INTERRELATION BETWEEN GROWTH AND INEQUALITY

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ABSTRACT

Inclusive growth should ensure "broad-based" economic growth which characterizes the pattern of growth. Beyond simple association identification implied by the Kuznets curve and cross-country panel regression analyses, this study attempts to shed light on the dynamic causality relationship and impact channel between economic growth and inequality—using vector error correction model (VECM) and vector autoregression (VAR) models for individual economies. If growth has a negative impact on inequality, renewed attention should be paid to curbing inequality. Those economies experiencing inclusive growth can further promote growth with less risk of sacrificing equity. This also provides useful implications for development interventions through designing and monitoring projects and programs. Given the growing challenges of reducing inequality, economies could create a proper inequality target as a binding constraint in pursuing economic growth, instead of using a growth–first and redistribution–later strategy.

Keywords: dynamic causality, economic growth, inequality

JEL Classification: C32, O1, O4

I. INTRODUCTION

Inclusive growth is one of the most important policy agendas—for the development community, among economic researchers and practitioners alike. It does not differentiate between developed, developing, or least developed economies. Advanced economies must deal with growing inequality coupled with dwindling middle income class, while rapidly developing emerging economies are seeing widening inequality as an offshoot of their spectacular economic growth. For example, in Asia, gross domestic product (GDP) grew in purchasing power parity terms an average 7% from 1990 to 2010. This rapid expansion helped more than 700 million people escape poverty and slashed the percentage of people living at or below the $1.25/day poverty line from 52% in 1990 to 21% in 2010. But widening inequality has undermined this success—and governments have taken notice. By some estimates, during the 1990s and 2000s, more than 80% of Asia's population lived in economies with worsening Gini coefficients, a common measure of inequality. These include the three most populous countries—the People's Republic of China (PRC), India, and Indonesia. Of the 36 Asian economies with available data in 2000s, 13 had Gini coefficients at or greater than 0.4. Eleven of 28 economies with comparable data show inequality worsened over the last 2 decades (*Asian Development Outlook 2014*). If inequality remained stable, an additional 240 million—or 6.5% of Asia's population—would have been lifted out of poverty. Had inequality not increased, India's poverty headcount would have been reduced from 32.7% to 29.5% in 2008, 4.9% instead of 13.1% in the PRC, and 6.1% instead of 16.3% in Indonesia by the Asian Development Bank's (ADB) estimates. Other regions have not fared any better. For example, Latin America and Sub-Saharan Africa have Gini coefficients above Asia's—although inequality in Latin America is decreasing quite remarkably. There are various factors behind growing inequality, but the conventional wisdom from research tells us that the same market forces that have driven growth—globalization, technological progress, and market reform—have exacerbated inequality along the way.

Much work has gone into illustrating the correlation and/or causality between economic growth and inequality—let alone testing the validity of the classic Kuznets curve (Barro 2008). Recently, various empirical researches have tackled this issue. Ostry, Berg, and Tsangarides (2014) show that more unequal societies tend to redistribute more; but lower net inequality is robustly correlated with faster and durable growth after controlling for the redistribution effect. Cevik and Correa-Caro (2015), using PRC and panel BRIC+ data have found evidence of the Kuznets curve and, for the PRC, government spending and taxation have opposite effects on income inequality. Davtyan (2014) uses structural vector autoregression (VAR) methodology to show that income inequality has a negative effect on economic growth in the case of the United Kingdom (UK), while a positive effect in the United States (US) and Canada. Given that measuring Gini coefficients might mask actual income distribution across income classes, most recently Dabla-Norris et al. (2015) have shown that if the income share of the top 20% increases, GDP growth declines over time, while an increase in the income share of the bottom 20% is associated with higher GDP growth.

Another important aspect of inclusive growth is its actual concept or definitional framework—which needs to be developed further. Sometimes the concept is confused with poverty reduction and/or inequality. Other times, it is combined with the issue of general economic growth with some redistribution added. The definition itself is elusive. And in many cases, those stressing its importance do not even attempt to define what it is. For example, as a multilateral development bank, ADB cites inclusive growth as one of its three key agendas in promoting an Asia and the Pacific region free of poverty.[1] Three pillars of inclusive growth are delineated as (i) high sustainable growth—to create and

[1] ADB's two other *Strategy 2020* agendas are environmentally sustainable growth and regional integration.

expand economic opportunities, (ii) broader access to these opportunities—to ensure all members of society participate in and benefit from growth, and (iii) social safety nets—to prevent extreme deprivation (Ali and Zhuang 2007). However, the ADB fails to clearly define what inclusive growth means as an institutional agenda. The rest of the paper is organized as follows. Section II discusses conceptual framework of inclusive growth. Section III analyzes conflicting policy objectives using some simulations. Section IV investigates the dynamic relation between growth and inequality in Asia. Section V examines the Organisation for Economic Co-operation and Development (OECD) countries and Latin American countries as comparator analyses. Section VI concludes.

II. CONCEPTUAL FRAMEWORK

This paper defines the concept of inclusive growth as "broad-based" economic growth,[2] one which supports the notion that economic benefits should spread across sectors, income strata, and regions.[3] This in turn implies that the growth pattern and speed should support these criteria, covering as much of their spectrum as possible, without confining participation and benefits to only a portion. Therefore, key words for conceptualizing the definition of inclusive growth include participation in the growth process, empowerment, productive employment opportunities across gender and age, diversification, and a level playing field, among others. Under the absolute definition, growth is considered to be pro-poor as long as the poor benefit in absolute terms even if their incomes do not grow quickly (World Bank 2009; Anand, Mishra, and Peiris 2013). However, if we stick to this mantra, we may not pay enough attention to the inequality problem—commonly measured by the Gini coefficient. While this paper does not advocate an absolute or relative sense of "pro-poor" growth, a strong emphasis is placed on improving relative poverty—by reducing inequality across the board. In this sense, the approach of this paper is more attuned to the notion of a relative sense of "pro-poor" growth, departing from the traditional view based on absolute "pro-poor" growth. We call the traditional approach a "weak axiom," while the approach in this paper a strong one.

Sources of increased inequality could be diverse. For example, in the US, the top 1% earner's share of total income rose from 8% in 1970 to 17% in 2010, according to Piketty-Saez data. And 68% of the increase in inequality is accounted for by labor income, while 32% comes from capital income (Furman 2014). This contrasts with the argument that capital is the important source of inequality—as discussed in Thomas Piketty's book, *Capital in the Twenty-First Century* (Furman 2014). The widening labor-income gap is in large part due to a skills and technological gap under a fast-changing, innovation-driven, and knowledge economy. Dabla-Norris et al. (2015) also points out that an education and skills gap is the most important determinant in explaining the income gap in advanced countries, while financial development is most important for emerging markets and developing economies.

A universal, classic measurement tool for measuring inequality is the Gini coefficient. A corporate results framework in development institutions also use this as a key outcome indicator in assessing the progress/regress of inclusive growth. However, changes in Gini coefficient—up or down—do not depend upon how equally absolute income is distributed across income classes. It depends on

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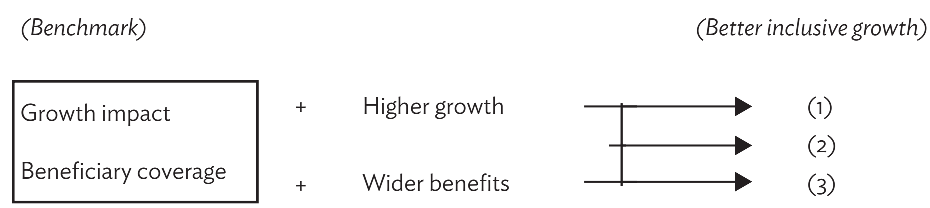
[2] This definition follows the approach of the World Bank, OECD, Asia-Pacific Economic Cooperation (APEC), and the European Union (EU). See World Bank note, "What is Inclusive Growth?", 10 February 2009; opening remarks by Angel Gurria, OECD Secretary-General at the Conference of Montreal, 9 June 2013; APEC Fact Sheets on "Inclusive Growth;" "Inclusive Growth—A High-Employment Economy Delivering Economic, Social and Territorial Cohesion, European Commission.

[3] In some approaches, inclusive growth emphasizes participatory and/or beneficiary aspects of growth. As participation in the growth process is less meaningful without accrued benefits through factor income, it boils down to benefit criterion.

how much percentage the distributed or redistributed income accounts for out of each class' original income. Even if longer-term income projections for each class diverge, the Gini coefficient may remain constant—as long as each class' income increases at the same rate. In this sense, using the Gini coefficient as a benchmark for measuring and targeting inequality is more the relative sense of "pro-poor" growth, not an absolute one. In a nutshell, if we use the Gini coefficient as a measure of inequality, its logical underpinning is to examine the relative connotation of "pro-poor" growth in the context of Gini coefficient changes. If we adopt a stronger axiom, then the absolute "pro-poor" growth argument falls prey to a more proactive distribution or redistribution issue in approaching inclusive growth, which should require lowering Gini coefficients instead of simply maintaining the status quo.

If we combine both notions—of the proactive concept of "pro-poor" growth and "broad-based" growth—then what could be the best way to view and assess the progress or regress of inclusive growth at both the macro and micro (project/program) levels? First, at the macro level, the Gini coefficient or quantile/decile ratio remains a useful tool for measurement. However, policy should aim to reduce the Gini coefficient instead of simply maintaining it. From a micro level perspective, a project's outcome should be measured in a relative sense along the wide spectrum of possible interventions. For example, if we consider decile income classification, a project or program for inclusive growth does not necessarily need to benefit all 10 deciles. A project that benefits the sixth to 10th decile is more conducive to inclusive growth than one that benefits just the ninth and 10th decile. Likewise, a project that benefits the third to seventh decile is more inclusive than one that benefits the sixth to eighth decile classes. An important caveat is that the project design of the former should not cause significant damage to the growth under the latter. This conceptual framework is summarized in Figure 1. Among the three cases, (2) and (3) ensure better inclusive growth compared with the benchmark case under a strong axiom.

Figure 1: Qualification of Inclusive Growth



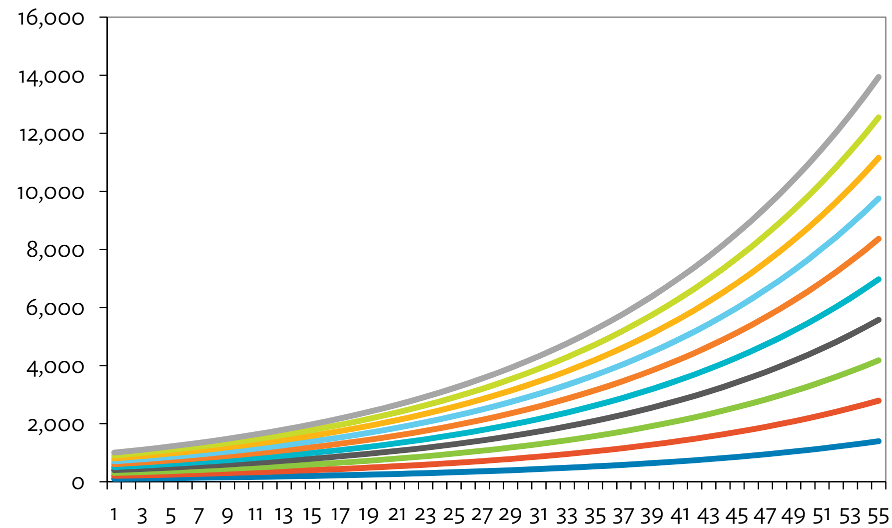
Source: Author.

III. ACHIEVABILITY OF POLICY OBJECTIVES

In this section, we examine the relative difficulty of different policies across growth and equity objectives. To do this, we experiment on an imaginary economy with 10 income classes and equal income gaps with 5,500 units of aggregate income. The first decile income group has 100 units of income; the 10th decile 1,000. We assume 5% economic growth per annum compounded over 55 years (Appendix A.1).[4] As Figure 2 shows, it is possible for this economy to achieve perpetual economic growth while keeping the Gini coefficient at 0.3. As long as each decile's income increases at the same rate, the inequality rate can be maintained.

