Causality and state dependence in the finance-growth nexus: an empirical investigation

als Inaugural-Dissertation
zur Erlangung des akademischen Grades eines Doktors
der Wirtschafts- und Sozialwissenschaften
der Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

vorgelegt von

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Kiel, 2012

Gedruckt mit Genehmigung der
Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

Dekan:
Prof. Horst Raff, Ph.D.

Erstberichterstattender:
Prof. Dr. Helmut Herwartz

Zweitberichterstattender:
Prof. Dr. Johannes Bröcker

Tag der Abgabe der Arbeit:
20. Dezember 2012

Tag der mündlichen Prüfung:
26. März 2013

Acknowledgements

Foremost, I thank God for His love and grace.

My first supervisor, Prof. Dr. Helmut Herwartz, has provided me excellent guidance and numerous critical comments at every step of writing this thesis. I had also the privilege to collaborate with him in three works, two of which constitute Chapters 4 and 5 of this thesis. So, I will always remain deeply grateful and thankful. I also thank Prof. Dr. Johannes Bröcker for his time and willingness to write the second referee report on this thesis.

I would also like to gratefully acknowledge that comments and suggestion from the following colleagues at the Institute of Statistics and Econometrics, Kiel, have been valuable to this thesis: Prof. Dr. Gerd Hansen, Prof. Dr. Roman Liesenfeld, Prof. Dr. Uwe Jensen, Prof. Dr. Vasyl Golosnoy, Dr. Florian Siedenburg, Dr. Jan Roestel, Dr. Matthias Hartmann, Marcus Pape, Christoph Strumann, and Bastian Gribisch. I am also thankful to Albrecht Mengel and Angelika Reinmüller for their kindness and support throughout my stay at the institute. Habtamu Fuje and Ulrike Dörr have proofread some of the chapters and I am grateful for that.

My special thanks go to my family. My wife, Desta Yeshitela, has first-hand endured with me the many frustrating moments in the process of writing this thesis and I can never forget that. Thank you Desiye for all your care, love, and encouragement. Playing with my daughter, Pheben (3), has been an unforgettable medicine that used to effectively kill my stresses. I thank my mother, Belaynesh Demewoz, and my father, Mulualem Walle, for their unreserved love and prayers. My father's careful follow-up and well-designed motivations for me and my siblings during our school times have decisively changed our future and I am always grateful for that. My brothers, Yelkal and Selemon, and my sisters, Saba and Zena, have been nice friends and competitors, as usual, and I am proud of all of them.

Finally, I would like to thank the German Academic Exchange Service (DAAD) for generously funding my doctoral study.

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1 Introduction

Whether financial development promotes economic growth or not has been a contentious research question over the past century. On the one hand, several economists such as Schumpeter (1911), McKinnon (1973), Shaw (1973), and Levine (2005) conjecture that financial development induces economic growth. They argue that the financial system provides the following crucial growth-promoting functions: mobilization of savings, identification of high-return projects, monitoring of investments, diversification of risks, and facilitation of transactions. Improvements in the way these functions are provided—which is basically what financial development amounts to—is expected to generate economic growth by raising the volume of financial resources available for investment and, most importantly, by enhancing the efficiency in which those resources are allocated (World Bank, 1989). On the other hand, Robinson (1952) argues that financial development does not cause economic growth; rather, it simply responds to the demand created by economic growth. Similarly, Lucas (1988) forwards a more conservative view by saying that "*the importance of financial matters is very badly over-stressed.*" Another group of economists postulate a bidirectional relationship between finance and growth. According to these economists, the financial system and its services develop as a result of the demand generated by economic growth, and financial development, in turn, causes economic growth (Patrick, 1966; Greenwood and Jovanovic, 1990). These theoretical expositions have important policy implications. Clearly, only those theories predicting either a one-way causality from finance to growth or a bidirectional finance-growth (henceforth FG) causality entail devising policies to build deeper and more sophisticated financial systems as a means of promoting economic performance.

The last two decades have seen a surge of interest in empirically testing the diverse theoretical discourse on the issue of FG nexus.[1] However, the literature has produced largely mixed evidence, both on the direction of causality, and on the question whether finance matters to growth regardless of the opposite causal

[1]This surge of interest is attributed partly to the advent of new growth theories which explicitly incorporate financial intermediation in the growth model (Pagano, 1993) and partly to the study by King and Levine (1993) that includes alternative measures of financial development in cross-country growth regressions.

impact.[2]

The goal of this work is to empirically re-investigate some of the main issues in the FG relationship by applying latest and more flexible econometric methods. In Chapter 2, we conduct Monte Carlo experiments to evaluate the finite sample performances of heteroskedasticity-robust panel unit root tests (PURTs). Dividing the causality issue based on time horizon, we examine the long-run FG causality in Chapters 2–3 by means of PURTs and panel cointegration tests. The causality in the short-to-medium run is explored in Chapter 4. Chapter 5 investigates state dependence in the FG nexus using a functional coefficient modeling approach. Application of this approach proceeds further to Chapter 6, this time with a special emphasis on trade and financial openness as factors underlying the FG link. Chapter 4 corresponds to the article by Hartmann, Herwartz and Walle (2012) as published in *Economics Bulletin*. To make each chapter self-contained and enhance readability, we introduce relevant literature as well as considered models separately in each chapter. Below, we will discuss each issue in more detail, highlight the contribution of this thesis and summarize the main findings.

Recently, a growing number of studies have applied panel cointegration tests to examine the existence of a long-run relationship between financial and economic development (Christopoulos and Tsionas, 2004; Apergis et al., 2007; Fowowe, 2010). The main reason for the focus towards panel cointegration tests is that, being able to utilize the cross-sectional dimension, these tests significantly overcome the small sample power deficiency inherent in their time series equivalents. In these applications, a standard methodological prerequisite involves applying PURTs to test whether the levels of financial development and economic development are each integrated of order one. A common assumption underlying most of the PURTs as in Levin et al. (2002), Im et al. (2003) and Breitung and Das (2005) is that variances are constant over time. However, it has been shown that volatility beaks could induce severe size distortions of these tests and, hence, inferences based on them could be misleading (Herwartz and Siedenburg, 2009; Demetrescu and Hanck, 2012b). Unfortunately, time-varying volatility seems to be more the rule than the exception as the volatility of several macroeconomic series displays recurrent shifts

[2] See Levine (2005) and Ang (2008a) for extensive surveys of the theoretical and empirical literature on the FG nexus.

or trending behavior. A case in point is the so-called "Great Moderation"—the substantial decline in the volatility of numerous key macroeconomic variables since the mid 1980s (see, for instance, Kim and Nelson, 1999, and Stock and Watson, 2003). PURTs that could perform well under time-varying volatility have been proposed in three recent papers: Herwartz and Siedenburg (2009), and Demetrescu and Hanck (2012a,b). In Chapter 2, we compare the small sample performances of these heteroskedasticity-robust PURTs by means of simulation exercises. Our results show that the Cauchy-based test considered in Demetrescu and Hanck (2012b) is severely undersized when the cross-sectional dimension is not relatively larger than the time series dimension. In contrast, the White-type test of Herwartz and Siedenburg (2008) and its Cauchy-instrumented version suggested in Demetrescu and Hanck (2012a) display reliable size control in most of the considered variance break scenarios. Another notable result is that Cauchy instrumenting mitigates the White-type test's overrejections (usually about 2%) in strongly correlated panels. This advantage, however, appears to come at a cost of inducing substantial oversizing of the test in short panels with independent or weakly correlated error terms.

As an empirical illustration, we analyze the long-run FG causality in a panel of 74 economies during 1975–2005 by means of the heteroskedasticity-robust PURTs and cross-sectional dependence robust panel cointegration tests suggested in Westerlund (2007). Moreover, taking advantage of the large cross-sectional dimension, we test the hypothesis put forward by Patrick (1966) that causal effects depend on economies' stage of development. This is done by assessing the causality test results for subgroups of economies classified according to their income levels. We find that the level of economic development and financial development are each integrated of order one and, in addition, they are cointegrated. Nevertheless, the direction of causality depends on the sample of economies considered. On the one hand, strong evidence of causality running from growth to finance is obtained in the most comprehensive panel. Similar, but somehow weakened, evidence is diagnosed in middle- and high-income economies. On the contrary, findings from low-income economies clearly support the "finance leads growth" hypothesis, and not the other way round.

In Chapter 3, we revisit the long-run FG causality in SSA. As part of the extensive search for factors that could boost economic growth in the least developed part of the world, the FG nexus in SSA has attracted considerable attention in the policy and academic circles. However, existing studies have provided inconclusive findings on the direction of causality between financial and economic development in the region (see, for example, Ghirmay, 2004; Gries et al., 2009; Fowowe, 2010). We re-examine the long-run FG nexus in the region using data from 17 economies over the period 1975-2005. This data set was initially employed in Fowowe's (2010) research on the topic. However, he applies panel cointegration tests that assume cross-sectional independence. We indicate that independence among SSA economies is a rather unrealistic assumption as the economies are somehow integrated through regional economic communities—and even through monetary union, in the case of West Africa. Furthermore, many of them are small economies which are highly affected by common shocks in global prices of their natural-resource-intensive exports. Therefore, we apply error-correction-based panel cointegration tests that take into account cross-sectional dependence among economies. Our results, unlike those reported in Fowowe (2010), indicate the existence of a long-run relationship between financial and economic development in the sub-region. Moreover, our results clearly demonstrate that the long-run causality runs from financial to economic development, although a muted support for the reverse causal impact is observed when financial development is measured by the percentage of liquid liabilities in GDP. The panel cointegration parameter estimated by means of Dynamic OLS estimation is positive and statistically significant. Therefore, our results strongly justify policies aimed at developing the financial sector in SSA in order to promote long-run economic development.

In Chapter 4, we will turn to the short-to-medium-run causality analysis. Specifically, we will consider causality in a period of less than one decade, corresponding to typical planning horizons of institutional decision takers. We investigate the causal impact of financial development on growth and the reverse direction by means of both in-sample tests and out-of-sample forecast comparisons. For this purpose, we rely on summarizing economy-specific evidence from bivariate SUR models. The analysis is performed on the same data set used to test long-run FG causality. Specifically in this chapter, we presume that the potentially time-dependent nature of causal relationships might be a reason for the existing mixed empirical evidences. Therefore, we test for causality in an iterative way, relying on a short sub-period of the entire time dimension at every estimation step. We find stronger evidence in favor of the hypothesis that economic growth influences financial development than for the reverse causal effect. Interestingly, the findings are consistent across income groups and confirmed by both in-sample and out-of-sample causality testing.

Subsequently, we will take a different perspective on the question why empirical findings on the FG nexus have so far been generally inconclusive. Perhaps the most straightforward way to answering this question could be taking a closer look at the differences in the econometric methodologies employed and the chosen financial development measures. Results also vary depending on the type and number of economies considered as well as the time periods covered in individual studies. Recently, some studies have considered the possibility that the variations in the empirical findings regarding the FG nexus may depend on some underlying economic factors. Theoretically, such a possibility has been suggested since Patrick (1966) who hinted that economies benefit from financial development at their earliest stages of development. Empirical investigations have been mostly done either by estimating the FG relationship for different economies grouped according to a certain economic criterion (Rioja and Valev, 2004) or by running threshold regressions (Ketteni et al., 2007; Yilmazkuday, 2011). In Chapter 5, we investigate the state dependence of the FG nexus by means of a functional coefficient model. In the spirit of semiparametric estimation, this flexible modeling approach allows the long-run FG nexus to depend on measurable economic factors. Applying this approach on the same data set used in Chapters 2 and 4, we find a generally positive effect of income level on the FG link. In particular, low-income economies obtain the least benefit from financial development while high-income economies enjoy three times more benefit than low-income economies. Similarly, financial development has a generally positive effect on the FG nexus, with the strongest FG link observed in low-income economies with a high level financial development. There are also cases where financial development could have an adverse effect on economic growth. This is observed in low- and lower-middle-income economies when they have very large government sizes or are extremely open to international trade.

The impact of trade openness on the FG nexus is found to vary between lower-middle- and upper-middle-income economies as well. Upper-middle-income economies show a pronounced FG nexus when they are very open to international trade. Yet, only a moderate level of trade openness is beneficial to lower-middle-income economies and being extremely open induces a negative FG relationship. With respect to financial openness, we find moderately increasing financial openness to strengthen the FG nexus, while, on the contrary, economies with the highest level of financial openness benefit the least from financial development. Furthermore, the FG nexus could even be negative if economies are highly open to both international trade and international finance.

The findings regarding trade and financial openness deserve special attention in light of the fact that opening trade and capital accounts to foster financial development is being emphasized by the so-called Rajan and Zingales hypothesis. Rajan and Zingales (2003) argue that incumbent industrialists and financiers resist financial development due to fear that it breeds domestic competition. However, openness could divert their focus to foreign competition, and thereby reduce their opposition to financial development. In this sense, trade and financial openness are necessary for financial development to transpire. Obviously, the main reason why some economists are trying to investigate determinants of financial development is that they believe financial development brings about economic growth. In the same way, the Rajan and Zingales hypothesis is founded on the assumption that financial development always—or at least when an economy is highly open—leads to economic growth. However, Chapter 5 of this work documents that financial development is unlikely to spur economic growth in states of simultaneous extreme financial and trade openness. In Chapter 6, we will revisit the impact of openness on the FG nexus using a different data set that spans the period 1981-2006 and is available for 78 economies. Most importantly, we employ a smooth financial openness measure, namely, the percentage of an economy's foreign assets plus liabilities in GDP. This measure, unlike the one used in Chapter 5, lends itself to treatment as a factor in the semiparametric estimation. Moreover, we split the measure into indicators that represent foreign assets and liabilities holdings. We also disaggregate the measure of trade openness to enable it to distinguish between imports and exports on the one hand and between goods exports (imports) and services exports (imports) on the other hand. To see the impact of simultaneously high trade and financial openness on the FG nexus, we estimate a bivariate factor model, with trade openness and financial openness as the first and the second factors. Our findings by and large confirm the evidence established in Chapter 5. In particular, very high levels of financial openness erode the growth-promoting role of financial development. With respect to trade openness, however, the impact depends on the level of economic development. While high openness leads to a high FG nexus in upper-middle-income economies, it exerts a deleterious influence in low- and lower-middle-income economies. Finally, it is only in upper-middle-income economies that we find simultaneously high trade and financial openness to lead to a significantly positive FG nexus.

2 Small sample performances of heteroskedasticity-robust panel unit root tests

2.1 Introduction

Over the last two decades, panel unit root tests (PURTs) have become a standard tool in testing the order of integration of macroeconomic series, which is often performed as a prerequisite for examining long-run relationships between nonstationary variables. For instance, several studies that presume a cointegrating finance-growth (FG) link repeatedly apply PURTs to test whether the levels of financial development and economic development are each integrated of order one (Christopoulos and Tsionas, 2004; Apergis et al., 2007; Fowowe, 2010). The prospect that PURTs could overcome the power deficiency of univariate unit root tests by utilizing the cross-sectional dimension is one of the main reasons behind the growing attention PURTs are receiving.

Depending on whether the tests allow for cross-sectional dependence among panel units, PURTs are classified into two generations. The first generation PURTs rely on the assumption of cross-sectionally independent error terms—an assumption which can hardly be satisfied in most economic research. This generation of PURTs include the popular tests suggested in Levin et al. (2002) and Im et al. (2003). However, O'Connell (1998) has shown that failure to satisfy the cross-unit independence assumption leads to severe size distortions of first generation tests. Consequently, tests that handle, or are robust to, cross sectional correlation have been suggested, for instance, in Breitung and Das (2005), Shin and Kang (2006) and Herwartz and Siedenburg (2008). Such PURTs are called second generation tests.[3]

Another crucial assumption in PURTs concerns the nature of innovation volatility. In most PURTs, model disturbances are assumed to be homoskedastic. However, similar to cross-sectional independence, the constant volatility assumption is also quite restrictive. For instance, it is well documented that volatilities of many economic variables exhibited significant decline towards the end of the last century—a phenomenon that is known as the Great Moderation (Stock and Watson, 2003). Several studies have shown that time-varying volatilities result in pronounced

[3] See Hurlin and Mignon (2007) and Breitung and Pesaran (2008) for detailed surveys.

size distortions of—and, hence, inferences based on—univariate unit root tests (see Hamori and Tokihisa, 1997; Cavaliere and Taylor, 2007a,b, 2008). Likewise, Herwartz and Siedenburg (2009) show that volatility beaks lead to severe size distortions of the PURTs suggested in Levin et al. (2002) and Breitung and Das (2005). Instead, they find that the "White-type" test in Herwartz and Siedenburg (2008), where the residuals obtained under the null are employed to construct the involved covariance matrix, display remarkable robustness to volatility shifts. In recent papers, Demetrescu and Hanck (2012a,b) propose heteroskedasticity-robust PURTs based on the Cauchy estimator—an estimator that uses the sign of the lagged variable as an instrument to the lagged variable itself. They argue that their White-type Cauchy test (Demetrescu and Hanck, 2012a) holds better size control than the other tests suggested in Demetrescu and Hanck (2012b). No comparison has been made, however, between the Cauchy tests and the test suggested in Herwartz and Siedenburg (2008), which is essentially a White-type test with out the Cauchy instrumenting. Therefore, in this chapter, we conduct Monte Carlo experiments to evaluate the small sample performances of the three most important heteroskedasticity-robust PURTs suggested to date: the two White-type tests and the best among the array of tests in Demetrescu and Hanck (2012b). This comparison helps us to find out the test which is of most empirical relevance. Furthermore, it allows us to examine the potential small sample gains and losses of applying the Cauchy instrumenting to the White-type test in Herwartz and Siedenburg (2008).

Our simulation results confirm that, overall, the Cauchy test suggested in Demetrescu and Hanck (2012b) has the poorest small sample performance of the considered tests even under time-invariant volatility. This test becomes severely undersized when the cross-sectional dimension increases faster than the time series one. In independent and weakly dependent panels, empirical rejection frequencies of both White-type tests display very small deviations from the nominal level. As an exception, however, the one with the Cauchy instrumenting is seen to be significantly oversized for the smallest considered time dimension. When the errors feature a strong form of cross-sectional dependence, the White-type test of Herwartz and Siedenburg (2008) is about 2.0 % more oversized than that of Demetrescu and Hanck (2012a). Shifts in innovation volatility increase the size distortion of the test in Demetrescu and Hanck (2012a) under relatively short time dimension, and, to some extent, induce similar overrejections for the one in Herwartz and Siedenburg (2008). However, only early downward and late upward volatility shifts cause the most severe of the above-mentioned size distortions. On the contrary, early and middle positive variance breaks appear to dampen the upward size distortions of the White-type test of Herwartz and Siedenburg (2008) in strongly correlated panels. In sum, we conclude that both White-type tests are the most empirically relevant heteroskedasticity-robust PURT, although the one without Cauchy instrumenting is the most dependable one when the time dimension is small, say less than 30.

As an illustrative example, we examine the cointegration relationship between financial and economic development in a panel of 74 economies over the period 1975-2005. A graphical representation of the variance profiles of the considered series reveals that the variances are time-varying. Applying the PURTs, we find that real GDP per capita and credit to the private sector as a percentage of GDP are each integrated of order one. The employed panel cointegration tests indicate that the finance-growth (FG) causality depends on the stages of economic development. On the one hand, results from low-income economies clearly support the "finance leads growth" hypothesis, and not the other way round. The evidence from the remaining income groups and the comprehensive panel, however, supports the "growth leads finance" hypothesis.

In Section 2.2, we formally sketch the panel model with variance breaks and describe the considered PURTs. Section 2.3 introduces deterministic terms and serial correlation, and discusses existing methods of handling them. Results of Monte Carlo simulations are provided in Section 2.4. An empirical illustration is given in Section 2.5. Section 2.6 concludes.

2.2 Panel unit root tests

A standard univariate unit root testing problem can be formalized as testing the hypothesis $H_0 : \rho = 1$ in the following equation:

$$y_t = \rho y_{t-1} + e_t, \quad t = 1, ..., T, \tag{2.1}$$

where $e_t \sim iidN(0, \sigma_{et}^2)$. In this model, a variance break, which is a typical example of time-varying volatility, can be introduced as

$$\sigma_{et}^2 = \begin{cases} \sigma_{e1}^2, & \text{if } t < \lfloor s_B T \rfloor,\ (0 < s_B < 1) \\ \sigma_{e2}^2, & \text{otherwise,} \end{cases} \tag{2.2}$$

where $\lfloor s_B T \rfloor$ denotes the integer part of $s_B T$.

The panel version of the heteroskedastic model can then be written as

$$\boldsymbol{y}_t = \rho \boldsymbol{y}_{t-1} + \boldsymbol{e}_t, \quad t = 1, ..., T, \tag{2.3}$$

where $\boldsymbol{y}_t = (y_{1t}, ..., y_{Nt})'$, $\boldsymbol{y}_{t-1} = (y_{1,t-1}, ..., y_{N,t-1})'$ and $\boldsymbol{e}_t = (e_{1t}, ..., e_{Nt})'$ are $N \times 1$ vectors and the index $i = 1, ..., N$ indicates the cross-sectional units.

Homogeneous PURTs (so called because they assume homogeneous ρ across panel units) are applied to test the hypothesis $H_0 : \rho = 1$ against $H_1 : \rho < 1$ in (2.3). In the following, we describe the three prominent heteroskedasticity-robust PURTs suggested so far.

2.2.1 The White-type test

Herwartz and Siedenburg (2008) put forward a PURT based on a White-type covariance estimator—an estimator that utilizes residuals obtained under H_0. Formally, the test statistic looks like

$$t_{HS} = \frac{\sum_{t=1}^{T} \boldsymbol{y}_{t-1}' \Delta \boldsymbol{y}_t}{\sqrt{\sum_{t=1}^{T} \boldsymbol{y}_{t-1}' \check{\boldsymbol{e}}_t \check{\boldsymbol{e}}_t' \boldsymbol{y}_{t-1}}} \xrightarrow{d} N(0,1), \quad \check{\boldsymbol{e}}_t = \Delta \boldsymbol{y}_t = \boldsymbol{e}_t. \tag{2.4}$$

This test is initially meant to overcome small sample problems of the test in Breitung and Das (2005) which displays significant size distortions when N is relatively large compared with T. Later, Herwartz and Siedenburg (2009) show that t_{HS} is asymptotically Gaussian under variance break. Their claim is supported by Monte Carlo results in small samples. A major problem highlighted in Herwartz and Siedenburg (2009) is that the test loses its robustness to heteroskedasticity if the underlying data generating process (DGP) contains a linear deterministic trend. Moreover, the cross-sectional correlation they assumed is somehow weaker than the widely used common factor models (see, for example, Moon and Perron, 2004; Shin and Kang, 2006; Demetrescu and Hanck, 2012a,b).

2.2.2 The Cauchy test

PURTs that are based on the so-called Cauchy estimator use the sign of the first lag as an instrument for the lag itself (Shin and Kang, 2006). Recently, Demetrescu and Hanck (2012b) have demonstrated that the Cauchy tests proposed by Shin and Kang (2006), where the employed orthogonalization scheme allows strong cross-sectional correlation, are also robust to heteroskedasticity. Of these tests, we consider the one recommended by Demetrescu and Hanck (2012b) due to its superior small sample performance. To briefly sketch the test, we begin by denoting the (prewhitened and detrended) first differences by $\varepsilon_{i,t}$ and $\boldsymbol{\varepsilon}_t = (\varepsilon_{1,t}, ..., \varepsilon_{N,t})'$. Next, we compute the sample covariance matrix as $\widehat{\boldsymbol{\Sigma}}_\varepsilon = \sum_{t=p+2}^{T} \boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'/(T-p)$, where p refers to the number of lags included in the prewhitening regression discussed in Section 2.3.1. Applying an appropriate LU decomposition yields $\widehat{\boldsymbol{\Sigma}}_\varepsilon^{-1} = \widehat{\Gamma}\widehat{\Gamma}'$, which, in turn, are used to obtain the orthogonalized differences: $\boldsymbol{\varepsilon}_t^* = \widehat{\Gamma}'\boldsymbol{\varepsilon}_t$. Thus, the orthogonalized Cauchy statistics $\hat{\tau}_{IV,i}$ are defined as

$$\hat{\tau}_{IV,i} = \frac{\sum_{t=p+2}^{T} h_i(\tilde{y}_{i,t-1}^{\mu})\varepsilon_{i,t}^*}{\sqrt{\sum_{t=p+2}^{T} h_i^2(\tilde{y}_{i,t-1}^{\mu})}}, \tag{2.5}$$

where $\varepsilon_{i,t}^*$ are the N elements of $\boldsymbol{\varepsilon}_t^*$ and $h(.)$ is a Huber-type instrument which is asymptotically equivalent to the sign function. Shin and Kang (2006) and Demetrescu and Hanck (2012b) have shown that, under the null of a unit root, the following panel statistic $\bar{\tau}_{IV}$ is asymptotically Gaussian:

$$\bar{\tau}_{IV} = N^{-1/2} \sum_{i=1}^{N} \hat{\tau}_{IV,i} \xrightarrow{d} N(0,1). \tag{2.6}$$

A proof that $\bar{\tau}_{IV}$ is robust to nonstationary volatility of innovations is provided in Demetrescu and Hanck (2012b). This robustness is argued to arise from the fact that the sign function $h(.)$ discounts the lagged level to 1 or -1 regardless of the change in volatility over time. A major drawback of Shin and Kang's (2006) orthogonalization scheme is that T must be greater than N for $\widehat{\boldsymbol{\Sigma}}_\varepsilon^{-1}$ to exist. Moreover, $\bar{\tau}_{IV}$ exhibits small sample distortions when T is only moderately larger than N. To circumvent this problem, Demetrescu and Hanck (2012b) suggest applying an estimator of the sample covariance matrix $\widehat{\boldsymbol{\Sigma}}_\varepsilon$ initially proposed by Ledoit and Wolf (2004). This estimator is a weighted sum of the sample covariance matrix $\widehat{\boldsymbol{\Sigma}}_\varepsilon$ and the identity matrix I. Formally,

$$S_T = \kappa_{1T} I + \kappa_{2T} \widehat{\boldsymbol{\Sigma}}_\varepsilon,$$

where the weights κ_{1T} and κ_{2T} are built as follows. Given

$$\bar{b}_T^2 = \frac{1}{N}\left[\sum_{t=p+2}^{T}\left(\frac{\bar{\boldsymbol{\varepsilon}}_t'\bar{\boldsymbol{\varepsilon}}_t}{T}\right)^2 - \frac{1}{T} tr\left(\widehat{\boldsymbol{\Sigma}}_\varepsilon^2\right)\right],$$

we define $m_T = tr(\widehat{\boldsymbol{\Sigma}}_\varepsilon)/N, \quad d_T^2 = tr[(\widehat{\boldsymbol{\Sigma}}_\varepsilon - m_T I)(\widehat{\boldsymbol{\Sigma}}_\varepsilon - m_T I)']/N, \quad b_T^2 = min(\bar{b}_T^2, d_T^2)$ and $a_T^2 = d_T^2 - b_T^2$. Then, $\kappa_{1T} = m_T.b_T^2/d_T^2$ and $\kappa_{2T} = a_T^2/d_T^2$.

For the purpose of this work, we only consider $\bar{\tau}_{IV}$ with shrinkage, as the one with out shrinkage is of very limited practical relevance.

2.2.3 The White-type Cauchy test

In another paper, Demetrescu and Hanck (2012a) come up with a better alternative to using shrinkage estimators of the orthogonalization process required by $\bar{\tau}_{IV}$ when T is not sufficiently larger than N. They argue that avoiding the orthogonalization issue altogether and applying White-corrected standard errors to the IV estimators yields better sized tests. The White-type IV test is defined as

$$t_{DH} = \frac{\sum_{t=1}^{T} sgn(\boldsymbol{y}_{t-1})'\Delta\boldsymbol{y}_t}{\sqrt{\sum_{t=1}^{T} sgn(\boldsymbol{y}_{t-1})'\check{\boldsymbol{e}}_t\check{\boldsymbol{e}}_t' sgn(\boldsymbol{y}_{t-1})}} \xrightarrow{d} N(0,1), \quad \check{\boldsymbol{e}}_t = \Delta\boldsymbol{y}_t = \boldsymbol{e}_t. \tag{2.7}$$

It should be noted, however, that t_{HD} is essentially a Cauchy version of t_{HS} given in (2.4). By comparing the small sample performances of t_{DH} and t_{HS}, we examine the extent to which instrumenting lagged values improves the size of the test. In addition, we study if any potential gain regarding size precision comes at the expense of reduced empirical power.

2.3 Deterministic terms and serial correlation

In this section, we discuss how serial correlation and deterministic terms are handled in panel unit root testing. Focusing on methods recommended in Herwartz and

Siedenburg (2009) and Demetrescu and Hanck (2012a,b), with the latter ones referring to Demetrescu and Hanck (2011), we highlight potential implications of time-varying volatility on those schemes.

2.3.1 Short run dynamics

To cope with serial correlation, all the three papers recommend prewhitening, which proceeds by running individual-specific ADF regressions under H_0, i.e.

$$\Delta y_{it} = \sum_{j=1}^{p_i} c_{ij} \Delta y_{i,t-j} + e_{it}. \tag{2.8}$$

The estimates $\widehat{\boldsymbol{c}}_i = (\widehat{c}_{i1}, ..., \widehat{c}_{ip})$ are then used to obtain prewhitened data as

$$y_{it}^* = y_{it} - \widehat{c}_{i1} y_{i,t-1} - ... - \widehat{c}_{ip_i} y_{i,t-p_i} \tag{2.9}$$

and

$$\Delta y_{it}^* = \Delta y_{it} - \widehat{c}_{i1} \Delta y_{i,t-1} - ... - \widehat{c}_{ip_i} \Delta y_{i,t-p_i}. \tag{2.10}$$

Any consistent lag-length selection criterion can be applied to decide the lag lengths p_i. Herwartz and Siedenburg (2009) note that if both short run dynamics and deterministic patterns are present in the data, prewhitening should precede detrending. Moreover, the prewhitening regression should include an intercept term if the model features linear time trends under the alternative hypothesis.

2.3.2 Deterministic terms

To illustrate the issues with respect to deterministic terms, we follow the two formalizations given in Herwartz and Siedenburg (2009). The first one is the case of distinguishing a driftless random walk from a stationary process with individual-specific intercept terms. Formally, this can be written as

$$\boldsymbol{y}_t = (1-\rho)\boldsymbol{\mu} + \rho \boldsymbol{y}_{t-1} + \boldsymbol{e}_t, \tag{2.11}$$

where $\boldsymbol{\mu} = (\mu_1, ..., \mu_N)'$ contains individual-specific intercepts. In this case, Herwartz and Siedenburg (2009) recommend subtracting the first observation from the data in levels. Breitung and Meyer (1994) have pointed out that the first observation is the best estimator of $\boldsymbol{\mu}$ under H_0. Accordingly, the pooled test regression will be based on the transformed data

$$\Delta \boldsymbol{y}_t = \phi \boldsymbol{y}^*_{t-1} + \boldsymbol{e}_t, \quad \text{with} \quad \boldsymbol{y}^*_{t-1} = \boldsymbol{y}_{t-1} - \boldsymbol{y}_0.$$

Herwartz and Siedenburg (2009) emphasize the claim by Breitung and Meyer (1994) that the power of tests based on a regression on the transformed data does not depend on the individual effects. Nevertheless, our simulation results that are available upon request do not confirm this claim. Although, power truly remains to be less sensitive for smaller values of $\boldsymbol{\mu}$, it is seen that the considered tests will be powerless whenever $\boldsymbol{\mu} > |10|$.

Demetrescu and Hanck (2011) on the other hand recommend the use of recursive demeaning (Shin and So, 2001) arguing that the Cauchy tests (the univariate versions) are marginally powerful under this scheme than demeaning by the first observation. Recursive demeaning proceeds as

$$\boldsymbol{y}^*_{t-1} = \boldsymbol{y}_{t-1} - \left(\frac{1}{t-1}\right) \boldsymbol{y}^c_{t-1}, \tag{2.12}$$

where $\boldsymbol{y}^c_{t-1}$ is a vector of the cumulative sums of the observations up to the time $t-1$. Our unreported results that available upon request show that centering by the first observation leads to generally better power of the considered tests than recursive demeaning, although the gain is marginal as claimed by Demetrescu and Hanck (2011). However, we observe that, if the errors are heteroskedastic, the considered tests exhibit better size control when they are performed on recursively demeaned data than on data centered by the first observation. Therefore, we rely on recursive demeaning for our small sample performance comparison experiments.

