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FINANCIAL DEVELOPMENT AND ECONOMIC GROWTH: A NEW INVESTIGATION

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This article applies a Bayesian dynamic factor model to examine the relationship between financial development and economic growth from a new angle. We estimate the common, country, and idiosyncratic factors that drive the dynamics and co-movement of financial development and economic growth across 89 countries in three different income groups, namely industrial countries (INDs), emerging market economies (EMEs), and other developing countries (ODCs), over the period 1970 to 2009. The results indicate that the common factor plays a more significant role in explaining the variance of output growth in INDs and EMEs, but not in ODCs. In contrast, financial development variability is mainly driven by the country and idiosyncratic factors. We also analyze the relation between country characteristics and the relative importance of the factors.

Keywords: Financial Development, Economic Growth, Dynamic Factor Model, Bayesian Analysis
JEL classification: C11, C32, O16

1. INTRODUCTION

Whether financial development boosts economic growth is of great concern to policymakers and researchers, especially after the outbreak of the recent global financial crisis and the European debt crisis. In this context, there are two streams of literature. One argues that a well-developed financial system can make the economy more productive and enhance economic growth. Specifically, a healthy financial system reduces asymmetric information between savers and investors, helps people share risks, and lowers transaction costs. However, there also exists a potential growth-retarding

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impact of financial development (King and Levine, 1993a), which suggests that higher returns on the improved resource allocation may decrease saving rates and then depress the economic activity. The U.S. financial crisis of 2007-2009 exampled these financial system malfunctions. Lartey and Farka (2011) find that financial crises have a negative effect on economic growth and the impact depends on the level of financial development, such that countries with better developed financial systems are more adversely affected by crises than those with underdeveloped ones.

Recent empirical literature has extensively investigated the relationship between financial development and economic growth. The findings, however, are inconclusive, varying with the econometric models and the data used. Most studies hold the view that there is a significantly positive relationship between financial development and economic growth using various measures of financial development (King and Levine, 1993a, b; Levine *et al*., 2000; Lartey, 2010; Gupta, 1986, among others). However, Kar *et al.* (2011) show that there is no clear consensus on the direction of causality between the two variables when using six financial development indicators for the Middle East and North African (MENA) countries. Al-Yousif (2002) finds that financial development and economic growth are mutually causal based on both time-series and panel data of 30 developing countries.

Mixed results are found when using vector autoregressive (VAR) models to study the relationship between financial development and economic growth. For instance, Shan *et al.* (2001) show the bidirectional causality in five countries and one-way causality from growth to finance in three others when studying nine OECD countries and China. Abu-Bader and Abu-Qarn's (2008) empirical results strongly support the hypothesis that finance leads to growth in five MENA countries. Shan (2005) documents weak evidence of one-way causality from finance to growth in a sample of eight industrial countries and three Asian economies. Esso (2010) and Hassan *et al.* (2011) have also shown that the causal relationship between finance and growth differs significantly among countries. In addition, using panel VAR analysis, Blanco (2009) finds two-way causality for the middle income group and for countries with stronger rule of law and creditor rights. However, economic growth causes financial development but not vice versa in the sample of all 18 Latin America countries.

A number of recent empirical studies have reported a non-linear relationship between financial development and economic growth in developed and developing countries; i.e., financial development may affect economic growth differently in countries with different income levels. For instance, Deidda and Fattouh (2002) apply a threshold regression model and Jude (2010) uses a panel smooth threshold regression approach to identify the existence of threshold effect in the nonlinear relationship between finance and growth. Lee and Wong (2005) find the existence of inflation threshold effects in the relationship between financial development and economic growth. In particular, financial development promotes economic growth under low and moderate inflation in Taiwan and Japan.

The motivation of our paper stems from the potential linkages between economic growth and financial development documented in previous studies. We employ a Bayesian dynamic factor model, suggested by Kose *et al*. (2003, 2008, 2010) and Crucini *et al*. (2011)[1], to examine the dynamics and the co-movement (or synchronization) of financial development and economic growth within and across 89 countries over the period 1970-2009. Our study aims to address four interesting questions: (1) Are there unobserved common factors driving the dynamics and the co-movement of financial development and economic growth globally and across different income groups, namely industrial countries (INDs), emerging market economies (EMEs), and other developing countries (ODCs)[2], given the fact that different income levels associate with various levels of financial development? (2) How have the unobserved factors evolved over time and can they trace major global and regional economic and financial cycles? (3) Which factor plays an important role in explaining fluctuations in economic growth and financial development? (4) How are the factors related to the structural characteristics of economies?