[4] The Appendix can be obtained from the web version of the paper: http://www.adb.org/publications/interrelation-between-growth-inequality

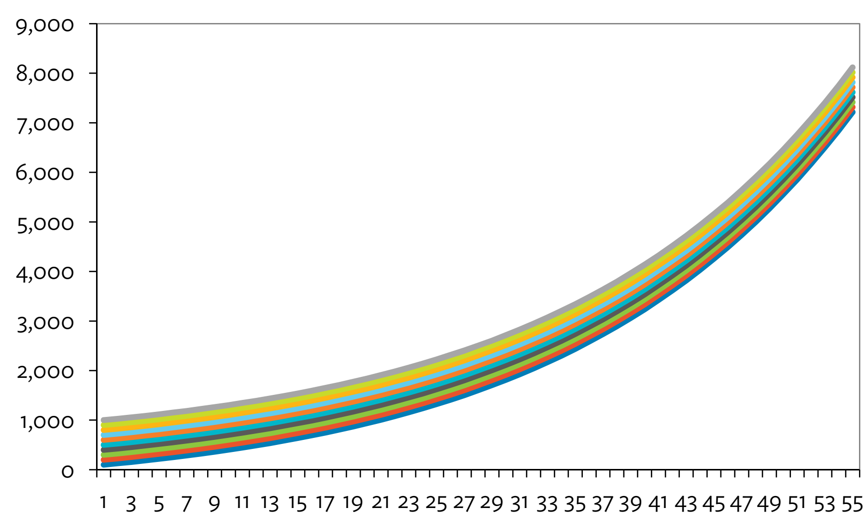
Figure 2: Income Schedule Forecast under the Same Growth and Inequality Rate



Source: Author's calculations.

If we assume the same 5% growth is distributed equally across decile groups (as in Appendix A.1),[5] we can see how the Gini coefficient evolves over time under constant economic growth.

Figure 3: Income Schedule Forecast under the Same Growth and Decreasing Inequality Rate



Source: Author's calculations.

In this case, the same perfectly equal income distribution leads to decreasing inequality over time as the Gini coefficient lowers (Figure 3).

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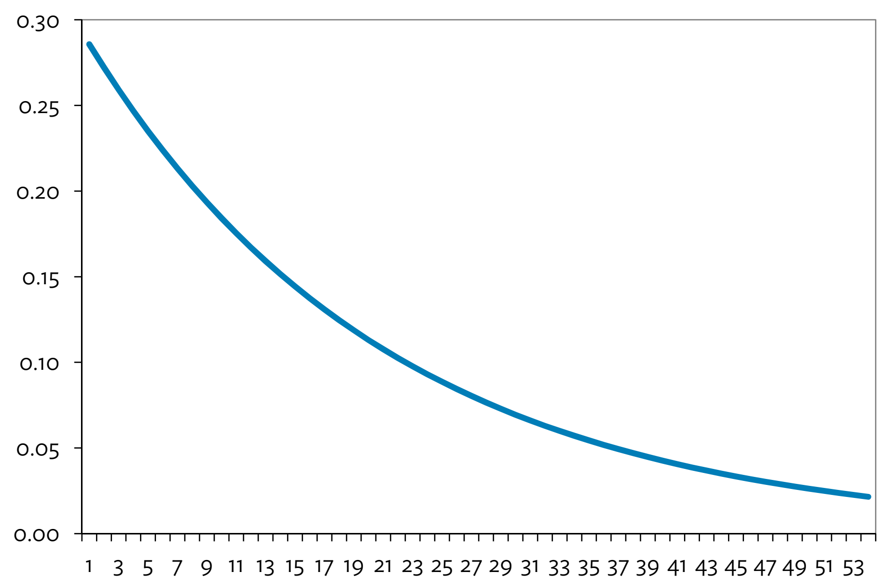
[5] The Appendix can be obtained from the web version of the paper: http://www.adb.org/publications/interrelation-between-growth-inequality

Two implications follow. First, the same level of economic growth can be obtained while promoting greater equality. At the same time, perfect equal distribution will not lead to a change in income class hierarchy—due to the different starting points based on an uneven initial endowment. Second, for highly unequal economies, promoting equity through income distribution and redistribution could be highly effective. However, as an economy's inequality improves, it takes greater effort and more resources to reach the same degree of improvement as before, as reflected in the declining marginal rate of improvement in Gini coefficient (Figure 4). For developing economies with high inequality, it is an opportunity to harvest so-called low hanging fruit. In reality, however, policy objectives should be set between the two extremes. Given inherent disincentives for high-income earners, promoting equality could be considered instead of vying for perfectly equal income distribution. This could improve inequality while keeping economic incentives intact. It is also better aligned with the strong axiom of the inclusive growth concept.

Figure 4: Trajectory of Gini Coefficient Schedule under Perfect Equal Distribution



Source: Author's calculations.

IV. DYNAMIC RELATIONSHIP BETWEEN GROWTH AND INEQUALITY IN ASIA

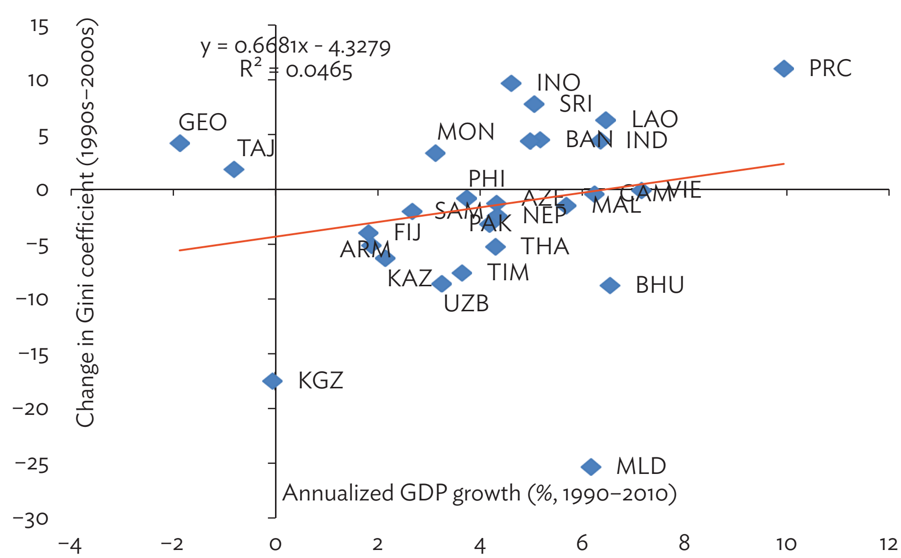
The simulation done in Section III posits an ideal situation where economic growth and declining income are compatible at the same time. In reality, however, this relationship is not an easy one to pursue. Studies have tested the relationship and causality between these two variables. And while some suggest a positive relationship, others found a negative one. More recently, as introduced in Section I, several studies recognize the positive impact of lower inequality on economic growth. Most used empirical analysis based on pooled country panel data.

A. Cross-Country Comparisons

In Asia, for example, cross-country analysis shows a week but positive relationship between economic growth and worsening inequality (*Asian Development Outlook, 2012*)—commensurate with the front portion of the inverse U-shaped Kuznets curve. This picture, however, may change if we examine time-series data—which better traces the changing relationship between growth and inequality over time.

Also, the above relationship does not necessarily show that economies with a positive relationship between economic growth and Gini coefficient will see lower inequality when economic growth slows. Depending on where a county is in Figure 5, different policy implications could follow. Those in the 1st quadrant—such as the PRC, India, and Indonesia—need to strengthen income redistribution and inclusion promotion by increasing public spending on, for example, education, health, and social protection. These are particularly effective at reducing income inequality by broadening access to vital services and increasing opportunities for the poor and low-income groups. Those in the second quadrant have been hit by both slow economic growth and rising inequality, while those in the third quadrant need to pursue policies that drive growth. Those in the fourth quadrant fare relatively well compared with other quadrant groups. While these policy prescriptions provide useful directions, more important is how growth or equality promotion affects other policy results. For example, even if economies in the first quadrant place higher emphasis on addressing inequality, it may excessively undermine growth, depending on the mutual impact and dynamics between growth and inequality. Alternatively, if the economic growth of an economy has positive causality by bringing inequality down further, it should continue to pursue a growth strategy even if positioned in the first quadrant.

Figure 5: Gross Domestic Product Growth and Change in Gini Coefficient in Asia



ARM= Armenia, AZE = Azerbaijan, BAN = Bangladesh, BHU = Bhutan, CAM = Cambodia, FIJ = Fiji, GEO = Georgia, GDP = gross domestic product, IND = India, INO = Indonesia, KAZ = Kazakhstan, KGZ = Kyrgyz Republic, LAO = Lao People's Democratic Republic, MAL = Malaysia, MLD = Maldives, MON = Mongolia, NEP = Nepal, PAK = Pakistan, PHI = Philippines, PRC = People's Republic of China, SAM = Samoa, SRI = Sri Lanka, TAJ = Tajikistan, THA = Thailand, TIM = Timor-Leste, UZB = Uzbekistan, VIE = Viet Nam.
Source: ADB. *Asian Development Outlook 2012*.

B. Dynamic Causality and Impact Analysis

Now we turn to detailed causality analyses based on historical country data. Given that pooled country data regression analysis might mask differences and distinctive features across different economies, we employ country-level time-series analysis, which should shed light on how various economies retain different dynamics between growth and inequality in their unique development context as well as economic and social standing.

1. Empirical Modeling

In order to explore the dynamic relationship between economic growth and inequality, we use a VAR model:

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{1}$$

where Y_t is an *n*x1 vector which includes each of the *n* variables, A_0 is an *n*x1 vector of intercepts, A_i are *n*x*n* matrices of coefficients, p is the number of lags chosen for each of n variables and ε_t is an *n*x1 vector of error terms. If data series are not stationary, we need to make a stationary transformation through difference or filtering. We conduct a stationary transformation through differencing before running the regression. When there is a shock to the system, it will affect other variables in the VAR along a path through which the variables return to equilibrium. This is called the impulse response. Based on the VAR results, impulse response functions (IRFs) can provide useful implications on the interactions among variables.

Even if each data series is nonstationary—but data pairs have a long-run relationship—those could be cointegrated at I(1). In this case, simply applying stationary transformation of data series for the VAR regression may lose significant information which could be available through a Vector Error Correction Model (VECM). Accordingly, we use VECM if cointegration relation(s) are identified among data series to account for long-run linear relationships among the elements of Y_t. In our VECM, we define Y_t as the vector of indicators of interest:

$$\Delta Y_t = \gamma + A_1 \Delta y_{t-1} + \delta_k z_k + v_t \tag{2}$$

where z_k is the vector of cointegrating terms. Its coefficient δ_k determines whether a long-run relationship exists among the elements of vector Y_t. To estimate Equation (2) and to validate the use of vector error correction, we first test the variables for stationarity and cointegration.

Variables that exhibit changing mean and variance across time are said to be nonstationary and may pose problems in inference. In a simple autoregressive process of order 1 [AR(1)]:

$$y_t = \delta + \rho y_{t-1} + \varepsilon_t \tag{3}$$

a highly persistent time series implies that the parameter $\rho \geq 1$. Normally, we test whether Equation (3) has a random walk such that $\rho = 1$. To test for stationarity, we employ the augmented Dickey-Fuller test by augmenting Equation (3) and testing for the significance of ρ. Failure to reject the null hypothesis—that $\rho = 0$—suggests there is no unit root. Note that the number of lags for Equation (3.a) should be determined using a test of residuals which we conduct for all variables in Y_t.

$$\Delta y_t = \delta + \rho y_{t-1} + \sum_{j=1}^{p-1} \varphi_j \, \Delta y_{t-j} + \varepsilon_t \tag{3.a}$$

Failure to reject the null hypothesis implies that the series are integrated of order (1). Integration of order 1, or I(1), signals a possible long-run relationship among variables. In Engle and Granger approach, variables are cointegrated of order 1 if their linear combinations are stationary. In a two-variable case, y_{1t} and y_{2t} are cointegrated if there exists a certain relation such that:

$$(y_{1t} - \varphi y_{2t}) \sim \mathrm{I}(0) \tag{4}$$

This can also be extended to a multivariable case, where (3) will be in vector form, and φ will be the cointegrating vector. Cointegration suggests that the vector of variables do not deviate from an equilibrium level that is dynamically stable, implying a long-run relationship among them. In this case, we can test for cointegration by obtaining linear combinations of the elements in Y_t and testing the significance of the cointegration vector φ. While the actual procedures for testing are quite complicated—and critical values are difficult to derive—this can easily be done by statistical software. After testing for cointegration, we can now estimate equation (2). A statistically significant δ_k means that there is a long-run relationship among indicators. We can also apply the usual Granger-causality test to the VECM estimates to test for short-run dynamics around the long-run cointegration relationship.