Another empirically relevant formalization of unit root testing with deterministic terms is the case of distinguishing between a random walk with drift on the one hand and a trend stationary process on the other. This problem can be written as

$$\boldsymbol{y}_t = \boldsymbol{\mu} + (1-\rho)\boldsymbol{\beta} t + \rho \boldsymbol{y}_{t-1} + \boldsymbol{e}_t, \tag{2.13}$$

where vector $\boldsymbol{\beta} = (\beta_1, ..., \beta_N)'$ stacks panel-specific trend parameters. Although the data may be detrended by means of popular detrending schemes such as OLS, GLS or recursive detrending, the resulting statistics will be dependent on $\boldsymbol{\mu}$ and $\boldsymbol{\beta}$, and, hence, necessitate bias-correction terms. A better approach that does not require bias-correction terms is proposed in Breitung (2000). This approach applies the so-called Helmert transformation, where the first differences of the data are centered in a forward looking manner, i.e.

$$\begin{aligned} \Delta \boldsymbol{y}_t^* &= s_t \left[\Delta \boldsymbol{y}_t - \frac{1}{T-t}(\Delta \boldsymbol{y}_{t+1} + ... + \Delta \boldsymbol{y}_T) \right], \text{ and} \\ & s_t^2 = (T-t)/(T-t+1). \end{aligned} \tag{2.14}$$

Subsequently, $\boldsymbol{y}_t$ is detrended as

$$\boldsymbol{y}_t^* = \boldsymbol{y}_t - \boldsymbol{y}_0 - \widehat{\boldsymbol{\beta}}_t = \boldsymbol{y}_t - \boldsymbol{y}_0 - \frac{\boldsymbol{y}_T - \boldsymbol{y}_0}{T} t. \tag{2.15}$$

Our simulation results confirm the claim by Breitung (2000) that this detrending scheme results in PURTs that are completely independent on $\boldsymbol{\mu}$ and $\boldsymbol{\beta}$, both under the null and the alternative. As such, this detrending method, albeit inducing statistical power inferior to the above-mentioned demeaning schemes, can be used to demean the series in (2.11) if $\boldsymbol{\mu}$ are suspected to be very large. The success of this transformation, however, depends critically on the assumption that $\Delta \boldsymbol{y}_t^*$ is a white noise with constant variance. Simulation results reported in Herwartz and Siedenburg (2009) clearly indicate that this detrending scheme does not yield pivotal t_{HS} under variance break. Hence, this detrending method is not relevant for our experiments. Likewise, Demetrescu and Hanck (2011) point out that the Cauchy estimator loses its robustness to heteroskedasticity if there is a non-zero intercept under the null. Furthermore, the standard detrending techniques do not solve the problem as demeaning differences generates nuisance components that affect the asymptotic distribution of the tests. Instead, Demetrescu and Hanck (2011) suggest, admitting its practical complexity, that this issue might be tackled by resorting to Dufour (1990) who proposes a series of steps that involve building confidence intervals for the autoregressive root as well as the trend parameters.

In conclusion, handling linear trends remains to be the biggest challenge of unit root testing under time-varying volatility. In view of this, our finite sample performance comparisons proceed excluding linear trends from the model, i.e., we consider the formalization in (2.11).

2.4 Monte Carlo study

2.4.1 The simulation design

To evaluate the relative small sample performances of the three heteroskedasticity-robust PURTs under different volatility scenarios, we consider the following data generating process (DGP):

$$y_{it} = \quad (1-\rho)\mu_i + \rho y_{it-1} + e_{it}, \quad i = 1, ..., N; \quad t = 1, ..., T.$$

The DGP formalizes the random walk without drift under H_0 with a panel stationary process with individual effects under the alternative. Rejection frequencies under H_0 are simulated with $\rho = 1$ whereas empirical power is calculated against the heterogeneous alternatives $\rho_i \sim U(0.9, 1.0)$. Individual effects are generated as $\mu_i \sim U(-1, 1)$ which amounts to a maximum growth (decline) rate of 100%. As noted in Section 2.3.2, the choice of μ is not with out loss of generality for empirical power. Nevertheless, our unreported simulation results indicate that it is only a constant as high as ten (in absolute terms) that could induce a sharp decline in the power of the tests. Similarly, power increases with decreasing μ. We consider serially uncorrelated errors, but we set $p = 1$ and perform prewhitening so as to capture the impact of not knowing the true lag length in practice.

As our goal is to find out the most relevant PURT test for empirical macroeconomic applications, for instance, the FG nexus, we evaluate the robustness of the tests not only under a range of variance break scenarios but also under varying degrees of cross-sectional dependence. In this way, we could also examine how the interaction between variance break and cross-sectional dependence scenarios impact on the small sample performances of the tests. With respect to cross-unit dependence, it is worthwhile noting that the test in Herwartz and Siedenburg (2008) is derived under a weaker form of cross-sectional dependence and, hence, how the test performs under a strong form of dependence remains unclear. In contrast, the two Cauchy tests in Demetrescu and Hanck (2012a,b) are pivotal under a very strong form of cross-sectional dependence modeled along a common factor structure. Accordingly, we will consider three alternative cross-sectional dependence scenarios: independent, weakly dependent and strongly dependent panels. Cross-sectionally independent errors are defined as $e_{i,t} = \tilde{e}_{i,t}$, where $\tilde{e}_{i,t}$ are independently normally distributed. For the weak form of cross-unit dependence, we consider the spatial autoregressive (SAR) error structure given in Herwartz and Siedenburg (2008). Denoting $\boldsymbol{e}_t = (e_{1t}, ..., e_{Nt})'$, the SAR model is defined as

$$\boldsymbol{e}_t = (I_N - \Theta W)^{-1}\tilde{\boldsymbol{e}}_{\boldsymbol{t}}, \quad \text{with} \quad \Theta = 0.8 \quad \text{and} \quad \tilde{\boldsymbol{e}}_{\boldsymbol{t}} = (\tilde{e}_{1,t}, ..., \tilde{e}_{N,t})',$$

where W is the so-called spatial weights matrix, which in this specific case is a row normalized symmetric contiguity matrix of the one-behind-one-ahead type (for more details on spatial panel models see e.g. Elhorst, 2003). Following Herwartz and Siedenburg (2008), we call this specification as SAR(1) model. For the case of a strongly correlated panel, the following factor model taken from Demetrescu and Hanck (2012a,b) is assumed:

$$e_{i,t} = \lambda_i \nu_t + \tilde{e}_{i,t},$$

where $\nu_t \sim iidN(0,1)$ and $\lambda_i \sim U(-1,3)$.[4]

The variance break scenarios are determined by two parameters: the type of variance shift, and the moment at which the shift occurs. For the homoskedastic case, we set the variances as $\sigma_{et} = \sigma_{e1} = \sigma_{e2} = 1$. Accordingly, we obtain variance shifts by adjusting the post-break variance to $\sigma_{e2} = 5$, for a positive break, and to $\sigma_{e2} = 1/5$, for a negative one. With respect to the timing of variance breaks, we first consider cases where the breaks occur at varied moments across panel units, i.e $s_B \sim iidU(0.1, 0.9)$. As volatilities sometimes show strong correlations among individual units, we subsequently assume variance breaks to occur at the same time across all the panel units. In this case, we consider scenarios of early, middle and late variance breaks by fixing $s_B = 0.1$, $s_B = 0.5$ and $s_B = 0.9$, respectively. At last, we extend the analysis to cases of multiple variance break per each single time series—a simulation exercise not reported in all the papers associated with the three tests

[4] Note that it is also possible to generate a weaker form of cross-sectional dependence from this factor model by assigning smaller values (in absolute terms) for λ_i. However, results obtained by setting $\lambda_i \sim U(0, 0.2)$ as in Pesaran (2007) are qualitatively similar to those under SAR(1) model, and, hence, are not reported here.

under consideration. To this end, we allow $T/10$ subperiods for each individual series i and then, for each subperiod k, we randomly assign $\sigma_{ek} \in [1/5, 1, 5]$. Here, we first specify the variances in such a way that other series, say j, follow similar variance shift movements to i, but later relax this assumption and allow contemporaneous subperiods to experience different volatility shifts.

We generate data for all combinations of $N \in [16, 26, 56, 106]$ and $T \in [25, 50, 100, 200]$. Rejection is decided by comparing the calculated values of each PURT statistic with the 5% critical value of the standard Gaussian distribution. Empirical rejection probabilities are based on 5000 replications.

2.4.2 Results

Simulation results are documented in Tables 2.1–2.6. Each table has upper, middle and lower panels representing empirical rejection frequencies obtained under cross-sectional independence, SAR(1) model and factor structure, respectively. Except in Tables 2.1 and 2.6, the left-hand side blocks refer to results obtained under negative variance breaks while the right-hand side blocks represent results under positive variance breaks. Table 2.1 reports results for the benchmark case of homoskedasticity against a general form of heteroskedasticity obtained by first drawing random variance break points for each panel unit ($s_B \sim iidU(0.1, 0.9)$) and then randomly assigning either constant ($\sigma_{e2} = 1$), negative ($\sigma_{e2} = 1/5$) or positive ($\sigma_{e2} = 5$) volatility shifts. While keeping heterogeneity of variance break moments, we distinguish between the impacts of positive and negative variance shifts in Table 2.2. In the subsequent three tables, emphasis is given to isolating the impacts of the timings of variance breaks on the relative small sample performances of the tests. Accordingly, Tables 2.3, 2.4 and 2.5 report results for cases in which variance breaks (homogeneously) occur early ($s_B = 0.1$), halfway ($s_B = 0.5$), and late ($s_B = 0.9$) in the time series. Finally, results for multiple variance breaks that occur every tenth data point in each individual time series are documented in Table 2.6. In this table, the left-hand side block represents simulation results for cases in which subperiods experience similar shifts across panel units while the right-hand block refers to results when contemporaneous subperiods are allowed to feature different volatility shifts. In the following, we discuss notable results documented in each table.

Table 2.1: Empirical rejection frequencies under constant variance and variance break

		Constant variance								Heterogeneous variance shifts							
		size				power				size				power			
	T N	16	26	56	106	16	26	56	106	16	26	56	106	16	26	56	106
CS independence																	
t_{HS}	25	5.4	5.0	5.5	5.5	52.3	60.9	87.2	99.0	6.4	6.3	5.9	6.5	23.9	27.2	38.1	58.9
	50	5.2	4.9	4.7	5.0	73.3	80.7	98.6	100.0	6.1	6.5	5.8	4.9	37.0	41.6	61.2	86.4
	100	5.6	5.5	5.6	4.9	79.3	84.9	99.3	100.0	6.8	6.0	5.8	5.2	47.9	52.4	76.7	94.9
	200	5.4	5.4	5.6	5.7	74.7	80.0	97.9	100.0	6.6	6.0	5.9	5.5	53.9	57.7	80.0	94.9
$\bar{\tau}_{IV}$	25	3.8	3.9	2.7	1.5	42.7	50.6	74.2	93.0	1.2	1.0	0.8	0.4	16.6	18.3	25.1	39.6
	50	4.4	4.6	4.3	3.6	76.0	88.4	99.5	100.0	1.8	1.4	1.0	0.6	46.0	54.4	80.0	97.5
	100	4.9	5.0	4.9	4.9	91.4	97.8	100.0	100.0	2.6	2.1	1.1	0.8	75.9	87.1	99.1	100.0
	200	5.2	5.0	5.8	5.3	96.7	99.6	100.0	100.0	3.4	2.6	2.0	1.4	90.5	97.7	100.0	100.0
t_{DH}	25	5.6	6.6	7.3	7.8	47.1	60.1	86.3	99.1	6.5	6.7	8.7	10.3	27.5	36.6	59.0	85.2
	50	5.3	5.5	5.4	5.8	75.9	88.9	99.6	100.0	5.1	5.8	6.0	6.4	46.6	59.3	88.6	99.4
	100	5.1	5.4	5.4	5.5	91.1	97.7	100.0	100.0	4.8	5.0	5.1	5.2	65.7	79.9	98.6	100.0
	200	5.3	5.4	6.1	5.5	96.5	99.6	100.0	100.0	5.0	4.8	5.3	5.4	77.1	91.0	99.9	100.0
SAR(1) model																	
t_{HS}	25	6.0	5.5	5.3	5.8	26.8	30.8	48.7	75.9	6.0	6.6	6.1	6.7	23.7	26.0	38.8	60.7
	50	6.6	5.9	5.8	5.0	39.2	46.4	72.4	95.0	6.5	5.9	5.6	4.7	36.4	42.5	60.9	86.8
	100	6.6	6.3	5.9	5.1	47.0	52.8	83.0	98.8	6.5	6.0	5.3	5.4	47.9	52.7	75.5	95.1
	200	7.1	6.2	5.8	6.0	47.0	53.7	85.5	99.1	6.8	5.9	5.5	5.4	53.4	58.7	79.4	94.6
$\bar{\tau}_{IV}$	25	3.2	3.4	2.6	1.7	20.0	25.4	37.1	58.4	1.7	1.3	0.8	0.2	17.4	18.6	25.5	40.8
	50	3.1	3.6	2.8	2.4	36.4	51.0	78.9	97.5	1.8	1.5	1.0	0.5	47.2	56.5	80.9	98.1
	100	4.1	3.6	3.1	3.1	52.7	70.6	96.2	100.0	2.8	2.0	1.3	1.1	77.9	88.2	99.4	100.0
	200	4.1	4.2	4.0	3.5	61.3	82.1	99.2	100.0	3.1	3.1	2.0	1.4	92.7	98.7	100.0	100.0
t_{DH}	25	5.9	6.2	6.5	7.3	24.9	31.5	52.9	80.8	6.4	7.1	8.3	10.2	28.7	36.1	59.3	86.2
	50	5.9	5.7	5.9	5.6	40.2	53.5	82.4	98.5	5.4	5.7	5.8	5.9	46.7	60.3	87.7	99.4
	100	6.1	6.1	6.3	5.4	56.1	70.0	96.1	100.0	4.5	4.7	5.3	5.1	67.1	81.3	98.7	100.0
	200	5.2	5.1	5.5	5.6	65.1	81.2	99.1	100.0	5.0	4.9	5.6	5.1	79.4	92.3	99.9	100.0
Factor model																	
t_{HS}	25	8.1	8.3	8.2	9.3	24.4	23.1	25.2	26.3	6.5	6.4	7.1	7.0	22.5	23.4	28.7	35.2
	50	8.6	8.5	8.6	8.6	33.6	29.8	30.6	31.9	6.3	6.4	6.8	7.2	33.7	34.2	41.9	52.4
	100	8.5	9.5	9.4	9.9	34.5	32.9	34.7	36.7	7.0	6.4	6.3	7.6	42.7	41.8	51.3	61.7
	200	9.0	8.7	9.1	9.1	34.8	33.9	36.1	38.3	7.2	7.0	7.4	7.0	45.6	45.7	56.8	65.4
$\bar{\tau}_{IV}$	25	1.8	1.5	0.3	0.0	17.0	19.8	11.3	7.6	1.9	1.3	0.8	0.1	14.6	17.5	14.9	14.1
	50	2.8	2.8	1.4	0.2	42.4	58.0	56.6	64.7	2.0	1.8	1.1	0.4	35.1	47.8	53.8	69.0
	100	3.8	3.7	3.2	1.8	62.6	81.0	85.4	92.3	2.7	2.5	1.8	1.0	59.0	74.5	84.6	94.7
	200	4.3	4.3	3.9	3.1	72.9	88.0	93.9	98.0	3.7	3.5	2.8	2.1	71.9	87.4	94.9	98.7
t_{DH}	25	6.5	7.2	7.4	7.9	21.6	21.7	22.5	23.5	6.3	6.3	7.1	7.7	22.0	24.0	27.3	30.7
	50	6.5	6.5	7.0	7.1	31.4	30.2	30.9	33.3	5.7	6.4	7.0	7.8	33.5	35.6	39.6	45.4
	100	6.3	7.2	7.7	7.2	38.1	38.0	39.4	42.0	5.5	6.1	7.1	7.2	46.5	47.8	52.3	56.7
	200	6.5	6.8	7.1	8.1	43.6	43.1	44.4	47.6	6.0	5.3	6.9	6.8	55.3	56.3	63.0	65.9

Notes: t_{HS}, $\bar{\tau}_{IV}$ and t_{DH} refer to the PURT statistics defined in (2.4), (2.6) and (2.7). Simulation results are based on 5000 replications and the nominal size equals 5%. All tests are computed on prewhitened and (recursively) detrended data.

We begin our discussion by comparing the finite sample properties of the tests under homoskedasticity and the three cross-sectional dependence scenarios. In Table 2.1, we see that all the tests display very good size control under the benchmark case of homoskedasticity and cross-sectional independence. An exception is observed for the smallest considered time dimension $T = 25$, in which case both Cauchy tests become increasingly distorted as N increases. Under weak cross-sectional dependence, the undersizing of $\bar{\tau}_{IV}$ becomes visible even for the remaining time dimensions, but t_{DH} continues to posses similar size control to t_{HS} unless T is small, i.e., $T = 25$. Strong cross-sectional dependence induces further size distortion in all the three tests. In particular, $\bar{\tau}_{IV}$ is virtually unable to reject the null when N is relatively large compared with T—a result documented in all the six tables of this section as well as in Demetrescu and Hanck (2012a,b). On the contrary, the two White-type tests become moderately over-sized, with t_{HS} showing about 2% more over-rejections than t_{DH}. With respect to empirical power, all tests appear to be equally powerful in independent panels apart from the fact that t_{HS} is less powerful for the smallest considered cross-sectional dimensions $N = 16$, and $= 26$. All the tests are less powerful under cross-sectional dependence than independence; the smallest empirical probabilities of rejecting the alternative hypothesis are reported when the errors are strongly correlated. In the latter case, t_{HS} and $\bar{\tau}_{IV}$ become the least and the most powerful tests, respectively. As generally similar patterns are seen in other variance break scenarios, we do not discuss empirical power results anymore and concentrate on documented frequencies of rejecting the null hypothesis. Nevertheless, we continue to provide empirical power results in the tables for the sake of completeness.

Turning to the results reported in the right-hand block of Table 2.1, we see in the upper panel that variance breaks amplify major patterns observed in homoskedastic and independent panels. Namely, the White-type test t_{HS} is now about 0.5% more oversized than the homoskedastic case, t_{DH} exhibits pronounced size distortions for $T = 25$, and $\bar{\tau}_{IV}$ completely loses size control when N is relatively large compared with T. Results under the heteroskedastic SAR(1) model are broadly similar to those under independent errors. Strongly cross-unit correlation, however, substantially reduces the size distortions of t_{DH} for $T = 25$ and renders the results comparable to the case of constant variance. Although t_{HS} displays slightly larger size distortions under strongly correlated panels than the other two cross-sectional dependence scenarios, heteroskedasticity seems to dampen the upward size distortions of t_{HS} induced by strongly correlated errors. As a consequence, t_{HS} appears to display the best size control of all the considered tests under variance break. However, clarifying whether this pattern is unique to the assumed specific heteroskedasticity scenario or could be taken as a general conclusion requires further robustness checks on the basis of alternative cases of volatility shifts.

Distinguishing between positive and negative variance breaks, we observe in Table 2.2 that, while most patterns remain qualitatively unchanged, the apparent good performance of t_{HS} under the factor structure emanates from upward volatility shifts. When strongly correlated panels feature downward volatility shifts, however, t_{HS} exhibits significant upward size distortions that are even slightly higher than the heteroskedastic case: its empirical rejection rates reach 10.1%. On the other hand, marked small T upward size distortion of t_{DH} observed under variance breaks with weak or no cross-unit correlation seem to increase when the shift is restricted to be either negative or positive for all the panel units. Furthermore, similar to t_{HS}, the Cauchy test t_{DH} is more oversized under negative variance breaks, with its empirical rejection rates rising up to 13.4%.

Besides the direction, the timing of volatility shifts also determines how distorted unit root tests become under variance breaks (Cavaliere and Taylor, 2007b, 2008). Results presented in Table 2.4 demonstrate that the distortionary effects of negative variance breaks on the considered PURTs are more pronounced when the breaks occur early in the time series. In this case, a new distortion is displayed by t_{HS} when $T = 25$. Likewise, t_{HD}'s over-rejections extend to $T = 50$, where empirical sizes climb up to 17.4%. Another striking pattern revealed in this table is that $\bar{\tau}_{IV}$ shows its best size performance under early negative variance break with no or weak cross-sectional correlation. Indeed, $\bar{\tau}_{IV}$ clearly outperforms the two White-type tests if independent or weakly dependent panels exhibit early negative variance shifts. Nevertheless, it is also in the same volatility shift scenario, but under strongly correlated errors, that $\bar{\tau}_{IV}$ exhibits its poorest small sample performance, with a maximum of only 0.2% rejection rates observed in more than half of the considered T and N combinations. Of the considered heteroskedasticity cases, early positive variance break, in contrast to the negative one, appears to exert the least adverse—if

Table 2.2: Empirical rejection frequencies under variance break with heterogeneous break moments

		Negative variance break								Positive variance break							
		size				power				size				power			
	T N	16	26	56	106	16	26	56	106	16	26	56	106	16	26	56	106
CS independence																	
t_{HS}	25	6.4	6.4	7.1	7.9	84.6	92.6	99.6	100.0	6.1	6.0	6.1	7.2	27.8	33.3	53.8	83.0
	50	5.8	5.2	5.6	5.6	96.1	97.7	100.0	100.0	5.7	4.6	5.5	5.5	50.5	59.0	84.2	99.0
	100	6.2	5.3	5.2	4.7	95.7	97.6	100.0	100.0	5.6	5.5	5.7	4.6	68.8	72.1	94.9	99.9
	200	6.1	5.3	5.2	5.2	92.6	95.7	99.8	100.0	6.1	6.3	5.8	5.3	72.1	75.1	95.0	99.8
$\bar{\tau}_{IV}$	25	3.5	3.3	2.6	1.2	53.8	67.8	90.8	99.5	3.8	3.6	2.2	1.4	20.7	23.6	35.1	51.8
	50	4.3	3.2	2.7	2.9	85.1	93.9	100.0	100.0	4.2	3.8	3.5	3.1	46.6	58.6	87.3	99.4
	100	4.1	3.4	3.4	3.3	95.0	99.4	100.0	100.0	3.9	3.5	3.8	3.4	74.9	88.0	99.5	100.0
	200	4.1	4.0	3.1	3.2	97.7	100.0	100.0	100.0	3.8	4.5	3.7	3.4	90.6	97.8	100.0	100.0
t_{DH}	25	6.9	8.1	10.9	13.1	62.8	78.6	97.0	100.0	6.8	7.8	8.1	11.1	28.7	38.0	61.3	88.2
	50	6.4	5.8	6.4	7.7	86.7	95.2	100.0	100.0	5.5	5.5	5.6	6.6	52.4	66.8	92.1	99.8
	100	5.3	5.0	5.8	5.9	95.3	99.4	100.0	100.0	4.7	4.6	5.6	5.5	78.0	90.0	99.7	100.0
	200	5.0	4.8	4.5	5.3	97.6	99.9	100.0	100.0	4.8	5.5	4.9	4.8	91.2	98.1	100.0	100.0
SAR(1) model																	
t_{HS}	25	6.3	6.6	7.1	7.5	86.9	92.9	99.7	100.0	5.7	5.0	6.4	7.1	28.2	34.8	55.0	82.6
	50	6.0	5.5	5.6	5.3	95.8	98.0	100.0	100.0	5.7	5.1	4.8	5.0	51.7	58.3	85.2	98.7
	100	5.5	5.9	5.3	4.6	95.7	97.9	100.0	100.0	5.4	5.8	5.1	4.4	69.5	73.1	95.0	99.8
	200	5.9	5.6	5.2	5.4	93.0	95.0	99.8	100.0	5.4	5.2	5.3	5.0	73.0	75.3	95.9	99.7
$\bar{\tau}_{IV}$	25	4.0	3.4	2.1	1.5	57.6	70.2	92.6	99.7	3.5	3.2	2.3	1.6	20.1	24.3	35.2	52.9
	50	4.3	4.1	3.6	2.4	87.3	95.5	100.0	100.0	4.4	3.7	3.4	2.7	48.4	60.7	87.4	99.4
	100	3.9	3.9	3.4	3.6	96.0	99.5	100.0	100.0	3.9	3.7	3.2	3.2	75.8	88.7	99.6	100.0
	200	3.6	3.6	3.6	3.4	98.4	100.0	100.0	100.0	4.0	3.7	3.6	3.5	92.0	98.0	100.0	100.0
t_{DH}	25	7.5	8.7	10.3	13.4	65.7	79.8	97.9	100.0	6.5	7.3	9.2	11.9	28.4	39.2	61.6	88.5
	50	6.4	6.8	7.0	7.1	88.6	96.4	100.0	100.0	5.8	5.5	5.9	6.4	54.6	68.6	92.4	99.8
	100	5.3	5.2	5.3	6.3	96.3	99.6	100.0	100.0	4.8	4.6	4.6	5.1	79.3	91.4	99.8	100.0
	200	4.3	4.6	5.4	5.4	98.4	100.0	100.0	100.0	4.6	4.7	4.8	4.7	92.7	98.3	100.0	100.0
Factor model																	
t_{HS}	25	8.2	8.0	9.0	9.2	24.4	22.5	22.6	23.7	6.4	5.9	6.6	7.1	27.2	30.5	41.8	55.3
	50	8.9	8.9	9.5	9.8	28.4	27.4	27.5	28.6	6.0	5.6	6.2	6.4	46.8	51.2	65.6	78.1
	100	9.0	8.9	9.4	10.1	30.4	28.1	29.8	30.2	6.3	5.8	6.4	6.6	61.9	63.0	79.9	88.7
	200	9.0	8.6	9.6	9.3	29.5	27.8	30.8	29.4	6.5	6.0	6.8	6.2	65.4	65.4	83.5	92.9
$\bar{\tau}_{IV}$	25	1.2	0.7	0.2	0.0	18.1	25.7	18.0	18.7	4.3	3.8	2.7	1.5	20.8	23.0	28.0	31.1
	50	2.0	1.4	0.6	0.2	44.6	66.0	59.5	71.5	4.3	3.9	3.1	1.8	44.0	53.2	68.4	81.8
	100	3.1	2.5	2.0	0.9	62.4	81.9	81.4	89.9	4.1	3.9	3.5	2.4	68.9	80.1	92.8	98.4
	200	3.5	3.8	3.5	2.5	70.1	86.0	91.2	97.0	4.7	4.5	4.1	3.0	83.0	92.5	98.8	100.0
t_{DH}	25	6.8	6.8	7.7	7.6	21.1	20.7	20.2	22.1	6.6	6.8	8.3	9.3	26.6	30.4	37.9	46.5
	50	7.0	7.3	7.3	7.9	27.8	28.6	27.9	29.9	5.6	5.7	6.6	7.2	44.0	50.4	59.9	67.9
	100	6.3	6.8	7.6	7.4	33.6	32.7	33.6	35.6	5.3	5.2	6.4	6.6	64.0	69.3	77.7	83.6
	200	6.7	6.5	6.7	7.1	36.8	35.9	38.4	37.7	5.7	5.1	5.7	5.3	76.6	81.4	88.5	91.8

Notes: t_{HS}, $\bar{\tau}_{IV}$ and t_{DH} refer to the PURT statistics defined in (2.4), (2.6) and (2.7). Simulation results are based on 5000 replications and the nominal size equals 5%. All tests are computed on prewhitened and (recursively) detrended data.

Table 2.3: Empirical rejection frequencies under early variance break

		Negative variance break								Positive variance break							
		size				power				size				power			
	T N	16	26	56	106	16	26	56	106	16	26	56	106	16	26	56	106
CS independence																	
t_{HS}	25	10.5	10.3	11.2	12.9	88.7	93.1	99.5	100.0	5.5	5.2	5.6	6.2	48.1	58.1	84.5	98.8
	50	6.4	6.1	7.2	7.9	96.6	98.3	100.0	100.0	5.4	5.2	5.3	4.9	73.0	80.2	98.0	100.0
	100	4.8	5.7	5.4	5.2	95.2	97.7	100.0	100.0	5.6	4.8	4.6	4.5	81.6	85.8	99.3	100.0
	200	5.1	4.8	5.4	5.2	90.1	96.0	100.0	100.0	5.7	5.2	5.6	5.2	77.7	81.5	98.7	100.0
$\bar{\tau}_{IV}$	25	7.7	6.9	5.8	4.5	83.8	92.4	99.5	100.0	4.6	3.7	2.7	1.4	33.9	43.8	61.9	80.9
	50	6.7	6.6	6.3	4.4	96.0	98.9	100.0	100.0	5.2	4.3	4.6	3.7	72.1	85.7	99.1	100.0
	100	6.1	5.4	5.6	5.4	97.7	99.8	100.0	100.0	4.5	5.0	4.1	4.4	91.8	98.1	100.0	100.0
	200	4.9	4.6	4.8	5.8	98.1	99.9	100.0	100.0	4.8	5.0	5.4	4.6	97.5	99.8	100.0	100.0
t_{DH}	25	8.6	10.4	13.2	13.3	86.9	95.3	99.7	100.0	6.2	6.0	7.9	9.9	40.0	53.8	81.7	98.2
	50	8.1	8.8	12.6	17.4	93.9	97.8	100.0	100.0	5.7	5.2	6.4	6.0	72.9	86.8	99.3	100.0
	100	6.8	6.4	6.8	8.7	95.8	99.5	100.0	100.0	4.7	5.1	4.8	5.0	91.8	98.0	100.0	100.0
	200	5.1	4.9	5.0	6.9	97.5	99.8	100.0	100.0	4.9	5.0	5.4	4.9	97.5	99.8	100.0	100.0
SAR(1) model																	
t_{HS}	25	8.9	10.6	11.3	11.8	92.7	95.6	99.7	100.0	5.0	5.2	5.3	5.7	47.3	59.1	84.2	99.0
	50	6.1	6.9	7.5	7.4	97.8	99.0	100.0	100.0	5.2	4.5	4.3	5.0	73.5	81.1	98.0	100.0
	100	5.3	5.7	5.0	5.4	96.4	98.6	100.0	100.0	5.4	4.7	4.6	4.7	81.8	86.2	99.5	100.0
	200	5.3	5.1	5.0	5.2	91.7	96.6	100.0	100.0	5.8	5.3	5.3	4.7	78.2	81.4	98.3	100.0
$\bar{\tau}_{IV}$	25	7.9	7.6	5.5	4.4	90.2	95.9	99.9	100.0	4.5	3.6	2.8	1.5	34.5	44.4	61.7	80.5
	50	6.9	6.9	6.0	3.9	97.3	99.5	100.0	100.0	4.8	4.7	4.4	3.1	71.7	85.6	98.9	100.0
	100	5.5	5.4	6.2	5.7	98.8	100.0	100.0	100.0	4.7	4.9	5.0	4.6	91.7	97.8	100.0	100.0
	200	4.7	5.5	5.3	5.4	99.2	100.0	100.0	100.0	4.9	4.4	4.5	4.1	97.5	99.9	100.0	100.0
t_{DH}	25	9.3	10.9	12.5	13.3	90.8	96.5	99.9	100.0	6.2	6.8	7.5	8.9	41.6	54.8	81.8	98.0
	50	7.6	9.4	13.0	16.2	95.1	98.9	100.0	100.0	5.4	5.2	6.0	5.3	71.9	86.6	99.3	100.0
	100	6.7	6.6	8.0	9.6	97.2	99.8	100.0	100.0	4.9	5.1	5.1	5.3	91.4	97.7	100.0	100.0
	200	5.0	6.0	5.9	6.2	98.6	100.0	100.0	100.0	5.1	4.5	4.8	4.2	97.4	99.8	100.0	100.0
Factor model																	
t_{HS}	25	8.6	8.5	8.9	9.1	17.3	16.4	16.0	17.6	5.7	5.4	6.0	6.8	45.0	53.7	72.5	87.2
	50	9.5	9.2	9.5	10.0	20.2	19.7	19.9	20.0	5.6	5.3	5.2	6.1	69.9	74.1	91.7	97.2
	100	9.7	9.4	9.3	9.9	22.2	19.9	21.1	21.2	5.4	5.2	5.1	4.9	78.8	81.2	96.2	99.1
	200	9.7	9.2	9.9	9.1	21.2	20.0	21.6	20.5	5.9	5.8	6.1	5.7	75.1	78.2	96.0	99.4
$\bar{\tau}_{IV}$	25	0.2	0.0	0.0	0.0	11.3	21.4	15.6	25.1	4.4	3.4	2.2	1.2	31.7	39.1	50.6	61.9
	50	0.5	0.2	0.0	0.0	31.7	55.5	38.6	53.5	4.8	4.0	3.2	2.1	68.2	79.2	94.4	98.8
	100	1.7	1.1	0.4	0.1	45.2	69.6	54.6	67.4	4.8	4.9	4.0	2.0	88.8	95.8	99.6	100.0
	200	2.5	1.8	1.5	0.8	54.3	73.6	71.1	81.8	4.5	4.3	4.4	3.0	96.3	98.8	100.0	100.0
t_{DH}	25	7.1	6.4	7.1	7.7	16.0	15.6	15.5	16.3	6.4	6.3	7.3	8.7	37.8	48.4	67.2	81.7
	50	6.8	7.4	7.6	8.3	19.7	19.5	19.7	20.7	5.4	5.8	5.8	6.6	66.8	76.9	90.0	94.9
	100	6.7	7.2	7.7	7.3	22.2	22.0	22.7	23.5	5.1	5.4	5.0	5.3	86.4	92.1	97.6	99.2
	200	7.0	6.6	7.3	7.4	24.6	24.2	25.8	24.1	4.6	5.0	6.3	5.5	94.1	97.1	99.5	99.9

Notes: t_{HS}, $\bar{\tau}_{IV}$ and t_{DH} refer to the PURT statistics defined in (2.4), (2.6) and (2.7). Simulation results are based on 5000 replications and the nominal size equals 5%. All tests are computed on prewhitened and (recursively) detrended data.

not beneficial—impact on the small sample performances of the tests. In fact, the impact of strong cross-unit correlation on t_{HS}'s performance is no more observed now and, hence, of all variance break scenarios, the test displays its best size control under early positive variance break.

Table 2.4 reports empirical rejection frequencies when volatility shifts occur in the middle of the time series. A notable observation here is that as the timing of variance breaks is delayed, size distortions associated with early negative variance break subside down while those of early upward shift become more pronounced. This general tendency is also strengthened by results obtained under late variance break as documented in Table 2.5. In particular, it is only as long as the shift does not occur late in the time series that positive variance break mitigates size distortions of t_{HS} in strongly correlated panels. Conversely, it is only when the break occurs early or halfway, but not late, in the time series that this test displays significant size distortions associated with negative variance break for $T = 25$.