Dynamic factor models, proposed by Sargent and Sims (1977) and Geweke (1977), have been widely used to extract common factors for forecasting and for examining co-movement among macroeconomic time series. Traditionally, the model is transformed into state-spaces and estimated using Kalman filters and log likelihood maximization. It is, however, difficult to perform when the cross-section dimension and the number of unknown parameters grow large. Since our data covers 89 countries with two variables for each country, the number of unknown parameters in a simple dynamic factor model with one common factor would be at least 178. A solution to the problem of high dimensionality and many unknown parameters in the state-space model is to use Bayesian methods. Recently, Kose *et al*. (2003, 2008, 2010), Crucini *et al*. (2011) and Mumtaz *et al*. (2011) have applied Bayesian Gibbs sampling simulation in estimating dynamic factor models to investigate the evolution and driving forces of international business cycles. Their studies build upon the work of Otrok and Whiteman (1998), who implemented a Bayesian dynamic factor model to forecast economic conditions.

One of the major advantages of Bayesian dynamic factor models over VAR models commonly used in previous studies is that they work well with large cross-sectional data and many unknown parameters. In addition, this method can also easily handle a large number of dynamic factors. Using a Bayesian dynamic factor model, we can study whether there is an unobserved common factor driving the co-movement of financial development and real GDP growth rates of 89 countries (i.e., extracting an unobserved common factor among 178 time series). Therefore, a simple VAR with two time series for a given country or a panel regression of two variables across 89 countries over time

[1] They use Bayesian dynamic factor models to investigate the evolution and driving forces of international business cycles.

[2] The same grouping method can be found in Kose *et al*. (2010).

would not be appropriate for our study. Furthermore, if using a VAR with 178 time series, the number of parameters to estimate would be too large as compared to the number of time observations. In contrast, using a Bayesian dynamic factor model, we can accommodate a large number of variables without running into scarce degrees of freedom problems. This method mitigates the curse of dimensionality by modeling the stochastic processes for both endogenous variables and exogenous variables with far fewer parameters than would be true had we employed a VAR (Crucini *et al*., 2011).

Using a Bayesian dynamic factor model, we estimate the unobserved common, country, and idiosyncratic factors that steer the co-movement of output growth and financial development across 89 countries in the period from 1970 to 2009. The common factor captures co-movement across all series in all countries, i.e., 178 series in our study; the country factors are common to the two series in a given country; and the idiosyncratic factors are specific to each series. This approach allows us to decompose the variance of output growth and financial development into these three factors to assess the relative contributions of each factor to the fluctuations in the two variables in each country. It also allows each variable to respond with its own magnitude and sign to the factors, and can simultaneously examine the co-movement of government debt and economic growth. Our study will provide extensive information on the evolution of the factors affecting output growth and financial development, which will supplement recent research on the relationship between the two.

Our empirical results show that the estimated unobserved common factors have closely tracked major economic booms and recessions globally and in different income groups over the period 1970-2009. This could indicate that our model fits the data well. Moreover, the common factor for ODCs is on average smaller in magnitude and less volatile but more persistent than that for INDs and EMEs. This evidence may reflect less exposure to external shocks and more rigid economic structure and regulatory framework in ODCs.

The variance decomposition analysis shows that the common factors play a more significant role in accounting for the variance of output growth in INDs and EMEs, while ODCs are more influenced by asymmetric shocks. This result is consistent with the findings in Kose *et al*. (2003, 2010) regarding business cycle synchronization. On the other hand, financial development variability is mainly driven by country-specific and idiosyncratic factors, such as different government regulations and monitoring of financial and banking systems in INDs, as well as various government policies to promote financial reform and liberalization and differentiated institutional environments in EMEs and ODCs.

To further study the pattern of variance decompositions, we use regressions of the fraction of the variance of each country's output growth and financial development attributable to a factor on a variety of explanatory variables related to country characteristics. The main findings are: (1) the common factor is of importance to explain output growth and financial development variance decompositions in less volatile economies while the country factor is more important in more volatile economies, a

pattern that is consistent in the different income groups of countries; (2) Other country characteristic variables, such as the level of income, the sizes of the government and the manufacturing sector, and interest rate spread show variations in explaining the cross-country patterns of the common and country factor variance decompositions in the different income groups of countries.

The remainder of this article is organized as follows. Section 2 describes the data and econometric framework. Section 3 presents the empirical results. Finally, section 4 concludes and sheds light on some policy implications.

2. DATA AND METHODOLOGY

2.1. Data

Our data covers 89 countries over the period from 1970 to 2009 and is obtained from the World Development Indicators and the Financial Development and Structure Database from the World Bank. We use the growth rate of real per capita Gross Domestic Product (GDP) as an economic growth indicator. For a financial development indicator, we use domestic credit to the private sector as a percentage of GDP, called PRIVY, which is widely used in the literature (King and Levine, 1993 a, b; Levine *et al*., 2000; Claessens *et al*., 2011a, b; among others). A larger PRIVY indicates a higher level of domestic investment and greater financial development. Alternatively, we also consider two other financial development indicators as in King and Levine (1993 a, b). One is the ratio of deposit money bank domestic assets to deposit money bank domestic assets plus central bank domestic assets, denoted as BANK. It measures the relative importance of specific financial institutions, but does not take into account to whom the financial system is allocating credit. Another indicator is the ratio of liquid liabilities of the financial system to GDP, termed LLY.[3] It measures the size of financial intermediaries. However, it may not be closely related to financial services such as risk management and information processing (King and Levine, 1993a). These two financial indicators are positively correlated with PRIVY, with contemporaneous correlations with PRIVY of 0.68 and 0.9, respectively.[4] They can serve as complements to the measure of PRIVY and maximize the information on financial development in our study. All data are transformed to be stationary by taking growth rates or first differences, and then demeaned.[5]

[3] LLY for China, Nicaragua, and Zimbabwe are not available over the period 1970-2009.

