income levels in the long run with sizable economic effects. Interestingly, results do not support the *financial services* view. Both of these findings are in sharp contrast to the voluminous empirical literature (the weight of evidence discussed above) which reports quite the opposite – i.e., the significance of the *financial services* but the insignificance of the financial structure. In contrast to the high-income group, financial structure has virtually no significance in the middle-and-low-income countries. This difference in results between the high and low income groups is consistent with the findings of Rioja and Valev (2004) and Rousseau and Wachtel (2011) who also report different effects of financial development across high and low income groups of countries. We find one structural break (regime shift) in the year 2008 in the panel of high-income countries which we attribute to the recent financial crisis. The rest of the paper is organized as follows. The following section specifies the empirical model and outlines the econometric methodology. Section 3 covers the data; Section 4 presents empirical results; Section 5 briefly discusses robustness issues and Section 6 concludes with policy implications.

2. Specification and the Bayesian Approach to Panel Cointegration with Multiple Breaks

2.1 Model Specification

Our empirical specification for testing the relationship between financial structure, financial development and economic growth follows the standard approach in the literature (see for example, Demirgüç-Kunt and Maksimovic, 2002; Levine, 2002; Luintel et al., 2008; to name but a few). Typically, in a non-stationary setup, the real GDP per capita is specified as the response variable (regressand) and the levels of per capita physical capital stock, and the separate measures of financial structure and development as the covariates (regressors).[5] The DOLS specification of our empirical panel model, under the Bayesian framework, which allows for multiple breaks (shifts) in the cointegrating parameters at unknown locations, is:

$$\begin{aligned} y_{i,t} = \gamma_{1i} + t\gamma_{2i} + t^2\gamma_{3i} + \sum_{j=-d_1}^{d_2} \gamma_{4ij}\Delta k_{i,t+j} + \sum_{j=-d_1}^{d_2} \gamma_{5ij}\Delta fd_{i,t+j} + \sum_{j=-d_1}^{d_2} \gamma_{6ij}\Delta fs_{i,t+j} \\ + \beta_{1t}k_{i,t} + \beta_{2t}fd_{i,t} + \beta_{3t}fs_{i,t} + \varepsilon_{i,t}, \qquad \varepsilon_{i,t} \sim i.i.d.\, N(0, \sigma^2), \end{aligned} \tag{1}$$

where $i = 1, 2, \ldots, N$; $t = 1, 2, \ldots, T$; $y_{i,t}$ is the log real per capita output (GDP), $k_{i,t}$ is the log of per capita physical capital stock, $fd_{i,t}$ and $fs_{i,t}$ respectively are measures of financial development and financial structure, d_1 and d_2 are non-negative scalars denoting the orders of lags and leads respectively, and $\varepsilon_{i,t}$ is the error term which follows a normal distribution with mean 0 and σ^2 variance. We assume that all cross-sectional units have a common cointegrating vector $\beta_t = (\beta_{1t}, \beta_{2t}, \beta_{3t})'$ which is time varying. The other coefficients in equation (1) are heterogeneous across *i* but time-invariant. Financial structure is measured such that a rise in $fs_{i,t}$ implies an increased weight (share) of capital markets relative to intermediaries, dubbed a *market-based* financial system in the literature (measures of $fd_{i,t}$ and $fs_{i,t}$ are discussed in Section 3). A close look at the country-specific data indicates that some of these variables may not be linearly trended, as is normally assumed. We show some of these plots in the Online Appendix, Figure 1. Hence, we allow for a quadratic trend in equation (1). At the estimation stage, the order of lags and leads as well as the inclusion of deterministic components (a constant and a linear or a quadratic trend) for each of our specifications is statistically identified through the predictive likelihood (Geweke, 1996). Specification (1) models the role of the financial structure on real per capita income while controlling for the potential effects of the overall financial development and per capita physical capital stock. This specification is in the tradition of a standard Cobb-Douglas production function augmented by measures of financial development and financial structure; the latter two variables are viewed to capture the total factor productivity (TFP).

Levine (2002) clearly lays out the parametric restrictions implied by the *bank-based*, *market-based* and *financial services* views vis-à-vis equation (1). The *market-based* view predicts that both capital markets and the overall financial development are conducive for output and growth. Since financial structure is measured such that a rise in $\boldsymbol{fs_{i,t}}$ implies a more *market-based* financial system, the predictions of *market-based* view imply *a priori* $\beta_{2,t} > 0$ and $\beta_{3,t} > 0$. In contrast, the *bank-based* view maintains that economies grow faster and achieve a higher level of income in a developed financial system that is intermediary-based, implying $\beta_{2,t} > 0$ and $\beta_{3,t} < 0$. The *financial services* view, on the other hand, emphasizes the role of overall financial development and de-emphasizes the *bank-based* versus *market-based* distinction, implying $\beta_{3,t} = 0$ and $\beta_{2,t} > 0$.

Equation (1) forms the basis of our empirical assessment. We have different measures of financial variables (more details provided in Section 3) which include: finance size (F^Z) and activities (F^A), structure size (S^Z) and activities (S^A) and the measures of finance aggregate (F^{AG}) and structure aggregate (S^{AG}). These measures capture different aspects of financial activities, hence are important. In our empirical work, we permit all possible combinations of these measures in the framework of equation (1) and evaluate the role of financial development and structure on economic growth. These combinations generate nine empirical specifications, for each panel, by pairing different measures of $fd_{i,t}$ and $fs_{i,t}$ as: (i) F^{AG} and S^{AG}, (ii) F^{AG} and S^A, (iii) F^{AG} and S^Z, (iv) S^{AG} and F^Z, (v) S^{AG} and F^A, (vi) S^A and F^Z, (vii) S^A and F^A, (viii) S^Z and F^Z, and (ix) S^Z and F^A. Thus, we estimate and report 27 models for three panels of sample countries. In these specifications, we allow the cointegrating vector (β_t) to be time varying to capture any shift in the cointegrating parameters. Its evolution process is:

$$\beta_{t+1} = \beta_t + B_t u_t, \tag{2}$$

where B_t is a binary variable indicating whether period t is a break ($B_t = 1$) or not ($B_t = 0$) and $u_t = (u_{1t}, u_{2t}, u_{3t})'$ is the difference between β_{t+1} and β_t when period t is a break. Let $\gamma_i = \left(\gamma_{1i}, \gamma_{2i}, \gamma_{3i}, \gamma_{4i,-d_1}, \dots, \gamma_{4i,d_2}, \gamma_{5i,-d_1}, \dots, \gamma_{5i,d_2}, \gamma_{6i,-d_1}, \dots, \gamma_{6i,d_2}\right)'$ so that the parameters to be estimated are γ_i (for i=1,2,…,N), β_1, σ^2, u_t, and B_t ($t = 1, \dots, T-1$). We specify prior distributions for these parameters as follows:

$$\boldsymbol{p(\gamma_i, \sigma^2) \propto \frac{1}{\sigma^2}}, \tag{3}$$

$$\boldsymbol{\beta_1 | \sigma^2 \sim N(0, \tau\sigma^2 I_3)}, \tag{4}$$

$$u_{jt} | \sigma_{uj}^2 \sim i.i.d.\, N\left(0, \sigma_{uj}^2\right),\ \sigma_{uj}^2 \sim IG(0.1,3), j = 1,2,3. \tag{5}$$

Equation (3) implies a flat prior for γ_i and the commonly used non-informative Jeffreys prior for σ^2 (e.g. Koop, 2003, p. 38). The conditional prior of β_1 on σ^2 is the initial distribution which is normal with $\tau\sigma^2 I_3$ as the variance. We choose a very high value of τ ($\tau = 10^5$) in our estimation so that the prior of β_1 becomes virtually non-informative, letting the data speak. The prior for u_t is normal and the prior for its variance, σ_{uj}^2, is an inverted gamma. We choose the prior mean of σ_{uj}^2 to be 0.1 and the degrees of freedom parameter to be 3, so that the prior variance is infinite. Note that u_t measures the difference between the cointegrating parameters of two regimes when period t is a break point. We expect the step change (i.e., the magnitude of u_t) to range between 0 and 1 because economically most parameter estimates (point elasticities) are expected to be within this range. This is why we have chosen the prior mean of σ_{uj}^2 to be 0.1, which ensures that β_t varies between 0 and 1.

Regarding the prior for the break indicator B_t we follow Li (2015) to specify a prior that allows for an unknown number of breaks at unknown locations. The unknown number of breaks ranges from 0 to T-1 and is specified as:

$$\boldsymbol{Pr(B_1 = 1 | D) = \frac{1}{D}, Pr\left(B_t = 1 \middle| B_{1:(t-1)}, D\right) = \frac{1}{D-(t-1)+\sum_{j=1}^{t-1} B_j}}, \tag{6}$$

$$\boldsymbol{Pr(B_1 = 0 | D) = 1 - Pr(B_1 = 1 | D)}, \tag{7}$$

$$\boldsymbol{Pr\left(B_t = 0 \middle| B_{1:(t-1)}, D\right) = 1 - Pr\left(B_t = 1 \middle| B_{1:(t-1)}, D\right)}, \tag{8}$$

where, t=2,…, T-1, $B_{1:(t-1)} = (B_1, \dots, B_{t-1})'$ and $D \geq T$ is a hyperparameter which controls prior information about the number of breaks. This prior is inspired by the seminal work of Chib

(1998) and is similar to that specified more recently in Koop and Potter (2009). Large values of D imply few break points whereas small values imply many breaks. Note that our prior implies that the elements of $B_{1:(T-1)}$ are not independent, because the probability of a break does depend on the number of breaks that have occurred previously. Also, as Li (2015) points out, for a fixed D the prior probability $Pr(B_t = 1|D)$, which is marginal over the previous periods, increases with t. We find that with a small value of D the prior shows a very pronounced upward trend, whereas with a high value of D the pattern appears very flat (we show these plots of marginal priors in Figure 2 of the Online Appendix). Following Li (2015), we treat D as an unknown parameter to be estimated and specify a uniform prior for D over the interval $[T, 5T]$, such that the prior density can be written as:

$$\boldsymbol{p}(\boldsymbol{D}) = \frac{\boldsymbol{I}(\boldsymbol{T} \leq \boldsymbol{D} \leq \boldsymbol{5T})}{\boldsymbol{4T}}, \tag{9}$$

where $I(.)$ is an indicator function. The uniform prior for D implies that the prior of B_t, unconditional on D, is

$$\boldsymbol{Pr}(\boldsymbol{B_1} = \boldsymbol{1}) = \frac{\boldsymbol{log}(\boldsymbol{5})}{\boldsymbol{4T}}, \boldsymbol{Pr}\left(\boldsymbol{B_t} = \boldsymbol{1} \middle| \boldsymbol{B_{1:(t-1)}}\right) = \frac{\boldsymbol{log}\left(\frac{\boldsymbol{5T} - (\boldsymbol{t}-\boldsymbol{1}) + \sum_{j=1}^{t-1} \boldsymbol{B_j}}{\boldsymbol{T} - (\boldsymbol{t}-\boldsymbol{1}) + \sum_{j=1}^{t-1} \boldsymbol{B_j}}\right)}{\boldsymbol{4T}}. \tag{10}$$

The computed marginal prior $Pr(B_t = 1)$, which is unconditional on the previous periods, implied by (10) is also shown in the Online Appendix, Figure 2. The prior probability of a break at any point ranges from 0.018 to 0.04. Our strategy is to calculate the posterior probability of $Pr(B_t = 1|y)$ and compare it with the prior. Whenever this probability is much higher than the prior we can conclude that there is strong evidence of a break. Note that the model in equation (1) assumes common break dates for all the cross-sectional units. Change point panel models with common break dates allow consistent estimations of break locations (see Bai, 2010). If the assumption of common break dates is not realistic *a priori* then one can separate the sample into more homogeneous cross-sectional groups, such that the common break hypothesis becomes more plausible. Our country grouping into high-income and low-and-middle-income panels is one way to address this issue.

2.2 Computation and Model Comparison

To describe our algorithm for computations, let θ be a vector containing the unknown parameters of interest and let *y* denote all the observed data. Our algorithm simulates draws from the posterior distribution $p(\theta|y)$ through a Gibbs sampler. Since the parameters of interest are the cointegrating vectors and the structural break indicators (B_t), we first integrate out the parameter γ_i from the posterior distribution and obtain simulated draws only for the remaining parameters. There are two blocks of parameters in our Gibb sampler, $(B_{1:(T-1)}{}', u', \beta_1{}')$ and $(D, \sigma^2, \sigma_u^2)$, where $\sigma_u^2 = (\sigma_{u1}^2, \sigma_{u2}^2, \sigma_{u3}^2)$. Each block of parameters is drawn conditional on the other using the conditional posterior distributions. The details of our simulation scheme are given in the Online Appendix. We used 100,000 iterations to estimate each of the models. Results using different starting points led to very similar results, indicating good convergence.