As a last simulation exercise, we consider cases of multiple variance breaks per each individual time series in a panel. The left-hand side block of Table 2.6 reports empirical rejection frequencies of the considered tests when contemporaneous subperiods are restricted to feature similar volatility shifts. In this case, and when the errors additionally feature weak to no cross-sectional correlation, t_{HS} holds superior size control while t_{DH} is oversized for small values of T and $\bar{\tau}_{IV}$ is undersized if T is not relatively larger than N. In strongly dependent panels, t_{DH} has the best size control of all the considered tests, as $\bar{\tau}_{IV}$ becomes even more undersized and t_{HS} shows about 0.5% overrejections than t_{DH}. Yet, it is evident that the presence of multiple variance breaks reduces t_{DH}'s advantage over t_{HS} for strongly correlated panel. Therefore, t_{HS} overall exhibits the best size precision of all tests under multiple variance breaks that follow identical trends across panel units. The right-hand side block of Table 2.6 documents results obtained by allowing contemporaneous subperiods to experience randomly different volatility paths. With the new setting, t_{HS} performs even better than under the former variance break scenario as the impact of strongly correlated errors appear to be offset by asynchronous volatility shifts. Although the distortions of both Cauchy tests, $\bar{\tau}_{IV}$ and t_{DH}, appear to be slightly smaller than their respective counterparts documented in the left-hand side, they, however, remain visibly substantial. In

Table 2.4: Empirical rejection frequencies under middle variance break

		Negative variance break								Positive variance break							
		size				power				size				power			
	T N	16	26	56	106	16	26	56	106	16	26	56	106	16	26	56	106
CS independence																	
t_{HS}	25	6.4	6.5	8.3	9.1	98.4	99.7	100.0	100.0	5.6	6.0	7.9	8.9	25.1	32.4	52.1	77.2
	50	5.6	5.0	5.1	5.6	99.8	99.9	100.0	100.0	5.5	5.5	5.2	5.7	51.2	60.1	86.2	99.0
	100	4.8	5.1	4.7	5.1	99.3	99.9	100.0	100.0	5.0	5.4	5.1	4.6	72.3	78.0	97.3	100.0
	200	5.0	6.0	5.0	4.9	98.1	99.7	100.0	100.0	5.4	5.4	5.8	5.1	77.0	82.5	98.6	100.0
$\bar{\tau}_{IV}$	25	4.8	3.7	2.4	1.3	63.3	75.7	95.7	99.9	4.6	3.5	2.5	1.2	20.5	23.6	30.9	40.4
	50	4.4	4.7	4.1	3.2	90.6	97.3	100.0	100.0	5.1	4.6	3.9	3.2	50.2	62.5	86.7	99.1
	100	4.8	5.0	4.6	4.7	97.6	99.6	100.0	100.0	4.4	4.6	4.6	4.1	78.9	91.1	99.8	100.0
	200	4.5	5.1	4.7	4.4	98.6	100.0	100.0	100.0	5.1	4.7	5.9	4.9	93.3	98.7	100.0	100.0
t_{DH}	25	7.4	8.0	10.5	13.7	68.8	81.5	97.9	100.0	6.4	7.3	10.0	11.5	27.0	36.5	58.6	83.3
	50	5.4	5.8	6.1	7.3	89.5	96.7	100.0	100.0	5.6	5.4	5.5	6.3	52.2	65.1	89.9	99.6
	100	5.5	5.5	5.4	5.8	96.7	99.4	100.0	100.0	4.5	5.1	5.0	4.8	78.7	91.0	99.8	100.0
	200	4.6	5.1	5.0	5.1	98.4	100.0	100.0	100.0	5.0	4.9	5.8	5.0	92.9	98.5	100.0	100.0
SAR(1) model																	
t_{HS}	25	6.6	7.3	6.8	8.8	99.0	99.7	100.0	100.0	6.2	6.6	7.3	9.4	26.1	30.9	50.0	79.0
	50	5.3	4.6	5.7	6.0	99.7	99.9	100.0	100.0	5.2	5.6	5.3	5.3	50.2	59.9	86.6	99.2
	100	5.0	5.2	4.8	4.8	99.5	100.0	100.0	100.0	5.5	4.4	5.0	5.3	72.8	78.7	97.6	100.0
	200	5.6	5.2	4.8	5.0	98.4	99.8	100.0	100.0	5.4	5.2	5.5	5.1	77.8	82.2	98.7	100.0
$\bar{\tau}_{IV}$	25	4.3	4.0	2.5	0.8	65.9	77.9	97.1	100.0	4.8	3.7	2.4	0.9	21.4	24.2	30.4	41.8
	50	4.9	4.6	4.2	2.9	92.1	98.3	100.0	100.0	4.5	4.5	3.7	3.4	50.7	62.9	87.9	99.2
	100	4.7	4.7	4.8	4.1	98.0	99.9	100.0	100.0	4.3	4.6	4.8	4.5	80.0	92.2	99.9	100.0
	200	5.0	5.2	4.3	4.6	99.0	100.0	100.0	100.0	4.6	5.0	5.2	4.6	93.9	98.8	100.0	100.0
t_{DH}	25	7.3	8.2	9.9	13.2	71.1	82.9	98.6	100.0	7.4	7.2	9.0	12.3	28.0	37.4	56.7	84.0
	50	5.9	5.6	6.2	7.2	90.8	97.9	100.0	100.0	5.4	5.6	6.0	6.6	52.9	66.2	91.0	99.7
	100	4.9	5.5	5.5	5.4	97.8	99.8	100.0	100.0	4.8	4.9	5.6	5.3	79.9	91.9	99.8	100.0
	200	5.1	5.3	4.8	4.8	98.9	99.9	100.0	100.0	4.7	5.3	5.5	5.0	93.8	98.7	100.0	100.0
Factor model																	
t_{HS}	25	8.8	8.3	8.5	8.9	24.6	23.0	23.5	24.8	6.4	6.7	7.7	8.9	24.8	28.8	38.5	47.0
	50	9.7	9.3	9.3	9.9	30.2	28.1	28.3	29.5	6.3	6.3	6.2	7.7	44.7	47.9	60.9	72.0
	100	9.5	9.2	9.2	10.0	31.9	29.2	30.3	31.2	6.2	6.6	6.0	6.5	62.3	64.2	78.4	85.7
	200	9.9	9.0	9.8	9.2	30.6	28.1	31.5	29.4	6.0	5.8	7.2	6.3	68.4	67.6	84.6	91.7
$\bar{\tau}_{IV}$	25	1.3	0.6	0.1	0.0	19.5	26.8	18.8	22.8	5.5	4.3	3.6	2.0	21.6	23.0	25.7	28.7
	50	2.3	1.5	0.4	0.1	47.8	69.1	61.4	72.2	5.1	5.1	3.1	2.0	44.8	51.0	63.4	75.3
	100	3.3	2.9	1.9	0.5	64.4	84.2	82.5	89.9	5.4	4.9	3.4	2.1	70.4	80.3	91.1	97.1
	200	4.3	3.6	3.3	2.3	72.9	87.6	92.0	96.7	4.9	4.3	4.3	2.7	85.3	92.9	98.8	99.8
t_{DH}	25	6.9	6.3	7.1	7.4	21.8	21.8	22.0	23.1	7.1	7.0	8.5	9.3	23.9	27.6	35.6	41.6
	50	6.4	6.9	6.9	7.9	29.1	29.2	29.2	31.0	5.8	6.5	6.2	7.8	42.4	46.7	55.6	63.0
	100	6.0	6.6	7.1	7.8	34.9	34.9	35.1	37.0	5.9	6.2	5.8	6.4	63.4	67.9	74.5	80.2
	200	7.0	6.5	7.1	7.4	38.7	36.6	40.0	39.9	5.7	5.0	6.3	6.2	77.3	79.3	87.5	90.4

Notes: t_{HS}, $\bar{\tau}_{IV}$ and t_{DH} refer to the PURT statistics defined in (2.4), (2.6) and (2.7). Simulation results are based on 5000 replications and the nominal size equals 5%. All tests are computed on prewhitened and (recursively) detrended data.

Table 2.5: Empirical rejection frequencies under late variance break

		Negative variance break								Positive variance break							
		size				power				size				power			
	T N	16	26	56	106	16	26	56	106	16	26	56	106	16	26	56	106
CS independence																	
t_{HS}	25	5.1	5.1	5.6	5.5	58.1	68.6	91.7	99.6	5.2	4.8	4.7	5.2	34.4	41.4	56.2	72.9
	50	5.3	5.4	5.2	4.7	83.2	88.6	99.7	100.0	4.4	4.7	5.3	4.3	34.4	38.8	59.6	82.2
	100	5.3	4.8	5.1	5.2	88.7	92.0	99.9	100.0	4.9	4.2	4.9	4.7	32.2	35.0	57.9	85.0
	200	4.9	5.5	4.7	4.8	83.5	89.4	99.5	100.0	4.7	5.3	4.8	4.6	34.3	35.9	59.6	86.1
$\bar{\tau}_{IV}$	25	4.1	3.8	2.4	1.3	44.1	54.9	78.0	95.3	4.1	3.6	2.4	1.6	28.6	38.0	58.5	86.3
	50	4.9	5.0	4.5	3.0	79.1	90.1	99.9	100.0	4.6	4.6	3.7	2.3	45.4	56.4	88.8	99.9
	100	4.6	4.8	4.9	5.1	94.5	98.9	100.0	100.0	4.6	4.5	4.4	4.4	53.5	69.7	95.1	100.0
	200	4.6	5.1	4.7	5.1	97.7	99.9	100.0	100.0	4.3	5.6	4.7	4.5	65.3	83.8	99.1	100.0
t_{DH}	25	5.5	6.1	6.9	7.8	48.2	63.5	89.3	99.6	6.5	7.4	8.3	10.4	39.1	50.8	73.1	91.1
	50	5.4	5.4	5.8	5.3	79.1	90.4	99.7	100.0	6.0	6.3	7.0	8.1	51.1	62.4	86.5	98.2
	100	5.1	4.9	5.4	5.5	93.5	98.9	100.0	100.0	5.2	5.2	5.4	6.2	56.4	71.1	94.6	99.9
	200	4.8	5.3	4.9	5.2	97.4	99.8	100.0	100.0	4.9	5.9	5.4	5.3	66.8	83.6	98.9	100.0
SAR(1) model																	
t_{HS}	25	5.6	5.1	5.8	6.5	57.9	69.3	92.1	99.7	5.6	5.6	5.5	5.8	34.3	40.2	57.1	72.4
	50	5.4	5.1	4.8	5.1	83.5	89.6	99.5	100.0	4.9	5.0	4.5	4.3	36.0	40.2	60.8	82.7
	100	5.5	5.0	4.7	5.0	89.3	92.4	100.0	100.0	4.4	4.8	4.6	4.4	32.8	36.0	59.3	85.5
	200	5.3	4.6	5.1	5.5	84.9	88.9	99.7	100.0	5.0	4.7	4.6	4.6	36.8	37.1	60.9	87.0
$\bar{\tau}_{IV}$	25	4.4	3.9	2.6	1.7	44.9	56.0	80.4	96.5	3.8	3.4	2.3	1.2	28.4	37.4	61.0	88.6
	50	4.8	4.9	4.2	3.6	80.8	92.2	99.8	100.0	4.3	4.5	3.5	2.9	46.0	60.1	90.4	99.8
	100	4.7	4.8	4.7	4.2	94.9	99.1	100.0	100.0	4.7	4.6	4.5	4.3	56.2	72.0	96.6	100.0
	200	4.7	4.4	5.3	5.1	98.7	99.9	100.0	100.0	4.6	4.2	5.1	4.8	72.0	86.3	99.4	100.0
t_{DH}	25	6.0	6.2	7.6	8.0	49.4	64.3	91.1	99.6	6.7	7.8	8.7	9.9	39.1	51.6	74.5	91.5
	50	5.1	5.7	4.8	6.4	80.5	92.2	99.9	100.0	5.5	6.3	6.8	8.0	51.7	65.3	88.2	98.3
	100	4.9	5.1	5.1	4.7	94.6	98.9	100.0	100.0	5.2	5.1	5.7	6.0	58.3	72.7	95.5	99.9
	200	4.8	4.6	5.5	5.3	98.5	100.0	100.0	100.0	4.8	4.7	5.0	5.1	72.0	86.8	99.3	100.0
Factor model																	
t_{HS}	25	7.9	8.3	8.6	8.7	25.3	23.8	24.7	26.3	8.2	8.8	9.0	9.1	22.4	22.0	22.7	25.3
	50	8.6	8.5	9.2	9.2	31.3	30.1	31.4	32.6	7.5	7.7	8.4	9.4	26.4	25.7	29.5	32.6
	100	8.6	8.5	9.0	9.4	34.6	32.6	34.5	35.8	7.5	6.9	7.6	8.4	27.4	27.3	33.0	37.1
	200	8.6	8.7	9.1	9.2	34.6	33.8	35.5	35.0	7.2	7.5	8.2	7.7	31.2	29.8	36.6	39.0
$\bar{\tau}_{IV}$	25	2.2	1.1	0.3	0.0	18.0	21.7	14.0	9.9	2.3	1.4	0.4	0.1	15.5	19.0	16.1	13.9
	50	3.2	2.7	1.2	0.2	44.4	61.6	60.9	70.1	2.7	2.4	1.2	0.3	31.0	43.3	53.6	67.4
	100	3.8	3.4	3.1	1.6	64.7	82.8	85.6	93.2	3.6	3.3	2.1	1.1	42.5	60.3	74.6	89.0
	200	4.3	4.1	3.9	3.2	74.5	89.1	94.6	98.5	4.1	3.9	3.4	2.5	52.7	69.5	85.9	95.6
t_{DH}	25	7.1	6.8	7.2	7.3	22.3	22.0	23.6	24.9	7.5	7.9	7.8	8.3	22.1	22.0	23.5	25.5
	50	6.4	6.5	7.9	7.7	31.4	30.4	31.8	34.0	6.4	7.0	7.8	8.4	28.8	29.1	31.6	34.9
	100	6.0	6.8	7.0	7.8	38.1	38.4	39.5	40.8	5.3	6.7	7.2	7.9	34.9	37.2	40.5	42.6
	200	6.5	5.6	7.3	6.9	43.1	42.2	45.7	45.5	5.8	5.5	6.9	6.9	42.5	44.2	49.2	49.9

Notes: t_{HS}, $\bar{\tau}_{IV}$ and t_{DH} refer to the PURT statistics defined in (2.4), (2.6) and (2.7). Simulation results are based on 5000 replications and the nominal size equals 5%. All tests are computed on prewhitened and (recursively) detrended data.

Table 2.6: Empirical rejection frequencies under multiple variance break

		Homogenous variance breaks								Heterogenous variance breaks							
		size				power				size				power			
	T N	16	26	56	106	16	26	56	106	16	26	56	106	16	26	56	106
CS independence																	
t_{HS}	30	6.4	6.2	7.3	8.6	65.7	70.5	82.2	92.0	6.1	6.8	6.1	6.8	61.7	69.5	89.0	99.0
	50	5.3	5.4	5.5	6.3	77.8	81.6	92.1	96.9	5.6	5.4	5.0	5.1	76.6	81.6	97.1	100.0
	100	5.0	4.9	4.8	4.9	82.1	86.7	96.7	99.7	5.2	4.8	4.8	4.7	83.0	84.8	98.6	100.0
	200	5.3	4.9	5.0	4.3	79.5	82.5	97.7	100.0	5.1	5.1	4.6	5.1	79.0	81.5	97.9	100.0
$\bar{\tau}_{IV}$	30	5.0	4.2	3.3	1.6	49.2	57.7	71.9	81.6	2.8	3.6	2.4	1.8	32.2	41.8	66.1	90.4
	50	5.7	5.2	4.1	2.9	71.1	80.5	92.9	97.6	4.1	3.5	3.5	3.1	64.9	77.5	97.8	100.0
	100	4.7	5.0	4.9	4.3	89.7	96.4	99.6	99.9	4.3	4.1	4.2	4.1	89.4	96.7	100.0	100.0
	200	4.8	5.0	4.8	4.7	96.8	99.5	100.0	100.0	5.0	4.2	4.3	4.3	96.8	99.5	100.0	100.0
t_{DH}	30	6.9	7.5	9.7	12.8	52.3	63.6	82.3	93.0	6.3	7.9	8.8	11.1	45.6	58.9	86.8	99.0
	50	6.1	6.0	7.4	9.3	72.5	81.7	94.4	98.6	6.7	6.1	7.5	8.5	70.6	83.8	99.0	100.0
	100	5.0	5.4	5.9	5.9	89.6	96.1	99.6	99.9	5.2	5.5	6.2	6.4	89.9	97.4	100.0	100.0
	200	5.1	5.0	5.1	5.2	96.5	99.4	100.0	100.0	5.3	4.7	5.1	5.1	96.8	99.5	100.0	100.0
SAR(1) model																	
t_{HS}	25	5.7	6.0	6.5	8.2	66.5	72.0	83.6	92.5	6.0	5.2	6.2	6.3	60.2	68.8	89.3	99.2
	50	5.4	5.5	5.8	6.2	77.4	83.0	93.1	97.3	5.2	5.2	5.4	5.2	76.2	81.5	97.1	99.9
	100	5.0	5.1	4.2	4.2	83.1	86.3	97.4	99.8	5.2	5.2	4.3	4.1	83.4	85.2	98.8	100.0
	200	5.3	4.9	5.0	4.6	78.8	82.9	97.8	99.9	5.2	5.2	5.0	4.8	79.2	82.1	98.0	100.0
$\bar{\tau}_{IV}$	25	4.7	4.3	2.8	1.7	50.6	59.1	75.1	85.8	2.9	2.6	2.0	2.0	33.6	42.8	68.1	91.3
	50	5.1	4.8	4.7	3.1	72.3	83.3	94.1	98.1	4.0	4.0	3.5	2.9	65.1	79.3	98.0	100.0
	100	5.1	5.0	4.5	4.7	90.9	96.3	99.7	100.0	4.1	4.2	3.8	3.9	90.2	97.3	100.0	100.0
	200	4.5	5.2	5.0	5.1	97.2	99.7	100.0	100.0	4.8	5.3	3.8	4.7	97.3	99.8	100.0	100.0
t_{DH}	25	6.6	7.1	9.4	12.1	55.1	67.1	84.9	95.2	6.9	6.7	8.5	11.1	45.0	59.2	88.4	99.3
	50	6.4	6.8	7.5	8.6	73.7	84.4	95.3	99.1	6.4	6.8	7.4	7.9	71.2	84.1	98.9	100.0
	100	5.5	5.9	5.6	6.3	90.2	96.2	99.8	100.0	5.2	5.6	5.5	6.0	90.9	97.6	100.0	100.0
	200	4.4	5.0	5.1	5.7	96.8	99.5	100.0	100.0	5.2	6.1	4.8	5.9	97.4	99.8	100.0	100.0
Factor model																	
t_{HS}	30	7.6	8.1	8.0	8.1	47.7	49.2	53.9	58.4	6.2	6.7	6.6	7.1	51.0	54.6	63.4	72.7
	50	6.8	6.8	7.9	8.0	59.2	59.6	67.3	71.4	6.1	5.5	6.2	6.8	63.2	64.2	76.1	82.6
	100	6.1	6.2	6.9	6.4	68.3	69.8	78.8	83.1	6.0	5.9	6.3	6.1	70.5	70.6	83.2	88.1
	200	6.4	6.1	6.6	6.7	68.6	68.8	82.5	87.2	5.9	6.3	6.2	6.4	69.5	68.8	83.5	90.1
$\bar{\tau}_{IV}$	30	3.4	2.7	1.8	0.8	36.4	43.3	48.0	52.4	3.1	3.2	2.2	0.8	31.7	38.8	44.7	52.4
	50	3.7	2.9	1.5	0.5	57.7	66.3	72.4	78.0	3.7	3.1	2.5	1.0	57.8	68.7	83.0	93.4
	100	3.7	3.1	1.6	0.6	79.1	88.1	93.4	95.9	3.8	3.5	3.2	2.0	83.2	92.3	98.9	99.8
	200	3.9	3.5	2.3	1.1	92.0	96.5	98.9	99.7	4.7	4.4	4.3	2.6	93.2	98.5	99.9	100.0
t_{DH}	30	6.6	7.6	7.8	8.3	39.6	44.5	50.0	53.2	6.0	7.1	8.4	8.4	37.5	42.7	48.7	55.0
	50	6.2	6.4	6.6	8.2	54.6	58.3	64.0	68.2	5.9	6.2	6.9	8.2	55.9	60.8	69.8	76.1
	100	5.1	6.1	6.5	6.9	72.5	76.7	82.5	84.3	5.3	5.4	6.4	6.7	75.7	81.2	87.0	91.3
	200	5.4	5.6	5.8	6.5	85.1	87.3	92.6	93.4	5.6	5.0	5.6	5.7	86.0	88.9	94.8	96.5

Notes: t_{HS}, $\bar{\tau}_{IV}$ and t_{DH} refer to the PURT statistics defined in (2.4), (2.6) and (2.7). Simulation results are based on 5000 replications and the nominal size equals 5%. All tests are computed on prewhitened and (recursively) detrended data.

particular, the empirical sizes reach as small as 0.8% for $\bar{\tau}_{IV}$ and as high as 11.1% for t_{DH} while rejection frequencies of t_{HS} range between 4.1–7.1%.

2.4.3 Summary of simulation results

Overall, the main findings of the Monte Carlo study on the comparative small sample properties of t_{HS}, $\bar{\tau}_{IV}$ and t_{DH} can be summarized as follows.

1. There are noticeable small sample performance differences among the three tests even under time-invariant volatility. In this case, the two White-type tests, t_{HS} and t_{DH}, exhibit very good size properties in independent and weakly dependent panels except that t_{DH} is slightly over-sized for the smallest considered time dimension ($T = 25$). In strongly correlated panels, however, t_{HS} is about 2.0 % more over-sized than t_{DH}. Of the three tests, $\bar{\tau}_{IV}$ displays the most severe size distortions, with its empirical size completely vanishing as N increases for a given T, and especially so under strong cross-sectional correlation.

2. The impact of volatility shifts on the empirical rejection frequencies of the tests depend on both the direction and timing of the breaks. In general, the most severe size distortions are observed when all the panel units uniformly experience early downward volatility shifts. In this setting, and under weak or no cross-unit dependence, even t_{HS} rejects the null hypothesis too frequently (12.9%) when $T = 25$ although t_{HD}'s over-rejections are seen when $T = 50$ as well, with its empirical sizes becoming as high as 17.4%. The two tests do not exhibit such distortion associated with small T for strongly correlated panels, however. In the latter case, it is $\bar{\tau}_{IV}$ that displays most severe size distortions, with a maximum of only 0.2% rejection rates observed in more than half of the considered T and N combinations.

3. On the contrary, positive variance break significantly distorts empirical sizes of the tests when it occurs late in the time series. The effects of late positive variance break, albeit being somehow muted, are by and large similar to those of early negative variance break. Interestingly, early and middle positive variance breaks appear to offset the upward size distortions of t_{HS} in strongly correlated panels observed even under homoskedasticity. In this volatility shift

scenario, t_{HS} clearly outperforms the two Cauchy tests irrespective of the type of cross-sectional dependence present in the data.

4. The occurrence of multiple variance breaks per each panel unit does not appear to pose additional challenges to the small sample performances of the considered tests. On the contrary, it allows t_{HS} to take advantage of the available early to middle upward volatility shifts and, thereby, display the best size control of all the considered tests in all the cross-sectional dependence scenarios.

5. All tests appear to be equally powerful in independent and weakly dependent panels apart from the fact that t_{HS} is less powerful for the smallest considered cross-sectional dimensions $N = 16$, and $= 26$. Moreover, all tests are less powerful under cross-sectional dependence than independence; the smallest empirical probabilities of rejecting the alternative hypothesis are reported when the errors are strongly correlated. In most of the volatility shift cases involving strongly correlated errors, t_{HS} and $\bar{\tau}_{IV}$ appear to be the least and the most powerful tests, respectively, although t_{HS} is only marginally less powerful than t_{DH}.

2.5 An empirical application: the long-run causality in the finance-growth nexus

2.5.1 Economic background

The relationship between financial development—improvements in the quality and quantity of financial instruments and services—and economic growth has been extensively discussed in the past century. Existing theoretical predictions on the direction of causality between finance and growth can be grouped into three. First, Schumpeter (1911), McKinnon (1973) and Levine (2005) emphasize that the financial sector development induces economic growth by enhancing both the volume and efficiency of investment through various ways. For instance, a developed financial sector mobilizes a larger volume of savings and more efficiently identifies high-return projects. It also allows economic agents to diversify inter-temporal and cross-sectional risks. Furthermore, it facilitates the exchange of goods and services, thereby reducing transaction costs. The latter is in particular crucial for technological innovation which increasingly demands a higher degree of specialization that, in turn, entails an increased number of transactions (Greenwood and Smith, 1997). Second, Robinson (1952) argues that financial development does not cause economic growth; rather, it simply occurs in response to the demand generated by a growing real sector. Third, Patrick (1966) and Greenwood and Jovanovic (1990) hypothesize that the causality between finance and growth is bidirectional. This group also propose that the direction of causality depends on an economy's level of development. According to Patrick (1966), the finance-growth (FG) causality runs from finance to growth at an earlier stage of economic development, and in the reverse direction as the economy develops. In contrast, Greenwood and Jovanovic (1990) emphasize that the creation and deployment of financial institutions is very costly. As a result, they predict that financial development arises—and, hence, starts to promote economic growth—endogenously at a later stage of economic development.

Empirically, the FG causality has attracted several contributions in the past two decades. However, the evidence remains generally mixed. On the one hand, several cross-country studies consistently document that financial development has a positive impact on economic growth (see King and Levine, 1993; Levine et al., 2000; Beck et al., 2000b; Hassan et al., 2011). Although most of these studies apply certain econometric tools to ensure that the potential endogeneity of financial development does not yield biased estimates, they, however, do not explicitly test whether growth indeed causes finance. On the other hand, the evidence from economy-specific time series studies, which usually apply cointegration tests, is inconclusive (see Demetriades and Hussein, 1996; Xu, 2000; Ang and McKibbin, 2007). These time-series-based contributions are, however, constrained by a typically small number of observations, making the reliability of the results from the cointegration tests questionable. For this reason, application of panel cointegration tests in the FG causality has received considerable attention in recent years (Christopoulos and Tsionas, 2004; Apergis et al., 2007). Using data from ten developing economies, Christopoulos and Tsionas (2004) find a unidirectional causality from financial depth to economic growth. On the contrary, Apergis et al. (2007) diagnose a bidirectional causality between finance and growth in a panel of 15 OECD and 50 non-OECD economies. These results, however, have to be interpreted carefully, as the employed PURTs exhibit significant size distortions under time-varying innovation variances. In the following, we will analyze the FG causality using data from 74 economies spanning the period 1975–2005. To this end, we first demonstrate the existence of volatility breaks in the employed economic growth and financial development measures. Subsequently, we apply the three PURTs considered in this chapter, utilize error-correction-based panel cointegration tests and discuss estimation results.

2.5.2 Data

Our data set covers 74 economies over the period 1975–2005. The economies are selected depending on data availability. To examine whether causal effects depend on stages of economic development, we classify economies into four income groups: low-income (19), lower-middle income (18), upper-middle income (16), and high-income (25) economies. The list of economies in each group is provided in Chapter 5.B. We measure financial development using credit by deposit money banks and other financial institutions to the non-financial private sector as a percentage of GDP (PRV). This data is taken from the 2008 update of the *Financial Development and Structure Database* of Beck et al. (2000a)[5]. PRV is a widely used measure of financial development for the reason that it excludes credit to the public sector and, moreover, it leaves out credit issued by the central bank (Beck et al., 2000a; Levine et al., 2000). Following standard practice in the FG nexus literature (e.g., Demetriades and Hussein, 1996; Christopoulos and Tsionas, 2004; Apergis et al., 2007), we measure economic growth by real GDP per capita ($GDPPC$). Summary statistics and a broader discussion of the data can be found in Chapter 5.3.1.

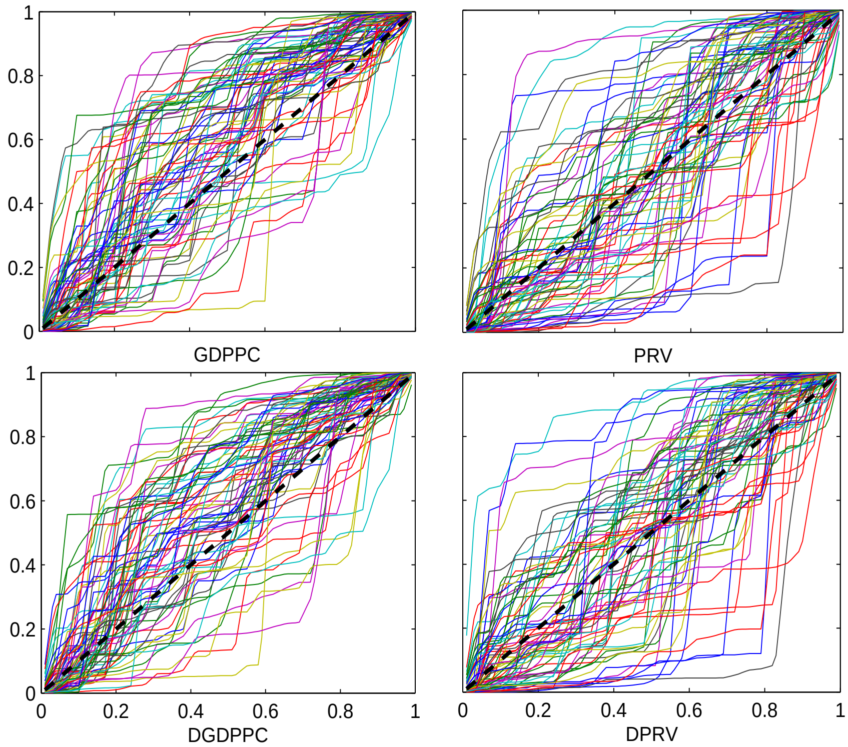
To get an impression of the volatility processes governing the sample data, we estimate variance profiles $\hat{\vartheta}_i(s)$ of $GDPPC$ and PRV, and their first differences, $DGDPPC$ and $DPRV$ (see Cavaliere and Taylor, 2007b for details and alternative estimators of variance profiles). Variance profiles $\vartheta_i(s)$ are calculated as

$$\hat{\vartheta}_i(s) = \frac{\sum_{t=1}^{\lfloor sT \rfloor} \hat{e}_{it}^2 + (sT - \lfloor sT \rfloor)\hat{e}_{i\lfloor sT \rfloor + 1}^2}{\sum_{t=1}^{T} \hat{e}_{it}^2}, \tag{2.16}$$

[5] `http://go.worldbank.org/X23UD9QUX0`

where the $\hat{e}_{it}$'s are residuals from the first order autoregression of the considered process. Figure 2.1 displays estimated variance profiles of the time series for the comprehensive cross section (74 economies). The broken 45ï¿½ line represents a (perfectly) homoskedastic variance profile, and significant deviations from the diagonal indicate time-varying volatilities. The figure reveals that variances are time

Figure 2.1: Estimated variance profiles, 74 economies



varying for most economies. Moreover, while estimated variance profiles markedly differ across economies, financial development exhibits greater volatility than economic growth. In the following, we apply heteroskedasticity-robust PURTs to examine the order of integration of $GDPPC$ and PRV. Subsequently, we diagnose the long-run FG casuality by means of error-correction-based panel cointegration tests.

2.5.3 Panel unit root test results

Testing the existence of a long-run FG relationship involves a two-step procedure. In the first step, the order of integration of $GDPPC$ and PRV should be diagnosed. These variables are expected to be integrated of order one, denoted as $I(1)$. To confirm this, it is necessary that we fail to reject the null of unit root when the variables are used in levels ($GDPPC$ and PRV), but not when the variables are first-differenced ($DGDPPC$ and $DPRV$). The second step involves testing whether the two $I(1)$ variables are cointegrated.

To test if $GDPPC$ and PRV are $I(1)$ variables, we first prewhiten the raw data according to the procedure discussed in Section 2.3.1. The lag length of the first-differenced series in the prewhitening regression is set to one.[6] Assuming that the variables contain a non-zero mean under the stationary alternative, we recursively demean the prewhitened data. In the FG literature, it is common to report PURT results with and with out trends. In fact, it seems more realistic to expect $GDPPC$ and PRV to be either random walks with drift or trend stationary processes. However, we have discussed in Section 2.3.2 that in such cases available PURTs and detrending schemes do not yield sensible results under time-varying volatility, which we have shown is the case in our data. As a result, we restrict ourselves to testing unit roots on recursively demeaned data, and hence, the results should be interpreted with caution.

Table 2.7 documents PURT results of the empirical application. Entries in the upper panel of the table refer to PURT statistics for the levels while the lower panel report results for first differences. Numbers in parentheses are $p-$values obtained from the standard Gaussian distribution. Results documented in the upper left block of Table 2.7 indicate that, in all considered cross sections, the null of a unit root for $GDPPC$ cannot be rejected at 5% significance level. Indeed, the minimum p-value we could obtain is 26%. This result is in line with our expectation and consistent with related literature (Christopoulos and Tsionas, 2004; Apergis et al., 2007). Regarding PRV, results documented in Table 2.7 indicate that applying either of the three tests leads to rejection of the null of nonstationarity of PRV in low-, upper-middle-, and high-income economies. For the panel of lower-middle income economies as well as for the comprehensive panel, however, the employed tests offer contradicting evidence about the order of integration of PRV. As we have established using Monte Carlo simulations that τ_{IV} displays severe downward size distortions for N not relatively smaller than T, its suggestion not to reject the null cannot be taken seriously. Observed patterns from the simulation exercise might also

[6]We prefer a common lag length to economy-specific lag lengths in order to retain a balanced panel.