[4] The correlations are close to those reported in King and Levine (1993a).

[5] All transformed variables are verified to be stationary using Augmented Dickey-Fuller unit root tests. Results are available upon request.

2.2. Bayesian Dynamic Factor Model

Dynamic factor models, which were developed by Geweke (1977), Watson and Engle (1983), and Stock and Watson (1989, 1991), have been widely used to extract common factors and to examine co-movement among many macroeconomic time series. Such models also mitigate the need for strong assumptions necessary for structural models.

In light of Kose *et al*. (2003, 2008, 2010) and Crucini *et al*. (2011), we apply a Bayesian dynamic factor model to study the joint properties of fluctuations in output growth and financial development for 89 countries over the period 1970-2009. The model contains: (i) a common factor capturing co-movement across the two variables in all countries; (ii) a country-specific factor common to the two variables in each country; and (iii) an idiosyncratic component for each series.

We estimate the Bayesian dynamic factor model as follows:

$$\begin{bmatrix} y_{i,t} \\ d_{i,t} \end{bmatrix} = \begin{bmatrix} \beta_{iy} \\ \beta_{id} \end{bmatrix} F_t + \begin{bmatrix} \gamma_{iy} \\ \gamma_{id} \end{bmatrix} f_{i,t} + \begin{bmatrix} u_{iy,t} \\ u_{id,t} \end{bmatrix}, \tag{1}$$

$$F_t = \varphi_F(L) F_{t-1} + v_t, \tag{2}$$

$$f_{i,t} = \varphi_f(L) f_{i,t-1} + v_{i,t}, \tag{3}$$

$$u_{ij,t} = \varphi_u(L) u_{ij,t-1} + \varepsilon_{ij,t}, \tag{4}$$

where $y_{i,t}$ is the growth rate of real per capita GDP and $d_{i,t}$ denotes a financial development indicator (e.g., PRIVY) for country *i* at time *t*. They are simultaneously estimated as a function of the unobserved common factor (F_t) and country-specific factors ($f_{i,t}$). The common factor (F_t) is common to the two variables in all countries, capturing common shocks affecting output growth and financial development in all countries. The country-specific factor ($f_{i,t}$) is specific for country *i*, reflecting any remaining co-movement of output growth and financial development in each country. The error terms (*u*'s) contain two components: one is simply the measurement error; the other is the idiosyncratic movement in a particular variable for a given country *i*. We are unable to distinguish between the two interpretations of the error term. Thereafter, we treat the *u*'s as the idiosyncratic component. We model the factors and the idiosyncratic component as autoregressive processes to capture the dynamic relationships in our annual data.[6]

[6] The lag polynomials $\varphi_F(L)$, $\varphi_f(L)$, and $\varphi_u(L)$ can be of different orders. We report our results

The coefficients β_{iy} and β_{id} capture the impact of the common factor F_t on output growth and financial development across all countries, respectively. The coefficients γ_{iy} and γ_{id} measure the effect of the country factor $f_{i,t}$ on output growth and financial development in country *i*, respectively. All coefficients and factors are estimated using the Bayesian approach employed by Otrok and Whiteman (1998), Kose *et al*. (2003, 2008, 2010), and Crucini *et al*. (2011).[7]

2.3. Variance Decomposition

The dynamic factor model also allows us to quantify the relative importance of the common, country, and idiosyncratic factors. We use variance decompositions to measure the relative contributions of the common, country, and idiosyncratic factors to the variations in output growth and financial development in each country. With the assumption of orthogonal factors, the variance of the observable, say *y*, in country *i* can be written as follows:

$$\text{var}(y_{i,t}) = (\beta_{iy})^2 \text{ var}(F_t) + (\gamma_{iy})^2 \text{ var}(f_{i,t}) + \text{var}(u_{iy,t}) . \quad (5)$$

Then the shares of variance due to the common, country, and idiosyncratic factors can be estimated by $\frac{(\beta_{iy})^2 \text{ var}(F_t)}{\text{var}(y_{i,t})}$, $\frac{(\gamma_{iy})^2 \text{ var}(f_{i,t})}{\text{var}(y_{i,t})}$, and $\frac{\text{var}(u_{iy,t})}{\text{var}(y_{i,t})}$, respectively.