Davtyan (2014) used VAR in exploring the interrelationships between growth and inequality for three countries—the UK, the US, and Canada—based on 1960 to 2010 annual data series. He shows that income inequality has a negative effect on economic growth in the UK, but that the effect is positive in the US and Canada. Building on the Davtyan (2014) approach, our basic model comprises two variables for economic growth and inequality. Further, the extended model includes a fiscal variable—as fiscal performance should have an impact on both growth and inequality. However, taking into account the limitations of the available time series—which could affect the degrees of freedom—we do not include multiple fiscal variables such as government spending, investment, and taxes. We add one fiscal variable in the extended model. Our basic model specification is

$$Y_t = \begin{bmatrix} LGDPPC_t \\ Gini_t \end{bmatrix}$$

through which we examine the dynamic relationship between GDP per capita and the Gini coefficient. Given that the fiscal variable can affect both economic growth and income equality (and vice versa), we also include a fiscal deficit (surplus) ratio in an extended model:

$$Y_t = \begin{bmatrix} LGDPPC_t \\ Gini_t \\ Fbalance_t \end{bmatrix}$$

As our main focus is in the dynamic relationships between the two in the basic model and the three in the extended model, we do not test a structural VAR model that allows for contemporaneous impacts by imposing certain short-term and long-term causality restrictions based on economic theory. However, the ordering of the variables in the VAR model is important. Growth is usually affected by past evolutions of inequality. But the same could hold for the relationship between growth and the fiscal balance. In the meantime, inequality can be directly affected by the current growth rate. Hence, the ordering of the variables in our analysis is presented as the vector above. While Davtyan's (2014) approach used a VAR model only in investigating the interrelationship between growth and inequality, we also use the VECM model to the extent possible when there exists cointegrating relations detected—given that the VECM model could provide useful information on the long-run causality relationship between indicators, keeping short-run dynamic movement around that relationship intact.

2. Data

The empirical analysis is conducted for individual Asian economies with available data. Among the 37 such economies screened from 1960 to 2013 time-series data, 19 economies fit neither VAR nor VECM. Hence, the analysis for Asia covers 18 economies—Armenia; Australia; Brunei Darussalam; the PRC; Georgia; Hong Kong, China; India; Indonesia; Japan; the Republic of Korea; Sri Lanka; Malaysia; New Zealand; Pakistan; the Philippines; Singapore; Thailand; and Tajikistan. For economic growth, we use the growth of GDP per capita to normalize the scale effect from population growth by taking the log of GDP per capita. To reflect the net effect after the policy impact, we use market (net) Gini coefficient instead of gross Gini data. Data on GDP per capita and the fiscal surplus (deficit) as percent of GDP are from the World Bank's *World Development Indicators*. GDP is the sum of gross value-added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the product values. It is calculated without deducting for depreciation of fabricated assets or for the depletion and degradation of natural resources. The Gini coefficients are from the *Standardized World Income Inequality Database* (SWIID) on a 0 to 100 scale. The SWIID maximizes the comparability of available income inequality data for the broadest possible sample of economies and years. It employs a custom missing-data algorithm that minimizes reliance on problematic assumptions by using as much information as possible from proximate years within the same economy to estimate missing economy-years. The inequality estimates and their associated uncertainty are represented by 100 separate imputations of the complete series: for any given observation, the differences across these imputations capture the uncertainty in this estimate (SWIID).

The SWIID data take the mean across the 100 imputations of the Gini index of inequality in equivalized (square root scale) household disposable (post-tax, post-transfer) income, using the Luxembourg Income study as the standard. GDP per capita is gross domestic product divided by midyear population and in constant 2005 US dollars. Fiscal surplus (deficit) data is the cash surplus or deficit in revenue (including grants) minus expenses, minus the net acquisition of nonfinancial assets.

3. Empirical Results

To decide the number of lags, we test Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). When two out of the three criteria indicate the same lag order selection, we choose the lag number. Otherwise, we use AIC as the main benchmark in deciding the lag number. Unit root testing is based on the Augmented Dickey-Fuller (ADF) test. When a unit root is identified through the ADF test, we continue testing cointegration between data series. The Johansen cointegration test is examined through both maximum eigenvalue and trace statistics. If a cointegration relationship is detected, we move on running the VECM. Otherwise, we run the VAR by differencing the data series with unit root for stationary transformation. When the VECM is chosen, we examine the sign and significance of the coinetrating equation to check the long-term causality, and also a Wald test is conducted to investigate the joint significance of short-term coefficients, which helps elucidate the existence of short-term causality. When VAR is the preferred methodology, we present an IRF to investigate the direction and magnitude of the short-term directional impact. As we present a response to Cholesky one standard deviations ± 2 standard errors, the result of the IRFs is sensitive to the ordering of the variables tested. Given the main focus of these analyses on the dynamic, directional impact between economic growth and inequality from the perspective of inclusive growth, we do not further analyze the magnitude of coefficients of lagged variables in the VAR. After running a VECM or VAR, we also test serial correlation and heteroskedasticity of the residuals to check the robustness of the model specification.

The empirical results for the selected Asian economies are as follows:

For the PRC, the VECM fits the characteristics of the two time series of GDP per capita and Gini coefficient. First, the regression results show a significant, long-term positive causality from the Gini coefficient to growth, and the coefficient of error correction term suggests a stable convergence to the long-run relationship. The short-term effect of three lagged variables of the Gini coefficient on growth shows a negative impact, but the *p*-values do not indicate any significant impact for all the three variables. In the meantime, the reverse causality also holds true for the PRC case. Per capita GDP growth has a significantly long-term positive effect on the Gini coefficient. The short-term lagged variables of per capita GDP growth indicate positive or negative impact on the Gini coefficient depending on the number of lags, but none are significant at the 5% level. In both regressions, residuals do not contain any serial correlation or heteroskedasticity. These results indicate that as inequality increases, it has a positive impact on economic growth in the PRC. At the same time, economic growth contributes to raising income inequality. Hence the causality works in both directions.

For India, both the log of GDP per capita and the Gini coefficient have unit roots but are not conintegrated. Hence, we run the VAR after taking the difference in each variable. According to the IRFs, one standard deviation shock of Gini coefficient change causes around 0.005 percentage point change of GDP per capita growth in period 2, and 0.01 percentage point change in period 3—and this effect subsides over time until period 8. On the other hand, the impact of one standard deviation shock of GDP per capita growth change on the Gini coefficient is unclear. Extended model analysis points to the validity of VAR with two lagged variables. According to the IRFs, one standard deviation shock of the Gini coefficient has a higher positive impact on GDP per capita growth than in the basic model, causing around 0.02 percentage point change in period 3. A one standard deviation shock of GDP per capita growth change has a negative impact on the fiscal balance, bringing around 0.2 percentage point change in periods 2 and 3. The response of a fiscal balance to a Gini coefficient shock is not decisive. Initially it rises in response to a fiscal balance shock, but falls in subsequent periods until it fluctuates over time.

In Indonesia, the VAR regression indicates a Gini coefficient shock has a positive impact on economic growth by raising the GDP per capita growth rate by around 0.01 percentage point in period 2, which then subsides over long periods until period 6. Likewise, a growth shock has a positive impact on inequality by raising the Gini coefficient by around 0.2 percentage point in periods 1 and 2, which subsides over time until period 6. An extended model points to the relevance of the VECM and results indicate significant long-run positive causality from the Gini coefficient to economic growth, with stable convergence between the two variables indicated by the negative sign and significance of error correction term. However, no such long-run causality is implied from economic growth to inequality. The fiscal balance has a negative long-run impact on growth.

Japan's case indicates long-run positive causality from the Gini coefficient to growth and the coefficient of error correction term indicates a stable convergence relationship. But the standard error of the coefficient of cointegrating equation is very small. Short-term lagged variables of the Gini coefficient also indicate a positive impact on growth at all three lagged variables, but only one lagged variable is significant at the 5% level. Reverse long-run causality from growth to the Gini coefficient is significant and positive, but the coefficient of error correction term is not significant. Hence, in Japan's case, we observe a weak positive causality from inequality to economic growth. An expanded model including the fiscal balance variable points to the validity of the VAR regression. A one standard deviation shock of the Gini coefficient has around 0.02 percentage point of growth effect in period 2, which gradually withers away until period 10. Growth impact on Gini is more muted. Fiscal balance impact on growth has around 0.01 percentage point impact in period 2 and subsides over time. A fiscal balance shock does not show any clear impact on the Gini coefficient.

The Republic of Korea's data suggests a VECM model with three lagged variables in the basic model. However, we use six lagged variables instead, as only with these the serial correlations problem in residuals disappears. The VECM results indicate long-run negative causality from GDP per capita growth to the Gini coefficient. Also, the Gini coefficient has long-run negative causality to GDP per capita growth. However, the *p* value of the coefficient of error correction term is slightly larger than 5%, hence a firm long-run causality in this case is not established. The extended model does not contain a serial correlation problem in residuals up to three lagged variables. Hence, we use three lagged variables as indicated by lag selection criteria. Under the extended model, the VECM results indicate the Gini coefficient has a clear long-run positive impact on GDP per capita growth. The fiscal balance also has a positive impact on economic growth. All in all, the Republic of Korea's growth pattern has had a positive impact on lowering inequality.

For Thailand, a long-run negative causality from the Gini coefficient to GDP per capita growth is detected from the cointegrating equation, but the error correction term is not significant. On the other hand, GDP per capita growth has a long-run negative impact on the Gini coefficient, also supported by a significant and negative error correction term. The short-run impact or lagged Gini variables are not significant, however. An extended model indicates the validity of the VAR model. However, the IRF does not provide any clear response among the three variables of GDP per capita growth, the Gini coefficient or fiscal balance.