Table 2.7: Panel unit root test results

	GDPPC			*PRV*		
Cross section	t_{HS}	$\bar{\tau}_{IV}$	t_{DH}	t_{HS}	$\bar{\tau}_{IV}$	t_{DH}
Variables in levels						
Low income	-0.642	0.492	0.385	-1.096	-0.510	-0.243
	(0.260)	(0.689)	(0.650)	(0.137)	(0.305)	(0.404)
Lower middle	0.824	0.617	0.952	**-1.774**	-1.227	-1.522
	(0.795)	(0.731)	(0.830)	(0.038)	(0.110)	(0.064)
Upper middle	1.452	1.799	2.038	-1.527	-0.778	-0.947
	(0.927)	(0.964)	(0.979)	(0.063)	(0.218)	(0.172)
High income	1.137	0.587	1.009	0.704	1.676	2.325
	(0.872)	(0.721)	(0.843)	(0.759)	(0.953)	(0.990)
World	0.719	1.600	1.777	**-1.949**	0.238	-0.284
	(0.764)	(0.945)	(0.962)	(0.026)	(0.594)	(0.388)
Variables in first differences						
Low income	-2.380	-5.323	-3.960	-3.387	-4.043	-3.928
	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower middle	-3.103	-4.420	-3.514	-2.782	-3.210	-3.950
	(0.001)	(0.000)	(0.000)	(0.003)	(0.001)	(0.000)
Upper middle	-3.881	-4.195	-3.570	-3.941	-3.839	-3.838
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High income	-3.131	-3.398	-2.910	-3.092	-3.190	-3.000
	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
World	-3.507	-6.312	-4.386	-4.089	-4.786	-4.564
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: t_{HS}, $\bar{\tau}_{IV}$ and t_{DH} refer to the PURT statistics defined in (2.4), (2.6),(2.7). Numbers in parentheses are $p-$values.

help in explaining the fact that t_{HS} but not t_{DH} supports rejection of the null at the 5% significance level. Considering that $T = 31$ in our data, financial development is correlated across economies, and the series display significant heteroskedasticity, we expect a higher rejection probability of the null by t_{HS} and of the alternative by t_{DH}. Accordingly, the obtained results are somehow indicative of nonstationarity of PRV. In the lower panel of Table 2.7, the tests suggest stationarity of the first differences of $GDPPC$ and PRV in all the cross sections. This implies that, in all cross sections, the employed financial development and economic growth measures are integrated of order one.

Table 2.8: Panel cointegration test results

	Dependent var.: $GDPPC$				Dependent var.: PRV		
	Statistic	Z-value	P-value	Robust P-value	Z-value	P-value	Robust P-value
Low income	Gt	-4.466	0.000	**0.000**	-1.052	0.146	0.095
	Ga	-1.035	0.150	**0.013**	0.126	0.550	0.115
	Pt	-4.316	0.000	**0.005**	-1.511	0.065	0.086
	Pa	-3.899	0.000	**0.004**	-1.370	0.085	0.056
Lower middle	Gt	1.253	0.895	0.643	-1.941	0.026	**0.020**
	Ga	2.645	0.996	0.923	0.545	0.707	0.170
	Pt	2.019	0.978	0.826	-1.756	0.040	0.130
	Pa	1.982	0.976	0.851	-0.371	0.355	0.230
Upper middle	Gt	1.253	0.895	0.643	-4.061	0.000	**0.000**
	Ga	2.645	0.996	0.923	0.366	0.643	0.073
	Pt	2.019	0.978	0.826	-2.425	0.008	**0.033**
	Pa	1.982	0.976	0.851	-0.440	0.330	0.121
High income	Gt	6.606	1.000	1.000	-1.942	0.026	**0.018**
	Ga	4.537	1.000	0.998	0.517	0.697	0.055
	Pt	5.643	1.000	0.993	-1.224	0.110	0.160
	Pa	3.876	1.000	0.991	-1.113	0.133	0.071
World	Gt	5.483	1.000	0.986	-4.522	0.000	**0.000**
	Ga	5.342	1.000	0.980	1.187	0.882	**0.019**
	Pt	5.090	1.000	0.941	-3.654	0.000	**0.015**
	Pa	4.310	1.000	0.935	-1.220	0.111	**0.030**

Notes: Both variables are used in their logarithmic forms. Fixed effects, and one lag and one lead of the first differences are included in the test equations. The null hypothesis in all the tests is no cointegration. P_a and P_t (called *panel statistics*), have an alternative hypothesis such that a rejection of the null hypothesis should be taken as evidence of cointegration for the panel as a whole. For G_a and G_t (called *group mean statistics*), a rejection should imply cointegration for at least one cross-sectional unit. Bold-faced values indicate rejections of the null at the 5%significance level. The number of bootstrap replications used to calculate robust p-values is 5,000. The tests are computed in STATA 11 using the user written command 'xtwest' of Persyn and Westerlund (2008).

2.5.4 Panel cointegration test results

We now move on to investigating the existence of a cointegrating relationship between finance and growth. Here, it should be noted that testing cointegration by applying panel unit root tests on the residuals obtained from regressions of $GDPPC$

on PRV and vice versa, as in Christopoulos and Tsionas (2004), could be misleading. Although residual-based cointegration tests typically apply unit root tests on the residuals from regressions of $I(1)$ variables, the tests will have to account for the fact that the residuals are estimated values. This implies that the usual PURT critical values are no longer appropriate and the distributional properties of the tests have to be adjusted accordingly. This adjustment is required even when testing cointegration between variables for a single cross-sectional unit. Accordingly, several panel cointegration tests have been forwarded in recent years. Among the existing panel cointegration tests, those suggested in Pedroni (1999, 2004) are perhaps the most popular ones. Notable applications of Pedroni's cointegration tests in the FG literature include the works of Apergis et al. (2007) and Fowowe (2010). A major limitation of these tests is, however, that they are not robust to cross-sectional dependence. To handle this issue, Pedroni (2004) suggests applying the tests on data demeaned with respect to common time effects; but, it is obvious that demeaning removes only a very specific form of cross-sectional dependence. In the increasingly integrated world, the presence of cross-sectional correlation among economies is unquestionable. As a result, we employ the tests suggested in Westerlund (2007) where the recommended bootstrapping procedure takes care of a more general form of cross-unit dependence.[7] It is not clear, however, whether the bootstrapping procedure is immune to the nonstationary volatility observed in our data. Therefore, the results should be interpreted with some degree of caution.

Westerlund's (2007) tests are error-correction-based tests, i.e., they are founded on the fact that two variables cointegrate if and only if there exists an error-correction representation for either or both of the variables (Engle and Granger, 1987). The null hypothesis for all his tests is that there is no error correction (no cointegration). Two of his tests, P_a and P_t (called *panel statistics*), have an alternative hypothesis such that a rejection of the null hypothesis should be taken as evidence of cointegration for the panel as a whole. For the other two, G_a and G_t (called *group mean statistics*), a rejection should imply cointegration for at least one cross-sectional unit.

[7]Another merit of these tests is that, being error-correction-based tests, they do not impose potentially invalid common-factor restrictions that are inherent in the residual-based cointegration tests. Specifically, residual-based cointegration tests invoke the assumption that the long-run cointegrating vector for the variables in their levels is equal to the short-run adjustment process for the variables in their (first) differences (Westerlund, 2007).

Estimation results are reported in Table 2.8. As argued above, we base our decision on the bootstrap (cross-sectional-dependence-robust) p-values. The results documented in the table indicate that the causality evidence varies across income groups. In low-income economies, there is strong evidence of long-run FG relationship, with the causality running from finance to growth. This is in line with Patrick's (1966) argument that finance matters most at earlier stages of economic development. In the other cross sections, we cannot reject the null of no error correction if $GDPPC$ is used as a dependent variable. Evidence of a long-run FG relationship with the causality running from the real to the financial sector is obtained on the comprehensive cross section of 74 economies. Although all the four tests do not usually lead to the same conclusion, some degree of support to the view that "*where enterprise leads finance follows*" (Robinson, 1952) is also found in middle- and high-income economies. In these cross sections, at least the Gt statistic suggests rejection of the null of no cointegration and, hence, implies a long-run FG nexus in at least one economy.

2.6 Conclusions

In this chapter, we investigated the small sample performances of the three most important heteroskedasticity-robust panel unit root tests (PURTs) suggested to date. These tests are the White-type test in Herwartz and Siedenburg (2008), the Cauchy test in Demetrescu and Hanck (2012b) and the Cauchy version of the White-type test as proposed by Demetrescu and Hanck (2012a). After formally defining the tests, we discussed recommended methods of handling serial correlation and deterministic terms. Notably, it is underlined that all the tests—and, hence, all PURT we are aware of—do not work if the data feature non-zero intercepts under the null of unit root with time-varying volatility. Neither do standard detrending schemes effectively remove the trend when the errors are heteroskedastic. Focusing on distinguishing between a driftless random walk and a stationary process with cross section specific intercepts, we conduct Monte Carlo experiments for a wide range of cross-sectional dependence and volatility break scenarios.

Our simulation results clearly demonstrate that the Cauchy estimator in Demetrescu and Hanck (2012b) is severely undersized when N is relatively larger than T. In contrast, the two White-type statistics display reliable size control in most of the considered variance break cases and sample dimensions. In the smallest considered time dimension, $T = 25$, however, the Cauchy-instrumented White-type test of Demetrescu and Hanck (2012a) is markedly oversized. Shifts in innovation volatility increase these size distortion of the test in Demetrescu and Hanck (2012a) under relatively small time dimension, and, to some extent, induce similar overrejections for the one in Herwartz and Siedenburg (2008). However, only early negative and late positive variance breaks cause the most severe of the above-mentioned size distortions. On the contrary, early and middle positive variance breaks appear to offset the upward size distortions of the White-type test of Herwartz and Siedenburg (2008) in strongly correlated panels. Therefore, we conclude that both White-type tests are empirically relevant heteroskedasticity-robust PURTs, although the one without Cauchy instrumenting is the most dependable one when the time dimension is small.

As an empirical illustration, the cointegration relationship between financial development and economic growth is considered using data from 74 economies during 1975-2005. Applying the heteroskedasticity-robust PURTs, we find that both financial development and economic growth are integrated of order one. The employed error-correction-based panel cointegration tests of Westerlund (2007) generally indicate the existence of a long-run relationship between financial development and economic growth. The direction of causality, however, differs across income groups. Strong evidence of the "finance leads growth" hypothesis is diagnosed in low-income economies. In the remaining income groups, however, the causality runs from growth to finance, and not vice versa. As a consequence, the latter evidence turns out to be the dominant direction of causality observed in the comprehensive panel, supporting Robinson's (1952) view that "*where enterprise leads finance follows.*"

3 The long-run finance-growth nexus in Sub-Saharan Africa

3.1 Introduction

The role of financial intermediaries in the process of technical innovation and economic development has been recognized since, at least, Schumpeter's (1911) work. Since then, a number of economists and institutions like McKinnon (1973), Shaw (1973), the World Bank (1989) and Levine (2005) have highlighted that development in the financial sector could foster economic development by raising the level of investment and facilitating the allocation of resources to their best uses. However, others like Robinson (1952) believe that it is the demand from a growing real sector that stimulates financial development, and not vice versa. Another group of economists such as Patrick (1966) and Greenwood and Jovanovic (1990) argue that the causal relationship between financial development and economic growth is bidirectional. According to Patrick (1966), the financial system and its services develop as a result of the demand generated by economic growth (called "demand-following" phenomenon) and financial development in turn causes economic growth (called "supply-leading" phenomenon). Over the last two decades, extensive empirical research works have tried to clarify the finance-growth (FG) causality using a range of econometric tools and data sets. The evidence, however, remains to be largely mixed.[8]

The inconclusiveness of the worldwide evidence and the ambiguity on the impact of the level of economic development on the FG nexus (Ghirmay, 2004) have triggered several region-specific empirical studies. In this regard, a few studies have tried to examine the FG causality in Sub-Saharan African (SSA) economies. For instance, Ghirmay (2004), using economy-specific time series analysis, finds one cointegrating vector linking finance and growth in 13 SSA economies. But, the obtained evidence on the direction of FG causality is mixed. In particular, he finds evidence for bidirectional FG causality in six, for the "finance leads growth" hypothesis in eight and for the "growth leads finance" hypothesis in nine economies. On the other

[8]See Levine (2005) and Ang (2008a) for extensive surveys of the theoretical and empirical FG literature.

hand, applying a trivariate Vector Autoregressive model, Gries et al. (2009) find a long-run relationship in only six out of 16 SSA economies and conclude that the results in Ghirmay (2004) are generated by a misspecified (i.e., bivariate) model. However, it is also possible that the lack of cointegration in their study might be a result of the decreasing degrees of freedom due to the increase in the number of model parameters or their usage of a different proxy for financial development.

Aiming at exploiting the superior statistical power of panel cointegration tests, Fowowe (2010) examines the FG nexus in 17 SSA economies over the period 1975–2005 by means of residual-based panel cointegration tests suggested in Pedroni (1999, 2004). Although Fowowe (2010) finds a homogeneous short-run bidirectional causality, he cannot reject the null of no cointegration (no long-run relationship) between finance and growth. However, these results should be interpreted carefully for two methodological reasons. First, residual-based panel cointegration tests like those in Pedroni (1999, 2004) are less powerful when the so-called "common-factor restrictions" are invalid (Westerlund, 2007).[9] Thus, it is possible that the obtained results are generated by the failure to satisfy those restrictions. Second, Fowowe (2010) does not take into account the cross-sectional dependence that could most likely exist among SSA economies. For instance, SSA economies are small economies that are highly dependent on export of unprocessed primary commodities like minerals and agricultural products (Wood and Mayer, 2001). The prices of these products are determined in the international market where small economies are often price takers. In line with this argument, Kose and Riezman (2001) show that trade shocks explain almost half of the aggregate output fluctuation in Africa. Therefore, it is very likely that SSA economies are vulnerable to common global macroeconomic shocks—a typical source of cross-sectional dependence considered in the econometric literature (Driscoll and Kraay, 1998). On the other hand, every economy in SSA is a member of one or more of the regional economic blocks—or even of a monetary union in the case of West Africa (Geda and Kebret, 2008). This regional economic integration lends a considerable interdependence to economic performances of SSA economies. Therefore, one can also imagine that the results in Fowowe (2010) are partly generated by the unrealistic cross-sectional independence assumption.

[9]Common-factor restriction is the assumption by residual-based cointegration tests that the long-run cointegrating vector for the variables in their levels is equal to the short-run adjustment process of the (first) differenced variables (Westerlund, 2007).

To overcome the problems associated with residual-based tests, Westerlund (2007) proposes error-correction-based tests that do not impose common-factor restrictions. Moreover, he suggests bootstrapping procedures that yield cross-sectional dependence robust p-values. Capitalizing on these two crucial merits of the tests in Westerlund (2007), we examine the long-run FG causality in SSA. This way, we check if the results in Fowowe (2010) would change when panel cointegration tests in Westerlund (2007), instead of those in Pedroni (1999, 2004), are applied on the same data.

In particular, this paper contributes to the literature on the FG nexus in SSA in at least two ways. First, given the typically small number of observations of annual macroeconomic data, it is not clear whether the inability to reject the null of no cointegration in economy-specific time series analyses is a small sample problem of the tests or indeed evidence of lack of long-run relationships. By pooling time series data of 17 SSA economies, we use information in an efficient way and make cointegration tests more powerful. Second, among panel cointegration tests, we exploit the ones proposed by Westerlund (2007), which do not impose potentially invalid common-factor restrictions, and take into account cross-sectional dependence among SSA economies.

Our results indicate the presence of a long-run relationship between financial development and economic growth in SSA. Although the direction of causality appears to depend somehow on the employed measures of financial development, there is unambiguous evidence that financial development has a long-run impact on economic growth. Furthermore, the long-run FG nexus estimates are positive and statistically significant, justifying policies aimed at developing the financial sector in SSA in order to promote long-run economic development.

Section 3.2 outlines the nature and measurement of the data. Section 3.3 briefly describes the employed unit root and cointegration tests as well as the dynamic OLS estimator of the long-run coefficients. Section 3.4 discusses empirical results. Section 3.5 concludes.

3.2 Data

One of the main challenges in the FG literature has been measuring financial development, mainly because the concept is very broad, which in turn is related to the size of the financial sector. In this study, we employ two of the most widely used financial development indicators. The first indicator is $LIQUID$, which equals currency plus demand and interest-bearing liabilities of banks and other financial intermediaries divided by GDP. This is the broadest indicator of financial intermediation (Beck et al., 2000a). A major weakness of $LIQUID$ is that it incorporates claims of financial intermediaries on both the public (governments and public enterprizes) and the private sector. It is generally agreed upon that a financial system that lends its resources to the public sector is less growth-promoting than a financial system that allocates credit to the private sector (King and Levine, 1993). The second measure, PRV, mitigates this problem by singling out credit to the private sector. Specifically, PRV equals credit by deposit money banks and other financial institutions to the non-financial private sector as a percentage of GDP. As such, it also excludes credit issued by the central bank. Therefore, PRV measures the activity of financial intermediaries in channeling savings to investors, and consequently, is well-suited to assess the impact of financial development on investment and economic growth (Beck et al., 2000b).

The stock-flow problem arising from dividing financial variables measured at the end of the year by nominal GDP measured over the year is addressed according to Beck et al. (2000a). Accordingly, real financial variables are obtained by deflating end-of-year financial variables by end-of-year consumer price index, and subsequently average real financial variables from year t and $t-1$ are divided by real GDP at year t.

Following a standard practice in the FG literature, we measure economic development by real GDP per capita (e.g., Demetriades and Hussein, 1996; Ghirmay, 2004; Fowowe, 2010). We pull together panel data of 17 SSA economies over the period 1975-2005.[10] The selection of economies is based on availability of data on financial variables for a sufficiently long time period. Furthermore, this is the cross-

[10]The economies are Burundi, Burkina Faso, Botswana, Cote d'Ivoire, Cameroon, Gabon, Ghana, Gambia, Kenya, Madagascar, Niger, Nigeria, Senegal, Sierra Leone, Swaziland, Seychelles and Togo.

section of economies studied by Fowowe (2010).[11]

Both LIQUID and PRV are obtained from the 2008 update of *Financial Development and Structure Database* of Beck et al. (2000a)[12], while real GDP per capita is drawn from the 2009 edition of World Development Indicators.

3.3 Methodology

3.3.1 Unit root tests

Panel unit root tests are usually more powerful than their time series equivalents as they utilize both the cross-sectional and time series dimensions of data. This property makes them more desirable in studies that involve short time series data like ours where statistical power of time series tests is generally low. However, switching from time series to panel unit root tests creates some new challenges such as specification of the alternative hypotheses and handling of cross-sectional dependence among the panel units. The former challenge gives rise to the so-called *homogeneous* and *heterogeneous* panel unit root tests and the latter triggers the *first generation* and *second generation* panel unit root tests (Breitung and Pesaran, 2008).

Rejecting the null hypothesis in *homogeneous* panel unit root tests like Levin et al. (2002), and Breitung and Das (2005) is considered as evidence of stationarity for the panel as a whole. Yet, in the alternative hypothesis of *heterogenous* panel unit root tests such as Im et al. (2003), some time series can still be nonstationary.

Applying the *first generation* unit root tests such as those in Levin et al. (2002) and Im et al. (2003) to macroeconomic series is problematic as economies are becoming increasingly integrated. When the cross-sectional independence assumption is violated, the *first generation* unit root tests exhibit marked size distortions (Breitung and Das, 2005). The *second generation* tests are those tests which are robust to cross-sectional dependence. This generation include tests suggested in Breitung and Das (2005) and Herwartz and Siedenburg (2008). Given their geographical proximity, their vulnerability to similar global price shocks and

[11] One of the difficulties in comparing empirical FG nexus evidence in SSA is the fact that researchers usually select different samples of economies. By sticking to Fowowe's (2010) sample, we not only make our results easily comparable to his, but also intend to make this sample somewhat standard and invite others to use this set of economies in the future.

[12] `http://go.worldbank.org/X23UD9QUX0`

their participation in various regional economic blocks, we argue that cross-sectional dependence among SSA economies cannot be ruled out. Hence, our decision about the stationarity of the series should be based on cross-sectional dependence robust panel unit root tests. Furthermore, as discussed in Chapter 2, most of the existing panel unit root tests display severe size distortions if the considered series feature time-varying volatility. Therefore, in this paper, we employ the tests suggested in Herwartz and Siedenburg (2008) and Demetrescu and Hanck (2012a) —tests that are robust to cross-sectional dependence as well as variance shifts.

3.3.2 Error-correction-based panel cointegration tests

As in unit root testing, the potential improvement in statistical power emanating from the use of both the time-series and cross-sectional dimensions of data is the main merit of panel cointegration tests in comparison with their time series counterparts. Perhaps the most widely used panel cointegration tests are those suggested in Pedroni (1999, 2004). These tests follow the Engle and Granger (1987) method of testing for unit roots in the residuals that are obtained from a standard OLS regression. However, Westerlund (2007) shows that such residual-based tests impose common-factor restrictions, which, when violated, can significantly reduce the power of the tests. Instead, Westerlund (2007) suggests error-correction-based tests that are founded on the famous representation theorem of Engle and Granger (1987) that two variables cointegrate if and only if there exists an error-correction representation for either or both of the variables. A notable property of error-correction-based tests is that they do not impose common-factor restrictions. To handle cross-sectional dependence among the panel units, Westerlund (2007) suggests a bootstrapping procedure that yields p-values that are robust to a very general form of cross-unit correlation. Therefore, in this study, we apply error-correction-based tests to examine if there exists a long-run relationship between financial development and economic growth in SSA.

In another similarity with unit root testing, there are two ways of specifying the alternative hypothesis of no cointegration. Two of the four error-correction-based tests proposed by Westerlund (2007), P_a and P_t, are called *panel statistics*. In these tests, the alternative hypothesis is specified such that a rejection of the null hypothesis is taken as evidence of cointegration for the panel as a whole. For the other two tests, G_a and G_t, called *group mean statistics*, a rejection implies cointegration for at least one cross-sectional unit.

An important assumption for the power of these tests is that the explanatory variable should be weakly exogenous with respect to the short-run and long-run parameters. This assumption is equivalent to saying that the explanatory variable should not be error correcting. In cases where the weak exogeneity assumption may not be satisfied, Westerlund (2007) recommends inclusion of leads, in addition to lags, in the error-correction equation to increase the power of tests.[13]

3.3.3 Estimating the cointegration parameter

The mere finding of a cointegration relationship between finance and growth in SSA economies is not sufficient to conclude that the economies benefit from financial development, as the relationship could also be negative, or very weak. Several estimators of cointegration parameters in panel data have been proposed in the literature. Of these estimators, the so-called Dynamic OLS (DOLS) and Fully Modified OLS (FMOLS) estimators appear to have gained considerable attention among practitioners. Kao and Chiang (2000) shows that the DOLS estimator outperforms FMOLS, and especially so in small samples. Accordingly, we estimate the long-run FG nexus by means of the DOLS estimator. This estimator is an OLS estimator of a cointegration equation in levels augmented with lags and leads of the explanatory variables in their first differences. The lag and lead augmentation is shown to be instrumental in mitigating estimation problems arising from endogeneity and serial correlation (Saikkonnen, 1991; Stock and Watson, 1993). Lastly, it is worth mentioning here that applying DOLS on panel data requires taking care of the economy-specific (fixed) effects as well as the cross-sectional dependence among panel units. The former issues is handled through the within and random effects estimators while the latter is addressed by employing cross-sectional dependence robust standard errors suggested in Driscoll and Kraay (1998).

[13]Computational work is done in STATA 11 using the user written command "xtwest" of Persyn and Westerlund (2008).

3.4 Empirical results

An important prerequisite for the existence of a long-run relationship between financial and economic development is that both variables should be integrated of order one. Accordingly, we test for unit roots in real GDP per capita (GDPPC), the percentage of liquid liabilities in GDP (LIQUID), and credit to the private sector as a percentage of GDP (PRV), first in levels and then in first differences. Table 3.1 reports results from unit root testing. The results indicate that the null of unit root for $GDPPC$ and PRV cannot be rejected (at the 5% level of significance) by applying either of the heteroskedasticity-robust panel unit root tests. Nevertheless, the two tests offer contradicting evidence on the order of integration of $LIQUID$: while the test in Demetrescu and Hanck (2012a) suggests rejecting the null of nonstationarity of $LIQUID$, the one in Herwartz and Siedenburg (2008) implies that the variable may not be integrated of order one. Hence, some caution should be exercised when interpreting the ensuing results on the “cointegration” relation between $GDPPC$ and $LIQUID$ as really cointegrating (long-run) ones.

Table 3.1: Panel unit root test results

Statistic	GDPPC	LIQUID	PRV	DGDPPC	DLIQUID	DPRV
HS	0.648	-1.280	-1.470	**-4.020**	**-4.476**	**-3.649**
	(.742)	(.100)	(.071)	(.000)	(.000)	(.000)
DH	1.469	**-1.785**	-0.070	**-4.210**	**-4.291**	**-3.997**
	(.929)	(.037)	(.472)	(.000)	(.000)	(.000)

Notes: All variables are in logarithmic forms. DGDPPC, DLIQUID, and DPRV refer to the first differences of GDPPC, LIQUID, and PRV, respectively. Entries corresponding to HS and DH are obtained by applying homogeneous panel unit root tests of Herwartz and Siedenburg (2008) and Demetrescu and Hanck (2012a), respectively. The tests are computed on data that are first prewhitened, to account for serial correlation, and then recursively demeaned. The number of lags included in the prewhitening regression is one. The null hypothesis in both tests is nonstationarity. P-values are given in parentheses and boldface values indicate rejections of the null hypothesis at the 5% level of significance.

We now proceed to conducting cointegration testing to examine whether a long-run relationship between financial development and economic growth exists or not. Table 3.2 reports estimation results obtained by applying the four error-correction-based cointegration tests suggested in Westerlund (2007) on our data. Two important remarks are in order before discussing the results. First, it should be noted that rejection of the null when $GDPPC$ is used as a dependent variable implies a cointegration FG relationship with a causality running from finance to growth. Similarly, if the tests suggest rejection of the null when PRV or $LIQUID$ is the dependent variable, we consider it as evidence of a long-run causality from growth to finance. Second, we have argued in Section 3.1 that cross-sectional dependence among SSA economies is a more realistic assumption. In this section, we perform a simple test to empirically augment our claim. Results from the Breusch and Pagan (1980) test of independence reported in Table 3.3 confirm that cross-sectional independence among SSA economies can be rejected at any conventional level of significance in all the considered cases. Accordingly, we base our discussion only on p-values that are robust to cross-sectional dependence.

Table 3.2 presents the cointegration test results, which display very high dependence on the specification of the error-correction equation regarding the deterministic terms as well as the lags and leads of the first differences of the explanatory variables. Therefore, drawing the most plausible conclusion from the documented results requires a somehow detailed analysis of each scenario. In general, when the model features only a constant, the evidence varies with the type of financial development indicator we consider; namely, employing PRV yields a long-run causality from finance to growth while using $LIQUID$ obtains the reverse causal link. With linear trend, however, clear evidence of causality from finance to growth emerges provided that the test equation contains three leads and lags of the first differences of the explanatory variables.

It is well known in the cointegration literature that over-parametrization induces a substantial loss of statistical power (Ng and Perron, 1995). However, the use of leads, in addition to lags, could offset the loss of power of error-correction-based tests arising from a failure to fulfill the weak exogeneity assumption of the regressors (Westerlund, 2007). In light of this reasoning, we include additional lags and leads until the obtained marginal benefit—in terms of rejecting the null—becomes negligible. For the data at hand, using three leads (and lags) appears to be a reasonable balance between over-parametrization and failing to fulfill the weak exogeneity assumption. In fact, our results, not reported here, confirm that further increasing the number of leads does not cause any qualitative change in the results obtained by using only three leads. If any, in the model with a linear trend, robust p-values are drawn down to zero when GDPPC is used as a dependent variable.

Table 3.2: Panel cointegration test results

Dependent variable	Explanatory variable	Test	1 lag and 1 lead *P*-values	1 lag and 1 lead Robust	2 lags and 2 leads *P*-values	2 lags and 2 leads Robust	3 lags and 3 leads *P*-values	3 lags and 3 leads Robust
Deterministic term: constant								
GDPPC	LIQUID	Gt	0.302	0.180	0.933	0.600	0.975	0.595
		Ga	0.924	0.576	0.982	0.638	0.998	0.559
		Pt	0.248	0.242	0.559	0.326	0.772	0.314
		Pa	0.828	0.598	0.951	0.668	0.981	0.437
	PRV	Gt	0.723	0.484	0.940	0.640	0.969	0.382
		Ga	0.887	0.478	0.989	0.767	0.999	**0.046**
		Pt	0.898	0.704	0.925	0.643	0.994	**0.002**
		Pa	0.940	0.791	0.949	0.684	0.992	**0.045**
LIQUID	GDPPC	Gt	**0.001**	**0.001**	0.106	**0.040**	0.764	0.322
		Ga	0.222	**0.011**	0.839	0.224	0.994	0.653
		Pt	**0.032**	0.056	0.392	0.256	0.904	0.490
		Pa	0.099	**0.048**	0.465	0.157	0.935	0.451
PRV		Gt	0.138	0.075	0.920	0.602	0.998	0.870
		Ga	0.813	0.231	0.994	0.809	1.000	0.964
		Pt	**0.034**	0.057	0.719	0.395	0.964	0.614
		Pa	0.264	0.093	0.867	0.437	0.987	0.721
Deterministic terms: constant, trend								
GDPPC	LIQUID	Gt	0.272	0.204	0.643	0.249	0.547	**0.022**
		Ga	0.859	0.204	0.997	0.445	1.000	**0.033**
		Pt	0.603	0.475	0.791	0.374	0.996	**0.004**
		Pa	0.599	0.256	0.973	0.486	1.000	**0.016**
	PRV	Gt	0.059	0.069	0.495	0.196	0.852	0.085
		Ga	0.553	**0.031**	0.966	0.149	1.000	**0.011**
		Pt	0.142	0.185	0.734	0.319	0.999	**0.000**
		Pa	0.264	0.087	0.808	0.162	1.000	**0.011**
LIQUID	GDPPC	Gt	**0.002**	**0.007**	0.923	0.526	0.888	0.327
		Ga	0.862	0.103	0.998	0.547	1.000	0.894
		Pt	0.380	0.331	1.000	0.870	0.992	0.467
		Pa	0.881	0.504	0.996	0.708	1.000	0.868
PRV		Gt	0.068	0.071	0.459	0.169	0.151	0.055
		Ga	0.750	**0.048**	0.995	0.341	1.000	0.433
		Pt	0.230	0.227	0.994	0.751	0.900	0.244
		Pa	0.711	0.248	0.989	0.677	1.000	0.672

Notes: All variables are in logarithmic forms. The null hypothesis in all the tests is no cointegration. Boldface values denote rejections of the null at the 5% level of significance. The number of bootstrap replications used to compute cross-sectional dependence robust *p*-values is 5000. The tests are computed in STATA 11 using the user written command 'xtwest' of Persyn and Westerlund (2008).

Therefore, the results clearly demonstrate the existence of a statistically significant long-run relationship between financial development and economic growth in the 17 SSA economies under consideration. This is in direct contrast to Fowowe (2010) who, using the same data set, concludes that there is no long-run relationship

Table 3.3: Breusch- Pagan test of cross-sectional independence

Dependent variable	Explanatory variable	Chi-squared Statistic	P-values
GDPPC	LIQUID	$chi2(136) = 916.889$	0.000
GDPPC	PRV	$chi2(136) = 755.822$	0.000
LIQUID	GDPPC	$chi2(136) = 411.160$	0.000
PRV	GDPPC	$chi2(136) = 737.996$	0.000

Notes: All variables are in logarithms. A constant is included in the regressions. The null hypothesis is independence in the residuals obtained from economy-specific regressions.

between finance and growth in SSA economies. It is worth noting here, however, that we would have arrived at a similar conclusion to Fowowe (2010) if we had not used robust p-values. Therefore, the contrast between our results and those of Fowowe (2010) should be attributed to our explicit handling of cross-sectional dependence among economies rather than to the avoidance of the potentially invalid common-factor restrictions.

Another notable result of this study is that the direction of log-run causality between finance and growth varies with the type of financial development considered. In particular, financial development as measured by PRV exerts a long-run causal impact on economic growth, but not vice versa. This result is independent of the inclusion of a linear trend in the test equation. With respect to $LIQUID$, however, contrasting causal effects are observed depending on whether a linear trend is assumed in the test regression. When only a constant is assumed in the equation, the evidence supports the "growth leads finance" hypothesis. Yet, incorporating a linear trend obtains results that imply that "finance leads growth", as is the case with measuring financial development by PRV.

Table 3.4 presents the long-run FG nexus estimates obtained by applying the DOLS estimator on our data. The results show that the relationship is strongly positive. This finding is robust to the use of fixed effects or random effects estimators, the number of lags and leads of the first-differenced explanatory variable, and the use of cross-sectional dependence robust or non-robust p-values. Hence, the results are overall supportive of policy measures that target developing the financial sector of SSA economies in order to bring about the much needed economic development

Table 3.4: Cointegrating parameter estimates using DOLS

	2 lags and 2 leads		3 lags and 3 leads	
Explanatory variable	FE	RE	FE	RE
LIQUID	0.177	0.180	0.197	0.199
	(0.000)	(0.000)	(0.000)	(0.000)
	(0.000)		**(0.000)**	
PRV	0.137	0.138	0.149	0.149
	(0.000)	(0.000)	(0.000)	(0.000)
	(0.000)		**(0.000)**	

Notes: The dependent variable is GDPPC. All variables are in logarithmic forms. FE stands for the fixed effects model (within) estimator and RE represents the random effects model estimator. The p-values are given in parentheses. Boldface values indicate the cross-sectional dependence robust p-values obtained by using Driscoll and Kraay's (1998) standard errors, applicable only for the fixed effects model.

in the region.