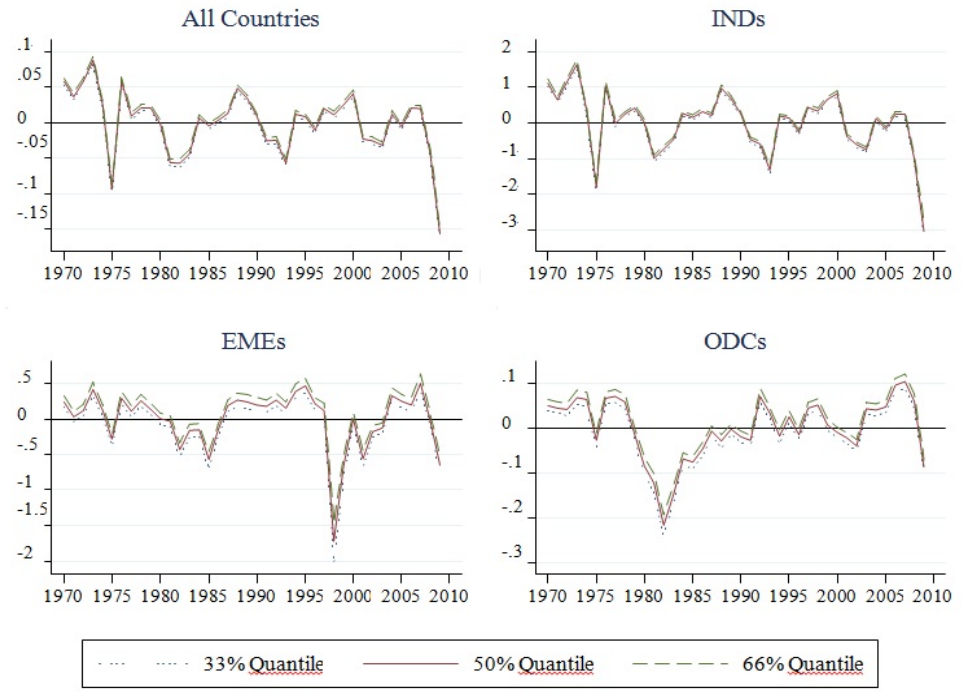
3. EMPIRICAL RESULTS

In this section, we first examine the evolution of the unobserved common factors and study their abilities to track important economic episodes since 1970. If the common factors appear to be good indicators of world cycles, our estimations would be appropriate. Second, we decompose the variance of output growth and financial development into the common, country, and idiosyncratic factors to analyze the relative contributions of each factor to the fluctuations in the two variables. Third, we analyze the relation between economic structure and the factors. We focus primarily on the results using the financial development indicator of PRIVY, and then consider BANK and LLY as robustness checks.

based on AR(3) processes as those in Kose *et al*. (2003, 2008, 2010) and Crucini *et al*. (2011) for comparison purposes. Our results do not change significantly when using other lag lengths.

[7] These articles provide technical details.

3.1. Evolution of the Unobserved Common Factors



Notes: We estimate the model over the full sample period and then plot the median of the posterior distribution of the estimated common factor for each income group (the solid line). The dotted line and the dashed line around the median show the 33% and 66% quantile bands for the posterior distribution of the estimated common factor for each income group. All, INDs, EMEs and ODCs refer to All countries in the sample, Industrial Countries, Emerging Market Economies and Other Developing Countries, respectively.

Figure 1. Common Factors for Different Groups of Countries from 1970 to 2009

Figure1 illustrates the median of the posterior distribution of the estimated common factors, along with the 33% and 66% quantile bands for the different groups of countries in the period 1970 to 2009. The narrowness of the bands suggests that the unobserved common factor is estimated precisely.[8] The estimated common factor for all the countries in our sample has closely tracked important economic episodes since 1970: the economic boom of the early 1970s; the recession due to the oil crisis in the mid-1970s;

[8] Because the factor is unobservable, we can only extract an estimate of it based on its hypothesized relationships to the observed variables.

the recession associated with the debt crisis and tight monetary policies in the early 1980s; the recession of the early 1990s and subsequent recovery; the recession of the early 2000s; and the recent global financial crisis since 2007. Since different income levels are associated with different levels of financial development (Levine *et al*., 2000), we then estimate the model separately for three income groups: 23 INDs, 20 EMEs, and 46 ODCs.[9] The estimated common factor for INDs is similar to that for all the countries, while the common factors for EMEs and ODCs show different pictures. In particular, the common factor for EMEs became significantly negative in 1998 when some Asian countries in the group encountered severe financial crises. The common factor for ODCs plunged in 1981-83 when oil price shocks hit most of the OPEC countries and the debt crisis occurred in some Latin American countries in the group.

Further, we investigate the volatility and autocorrelation coefficients (indicated as $\varphi_F(L)$ in Equation (2)) of the common factors, which shed light on their dispersion and persistence properties. Table 1 reports the results. On average, the common factors for EMEs and ODCs are smaller in magnitude and less volatile since these countries are less exposed to external shocks than INDs.[10] In addition, we interpret the persistence property as an indicator of the speed of adjustment to shocks. Larger autocorrelation coefficients indicate higher degrees of persistence and imply longer effects of previous shocks or slower adjustment to shocks. The common factor for ODCs appears to be the most persistent. Its autocorrelation coefficient is 0.697, indicating that ODCs responds slowly to common shocks. INDs and EMEs adjust faster, with the coefficients of 0.354 and 0.357, respectively. Possible reasons include less developed economic structure and more rigid regulatory framework in ODCs.