In order to determine the number of leads and lags in equation (1), as well as the specification of the trend, we use the predictive likelihood criterion proposed by Geweke (1996) for all 27 models. The predictive likelihood assesses the fit of the model to the data by evaluating the quality of out of the sample density forecasts. Essentially, this involves estimating the model for an initial sample $y_{1:T_0} = (y_1,..., y_{T_0})$, and defining the predictive likelihood as the predictive distribution evaluated for the rest of the sample $y_{(T_0+1):T} = (y_{T_0+1},..., y_T)$. By denoting the collection of parameters up to period t by θ_t, the predictive likelihood is defined as:

$$p_{T_0}^T = p\left(y_{(T_0+1):T} \middle| y_{1:T_0}\right) = \int p\left(y_{(T_0+1):T} \middle| \theta_T, y_{1:T_0}\right) p(\theta_T | \theta_{T_0}, y_{1:T_0}) p(\theta_{T_0} | y_{1:T_0}) d\theta_T \tag{11}$$

This quantity can be calculated as described in the appendix. The larger the value of the predictive likelihood, the better the fit. When $T_0 = 0$ the predictive likelihood coincides with the marginal likelihood (e.g. Koop, 2003, p. 24). However, for moderate values of T_0 the predictive likelihood is less sensitive to the specification of the prior. We set the maximum number of lags and leads to be 1, $T_0 = 15$ and choose the specification based on the highest value of the log of predictive likelihood.[6]

3. Data Sources and Description

We analyze a panel of 69 countries for which complete data series on the relevant financial variables of intermediaries and capital markets exist. The raw data series are obtained from CDFL (2013). This is a new and extensively revised and updated dataset which ensures ‘higher quality’ and ‘consistency over time’. Although this dataset covers 203 jurisdictions across the world, data for most countries, especially the stock market variables, are either incomplete or are only available for a relatively short sample period. In fact, data on stock market variables only go as far back as 1989 and we identify 69 countries with complete datasets for 1989-2011, hence our sample. Following the World Bank classification (2013), these 69 countries consist of 33 high-income and 36 middle-and-low-income countries. We model them as three panels of – (i) full sample (69), (ii) high-income (33) and (iii) middle-and-low-income (36) – countries. [7] Literature (Rioja and Valev, 2004; Rousseau and Wachtel, 2011) reports different effects of financial development across industrialized and emerging countries, hence our separate analyses of three panels is consistent with the literature. By analyzing these three separate panels, we are able to reveal important differences in the role of financial development and structure between groups of countries that are at different stages of development and income levels.

We have a balanced panel of 1587 observations (country years) for the full sample; 759 observations for the high-income panel and 828 observations for the panel of middle-and-low-income countries. The relevant stock market and intermediary variables for this analysis include: stock market capitalization ratio (value of listed shares / GDP), stock market total value traded ratio (total shares traded on stock market exchange / GDP), stock market turnover ratio (value of total shares traded / average market capitalization) and private credit ratio (private credit by deposit money banks and other financial institutions / GDP), all of which are obtained from CDFL (2013).

We compute the standard measures of financial development and structure following the main stream literature (Beck and Levine, 2002; Levine, 2002; Luintel et al., 2008). Financial structure measures include Structure-Activity (S^A) and Structure-Size (S^Z). S^A is the ratio of stock market total value traded to private credit (by deposit money banks and other financial institutions) and S^Z is the ratio of stock market capitalization to private credit. S^A measures the stock market trading activity relative to intermediaries' lending to the private sector, whereas S^Z measures the stock market capitalization (size) relative to intermediaries' lending. These size and activity measures are important because a stock market of a bigger size (large listings) does not always mean that it is actively trading and *vice versa*. An aggregate measure of financial structure (S^{AG}), which encapsulates activities and the size of capital market relative to intermediaries, is proxied by the first principal component of S^A and S^Z. Indicators of financial development, inclusive of capital markets and intermediaries, are Finance-Activity (F^A) and Finance-Size (F^Z). F^A, which captures the activities of capital market and intermediaries jointly, is measured as the log of the product of private credit ratio (credit to private sector by deposit money banks and other financial institutions to GDP) and stock market value traded ratio. Likewise, F^Z, which measures the size of the country's financial sector relative to the size of its economy, is the log of the product of the private credit ratio of deposit money banks and other financial institutions and stock market capitalization ratio. The overall (aggregate) financial development (F^{AG}), which captures the sizes and activities of markets and intermediaries, is measured by the first principal component of F^Z and F^A. All these measures are standard in the literature.

Data on Gross Domestic Product (GDP), Gross Fixed Capital Formation (GFCF), GDP deflator, Purchasing Power Parity (PPP) exchange rate and population are obtained from the World Development Indicators of the World Bank. Nominal GDP and GFCF variables are deflated by the GDP deflator and expressed in 2005 PPP US dollars ($). Consistent data on total physical capital stock are unavailable for all sample countries; therefore, we compute this series for each country in the sample by integrating the time series on respective real GFCF through the perpetual inventory method. Following Luintel and Khan (2004) and Luintel et al. (2008), amongst others, a depreciation rate of 8% and the sample-average growth rate of real GFCF are used to compute the initial capital stock.

Table 1 near here

Table 1 reports the country-by-country descriptive statistics of some of the main variables of our dataset. High-income countries (Panel A) have an average income of $28,791, which is fivefold higher than that of middle-and-low-income countries ($5,754). In the high-income group, Luxembourg has by far the highest per capita income of $58,001 followed by Norway ($42,039) and the US ($39,385); Hungary ($14,484) has the lowest income per capita in this group. The Republic of Korea (4.8%), Singapore (3.9%), Trinidad and Tobago (3.5%) and Hong Kong (3%) record high average annual growth rates during the sample period, whereas Switzerland (0.8%), Japan (0.9%), the US (1.4%) and the UK (1.5%) show quite modest growth rates. In the middle-and-low-income group, the real per capita income ranges between the highest of $12,730 (Argentina) and the lowest of $1,010 (Bangladesh). In this group of countries, the highest average annual growth rate is achieved by China (9.2%), followed by India (4.8%) and Sri Lanka (4.4%). The middle-and-low-income group shows an average annual growth rate of 2.5% during the sample period of 23 years which is higher than that of the high-income group (1.7%). However, 14 of the middle-and-low-income countries grew by less than 2% a year during the sample period and one of them (Côte d'Ivoire) recorded a negative growth rate. It is evident that there are significant differences in income levels and growth rates amongst countries within and across these two panels.

As expected, on average, the size and activity of the financial sector is bigger in high-income countries than in the middle-and-low-income countries relative to the size of their economies. Within the high-income group, small and open countries – Hong Kong (4.5), Switzerland (3.36), Luxembourg (2.72) and Singapore (2.56) – have a very large financial sector relative to the size of their economies (F^Z: see notes to Table 1) and so are the financial sectors of some of the big industrialized countries, such as the US (2.69), UK (2.60) and Canada (2.09). Oman has the smallest financial sector ($F^Z = 0.55$) amongst the sample of high-income countries.

Finance activity (F^A) appears highest in Hong Kong (3.68) followed by the US (3.26), Switzerland (3.14), Japan (2.52) and the UK (2.45). In fact, the US shows the highest degree of financial activities relative to the size of the financial sector (compare F^A and F^Z). Only six of the middle-income countries in our sample (Chile, China, Jordan, Malaysia, South Africa and Thailand) have a financial sector that is larger than the size of their economy ($F^Z>1$); the rest of the sample countries in Panel B have financial sectors that are smaller than the size of their economy (i.e., $F^Z<1$).

Structure size (S^Z) measures the size of capital market relative to the intermediaries; the sample average S^Z is largest in Hong Kong (2.09) followed by Singapore (1.57), Kuwait (1.46), Finland (1.33) and Luxembourg (1.32) in the high-income group of countries. Cyprus has the smallest S^Z of 0.18. The UK (0.95) and the US (0.68), dubbed market-based financial systems, appear to have a structure size of smaller than unity. Levine (2002) reported S^Z measures of 0.90 and 1.02, respectively for the US and the UK. This revised new dataset shows a rather low structure size for the US. Germany and Japan, respectively, have structure size measures of 0.35 and 0.42, which appear consistent with their characterization as having the *bank-based* financial systems.

Ignoring Bangladesh and Kenya (which are classed as low-income countries and have a structure size of below unity), only 13 of the 34 middle-income sample countries – i.e., 38% of the sample cohort – have a structure size of above unity, signifying capital market activities being dominant over the intermediaries in these countries. Interestingly, this proportion is even smaller in the high-income panel – only 30% (10 out of 33) of sample countries have a structure size of above unity. The fact that 38% of the middle-income counties have a structure size of above unity may be explained by the relatively small size of their intermediaries rather than these countries having more developed capital markets. Five of the 33 high-income countries (i.e., 15%) have a structure activity measure of above unity, whereas only 3 out of 36 (i.e., 8%) middle-and-low-income countries have a structure activity of above unity. Overall, the size and activities of intermediaries appear to dominate those of the capital market in the majority of countries across both the high-income and middle-income groups.

How different is this new dataset from those analyzed by the previous literature? In order to shed some light on this aspect, we report comparable measures of S^A, S^Z and F^A computed from the current dataset and those used by Levine (2002) for 20 of our common sample countries. Table 2 reports these comparative measures. Our computations are defined in the notes to Table 1 and we take anti-log of the numbers reported in Tables I and II of Levine (2002) as they are log values.

Table 2 near here

It is evident that there are striking differences in these measures of financial development and structure between the previously used and this new dataset across the vast majority of sample countries. For example, our (Levine's, 2002) measure of S^A is 0.96 (0.54) for US, 0.73 (0.48) for UK, 1.00 (0.68) for Switzerland, 0.41 (0.21) for Germany, 0.54 (0.10) for France, 0.61 (0.31) for Australia, 1.22 (0.20) for India and 1.16 (0.08) for Pakistan. Of the 20 common sample countries, only Brazil, Colombia, Mexico and Japan show a close resemblance to the measures of S^A between these two datasets. Significant differences are also evident in the measures of S^Z and F^A between these two datasets. [8] Overall, there are important differences between the previously used and this new dataset which reinforces our earlier argument that the relationship between financial development, structure and economic growth necessities re-examination using (exploiting) this new dataset (information).

4. Empirical Results

We begin by testing if our panel datasets are non-stationary unit root processes through a range of standard panel unit root tests. The Levin et al. (2002) and Breitung (2000) t-tests test the null of the unit root in the panel under the assumption of a common unit root process across panel units. Both of these tests cannot reject the null of the unit root in any of the variables across all three panels. The PP-Fisher Chi square (Maddala and Wu, 1999) test assumes individual unit root processes, which also confirms that all data series are unit root processes. Furthermore, Hadri's (2000) test strongly rejects the null of stationarity in all cases. Panel unit root tests are implemented with a constant and linear time trend in the specification, and are robust up to a third order lag. Results of unit root tests are not reported to conserve space but are available on request. Given that panel data are unit root processes, we employ the group-ADF statistic of Pedroni (1999) to test if our models are cointegrated. The results are reported in Table 3.

Table 3 near here

Panel cointegration tests clearly reject the null of no cointegration in all nine specifications across all the three panels at the 5% significance level or better. In fact, in 26 of the 27 cases (models), the null of no cointegration is rejected at the 1% significance level. These results confirm that all empirical specifications are cointegrated. We apply the DOLS estimator in the Bayesian framework, as explained above, to estimate the parameters of cointegrating vectors. DOLS addresses the issues of endogeneity and residual serial correlation in the regression equation, which are important for reliable inferences.