A summary of regression methodology and results for the 18 Asian economies is provided below (Table 1). Detailed regression results are presented in Appendix A.2.[6]

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[6] The Appendix can be obtained from the web version of the paper: http://www.adb.org/publications/interrelation-between-growth-inequality

Table 1: Regression Methodology and Results for Selected Asian Economies

Economy		Cointe-gration	Stationary transfor-mation	Lag	VECM(causality)/ VAR (impulse response)	Serial correlation	Heteroske -dasticity
Armenia	Basic	Yes	No	1	Gini → LGDPPC (-)	No	No
	Extended	No	Yes	3	-		
Australia	Basic	No	Yes	1	Gini → LGDPPC (-) LGDPPC → Gini (+)	No	No
	Extended	No	Yes	2	Fbal → LGDPPC (+) LGDPPC → Fbal (+) LGDPPC → Gini (+)	No	No
Brunei Darussalam	Basic	No	Yes	2	Gini → LGDPPC (-) LGDPPC → Gini (+)	No	No
	Extended	No	Yes	2	-	No	No
People's Republic of China	Basic	Yes	No	3	Gini → LGDPPC (+) LGDPPC → Gini (+)	No	No
	Extended	No	No	-	-	-	-
Georgia	Basic	Yes	No	3	Gini → LGDPPC (+) LGDPPC → Gini (+)	Yes at lag=2	No
	Extended	-	-	-	-		
Hong Kong, China	Basic	Yes	No	2	Gini → LGDPPC (+)	No	No
	Extended	No	Yes	2	Gini → LGDPPC (-) Fbal → LGDPPC (+) LGDPPC → Gini (-)	No	No
India	Basic	No	Yes	2	Gini → LGDPPC (+)	No	No
	Extended	No	Yes	2[a]	Gini → LGDPPC (+) LGDPPC → Fbal (-)	No	No
Indonesia	Basic	No	Yes	1	Gini → LGDPPC (+) LGDPPC → Gini (+)	No	No
	Extended	Yes	No	3	Gini → LGDPPC (+) Fbal → LGDPPC (-)	No	No
Japan	Basic	Yes	No	3	Gini → LGDPPC (+)	No	No
	Extended	No	Yes	1	Gini → LGDPPC (+) Fbal → LGDPPC (+)	No	No
Republic of Korea	Basic	Yes	No	6[b]	LGDPPC → Gini (-)	No	No
	Extended	Yes	No	3	Gini → LGDPPC (+) Fbal → LGDPPC (+)	No	No
Sri Lanka	Basic	No	Yes	1	Gini → LGDPPC (+)	No	No
	Extended	Yes	No	3	-		
Malaysia	Basic	No	Yes	3	Gini → LGDPPC (-) LGDPPC → Gini (+)	No	No
	Extended	No	Yes	1	Gini → LGDPPC (-) Fbal → LGDPPC (+) LGDPPC → Gini (+) Fbal → Gini (+) LGDPPC → Fbal (+) Gini → Fbal (-)	No	No
New Zealand	Basic	Yes	No	3	Gini → LGDPPC (+) LGDPPC → Gini (+)	No	No
	Extended	No	Yes	3	-		
Pakistan	Basic	No	Yes	1	Gini → LGDPPC (+) LGDPPC → Gini (-)	No	Yes at 10%
	Extended	Yes	No	3	-		

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Table 1 continued

Economy		Cointe-gration	Stationary transfor-mation	Lag	VECM(causality)/ VAR (impulse response)	Serial correlation	Heteroske -dasticity
Philippines	Basic	No	Yes	3	Gini → LGDPPC (-,+) LGDPPC → Gini (+)	No	No
	Extended	Yes	No	3	-		
Singapore	Basic	No	Yes	3	Gini → LGDPPC (-) LGDPPC → Gini (-)	No	Yes at 5%
	Extended	No	Yes	2	Gini → LGDPPC (-) Fbal → LGDPPC (+) LGDPPC → Gini (+) Fbal → Gini (-)	Yes at lag = 1	No
Thailand	Basic	Yes	No	3	LGDPPC → Gini (-)	No	No
	Extended	No	Yes	3	-		
Tajikistan	Basic	Yes	No	3	Gini → LGDPPC (+)	No	No
	Extended	No	Yes	3	LGDPPC → Gini (+,-)	-[c]	-

VAR = vector autoregression, VECM = vector error correction model.

[a] Although the lag order selection criteria indicate lag number 1, we use lag number 2 to correct serial correlation problem in the residuals.

[b] Although the lag order selection criteria indicate lag number 3, we use lag number 6 to correct serial correlation problem in the residuals.

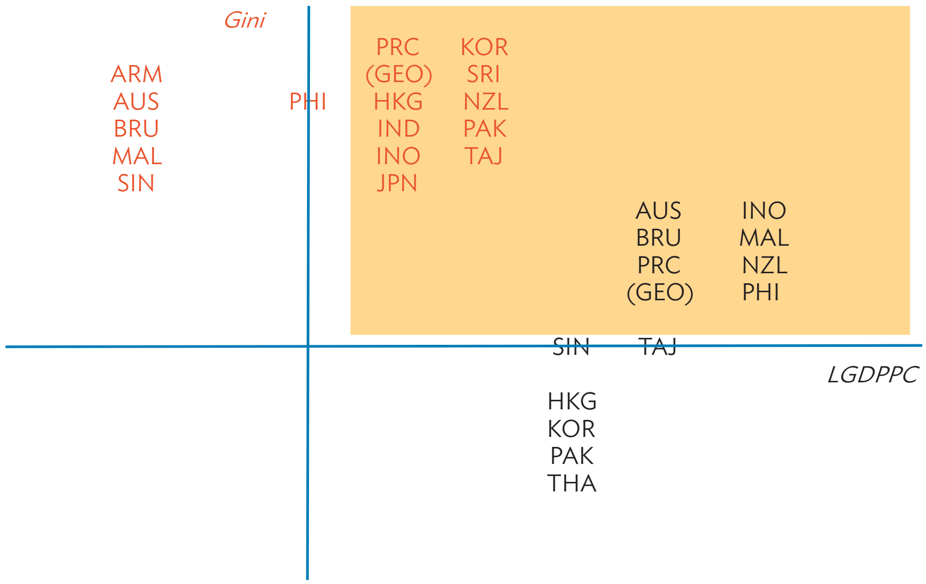
[c] Untestable due to insufficient number of observations.

Source: Author.

As shown in Table 1, there is not much difference between the results under basic and extended models, and most results pass the robustness check of serial correlation and heteroskedasticity tests. As the results from the extended model indicate, in most cases increasing fiscal surplus or decreasing fiscal deficit leads to higher economic growth. This may seem counterintuitive from the perspective of pump-priming fiscal policy. However, improving fiscal status may presage better economic performance of the economy, highlighting the importance of fiscal soundness. In the meantime, when economic growth rises, the fiscal surplus expands or the deficit shrinks in most cases. In Malaysia, rising inequality has led to an expansionary fiscal stance, while it has not in India. Based on these regression results, we can draw a diagram to represent a dynamic relationship between growth and inequality for individual economies.

Countries in the first quadrant retain a positive causality and impact relationship between economic growth and inequality. For the group in red, rising inequality causes higher economic growth, while the group in black implies higher economic growth causes rising inequality. Three countries—the Philippines, Singapore, and Tajikistan—are borderline. The second quadrant includes economies where rising inequality leads to lower economic growth. Economies in the fourth quadrant have seen that higher economic growth lowers inequality. When we compare the static correlation analysis results in Figure 5 with the dynamic VECM/VAR analysis results in Figure 6, there are some interesting findings, despite the different coverage between the two. In line with the positive cross-country correlation regression line in Figure 5, most of the economies analyzed for dynamic causality fall into quadrant 1 in Figure 6, suggesting the majority of Asian economies have experienced positive causality between growth and inequality from either direction. Several of the economies that show a negative correlation between growth and inequality in Figure 5 (positioned in the second quadrant or fourth) are also in the same quadrants in Figure 6, indicating significant commonality between these two analyses. These include Armenia, Malaysia, Pakistan, Thailand; and the Philippines and Tajikistan, which are on the borderline in both cases.

Figure 6: Dynamic Causality and Impact Relationship between Economic Growth and Inequality (Asia)



ARM = Armenia; AUS = Australia; BRU = Brunei Darussalam; GEO = Georgia; HKG = Hong Kong, China; IND = India, INO = Indonesia; JPN = Japan; KOR = Republic of Korea; MAL = Malaysia; NZL = New Zealand; PAK = Pakistan; PHI = Philippines; PRC = People's Republic of China; SIN = Singapore; SRI = Sri Lanka; THA = Thailand; TAJ = Tajikistan.
Source: Author.

C. Policy Implications

Now we turn to the unique implications drawn from the dynamic causality analyses in this study. These analyses provide a deeper understanding of the unique causality and its direction for individual economies—compared with static analysis and other types of analyses done based on pooled country data. First, we cannot definitely argue that either economic growth or inequality is a dominant factor affecting one another in Asia. There is almost symmetry in the number of economies where inequality affects growth and that growth affects inequality (Figure 6). In most cases causality works in both directions. But there are several where inequality has a dominant impact on growth such as in Armenia and Brunei Darussalam and growth affects inequality in a powerful way such as in Thailand. Second, there is one case where the static and dynamic analyses results do not match. For Georgia, while the static analysis suggests a negative correlation between inequality and growth, the dynamic analysis indicates the usual positive causality relationship from both directions. Given the serial correlation of the residuals, however, this result is not robust enough to support the causality. Third, still developing, most Asian economies are placing them somewhere on the first half of the Kuznets curve. This contrasts against developed countries (for example, OECD members). Fourth, different economies require different policy prescriptions.

For the majority of countries in the first quadrant (Figure 6), economic growth exacerbates inequality, but at the same time rising inequality fosters economic growth. These pose a difficult policy choice—depending on where the economy puts higher priority between growth and equity/inclusiveness. For those countries in the second quadrant (Armenia, Australia, Brunei Darussalam, and Malaysia, Singapore, and the Philippines to a lesser extent) rising inequality harms economic growth. In these countries, a higher priority should be given to addressing inequality. The economies in the fourth quadrant (Hong Kong, China; the Republic of Korea; Pakistan; and Thailand; and Singapore and Tajikistan to a lesser extent) have seen higher economic growth lower inequality. These economies can pay more attention to promoting or maintaining economic growth with less concern about widening inequality as a side effect.

These cases offer great opportunity for enhancing inclusive growth. Those economies in the fourth quadrant contrast well with comparator counties that have seen economic growth worsen inequality. Historically, the growth performance of comparator economies has been remarkable (Figure 10). Those in the fourth quadrant also performed quite well in terms of economic growth (Figure 8). A more stark contrast is seen at the recent stages of evolving inequality (Figure 7 and Figure 9). The latter group has seen stable or downward trending inequality—except for recent hikes since 2008 in Pakistan. On the other hand, inequality in comparator group economies has worsened quite rapidly (Figure 9). This implies that an inclusiveness-promoting growth pattern more critically hinges on how to effectively address inequality. This result—combined with the growth/Gini simulation in Section III—suggests economies need to pay proper attention to (in)equality issue and harmonize such purpose with growth goal.

Figure 7: Gini Trend for Inclusive Growth Economies

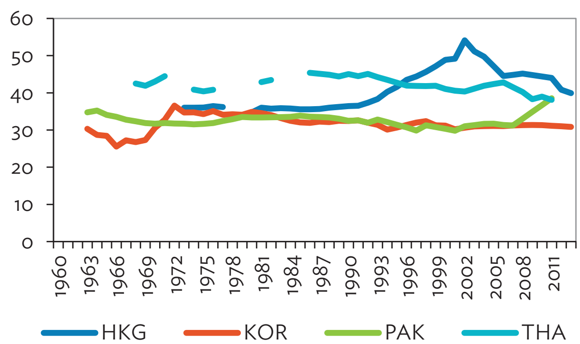


Figure 8: Growth Trend for Inclusive Growth Economies

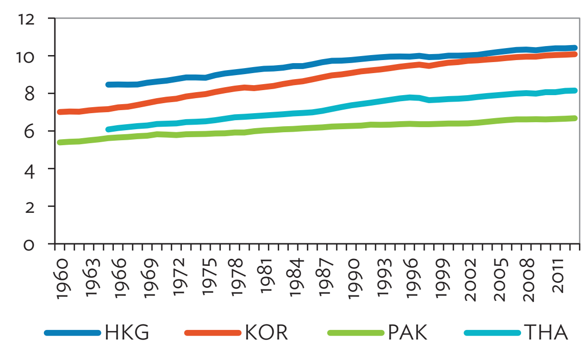


Figure 9: Gini Trend for Comparator Economies

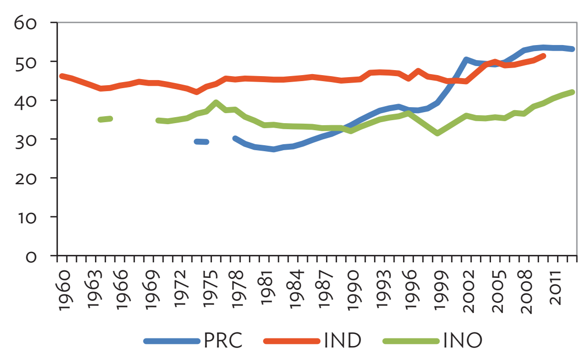
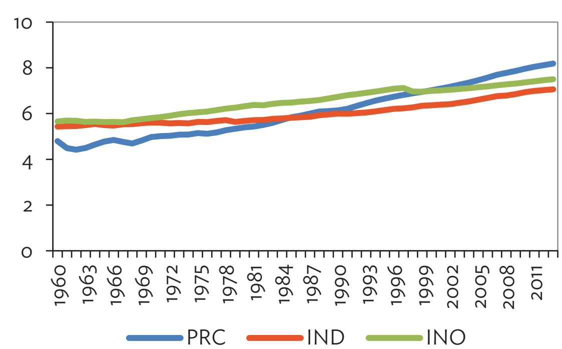


Figure 10: Growth Trend for Comparator Economies



HKG = Hong Kong, China; IND = India; INO = Indonesia; KOR = Republic of Korea; PAK = Pakistan; PRC = People's Republic of China; THA = Thailand.
Source: Author's calculations.