Table 1. Volatility and Autocorrelation of the Common Factors

	1970-2009	
Group	Volatility	Autocorrelation
All	0.045	0.344
INDs	0.864	0.354
EMEs	0.408	0.357
ODCs	0.069	0.697

Notes: We estimate the model over the full sample period (1970-2009) and obtain the unobserved common factors at the 50% posterior quantile. Results for the 33% and 66% quantiles are not reported due to space. All, INDs, EMEs and ODCs refer to All countries in the sample, Industrial Countries, Emerging Market Economies and Other Developing Countries, respectively.

[9] See appendix for the list of countries.

[10] The magnitude can be seen in Figure 1.

3.2. Variance Decompositions

In order to analyze the sources of fluctuations in output growth and financial development, we decompose their variance into the common, country, and idiosyncratic factors over the full sample period. We focus on the 50% posterior quantile for the estimated factors.[11] Table 2a presents the cross-sectional means of the variance shares for the different groups of countries. It shows that the unobserved common factor plays a more significant role than the country factor in accounting for the variance of output growth in INDs and EMEs, but not in ODCs. If a larger share of variance in output growth is explained by the common factor of the group, there exists more business cycle synchronization among the countries in the group; if a large share of variance is explained by the country factor, then the country experiences asymmetric shocks and synchronization might be undesirable. Therefore, our results suggest that business cycles are more synchronized among INDs and EMEs, while ODCs are more influenced by asymmetric shocks. This finding coincides with the evidence of business cycle synchronization among INDs and EMEs found in Kose *et al.* (2003, 2010). Greater synchronization of business cycles among INDs and EMEs may arise from the increasing intra-group trade linkages during the globalization period. Such changes have been associated with a greater degree of sectoral similarity across countries within each group due to intra-group technology spillovers (Akin and Kose, 2008). As for ODCs, the group is less synchronized in the real economy in that those countries are least exposed to the forces of globalization and have weaker economic linkages.

On the other hand, the unobserved common factor, on average, accounts for less than 10 percent of fluctuations in financial development, while the country and idiosyncratic factors account for most of the variations in financial development in all income groups. Since domestic private credit, the proxy for financial development, is an important link between savings and investment, it is also viewed as a natural aggregate to analyze financial or credit cycles (Claessens *et al*., 2011a, b). Our results may imply that financial or credit cycles are mainly driven by country-specific and idiosyncratic factors, such as different government regulations and monitoring of financial and banking systems in INDs, as well as various government policies to promote financial reform and liberalization and differentiated institutional environments in EMEs and ODCs.

As robustness checks, we consider two other financial development indicators, BANK and LLY, run the Bayesian dynamic factor model, and perform variance decomposition analysis for each indicator.[12] Tables 2b and 2c report the results of variance decompositions using BANK and LLY, respectively. They both show similar patterns as in Table 2a. The common factor is on average more important in explaining

[11] Results for the 33% and 66% quantiles are not reported due to space and are available upon request.

[12] Since LLY for China, Nicaragua, and Zimbabwe are not available over the period 1970-2009, the estimation using LLY is conducted based on 86 countries, including 23 INDs, 19 EMEs, and 44 ODCs.

output growth fluctuations than in explaining financial development variations, while the country and idiosyncratic factors show the reverse. This is consistent with the fact that financial development usually takes place after economic growth, and the sequence of capital market liberalization and entering financial integration vary across countries even within the same income group.

Table 2a. Variance Decompositions for Output Growth and Financial Development
(Full sample: 1970-2009, unit: %)

Group	Factor	Output Growth	PRIVY
All	Common	16.69	2.68
	Country	15.65	18.78
	Idiosyn	67.28	78.41
INDs	Common	46.59	1.73
	Country	6.64	16.49
	Idiosyn	46.01	81.65
EMEs	Common	15.83	6.10
	Country	13.88	20.73
	Idiosyn	68.63	72.55
ODCs	Common	11.50	3.49
	Country	16.22	19.10
	Idiosyn	71.10	76.67

Notes: PRIVY is the domestic credit to the private sector as a percentage of GDP. We estimate the model over the full sample period (1970-2009) and obtain the unobserved common, country, and idiosyncratic factors at the 50% posterior quantile. Results for the 33% and 66% quantiles are not reported due to space. We compute the variance decompositions for each country and each variable. We then calculate the cross-sectional means of the variance shares for the relevant cluster of countries in each group. All, INDs, EMEs and ODCs refer to All countries in the sample, Industrial Countries, Emerging Market Economies and Other Developing Countries, respectively.