Table 4 near here

Table 4 reports the results of cointegrating parameters estimated by DOLS under the Bayesian method for the full sample period, 1989-2011, without structural breaks, and Tables 5-6 present results regarding breaks. Each model follows the specification structure (leads, lags and deterministic components) based on the highest value of the predictive likelihood, as discussed in Section 2.2 (results of predictive likelihood are reported in the Online Appendix Table A1). Table 4 contains three set of results: the high-income group (Panel A), the middle-and-low-income group (Panel B) and the full sample of countries (Panel C). Results are striking. All three measures of financial structure (S^{AG}, S^{A} and S^{Z}) appear with positive and significant coefficients for the panel of rich countries (i.e., zero is outside the 95% credible interval). The significance of financial structure variables holds across all nine specifications but the measure of overall financial development (F^{AG}), the proxy for the *financial services* view, does not appear statistically significant in any of the specifications. These findings are in sharp contrast to the bulk of the existing literature, discussed above, which reports insignificance of the financial structure but significance of the overall financial development. Finance size (F^{Z}) appears positive and significant in only one of the three specifications – Model (6). Finance activity appears with negative and significant coefficients in two – Models (5) and (9) – of the three specifications. The negative effect of finance activity is rather unexpected and hard to explain.[9] A clear message coming from the results of the high-income group is that financial structure matters for these countries. Structure measures contribute positively and significantly to their income levels in the long run. Given that F^{AG} is insignificant across all three specifications, the *financial services* view, which emphasizes the overall financial development rather than its separation into *bank-* and *market-based* systems, is not supported.[10]

The results from the panel of middle-and-low-income countries (Panel B) provide an entirely different picture, however. The overriding message is that financial structure virtually has no significance in middle-and-low-income countries (zero is inside the 95% credible interval). Structure variables appear insignificant in all but one specification; the only exception is Model (6) where S^{A} appears positive and significant. However, finance activity (F^{A}: a combined measure of stock market trading and private sector lending by the intermediaries) appears positively signed and significant in all specifications. The overall message stemming from these results is that financial structure and finance size do not matter for the middle-and-low-income countries; what matters is the finance activity, measured by stock market trading and intermediaries' lending to the private sector. Again, the measure of overall financial development (inclusive of size and activity), which proxies the *financial services* view in the literature, appears insignificant.

Table 4 (Panel C) reports the results obtained from the full sample of countries. These results closely resemble those of the high-income group but are in sharp contrast to those of the middle-and-low-income group. Basically, structure variables appear positive and statistically significant across all specifications but one – the only exception is Model (7). In contrast, finance aggregates appear insignificant in all specifications, resonating that financial structure is relevant but the *financial services* view is not. Finance activity is insignificant in all specifications but finance size is insignificant in one count and negatively signed and significant in two counts. Thus, finance size does not appear conducive to long-run income levels when both high- and middle-and-low-income countries are pooled. On the role of financial structure, the results of the full sample appear similar to those of the high-income group echoing qualitatively the same message.

The output elasticity of physical capital stock is quite different across the two groups of countries. The elasticity for the high-income group is close to unity, which ranges from 0.917 to 1.026 across the nine models. In fact, the point elasticity for the high-income group is not different from unity as the value of unity (1.0) is inside the credible bounds. In contrast, the elasticity of physical capital stock for the panel of middle-and-low-income countries ranges from 0.397 to 0.493. The magnitudes of the point estimates for the full sample range from 0.59 to 0.631. Obviously, these point estimates are far from unity statistically.

How sizable are these parameter estimates economically? Financial structure not only appears statistically significant in explaining income levels for the high-income group and the full sample, its growth effects also appear sizable. The coefficients of S^A and S^Z are semi-elasticities as these covariates are measured as ratios. Therefore, the interpretation of their coefficients is that if S^A or S^Z changes by 0.01 (i.e., the ratio changes by 1%), then the percentage change in the real per capita income of high-income panel is 0.02% (the coefficient of S^A ranges 0.018 to 0.020). The mean S^A of high-income group is 0.53 (Table 1); approximately doubling of the S^A – i.e., raising the sample mean of S^A from 0.53 to 1.00 – increases the income level by about 1.0%. This is a sizable economic (growth) effect on sample countries, especially when their sample period's average annual growth rate is just 1.7%. The average S^A of the 25th percentile of high-income group is 0.105 and the 75th percentile is 0.739. The average annual growth rate of the 25th percentile is 0.32%. If the countries in the 25th percentile are able to push their financial system to be more market oriented by achieving the mean S^A level of the 75th percentile then they appear to add in their average annual growth rate by 1.27% which, again, is a big growth effect.

Likewise, the point elasticity of structure size is about 0.04, which exerts an even bigger economic effect than that of S^A, suggesting that both size and activities of securities markets relative to banks matter for the high-income group. The average S^Z of the 25th and 75th percentiles are 0.379 and 1.250, respectively. Applying the same approach as above, it is not difficult to see the big economic effects of S^Z. Structure aggregate (S^{AG}) is the first principal component of S^A and S^Z (the first principal component explains 70.1% of total variation; see notes to Table 4), which resumes parameters of approximately similar magnitude of S^A (0.02) and similar magnitude of economic effect. The effect of S^A for the full sample appears slightly bigger, whereas that of S^Z is somewhat smaller compared to the high-income panel (but the results of the full sample should be taken with some caution as they seem to be driven by the results of the high-income group because financial structure measures appear insignificant for the middle-and-low-income countries which are in the majority in the full sample).

For the middle-and-low-income countries, only the finance activity measure (i.e., the activities of intermediaries and markets together, exclusive of their size measures) shows positive and significant parameters across all specifications. The parameter of F^A is 0.010 across specifications (Table 4). F^A is measured in logarithms, therefore the parameters are point elasticities. By approximately doubling the F^A – i.e., raising the sample mean of 0.52 to 1.00 – these countries could add to their growth rate by almost 0.92% (92 basis points). For example, Kenya grew by 0.4% per annum with a sample mean F^A of 0.30. Had this country pursued policies that would have increased its finance activity to a sample mean of 0.52, it would have realized an average annual growth rate of 1.13% (an addition of 73 basis points). The mean F^A of the 25th and 75th percentiles of middle-and-low countries are 0.223 and 0.661 which are much lower than their high-income counterparts of 0.822 and 2.038 (but note F^A is not significant for the high-income panel). Along similar lines, F^A shows potentials of large economic effects for the middle-and-low countries.

Overall, our results suggest that financial structure is statistically significant in explaining long-run income levels for the group of high-income countries with sizable economic effects. Likewise, finance activities appear important for the group of middle-and-low-income countries – again with large economic effects. Our findings that a market oriented financial system is conducive to economic growth in high-income countries with a sizable economic effect implicitly corroborates the recent findings of Langfield and Pagano (2016) and reinforces their policy suggestions. They report the negative effects of oversized banks in Europe – that bank bias in Europe has increased systemic risk and lowered economic growth – and make policy suggestions for rebalancing the financial structure in Europe by way of policy support for "the development of security markets as an alternative source of external funding (p. 91)". Likewise, our findings of the significance of finance activity but the insignificance of financial structure in the middle-and-low income countries is consistent with the findings of Demirgüç-Kunt et al. (2013) who find bank credit to be important for the countries in the lower income strata (25th percentile of their sample) but the effect of bank finance on growth gradually declines while the effect of capital markets gradually increases when economies grow richer and reach the 75th percentile of their sample (ordered by the level of per capita income).[11]

The significance of financial structure is a new result. It is therefore important to pause and ask what is behind it. Is it the new dataset or the new econometric method? To answer this, we re-run the specifications and econometric methods employed by most of the existing literature with this new dataset. We then examine if they yield the widely reported insignificance of the financial structure. Following much of this literature (Beck et al., 2001; Levine, 2002; Beck and Levine, 2002), we specify the per capita real GDP growth rate ($g_{y,i,t}$) as the dependent variable and the initial (1989) level of real income ($y_{0,i}$), per capita physical capital stock ($k_{i,t}$) and the measures of financial development ($fd_{i,t}$) and structure ($fs_{i,t}$), as the covariates, as shown in models M1 through M9 in Table 4.

As our first re-run, we estimate the panel data models with country and time fixed effects, employing Ordinary Least Squares (OLS) with heteroscedasticity consistent standard errors. All nine variants of our model are re-estimated. The results confirm our new findings: financial structure variables appear positive and significant across all specifications for the high-income panel. For the middle-and-low-income group and the full panel, both financial structure and finance aggregate (*financial services* view) appear statistically significant in most specifications. We also estimate the same fixed effects models using Instrumental Variable (IV) estimators, again with heteroscedasticity consistent standard errors. Results are qualitatively similar to those from the OLS.[12] Thus, in the panel framework, the significance of financial structure is upheld in the new dataset irrespective of the econometric approaches – our method or those employed in the previous literature. This suggests that the dataset may indeed have an important role in these new results. However, the existing literature also estimates cross-sectional regressions utilizing the sample period or periodic mean values of both the regressand and the regressors and, at times, enters each measure of financial development and structure one-by-one rather than pairwise (e.g., Levine, 2002). We also estimate such specifications using sample averages data and estimators following the literature. Interestingly, in these cross-sectional estimates, both financial development and structure variables appear insignificant in almost all specifications with the new dataset. The dataset does not necessarily always produce the existing results when replicated. Hence we conclude that our new results are due to both the new dataset and our method. For brevity, we do not report the results of these re-runs but they are available upon request.

4.1 Structural Break

The results presented so far do not allow for potential structural breaks in the relationship. We have at most 23 years of data (when no lag and lead is required) for a typical model giving rise to, at most, 22 potential breaks with 23 regimes. Of course, these 23 regimes are theoretical possibilities; only empirical tests will reveal if there have been single or multiple regimes. We allow for all these break possibilities and identify the break dates by computing the posterior probability for the break indicator, B_t in equation (2). Simulation details are provided in the Online Appendix. Table 5 reports the results showing the most probable regimes and break locations.

Table 5 near here

The first column of Table 5 indicates nine different specifications for each panel; the second column reports the number of regimes along with the associated prior [.] and the computed posterior (.) probability. Since most data points resume very small probability, we report the two regimes with the highest posterior probabilities in the sample period. The final column in each panel reports the two break dates with the highest posterior probabilities across all 22 potential break dates for each of the models. Reported results are computed based on 100,000 iterations for each model. A considerably higher posterior probability than the prior signifies a break date and/or a regime change. For example, Model (2) for the high-income group shows two regimes with a probability of 76.9%, which is sizably larger than its prior of 32.9%. Further, the probability of a single regime is only 22.7% which is lower than the prior of 57.2%. Year 2008 appears as the date of a break, with a probability of 65.6%, the highest posterior probability across all 22 break dates. The other possible break date is 1990, which has the second highest probability of 12.1% across all simulations. Hence, there is one break in Model (2) and the year 2008 seems to be the most probable break date which is the immediate aftermath of the recent financial crisis.

Following the same line of inference, all in all, six of the nine models show one break (regime change). Five models involving – finance and structure aggregates (Model 1), finance aggregate and structure activity (Model 2), finance aggregate and structure size (Model 3), structure aggregate and finance activity (Model 5) and structure activity and finance activity (Model 7) – show one break / two regimes and the year 2008 as the break location. For these models, the probability of two regimes ranges from 42.3% to 92.5% and the year 2008 as the break date resumes probabilities in the range of 35.1% to 78.5%. Model (9) also shows one break (two regimes) but the break date appears to be 1996. However, the posterior probability of having only one break takes a value of unity in this case, which we take with some caution. Models (4), (6) and (8) exhibit a very high probability of only one regime throughout the sample period and the probabilities associated with break dates are also low in comparison to the prior probabilities, signifying that there is no break in these relationships.

In contrast, the results of the middle-and-low-income group do not show any break. For this group of countries, the posterior probabilities of only one regime are very high (99.9% or so) across all the models during the sample period. The posterior probabilities of two regimes appear virtually nil. The results for the full sample of countries (Panel C) are qualitatively similar to those of the middle-and-low-income group; there is no evidence of any break and/or regime change in the full panel of countries. The regime change found in the high-income group is not evident in the full sample of countries. This suggests that the group of high-income countries went through a regime shift in the relationship between financial development, structure and income level following the financial crisis of 2008. However, the panel of middle-and-low-income has not gone through such a regime shift.

Since only the high-income group of countries shows structural breaks, we estimate the cointegrating vector allowing for breaks for these countries alone. In order to allow for all potential break combinations, we estimate at least 2^{21} models for each specification and the probability weighted mean of these parameters is computed. For brevity, we discuss the main results and report the selected results in Table A2 of the Online Appendix. These estimates reveal that the elasticity of capital stock changes little across regimes in any of the nine models but the coefficients of financial development and financial structure seem to be affected by the breaks. Specifically, S^{AG} is not significant in the first regime and only becomes significant in the second regime in Models (1), (4) and (5). Likewise, S^{A} appears insignificant in the first regime but becomes briefly significant in the second regime and again turns insignificant during 2009-2011 (e.g. Models 2 and 7). S^{Z} and F^{Z} seem to be less affected by regime changes overall (except S^{Z} in Model 9), while the coefficient of F^{AG} tends to become smaller after 2008 (e.g. Models 1 and 3), but they remain insignificant throughout.