V. COMPARATOR ANALYSES

To investigate if there are any systematic characteristics that differentiate Asian economies from others, we consider two other country groups—the OECD and Latin American countries. The OECD is used as a benchmark for advanced countries with the latter well-known as a group that has seen a drastic improvement in narrowing inequalities over the past decades. These may offer an unique and dynamic picture of the relationship between growth and inequality.

A. OECD Countries

We consider the OECD excluding Asian and Latin American members, as they are reviewed separately as members of other groups. For many OECD countries, time-series fiscal balance data are insufficient, while in several cases the Gini coefficient or fiscal balance data cannot be transformed into stationary series. As a result, the extended model cannot apply to many countries. Table 2 shows VECM/VAR results for OECD members Detailed regression results are presented in Appendix A.3.[7] In line with Asia, the regression results under both basic and extended models do not conflict with each other and point to very similar results. Most important, many OECD countries have an inclusive growth pattern where economic growth reduces inequality—as was the case for Hong Kong, China; the Republic of Korea; Pakistan; and Thailand. OECD countries that belong to this group include Belgium, Denmark, Estonia, France, Greece, Hungary, Ireland, the Slovak Republic and Sweden. This may indicate that, unlike in most Asian economies, many developed countries have already entered the mature stage (latter half) of the Kuznets curve. Among these countries, Denmark, France, and Sweden stand out in particular—the dynamic negative causality has worked both ways; economic growth lowers inequality while higher inequality undermines economic growth. Particularly notable for these three countries are the underlying synergies between economic growth and equity promotion.

A diagram of dynamic causality and impact relationship between growth and inequality for OECD countries can be constructed comparable to Asia (Figure 11). Unlike most of the analysis results drawn from pooled country or country panel data in previous studies, most advanced countries fall into the second quadrant, which indicates positive causality between economic growth and rising inequality. In most cases, economic growth exacerbates inequality, and rising inequality leads to higher economic growth. As was discussed earlier, however, relatively more countries retain an inclusive growth pattern compared to Asia.

B. Latin American Countries

Latin American countries have seen rapidly declining inequality over the past few decades—providing another useful benchmark in comparing dynamic causality relationships between economic growth and inequality. Data constraints in terms of series length and difficulties in stationary transformation limit the number of Latin American countries analyzed. In addition, most of the time-series data of interest are not cointegrated with each other, making the VECM approach inapplicable. Below the summary of analysis results for six countries are presented in Table 3. Detailed regression results are presented in Appendix A.4.[8] For the effect of inequality on growth, the Dominican Republic and Honduras have had a positive impact, while in Panama the increase in inequality has undermined economic growth. For the

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7 The Appendix can be obtained from the web version of the paper: http://www.adb.org/publications/interrelation-between-growth-inequality

8 The Appendix can be obtained from the web version of the paper: http://www.adb.org/publications/interrelation-between-growth-inequality

impact of growth on inequality, all countries except Ecuador have seen economic growth lowering inequality—in Paraguay a serial correlation is detected at lag number 1, indicating a potential common shock to variables, or an omitted variable bias. Particularly in Mexico, such long-run causality is detected through VECM in the basic model. Income inequality in Latin America has declined during the last decade in contrast to many other emerging and developed regions (Tsounta and Osueke 2014). The results below corroborate the argument that the region has not only effectively reduced inequality over time, but the growth pattern itself has been supporting inclusion.

Table 2: Regression Methodology and Results for OECD Countries

Country		Cointe-gration	Stationary transfor-mation	Lag	VECM(causality)/ VAR (impulse response)	Serial correlation	Heteroske-dasticity
Austria	Basic	Yes	No	2	Gini → LGDPPC (+)	No	Yes at 10%
	Extended	No	Yes	3	Gini → LGDPPC (+)	-	-
Belgium	Basic	No	Yes	1	Gini → LGDPPC (+)	No	Yes at 1%
	Extended	Yes	No	1	LGDPPC → Gini (-) Fbal → Gini (+)	No	No
Canada	Basic	Yes	No	3	LGDPPC → Gini (+)	No	Yes at 5%
	Extended	No	Yes	2	Gini → LGDPPC (+) Fbal → LGDPPC (+) Fbal → Gini (+)	No	No
Switzerland	Basic	No	Yes	1	Gini → LGDPPC (+) LGDPPC → Gini (+)	No	No
	Extended	No	No	-	-		
Czech Republic	Basic	No	Yes	1	Gini → LGDPPC (+) LGDPPC → Gini (+)	No	Yes at 5%
	Extended	No	Yes	1	Fbal → LGDPPC (-) LGDPPC → Gini (+) Fbal → Gini (-)	No	No
Denmark	Basic	Yes	No	2	Gini → LGDPPC (-) LGDPPC → Gini (-)	No	No
	Extended	No	Yes	3	Gini → LGDPPC (-) Fbal → Gini (+)	-	-
Spain	Basic	Yes	No	3	LGDPPC → Gini (+)	No	Yes at 10%
	Extended	No	No	-	-		
Estonia	Basic	No	Yes	3	Gini → LGDPPC (+)	No	No
	Extended	No	Yes	2[a]	Gini → LGDPPC (+) Fbal → LGDPPC (-) LGDPPC → Gini (-) Fbal → Gini (-)	No	No
Finland	Basic	No	Yes	2	Gini → LGDPPC (+)	No	Yes at 5%
	Extended	Yes	No	2	LGDPPC → Gini (+) Fbal → Gini (-)	No	-
France	Basic	Yes	No	3	Gini → LGDPPC (-) LGDPPC → Gini (-)	No	Yes at 1%
	Extended	No	No	-	-		

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Table 2 continued

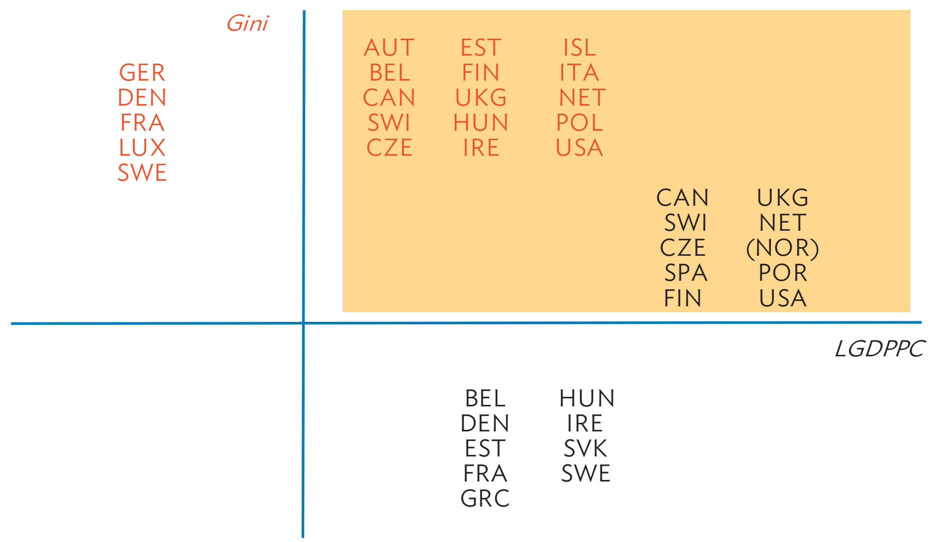
Country		Cointe-gration	Stationary transfor-mation	Lag	VECM(causality)/ VAR (impulse response)	Serial correlation	Heteroske-dasticity
United Kingdom	Basic	No	Yes	2	Gini → LGDPPC (+) LGDPPC → Gini (+)	No	No
	Extended	No	Yes	3	LGDPPC → Gini (+)	-	-
Germany	Basic	No	Yes	1	Gini → LGDPPC (-)	No	No
	Extended	No	No	-	-		
Greece	Basic	Yes	No	2	LGDPPC → Gini (-)	No	No
	Extended	Yes	No	1	LGDPPC → Gini (-) Fbal → Gini (-)	No	-
Hungary	Basic	Yes	No	3	Gini → LGDPPC (+)	No	No
	Extended	No	Yes	3	LGDPPC → Gini (-)	-	-
Ireland	Basic	No	Yes	1	Gini → LGDPPC (+) LGDPPC → Gini (-)	No	No
	Extended	No	No	-	-		
Iceland	Basic	No	No	-	-		
	Extended	No	No	-	-		
Israel	Basic	No	Yes	1	Gini → LGDPPC (+)	No	No
	Extended	No	No	-	-		
Italy	Basic	Yes	No	1	Gini → LGDPPC (+)	No	No
	Extended	No	Yes	3	Gini → LGDPPC (+) Fbal → LGDPPC (-)	-	-
Luxemburg	Basic	No	Yes	1	Gini → LGDPPC (-)	No	No
	Extended	No	No	-	-		
Netherlands	Basic	No	Yes	3	Gini → LGDPPC (+) LGDPPC → Gini (+)	No	-
	Extended	No	Yes	3	Gini → LGDPPC (+) Fbal → LGDPPC (+) LGDPPC → Gini (+) Fbal → Gini (+)	-	-
Norway	Basic	Yes	No	2	LGDPPC → Gini (+)	Yes at lag=1	No
	Extended	No	No	-	-		
Poland	Basic	Yes	No	3	Gini → LGDPPC (+) 10%	No	No
	Extended	No	No	-	-		
Portugal	Basic	Yes	No	2	LGDPPC → Gini (+)	No	No
	Extended	No	No	-	-		
Slovak Republic	Basic	Yes	No	1	LGDPPC → Gini (-)	No	No
	Extended	No	No	-	-		
Slovenia	Basic	No	No	-	-		
	Extended	No	No	-	-		
Sweden	Basic	No	Yes	1	Gini → LGDPPC (-) LGDPPC → Gini (-)	No	Yes at 1%
	Extended	No	No	-	-		
Turkey	Basic	No	No	-	-		
	Extended	No	No	-	-		
United States	Basic	Yes	No	3	Gini → LGDPPC (+) LGDPPC → Gini (+)	No	No
	Extended	No	No	-	-		

OECD = Organisation for Economic Co-operation and Development, VAR = vector autoregression, VECM = vector error correction model.

[a] Although the lag order selection criteria indicate lag number 1, we use lag number 2 to correct serial correlation problem in the residuals.

Source: Author.

Figure 11: Dynamic Causality and Impact Analysis between Economic Growth and Inequality (OECD countries)



AUT = Austria, BEL = Belgium, CAN = Canada, CZE = Czech Republic, DEN = Denmark, EST = Estonia, FIN = Finland, FRA = France, GER = Germany, GRC = Greece, HUN = Hungary, IRE = Ireland, ISL = Iceland, ITA = Italy, LUX = Luxemburg, NET = Netherlands, NOR = Norway, OECD = Organisation for Economic Co-operation and Development, POL = Poland, POR = Portugal, SPA = Spain, SVK = Slovakia, SWE = Sweden, SWI = Switzerland, UKG = United Kingdom, USA = United States.
Source: Author.