Table 2b. Variance Decompositions for Output Growth and Financial Development

Group	Factor	Output Growth	BANK
All	Common	16.65	2.89
	Country	14.77	18.17
	Idiosyn	68.30	78.86
INDs	Common	46.77	4.90
	Country	9.14	17.84
	Idiosyn	43.47	77.12

EMEs	Common	15.64	3.01
	Country	15.98	21.61
	Idiosyn	67.20	74.80
ODCs	Common	11.21	4.52
	Country	12.71	17.32
	Idiosyn	74.96	77.33

Notes: BANK is the ratio of deposit money bank domestic assets to deposit money bank domestic assets plus central bank domestic assets. We estimate the model over the full sample period (1970-2009) and obtain the unobserved common, country, and idiosyncratic factors at the 50% posterior quantile. Results for the 33% and 66% quantiles are not reported due to space. We compute the variance decompositions for each country and each variable. We then calculate the cross-sectional means of the variance shares for the relevant cluster of countries in each group. All, INDs, EMEs and ODCs refer to All countries in the sample, Industrial Countries, Emerging Market Economies and Other Developing Countries, respectively.

Table 2c. Variance Decompositions for Output Growth and Financial Development

Group	Factor	Output Growth	LLY
All	Common	16.78	6.12
	Country	14.29	18.99
	Idiosyn	69.02	75.20
INDs	Common	46.28	7.46
	Country	6.92	15.19
	Idiosyn	46.19	77.15
EMEs	Common	15.56	12.52
	Country	11.60	18.69
	Idiosyn	71.83	68.14
ODCs	Common	10.79	2.30
	Country	11.70	21.57
	Idiosyn	76.27	75.38

Notes: LLY, a measure of financial depth, equals to the ratio of liquid liabilities of the financial system to GDP. Liquid liabilities consist of currency held outside the banking system plus demand and interest-bearing liabilities of banks and nonbank financial intermediaries. Since LLY for China, Nicaragua, and Zimbabwe are not available over the period 1970-2009, the estimation is conducted based on 86 countries, including 23 INDs, 19 EMEs, and 44 ODCs. We estimate the model over the full sample period (1970-2009) and obtain the unobserved common, country, and idiosyncratic factors at the 50% posterior quantile. Results for the 33% and 66% quantiles are not reported due to space. We compute the variance decompositions for each country and each variable. We then calculate the cross-sectional means of the variance shares for the relevant cluster of countries in each group. All, INDs, EMEs and ODCs refer to All countries in the sample, Industrial Countries, Emerging Market Economies and Other Developing Countries, respectively.

3.3. The Relation between Economic Structure and the Factors

Following Kose *et al.* (2003), we employ regression analysis to interpret the 178 variance decompositions obtained from the previous section. The purpose is to characterize the relationship between the structural characteristics of economies and the relative importance of the common and country factors in each group. In particular, we choose the same four explanatory variables as in Kose *et al.* (2003) which are useful to explain output variance decompositions. We also consider other explanatory variables which can account for financial development variance decompositions.[13] Table 3 reports the results using five explanatory variables: (1) ratio of real per capita GDP to U.S. real per capita GDP (PC GDP), (2) the share of government expenditure in GDP (Gov Shr), (3) manufacturing's share of output (Man Shr), (4) volatility of GDP growth (GDP Vol), and (5) interest rate spread (Spread), a key indicator of financial performance and efficiency, which is equal to lending rate minus deposit rate. All five series are related to country characteristics and obtained from the World Development Indicators.[14]

Table 3a summarizes the results of regressing the (median) fraction of variance of each country's output growth attributable to the common and country factors on the set of five explanatory variables. In the group of All countries, the level of income, the relative sizes of government, and the volatility of GDP growth help explain the cross-country pattern of common factor variance decompositions. In particular, the significant negative coefficient on the volatility of GDP growth is consistent with Kose *et al*. (2003), indicating that in less volatile economies, the common factor is more important in explaining output growth fluctuations. The significant positive coefficient on the ratio of real per capita GDP and the government's share may suggest that, in developed economies with larger government size, the common factor is more important in explaining output growth fluctuations. Some differences show in the group of ODCs: the level of income, the share of manufacturing, the volatility of GDP growth, and interest rate spread help explain common factor variance decompositions. Specifically, the significant negative coefficient on interest rate spread suggests that the common factor is more important in accounting for output growth variations in the ODCs economies with

[13] We have examined other explanatory variables such as trade openness, money and quasi money (M2) as a percentage of GDP, broad money as a percentage of GDP, claims on central government (annual growth as a percentage of broad money), claims on private sector (annual growth as a percentage of broad money), private capital flows as a percentage of GDP, consumer price index, inflation rate, interest rate spread, risk premium on lending, and commercial bank branches (per 100,000 adults). They are from the World Development Indicators. We choose to report interest rate spread because it has the largest explanatory power to explain financial development variance decompositions in our regression analysis. Results using other explanatory variables are available upon request.

[14] Due to space limits, we report only the results using PRIVY as the financial development indicator. Results using BANK or LLY are available upon request.

smaller interest rate spreads. The significant positive coefficient on the ratio of real per capital GDP and manufacturing's share of output may imply that the common factor is more important in the ODCs economies with a higher level of income and a larger size of the manufacturing sector. Finally, the volatility of GDP growth is significantly negative, indicating that the common factor is more important in explaining output growth variations in less volatile economies. However, there is no apparent evidence between structural characteristics and the relative importance of the common factor in the groups of INDs and EMEs.