The break date of 2008 identified above is determined endogenously (statistically). An alternative approach would be to split the sample period in 2008 and report the results for the period of 1989-2008 for all three panels (since Table 4 contains the results for the full sample for 1989-2011). This is equivalent to imposing a break date in 2008 exogenously and estimating all models leading up to the crisis period of 2008, and beyond, separately. A comparison of these results provides insights if the relationship has changed post-2008 crisis. Table 6 reports these results.

Table 6 near here

The results show that for the high-income countries all financial structure variables are statistically significant in explaining income levels, whereas finance activity, finance size and finance aggregate are insignificant. These results uphold our earlier findings that financial structure is important for the high-income group. Put differently, the results of the full sample period, which showed the significance of structure variables, are robust in the sample period leading only up to the crisis period. Two differences are (i) finance size which is insignificant for the period leading up to the crisis (1989-2008) turns positive and significant in the full sample (1989-2011) in one of the three specifications, and (ii) finance activity, which is insignificant leading up to the crisis period, turns negative and significant post-2008 in two specifications. This implies that the relationship between finance size and income levels appears to have improved whereas between the finance activity and the income level it appears to have deteriorated following the financial crisis for high-income groups. The significance of F^{Z} post-

2008 may reflect that the size matters – i.e., “too big to fail” – phenomenon which was also evident in various bailouts. The negative effect of F^A, as admitted above, is hard to explain.

For the panel of middle-and-low-income countries, the importance of the finance activity variable, as found above in the full sample period, remains robust. One noticeable difference is that the finance aggregate variable appears significant in two of the three specifications during 1989-2008 but all appear insignificant in the full sample period. This suggests that the financial crisis of 2008 has weakened the relationship between finance aggregate and income levels – *financial services* view – across the sample of medium-and-low-income countries. When high-income and middle-and-low-income countries are pooled, the results appear qualitatively similar between pre- and post-crisis periods.

5**. Robustness**

We perform a range of sensitivity checks on our reported results. First, we examine if the results are sensitive to the exclusion of some of the major countries in the panel. We dropped major countries – the US, Germany, the UK and Japan – one at a time from the high-income panel and re-estimated all the models. Our main findings – (i) financial structure is important in explaining income levels of this group of countries, and (ii) *financial services* view is insignificant – remain robust.

As stated above, Bangladesh and Kenya are classed as low-income countries. We, therefore, dropped these two countries from the panel of middle-and-low-income countries and re-estimated all models in the panel of 34 middle-income countries only. Dropping these two countries does not change any of the reported results for the panel of 36 counties qualitatively. We also checked if our results of middle-and-low-income countries are sensitive to any one major country in the panel. We re-estimated all the models by dropping Brazil, China, India and Mexico, one at a time, from the panel, yet the reported results for this group of countries remain robust. We also sequentially dropped these major countries from the full panel of 69 countries; results across all specifications remain qualitatively the same. Our results, obtained from the sample leading up to the crisis period (1989-2008), also remain robust to these sensitivity checks.

6. **Conclusion**

It is widely believed that the effectiveness of the financial system and its contribution to economic development and growth is not independent of its institutional structure (i.e., the financial structure). However, the weight of evidence accumulated in the last two decades or so suggests otherwise – i.e., financial structure is irrelevant for growth. Lately, there have been advances both on data and econometric fronts. We re-examine this issue – the relevance or otherwise of financial structure on economic growth – following the standard literature but employing a new dataset and a new empirical methodology.

We employ a novel dataset of CDFL (2013). This dataset ensures 'higher quality' and 'consistency over time'. Indeed, a comparison of this dataset with the previously analyzed data shows important differences in the measures of relevant variables. We analyze a sample of 69 countries – 33 high-income and 36 middle-and-low-income countries – with the longest and complete data series (1989-2011) reported in the database. Our sample has a balanced panel of 1587 observations (country years) for the full sample; 759 observations for the high-income group and 828 observations for the panel of middle-and-low-income group. We separately model the panels of (i) high-income, (ii) middle-and-low-income, and (iii) the full sample of countries. Methodologically, we have extended the Dynamic OLS estimator of cointegrating vectors to the Bayesian framework which allows for multiple breaks (shifts) in the cointegrating parameters. We follow a very general approach in modeling regime shifts (breaks) such that a regime shift could occur in any or every data point in the sample. We estimate nine different specifications to cater for different measures and combinations of financial structure and growth.

Our results are quite unique and interesting. We find that real income levels, financial development and structure share an equilibrating (cointegrating) relationship in the long run across all specifications and panels. All measures of financial structure appear significant for high-income countries with sizable economic effects. Interestingly, our results are not supportive of the *financial services* view, as known in the literature. Thus, our findings are in sharp contrast to the weight of evidence accumulated in the last two decades or so which reports the insignificance of the financial structure but the significance of the *financial services* view.

We also find that results are not uniform across the high-income and the middle-and-low-income group of countries. For the latter group, neither the financial structure nor the overall financial development (the usual proxy of *financial services* view in the literature) appears significant; instead, just finance activity (a joint measure of stock market trading and private sector lending by the intermediaries exclusive of their size) appears positive and significant in explaining their income levels with sizable economic effects.

We find one structural break (regime shift) in the year 2008 which we attribute to the financial crisis of 2008. Again, this regime shift is only evident in the panel of high-income countries; there is no evidence of any break in the panel of middle-and-low-income countries. This is not surprising, given that the financial crisis of 2008 is mainly confined to the high-income countries. Robustness checks confirm that our results are not susceptible to any large or small countries in the sample – results remain robust to the sequential exclusion of a large number of countries from the sample. Our findings, based on a novel dataset and a new empirical method, are consistent with the widely held belief that financial structure matters for growth – we find evidence of this for the panel of high-income countries. Hence, our results may be viewed as an important counterexample to the weight of evidence that reports financial structure to be irrelevant.

Our findings that a more *market-based* financial system relative to a *bank-based* one contributes to economic growth in industrialized (high-income) countries imply that policy makers in these countries should follow financial sector policies that help further develop financial markets. In fact, our policy prescription is very similar to those of Langfield and Pagano (2016) who also prescribe re-balancing the financial structure of European countries by downsizing big banks and further developing the securities markets, i.e., making the European financial system more *market-based*. Their policy prescription originates from their findings that the European financial structure has become "bank-biased" which has increased systemic risk and impacted adversely on economic growth, whereas our policy prescription is based on the results obtained from our direct tests of the relevance or otherwise of financial structure on real income levels. Likewise, our findings of the relevance of finance activity but the irrelevance of financial structure for middle-and-low income countries – which, as discussed above, is consistent with Demirgüç-Kunt et al. (2013) – imply that authorities in these countries should focus both on the development of sound banking and securities markets through prudent financial laws and regulations but they should also be mindful that as economies grow and become richer then a gradual re-balancing between intermediaries and security markets may be required.

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Table 1: Descriptive statistics

	Panel A: High-income Countries									
	Sample mean (1989-2011)					Average annual growth (1989-2011)				
	Y	F^A	F^Z	S^A	S^Z	Y	F^A	F^Z	S^A	S^Z
Australia	29,117	1.43	1.73	0.61	1.02	1.8	6.0	4.0	4.1	-1.2
Austria	31,784	1.11	1.21	0.09	0.19	1.8	1.7	1.7	1.8	0.5
Barbados	21,454	0.61	1.40	0.07	1.36	0.5	3.3	6.0	-3.8	5.8
Belgium	30,038	0.90	1.28	0.23	0.79	1.4	5.1	3.1	2.3	-3.5
Canada	32,230	1.76	2.09	0.45	0.74	1.2	3.6	2.9	6.2	2.1
Cyprus	16,453	2.04	2.28	0.06	0.18	1.7	4.1	3.7	-0.7	-3.4
Denmark	30,879	1.43	1.59	0.40	0.69	1.3	7.3	6.0	0.6	-3.6
Finland	27,807	1.44	1.54	1.09	1.33	1.6	2.7	1.6	9.3	2.2
France	28,081	1.42	1.53	0.54	0.67	1.2	2.8	2.1	7.4	2.3
Germany	30,784	1.49	1.43	0.41	0.35	1.5	1.4	1.3	2.8	2.5
Greece	21,629	0.79	0.96	0.46	0.80	1.0	6.4	5.8	8.8	-1.0
Hong Kong	32,237	3.68	4.50	1.48	2.09	3.0	7.1	3.9	11.6	4.6
Hungary	14,484	0.53	0.57	0.34	0.47	1.2	2.8	2.7	19.9	10.1
Iceland	31,000	1.38	1.53	0.21	0.41	1.5	4.4	4.0	3.6	-1.9
Israel	22,012	1.03	1.30	0.38	0.72	2.8	4.0	4.2	7.0	5.3
Italy	27,641	1.07	1.06	0.40	0.42	0.8	4.8	3.3	6.0	-3.6
Japan	28,959	2.52	2.70	0.33	0.42	0.9	-0.2	-1.1	-0.6	-3.0
Kuwait	38,571	0.97	1.27	0.82	1.46	2.0	-0.9	-0.2	5.4	3.5
Luxembourg	58,001	1.22	2.72	0.02	1.32	2.4	2.4	-0.6	-10.5	-4.9
Netherlands	34,048	2.23	2.18	0.69	0.73	1.8	4.5	3.4	0.4	-2.7
New Zealand	22,542	1.19	1.45	0.13	0.40	1.3	3.5	3.1	1.6	-0.7
Norway	42,039	1.16	1.19	0.44	0.49	1.8	1.9	1.5	7.4	3.9
Oman	20,854	0.38	0.55	0.17	0.70	1.1	2.5	3.3	5.4	3.2
Portugal	20,280	1.28	1.40	0.15	0.28	1.5	6.5	5.9	2.0	-2.6
Republic of Korea	19,921	1.76	1.31	1.19	0.68	4.8	5.1	3.1	4.1	0.4
Saudi Arabia	20,596	1.19	1.12	1.25	1.08	1.7	1.3	0.2	16.0	3.5
Singapore	38,682	1.89	2.56	0.90	1.57	3.9	2.8	1.3	5.4	0.9
Spain	24,603	1.99	1.74	0.71	0.53	1.6	6.1	4.8	7.0	0.2
Sweden	30,252	1.85	1.92	0.81	0.88	1.6	3.5	2.0	9.9	1.8
Switzerland	37,452	3.14	3.36	1.00	1.15	0.8	2.7	2.0	7.1	3.3
Trinidad and Tobago	16,069	0.39	0.85	0.05	1.40	3.5	-1.4	2.6	2.1	11.3
United Kingdom	30,212	2.45	2.60	0.73	0.95	1.5	3.4	2.4	1.2	-1.4
United States of America	39,385	3.26	2.69	0.96	0.68	1.4	4.5	2.5	6.1	0.7
Mean	**28,791**	**1.54**	**1.74**	**0.53**	**0.82**	**1.7**	**3.7**	**2.5**	**5.6**	**1.0**
Panel B: Middle-and-low-income countries										
	Sample mean (1989-2011)					Average annual growth (1989-2011)				
	Y	F^A	F^Z	S^A	S^Z	Y	F^A	F^Z	S^A	S^Z
Argentina	12,730	0.19	0.41	0.21	1.62	3.0	0.1	2.5	-0.4	9.7