3.5 Conclusion

The impact of financial development on economic growth remains to be controversial despite extensive research on the issue. Moreover, the correlation between this impact and the level of economic development is not clear. As a result, a few studies have empirically examined the FG nexus in SSA. We contribute to this strand of literature by applying error-correction-based panel cointegration tests (Westerlund, 2007), which, unlike their residual-based counterparts, do not impose common-factor restrictions. Without handling the problem of cross-sectional dependence, however, we fail to reject the null of no cointegration between financial development and economic growth in 17 SSA economies. However, after properly taking care of the cross-sectional dependence among these economies, we are able to observe a long-run relationship between financial development and economic growth. Measuring financial development by the percentage of credit to the private sector to GDP, financial development is found to be weakly exogenous implying that the long-run causality runs from finance to growth. Employing the percentage of liquid liabilities in GDP as a measure of financial development yields results that hint at the possibility that growth might also affect finance. Overall, our results clearly demonstrate that financial development has a long run impact on economic growth. Furthermore, the dynamic OLS estimates of the long-run FG parameters are positive and statistically significant highlighting the long-run benefit SSA economies could enjoy by developing their financial systems.

4 In-sample and out-of-sample evidence on the short-to-medium run finance-growth causality

4.1 Introduction

Whether financial development causes economic growth or vice versa is highly debated. On the one hand, several economists such as Schumpeter (1911), McKinnon (1973), Shaw (1973), and Levine (2005) emphasize the importance of a developed financial system as a prerequisite for economic growth. They argue that a developed financial system enhances the mobilization of savings, identifies high return projects, diversifies risks and facilitates transactions. These functions might promote both the overall level and the efficiency of investment. On the other hand, arguments in favor of the reverse causal direction have been put forth by Robinson (1952), who asserts that "*where enterprise leads finance follows*". According to this view, the financial system develops in response to the demand generated by a growing real economy. Thirdly, a bidirectional causality between finance and growth has been explicitly asserted by Patrick (1966) and Greenwood and Jovanovic (1990). Patrick (1966) refers to the view that the financial system develops as a result of the demand emanating from growth in the real sector as "demand-following phenomenon". Likewise, he calls the claim that the development of the financial sector ahead of demand induces economic growth as "supply-leading phenomenon".

The literature also suggests that the direction of the finance-growth causality may depend on the level of economic development. In this respect, Patrick (1966) conjectures that "supply-leading" might be more dominant at earlier stages of economic development while "demand-following" plays a significant role at later stages. In the growth model by Greenwood and Jovanovic (1990), however, financial development occurs endogenously at a later stage of economic development, since the creation and deployment of financial institutions is costly.

Extensive empirical research on the causality between finance and growth has provided conflicting evidence. Cross-country studies repeatedly show that financial development impacts positively on economic growth (see King and Levine, 1993; Levine et al., 2000; Beck et al., 2000b; Hassan et al., 2011). However, most of these studies do not explicitly test the possibility that growth might also affect finance.

On the other hand, time series based studies arrive at ambiguous conclusions (see Demetriades and Hussein, 1996; Xu, 2000; Christopoulos and Tsionas, 2004; Apergis et al., 2007; Ang and McKibbin, 2007; Ang, 2008a; Hassan et al., 2011). Similarly, the evidence with regard to the dependence of the causal directions on the level of economic development is inconclusive. Contrary to Patrick's conjecture, Xu (2000) reports weaker and, for some economies negative, causality from finance to growth in low-income economies and a strong causal impact of finance on growth in high-income economies. However, Hassan et al. (2011) find evidence for bidirectional causality between finance and growth for most geographic regions and evidence of causality from growth to finance in two of the poorest regions. These findings apparently support the predictions of the model by Greenwood and Jovanovic (1990).

We contribute to the empirical literature in three aspects. Firstly, we investigate the causal impact of financial development on growth (abbreviated FG henceforth) and the reverse direction (GF) by means of both in-sample (IS) tests and out-of-sample (OS) forecast comparisons. To this end, we rely on summarizing economy-specific evidence from bivariate SUR models. We focus on causal relations regarding the short-to-medium term, hence we examine growth rates of the observed time series. This means that causality tests refer to short and medium term periods of less than one decade, corresponding to typical planning horizons of institutional decision takers. Furthermore, impulse response functions are employed to investigate the direction and dynamic behavior of the causal relations.

Secondly, a large cross section dimension allows us to examine whether causal effects depend on an economy's individual stage of development (Patrick, 1966). Hence, we examine causality test results for subgroups of economies, which are distinguished according to their level of income. Thirdly, the potentially time-dependent nature of causal relationships might be a reason for conflicting empirical evidence. Therefore, we test for causality in an iterative way, relying on a short subperiod of the entire time dimension at each estimation step. The remainder of this study begins with an introduction of the data in Section 4.2. The IS and OS approaches to causality testing are described in Section 4.3, followed by a discussion of results. Section 4.4 concludes.

4.2 Data

We employ annual data from 74 economies covering the period 1975–2005. Economies are classified into four income groups based on their latest (2005) real GDP per capita and the World Bank's classification criteria in 2006. The list of economies in each group is provided in Chapter 5.B. We employ a widely used measure of financial development, namely credit by deposit money banks and other financial institutions to the non-financial private sector as a percentage of GDP ($PRIV$, in growth rates). This data is taken from the 2008 update of the *Financial Development and Structure Database* of Beck et al. (2000a)[14]. The merits of $PRIV$ are that it singles out credit to the private sector and, moreover, excludes credit issued by the central bank. Consequently, it is argued to be more suitable to examine the impact of financial development on economic growth than other measures, as, for instance, the ratio of monetary aggregates M2 or M3 to GDP (Levine et al., 2000. Economic growth is expressed by the growth rate of real GDP per capita ($GROW$). We control for inflation and an economies' openness to trade as two widely used determinants of economic growth and financial development (Levine et al., 2000; Baltagi et al., 2009; Bittencourt, 2011; Badinger and Nindl, 2012). Inflation obtains as the growth rate of the GDP deflator ($INFL$). Trade openness is the growth rate of the ratio of imports plus exports to GDP ($OPEN$). All data series except $PRIV$ are drawn from the 2009 edition of the World Bank's *World Development Indicators* database. Summary statistics and a broader discussion of the data can be found in Chapter 5.3.1.

4.3 Causality testing

Subsequently, we describe the IS and OS approach to testing for causality and discuss the results.

[14] `http://go.worldbank.org/X23UD9QUX0`

4.3.1 In-sample schemes

For $GROW$ and $PRIV$ in economy i at time t, we estimate bivariate SUR regressions

$$\begin{pmatrix} PRIV_{it} \\ GROW_{it} \end{pmatrix} = \begin{pmatrix} \mu_{i1} \\ \mu_{i2} \end{pmatrix} + \underbrace{\begin{bmatrix} a_{11,i} & a_{12,i} \\ a_{21,i} & a_{22,i} \end{bmatrix}}_{A_i} \begin{pmatrix} PRIV_{i,t-1} \\ GROW_{i,t-1} \end{pmatrix} \tag{4.1}$$
$$+B_i \begin{pmatrix} x^{\bullet}_{i,t-1} \\ x^{\bullet}_{i,t-1} \end{pmatrix} + \begin{pmatrix} v_{i1t} \\ v_{i2t} \end{pmatrix}, \qquad \begin{array}{c} i = 1, ..., N_g, \\ t = \tau - E + 1, ..., \tau, \end{array}$$

where $(v_{i1t}, v_{i2t})' \sim (0, \Omega_i)$ and τ denotes the end of the estimation window E and $N_g \in \{19, 16, 14, 25\}$ refers to the number of economies in each income group. To address potential structural changes in causal relations, we estimate (4.1) in a stepwise manner for $\tau = T - T_0, ..., T - 1$. Overall evidence on causality is obtained by subsuming time-local evidence across economies. Predetermined influences are represented as $x^{\bullet}_{i,t-1} \in \{OPEN_{i,t-1}, INFL_{i,t-1}\}$. Distinct control variables $x^{\bullet}_{i,t-1}$ are included in (4.1) interchangeably to retain a parsimonious model structure for economy-specific estimation. Analyzing annual observations, the choice of a single lagged term seems sufficient to model the dynamics in $PRIV$ and $GROW$.[15] The parameters in A_i and B_i express the impact of finance, growth and further predetermined variables, respectively. We distinguish five related null hypotheses of noncausality. In all cases, the alternative hypothesis is that both causal effects hold jointly, i.e. $H_1: \ a_{12} \neq 0 \ \wedge \ a_{21} \neq 0$ in (4.1). Conversely, the most restrictive assertion is that both causal effects are absent, i.e. $H_0: \ a_{12} = a_{21} = 0$. Rejections of $H_{01}: \ a_{12} = 0$ or $H_{02}: \ a_{21} = 0$ indicate that $GROW$ influences $PRIV$ in the former, or the reverse causal effect in the latter. Furthermore, by consideration of the conditional hypotheses $H_{03}: \ a_{12} = 0 \mid a_{21} = 0$ and $H_{04}: \ a_{21} = 0 \mid a_{12} = 0$, we focus on those instances where only a single causal effect is present, meaning that only one of the unconditional hypothesis H_{01} and H_{02} can be rejected. Rejections of H_{03} or H_{04} provide more clear-cut evidence on the respective importance of the two alternative causal directions. More pronounced evidence for H_{03} than for H_{04} means

[15] Inferential results are qualitatively unaffected by consideration of higher lag orders or the joint incorporation of $OPEN_{i,t-1}$ and $INFL_{i,t-1}$ and are available from the authors upon request. Furthermore, we employ several diagnostic tests regarding disturbances from (4.1) to assess the admissibility of the model specification.

that where growth increases, the financial development of an economy is likely to follow. For hypotheses testing, we consider F-tests at the 5% significance level.[16]

4.3.2 Out-of-sample schemes

Causality may also be detected with reference to forecasting ability. Within each subperiod, one-step predictions obtain as

$$\begin{pmatrix} \widehat{PRIV}^{(\circ)}_{i,\tau+1|t} \\ \widehat{GROW}^{(\circ)}_{i,\tau+1|t} \end{pmatrix} = \begin{pmatrix} \hat{\mu}_{i1} \\ \hat{\mu}_{i2} \end{pmatrix} + \hat{A}^{(\circ)}_i \begin{pmatrix} PRIV_{i,\tau} \\ GROW_{i,\tau} \end{pmatrix} + \hat{B}_i \begin{pmatrix} x^{\bullet}_{i,\tau} \\ x^{\bullet}_{i,\tau} \end{pmatrix}, \tag{4.2}$$

where $\tau = T - T_0, ..., T - 1$ and '$\circ$' refers to estimates under distinct hypotheses $\circ \in \{H_{01}, H_{02}, H_1\}$.[17] At the end of each estimation window τ, forecasts are obtained from estimates $\hat{\mu}_{i1}, \hat{\mu}_{i2}, \hat{A}^{(\circ)}_i, \hat{B}_i$. Forecasting accuracy is evaluated by means of absolute forecast errors

$$\mathrm{AE}^{(\circ)}_{\tau+1|\tau}(y_i) \quad = \quad |\hat{y}^{(\circ)}_{i,\tau+1|t} - y_{i,\tau+1}|, \tag{4.3}$$

with $y_{i,\tau+1} \in \{PRIV_{i,\tau+1}, GROW_{i,\tau+1}\}$. Cases where $\mathrm{AE}^{(\circ)}_{\tau+1|\tau}(y_i)$ are lower for predictions from (4.2) under H_1 than under H_{01} or H_{02} are regarded as evidence for the GF or FG hypothesis, respectively. Rejections of H_0 obtain if predictions under H_{01} and H_{02} are both outperformed by those under H_1. In addition, we consider the binary directional accuracy (DA)

$$\mathrm{DA}^{(\circ)}_{\tau+1|\tau}(y_i) \quad = \quad \mathrm{I}(\hat{y}^{(\circ)}_{i,\tau+1|\tau} \times y_{i,\tau+1|\tau} \geq 0),$$

where $\mathrm{I}(\cdot)$ is an indicator function. Thus, if the sign of a prediction $\hat{y}^{(\circ)}_{i,\tau+1|\tau}$ matches the one of $y_{i,\tau+1|\tau}$, positivity of $\hat{y}^{(\circ)}_{i,\tau+1|\tau} \times y_{i,\tau+1|\tau}$ indicates a directionally accurate forecast. Since, in contrast to $\mathrm{AE}^{(\circ)}_{\tau+1|\tau}(y_i)$, $\mathrm{DA}^{(\circ)}_{\tau+1|\tau}(y_i)$ increases with predictive accuracy, higher DA under H_1 indicates evidence for the GF or FG hypothesis in this case. The most recent $T_0 \in \{10, 15\}$ years are considered as alternative

[16] Test outcomes are qualitatively similar for alternative significance levels of 1% or 10% and are available from the authors on request.

[17] The testing procedure could equivalently depart from imposing an a priori constraint on A_i according to H_0 and, consequently, regarding $H_{01}, ..., H_{04}$ and H_1 as alternative hypotheses. However, since this setting might give rise to omitted variables bias, we regard H_1 as the superior reference.

evaluation samples.

4.3.3 Results

Firstly, the specification of (4.1) is evaluated by means of residual diagnostics. The total number of tests conducted for each income group of economies is $\mathcal{T}_g = T_0$ (time instances) $\times$ N_g (economies). To test for serial correlation, LM tests as introduced by Breusch (1978) and Godfrey (1978) are employed, whereas ARCH-LM tests (Engle, 1982) serve as a means to assess heteroskedastic features in the estimated residuals. Additionally, we test for nonnormality of the residuals from (4.1) by means of the Lilliefors (2007) test. Since residual characteristics might differ across economies and given the relatively large number of model evaluations $\mathcal{T}_g$, the application of a nonparametric test might be preferable to more restrictive testing procedures. Test results are summarized in Table 4.1. On average over economies and time instances, we find only little evidence for serial correlation. Rejection frequencies hardly exceed the significance level of 5%. The ARCH-LM tests and nonnormality tests additionally indicate that SUR disturbances may be characterized as white noise processes in the majority of cases.

The outcomes of the IS tests and OS results are reported in Table 4.2 and 4.3, respectively. Summary statistics for IS tests refer to fractions of all $\mathcal{T}_g$ cases where F tests indicate rejections of $H_0, ..., H_{04}$ with 5% significance. The results of the OS study in table 3 are summarized analogously as percentages of all $\mathcal{T}_g$ cases where the prediction scheme in (4.2) obtains higher AE losses or lower (DA) gains than under H_0, H_{01} or H_{02} than under H_1. Given a significant amount of evidence for bidirectional causality, the results in Table 4.2 show that evidence in favor of the GF effect is stronger than for the reverse causal impact. Rejection frequencies for H_{01} are in almost all cases higher than for H_{02}, irrespectively of further control variables. The outcomes are also robust across income groups. Rejections of H_{03} and H_{04} reinstate these findings, i.e. for cases where causality points in only one direction, the impact of growth on finance is more pronounced than vice versa. Similarly, the higher rejection frequencies in Table 4.3 suggest that there is stronger OS evidence against H_{01} than against H_{02}. Hence, the incorporation of $GROW$ as a predictor variable for $PRIV$ is more likely to decrease the AE (and increase DA) of forecasts

Table 4.1: Residual diagnostic tests results

$T_0 = 15$ (1991-2005)			$T_0 = 10$ (1996-2005)	
Dep. var.:	*PRIV*	*GROW*	*PRIV*	*GROW*
Serial correlation LM test				
low	0.70	3.16	0.53	3.16
lower middle	8.75	7.50	6.88	6.88
upper middle	3.81	1.90	0.71	2.14
high	8.27	5.33	7.60	6.80
Heteroskedasticity (ARCH-LM) test				
low	10.53	10.18	13.16	12.11
lower middle	13.75	12.08	14.37	15.63
upper middle	10.48	6.67	10.71	9.29
high	15.20	9.87	17.60	10.00
Nonnormality test (Lilliefors test)				
low	8.07	12.98	6.32	12.11
lower middle	12.92	12.08	15.00	15.63
upper middle	12.38	15.71	14.29	14.29
high	14.13	8.80	18.40	9.60

Note: Reported numbers represent percentages of $\mathcal{T}_g$ instances where test statistics indicate rejections of the null hypotheses of 1.) no first order serial correlation, 2.) no conditional heteroskedasticity or 3.) no deviations from normality in estimation disturbances from (1) at the 5% level. Results for alternative significance levels of 1% or 10% are qualitatively similar and available from the authors upon request.

than the reverse way.[18]

Apart from the direction of causality, the sign and the dynamics of the relation between $PRIV$ and $GROW$ might be of interest for economic policy. To investigate these issues, we report generalized impulse response functions (IRF) as introduced by Pesaran and Shin (1998). This sort of IRF addresses the potential emergence of instantaneously correlated shocks without being affected by the ordering of the variables in (4.1), in contrast to orthogonal IRFs based on the Cholesky decomposition.[19] In Figure 4.1, these IRFs display the dynamic responses as implied by estimation of (4.1) to shocks in $PRIV$ and $GROW$, on average across $\mathcal{T}_g$ instances. The graphs show that the impact of shocks in $GROW$ on $PRIV$ and the reverse effect are positive for lower and intermediate income groups. However, the

[18] The DA statistics are throughout above 50%, which implies that all model specifications deliver economically meaningful predictions. To economize on space, we do not report DA statistics for predictions under each hypothesis. However, corresponding results are available from the authors upon request.

[19] The results obtained with orthogonalized IRFs as implied by the Cholesky decomposition are, however, qualitatively equivalent to the ones reported in Figure 4.1 and may be obtained from the authors upon request.

Table 4.2: In-sample results

$T_0 = 15$ (1991-2005)															
Control var.:	none					$OPEN_{i,\tau-1}$					$INFL_{i,\tau-1}$				
	H_0	H_{01}	H_{02}	H_{03}	H_{04}	H_0	H_{01}	H_{02}	H_{03}	H_{04}	H_0	H_{01}	H_{02}	H_{03}	H_{04}
low	16.49	13.33	11.23	12.28	10.18	9.82	12.28	10.88	11.58	10.18	11.93	10.18	12.28	9.12	11.23
lower middle	24.58	22.08	12.92	19.17	10.00	30.42	25.83	13.33	22.08	9.58	22.92	23.33	8.33	20.83	5.83
upper middle	29.05	23.81	21.43	14.29	11.90	25.71	20.00	21.90	10.48	12.38	20.95	18.10	16.67	10.00	8.57
high	30.40	32.53	14.13	25.87	7.47	29.33	30.40	13.07	25.33	8.00	30.40	29.33	14.93	24.27	9.87
$T_0 = 10$ (1996-2005)															
low	17.89	12.63	11.58	12.11	11.05	8.95	15.79	6.84	15.79	6.84	10.53	12.63	9.47	12.11	8.95
lower middle	27.50	25.00	13.75	21.88	10.63	31.87	29.38	11.88	25.62	8.13	25.62	25.00	7.50	21.88	4.38
upper middle	30.71	22.86	20.00	15.71	12.86	25.00	18.57	19.29	10.00	10.71	20.00	16.43	15.00	9.29	7.86
high	35.20	36.80	16.00	28.00	7.20	32.40	33.60	14.80	27.20	8.40	34.00	33.20	16.80	25.60	9.20

Note: Cell entries report rejection frequencies of distinct null hypotheses of noncausality at the 5% significance level. Evidence for GF obtains as rejections of H_{01} and H_{03}, respectively, whereas evidence for FG is measured by rejection frequencies of H_{02} and H_{04}. Rejecting H_0 indicates bidirectional influence. Columns $OPEN_{\tau-1}$ and $INFL_{\tau-1}$ refer to cases where (1) includes additional control variables.

Table 4.3: Out-of-sample results

$T_0 = 15$ (1991-2005)	AE criterion								
Control var.:	none			$OPEN_{i,\tau-1}$			$INFL_{i,\tau-1}$		
	H_0	H_{01}	H_{02}	H_0	H_{01}	H_{02}	H_0	H_{01}	H_{02}
low	22.63	50.53	42.63	20.53	45.26	45.26	24.74	46.84	50.00
lower middle	27.50	51.88	49.38	24.38	47.50	49.38	23.13	51.25	46.88
upper middle	23.57	51.43	45.00	19.29	50.00	44.29	21.43	47.14	49.29
high	24.40	56.80	44.00	22.00	53.20	41.60	21.20	53.20	40.80
$T_0 = 10$ (1996-2005)									
low	23.16	45.79	43.68	22.63	43.68	47.37	23.16	47.89	46.32
lower middle	23.75	53.75	43.13	21.25	56.25	42.50	24.38	53.75	43.13
upper middle	25.00	57.14	44.29	17.86	52.14	37.86	21.43	56.43	38.57
high	20.80	52.00	42.80	20.80	50.40	42.00	22.40	52.80	46.40
$T_0 = 15$ (1991-2005)	DA criterion								
low	1.05	7.37	6.84	0.53	10.00	3.68	0.00	8.95	5.26
lower middle	0.63	6.88	2.50	0.00	6.88	3.13	0.63	8.13	4.38
upper middle	0.00	6.43	5.00	0.00	8.57	2.86	0.00	5.71	5.00
high	0.00	4.40	4.40	0.00	7.60	2.40	0.00	7.20	3.20
$T_0 = 10$ (1996-2005)									
low	1.05	10.00	4.21	0.53	9.47	4.21	0.00	10.00	4.74
lower middle	0.00	8.25	3.63	0.00	6.25	3.75	0.00	10.00	3.13
upper middle	0.00	9.00	3.86	0.00	9.29	2.14	0.00	8.57	5.00
high	0.00	6.80	4.00	0.00	8.00	2.00	0.80	9.60	4.00

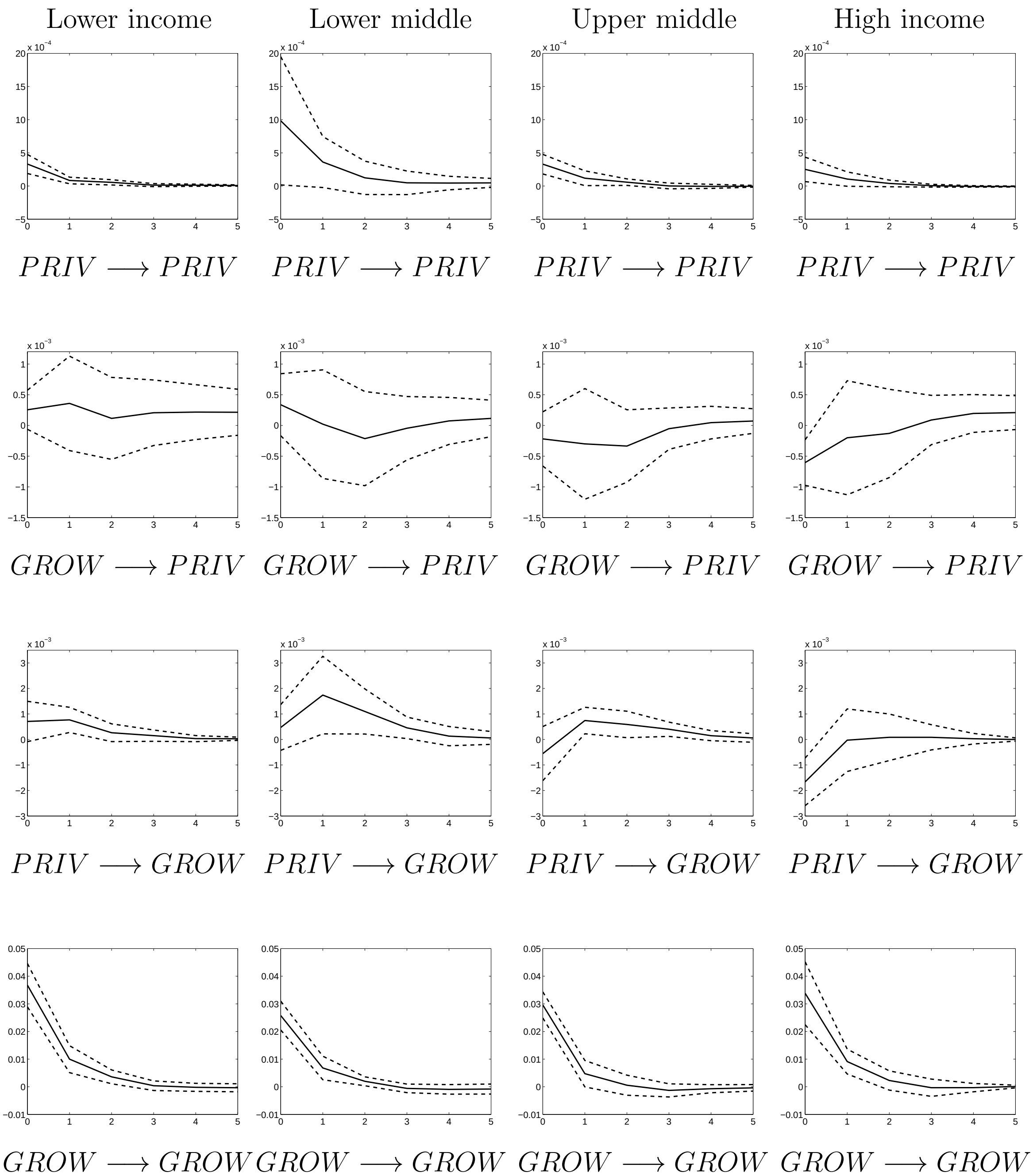
Note: Cell entries in columns H_{01} and H_{02} denote fractions of $\mathcal{T}_g$ cases where AE$^{(H01)}$ >AE$^{(H1)}$ or AE$^{(H02)}$ >AE$^{(H1)}$, respectively. Instances of H_0 obtain as the number of cases where evidence for both AE$^{(H01)}$ >AE$^{(H1)}$ and AE$^{(H02)}$ >AE$^{(H1)}$ is found. Conversely, in the lower panel, DA$^{(H01)}$ <DA$^{(H1)}$ means rejection of H_{01}.

instantaneous effect of $PRIV$ on $GROW$ and vice versa are significantly negative for high-income economies, though the impact of $GROW$ on $PRIV$ is relatively small in magnitude. The most pronounced negative impact points from $PRIV$ to $GROW$ for high-income economies. These findings are largely in line with those obtained, e.g., by Hassan et al. (2011). In sum, evidence from both IS and OS schemes more strongly supports the view that "*where enterprise leads finance follows*" (Robinson, 1952) than the "finance leads growth" hypothesis.

4.4 Conclusions

We find stronger evidence for the hypothesis that economic growth influences financial development than for the reverse causal effect. Our findings are consistent across income groups and confirmed by in-sample and out-of-sample causality testing. By means of impulse response functions we document that the positive

Figure 4.1: Impulse response functions



Note: Income-group specific IRFs obtain as averages over $\mathcal{T}_g$ instances. Dashed lines indicate approximate ± 2 standard error confidence bands.

association between finance and growth might turn negative in the short run for high-income economies.

5 State dependence in the finance-growth nexus: a functional coefficient approach

5.1 Introduction

The importance of services and instruments of the financial system to the real economic sector has been recognized in the literature at least since Schumpeter (1911). However, there are economists who argue that finance does not matter to economic development. According to this view, either the financial system passively responds to the demand arising from the real sector and not vice versa (Robinson, 1952) or there is not at all a meaningful relationship between finance and growth (Lucas, 1988). The extensive research on the finance-growth (FG) nexus in the last two decades has documented mixed results. While there are many studies showing that financial development promotes economic growth (e.g., Christopoulos and Tsionas, 2004; King and Levine, 1993; Levine et al., 2000), there are others which report that it is economic growth which leads to financial development (Ang and McKibbin, 2007). In addition, there are a few studies that diagnose a negligible FG relationship (Andersen and Tarp, 2003).

The inconclusiveness of empirical evidence has recently triggered a growing body of literature that attempts to investigate underlying economic factors which might determine the FG nexus. This has been mostly done either by estimating the FG relationship for different economies grouped according to a certain economic criterion (Rioja and Valev, 2004) or by applying threshold regressions (Ketteni et al., 2007; Yilmazkuday, 2011). So far, the levels of economic and financial development, government size, inflation and openness to trade have been identified to have an impact on the FG nexus (Rioja and Valev, 2004; Rousseau and Wachtel, 2002; Rousseau and Yilmazkuday, 2009; Yilmazkuday, 2011). However, contrasting evidence has emerged with regard to their impact on the FG nexus. For instance, three studies have associated the highest positive FG nexus with three different stages of economic development: low (Huang and Lin, 2009), medium (Yilmazkuday, 2011) and high (Deidda and Fattouh, 2002). Moreover, existing studies have not uncovered conditions which could lead to a negative FG relationship observed by Xu (2000).

We contribute to the empirical literature on the state dependence of the FG nexus in five directions. Firstly, most studies, including Ketteni et al. (2007), Rioja and Valev (2004) and Yilmazkuday (2011), have utilized the same data set that was initially employed by Levine et al. (2000). In this data set, annual time series have been converted to five-year averages to immunize empirical results against the effects of business cycle fluctuations. However, the problems of averaging data have not gone unnoticed in the literature. For example, Ang (2008a) argues that averaging may induce a new type of correlation between time-averaged variables which could markedly differ from the correlation between non-averaged series. Besides, averaging obviously entails a significant (80%) reduction of the sample (Baltagi et al., 2009). In this study, we employ (non-averaged) annual data for 74 economies spanning the period 1975–2005.

Secondly, in the literature thus far, the effects of each factor on the FG nexus have been mostly taken as invariant across stages of economic development or, when considered variant, the association has been made only indirectly. For example, Yilmazkuday (2011) interprets results for economies with small governments to be characteristics for low-income economies by noting that the former have the lowest average income level. Such kind of associations might be problematic especially if the correlation between the considered factor and the income level is low. In this contribution, we subdivide economies into four income groups by means of the World Bank's classification criteria to examine the inter- and intra-group variations of the impacts of the considered economic factors on the FG nexus.

Thirdly, except Ketteni et al. (2007), the related literature has imposed a rather strong linear FG relationship below, above or within threshold levels. We relax this assumption by employing a data driven functional coefficient modeling approach. In the spirit of non-parametric kernel estimation, this method attaches more weight to observations close to, and less weight to observations farther away from a local point at which the FG nexus is to be evaluated.

Fourthly, recent studies have shown that financial openness has a significantly positive impact on both economic growth (Bekaert et al., 2011) and financial development (Baltagi et al., 2009). This suggests a positive effect of financial openness on the FG nexus. However, financial openness may replace financial development in terms of key growth-promoting roles, for instance, the provision of risk diversification (Obstfeld, 1994). As a consequence, financial openness might also exert a negative impact on the FG link. In light of conflicting economic reasoning, thus, we empirically assess the net impact of financial openness on the FG link.

Finally, Rousseau and Wachtel (2011) argue that the FG nexus has weakened over time. This trend is supposed to reflect the recent acceleration of financial development that, in turn, has eventually led to financial crises. However, they have employed five-year averaged data. In this work, we test if their finding is consistent across income groups and is robust to the use of non-averaged annual data by conducting estimations on cross sections split into two subperiods, 1975–1989 and 1990–2005.

To preview some results, the average FG link is found to be positive and increase with the average income level. Yet, there are significant variations within each income group. For instance, increasing financial development appears to strengthen the FG nexus while increasing government size is generally associated with a weakening of the FG link. On the other hand, a negative FG nexus is diagnosed in low-income and lower-middle-income economies where the government size is very large or when they are highly open to international trade. Finally, while the average FG nexus initially increases with the average level of financial openness, economies with the highest level of financial openness stand to benefit the least from financial development. In sum, the FG nexus is found to depend on the levels of economic development, financial development, government size, trade openness and financial openness. Moreover, the impacts of these factors vary across distinct stages of economic development and financial openness.

Section 5.2 reviews briefly the literature on the state dependence of the FG nexus. Section 5.3 describes the data and provides parametric estimation results. Section 5.4 briefly sketches the functional coefficient model and discusses empirical functional estimates. Section 5.5 concludes. Some technical issues of functional modeling are addressed in Appendix 5.A.

5.2 Literature review

In this section, we briefly review the theoretical and empirical literature on the state dependence in the FG nexus. Several factors have been suggested in the literature to affect the FG nexus. We discuss each potential determinant in turn.

1. Level of economic development. The debate on the possible dependence of the FG link on the level of economic development can be traced back to Patrick (1966) who conjectures that finance leads to economic growth at earlier stages of economic development while growth induces financial development at later stages. The view that financial development is more beneficial to less developed economies is also shared by Fry (1995) and McKinnon (1973). However, Deidda (2006) and Greenwood and Jovanovic (1990) argue that minimum size requirements or huge startup and maintenance costs necessitate a certain critical level of economic development before financial development may foster economic growth. In view of these conflicting conjectures, it has become quite common to test the FG nexus on distinct samples of high-income and low-income economies. The results are mixed, however. A cross-sectional study by De Gregorio and Guidotti (1995) shows that the FG link is stronger in low-income economies in comparison with high-income economies. These findings are supported by recent evidence from panel data based threshold analysis in Huang and Lin (2009). On the contrary, based on country specific Granger causality tests, Xu (2000) reports a weaker, and for some economies a negative, causality from finance to growth in low-income economies. Similarly, Deidda and Fattouh (2002) and Hassan et al. (2011) have obtained a significantly positive FG nexus for high-income economies and a negligible FG relationship for low-income economies. On the other hand, Yilmazkuday (2011) finds that economies need to have a per capita income of $665 in order to benefit from financial development and the benefits start declining once the income level reaches $1636.