Table 3: Regression Methodology and Results for Latin American Countries

Country		Cointe-gration	Stationary transfor-mation	Lag	VECM(causality)/ VAR (impulse response)	Serial correlation	Heteroske-dasticity
Dominican Republic	Basic	No	Yes	2	Gini → LGDPPC (+) LGDPPC → Gini (-)	No	No
	Extended	No	No	-	-		
Ecuador	Basic	No	Yes	2	LGDPPC → Gini (+)	No	No
	Extended	No	No	-	-		
Honduras	Basic	No	Yes	2	Gini → LGDPPC (+) LGDPPC → Gini (-)	No	No
	Extended	-	-	-	-		
Mexico	Basic	Yes	No	3	LGDPPC → Gini (-)	No	No
	Extended	No	No	-	-		
Panama	Basic	No	Yes	3	Gini → LGDPPC (-) LGDPPC → Gini (-)	No	No
	Extended	No	No	-	-		
Paraguay	Basic	Yes	No	1	LGDPPC → Gini (+)	Yes at lag=1	No
	Extended	No	No	-	-		

VAR = vector autoregression, VECM = vector error correction model.
Source: Author.

VI. CONCLUSION

Inclusive growth will likely continue at the core of the development agenda at both national and international levels. If we accept the notion of "broad-based" economic growth as the underlying concept behind inclusive growth, we need to pay sufficient attention to the pattern of growth—including whether it promotes equity or exacerbates inequality. The classical Kuznets curve model posits an inverted U-shaped relationship between GDP per capita and the Gini coefficient. Accordingly, economic growth is associated with rising income inequality up to a certain income level—after which further economic growth is associated with declining inequality.

Recently, many studies have highlighted the negative impact of inequality on economic growth using cross-country panel data. This study attempts to shed light on the dynamic causality relationship and impact between economic growth and inequality—by using VECM and VAR models beyond simple correlation analyses. In addition, used for individual economies based on country-specific time-series data, this approach allows for a rich set of implications tailored to each economy—which cannot be drawn from country panel data regressions. Policy prescriptions should be based on accurate diagnosis of the underlying dynamics of growth and inequality.

If a growth pattern worsens inequality, renewed attention should be paid to curbing inequality. Those economies showing an inclusive growth pattern are encouraged to further promote growth with a lower risk of sacrificing equity. This also provides some useful implications for development interventions. For those economies with an embedded inclusive growth pattern, national or multilateral development projects/programs can be devised in a way to support the economic growth—as that growth will eventually reduce inequality. On the other hand, if the economy's growth pattern does not reduce inequality, more direct efforts should be made to address the inequality issue.

Also, if we expand our scope from static to dynamic causality—and the relationship between growth and inequality—the time horizon for assessing the impact of development projects/programs may not need be confined to the present. Although a certain project/program has a negligible impact on inequality compared with growth, it may have a stronger effect on inequality in the long run through reducing inequality via the growth channel. Hence, comprehensive longer-run effects should be considered in designing projects/programs and assessing those under the dynamic causality perspective. Finally, given the growing challenges of reducing inequality, economies are advised to create a proper inequality target and use it as an important qualifier in pursuing economic growth—instead of employing a growth-first and redistribution-later strategy. This study has focused on the directional causality and impact between growth and inequality. Future study could shed more light on forgone growth potential in lowering inequality to gauge the net inclusive growth portion in the context of the growth-equality nexus.

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* ADB recognizes "China" as the People's Republic of China.

APPENDIX A.1

Table A1.1: Income Growth Schedule under 5% Economic Growth with the Same Equality

100	105	110	116	122	128	134	141	148	155	163	171	180	189	198	208	218	229	241	253	265	279	293	307	323	339	356	373
200	210	221	232	243	255	268	281	295	310	326	342	359	377	396	416	437	458	481	505	531	557	585	614	645	677	711	747
300	315	331	347	365	383	402	422	443	465	489	513	539	566	594	624	655	688	722	758	796	836	878	921	968	1,016	1,067	1,120
400	420	441	463	486	511	536	563	591	621	652	684	718	754	792	832	873	917	963	1,011	1,061	1,114	1,170	1,229	1,290	1,355	1,422	1,493
500	525	551	579	608	638	670	704	739	776	814	855	898	943	990	1,039	1,091	1,146	1,203	1,263	1,327	1,393	1,463	1,536	1,613	1,693	1,778	1,867
600	630	662	695	729	766	804	844	886	931	977	1,026	1,078	1,131	1,188	1,247	1,310	1,375	1,444	1,516	1,592	1,672	1,755	1,843	1,935	2,032	2,133	2,240
700	735	772	810	851	893	938	985	1,034	1,086	1,140	1,197	1,257	1,320	1,386	1,455	1,528	1,604	1,685	1,769	1,857	1,950	2,048	2,150	2,258	2,370	2,489	2,613
800	840	882	926	972	1,021	1,072	1,126	1,182	1,241	1,303	1,368	1,437	1,509	1,584	1,663	1,746	1,834	1,925	2,022	2,123	2,229	2,340	2,457	2,580	2,709	2,845	2,987
900	945	992	1,042	1,094	1,149	1,206	1,266	1,330	1,396	1,466	1,539	1,616	1,697	1,782	1,871	1,965	2,063	2,166	2,274	2,388	2,507	2,633	2,764	2,903	3,048	3,200	3,360
1,000	1,050	1,103	1,158	1,216	1,276	1,340	1,407	1,477	1,551	1,629	1,710	1,796	1,886	1,980	2,079	2,183	2,292	2,407	2,527	2,653	2,786	2,925	3,072	3,225	3,386	3,556	3,733
5,500	**5,775**	**6,064**	**6,367**	**6,685**	**7,020**	**7,371**	**7,739**	**8,126**	**8,532**	**8,959**	**9,407**	**9,877**	**10,371**	**10,890**	**11,434**	**12,006**	**12,606**	**13,236**	**13,898**	**14,593**	**15,323**	**16,089**	**16,893**	**17,738**	**18,625**	**19,556**	**20,534**
Gini	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3

392	412	432	454	476	500	525	552	579	608	639	670	704	739	776	815	856	899	943	991	1,040	1,092	1,147	1,204	1,264	1,327	1,394
784	823	864	908	953	1,001	1,051	1,103	1,158	1,216	1,277	1,341	1,408	1,478	1,552	1,630	1,711	1,797	1,887	1,981	2,080	2,184	2,293	2,408	2,529	2,655	2,788
1,176	1,235	1,297	1,361	1,429	1,501	1,576	1,655	1,738	1,824	1,916	2,011	2,112	2,218	2,328	2,445	2,567	2,696	2,830	2,972	3,120	3,276	3,440	3,612	3,793	3,982	4,182
1,568	1,646	1,729	1,815	1,906	2,001	2,101	2,206	2,317	2,433	2,554	2,682	2,816	2,957	3,105	3,260	3,423	3,594	3,774	3,962	4,161	4,369	4,587	4,816	5,057	5,310	5,575
1,960	2,058	2,161	2,269	2,382	2,502	2,627	2,758	2,896	3,041	3,193	3,352	3,520	3,696	3,881	4,075	4,279	4,493	4,717	4,953	5,201	5,461	5,734	6,020	6,321	6,637	6,969
2,352	2,470	2,593	2,723	2,859	3,002	3,152	3,310	3,475	3,649	3,831	4,023	4,224	4,435	4,657	4,890	5,134	5,391	5,661	5,944	6,241	6,553	6,880	7,224	7,586	7,965	8,363
2,744	2,881	3,025	3,177	3,335	3,502	3,677	3,861	4,054	4,257	4,470	4,693	4,928	5,174	5,433	5,705	5,990	6,290	6,604	6,934	7,281	7,645	8,027	8,429	8,850	9,292	9,757
3,136	3,293	3,458	3,630	3,812	4,003	4,203	4,413	4,633	4,865	5,108	5,364	5,632	5,914	6,209	6,520	6,846	7,188	7,547	7,925	8,321	8,737	9,174	9,633	10,114	10,620	11,151
3,528	3,705	3,890	4,084	4,288	4,503	4,728	4,964	5,213	5,473	5,747	6,034	6,336	6,653	6,985	7,335	7,701	8,087	8,491	8,915	9,361	9,829	10,321	10,837	11,379	11,947	12,545
3,920	4,116	4,322	4,538	4,765	5,003	5,253	5,516	5,792	6,081	6,385	6,705	7,040	7,392	7,762	8,150	8,557	8,985	9,434	9,906	10,401	10,921	11,467	12,041	12,643	13,275	13,939
21,561	**22,639**	**23,771**	**24,959**	**26,207**	**27,518**	**28,893**	**30,338**	**31,855**	**33,448**	**35,120**	**36,876**	**38,720**	**40,656**	**42,689**	**44,823**	**47,064**	**49,418**	**51,888**	**54,483**	**57,207**	**60,067**	**63,071**	**66,224**	**69,535**	**73,012**	**76,663**
0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3

Source: Author's calculations.

Table A1.2: Income Growth Schedule under 5% Economic Growth with Perfect Redistribution

100	128	156	187	219	252	287	324	363	403	446	491	538	587	639	693	751	811	874	940	1,009	1,082	1,159	1,239	1,324	1,412	1,506	1,603
200	228	256	287	319	352	387	424	463	503	546	591	638	687	739	793	851	911	974	1,040	1,109	1,182	1,259	1,339	1,424	1,512	1,606	1,703
300	328	356	387	419	452	487	524	563	603	646	691	738	787	839	893	951	1,011	1,074	1,140	1,209	1,282	1,359	1,439	1,524	1,612	1,706	1,803
400	428	456	487	519	552	587	624	663	703	746	791	838	887	939	993	1,051	1,111	1,174	1,240	1,309	1,382	1,459	1,539	1,624	1,712	1,806	1,903
500	528	556	587	619	652	687	724	763	803	846	891	938	987	1,039	1,093	1,151	1,211	1,274	1,340	1,409	1,482	1,559	1,639	1,724	1,812	1,906	2,003
600	628	656	687	719	752	787	824	863	903	946	991	1,038	1,087	1,139	1,193	1,251	1,311	1,374	1,440	1,509	1,582	1,659	1,739	1,824	1,912	2,006	2,103
700	728	756	787	819	852	887	924	963	1,003	1,046	1,091	1,138	1,187	1,239	1,293	1,351	1,411	1,474	1,540	1,609	1,682	1,759	1,839	1,924	2,012	2,106	2,203
800	828	856	887	919	952	987	1,024	1,063	1,103	1,146	1,191	1,238	1,287	1,339	1,393	1,451	1,511	1,574	1,640	1,709	1,782	1,859	1,939	2,024	2,112	2,206	2,303
900	928	956	987	1,019	1,052	1,087	1,124	1,163	1,203	1,246	1,291	1,338	1,387	1,439	1,493	1,551	1,611	1,674	1,740	1,809	1,882	1,959	2,039	2,124	2,212	2,306	2,403
1,000	1,028	1,056	1,087	1,119	1,152	1,187	1,224	1,263	1,303	1,346	1,391	1,438	1,487	1,539	1,593	1,651	1,711	1,774	1,840	1,909	1,982	2,059	2,139	2,224	2,312	2,406	2,503
5,500	**5,775**	**6,064**	**6,367**	**6,685**	**7,020**	**7,371**	**7,739**	**8,126**	**8,532**	**8,959**	**9,407**	**9,877**	**10,371**	**10,890**	**11,434**	**12,006**	**12,606**	**13,236**	**13,898**	**14,593**	**15,323**	**16,089**	**16,893**	**17,738**	**18,625**	**19,556**	**20,534**
Gini	0.29	0.27	0.26	0.25	0.24	0.22	0.21	0.20	0.19	0.18	0.18	0.17	0.16	0.15	0.14	0.14	0.13	0.12	0.12	0.11	0.11	0.10	0.10	0.09	0.09	0.08	0.08