Bangladesh	1,010	0.29	0.30	0.09	0.18	3.6	6.4	6.0	28.8	4.7
Botswana	10,174	0.16	0.34	0.05	1.14	2.7	6.1	6.2	-0.6	0.2
Brazil	8,196	0.54	0.70	0.40	0.86	1.4	3.8	4.4	13.2	11.6
Chile	10,997	0.81	1.59	0.19	1.36	3.7	4.0	5.0	6.2	3.6
China	3,244	1.44	1.33	0.45	0.34	9.2	5.4	4.2	17.2	13.1
Colombia	7,018	0.31	0.50	0.07	0.71	1.9	3.7	6.7	15.9	12.3
Côte d'Ivoire	1,904	0.20	0.34	0.02	0.86	-1.0	-2.7	0.8	13.1	11.6
Ecuador	6,776	0.24	0.30	0.02	0.26	1.3	3.3	3.5	-5.9	0.9
Egypt	4,254	0.53	0.74	0.25	0.70	2.8	1.7	2.5	21.1	8.8
Ghana	1,140	0.09	0.21	0.07	1.46	2.8	4.9	6.7	-8.4	3.7
India	1,904	0.70	0.73	1.22	1.31	4.8	5.1	5.7	8.3	7.6
Indonesia	2,906	0.43	0.55	0.37	0.83	3.4	2.0	4.2	20.6	17.9
Iran	8,067	0.32	0.41	0.07	0.38	3.3	2.0	2.7	8.6	6.4
Jamaica	6,651	0.24	0.72	0.12	2.49	0.5	-0.7	1.8	1.6	5.1
Jordan	3,955	1.08	1.72	0.48	1.36	2.0	0.5	1.7	4.1	4.0
Kenya	1,356	0.30	0.50	0.05	0.76	0.4	1.0	3.2	14.7	8.1
Malaysia	10,560	1.71	2.60	0.57	1.42	3.7	1.8	1.9	4.4	1.7
Mauritius	8,964	0.57	0.90	0.03	0.60	3.7	5.1	6.4	9.6	4.1
Mexico	11,297	0.29	0.47	0.40	1.30	1.2	3.9	5.3	2.7	4.0
Morocco	3,249	0.54	0.81	0.12	0.64	2.6	8.4	10.4	13.4	8.1
Namibia	4,910	0.43	0.49	0.01	0.16	1.8	3.4	4.2	-9.4	7.8
Nigeria	1,476	0.16	0.27	0.08	0.84	2.9	4.1	4.8	19.0	3.2
Pakistan	1,946	0.52	0.41	1.16	0.75	1.7	-0.2	0.7	13.6	6.3
Panama	8,283	0.70	0.90	0.01	0.26	3.9	2.7	3.8	6.8	6.3
Paraguay	4,754	0.23	0.25	0.01	0.10	0.9	4.6	4.8	-9.5	2.1
Peru	5,595	0.21	0.46	0.18	1.47	2.8	7.9	12.0	5.1	9.2
Philippines	2,832	0.44	0.79	0.32	1.45	1.7	3.2	4.9	3.7	4.2
South Africa	8,147	1.69	2.78	0.41	1.41	0.7	5.3	2.4	10.8	-1.5
Sri Lanka	3,099	0.26	0.39	0.11	0.81	4.4	2.6	4.1	18.3	6.7
Swaziland	4,248	0.17	0.26	0.00	0.59	1.5	1.8	2.5	-17.7	3.9
Thailand	5,957	1.50	1.63	0.38	0.50	3.7	4.4	4.1	4.2	2.4
Tunisia	6,275	0.62	0.73	0.02	0.19	3.1	1.6	2.2	11.3	4.7
Turkey	10,108	0.45	0.39	1.34	1.01	2.7	8.8	6.8	19.4	5.7
Uruguay	9,471	0.29	0.30	0.00	0.03	2.8	-1.1	-1.2	-9.6	-3.8
Venezuela	8,379	0.18	0.24	0.09	0.52	0.9	-3.2	-3.3	-9.8	-2.3
Mean	**5,754**	**0.52**	**0.73**	**0.26**	**0.85**	**2.5**	**3.3**	**3.7**	**7.9**	**4.9**
Full sample mean	**16,840**	**1.01**	**1.22**	**0.39**	**0.84**	**1.9**	**3.6**	**2.9**	**6.2**	**2.9**

Note: Y denotes real per capita income. Finance-activity (F^A) = (private credit + total value traded)/GDP; Finance-size (F^Z) = (private credit + market capitalization)/GDP. Although F^A and F^Z are defined as the log of the product of two respective ratios in the text, in this Table we report the mean of the ratios, as defined here, for the ease of inference and interpretation. These measures directly give the size (proportion) of the financial sector and its activity relative to the country's economy (GDP). In any case, these ratio measures are equivalent to the anti-log (exponential) of the mean log values as defined in the text and elsewhere in the literature (e.g., Levine, 2002). Structure-activity (S^A) = stock market value traded/private credit; Structure-size (S^Z) = stock market capitalization/private credit.

Table 2: Measures of financial development and structure based on previous and new (current) datasets

	S^A		S^Z		F^A	
	previous	new	previous	new	previous	new
Australia	0.31	0.61	0.09	1.02	0.12	1.43
Canada	0.32	0.45	0.94	0.74	0.12	1.76
Denmark	0.15	0.40	0.54	0.69	0.03	1.43
France	0.10	0.54	0.24	0.67	0.08	1.42
Germany	0.22	0.40	0.22	0.35	0.17	1.49
Japan	0.37	0.33	0.70	0.42	0.65	2.52
Sweden	0.31	0.81	0.86	0.88	0.15	1.85
Switzerland	0.68	1.00	0.49	1.15	1.73	3.14
UK	0.48	0.73	1.02	0.95	0.26	2.45
USA	0.53	0.96	0.99	0.68	0.45	3.26
Brazil	0.40	0.40	0.73	0.86	0.02	0.54
Chile	0.09	0.19	0.97	1.36	0.02	0.81
Colombia	0.05	0.07	0.46	0.71	0.00#	0.31
India	0.22	1.22	0.55	1.31	0.01	0.70
Malaysia	0.73	0.57	1.82	1.42	0.34	1.71
Mexico	0.44	0.40	0.98	1.30	0.01	0.29
Pakistan	0.08	1.16	0.38	0.75	0.00#	0.52
Philippines	0.23	0.32	0.98	1.45	0.02	0.44
Thailand	0.42	0.38	0.52	0.50	0.14	1.50
Turkey	0.48	1.34	0.48	1.01	0.00#	0.45

Note: Data used by Levine (2002) are treated as the previous dataset which covers 48 countries over the 1980-1995 period. Numbers reported in the 'previous' columns are directly obtained from Tables I and II of Levine (op. cit.) and their anti-logs are reported. Numbers reported in the 'new' columns are based on the dataset used in this study: different measures are the authors' own calculations (Table 1).

For these countries F^A resumes a positive value only in the third decimal place.

Table 3: Results of Panel Cointegration Tests

	Panel A: High-income		Panel B: Middle-and-low-income		Panel C: Full Sample	
	Group ADF-Statistics	P-value	Group ADF-Statistics	P-value	Group ADF-Statistics	P-value
M1	-3.391	3e-4	-6.525	0.000	-7.059	0.000
M2	-3.475	3e-4	-7.856	0.000	-8.078	0.000
M3	-4.264	0.000	-5.585	0.000	-6.983	0.000
M4	-3.924	0.000	-5.941	0.000	-7.005	0.000
M5	-2.548	0.005	-6.634	0.000	-6.554	0.000
M6	-3.777	1e-4	-5.440	0.000	-6.541	0.000
M7	-2.231	0.0128	-7.917	0.000	-7.261	0.000
M8	-5.099	0.000	-5.330	0.000	-7.376	0.000
M9	-3.677	1e-4	-6.088	0.000	-6.940	0.000

Note: H_0: no cointegration. Reported results are Group-ADF tests. The lag length is chosen by the Schwarz information criterion with the maximum length set to 3. The test was carried out including an intercept and trend. The generic cointegrating regression for the test is:

$$y_{i.t} = \gamma_{1,i} + \gamma_{2,i} t + \beta_1 k_{i,t} + \beta_2 fd_{i,t} + \beta_3 fs_{i,t} + \varepsilon_{i,t}.$$

Models M1 through M9 are obtained by replacing the pairs of $fd_{i,t}$ and $fs_{i,t}$ as: (i) F^{AG} and S^{AG}, (ii) F^{AG} and S^{A}, (iii) F^{AG} and S^{Z}, (iv) S^{AG} and S^{Z}, (v) S^{A} and F^{Z}, (vi) S^{A} and F^{Z}, (vii) S^{A} and F^{A}, (viii) S^{Z} and F^{Z}, and (ix) S^{Z} and F^{A}. These models are denoted by Model (1) through Model (9) in the text. The findings of cointegration are largely robust to other test statistics proposed by Pedroni (1999), such as the Panel ADF, Panel PP and Group PP.

Table 4: Estimation results with no structural breaks in 1989-2011.

Model	k	F^{AG}	S^{AG}	S^{A}	S^{Z}	F^{Z}	F^{A}
Panel A: High-Income Panel							
M1	0.94* (0.704,1.175)	0.0078 (-0.005,0.02)	0.0196* (0.006,0.033)	—	—	—	—
M2	0.943* (0.703,1.183)	0.0093 (-0.003,0.022)	—	0.0187* (0.003,0.034)	—	—	—
M3	0.921* (0.693,1.148)	0.008 (-0.003,0.019)	—	—	0.0357* (0.016,0.055)	—	—
M4	0.929* (0.695,1.162)	—	0.0174* (0.004,0.031)	—	—	0.0228 (-2e-4,0.046)	—
M5	1.026* (0.841,1.211)	—	0.0209* (0.009,0.033)	—	—	—	-0.0129* (-0.023,-2e-3)
M6	0.932* (0.701,1.164)	—	—	0.0176* (0.003,0.032)	—	0.0266* (0.006,0.047)	—
M7	0.956* (0.727,1.186)	—	—	0.0202* (0.005,0.035)	—	—	0.0079 (-0.005,0.021)
M8	0.917* (0.687,1.147)	—	—	—	0.0324* (0.01,0.055)	0.0198 (-0.003,0.042)	—
M9	0.982* (0.791,1.174)	—	—	—	0.0377* (0.013,0.062)	—	-0.0115* (-0.023,-4e-4)
Panel B: Middle-and-Low-Income Panel							
M1	0.443* (0.404,0.481)	0.003 (-8e-4,0.007)	-0.005 (-0.014,0.003)	—	—		—
M2	0.466* (0.424,0.509)	0.002 (-0.004,0.008)	—	0.004 (-0.01,0.018)	—	—	—
M3	0.433* (0.407,0.458)	0.003 (-6e-4,0.007)	—	—	-0.006 (-0.015,0.003)	—	—
M4	0.438* (0.386,0.491)	—	-0.005 (-0.017,0.007)	—	—	0.0038 (-0.002,0.009)	—
M5	0.412* (0.347,0.476)	—	-0.006 (-0.015,0.003)	—	—	—	0.010* (0.008,0.013)
M6	0.493* (0.44,0.547)	—	—	0.018* (0.009,0.028)	—	0.004 (-4e-4,0.008)	—
M7	0.431* (0.375,0.488)	—	—	-0.008 (-0.017,0.003)	—	—	0.009* (0.007,0.011)
M8	0.419* (0.356,0.483)	—	—	—	-0.007 (-0.021,0.005)	0.005 (-8e-4,0.011)	—
M9	0.397* (0.339,0.456)	—	—	—	-0.006 (-0.015,0.003)	—	0.010* (0.008,0.012)
Panel C: Full Sample							
M1	0.626* (0.529,0.722)	-0.005 (-0.011,0.001)	0.010* (0.004,0.016)	—	—	—	—
M2	0.628* (0.54,0.717)	-0.004 (-0.01,0.002)	—	0.0104* (0.002,0.019)	—	—	—
M3	0.605* (0.52,0.69)	-0.005 (-0.01,0.001)	—	—	0.014* (0.007,0.021)	—	—
M4	0.631* (0.522,0.739)	—	0.012* (0.004,0.02)	—	—	-0.014* (-0.026,-0.001)	—
M5	0.608* (0.51,0.707)	—	0.009* (0.003,0.016)	—	—	—	-0.003 (-0.008,0.002)

M6	0.619* (0.533,0.705)	—	—	0.0096* (0.001,0.018)	—	-0.008 (-0.016,2e-4)	—
M7	0.621* (0.514,0.728)	—	—	0.009 (-1e-4,0.019)	—	—	-0.003 (-0.008,0.002)
M8	0.618* (0.523,0.712)	—	—	—	0.018* (0.008,0.028)	-0.014* (-0.027,-6e-4)	—
M9	0.590* (0.501,0.678)	—	—	—	0.013* (0.005,0.021)	—	-0.003 (-0.008,0.003)

Estimation results for the full sample period (1989-2011) with no structural breaks. The numbers within parentheses indicate the 95% posterior credible intervals. The variables are: k = per capita physical capital stock; F^{AG} = finance aggregate (the first principal component of F^A and F^Z); S^{AG} = structure aggregate (the first principal component of S^A and S^Z). The first principal components of F^A and F^Z and S^A and S^Z respectively explain 94.3% and 70.1% of their pairwise total variations. S^A = structure activity (stock market total value traded to private credit ratio); S^Z = structure size (stock market capitalization to private credit ratio); F^A = finance activity (Ln(private credit ratio × stock market value traded ratio)); F^Z = finance size (Ln(private credit ratio × stock market capitalization ratio)). The generic model is:

$$y_{i.t} = \gamma_{1,i} + \gamma_{2,i}t + \gamma_{3,i}t^2 + \sum_{j=-d_1}^{d_1} \gamma_{4,i,j}\Delta k_{i,t+j} + \sum_{j=-d1}^{d_1} \lambda_{5,i,j}\Delta fd_{i,t+j} + \sum_{j=-d1}^{d_1} \lambda_{6,i,j}\Delta fs_{i,t+j}$$
$$+ \beta_1 k_{i,t} + \beta_2 fd_{i,t} + \beta_3 fs_{i,t} + \varepsilon_{it}; \qquad \varepsilon_{i,t} \sim i.i.d.\,\mathrm{N}(0,\sigma^2)$$

The nine different models (M1 through M9) are specified as outlined in the notes for Table 3. * denotes parameter significance at 5%, i.e., zero is outside of the 5% credible bounds.