2. Level of financial development. Rioja and Valev (2004) have examined if the level of financial development impacts on the FG nexus. They find that a certain threshold level of financial development is required for a meaningful FG nexus. This is attributed to economies of scale that financial intermediaries could enjoy in agglomerating savings and financing high-return investments. Yet, they have also diagnosed the FG nexus to be smaller in economies with a very high level of financial development than in economies with a medium level of financial development. This is supposed to imply the existence of diminishing marginal returns to improvements in the financial sector. However, Ketteni et al. (2007) have questioned the robustness of the findings in Rioja and Valev (2004) arguing that the likely nonlinear relationship between economic growth and other growth determinants, i.e. initial income and human capital, have been ignored in Rioja and Valev (2004).

3. Level of inflation. A few studies have also shown that finance leads to economic growth only when the level of inflation is low (Huang et al., 2010; Rousseau and Wachtel, 2002; Rousseau and Yilmazkuday, 2009; Yilmazkuday, 2011). This is argued to be a result of the growth-damaging effects of inflation. Inflation is believed to have a negative impact on economic growth because it is usually associated with increased variations in relative prices, which in turn are considered to impact adversely on long-term investments (Temple, 2000; Yilmazkuday, 2011).

4. Government size. A potential determinant of the FG nexus that has not attracted much attention yet is government size. Yilmazkuday (2011) finds that low-income economies benefit from financial development when they have large governments. This indicates that certain types of government expenditures (like on securing property rights, national defence and the legal system) are important for a growth-promoting financial system. Meanwhile, high-income economies are found to achieve a comparably strong FG linkage only if they are characterized by relatively small government sizes. These results are attributed to the possibility that the private sector might be crowded out by the government.

5. Degree of openness to international trade. Yilmazkuday (2011) has also considered trade openness as a possible factor to affect the FG link. He finds that trade openness strengthens the FG link in low-income economies, but its effect is minimal in high-income economies. He argues that increased access to low-cost intermediate inputs, large and high-income markets, and technologies benefits open low-income economies. However, the FG nexus in high-income economies is less affected by trade openness as those economies have their own large domestic markets. Instead, higher financial development coupled with high trade and financial openness might lead to higher vulnerability to international shocks.

6. Degree of financial openness. The impact of financial openness on the FG nexus has not been studied so far. However, there are studies which imply that financial openness could have two opposite effects on the FG nexus. On the one hand, Bekaert et al. (2011) have found a significantly positive impact of financial openness on economic growth. Moreover, Baltagi et al. (2009) have shown that the increasing global trend in financial openness significantly explains the recent surge in the level of financial development. Accordingly, we may expect a positive impact of financial openness on the FG nexus. On the other hand, financial openness could play some of the most important roles of financial development in economic growth, for instance, risk diversification (Obstfeld, 1994). This implies a negative effect of financial openness on the FG nexus. Because of these two contrasting effects, the direction and strength of the impact of financial openness on the FG nexus is not clear at the outset. In this study, we examine empirically the dependence of the FG nexus on the level of financial openness.

In sum, there appears to be a broad consensus that the FG nexus is state dependent. Levels of economic development, financial development, inflation, government size and openness to trade have been shown to affect the FG nexus. However, the empirical evidence has been largely inconclusive in terms of both the sign and magnitude of the effects of each factor on the FG nexus. In re-examining this issue, we conjecture that applying a more direct way of classifying economies as well as introducing the middle-income categories might solve some of the contradictory results and uncover new important dependencies. We also use functional coefficient modeling that does not impose a linear relationship between finance and growth within estimation windows. Moreover, we introduce financial openness as a new potential determinant of the FG relationship.

5.3 Data and preliminary analysis

5.3.1 Data

To investigate state dependence in the FG nexus, we construct panel data sets comprising 74 economies for the period 1975–2005. The economies are selected with regard to data availability of all variables for a sufficiently long time period. As a broad concept involving improvements in the quality and quantity of various financial intermediary services measuring financial development is always difficult. We use the arguably most common measure, namely, credit by deposit money banks and other financial institutions to the non-financial private sector as a percentage of GDP (PRV). It excludes credit to public institutions and credit issued by the central bank. As a result, it measures the activity of financial intermediaries in channeling

Table 5.1: Summary statistics, 1975–2005

Variable	Mean	Max	Min	Std	CV	Mean	Max	Min	Std	CV
	World, 74 economies									
GDPPC	7469.0	40617.8	107.0	8939.3	1.20					
PRV	44.4	200.6	1.4	37.2	0.84					
GOV	16.5	54.5	3.2	6.3	0.38					
OPEN	71.9	220.4	6.3	36.7	0.51					
FOPEN	0.1	2.5	-1.8	1.5	18.97					
INF	11.6	439.0	-23.5	22.6	1.94					
	Low-income economies, 19					*Low-FOPEN economies, 19 (10,5,2,2)*				
GDPPC	357.2	1106.7	107.0	185.4	0.52	2492.7	18136.4	107.0	4060.2	1.63
PRV	16.3	41.2	1.4	8.8	0.54	30.2	160.9	1.4	30.6	1.01
GOV	14.7	54.5	5.9	6.7	0.46	14.4	38.8	3.2	5.8	0.40
OPEN	59.6	187.7	6.3	33.7	0.57	67.3	194.8	6.3	39.8	0.59
FOPEN	-0.8	2.5	-1.8	0.8	-0.94	-1.1	1.7	-1.8	0.5	-0.46
INF	12.0	165.7	-12.3	16.3	1.36	14.6	439.0	-12.3	27.5	1.88
	Lower-middle-income economies, 16					*Lower-middle-FOPEN economies, 18 (8,6,3,1)*				
GDPPC	1542.1	3561.3	368.7	655.9	0.43	1654.2	13801.8	149.7	2089.8	1.26
PRV	31.4	166.0	3.6	25.3	0.81	26.3	144.6	3.5	20.9	0.79
GOV	13.8	38.8	3.2	6.0	0.44	15.0	43.0	5.7	5.9	0.40
OPEN	73.0	209.4	24.9	32.5	0.45	77.5	209.4	26.6	35.3	0.46
FOPEN	-0.6	2.5	-1.8	1.1	-1.88	-0.5	2.5	-1.8	0.9	-1.59
INF	12.6	439.0	-23.5	26.0	2.06	10.8	334.6	-20.8	20.1	1.86
	Upper-middle-income economies, 14					*Upper-middle-FOPEN economies, 18 (1,5,5,7)*				
GDPPC	4801.0	16429.0	830.8	2578.7	0.54	8095.8	40617.8	306.6	8683.7	1.07
PRV	37.1	155.3	3.7	26.9	0.73	44.3	197.4	6.5	30.4	0.69
GOV	16.7	38.8	5.0	6.4	0.38	16.1	54.5	5.0	6.8	0.43
OPEN	94.4	220.4	16.5	43.4	0.46	69.3	148.3	16.5	27.1	0.39
FOPEN	0.3	2.5	-1.8	1.5	4.70	0.2	2.5	-1.8	1.4	6.04
INF	15.8	334.6	-20.8	27.9	1.77	14.5	390.7	-23.5	26.4	1.83
	High-income economies, 25					*High-FOPEN economies, 19 (0,0,4,15)*				
GDPPC	18161.4	40617.8	2595.1	7297.2	0.40	17360.4	38971.8	1430.6	8018.7	0.46
PRV	78.3	200.6	19.3	36.7	0.47	75.9	200.6	3.7	40.9	0.54
GOV	19.5	43.4	10.4	4.8	0.25	20.4	38.8	9.8	4.8	0.24
OPEN	67.9	184.7	16.0	31.2	0.46	73.4	220.4	16.0	41.5	0.57
FOPEN	1.1	2.5	-1.8	1.4	1.37	1.7	2.5	-1.8	1.0	0.57
INF	8.4	390.7	-1.8	20.6	2.44	6.8	106.8	-18.6	12.3	1.81

Note: Full definitions of the variables and data sources are given in the text. Except GDPPC and FOPEN, all variables are measured as percentage values. Max, min, std and CV represent maximum, minimum, standard deviation and coefficient of variation, respectively. Entries next to the number of economies in each financial openness category denote, respectively, the number of low-income, lower-middle-income, upper-middle-income and high-income economies that belong to the corresponding financial openness category.

savings to investors. Consequently, it is argued to be more closely associated with the impact of financial development on investment and economic growth than other measures like the percentage of monetary aggregates M2 or M3 in GDP (Levine et al., 2000). Following standard practice in the FG nexus literature (e.g., Apergis et al., 2007; Christopoulos and Tsionas, 2004; Demetriades and Hussein, 1996), economic development is measured by means of real GDP per capita (GDPPC). Government size is approximated in terms of government consumption expenditure as a percentage of GDP (GOV). Due to several missing values in the data for inflation implied by the Consumer Price Index, we instead use the growth rate of the GDP deflator (INF). Trade openness is measured as the percentage of imports plus exports in GDP (OPEN). We employ the financial openness measure (FOPEN) suggested in Chinn and Ito (2008). FOPEN is derived as the first principal component of the reverse of four dummy variables that indicate major restrictions on cross-border capital transactions as reported in the Annual Report on Exchange Arrangements and Exchange Restrictions of the IMF.

PRV is obtained from the 2008 update of the *Financial Development and Structure Database* of Beck et al. (2000a)[20] while FOPEN is taken from Menzie Chinn's website.[21] The remaining time series are drawn from the 2009 edition of the World Development Indicators of the World Bank.

To get deeper insights into each factor's effects on the FG link across stages of economic development, we categorize the 74 economies into four by their latest (2005) income level according to the World Bank's contemporary classification criteria.[22] In particular, economies whose latest real per capita GDP (in constant 2000 US Dollar) fall in the ranges less than 876, 876–3465, 3466–10725, and over 10725 are classified as low-income (19 economies), lower-middle-income (16), upper-middle-income (14) and high-income (25), respectively.[23] The list of economies included in each sample is provided in Appendix 5.B. The low-income category includes 15 Sub-Saharan African (SSA) economies plus India, Nepal, Pakistan and Papua New Guinea while the high-income group adds Bahamas and Cyprus to 23 OECD economies. The remaining 14 Latin American economies considered in this study are equally divided into lower- and upper-middle-income economies.

As an alternative means of classifying sample information, we categorize economies into four groups with respect to their average level of FOPEN. Additionally, we subdivide each cross section into two subperiods, 1975–1989 and

[20] `http://go.worldbank.org/X23UD9QUX0`

[21] `http://www.ssc.wisc.edu/~mchinn/research.html`

[22] `http://data.worldbank.org/about/country-classifications/a-short-history`.

[23] As in the standard growth literature, we measure economic development by means of GDP per capita. Accordingly, to see the state dependence of the FG nexus across stages of economic development, we classify economies based on their GDP per capita. However, the World Bank classifies economies based on their per capita Gross National Income (GNI). Moreover, noting that economy specific quotes of GNI per capita and GDP per capita may differ markedly, there are five economies which we group differently than the World Bank. These are Algeria, Cameroon, Malta, Saudi Arabia, and Trinidad and Tobago.

1990–2005, to test recent findings by Rousseau and Wachtel (2011) that the FG nexus is weakening over time.

Table 5.1 shows some descriptive statistics of the data covering the full-sample period. It provides the means, maximum and minimum values and standard deviations for the different cross sections. It can be seen that the data set is characterized by considerable variations within/between cross sections. The mean of the financial development measure PRV increases with the stage of economic development. However, across stages of financial openness, both average PRV and average per capita income GDPPC initially decrease and later increase with financial openness, indicating positive but nonlinear PRV-FOPEN and GDPPC-FOPEN relationships. The table also documents how economies in a certain category of financial openness are distributed over the income groups. In particular, low-income economies predominate in low and lower-middle financial openness categories while high-income economies take the largest shares in upper-middle and high financial openness categories.

5.3.2 Parametric regression results

Before moving to the functional coefficient modeling in the next section, we first look at parametric estimations of the FG nexus across distinct income groups and categories of financial openness. This allows comparability with related studies. Moreover, as the economies are classified with regard to their income level (financial openness), differences in the parametric FG nexus estimates could also hint at the impact of economic development (financial openness) on the FG nexus. For this purpose, we employ a standard panel dynamic OLS (DOLS) approach where GDP per capita is regressed on financial development and a few control variables (Ang, 2008b; Apergis et al., 2007; Christopoulos and Tsionas, 2004). In DOLS estimation, the explanatory variables in levels are augmented with the lags and leads of their first differences to account for potential endogeneity and serial correlation (Saikkonen, 1991; Stock and Watson, 1993). Formally, the model reads as

$$
\begin{aligned}
GDPPC_{it} = \mu_i + \beta_1 PRV_{it} + \beta_2 GOV_{it} + \beta_3 OPEN_{it} + \beta_4 INF_{it} + \sum_{j=-1}^{1} c_{1j} \Delta PRV_{it+j} \\
+ \sum_{j=-1}^{1} c_{2j} \Delta GOV_{it+j} + \sum_{j=-1}^{1} c_{3j} \Delta OPEN_{it+j} + \sum_{j=-1}^{1} c_{4j} \Delta INF_{it+j} + u_{it}, \\
t = 1, ..., T, \quad i = 1, ..., N,
\end{aligned}
\tag{5.1}
$$

where $GDPPC_{it}$, PRV_{it}, GOV_{it}, $OPEN_{it}$, and INF_{it} represent GDP per capita, financial development, government size, openness to trade, and inflation, respectively, in time t and economy i. Moreover, Δ is short for the first difference operator, e.g. $\Delta PRV_{it} = PRV_{it} - PRV_{it-1}$, μ_i are fixed effects and $u_{it} \sim (0, \sigma_u^2)$. [24] Equation (5.1) can be written compactly as

$$y_{it} = \boldsymbol{x}_{it}' \boldsymbol{\beta} + \boldsymbol{z}_{it}' \boldsymbol{\gamma} + u_{it}, \tag{5.2}$$

where $y_{it} = GDPPC_{it}$, $\boldsymbol{x}_{it} = (PRV_{it}, GOV_{it}, OPEN_{it}, INF_{it})'$, and $\boldsymbol{z}_{it}$ collects the fixed effects and lags and leads of first differences of the explanatory variables. Accordingly, $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3, \beta_4)'$ while $\boldsymbol{\gamma}$ contains the parameters attached to the fixed effects and short-run dynamics. To allow for heterogeneous short-run coefficients, we partial out $\boldsymbol{z}_{it}$ from (5.2). To this end, we denote matrices collecting observations in $y_{it}, \boldsymbol{x}_{it}$ and $\boldsymbol{z}_{it}$ for economy i by $Y_i, \boldsymbol{X}_i$ and $\boldsymbol{Z}_i$, respectively, and henceforth consider the partial system

$$\tilde{y}_{it} = \tilde{\boldsymbol{x}}_{it}' \boldsymbol{\beta} + \tilde{u}_{it} \tag{5.3}$$

where $\tilde{y}_{it}$, $\tilde{\boldsymbol{x}}_{it}$ and $\tilde{u}_{it}$ are typical elements of, respectively, $\tilde{Y}_i = \boldsymbol{M}_i Y_i$, $\tilde{\boldsymbol{X}}_i = \boldsymbol{M}_i \boldsymbol{X}_i$ and $\tilde{u}_i = \boldsymbol{M}_i u_i$; $\boldsymbol{M}_i = I_i - \boldsymbol{Z}_i (\boldsymbol{Z}_i' \boldsymbol{Z}_i)^{-1} \boldsymbol{Z}_i'$; and I_i denotes the $(T \times T)$ identity matrix.

The left and right hand sides of Table 5.2 document estimation results using data from the four categories of income and financial openness, respectively. Moreover, full sample results (74 economies) are shown. Results on the full-period samples demonstrate a statistically and economically significant, positive, long-run impact

[24] Estimation results are qualitatively unaffected by consideration of higher lag and lead orders.

Table 5.2: Parametric regression results

Variables	Cross sections *Low income*	*Lower-middle*	*Upper-middle*	*High income*	*Low FOPEN*	*Lower-middle*	*Upper-middle*	*High FOPEN*	*World*
Panel 1: 1975–2005									
PRV	**0.118**	**0.142**	**0.268**	**0.345**	**0.219**	**0.215**	**0.246**	**0.114**	**0.226**
	(.016)	(.021)	(.031)	(.016)	(.019)	(.023)	(.024)	(.015)	(.010)
GOV	0.033	**-0.304**	-0.099	-0.017	**-0.157**	-0.039	-0.004	**-0.460**	**-0.120**
	(.024)	(.039)	(.089)	(.070)	(.039)	(.042)	(.041)	(.068)	(.021)
OPEN	**0.168**	**0.268**	**0.242**	**0.378**	**0.135**	0.057	**0.264**	**0.715**	**0.215**
	(.026)	(.029)	(.062)	(.042)	(.029)	(.043)	(.040)	(.038)	(.018)
INF	**0.211**	0.026	0.003	**-0.173**	0.096	**-0.568**	**-0.099**	**-0.526**	**-0.067**
	(.055)	(.057)	(.103)	(.031)	(.050)	(.162)	(.035)	(.071)	(.026)
Serial corr.	10.526	12.500	28.571	8.000	15.789	5.556	22.222	10.526	13.514
Poolability	8.584	3.487	2.968	7.948	3.691	1.246	8.108	**11.627**	6.570
HS	**-3.893**	**-3.466**	**-2.791**	**-3.344**	**-3.735**	**-3.628**	**-3.194**	**-3.313**	**-4.333**
DH	**-4.031**	**-3.366**	**-2.743**	**-3.587**	**-3.935**	**-3.973**	**-3.716**	**-3.455**	**-4.415**
Panel 2: 1975-1989									
PRV	**0.065**	**0.087**	0.093	**0.380**	**0.110**	**0.189**	**0.118**	**0.166**	**0.155**
	(.027)	(.024)	(.054)	(.024)	(.028)	(.036)	(.041)	(.025)	(.016)
GOV	**0.128**	-0.312	-0.165	-0.073	-0.055	-0.020	0.008	**-0.611**	**-0.092**
	(.038)	(.048)	(.118)	(.100)	(.059)	(.061)	(.066)	(.106)	(.032)
OPEN	**0.219**	**0.131**	**0.272**	**0.246**	**0.207**	0.038	**0.273**	**0.455**	**0.213**
	(.039)	(.034)	(.113)	(.064)	(.039)	(.061)	(.065)	(.069)	(.026)
INF	**0.141**	0.059	-0.062	-0.022	0.091	-0.018	-0.011	**-0.304**	0.018
	(.068)	(.082)	(.155)	(.033)	(.071)	(.199)	(.044)	(.133)	(.034)
Serial corr.	21.053	25.000	14.286	12.000	36.842	5.556	11.111	15.789	17.568
Poolability	7.073	3.159	1.769	**11.283**	4.593	1.432	4.229	**17.882**	**9.597**
HS	**-2.690**	**-2.864**	**-2.086**	**-2.328**	**-2.647**	**-2.206**	**-1.772**	**-2.494**	**-2.874**
DH	**-2.644**	**-2.952**	**-2.637**	**-2.756**	**-2.638**	**-2.178**	**-2.428**	**-2.732**	**-2.974**
Panel 3: 1990-2005									
PRV	**0.120**	**0.152**	**0.283**	**0.307**	**0.241**	**0.204**	**0.259**	**0.061**	**0.224**
	(.022)	(.022)	(.041)	(.022)	(.027)	(.027)	(.030)	(.022)	(.014)
GOV	-0.029	**-0.124**	0.078	-0.008	-0.136	-0.100	0.070	**-0.327**	**-0.090**
	(.035)	(.044)	(.124)	(.092)	(.051)	(.052)	(.064)	(.093)	(.029)
OPEN	**0.135**	**0.267**	0.175	**0.413**	0.079	0.104	**0.216**	**0.692**	**0.196**
	(.035)	(.039)	(.097)	(.054)	(.045)	(.054)	(.056)	(.052)	(.026)
INF	**0.234**	0.034	-0.131	**-0.243**	0.077	**-0.782**	-0.077	**-0.409**	-0.036
	(.064)	(.045)	(.137)	(.062)	(.054)	(.173)	(.068)	(.079)	(.036)
Serial corr.	31.579	18.750	7.143	12.000	21.053	22.222	22.222	5.263	17.567
Poolability	9.044	5.875	5.461	5.491	3.245	3.930	**12.456**	**13.079**	7.490
HS	**-3.061**	**-2.788**	**-2.573**	**-2.863**	**-3.094**	**-2.983**	**-2.944**	**-2.589**	**-3.377**
DH	**-3.040**	**-2.837**	**-2.563**	**-2.985**	**-2.965**	**-2.693**	**-3.287**	**-2.654**	**-3.323**

Notes: The dependent variable is GDPPC. The model includes a constant and contemporaneous as well as one lag and lead of the first differences of all explanatory variables. Apart from INF, all variables are in logarithmic form. The values provided in parentheses are estimated standard errors. Boldface values indicate rejections of the null hypothesis at the 5% level of significance. Reported numbers of the serial correlation tests of Breusch (1978) and Godfrey (1978) represent percentages of economy specific regressions where tests indicate rejections of the null hypothesis of no first order serial correlation with 5% significance. Entries corresponding to HS and DH are obtained by applying homogeneous panel unit root tests of Herwartz and Siedenburg (2008) and Demetrescu and Hanck (2012a), respectively, on the pooled residuals. The null hypothesis of the employed poolability test is that reported long-run parameter estimates are not systematically different from mean group estimates.

of financial development on economic growth in all the cross sections. This positive impact is in line with much of the empirical FG literature (see Levine, 2005, for a broad survey). Furthermore, the estimated coefficients are the larger the higher is the income level of the subsamples. In particular, the FG coefficient estimate for high-income economies is three times larger than that for low-income economies. This underpins the dependence of the FG nexus on the income level.

The right hand part of Table 5.2 indicates that economies with the highest level of financial openness benefit the least from financial development. Moreover, the weakest FG link in those economies is observed in the recent period. This negative impact of very high financial openness on the FG nexus could be explained by noting that both financial development and financial openness might serve the same beneficial roles to economic development. For example, providing risk diversification and hence increasing the probability of investment in high-risk, high expected-return projects is generally considered as an important function ascribed to both financial development (Greenwood and Jovanovic, 1990; Levine, 2005) and financial openness (Bekaert et al., 2011; Obstfeld, 1994).

On the other hand, breaking the samples into two periods (Panels 2 and 3 of Table 5.2) reveals that, in contrast to the findings in Rousseau and Wachtel (2011), most of the cross sections are characterized by a stronger FG nexus in the recent period. It is only in high-income and in high-financial openness economies that we find a weakened FG link. The result in high-income economies might be explained by noting that the financial development occurring outside the banking sector, which is not be captured by PRV, makes up a large and growing share of the overall financial development in those economies.

Table 5.2 also documents some model diagnostics with respect to the presence of serial correlation and unit roots in the residuals as well as poolability tests. In most cross sections, we obtain satisfactory results for all the three diagnostic tests. Specifically, in all cross sections, the null hypothesis of a panel unit root using the diagnostics of Herwartz and Siedenburg (2008) and Demetrescu and Hanck (2012a) is rejected. Thus, at the panel level the performed DOLS regression does not suffer from spurious dependence. Poolability test results also indicate that the pooled regression estimates are not systematically different from mean group estimates for most cross sections. Thus, after allowing for fixed effects and cross-section-specific transitory dynamics, pooling is not overly restrictive to uncover the long-run determinants of per capita income. Mitigating this overall evidence slightly, however, results from high financial openness economies show a failure to satisfy the poolability restrictions in both the full-period and sub-period regressions. Therefore, a fair degree of caution should be given in interpreting the corresponding FG estimates. Finally, the null hypothesis of no first order serial correlation is rejected for about 13% of the economies, a large proportion of which are upper-middle-income economies. Although the empirical rejection frequency exceeds the nominal significance level of the diagnostic tests to some extent, we refrain from model respecification for two reasons. First, serial correlation diagnostics improve if we use more than one lag of the first differences in the DOLS regression while higher order transitory dynamics leaves the evaluation of the FG link qualitatively unaffected. Second, eventual residual correlation does not invalidate consistency of the long-run DOLS parameter estimates.

5.4 Functional coefficient modeling

In this section, we first briefly outline the functional coefficient model that allows the long-run parameters in (5.1) to depend on potential economic states and then discuss empirical results. Issues of estimation and inference within the functional coefficient model are deferred to Appendix 5.A.

5.4.1 The semiparametric model

We denote a factor or state variable, for instance, the degree of trade openness, by ω. The full list of factors that we actually employ is provided below. As we are interested in the state dependence of the long-run parameters, we presume that all the short-run parameters and the deterministic terms are factor invariant. Thus, we generalize (5.3) towards a functional representation. The functional model reads as

$$\tilde{y}_{it} = \tilde{\boldsymbol{x}}_{it}'\boldsymbol{\beta}(\omega_{it}) + \tilde{u}_{it}, \quad \omega_{it} = \{\sigma_t(\tilde{\omega})\}^{-1}(\tilde{\omega}_{it} - \bar{\omega}_t), \tag{5.4}$$

where $\bar{\omega}_t = N^{-1}\sum_{i=1}^{N}\tilde{\omega}_{it}$ and $\sigma_t(\tilde{\omega})$ are the time-specific cross-sectional mean and standard deviation of the factor observations $\tilde{\omega}_{it}$, respectively. Equation (5.4) allows the relation between economic development and its long-run determinants to depend on the measurable economic factor $\tilde{\omega}_{it}$.

As outlined in Appendix 5.A, kernel-based estimates of the semiparametric model can be interpreted as weighted pooled regression estimates, where the weights attached to particular observations $\{\tilde{y}_{it}, \widetilde{\boldsymbol{x}}_{it}\}$ depend on the time local position of the factor in the cross section of time series. As we are interested only in the functional dependence of the FG nexus, our discussion is, henceforth, restricted to $\hat{\beta}_1(\omega_{it})$. Functional estimates $\hat{\beta}_1(\omega_{it})$ can be displayed graphically. Noting that we have standardized the factor, the following grid is used:

$$\hat{\beta}_1(\omega), \omega = -2 + 0.1\kappa, \kappa = 0, 1, 2, ..., 40. \tag{5.5}$$

Thus, estimates $\hat{\beta}_1(\omega)$ reflect the effect of attaching relatively high kernel weights to economies which are above ($\omega > 0$), close to ($\omega = 0$) or below ($\omega < 0$) the factor's average time path.

5.4.2 Functional coefficient estimates

In this section, we discuss results obtained from the functional coefficient model in (5.4)[25]. Potential factor variables are mainly selected in light of the related literature (Rioja and Valev, 2004; Yilmazkuday, 2011). They include the level of the government size (GOV), financial development (PRV), openness to international trade (OPEN), and inflation (INF). As it is generated from four dummy variables, the financial openness measure, FOPEN, has poor scale properties. Therefore, we do not employ it as a factor in the functional coefficient modeling. Instead, we examine its impact on the state dependence of the FG nexus by considering cross sections of distinct degrees of financial openness.

To test if the FG nexus is dependent on a particular factor, we apply the factor based bootstrap approach proposed in Herwartz and Xu (2009). A brief discussion of the tests is provided in Appendix 5.A. We first look at the global factor-invariance test results and then discuss the factor-dependent FG nexus with respect to local parametric estimation. The conventional 5% significance level is used to decide if a given factor has a statistically significant impact on the FG nexus.

The global factor-invariance test results documented in Table 5.3 show that the

[25] All computations are done in MATLAB 2011a.

Table 5.3: Global factor invariance test results

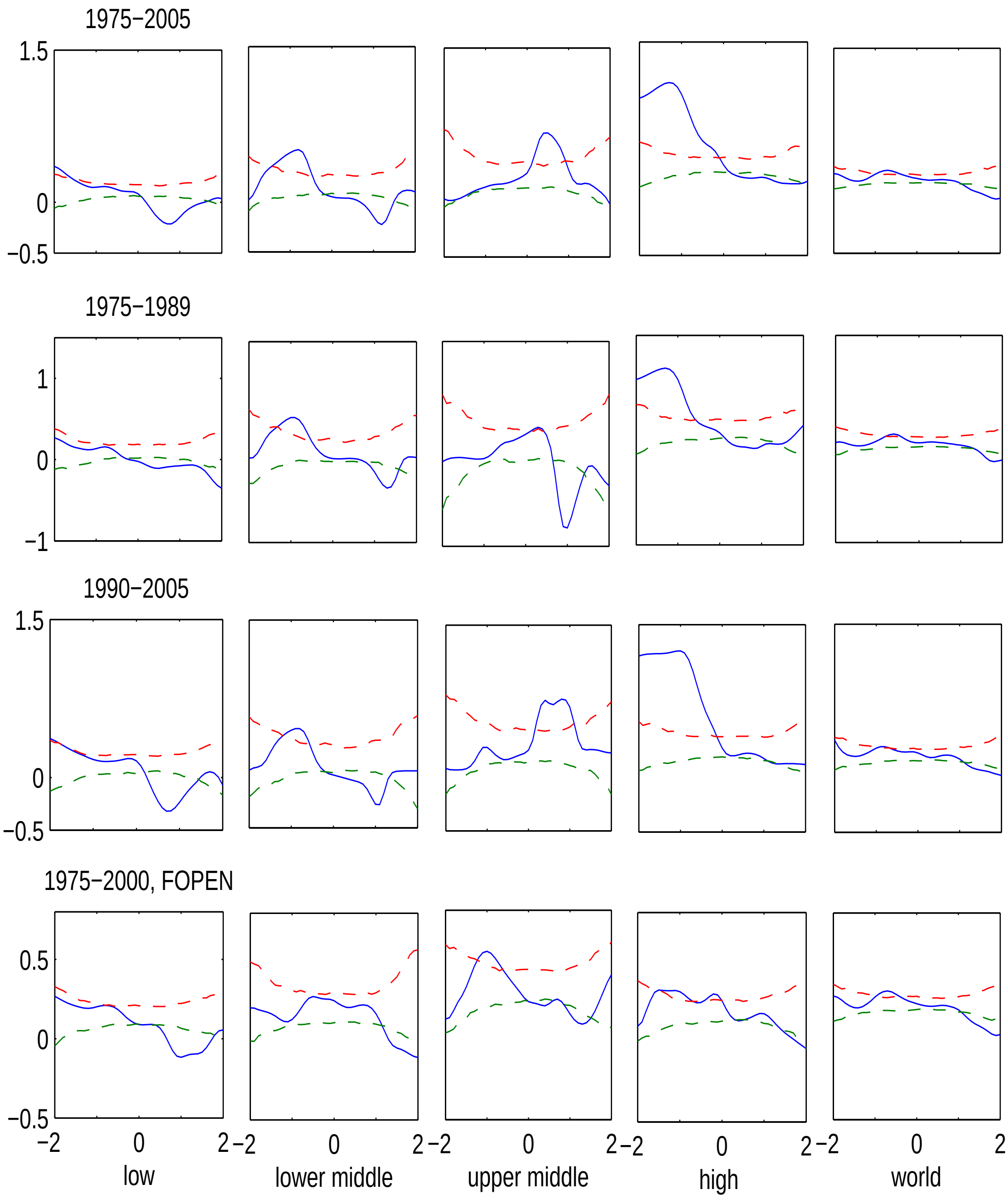
		Income groups					FOPEN categories				
Factor	period	low	lower-middle	upper-middle	high	world	1st	2nd	3rd	4th	pooled
GOV	1975–2005	.000	.015	.000	.024	.003	.000	.000	.015	.065	.005
	1975-1989	.000	.180	.015	.195	.182					
	1990-2005	.000	.035	.074	.004	.040					
PRV	1975–2005	.000	.000	.149	.000	.000	.000	.000	.000	.000	.000
	1975-1989	.012	.015	.099	.172	.000					
	1990-2005	.000	.000	.011	.001	.000					
OPEN	1975–2005	.000	.000	.014	.000	.001	.042	.432	.016	.000	.014
	1975-1989	.003	.019	.053	.304	.011					
	1990-2005	.001	.000	.003	.004	.083					
INF	1975–2005	.355	.654	.241	.829	.010	.362	.353	.133	.253	.013
	1975-1989	.891	.920	.850	.408	.545					
	1990-2005	.143	.567	.106	.895	.005					

Notes: Apart from INF, all variables are in logarithmic form. Reported numbers are (bootstrap) p-values. The number of bootstrap replications is 1000. The columns corresponding to "FOPEN categories" refer to p-values obtained by applying the test on the four quartiles of the pooled data sorted with respect to the level of FOPEN.

null hypothesis of a constant FG nexus can be rejected if we use government size, financial development or trade openness as a state variable. One exception is when financial development is employed as a factor in upper-middle-income economies. As it turns out, inflation fails to be a significant determinant of the FG link in all the cross sections except the most comprehensive sample. Consequently, we will not take inflation as a factor in the ensuing discussions.

5.4.2.1 Government size Figure 5.4.2.1 depicts the estimated functional FG nexus obtained by employing government size as a factor variable. The displayed functional estimates show that in low-income and high-income economies the FG link weakens with increasing government size. More importantly, we obtain a negative FG nexus in low- and lower-middle-income economies with large government sizes. This result supports the conjecture raised by Xu (2000) that a high degree of government regulation could be the reason for the negative FG nexus in low-income economies. In upper-middle-income economies, a medium government size appears to be favorable for a higher FG relationship while economies with very small

Figure 5.1: Functional FG estimates conditional on the level of government size (GOV).



Note: The figures show estimated long-run effects $\hat{\beta}_1(\omega)$, with $\hat{\beta}_1$ on the vertical and ω on the horizontal axes. The solid line shows the point estimates and the two dashed lines are the 95% confidence intervals of the model excluding functional dependence.