1,706	1,814	1,927	2,046	2,171	2,302	2,439	2,584	2,735	2,895	3,062	3,238	3,422	3,616	3,819	4,032	4,256	4,492	4,739	4,998	5,271	5,557	5,857	6,172	6,504	6,851	7,216
1,806	1,914	2,027	2,146	2,271	2,402	2,539	2,684	2,835	2,995	3,162	3,338	3,522	3,716	3,919	4,132	4,356	4,592	4,839	5,098	5,371	5,657	5,957	6,272	6,604	6,951	7,316
1,906	2,014	2,127	2,246	2,371	2,502	2,639	2,784	2,935	3,095	3,262	3,438	3,622	3,816	4,019	4,232	4,456	4,692	4,939	5,198	5,471	5,757	6,057	6,372	6,704	7,051	7,416
2,006	2,114	2,227	2,346	2,471	2,602	2,739	2,884	3,035	3,195	3,362	3,538	3,722	3,916	4,119	4,332	4,556	4,792	5,039	5,298	5,571	5,857	6,157	6,472	6,804	7,151	7,516
2,106	2,214	2,327	2,446	2,571	2,702	2,839	2,984	3,135	3,295	3,462	3,638	3,822	4,016	4,219	4,432	4,656	4,892	5,139	5,398	5,671	5,957	6,257	6,572	6,904	7,251	7,616
2,206	2,314	2,427	2,546	2,671	2,802	2,939	3,084	3,235	3,395	3,562	3,738	3,922	4,116	4,319	4,532	4,756	4,992	5,239	5,498	5,771	6,057	6,357	6,672	7,004	7,351	7,716
2,306	2,414	2,527	2,646	2,771	2,902	3,039	3,184	3,335	3,495	3,662	3,838	4,022	4,216	4,419	4,632	4,856	5,092	5,339	5,598	5,871	6,157	6,457	6,772	7,104	7,451	7,816
2,406	2,514	2,627	2,746	2,871	3,002	3,139	3,284	3,435	3,595	3,762	3,938	4,122	4,316	4,519	4,732	4,956	5,192	5,439	5,698	5,971	6,257	6,557	6,872	7,204	7,551	7,916
2,506	2,614	2,727	2,846	2,971	3,102	3,239	3,384	3,535	3,695	3,862	4,038	4,222	4,416	4,619	4,832	5,056	5,292	5,539	5,798	6,071	6,357	6,657	6,972	7,304	7,651	8,016
2,606	2,714	2,827	2,946	3,071	3,202	3,339	3,484	3,635	3,795	3,962	4,138	4,322	4,516	4,719	4,932	5,156	5,392	5,639	5,898	6,171	6,457	6,757	7,072	7,404	7,751	8,116
21,561	**22,639**	**23,771**	**24,959**	**26,207**	**27,518**	**28,893**	**30,338**	**31,855**	**33,448**	**35,120**	**36,876**	**38,720**	**40,656**	**42,689**	**44,823**	**47,064**	**49,418**	**51,888**	**54,483**	**57,207**	**60,067**	**63,071**	**66,224**	**69,535**	**73,012**	**76,663**
0.08	0.07	0.07	0.07	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02

Source: Author's calculations.

APPENDIX A.2: REGRESSION RESULTS FOR ASIAN ECONOMIES

Armenia

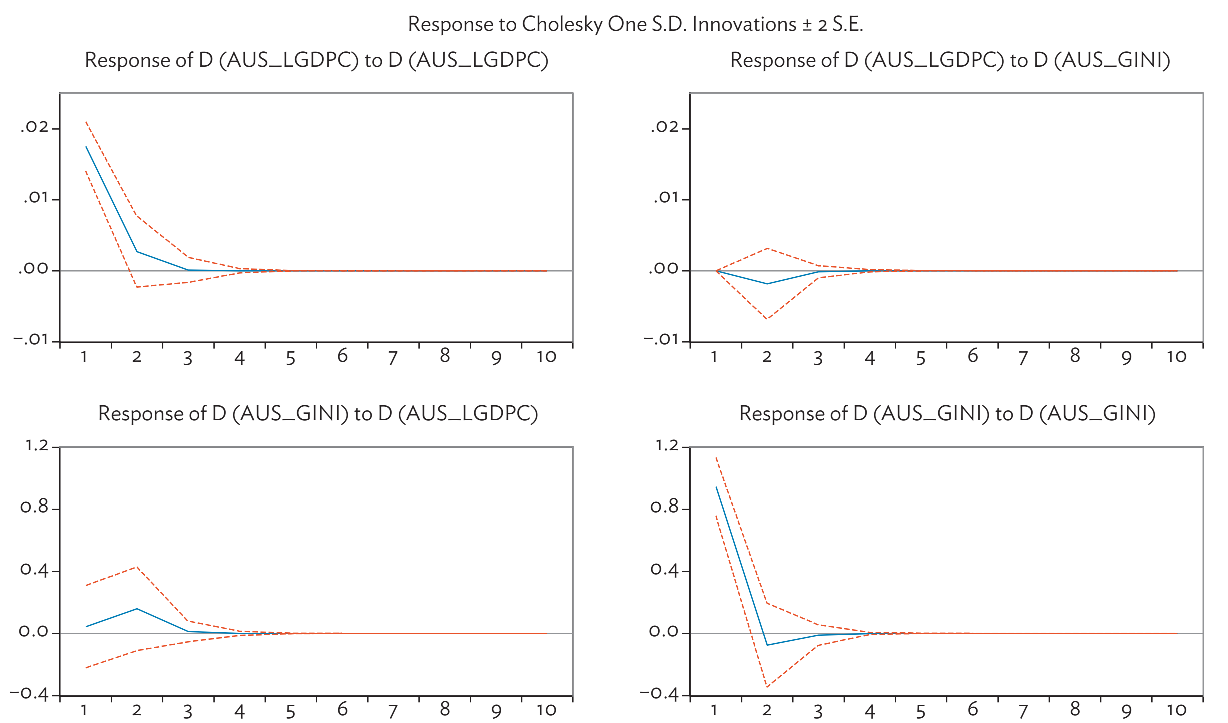
Vector Error Correction Estimates
Sample (adjusted): 1992 2012
Standard errors in ( ) & t-statistics in [ ]

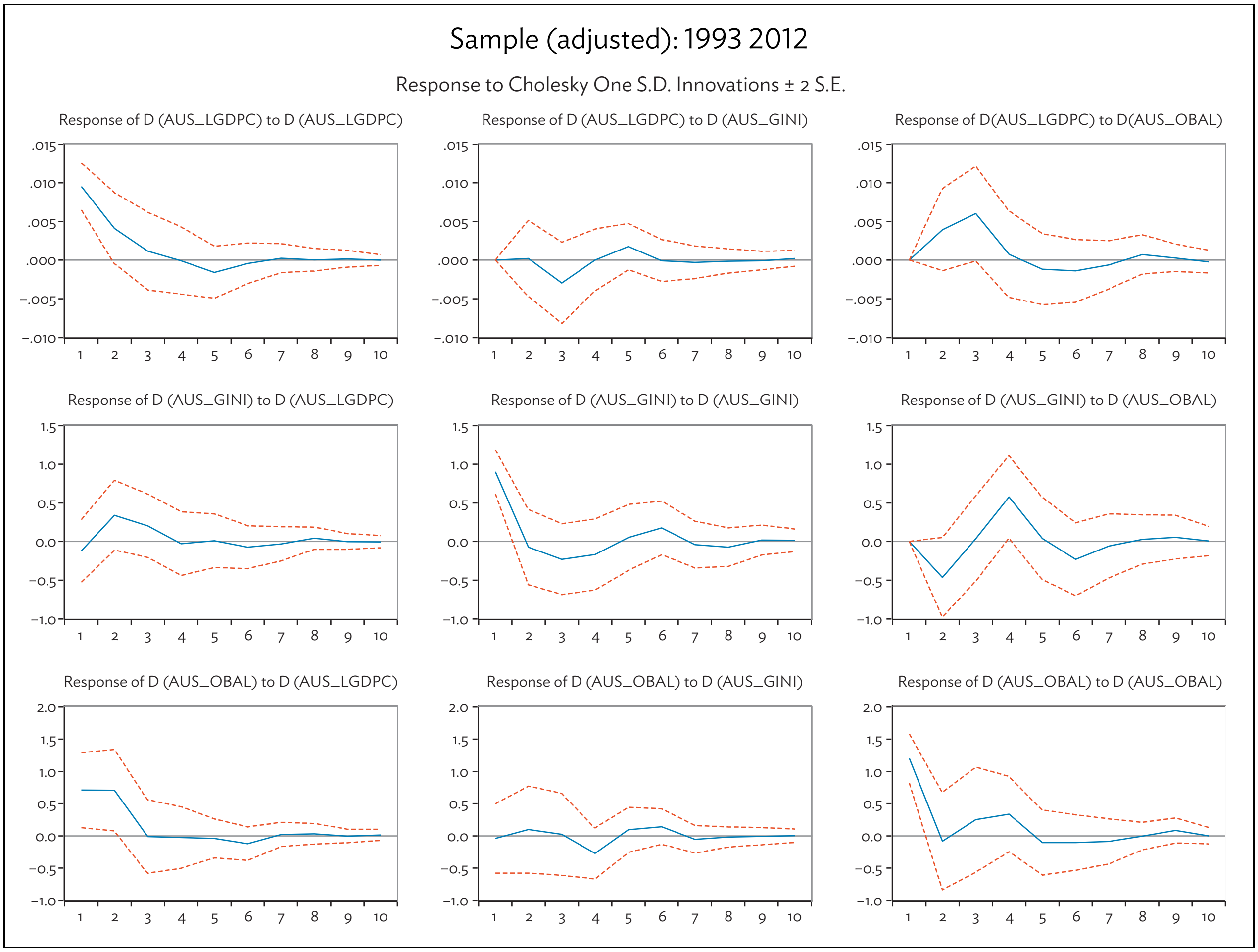
Cointegrating Eq:	CointEq1
ARM_LGDPC(−1)	1
ARM_GINI(−1)	0.000047
	(−0.000025)
	[1.88006]
C	−3.623077

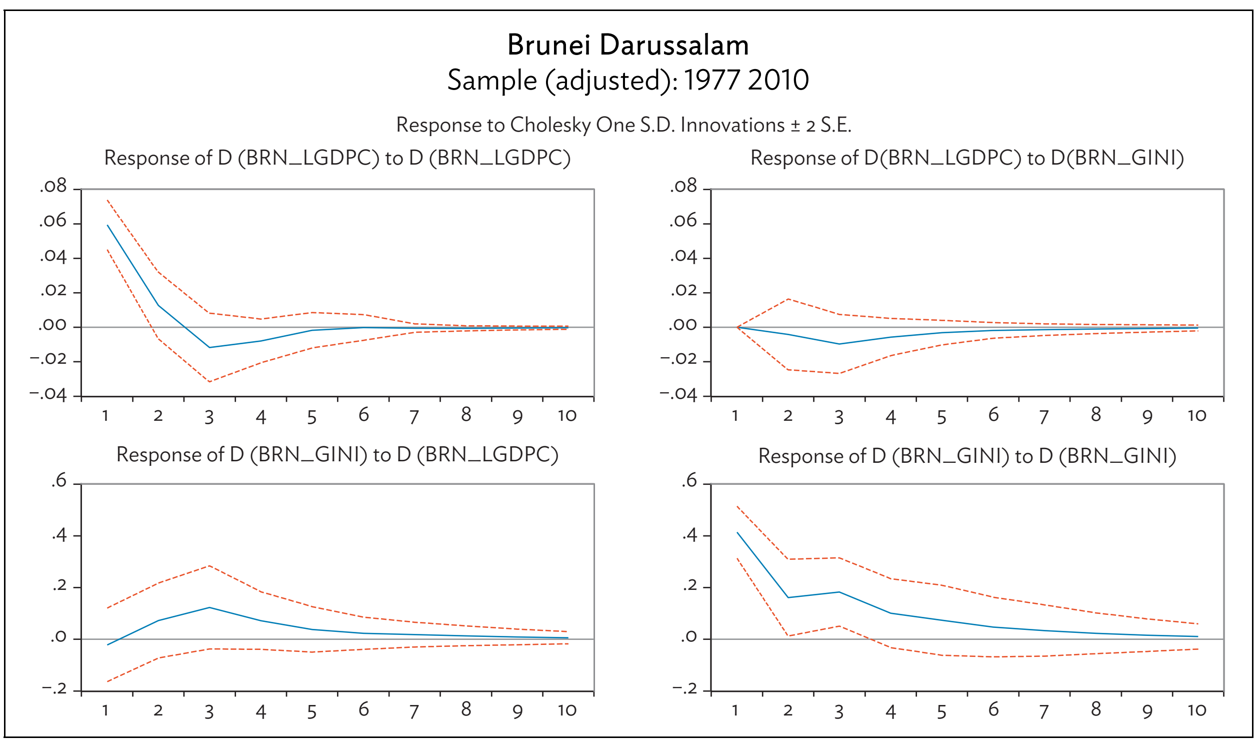
Dependent Variable: D(ARM_LGDPC)
Sample (adjusted): 1992 2012
D(ARM_LGDPC) = C(1)*(ARM_LGDPC(−1) + 4.67455844964E−05 *ARM_GINI(−1) − 3.62307737231) + C(2)*D(ARM_LGDPC(−1)) + C(3)*D(ARM_GINI(−1)) + C(4)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.535831**	**0.132342**	**−4.04885**	**0.0008**
C(2)	0.090929	0.174369	0.521472	0.6088
C(3)	9.71E−05	6.79E−05	1.430287	0.1708
C(4)	0.003356	0.009514	0.352802	0.7286
R-squared	0.52317	Mean dependent var		0.009212
Adjusted R-squared	0.439023	S.D. dependent var		0.049516