Table 5: The number of regimes and the location of break points for full, high-income and middle-and-low-income countries.

Models	Panel A: High-Income Panel		Panel B: Middle-and-Low-Income Panel		Panel C: Full Sample	
	number of regimes	location of breaks	number of regimes	location	number of regimes	location of breaks
M1	1 , 2♣ (0.5051) (0.4928) [0.5724] [0.3288]	2008♣ , 1990 (0.3501) (0.1465) [0.0335] [0.0178]	1 , 2 (0.9996) (4e-4) [0.5752] [0.3281]	2003 (4e-4) [0.0287]	1 , 2 (0.9656) (0.0344) [0.5737] [0.3284]	2003 , 2008 (0.0316) (0.0028) [0.0267] [0.0346]
M2	2♣ , 1 (0.7692) (0.2268) [0.3288] [0.5724]	2008♣ , 1990 (0.6556) (0.1213) [0.0335] [0.0178]	1 , 2 (1) (0) [0.5752] [0.3281]		1 , 2 (0.9069) (0.0931) [0.5737] [0.3284]	2003 , 2008 (0.0926) (4e-4) [0.0267] [0.0346]
M3	1 , 2♣ (0.5753) (0.4232) [0.5724] [0.3288]	2008♣ , 1990 (0.4055) (0.0191) [0.0335] [0.0178]	1 , 2 (0.9985) (0.0015) [0.5752] [0.3281]	2003 (0.0015) [0.0287]	1 , 2 (0.9593) (0.0407) [0.5737] [0.3284]	2003 , 2008 (0.0353) (0.0054) [0.0267] [0.0346]
M4	1 , 2 (0.8736) (0.1263) [0.5724] [0.3288]	2008 , 1990 (0.0986) (0.0275) [0.0335] [0.0178]	1 , 2 (1) (0) [0.5752] [0.3281]		1 , 2 (0.9985) (0.0015) [0.5737] [0.3284]	2008 , 1997 (0.0013) (1e-4) [0.0346] [0.0218]
M5	2♣ , 1 (0.7676) (0.2291) [0.3288] [0.5724]	2008♣ , 1990 (0.444) (0.329) [0.0335] [0.0178]	1 , 2 (1) (0) [0.5752] [0.3281]		1 , 2 (0.9957) (0.0043) [0.5737] [0.3284]	2008 , 2003 (0.0032) (0.0011) [0.0346] [0.0267]
M6	1 , 2 (0.7577) (0.2422) [0.5724] [0.3288]	2008 , 1990 (0.2316) (0.0107) [0.0335] [0.0178]	1 , 2 (0.9999) (0.0001) [0.5752] [0.3281]	1999 (1e-04) [0.0245]	1 , 2 (0.9968) (0.0032) [0.5737] [0.3284]	2003 , 2008 (0.002) (0.0012) [0.0267] [0.0346]
M7	2♣ , 1 (0.9248) (0.0676) [0.3288] [0.5724]	2008♣ , 1990 (0.7854) (0.1534) [0.0335] [0.0178]	1 , 2 (1) (0) [0.5752] [0.3281]		1 , 2 (0.9988) (0.0012) [0.5737] [0.3284]	2008 , 2003 (7e-4) (5e-4) [0.0346] [0.0267]
M8	1 , 2 (0.8012) (0.1986) [0.5724] [0.3288]	2008 , 1990 (0.1839) (0.0136) [0.0335] [0.0178]	1 , 2 (0.9999) (0.0001) [0.5752] [0.3281]	2000 (1e-04) [0.0254]	1 , 2 (0.9832) (0.0168) [0.5737] [0.3284]	2008 (0.0168) [0.0346]
M9	2♣ , 3 (0.9749) (0.0251) [0.3284] [0.0835]	1996♣ , 2005, 2004 (1) (0.024) (0.001) [0.021] [0.029] [0.028]	1 , 2 (1) (0) [0.5752] [0.3281]		1 , 2 (0.9915) (0.0085) [0.5737] [0.3284]	2008 , 2003 (0.0066) (0.0019) [0.0346] [0.0267]

Note: The numbers inside () are the posterior probabilities and the numbers inside [] are the prior probabilities. Models are defined in the notes to Tables 3 and 5. ♣ signifies one regime shift (break) and the most probable break date.

Table 6: Estimation results with no structural breaks (1989-2008).

	k	F^{AG}	S^{AG}	S^{A}	S^{Z}	F^{Z}	F^{A}
Panel A: High-Income Panel							
M1	0.844* (0.547, 1.14)	0.003 (-0.008, 0.015)	0.023* (0.005, 0.041)	–	–	–	–
M2	0.865* (0.556, 1.174)	0.006 (-0.006, 0.017)	–	0.023* (0.002, 0.045)	–	–	–
M3	0.827* (0.53, 1.122)	0.004 (-0.007, 0.015)	–	–	0.036* (0.013, 0.06)	–	–
M4	0.841* (0.536, 1.146)	–	0.022* (0.002, 0.042)	–	–	0.010 (-0.015, 0.035)	–
M5	0.847* (0.557, 1.138)	–	0.023* (0.006, 0.040)	–	–	–	0.004 (-7e-3,0.015)
M6	0.858* (0.541, 1.175)	–	–	0.022* (0.001, 0.043)	–	0.018 (-0.003, 0.038)	–
M7	0.871* (0.57, 1.171)	–	–	0.0231* (0.003, 0.043)	–	–	0.006 (-4e-3,0.017)
M8	0.826* (0.526, 1.126)	–	–	–	0.036* (0.007, 0.065)	0.006 (-0.021, 0.032)	–
M9	0.832* (0.541, 1.123)	–	–	–	0.036* (0.013, 0.059)	–	0.005 (-5e-3,0.015)
Panel B: Middle-and-Low-Income Panel							
M1	0.514* (0.415, 0.613)	0.005* (0.001,0.008)	0.004 (-0.005,0.013)	–	–	–	–
M2	0.548* (0.437, 0.659)	0.0047 (-0.001,0.01)	–	0.006 (-0.009,0.02)	–	–	–
M3	0.482* (0.398, 0.567)	0.006* (0.002,0.009)	–	–	0.004 (-0.005,0.013)	–	–
M4	0.504* (0.344,0.665)	–	0.004 (-0.006,0.013)	–	–	0.001 (-0.006,0.007)	–
M5	0.490* (0.406,0.574)	–	0.003 (-0.002,0.007)	–	–	–	0.010* (6e-3,0.014)
M6	0.532* (0.416,0.649)	–	–	0.015* (0.004,0.027)	–	0.007 (-0.002,0.015)	–
M7	0.531* (0.437,0.624)	–	–	-0.0005 (-0.011,0.01)	–	–	0.009* (5e-3,0.013)
M8	0.497* (0.35,0.644)	–	–	–	0.004 (-0.006,0.014)	0.001 (-0.005,0.006)	–
M9	0.473* (0.391,0.555)	–	–	–	0.002 (-0.002,0.006)	–	0.011* (7e-3,0.015)
Panel C: Full Sample							
M1	0.617* (0.388, 0.847)	-0.0029 (-0.01, 0.004)	0.020* (0.01,0.031)	–	–	–	–
M2	0.709* (0.438, 0.981)	-0.0053 (-0.013, 0.002)	–	0.047* (0.018, 0.075)	–	–	–
M3	0.702* (0.626, 0.778)	-0.0059 (-0.014, 0.002)	–	–	0.016* (0.008, 0.024)	–	–
M4	0.601* (0.372, 0.829)	–	0.018* (0.006, 0.03)	–	–	-0.012 (-0.03, 0.002)	–
M5	0.605* (0.404, 0.807)	–	0.017* (0.01, 0.025)	–	–	–	0.002 (-5e-3, 8e-3)
M6	0.641* (0.416, 0.865)	–	–	0.033* (0.009, 0.057)	–	-0.005 (-0.018, 0.009)	–

M7	0.709* (0.461, 0.958)	–	–	0.046* (0.018, 0.075)	–	–	-4e-3 (-0.01,4e-3)
M8	0.735* (0.644, 0.825)	–	–	–	0.021* (0.008, 0.034)	-0.020* (-0.037, -0.004)	–
M9	0.678* (0.57, 0.787)	–	–	–	0.014* (0.007, 0.021)	–	-0.003 (-0.01, 4e-3)

Note: The numbers within () indicate the 95% posterior credible intervals. Variable definition and specifications are described in the notes to Table 5. * denotes parameter significance at 5%, i.e., zero is outside of the 5% credible bounds.

[1] The theoretical debate surrounding the *bank-based, market-based*, *financial services* and the *law-and-finance* views are well documented elsewhere, hence we do not detail the arguments for and against them. A succinct summary of these could be found in, among others, Beck et al. (2001), Beck and Levine (2002), Levine (2002), Demirgüç-Kunt and Maksimovic (2002) and Luintel et al. (2008).

[2] The *law-and-finance* view is associated with and well elaborated by La Porta et al. (1998), Gorton and Schmid, (2000), La Porta et al. (2008); Djankov et al. (2007); Djankov et al. (2008), among others.

[3] This dataset is available at http://go.worldbank.org/X23UD9QUX0

[4] For example, if there is one break then there will be T-1 possible break locations, where T is the sample period; if there are two breaks then there will be $\frac{(T-1)(T-2)}{2}$ possible combinations of the break locations. The number of breaks can range from 0 to T-1. Hence the total number of possibilities is 2^{T-1}.

[5] In a panel with short time dimension and/or cross-sectional setups it is commonplace to employ several other determinants of growth, namely, the years of schooling (human capital), black market premiums, indicators of civil liberty, revolutions and coups, assassinations, bureaucratic efficiency, corruptions etc. as in Levine (2002) and Beck and Levine (2004). However, data on these variables are collected through periodic surveys and are not sufficiently long to include in panel studies such as this one which has a time series dimension of 23 years for each variable.

[6] This gives rise to 15 possible specifications. Due to the large amount of parameters in the DOLS model, we cannot set the maximum number of lags and leads to be bigger than our choice of the one given T_0=15. Our data span is from 1989 to 2011. The actual number of periods (T) in the estimation depends on the number of lags and leads. If both the number of lags and leads is 1, then the choice T_0=15 implies that we evaluate models on the basis of predictions for the years from 2006-2010.

[7] To be precise, according to the World Bank classification (2013), 34 of these 36 are middle-income countries and only two (Bangladesh and Kenya) are low-income countries. However, the latter two countries have complete datasets and they do not differ materially, in terms of their income levels, from some of the middle-income countries (e.g., Ghana and Nigeria) hence we have included them in the analysis. We evaluate the sensitivity of our results to the inclusion of Bangladesh and Kenya in Section 5. The focus is to include as many countries as possible that have a complete dataset.

[8] The measures of F^Z reported by Levine (2002) are unusually high – for example, F^Z for Switzerland (Ln(5.51)), Japan (Ln(5.59)), US (Ln(5.24)) and UK (Ln(5.02)) imply very high ratios ranging from 151(UK) to 247(Switzerland). The note to Table II (Levine, 2002) suggests that there may have been an error in computing F^Z reported in Table II; hence, we do not compare F^Z measures. If we were to compare, then big differences are clearly apparent.

[9] The negative effects of F^A is an uncomfortable result but that is what the data tell us. As discussed above, our data are from a highly credible source. The original data, our construction and estimation codes will be available on request.