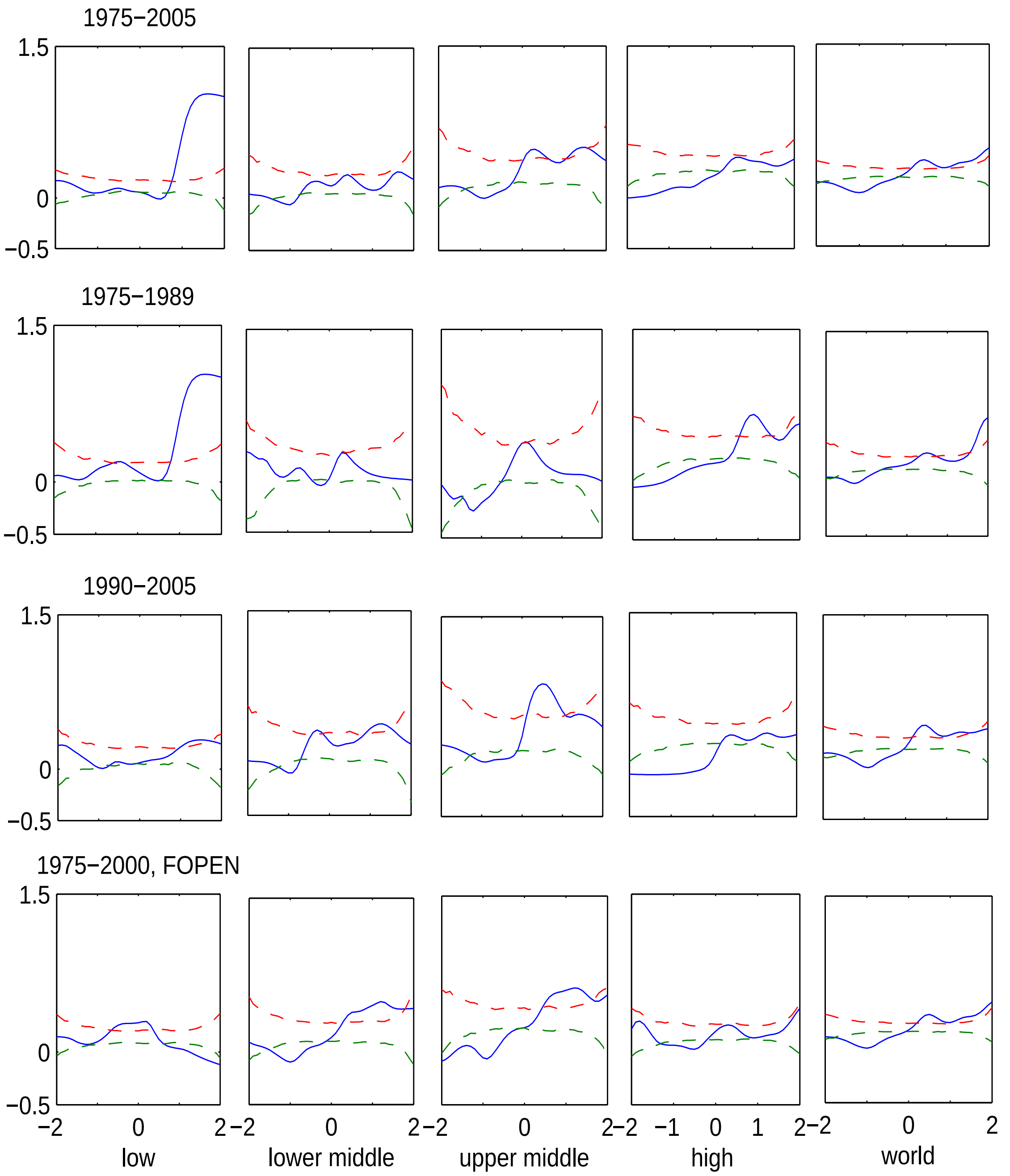
or very large governments tend to lose the growth promoting effects of financial development. This is in accordance with findings in Yilmazkuday (2011). These results likely underscore the importance of certain types of government expenditure like on securing property rights, national defense and the legal system that facilitate the efficient functioning of the financial sector. Yet, the fact that the FG nexus becomes low when the size of the government is large hints at the prevalence of excessive government regulations in such economies. In high-income (OECD) economies, governments are relatively larger (see Table 5.1) and strong legal systems that enforce property rights and financial contracts are already in place. As a result, additional government consumption mainly crowds out the private sector. This leads to a lesser efficiency in the utilization of the funds channeled to the private sector (PRV), and hence a decline in the FG link. In line with this reasoning, functional estimates in the fourth column of Figure 1 show that in high-income economies small governments are associated with a very strong FG link and increasing government size weakens the FG nexus.

Additionally, the second and the third rows of Figure 5.4.2.1 illustrate that the functional dependence of the FG nexus on the government size remains largely similar in the two subperiods. If any, large government sizes in upper-middle-income economies are associated with a negative FG nexus in the first period, casting additional doubt on the benefit of having large governments even in those economies. Furthermore, a negative relationship between government size and the FG nexus is obtained in all categories of financial openness. This strengthens the general implications from the above discussion that large government sizes adversely affect the FG nexus.

5.4.2.2 Financial development Figure 5.4.2.2 displays the estimated functional dependence of the FG nexus with respect to the level of financial development. It can be seen that low-income economies with high level of financial development show a relatively high FG nexus. In general, there is an increasing FG nexus for additional degrees of financial development, most likely because the scale of the growth-promoting functions of the financial sector (Levine, 2005) increases as the financial system develops. For example, the financial sector has to reach a certain threshold of development before it could agglomerate savings that are high enough to finance indivisible, high return, investments (Rioja and Valev, 2004). The risk diversification and high-return project identification (Rioja and Valev, 2004) functions also require a relatively high level of financial development.

Splitting full-period cross sections into two obtains that most of the functional relations discussed above prevail in both subperiods. However, the higher FG

Figure 5.2: Functional FG estimates conditional on the levels of financial development (PRV).



Note: The figures show estimated long-run effects $\hat{\beta}_1(\omega)$, with $\hat{\beta}_1$ on the vertical and ω on the horizontal axes. The solid line shows the point estimates and the two dashed lines are the 95% confidence intervals of the model excluding functional dependence.

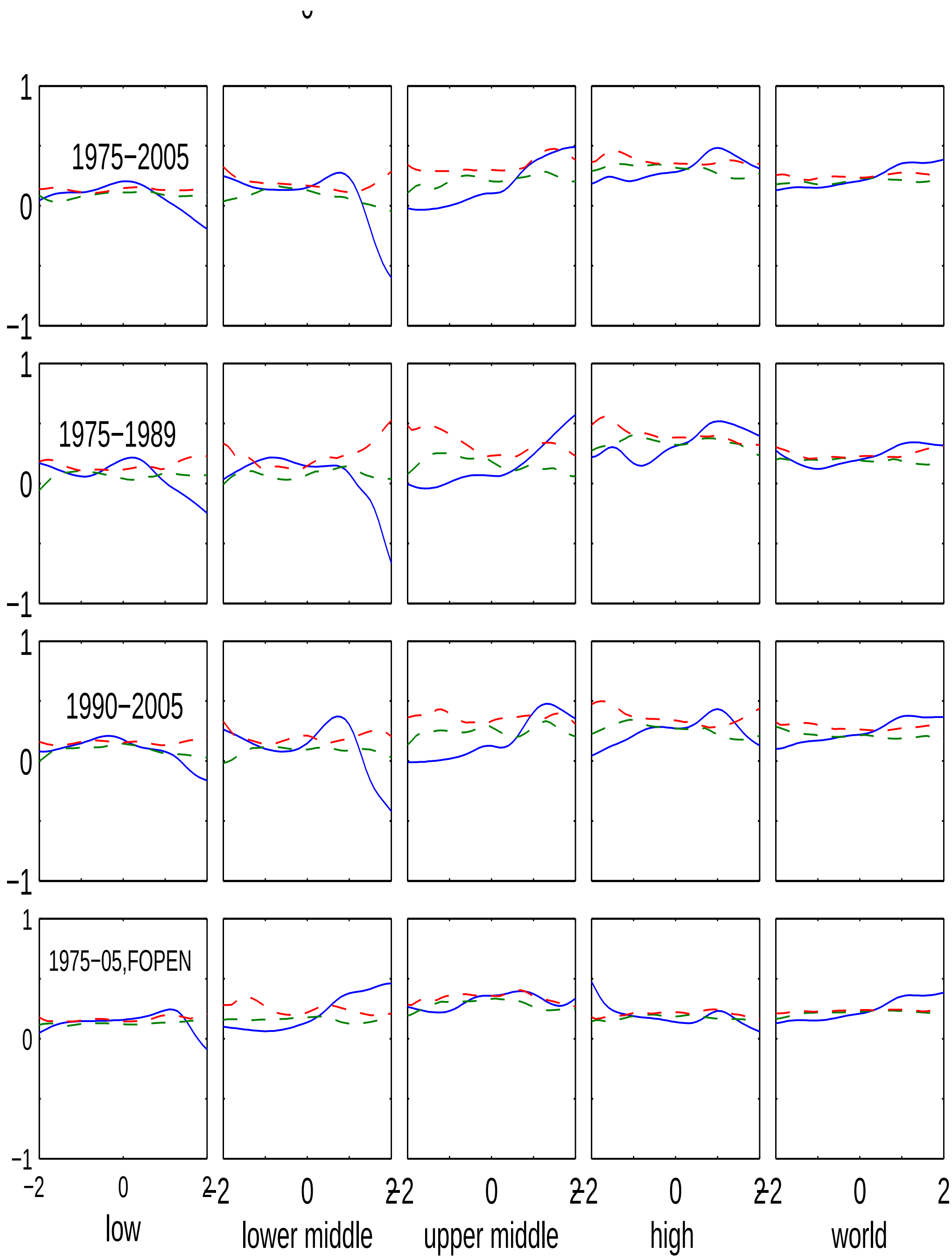
nexus in low-income economies with very high level of financial development is not diagnosed in the second subperiod. Results documented in the fourth row of Figure 2 illustrate that the effect of financial development on the FG nexus depends on the level of financial openness. A moderate level of financial openness is associated with a beneficial role of financial development on the FG nexus. However, the average FG link is apparently the weakest in states of higher financial openness. These findings highlight that the similar growth-promoting roles of financial openness and financial development (Obstfeld, 1994) are likely complementary for moderate levels of both trigger variables.

5.4.2.3 Openness to trade Trade openness can result in two opposite effects on the overall macroeconomic performance of an economy. On the one hand, it may lead to enhanced efficiency by providing access to new raw materials and products, low-cost intermediate goods, larger markets and latest technologies (Yanikkaya, 2003). On the other hand, it could also induce macroeconomic instability (Rodrik, 1992) and increase vulnerabilities to international shocks (Yilmazkuday, 2011). Trade openness may also impact on financial development. Rajan and Zingales (2003) argue that trade openness, if coupled with financial openness, can weaken the industrial and financial incumbents' resistance and promote financial development.[26] In testing this claim, Baltagi et al. (2009) find that trade openness induces financial development even in financially closed economies. As a result, the possible effect of trade openness on the FG nexus is not clear at the outset.

The results depicted in Figure 5.4.2.3 indicate that the impact of trade openness on the FG nexus varies across stages of economic development. In low- and lower-middle-income economies, a moderate level of trade openness stimulates the FG nexus, but extreme openness could lead to a negative FG relationship. Except the negative FG link, the hump-shaped relationship between trade openness and the FG nexus corroborates the results reported in Yilmazkuday (2011). The negative FG nexus might highlight the failure of domestic firms in extremely open low- and lower-middle-income economies to withstand foreign competition. In contrast, upper-middle-income economies show a marked FG nexus when they are highly open to trade. This might be because of the better utilization of credits by firms in those economies when they are given access to a broader international market and/or when they face strong competition of foreign firms. However, we do not observe any clear pattern for the impact of openness on the FG nexus in high-income economies. For

[26] Rajan and Zingales (2003) argue that incumbents in the industrial and financial sector are opposed to financial development because it generates competition and erodes their rents.

Figure 5.3: Functional FG estimates conditional on the levels of trade openness (OPEN).



Note: The figures show estimated long-run effects $\hat{\beta}_1(\omega)$, with $\hat{\beta}_1$ on the vertical and ω on the horizontal axes. The solid line shows the point estimates and the two dashed lines are the 95% confidence intervals of the model excluding functional dependence.

most income groups, subperiod estimation results are qualitatively similar to the full-period estimates. However, the FG link in upper-middle-income economies that are less open to international trade turned out to be negative in the recent period. This might imply that, in a period when most upper-middle-income economies have become increasingly open to international trade, those economies with a lower level of trade openness are most likely poor performing ones.

The effects of trade openness on the FG nexus also differ across categories of financial openness. When financial openness is low, moderate trade openness increases the FG nexus while a very high level of trade openness induces a declining FG link. When financial openness is high, however, the negative relationship between trade openness and the FG nexus begins with the minimum level of trade openness under consideration. This result supports our conclusion from the parametric estimations that both financial openness and financial development play similar roles in economic development. More importantly, the fact that the FG nexus could even be negative if trade openness is also very high underscores the increased vulnerability to international shocks in such states.

5.5 Conclusions

We investigate the state dependence in the FG nexus by means of semiparametric functional coefficient models on a data set comprising 74 economies over the period 1975–2005. We find that the FG link is dependent on an economy's level of economic and financial development, government size, trade openness and financial openness, but not on the level of inflation. Moreover, the effects of the economic factors on the FG link are diagnosed to be variant across the distinct stages of economic development.

We find a generally positive effect of income level on the FG link. In particular, low-income economies obtain the least benefit from financial development while high-income economies enjoy three times as much benefit. Similarly, financial development has a generally positive effect on the FG nexus, with the strongest FG link observed in low-income economies with a high level financial development. There are also cases where financial development could have an adverse effect on economic growth. This is observed in low- and lower-middle-income economies when they have very large governments or are extremely open to international trade. The impact of openness to trade varies even between lower-middle- and upper-middle-income economies. Upper-middle-income economies show a pronounced FG nexus when they are highly open to international trade. Yet, only a moderate level of trade openness is beneficial to lower-middle-income economies and being extremely open is found to induce a negative FG relationship. Finally, while increasing financial openness to some extent strengthens the FG nexus, economies with the highest level of financial openness are found to benefit the least from financial development. Furthermore, the FG nexus could even be negative if economies are highly open to both international trade and international finance. This implies not only substitutability in the roles of financial openness and financial development in economic development but also an accompanying high degree of vulnerability to international shocks.

5.A Semiparametric modeling

5.A.1 Estimation

We apply a semiparametric estimator of $\boldsymbol{\beta}(\omega)$ similar to the Nadaraya-Watson estimator (Nadaraya, 1964; Watson, 1964) which is given by

$$\hat{\boldsymbol{\beta}}(\omega) = X^{-1}(\omega)Y(\omega), \tag{5.6}$$

where $X(\omega) = \sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{x}_{it}\tilde{x}'_{it}K_h(\omega_{it} - \omega)$ and $Y(\omega) = \sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{x}_{it}\tilde{y}_{it}K_h(\omega_{it} - \omega)$, $K_h(\cdot) = K(\cdot/h)/h$, with $K(.)$ being a kernel function and h the bandwidth parameter. In this study, $K_h(\cdot)$ is the Gaussian kernel, $K(\cdot/h) = (2\pi)^{-1/2}\exp(-0.5(\cdot/h)^2)$. To select the bandwidth h, we apply Scott's (1992) rule of thumb, $h = 1.06\hat{\sigma}_\omega(NT)^{-1/5}$, where $\hat{\sigma}_\omega$ is the estimated standard deviation of the factor observations. Note that $\hat{\sigma}_\omega$ approximately equals to unity as we standardize the factors.

5.A.2 Inference

For inferential purposes, we follow the factor-based bootstrap approach of Herwartz and Xu (2009) that contrasts the factor invariant coefficient model with the state dependent model. Herwartz and Xu (2009) suggest two types of tests for factor dependence, global and local. The global test is a bootstrap approximation of an F-statistic and contrasts the residual sum of squares under the factor dependent model to that under invariant coefficients. The local test on the other hand examines the factor dependence for a given value of the factor. Confidence intervals under the null of a factor invariant FG nexus are constructed using bootstrap FG nexus estimates $\hat{\boldsymbol{\beta}}^*(\omega)$ obtained by means of pseudo samples ω^*_{it} of factors that are drawn with replacement from the given factor variables ω_{it} keeping other variables unchanged. This bootstrap resampling scheme destroys any systematic relationship between the model parameters and ω^*_{it}. For any local point ω, if an estimate $\hat{\beta}_1(\omega)$ lies outside its 95% confidence interval (based on 1000 bootstrap replications), then we reject the null hypothesis of constant FG nexus at 5% level of significance.

5.B List of economies included in each sample

5.B.1 Low-income economies

Burkina Faso, Burundi, Cameroon, Cote d'Ivoire, Gambia, Ghana, India, Kenya, Lesotho, Madagascar, Nepal, Niger, Nigeria, Pakistan, Papua New Guinea, Rwanda, Senegal, Sierra Leone, Togo.

5.B.2 Lower middle income economies

Algeria, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Guatemala, Honduras, Paraguay, Philippines, South Africa, Sri Lanka, Suriname, Swaziland, Syrian Arab Republic, Thailand.

5.B.3 Upper middle income economies

Botswana, Chile, Costa Rica, Gabon, Malaysia, Malta, Mauritius, Mexico, Saudi Arabia, Seychelles, St. Vincent and the Grenadines, Trinidad and Tobago, Uruguay, Venezuela.

5.B.4 High-income economies

Australia, Austria, Bahamas, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Republic of Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, United Kingdom, United States of America.

6 Openness and the finance-growth nexus

6.1 Introduction

Rajan and Zingales (2003) hypothesize that both trade and financial openness are crucial for financial development. They argue that financial development is opposed by incumbent industrialists and financiers who are wary of the ensuing competition and, hence, erosion of their rents. However, trade openness, together with financial openness, could mute industrial and financial incumbents' resistance to financial development for two important reasons. On the one hand, incumbents who are doing well in an open economy environment may not oppose financial development as they may see domestic competition less pressing. On the other hand, firms that are struggling to survive foreign competition will need to invest a lot, and, as a result, they will push for financial development so as to get better access to external credit. In this sense, openness could be considered as an important determinant of financial development. In a partial support for this claim, Baltagi et al. (2009) find that opening up either the trade or the capital accounts—but not necessarily both—could induce financial development. Evidently, the principal reason why Rajan and Zingales (2003) forward their hypothesis is that they believe financial development brings about economic growth. However, it is now widely accepted that finance does not always promote economic growth. More specifically, the impact of financial development on economic growth could depend on the level of trade and financial openness (Yilmazkuday, 2011). We have also documented in the preceding chapter that financial development is unlikely to spur economic growth in states of extreme financial or trade openness.

In this chapter, we will revisit the impact of openness on the finance-growth nexus using a different panel data set from 78 economies during the period 1981-2006. This data set differs from the one employed in the preceding chapter in two respects. First and foremost, we now employ a continuous financial openness measure, namely, the percentage of the economy's aggregate foreign assets and liabilities in GDP. Due to its smoothness, this measure, unlike the one used in the previous chapter, can be treated as a factor in the semiparametric estimation. Second, we utilize disaggregated openness measures. The financial openness measure is divided into two indicators: foreign asset holdings and foreign liability holdings indicators.

Similarly, the trade openness measure is disaggregated so that it distinguishes between imports and exports, on the one hand, and between goods exports (imports) and services exports (imports), on the other. Taking advantage of the smoothness of the new financial openness measure, we pursue a new empirical strategy of estimating a bivariate factor model, with trade openness and financial openness as the first and the second factors, respectively. This method helps to investigate whether financial development is beneficial when an economy has simultaneously high levels of trade and financial openness.

Our findings by and large confirm the evidence established in Chapter 5. To recap some of them, the impact of trade openness on the FG relationship varies across stages of economic development. While openness enhances the FG nexus in upper-middle-income economies, it exerts a negative impact in low- and lower-middle-income economies. On the other hand, very high level of financial openness tends to erode the growth-promoting role of financial development. We ascribe this result to the fact that financial openness is a likely substitute to financial development in its growth-promoting roles such as risk diversification (Obstfeld, 1994). Finally, it is only in upper-middle-income economies that we find simultaneously opening the trade and capital accounts to significantly enhance the FG nexus. Therefore, our results offer only a partial support to the Ragan and Zingales hypothesis that suggests opening up both trade and capital accounts as a means of fostering growth-promoting financial development.

Section 6.2 describes the data and presents results from parametric estimation. Section 6.3 introduces the functional coefficient model and discusses empirical functional estimates. Section 6.4 concludes. It should, however, be noted that this and the preceding chapter have a lot of similarities, especially with respect to the concept of state dependence and the functional coefficient modeling approach. Accordingly, we will not repeat the technical details of functional modeling provided in Appendix 5.A. Likewise, we only mention in passing that a brief review of the literature on the impact of openness on the FG nexus is discussed in Section 5.2.

6.2 Data and preliminary analysis

6.2.1 Data

The data set we have been utilizing in the previous three chapters is not suited for this chapter as the data for the new financial openness measure as well as for the disaggregated trade and financial openness indicators are not available for the same economies and the period 1975–2005. The new panel data set covers the period 1981-2006 and comprises 78 economies whose selection is dictated by data availability. Except the openness measures, indicators and data sources of all the remaining variables are similar to the data employed in the preceding chapters (see Section 5.3.1 for the detail). We measure financial development using credit by deposit-money banks and other financial institutions to the non-financial private sector as a percentage of GDP (PRV). Our measure of economic development is real GDP per capita (GDPPC). Government size is measured by government consumption expenditure as a percentage of GDP (GOV) and the growth rate of the GDP deflator is used to measure inflation (INF).

Trade openness is approximated in terms of the percentage of imports plus exports in GDP (OPEN). Furthermore, we will do a sensitivity check by employing the following alternative trade openness measures: the volumes of imports (IMP), exports (EXP), goods imports (GIMP), services imports (SIMP), goods exports (GEXP), or services exports (SEXP), all taken as a % of GDP. To measure financial openness, we use the financial globalization indicator (FOPEN) suggested in Lane and Milesi-Ferretti (2007). FOPEN is the volume of an economy's foreign assets plus liabilities holdings as a percentage of GDP. The robustness checks in this case are done by utilizing the percentage of foreign assets (FA) or foreign liabilities (FL) in GDP.

PRV is obtained from the November 2010 update of the *Financial Development and Structure Database* of Beck et al. (2000a)[27] while FOPEN is taken from Philip Lane's website.[28] The remaining series are drawn from the World Bank's World Development Indicators.

As the impact of openness on the FG nexus is likely to vary across stages of

[27] `http://go.worldbank.org/X23UD9QUX0`

[28] `http://www.philiplane.org/EWN.html`

economic development, we categorize the 78 economies four according to the World Bank's contemporary classification criteria, based on their latest (2006) GDP per capita.[29] In particular, economies whose latest real per capita GDP (in constant 2000 US Dollar) fall in the ranges less than 905, 906–3595, 3596–11115, and over 11115 are classified as low-income (17 economies), lower-middle-income (17), upper-middle-income (19) and high-income (25), respectively. The list of economies included in each sample is provided in Appendix 6.A.

Table 6.1: Summary statistics, 1981–2006

Variable	Mean	Max	Min	Std	CV	Variable	Mean	Max	Min	Std	CV
	World (78 economies)										
GDPPC	7810.4	41245.8	102.2	9550.8	1.22	IMP	42.0	204.5	3.0	26.3	0.63
PRV	51.0	269.8	1.4	41.1	0.81	EXP	37.6	234.4	3.2	25.0	0.67
GOV	16.1	43.0	3.2	6.2	0.39	GIMP	32.3	182.5	3.4	22.3	0.69
INF	10.5	390.7	-23.5	19.6	1.86	SIMP	9.9	47.0	0.7	6.6	0.67
OPEN	79.6	438.9	6.3	49.2	0.62	GEXP	27.0	197.9	0.9	20.8	0.77
FOPEN	169.2	2381.4	7.5	178.4	1.05	SEXP	10.7	66.3	0.1	10.6	0.99
						FA	65.0	1189.9	1.5	95.8	0.39
						FL	104.2	1191.5	6.0	90.8	0.87
	Low income (17)										
GDPPC	361.0	976.1	102.2	189.1	0.52	IMP	34.7	147.7	3.0	26.1	0.75
PRV	16.6	41.2	1.4	9.2	0.55	EXP	23.5	82.1	3.2	13.4	0.57
GOV	13.6	43.0	4.8	6.3	0.46	GIMP	27.4	134.1	3.4	24.3	0.89
INF	14.1	165.7	-8.2	20.8	1.48	SIMP	8.9	35.4	1.1	5.5	0.61
OPEN	58.2	187.7	6.3	34.5	0.59	GEXP	18.7	75.1	0.9	12.8	0.68
FOPEN	118.6	628.2	7.5	74.9	0.63	SEXP	5.3	22.7	0.1	3.5	0.67
						FA	20.4	83.0	1.5	14.1	0.66
						FL	98.2	561.8	6.0	65.8	0.67
	Lower middle (17)										
GDPPC	1498.1	3561.3	407.7	637.4	0.43	IMP	43.0	105.8	13.0	19.4	0.45
PRV	35.9	166.0	4.8	27.1	0.76	EXP	35.7	100.9	11.5	15.6	0.44
GOV	13.7	37.2	3.2	6.1	0.44	GIMP	32.9	87.6	9.8	15.3	0.47
INF	9.3	102.8	-23.5	10.5	1.12	SIMP	9.5	31.5	1.9	5.7	0.60
OPEN	78.8	202.8	24.9	33.8	0.43	GEXP	25.3	92.8	5.0	14.2	0.56
FOPEN	113.5	340.0	32.3	55.5	0.49	SEXP	10.5	47.7	0.5	9.4	0.89
						FA	37.2	260.0	2.4	35.1	0.42
						FL	76.3	238.6	23.7	34.5	0.45
	Upper middle (20)										
GDPPC	4733.4	15413.9	1213.8	2059.2	0.44	IMP	51.1	106.9	9.4	23.9	0.47
PRV	42.9	155.3	6.5	27.1	0.63	EXP	48.8	121.3	8.2	21.5	0.44
GOV	16.7	38.8	5.0	6.0	0.36	GIMP	38.5	84.5	8.0	19.3	0.50
INF	13.0	139.7	-20.8	21.0	1.62	SIMP	13.1	35.9	0.7	7.3	0.56
OPEN	100.0	220.4	21.1	43.4	0.43	GEXP	32.2	106.3	2.1	19.0	0.59
FOPEN	168.6	1324.5	26.1	153.7	0.91	SEXP	16.4	66.3	0.8	14.4	0.88
						FA	64.6	604.0	4.2	75.5	0.33
						FL	104.1	720.5	11.2	87.1	0.84
	High income (24)										
GDPPC	20122.3	41245.8	3510.0	8097.5	0.40	IMP	38.9	204.5	6.9	30.2	0.78
PRV	92.8	269.8	22.0	38.9	0.42	EXP	39.6	234.4	7.2	33.2	0.84
GOV	19.2	41.5	8.2	5.0	0.26	GIMP	30.2	182.5	4.9	25.7	0.85
INF	6.7	390.7	-4.8	21.5	3.21	SIMP	8.2	47.0	1.4	6.3	0.77
OPEN	78.5	438.9	16.0	63.2	0.80	GEXP	29.6	197.9	4.1	27.7	0.94
FOPEN	245.0	2381.4	33.0	260.6	1.06	SEXP	9.9	50.8	1.2	8.7	0.88
						FA	116.8	1189.9	7.7	139.5	0.28
						FL	128.2	1191.5	16.9	124.2	0.97

Note: Full definitions of the variables and data sources are given in the text. Except GDPPC, all variables are measured as percentage values. Max, min, std and CV represent maximum, minimum, standard deviation and coefficient of variation, respectively.

Table 6.1 presents descriptive statistics. The summary includes the means,

[29] `http://data.worldbank.org/about/country-classifications/a-short-history.`

minimum and maximum values and standard deviations for different income groups. In addition to the fact that the data set is characterized by considerable variations within/between cross sections, a number of distinctive features of the data are worth emphasizing. First, as expected, the mean of the financial development measure PRV increases with economic development. Second, the average degree of trade openness (measured by OPEN) initially increases with income level, reaches a maximum (for upper-middle-income economies) and then declines. In contrast, the mean level of financial openness (FOPEN) shows a marginal decrease initially, but then increases markedly as economies develop. In particular, high-income economies are twice as much open as low-income economies. Disaggregating the openness measures OPEN and FOPEN reveals some interesting features. For instance, while OPEN is more or less evenly divided into IMP and EXP, FL is much higher than FA in all income groups. Besides, high-income economies are about six times as much open as low-income economies in terms of their foreign asset holdings. Further decomposing the trade openness measures, we find that the volume of trade in goods (GIMP and GEXP) is about three times that of trade in services (SIMP and SEXP). Given that low-income economies are highly dependent on concessional debts to run their economies, it is clear that the amount of debts does not reflect capital account openness in those economies.[30] Hence, the (disaggregated) foreign-assets-based indicator of financial openness (FA) seems to be a more reasonable measure in this case.

6.2.2 Parametric regression results

Before we embark on examining the dependence of the FG nexus on openness by means of a functional coefficient modeling approach, we begin our analysis by applying a typical parametric regression widely used in the FG literature. Namely, we employ a dynamic OLS (DOLS) model, where the explanatory variables in levels are augmented with the lags and leads of their first differences to account for potential endogeneity and serial correlation (Stock and Watson, 1993; Christopoulos

[30]For example, 73.4% of the external debt in all low-income economies in 2006 constitute concessional debt (World Development Indicators online accessed on August 29, 2012).

and Tsionas, 2004; Apergis et al., 2007). Formally, the model reads as

$$y_{it} = \boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{z}'_{it}\boldsymbol{\gamma} + u_{it}, \tag{6.1}$$

where y_{it} represent GDP per capita; $\boldsymbol{x}_{it}$ is a vector of explanatory variables comprising PRV, GOV, $OPEN$, INF and $FOPEN$; $\boldsymbol{z}_{it}$ includes the fixed effect and one lag and one lead of the first difference of the right-hand side variables $\boldsymbol{x}_{it}$; and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, respectively, are vectors of long-run and short-run parameters. To allow for heterogeneous short-run coefficients, we partial out $\boldsymbol{z}_{it}$ from (6.1). To this end, we denote matrices collecting observations in y_{it}, $\boldsymbol{x}_{it}$ and $\boldsymbol{z}_{it}$ for economy i by Y_i, $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$, respectively, and henceforth consider the partial system

$$\tilde{y}_{it} = \widetilde{\boldsymbol{x}}'_{it}\boldsymbol{\beta} + \tilde{u}_{it}, \tag{6.2}$$

where $\tilde{y}_{it}$, $\widetilde{\boldsymbol{x}}_{it}$ and $\tilde{u}_{it}$ are typical elements of, respectively, $\tilde{\boldsymbol{Y}}_i = \boldsymbol{M}_i\boldsymbol{Y}_i$, $\tilde{\boldsymbol{X}}_i = \boldsymbol{M}_i\boldsymbol{X}_i$, $\tilde{u}_i = \boldsymbol{M}_i u_i$, $\boldsymbol{M}_i = (I_i - \boldsymbol{Z}_i(\boldsymbol{Z}'_i\boldsymbol{Z}_i)^{-1}\boldsymbol{Z}'_i)$, and I_i is a $(T \times T)$ identity matrix.

Table 6.2 documents estimation results using data from the four income groups and the comprehensive sample. It can be seen that financial development has a statistically and economically significant positive long-run impact on economic development in all the cross sections. This positive impact is consistent with much of the empirical FG literature (see Levine, 2005, for a broad survey). The estimated FG coefficient initially increases with income level but finally declines with high-income economies exhibiting the weakest FG link of all income groups. This dependence of the FG nexus on the income level is also diagnosed in the preceding chapter as well as in Yilmazkuday (2011). A noticeable difference from the parametric results documented in the previous chapter is that high-income economies now exhibit a weaker FG link. This could be explained by their higher degree of financial openness (see Table 6.1), which is now included as an explanatory variable. Indeed, we have established in the previous chapter (specifically Table 5.2) that economies with the highest level of financial openness benefit the least from financial development.[31]

[31] To be precise, excluding $FOPEN$ from the model increases the coefficient attached to PRV in high-income economies to 0.236. However, as our aim is to see the impact of PRV on $GDPPC$ after taking into account $FOPEN$'s impact on $GDPPC$, we proceed by including $FOPEN$ as a regressor. The only reason why it has been left out of the regressions in the previous chapters is that the $FOPEN$ measure employed there, being an index derived from four dummy variables, does not feature frequent, if any, variations within an economy.