Table 3a. Regression of Output Growth Variance Decomposition on Economic Structure Variables

		Common Factor		Country Factor	
Group	Variable	Coefficient	Robust Std Error	Coefficient	Robust Std Error
All	PC GDP	0.0035***	0.0006	-0.0005	0.0004
	Gov Shr	0.0089***	0.0030	-0.0014	0.0023
	Man Shr	0.0027	0.0018	0.0031*	0.0018
	GDP Vol	-0.0215***	0.0063	0.0315***	0.0057
	Spread	-0.0001	0.0000	0.0003**	0.0001
INDs	PC GDP	0.0001	0.0021	-0.0003	0.0008
	Gov Shr	0.01	0.0122	0.0021	0.0057
	Man Shr	0.01	0.0101	0.0046	0.0031
	GDP Vol	-0.0209	0.0695	0.0025	0.0167
	Spread	0.0610	0.0381	-0.0139	0.0253
EMEs	PC GDP	-0.0055	0.0084	0.0036	0.0034
	Gov Shr	-0.0047	0.0134	0.0085	0.0052
	Man Shr	0.0095	0.0114	-0.0076*	0.0043
	GDP Vol	0.0244	0.0475	0.0416**	0.0178
	Spread	-0.0012	0.0008	-0.0006*	0.0003
ODCs	PC GDP	0.0067***	0.0024	0.0011	0.0024
	Gov Shr	-0.0016	0.0024	0.0002	0.0027
	Man Shr	0.0142***	0.0038	-0.0008	0.0020
	GDP Vol	-0.0142**	0.0058	0.0300***	0.0077
	Spread	-0.0002***	0.0001	0.0003***	0.0000

Notes: All, INDs, EMEs and ODCs refer to All countries in the sample, Industrial Countries, Emerging Market Economies and Other Developing Countries, respectively. PC GDP is ratio of per capita GDP to U.S. per capita GDP. Gov Shr is the share of government expenditure in GDP. Man Shr is manufacturing's share of output. GDP Vol is the volatility of GDP growth. Spread is interest rate spread which is equal to lending rate minus deposit rate. We regress common factor and country factor on five explanatory variables respectively for All, INDs, EMEs, and ODCs. ***, **,* indicate significance at 1%, 5% and 10% level.

Table 3b. Regression of Financial Development (PRIVY) Variance Decomposition on Economic Structure Variables

		Common Factor		Country Factor	
Group	Variable	Coefficient	Robust Std Error	Coefficient	Robust Std Error
All	PC GDP	-0.0002	0.0002	-0.0008*	0.0005
	Gov Shr	0.0006	0.0008	0.0038	0.0025
	Man Shr	0.0005	0.0009	0.0052**	0.0020
	GDP Vol	0.0031	0.0023	0.0147**	0.0056
	Spread	0.00002	0.0000	-0.0002*	0.0001
INDs	PC GDP	-0.0001	0.0002	-0.0004	0.0009
	Gov Shr	0.00	0.0009	-0.0043	0.0086
	Man Shr	0.0017**	0.0007	0.0054	0.0063
	GDP Vol	0.0037	0.0096	-0.0034	0.0361
	Spread	-0.0064***	0.0021	0.0445	0.0385
EMEs	PC GDP	-0.0068***	0.0018	-0.0037	0.0037
	Gov Shr	-0.0072**	0.0029	0.0098	0.0083
	Man Shr	0.0084***	0.0022	-0.0068	0.0045
	GDP Vol	0.0116	0.0100	0.0748**	0.0249
	Spread	-0.0006***	0.0002	-0.0015***	0.0004
ODCs	PC GDP	0.0018	0.0013	-0.004	0.0024
	Gov Shr	0.0019**	0.0009	0.0019	0.0038
	Man Shr	0.0019	0.0013	0.0057**	0.0028
	GDP Vol	-0.0053*	0.0029	0.0198***	0.0070
	Spread	0.0001***	0.0000	0.0001***	0.0000

Notes: All, INDs, EMEs and ODCs refer to All countries in the sample, Industrial Countries, Emerging Market Economies and Other Developing Countries, respectively. PC GDP is ratio of per capita GDP to U.S. per capita GDP. Gov Shr is the share of government expenditure in GDP. Man Shr is manufacturing's share of output. GDP Vol is the volatility of GDP growth. Spread is interest rate spread which is equal to lending rate minus deposit rate. We regress common factor and country factor on five explanatory variables respectively for All, INDs, EMEs, and ODCs. ***, **,* indicate significance at 1%, 5% and 10% level.