[10] Although finance size (F^Z) appears positive and significant in one of the three cases, the financial services view emphasizes overall financial development – inclusive of F^A and F^Z – measured by F^{AG}, hence the conclusion.

[11] One of the anonymous referees suggested that we evaluate if financial development (FD) and structure (FS) would affect financial and economic stability. We focus on economic stability simply because acute financial instability which exacerbates economic instability is of more concern. We proxy economic instability by growth volatility and compute: (i) five yearly moving standard deviation of real per capita GDP growth, (ii) ARCH (1) volatility of real per capita GDP growth, and (iii) the square of the residuals of equation (1) as a measure of the conditional volatility of real GDP per capita. All three volatility measures are stationary. Hence, we estimated fixed effects (OLS) models for each measure of growth volatility on ΔFD and ΔFS across all nine specifications as shown in Table 4. Results reveal that both covariates are insignificant across all specifications (robust standard errors are used). Thus, we do not find any evidence that financial development and structure explains growth volatility.

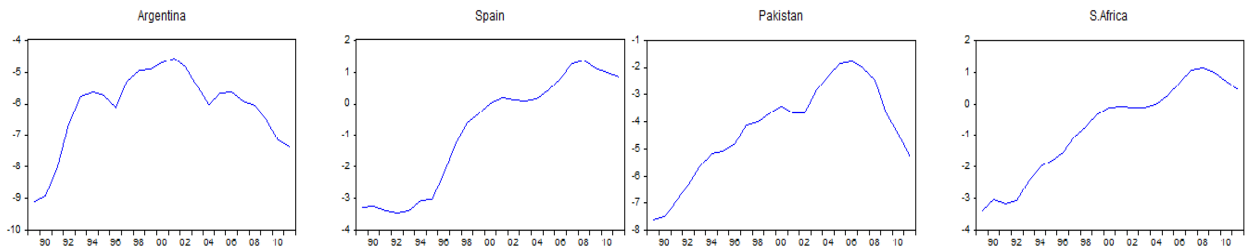
[12] We use lagged (one and two periods) values of explanatory variables as instruments. As stated above (footnote 5), our specifications do not include some of the covariates – such as schooling, inflation, black market premium etc. – used in the literature. Nevertheless, our specifications compare very favourably with Levine’s (2002) simple conditioning set which only includes initial income and schooling.

Financial Development, Structure and Growth: New Data, Method and Results

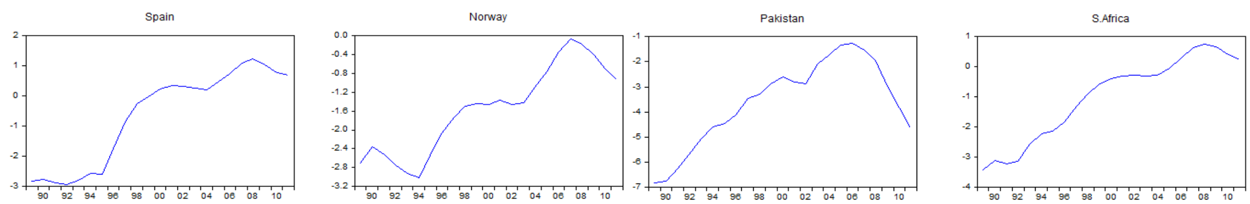
Online Appendix

Figure 1: Plots of selected time series for selected countries.

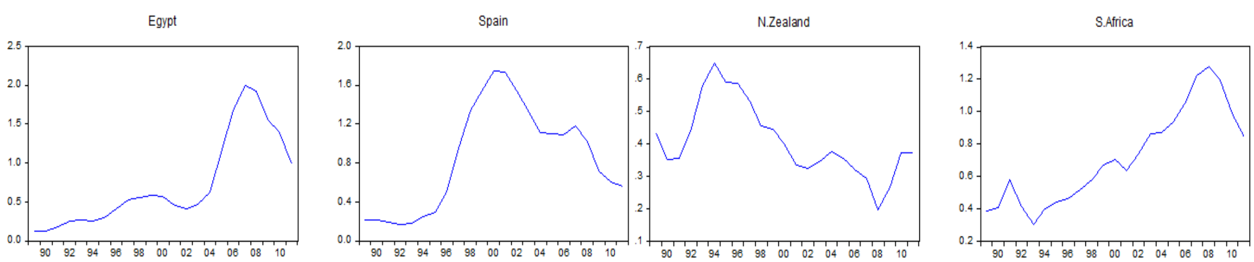
F^{AG} for Selected Countries



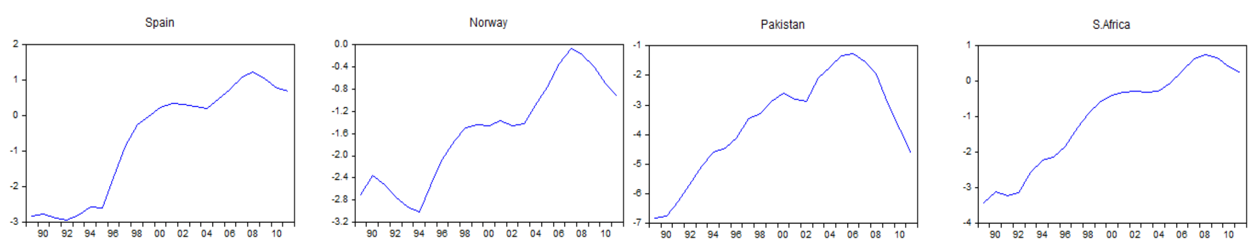
S^{AG} for Selected Countries



F^{A} for Selected Countries

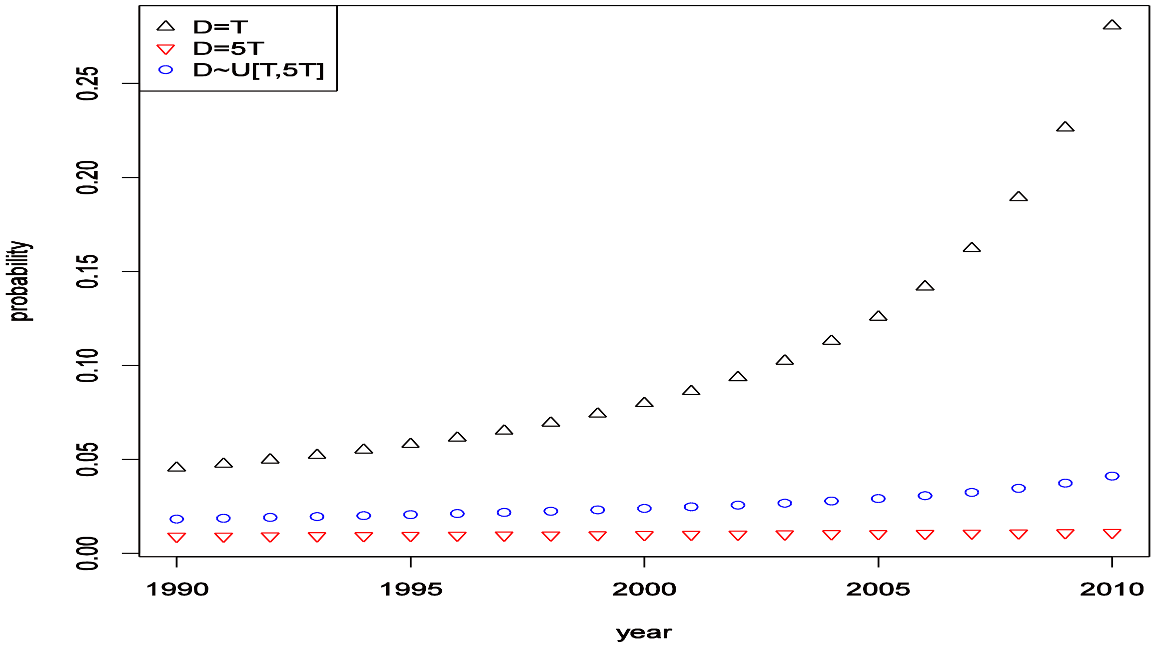


S^{A} for Selected Countries



F^{AG}, S^{AG}, F^{A} and S^{A} respectively stand for finance aggregate, structure aggregate, finance activity and structure activity as defined in the notes to Table 3 in the paper.

Figure 2: The priors for a particular period being a break unconditional on the previous periods for different specifications of D when T=22



The vertical axes shows the probability $Pr(B_t = 1)$ unconditional on previous periods. It is represented with the symbol △ when D=T and in this case the prior probability of a break significantly increases with time. When D=5T the prior probability of a break (represented with ▽) remains roughly constant over the whole sample period. In our empirical analysis we specify a uniform distribution in (T, 5T) as a prior for D, such that there is only a slight increase in the prior probability of a break over time (as shown in the graph with the symbol o) .

Table A1: Identification of the order of lags, leads and the deterministic components

		With breaks					no breaks				
Case		Δx_t	$L\Delta x_t$	$L^{+}\Delta x_t$	trend	LPL	Δx_t	$L\Delta x_t$	$L^{+}\Delta x_t$	trend	LPL
High-Income-Panel	M1	0	0	0	quadratic	475.879	0	0	0	quadratic	475.849
	M2	0	0	0	quadratic	474.205	0	0	0	quadratic	474.094
	M3	0	0	0	quadratic	481.865	0	0	0	quadratic	481.843
	M4	0	0	0	quadratic	479.997	0	0	0	quadratic	479.959
	M5	0	0	0	quadratic	474.174	1	0	0	quadratic	474.545
	M6	0	0	0	quadratic	480.432	0	0	0	quadratic	480.416
	M7	0	0	0	quadratic	472.225	0	0	0	quadratic	471.795
	M8	0	0	0	quadratic	483.329	0	0	0	quadratic	483.31
	M9	1	0	0	quadratic	487.872	1	0	0	quadratic	482.111
Middle-and-Low-Income-Panel	M1	1	0	1	quadratic	515.413	1	0	1	quadratic	515.413
	M2	1	0	1	quadratic	516.066	1	0	1	quadratic	516.068
	M3	1	0	1	quadratic	510.099	1	0	1	quadratic	510.098
	M4	1	0	1	quadratic	525.447	1	0	1	quadratic	525.529
	M5	1	0	1	quadratic	524.622	1	0	1	quadratic	524.621
	M6	1	0	1	quadratic	520.706	1	0	1	quadratic	520.877
	M7	1	0	1	quadratic	528.244	1	0	1	quadratic	528.244
	M8	1	0	1	quadratic	524.735	1	0	1	quadratic	524.788
	M9	1	0	1	quadratic	517.057	1	0	1	quadratic	517.056
Full-Panel	M1	1	0	0	quadratic	992.417	1	0	0	quadratic	992.416
	M2	1	0	0	quadratic	991.15	1	0	0	quadratic	991.146
	M3	1	0	0	quadratic	990.524	1	0	0	quadratic	990.523
	M4	1	0	0	quadratic	1001.024	1	0	0	quadratic	1001.024
	M5	1	0	0	quadratic	990.744	1	0	0	quadratic	990.743
	M6	1	0	0	quadratic	993.985	1	0	0	quadratic	994.029
	M7	1	0	0	quadratic	985.209	1	0	0	quadratic	985.212
	M8	1	0	0	quadratic	1002.025	1	0	0	quadratic	1002.019
	M9	1	0	0	quadratic	990.964	1	0	0	quadratic	990.964

Note: This Table reports the log of predicted likelihood (LPL) for our empirical specifications (DOLS). Each reported specification is based on the highest value of the LPL. We search through the first order leads and lags and the deterministic components consisting of a constant, a linear and a quadratic trend. This generates 15 potential specifications to exhaust all possible combinations of leads ($L^{+}\Delta x_t$), lags ($L\Delta x_t$) and contemporaneous first differences terms (Δx_t) of I(1) regressors and the deterministic components. In all specifications, all three deterministic components – a constant, a linear and a quadratic trend – appear significant, showing the highest predictive likelihood hence maintained.

Table A1 reports the highest value of the log of predictive likelihood computed across all 15 specifications to exhaust all possible combinations of leads, lags and the deterministic components for each specification. The results show that the empirical specifications of DOLS regressions differ across panels and models. When models do not allow for breaks, the DOLS specifications for the full panel require augmentation only by the contemporaneous first differences of I(1) regressors; no lead and lag augmentations are required. The panel of high-income countries does not require any augmentations except in two cases (Models 5 and 9) – these two requiring augmentation by contemporaneous difference terms only. In contrast, the panels of middle-and-low-income countries require augmentations by contemporaneous and lead terms of first differenced covariates. Allowing for potential breaks does not alter the empirical specifications except for only one case (Model 5 for high-income countries).