Table 6.2: Parametric regression results

Variables	low income	lower middle	upper middle	high income	world
PRV	**0.113**	**0.215**	**0.289**	**0.104**	**0.216**
	(0.016)	(0.028)	(0.023)	(0.017)	(0.010)
GOV	**-0.091**	**-0.140**	**-0.217**	**-0.361**	**-0.206**
	(0.030)	(0.038)	(0.046)	(0.064)	(0.020)
OPEN	**0.160**	**0.217**	**0.287**	**-0.220**	**0.110**
	(0.026)	(0.039)	(0.038)	(0.048)	(0.018)
INF	**0.429**	**-0.517**	**0.177**	-0.077	0.006
	(0.061)	(0.176)	(0.079)	(0.050)	(0.038)
FOPEN	-0.024	0.031	**0.261**	**0.276**	**0.162**
	(0.015)	(0.035)	(0.019)	(0.013)	(0.009)
Serial corr.	82.353	76.471	65.000	70.833	73.077
Poolability	9.472	6.621	4.522	9.741	5.677
HS	**-3.987**	**-3.528**	**-4.020**	**-3.522**	**-4.437**
DH	**-4.194**	**-3.801**	**-3.821**	**-3.882**	**-4.417**

Notes: The dependent variable is GDPPC. The model includes a constant and contemporaneous as well as one lag and lead of the first differences of all explanatory variables. Apart from INF, all variables are in logarithmic form. The values provided in parentheses are estimated standard errors. Rejections of the null hypothesis at the 5% level of significance are indicated by boldface numbers. Reported numbers of the serial correlation tests of Breusch (1978) and Godfrey (1978) represent percentages of economy specific regressions where tests indicate rejections of the null hypothesis of no first order serial correlation with 5% significance. Entries corresponding to *HS* and *DH* are obtained by applying homogeneous panel unit root tests suggested, respectively, in Herwartz and Siedenburg (2008) and Demetrescu and Hanck (2012a) on the pooled residuals. The null hypothesis of the employed poolability test is that reported long-run parameter estimates are not systematically different from mean group estimates.

Table 6.2 also presents some model diagnostics: serial correlation and unit roots tests for the residuals, and poolability tests. Except for serial correlation, we obtain satisfactory results for the two diagnostic tests. In particular, the null hypothesis of a panel unit root is rejected using both unit root tests (Herwartz and Siedenburg, 2008; Demetrescu and Hanck, 2012a) indicating that at the panel level the performed DOLS regression does not suffer from spurious dependence. Poolability test results also indicate that the pooled regression estimates are not systematically different from mean group estimates for most cross sections. Thus, after allowing for fixed effects and cross section- specific transitory dynamics, pooling is not overly restrictive to uncover the long-run determinants of per capita income. However, the null hypothesis of no first order serial correlation is rejected in most of the economies. Still, we refrain from model respecification for two reasons. First, serial correlation diagnostics improve if we use more than one lag of the first differences in the DOLS regression while higher order transitory dynamics leaves the evaluation of the FG link qualitatively unaffected. Second, eventual residual correlation does not invalidate consistency of the long-run DOLS parameter estimates.

6.3 Functional coefficient modeling

In this section, we briefly outline a one-dimensional functional coefficient model similar to the one suggested by Cai et al. (2000). This model is used to assess the dependence of the long-run FG nexus as formalized in (6.2) on alternative measures of trade and financial openness, with only one factor considered at a time. Moreover, we introduce a bivariate state dependent model that allows us to examine the simultaneous impact of trade and financial openness on the FG nexus. Finally, empirical results from the employed functional coefficient models are discussed.

6.3.1 The semiparametric model

Denoting a measurable factor, for instance, OPEN, by w, a functional coefficient representation of (6.2) looks like

$$\tilde{y}_{it} = \widetilde{\boldsymbol{x}}'_{it}\boldsymbol{\beta}(\omega) + \tilde{u}_{it}. \tag{6.3}$$

where $\omega = w_{it}$, for a one dimensional factor model, and $\omega = (w^1_{it}, w^2_{it})$ for a bivariate factor model, with the superscripts 1 and 2 representing trade and financial openness, respectively.

To facilitate comparability among economies, we standardize factors as

$$w_{it} = \frac{(\tilde{w}_{it} - \bar{w}_t)}{\sigma_t(\tilde{w})},$$

$$\text{with} \quad \bar{w}_t = 1/N \sum_{i=1}^{N} \tilde{w}_{it}, \quad \sigma_t(\tilde{w}) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\tilde{w}_{it} - \bar{w}_t)^2}$$

Estimation and inferential methods within the functional coefficient model are similar to Herwartz and Xu (2009) and have been briefly reviewed in Appendix 5.A. The functional estimates are essentially weighted regression estimates, where the weight assigned to a particular observation reflects the time local position of the factor in the cross section of time series. As the question of interest in this work is the functional dependence of the FG nexus, we discuss only $\hat{\beta}_1(\omega)$. For a one-dimensional factor model, functional estimates $\hat{\beta}_1(\omega)$ can be displayed in a two dimensional graph. Given that our factors are standardized, the following grid is used to depict functional estimates:

$$\hat{\beta}_1(\omega), \omega = -2 + 0.1\kappa, \kappa = 0, 1, 2, ..., 40. \tag{6.4}$$

In this case, estimates $\hat{\beta}_1(\omega)$ reflect the effect of attaching relatively high kernel weights to economies which are above ($\omega > 0$), close to ($\omega = 0$) or below ($\omega < 0$) the factor's average time path. Similarly, estimates from the bivariate functional coefficient model are displayed in a three dimensional graph using the same grid as in (6.4).

6.3.2 Functional coefficient estimates

In this section, results obtained from the functional coefficient model in (6.3) are discussed.[32] We employ the factor-based bootstrap approach proposed in Herwartz and Xu (2009) to examine state dependence of the FG relationship on trade and/or financial openness. Accordingly, we first present the global factor-invariance test results and then discuss the local dependence of the FG nexus on openness. Throughout, we use the conventional 5% significance level to decide if a given openness measure has a statistically significant impact on the FG link.

Table 6.3 documents the global factor-invariance test results. It can be seen that, with the exception of lower-middle-income economies, the null hypothesis of a constant FG nexus can be rejected if $OPEN$ is used as a state variable. Even in lower-middle-income economies, the FG link is dependent on the import-based trade openness measure (IMP). On the other hand, the FG link significantly depends on financial openness ($FOPEN$) in low- and high-income, but not in middle-income categories. Moreover, it is important to emphasize here that each measure of trade and financial openness significantly affects the FG nexus in high-income economies. The last row in Table 6.3 presents the results for the test on whether the FG link is dependent on the bivariate factors, $OPEN$ and $FOPEN$. As it turns out, it is in

[32] All computations are done in MATLAB 2011a.

Table 6.3: Global factor invariance test results

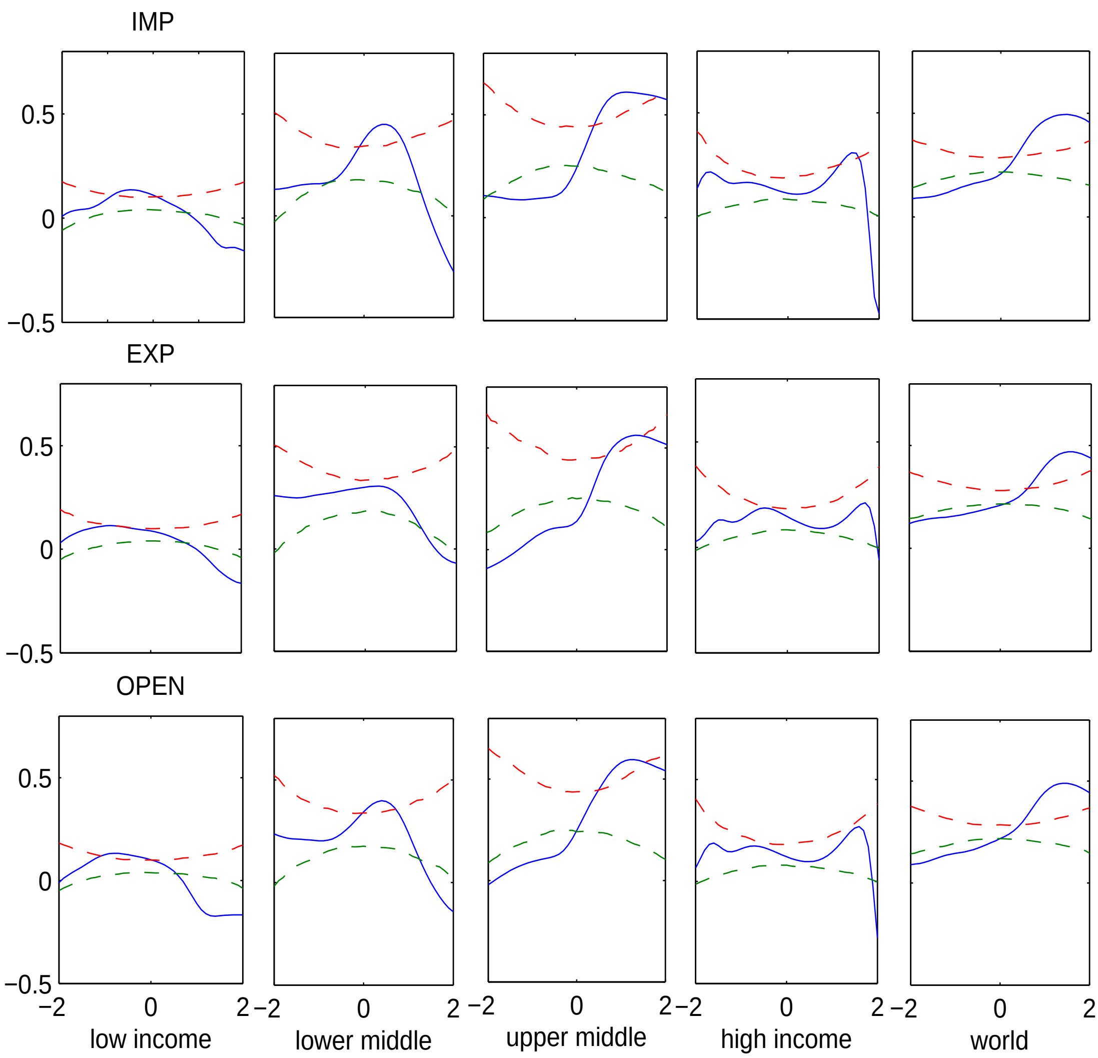
Factors	low income	lower middle	upper middle	high income	world
OPEN	.010	.061	.000	.000	.000
EXP	.092	.867	.000	.000	.000
GOODS EXP	.002	.381	.000	.000	.000
SER. EXP	.000	.000	.000	.009	.000
IMP	.194	.000	.000	.000	.000
GOODS IMP	.340	.000	.000	.000	.000
SER. IMP	.104	.000	.000	.000	.000
FOPEN	.006	.769	.683	.009	.002
FA	.600	.238	.332	.045	.000
FL	.000	.911	.004	.011	.120
OPEN, FOPEN	.390	.020	.000	.970	

Notes: All variables are used in logarithmic forms. Reported numbers are (bootstrap) p-values. Except for the last row, the bivariate factors, the number of replications is 1000. As a very long computation time is required, the number of replications used for the bivariate factors is 500. Even then, obtaining a result for the comprehensive sample has been computationally infeasible.

middle-income economies only that the bivariate factors significantly affect the FG nexus.

6.3.2.1 Trade openness Figure 6.3.2.1 displays the estimated functional FG nexus obtained by employing IMP, EXP and $OPEN$ as factor variables. One important finding from the graphs is that using either of the three openness measures provides very similar results. This is consistent with the international trade theory that trade promotes efficiency not only through exports but also through the import of goods and services that otherwise are too costly to produce domestically (Yanikkaya, 2003). Thus, we prefer to discuss only the evidence obtained by using the most aggregated trade openness measure, OPEN, as depicted in the third row of Figure 6.3.2.1. Here, we can see that the impact of trade openness on the FG nexus varies across stages of economic development. In particular, in low- and lower-middle-income economies, while a moderate level of trade openness stimulates the FG nexus, extreme openness could lead to a negative FG relationship. This hump-shaped relationship between trade openness and the FG nexus corroborates

Figure 6.1: Functional FG estimates conditional on EXP, IMP and OPEN.



Note: The figures show estimated long-run effects $\hat{\beta}_1(\omega)$, with $\hat{\beta}_1$ on the vertical and ω on the horizontal axes. The solid line shows the point estimates and the two dashed lines are the 95% confidence intervals of the model excluding functional dependence.

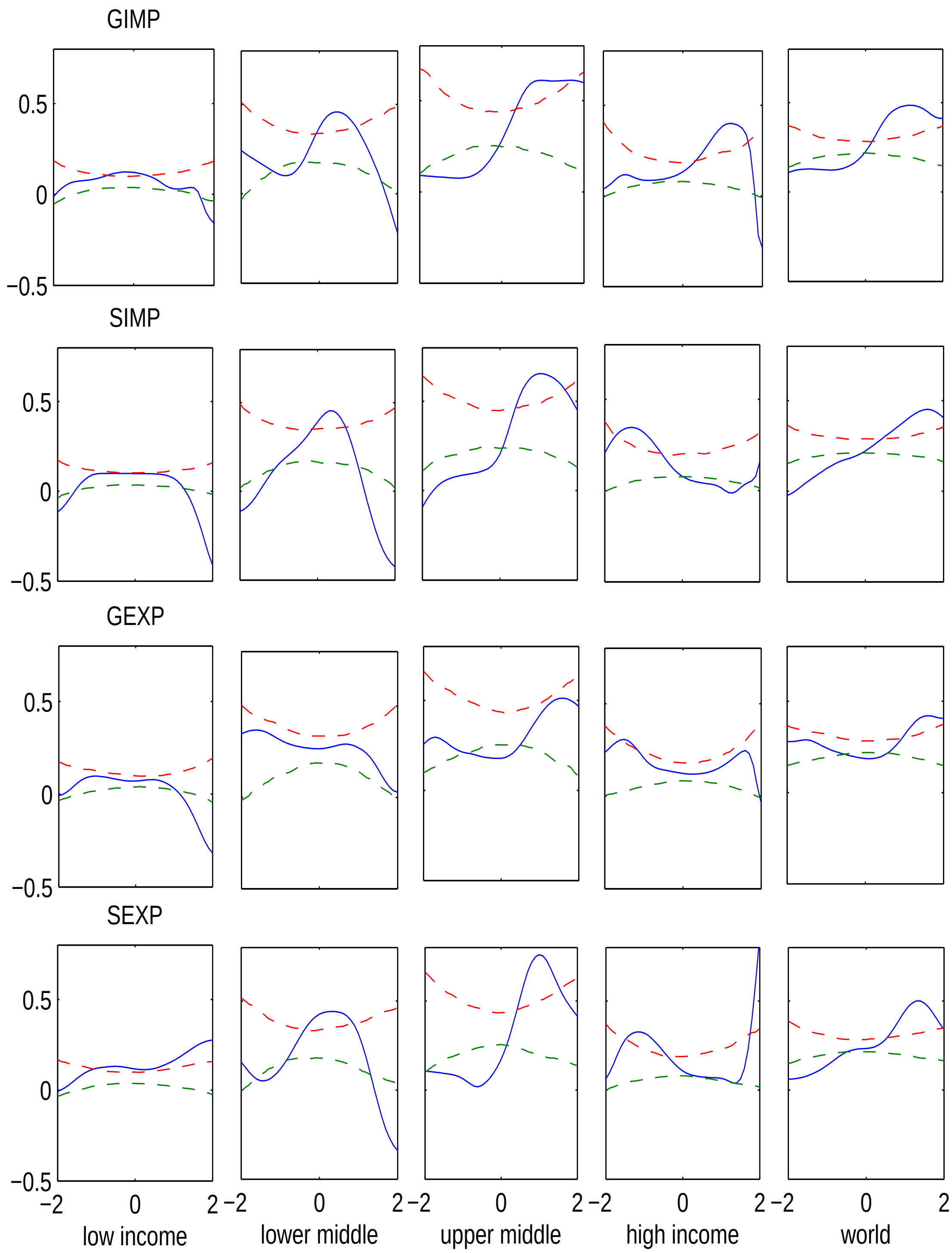
the results reported in Yilmazkuday (2011) as a worldwide evidence. The negative FG nexus might highlight the challenge fierce international competition is posing to small firms in highly open low- and lower-middle-income economies, a view echoed by trade protectionists like Young (1991). Moreover, it could also be a consequence of open economies' increased vulnerability to macroeconomic shocks as argued in Rodrik (1992).

On the contrary, high trade openness increases the FG nexus in upper-middle-income economies. This might indicate the fact that firms in those economies are strong enough to withstand foreign competition. Furthermore, it might imply that those firms are able to efficiently utilize the obtained credit when they get access to bigger markets and/or when they face strong competition of foreign firms (Yanikkaya, 2003). In high-income economies, trade openness does not appear to affect the FG nexus for a wide range of openness levels. When openness becomes extremely high, then a likely negative impact is observed. The negative impact becomes even clearer when we measure openness by IMP, but not by EXP, possibly implying that a higher degree of imports might indicate poor performance by domestic firms facing international competition.

Further decomposing the trade openness measures into goods and services imports (exports) gives the functional estimates displayed in Figure 6.3.2.1. Interestingly, the estimates demonstrate a fair degree of similarity to the results presented in Figure 6.3.2.1 and corroborate the foregoing discussions. However, one peculiarity is worth mentioning here. If openness is measured by the volume of services exports as a percentage of GDP ($SEXP$), then even low-income and high-income economies are characterized by an increasing FG nexus. This is in line with the argument by Konan and Maskus (2006) that openness in services trade results in a more profound upgrading of economy-wide efficiency than openness in goods trade as financial, communications, and professional services are essential intermediate inputs into production in all sectors.

6.3.2.2 Financial openness Figure 6.3.2.1 depicts the estimated functional dependence of the FG nexus on three alternative measures of financial openness. Again, the functional relations obtained by using the comprehensive measure, $FOPEN$, remains qualitatively unaffected by disaggregation of FOPEN into foreign assets (FA) and liabilities (FL) holdings. Basing the ensuing discussion on the third row of Figure 6.3.2.1, we see that financial openness has a clearly negative impact on the FG nexus at all levels of economic development. In particular, the functional estimates demonstrate that high-income economies could have a very high FG nexus if they are characterized by very low financial openness and the nexus declines as economies open up their capital accounts. This substantiates our conjecture in Section 6.2.2 that high-income economies exhibit the lowest FG nexus, most likely, because of the very high financial openness in those economies. This is also consistent with the theoretical expectations outlined in the previous chapter

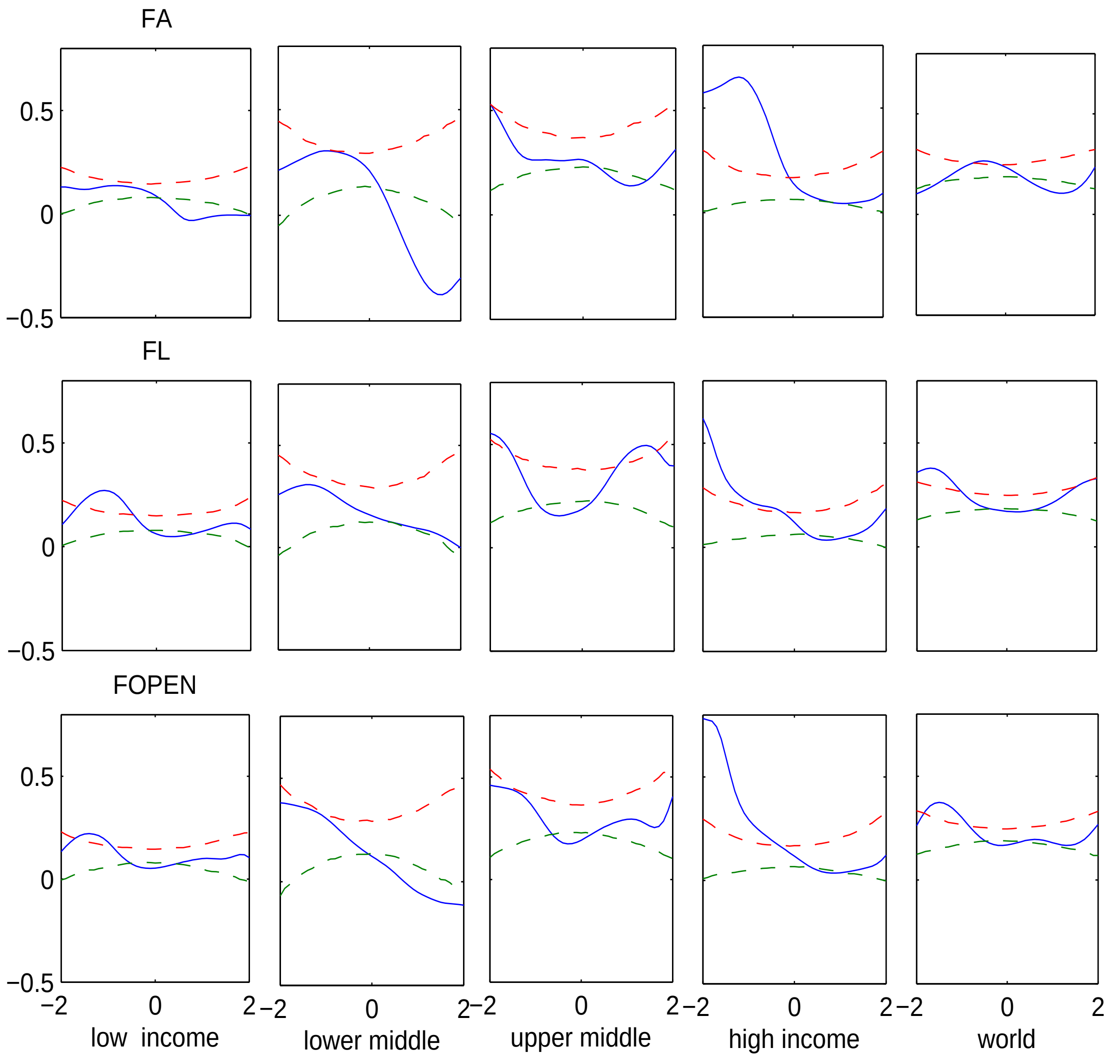
Figure 6.2: Functional FG estimates conditional on GIMP, GEXP, SIMP, SEXP.



Note: The figures show estimated long-run effects $\hat{\beta}_1(\omega)$, with $\hat{\beta}_1$ on the vertical and ω on the horizontal axes. The solid line shows the point estimates and the two dashed lines are the 95% confidence intervals of the model excluding functional dependence.

(see Section 5.2). Most importantly, there is an overlap between the roles that both financial development and financial openness could play in economic development. For instance, both financial development and financial openness are believed to help

Figure 6.3: Functional FG estimates conditional on FA, FL and FOPEN.

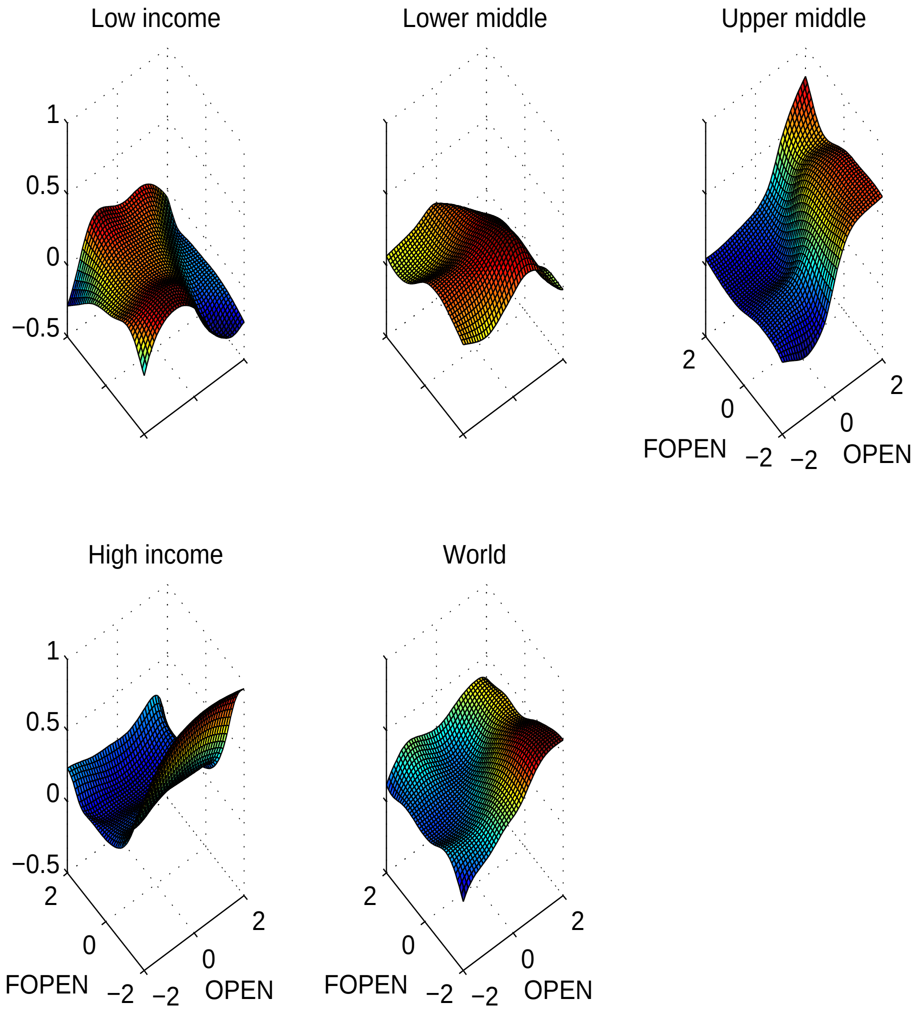


Note: The figures show estimated long-run effects $\hat{\beta}_1(\omega)$, with $\hat{\beta}_1$ on the vertical and ω on the horizontal axes. The solid line shows the point estimates and the two dashed lines are the 95% confidence intervals of the model excluding functional dependence.

agents diversify inter-temporal and cross-sectional risks and consequently increase the likelihood that high-risk, high-expected-return projects are not left out unfunded (Obstfeld, 1994; Bekaert et al., 2011).

This evidence is in a stark contrast to the Rajan and Zingales (2003) hypothesis that economies benefit—in terms of economic growth—by opening up their capital accounts as this helps to develop their domestic financial sector. While this study does not examine whether financial openness promotes financial development, it clearly shows that financial development is of little significance for economic development in states of very high financial openness. Needless to say, our results should not be interpreted as implying a negative or negligible consequence of financial openness on economic development. In this regard, we have seen from the parametric regression results provided in Section 6.2.2 that financial openness has a significantly positive impact on economic growth in upper-middle and high-income economies. What our findings indicate, however, is that opening up capital accounts does not likely have a beneficial impact on economic growth if the benefit is expected to be delivered through enhanced growth-promoting financial development, as advocated by Rajan and Zingales (2003) and Baltagi et al. (2009).

Figure 6.4: Functional FG estimates conditional on bivariate factors OPEN and FOPEN.



Note: The figures show estimated long-run effects $\hat{\beta}_1(\omega)$, with $\hat{\beta}_1$ on the vertical (z-) axes and the factors ω on the x- and y-axes.

6.3.2.3 Simultaneous trade and financial openness One of the main features of the Rajan and Zingales (2003) hypothesis is that a simultaneous opening up of the trade and capital accounts is necessary for financial development. Baltagi et al. (2009) note that this view is in sharp contrast to most of the previous literature (e.g. McKinnon, 1991) which promotes a sequential approach where trade liberalization should come before financial liberalization. Therefore, testing the validity of the Rajan and Zingales hypothesis could more directly proceed via examining the impact of a simultaneous increase in trade and financial openness on the FG link. To this end, we have estimated a bivariate functional coefficient model in (3). Estimation results are depicted in Figure 6.3.2.3. Closer examination of the bivariate functional estimates reveals that overall patterns are, by and large, dominated by a single factor, namely, financial openness in high-income economies and trade openness in the remaining cross sections. Consequently, strong support for the Rajan and Zingales hypothesis comes from the data in the upper-middle-income economies where a simultaneous increase in trade and financial openness enhances the impact of financial development on economic growth. For the rest of the cross sections, however, a simultaneously high level of financial and trade openness is associated with a negligible, and at times a negative, FG nexus. This is most likely because of the reasons conjectured in Section 6.3.2.1, for low- and lower-middle-income economies, and in Section 6.3.2.2, for high-income economies.

6.4 Conclusions

In this chapter, we examined the state dependence of the FG nexus on various aspects of trade and financial openness. Our findings, which are fairly robust to a range of alternative and disaggregated openness measures, indicate that the impact of financial development on economic growth significantly depends on the degree of an economy's trade and financial openness. Most importantly, although financial openness might promote financial development as argued by Rajan and Zingales (2003), it is associated with an exceedingly diminishing impact of financial development on economic growth. The evidence on the impact of trade openness on the FG link is, however, mixed. Higher trade openness strengthens the FG link in upper-middle-income economies, but it has a weakening effect in low- and lower-middle-income economies. On the other hand, it is in upper-middle-income economies only that we find a significantly positive FG nexus in states of simultaneously high trade and financial openness. Therefore, our findings offer only limited support to the Ragan and Zingales hypothesis which suggests opening up trade and capital accounts in order to bring about economic growth through financial development.

This study demonstrates that, if the goal is to achieve a high level of finance-induced growth, theories or empirical findings showing that openness induces financial development are not sufficient to suggest policies in favor of financial and trade openness. As such, it highlights the need to coordinate the research direction that examine the determinants of financial development with the one which investigates state dependence in the FG nexus. Therefore, investigating the impact of financial development, government expenditure, and institutions on the FG relationship while studying their role in financial development will be an interesting area for future research.

6.A List of economies included in each sample

6.A.1 Low-income economies

Cameroon, Cote d'Ivoire, Ghana, India, Kenya, Lesotho, Madagascar, Malawi, Nepal, Niger, Pakistan, Papua New Guinea, Senegal, Sierra Leone, Sudan, Togo.

6.A.2 Lower-middle-income economies

Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Guatemala, Honduras, Indonesia, Jordan, Paraguay, Philippines, South Africa, Sri Lanka, Swaziland, Syrian Arab Republic, Thailand, Vanuatu.

6.A.3 Upper-middle-income economies

Botswana, Chile, Costa Rica, Dominica, Gabon, Grenada, Malaysia, Malta, Mauritius, Mexico, Panama, Saudi Arabia, Seychelles, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Trinidad and Tobago, Turkey, Uruguay, Venezuela.

6.A.4 High-income economies

Austria, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Republic of Korea, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States of America.

7 Concluding Remarks

This thesis is an empirical contribution to the century-old debate on the finance-growth (FG) nexus. Special focus has been given to two important issues in the area: causality and state-dependence in the FG nexus. We examined the first issue by dividing it based on time horizon. Using panel data from 74 economies during 1975–2005, the long-run FG causality is analyzed in Chapter 2 and the short-to-medium-run causality is investigated in Chapter 4. Regarding the short-to-medium-run causality, there is stronger evidence in favor of the view that "*where enterprise leads finance follows*" (Robinson, 1952) than the reverse causal impact. Interestingly, this evidence is uniform across stages of economic development. The long-run causality, however, varies across stages of economic development. Strong evidence of causality from finance to growth—and not vice versa—is diagnosed in low-income economies. In the remaining cross-sections, however, there is a weakened evidence of causality from growth to finance. Nevertheless, the employed financial development measure in middle-income economies and in the comprehensive cross section is found to be panel stationary implying that the observed causality may not be a long-run one. Focusing attention on Sub-Saharan African (SSA) economies, we find in Chapter 3 that financial development has a significantly positive long-run impact on economic development in the region.

Overall, our results demonstrate that economic growth generates financial development. This evidence, however, is of lesser policy relevance. What is more important for policy making is whether finance has an impact on economic growth or not. In this respect, it is only in low-income economies (and in SSA region) that our findings entail devising policies to build deeper and more sophisticated financial systems as a means of promoting economic performance.

A key assumption in most of the empirical literature is that the FG nexus is invariant across economies and over time, but findings repeatedly show just the opposite. In Chapter 5, we not only test whether the assumption of invariant FG nexus is realistic, but also try to investigate economic factors that may determine the FG link. For this purpose, we employ a functional coefficient model—a flexible semiparametric approach that is well-suited to allow the FG nexus to depend on state or factor variables. We find that the FG nexus is dependent on an economy's level of income, financial development, government size, trade openness and financial openness. The following are some of the notable results: (1) financial development has a generally positive effect on the FG nexus, with the strongest FG link observed in low-income economies with a high level financial development; (2) financial development could have an adverse effect on economic growth in low- and lower-middle-income economies when they have very large government sizes or are extremely open to international trade; (3) upper-middle-income economies show a pronounced FG nexus when they are very open to international trade; (4) economies with the highest level of financial openness benefit the least from financial development.

Chapter 6 extends the approach followed in the preceding chapter to extensively examine the impact of trade and financial openness on the FG nexus. This special emphasis is motivated by the fact that Rajan and Zingales (2003) and accompanying empirical studies suggest that openness is crucial for financial development. The argument is, however, founded on the assertion that finance promotes growth regardless of an economy's level of trade and financial openness—a view that is not supported by our findings in Chapter 5. Using a new data set, alternative and disaggregated measures of trade and financial openness, and a bivariate functional coefficient model, we obtain results that largely confirm those established in Chapter 5. In particular, finance is not growth promoting in states of very high level of financial openness. Furthermore, high trade openness leads to a high FG nexus in upper-middle-income economies, but it exerts a deleterious influence in low- and lower-middle-income economies. Finally, it is only in upper-middle-income economies that simultaneously high trade and financial openness lead to a significantly positive FG nexus.

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Ich erkläre hiermit an Eides Statt, dass ich meine Doktorarbeit "Causality and state dependence in the finance-growth nexus: an empirical investigation" selbständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

Kiel, 20. Dezember 2012

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- "Where enterprise leads, finance follows. In-sample and out-of-sample evidence on the causal relation between finance and growth," *Economics Bulletin*, 2012, Vol. 32 No. 1 pp. 871–882 (with Matthias Hartmann and Helmut Herwartz).

Papers currently under review

- "Homogeneous panel unit root testing under variance breaks" (with Helmut Herwartz and Florian Siedenburg), *invited to revise and resubmit.*
- "State dependence in the finance-growth nexus: a functional coefficient approach" (with Helmut Herwartz)
- "Revisiting the finance-growth nexus in Sub-Saharan Africa: results from error-correction-based panel cointegration tests"

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