In terms of the relative importance of the country factor in explaining output growth variance decompositions in each group, we observe that the country factor is more important in economies with higher volatility of GDP growth in the groups of All, EMEs, and ODCs. This finding is also consistent with Kose *et al.* (2003). However, we find no clear evidence in the relationship between the structural characteristics of economies and the relative importance of the country factors for INDs. Furthermore, in the group of All countries, the larger are the size of the manufacturing sector and the interest rate spread, the more important the country factor. However, in the group of EMEs, the smaller are the size of the manufacturing sector and the interest rate spread, the more important the

country factor. Finally, the country factor is more important in the ODCs economies with larger interest rate spreads.

Table 3b reports the connection between the structural characteristics and the role of common and country factors in explaining fluctuations in financial development indicator (PRIVY). Overall, the pattern of results shows some variations from that for output growth volatility. First of all, the common factor is of no importance in explaining financial development variance decompositions in the group of All countries; however, the country factor is more important in economies with lower levels of income, larger sizes of government and manufacturing sector, and lower interest rate spreads. In the group of INDs, a larger size of manufacturing sector and lower interest rate spreads help explain common factor variance decompositions. In the group of EMEs, the common factor plays an important role in explaining financial development variability in countries with lower income levels, smaller sizes of government, larger manufacturing's shares, and smaller interest rate spreads. However, the country factor is important in more volatile economies with smaller interest rate spreads. Finally, in the group of ODCs, a larger size of government, less volatile output growth, and larger interest rate spreads help explain the cross-country pattern of common factor variance decompositions, while the country factor is more important in more volatile economies with larger sizes of government and interest rate spreads.

To summarize, the key pattern is that the common factor is more important in explaining both output growth variance decompositions and financial development variance decompositions in less volatile economies while the country factor is more important in economies with the opposite characterization. This pattern is consistent in the different income groups of the countries we study.

4. CONCLUSION

The empirical literature on financial development and economic growth mainly focuses on the relationship between the two. This article presents an empirical investigation on financial development and economic growth from a new angle. Using a Bayesian dynamic factor model, we extract the unobserved common factors driving both financial development and economic growth among different income groups. The estimated common factors meticulously trace global and regional economic episodes over the period 1970-2009, which indicates a good fit of our estimates.

The variance decomposition analysis reveals that the common factors play a more significant role in accounting for the variance of output growth in INDs and EMEs while ODCs are more influenced by asymmetric shocks. This could imply that business cycles are more synchronized among INDs and EMEs than among ODCs. In contrast, financial development dynamics are driven more by country-specific and idiosyncratic factors in INDs, EMEs, and ODCs. This could be attributed to different government regulations and monitoring of financial and banking systems in INDs, as well as various government

policies to promote financial reform and liberalization and differentiated institutional environments in EMEs and ODCs.

The regression analysis of output growth and financial development variance decompositions on a set of five country characteristic variables is conducted as in Kose *et al.* (2003) to demonstrate the relative importance of the common and country factors. The empirical results suggest that the common factor is more important the less volatile the economy while the country factor is more important the more volatile the economy. However, four other country characteristic variables (the ratio of real per capita GDP to U.S. real per capita GDP, the share of government expenditure in GDP, manufacturing's share of output, and interest rate spread) show variations in explaining the cross-country patterns of the common and country factor variance decompositions .

Meanwhile, our results provide additional evidence of the nonlinear relationship between financial development and economic growth since the unobserved common factors and the variance decomposition analysis show clear variations in countries with different income levels. Therefore, a threshold income level may exist, across which financial development would interact with economic activities differently. Future research on finance and growth should take into account various income levels.

Finally, our study carries important policy implications. For well-developed countries, government regulations and monitoring of financial and banking systems are critical to avoiding or minimizing the chances of financial crises. However, if a country's financial market is still underdeveloped, government policies to promote financial reform and liberalization should be a priority.

APPENDIX TABLE

List of Countries

Industrial	Emerging	Other Developing Countries	
Australia	Argentina	Burundi	Srilanka
Austria	Brazil	Benin	Lesotho
Belgium	Chile	Burkinafaso	Madagascar
Canada	China	Bangladesh	Mali
Switzerland	Colombia	Bolivia	Mauritania
Germany	Egypt, Arab Rep.	Botswana	Niger
Denmark	Indonesia	Cotedivoire	Nigeria
Spain	India	Cameroon	Nicaragua
Finland	Israel	Congo, Dem. Rep.	Nepal
France	Korea, Rep.	Congo, Rep.	Panama
United Kingdom	Morocco	Costarica	Paraguay

Greece	Mexico	Dominican Rep.	Rwanda
Ireland	Malaysia	Algeria	Senegal
Iceland	Pakistan	Ecuador	Elsalvador
Italy	Peru	Gabon	Seychelles
Japan	Philippines	Ghana	Syrian Arab Rep.
Luxembourg	Thailand	Gambiathe	Chad
Netherlands	Turkey	Guatemala	Togo
Norway	Venezuela, RB	Guyana	Trinidad and Tobago
Newzealand	South Africa	Honduras	Tunisia
Portugal		Iran, Islamic Rep.	Uruguay
Sweden		Jamaica	Zambia
United States		Kenya	Zimbabwe

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