Table A2: Estimation results with structural breaks for high-income countries in selected years.

Models	Year	k	F^{AG}	S^{AG}	S^{A}	S^{Z}	F^{Z}	F^{A}
M1	1990	0.924 (0.796,1.05)	0.0058 (-0.006,0.013)	0.0175 (-0.054,0.026)	–	–	–	–
	2008	0.923 (0.796,1.049)	0.0058 (-0.002,0.013)	0.0186 (0.011,0.027)	–	–	–	–
	2009	0.922 (0.792,1.049)	0.005 (-0.006,0.013)	0.0189 (0.001,0.030)	–	–	–	–
M2	1990	0.918 (0.79,1.043)	0.0061 (-0.005,0.013)	–	0.0151 (-0.121,0.026)	–	–	–
	2008	0.917 (0.789,1.043)	0.0061 (-0.0008,0.01)	–	0.0163 (0.006,0.026)	–	–	–
	2009	0.914 (0.786,1.042)	0.0062 (-0.003,0.015)	–	0.0091 (-0.02,0.027)	–	–	–
M3	1990	0.903 (0.78,1.028)	0.0065 (-0.0007,0.013)	–	–	0.0343 (0.020,0.045)	–	–
	2008	0.903 (0.78,1.028)	0.0064 (-0.0005,0.013)	–	–	0.0345 (0.023,0.045)	–	–
	2009	0.901 (0.775,1.027)	0.0057 (-0.007,0.013)	–	–	0.0376 (0.021,0.068)	–	–
M4	1990	0.924 (0.802,1.046)	–	0.0170 (-0.013,0.024)	–	–	0.0220 (0.008,0.033)	–
	2008	0.924 (0.801,1.046)	–	0.0172 (0.01,0.024)	–	–	0.0220 (0.009,0.033)	–
	2009	0.924 (0.801,1.046)	–	0.0171 (0.002,0.025)	–	–	0.0221 (0.007,0.034)	–
M5	1990	0.923 (0.798,1.049)	–	0.0157 (-0.065,0.026)	–	–	–	0.0029 (-0.010,0.011)
	2008	0.921 (0.797,1.046)	–	0.0193 (0.011,0.027)	–	–	–	0.0032 (-0.004,0.011)
	2009	0.919 (0.794,1.045)	–	0.0194 (0.0002,0.031)	–	–	–	0.0017 (-0.008,0.011)
M6	1990	0.925 (0.802,1.044)	–	–	0.0166 (0.006,0.026)	–	0.0249 (0.011,0.036)	–
	2008	0.925 (0.801,1.044)	–	–	0.0167 (0.007,0.026)	–	0.0249 (0.011,0.036)	–
	2009	0.924 (0.8,1.044)	–	–	0.0159 (-0.018,0.026)	–	0.0261 (0.010,0.038)	–
M7	1990	0.914 (0.787,1.04)	–	–	0.0153 (-0.175,0.026)	–	–	0.0047 (-0.005,0.013)
	2008	0.913 (0.787,1.039)	–	–	0.0169 (0.007,0.027)	–	–	0.0044 (-0.002,0.011)
	2009	0.91 (0.783,1.036)	–	–	0.0043 (-0.023,0.027)	–	–	0.0061 (-0.004,0.017)
M8	1990	0.909 (0.787,1.031)	–	–	–	0.0318 (0.019,0.043)	0.0185 (0.003,0.030)	–
	2008	0.909 (0.787,1.031)	–	–	–	0.0319 (0.021,0.043)	0.0184 (0.003,0.030)	–
	2009	0.908 (0.786,1.031)	–	–	–	0.0327 (0.017,0.056)	0.0187 (-0.003,0.030)	–
M9	1996	1.01 (0.895,1.124)	–	–	–	0.1148 (0.093,0.136)	–	-0.0194 (-0.028,-0.011)
	2005	1.016 (0.901,1.131)	–	–	–	0.0292 (0.018,0.040)	–	-0.0087 (-0.015,-0.002)
	2006	1.016 (0.901,1.131)	–	–	–	0.0296 (0.019,0.045)	–	-0.0088 (-0.016,-0.003)

Note: The numbers inside () indicate the 95% posterior credible intervals. Variables and specifications are given in the notes to Table 4 of the paper.

2. Simulation Details

Denote $x_{it} = (k_{it}, fd_{it}, fs_{it})'$ and $X_i = (x_{i1}, x_{i2}, \dots, x_{iT})'$, which is a $T \times 3$ matrix. For each cross-sectional unit i, stack up all the observations of T periods to obtain,

$$\boldsymbol{y_i = W_i\gamma_i + X_i\beta_1 + \Xi_i u + \varepsilon_i} \tag{A1}$$

where,

$y_i = (y_{i1}, \dots, y_{iT})'$, $\gamma_i = \left(\gamma_{1i}, \gamma_{2i}, \gamma_{3i}, \gamma_{4i,-d_1}, \dots, \gamma_{4i,d_2}, \gamma_{5i,-d_1}, \dots, \gamma_{5i,d_2}, \gamma_{6i,-d_1}, \dots, \gamma_{6i,d_2}\right)'$; $u = ({u_1}', {u_2}', \dots, {u_{T-1}}')'$; W_i is a matrix of T rows with the t[th] row being,
$\left(1, t, t^2, \Delta k_{i,t-d_1}, \dots, \Delta k_{i,t+d_2}, \Delta fd_{i,t-d_1}, \dots, \Delta fd_{i,t+d_2}, \Delta fs_{i,t-d_1}, \dots, \Delta fs_{i,t+d_2}\right)$ for $t = 1, \dots, T$; $\Xi_i = (B_1 X_{1,i}, B_2 X_{2,i}, \dots, B_{T-1} X_{T-1,i})$ and $X_{j,i}$ is a matrix with the first j rows being 0 and the remaining rows being the same as those in X_i. The posterior of $p(\theta|y)$ is proportional to the product of the prior $p(\theta)$ and the likelihood function $p(y|\theta)$:

$$\boldsymbol{p(\theta|y) \propto p(\beta_1|\sigma^2)p(u|\sigma_u^2)p(\sigma_u^2)p\left(B_{1:(T-1)}\middle|D\right)p(D)} \tag{A2}$$
$$\boldsymbol{(\sigma^2)^{-\frac{NT-2}{2}} exp\left[-\frac{\sum_{i=1}^N (y_i - W_i\gamma_i - X_i\beta_1 - \Xi_i u)'(y_i - W_i\gamma_i - X_i\beta_1 - \Xi_i u)}{2\sigma^2}\right]}.$$

After integrating out γ_i from the posterior kernel, one can obtain:

$$\boldsymbol{p\left(\sigma^2, \beta_1, u, \sigma_u^2, B_{1:(T-1)}, D\right) \propto p(\beta_1|\sigma^2)p(u|\sigma_u^2)p(\sigma_u^2)p\left(B_{1:(T-1)}\middle|D\right)} \tag{A3}$$
$$\boldsymbol{(\sigma^2)^{-\frac{N(T-k_\gamma)-2}{2}} exp\left[-\frac{\sum_{i=1}^N (y_i - X_i\beta_1 - \Xi_i u)' M_i (y_i - X_i\beta_1 - \Xi_i u)}{2\sigma^2}\right]},$$

where k_γ is the number of elements in γ_i and $M_i = I_T - W_i({W_i}'W_i)^{-1}{W_i}'$. We can then derive the posterior distribution of $(\beta_1, u, B_{1:(T-1)})$ conditional on $(D, \sigma^2, \sigma_u^2)$ as the following:

$$\boldsymbol{\beta_1|u, y, B_{1:(T-1)}, \sigma^2, \sigma_u^2 \sim N(V_\beta \textstyle\sum_{i=1}^N X_i' M_i (y_i - \Xi_i u), \sigma^2 V_\beta)}, \tag{A4}$$
$$\boldsymbol{u|\, y, B_{1:(T-1)}, \sigma^2, \sigma_u^2 \sim N(V_u \textstyle\sum_{i=1}^N \Xi_i' M_i X_i V_\beta \sum_{i=1}^N X_i' M_i y_i\,, \sigma^2 V_u)}, \tag{A5}$$

$$p\left(B_{1:(T-1)}\middle|y, D, \sigma^2, \sigma_u^2\right)$$
$$\propto p(B_{1:(T-1)}|D)|\sigma^2 V_u|^{\frac{1}{2}} exp\left[-\frac{\sum_{i=1}^N {y_i}'y_i - \sum_{i=1}^N {y_i}' M_i X_i V_\beta \sum_{i=1}^N X_i' M_i y_i}{2\sigma^2}\right] \tag{A6}$$
$$exp\left[\frac{\sum_{i=1}^N {y_i}' M_i X_i V_\beta \sum_{i=1}^N {X_i}' M_i \Xi_i V_u \sum_{i=1}^N {\Xi_i}' M_i X_i V_\beta \sum_{i=1}^N {X_i}' M_i y_i}{2\sigma^2}\right],$$

where $V_\beta = \left(\sum_{i=1}^N {X_i}' M_i X_i + \frac{1}{\tau} I_3\right)^{-1}$ and $V_u = \left(\sum_{i=1}^N {\Xi_i}' M_i X_i V_\beta \sum_{i=1}^N {X_i}' M_i \Xi_i + \frac{\boldsymbol{\sigma^2}}{\boldsymbol{\sigma_u^2}} I\right)^{-1}$. To sample $B_{1:(T-1)}$ from its conditional posterior, we set up another Gibbs sampler, which draws each element in $B_{1:(T-1)}$ conditional on the other elements. The posterior of $(D, \sigma^2, \sigma_u^2)$ conditional on $(\beta_1, u, B_{1:(T-1)})$ is:

$$p(D|B_{1:(T-1)}, y) \propto p(D)p(B_{1:(T-1)}|D) \tag{A7}$$
$$\sigma^2|\beta_1, u, B_{1:(T-1)}, y \sim IG\left(\textstyle\sum_{i=1}^N (y_i - W_i\gamma_i - X_i\beta_1 - \Xi_i u)'(y_i - W_i\gamma_i - X_i\beta_1 - \Xi_i u), N(T - k_\gamma)\right), \tag{A8}$$
$$\sigma_{uj}^2|\, u, B_{1:(T-1)}, y \sim IG\left(\textstyle\sum_{t=1}^{T-1} B_t u_{jt}^2 + 0.1, 3 + \sum_{t=1}^{T-1} B_t\right), for\ j = 1,2,3. \tag{A9}$$

Regarding the calculation of the predictive likelihood, Geweke (1995, 1996) shows that the predictive likelihood $p_{T_0}^{T}$ can be decomposed as the following product,

$$p_{T_0}^{T} = p_{T_0}^{T_0+1} p_{T_0+1}^{T_0+2} \dots p_{T-1}^{T} \tag{A10}$$

where each of the components of the predictive likelihood is a one-step-ahead predictive likelihood, which can be approximated by using draws from the posterior as:

$$\hat{p}_{T_0+t}^{T_0+t+1} = \frac{\sum_{s=1}^{S} p\left(y_{T_0+t+1} \middle| \theta_{T_0+t+1}^{s}, y_{1:(T_0+t)}\right)}{S}, for\ t = 0,1, \dots, (T - T_0 - 1). \tag{A11}$$

where $(\theta_{T_0+t+1}^{1}, \dots, \theta_{T_0+t+1}^{S})$ are S draws from the posterior of θ_{T_0+t+1} given $y_{1:(T_0+t)}$. For the model (1) in page 7, we just need to predict B_{T_0+t} and u_{T_0+t} after the estimation with the initial sample up to period $T_0 + t$. The posterior of θ_{T_0+t+1} given $y_{1:(T_0+t)}$ for our model is

$$\begin{aligned} p\left(\theta_{T_0+t+1} | y_{1:(T_0+t)}\right) &= p\left(u_{T_0+t} \middle| B_{T_0+t}, \sigma_u^2, y_{1:(T_0+t)}\right) \\ &\quad p(B_{T_0+t} | B_{1:(T_0+t-1)}, D, y_{1:(T_0+t)}) p(D, \sigma^2, \sigma_u^2, \beta_1, u_{1:(T_0+t-1)}, B_{1:(T_0+t-1)} | y_{1:(T_0+t)}). \end{aligned} \tag{A12}$$

We used 10,000 iterations to estimate each of the components of the predictive likelihood.