Australia
Sample (adjusted): 1962 2012




Sample (adjusted): 1993 2012
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of D (AUS_LGDPC) to D (AUS_LGDPC)
Response of D (AUS_LGDPC) to D (AUS_GINI)
Response of D(AUS_LGDPC) to D(AUS_OBAL)
Response of D (AUS_GINI) to D (AUS_LGDPC)
Response of D (AUS_GINI) to D (AUS_GINI)
Response of D (AUS_GINI) to D (AUS_OBAL)
Response of D (AUS_OBAL) to D (AUS_LGDPC)
Response of D (AUS_OBAL) to D (AUS_GINI)
Response of D (AUS_OBAL) to D (AUS_OBAL)


Brunei Darussalam
Sample (adjusted): 1977 2010
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of D (BRN_LGDPC) to D (BRN_LGDPC)
Response of D(BRN_LGDPC) to D(BRN_GINI)
Response of D (BRN_GINI) to D (BRN_LGDPC)
Response of D (BRN_GINI) to D (BRN_GINI)

People's Republic of China

Vector Error Correction Estimates
Sample (adjusted): 1982 2013
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
CHN_LGDPC(−1)	1
CHN_GINI(−1)	−0.088077
	(−0.00437)
	[−20.1577]
C	−3.21413

Dependent Variable: D(CHN_LGDPC)
Sample (adjusted): 1982 2013
D(CHN_LGDPC) = C(1)*(CHN_LGDPC(−1) −0.0880770839508*CHN_GINI(−1) −3.21413044122) + C(2)*D(CHN_LGDPC(−1)) + C(3)*D(CHN_LGDPC(−2)) + C(4)*D(CHN_LGDPC(−3)) + C(5)*D(CHN_GINI(−1)) + C(6)*D(CHN_GINI(−2)) + C(7)*D(CHN_GINI(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.064876**	**0.023796**	**−2.72629**	**0.0118**
C(2)	0.774997	0.166837	4.64524	0.0001
C(3)	−0.492135	0.199221	−2.4703	0.021
C(4)	0.152043	0.171864	0.88467	0.3851
C(5)	−0.000239	0.003376	−0.07077	0.9442
C(6)	−0.003987	0.003997	−0.99742	0.3285
C(7)	−0.002352	0.003328	−0.70678	0.4865
C(8)	0.054019	0.01603	3.369857	0.0025
R-squared	0.589281	Mean dependent var		0.085941
Adjusted R-squared	0.469488	S.D. dependent var		0.024526

Vector Error Correction Estimates
Sample (adjusted): 1982 2013
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
CHN_GINI(−1)	1
CHN_LGDPC(−1)	−11.35369
	(−0.56252)
	[−20.1836]
C	36.49224

Dependent Variable: D(CHN_LGDPC) Method: Least Squares Sample (adjusted): 1982 2013 D(CHN_GINI) = C(1)*(CHN_GINI(−1) – 11.3536910527*CHN_LGDPC(−1) + 36.4922440327) + C(2)*D(CHN_GINI(−1)) + C(3)*D(CHN_GINI(−2)) + C(4)*D(CHN_GINI(−3)) + C(5)*D(CHN_LGDPC(−1)) + C(6) *D(CHN_LGDPC(−2)) + C(7)*D(CHN_LGDPC(−3)) + C(8)				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.271743**	**0.106567**	**−2.54998**	**0.0176**
C(2)	0.548053	0.171655	3.192762	0.0039
C(3)	0.208756	0.203231	1.027185	0.3146
C(4)	−0.207072	0.169213	−1.22374	0.2329
C(5)	0.587178	8.482795	0.06922	0.9454
C(6)	−4.030711	10.12937	−0.39792	0.6942
C(7)	−8.967415	8.738429	−1.02621	0.315
C(8)	1.395734	0.815042	1.712468	0.0997
R-squared	0.530432	Mean dependent var		0.796461
Adjusted R-squared	0.393474	S.D. dependent var		1.166261

Georgia

Vector Error Correction Estimates Sample (adjusted): 1990 2013 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
GEO_LGDPC(−1)	1
GEO_GINI(−1)	−1.21465
	(−0.18043)
	[−6.73209]
C	39.32298

Dependent Variable: D(GEO_LGDPC) Sample (adjusted): 1990 2013 D(GEO_LGDPC) = C(1)*(GEO_LGDPC(−1) – 1.21464556115*GEO_GINI(−1) + 39.3229832038) + C(2)*D(GEO_LGDPC(−1)) + C(3) *D(GEO_LGDPC(−2)) + C(4)*D(GEO_LGDPC(−3)) + C(5)*D(GEO_GINI(−1)) + C(6)*D(GEO_GINI(−2)) + C(7)*D(GEO_GINI(−3)) + C(8)				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.01453**	**0.003032**	**−4.7932**	**0.0002**
C(2)	0.376821	0.167693	2.247085	0.0391
C(3)	−0.01684	0.167041	−0.10083	0.9209
C(4)	−0.04	0.145202	−0.27547	0.7865
C(5)	−0.04629	0.020405	−2.26849	0.0375
C(6)	−0.02576	0.021154	−1.2178	0.241
C(7)	0.086434	0.02063	4.189807	0.0007
C(8)	−0.02176	0.021842	−0.99611	0.334
R-squared	0.912592	Mean dependent var		−0.012637
Adjusted R-squared	0.874351	S.D. dependent var		0.17227

Vector Error Correction Estimates	
Sample (adjusted): 1990 2013	
Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
GEO_GINI(−1)	1
GEO_LGDPC(−1)	−0.82329
	(−2.45348)
	[−0.33556]
C	−32.37404

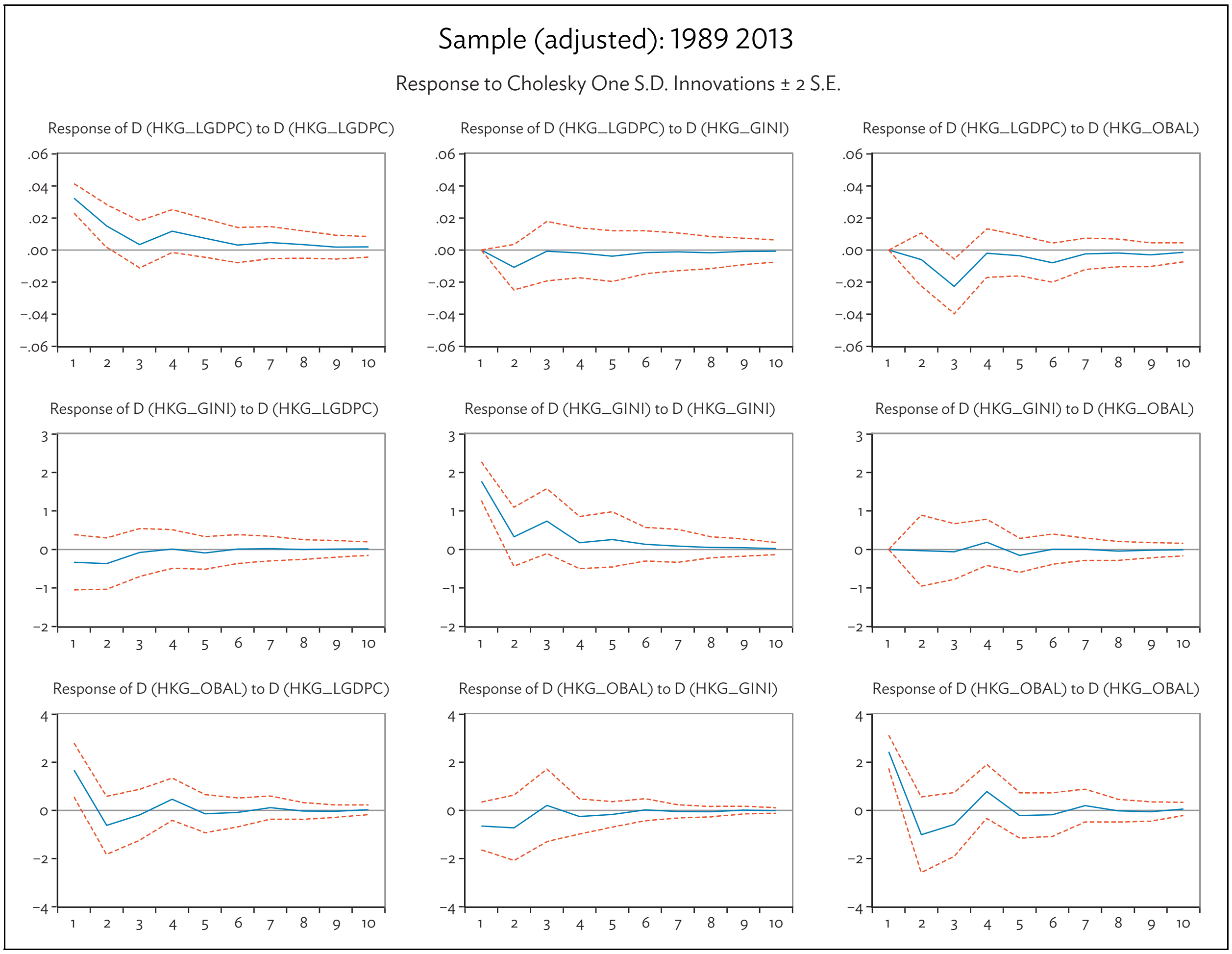
Dependent Variable: D(GEO_GINI)
Sample (adjusted): 1990 2013
D(GEO_GINI) = C(1)*(GEO_GINI(−1) − 0.823285435672*GEO_LGDPC(−1) −32.3740393589) + C(2)*D(GEO_GINI(−1)) + C(3)*D(GEO_GINI(−2)) +C(4)*D(GEO_GINI(−3)) + C(5)*D(GEO_LGDPC(−1)) + C(6) *D(GEO_LGDPC(−2)) + C(7)*D(GEO_LGDPC(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.163**	**0.027814**	**−5.8604**	**0**
C(2)	0.404455	0.154125	2.62421	0.0184
C(3)	0.064756	0.159779	0.405283	0.6906
C(4)	−0.10138	0.155821	−0.65059	0.5245
C(5)	1.328167	1.266636	1.048578	0.31
C(6)	−0.79855	1.261712	−0.63291	0.5357
C(7)	−0.11991	1.096756	−0.10933	0.9143
C(8)	0.374558	0.164977	2.270365	0.0374
R-squared	0.844462	Mean dependent var		0.570071
Adjusted R-squared	0.776414	S.D. dependent var		0.975447

Hong Kong, China

Vector Error Correction Estimates	
Sample (adjusted): 1976 2013	
Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
HKG_LGDPC(−1)	1
HKG_GINI(−1)	−0.00697
	(−0.01379)
	[−0.50513]
C	−9.582433

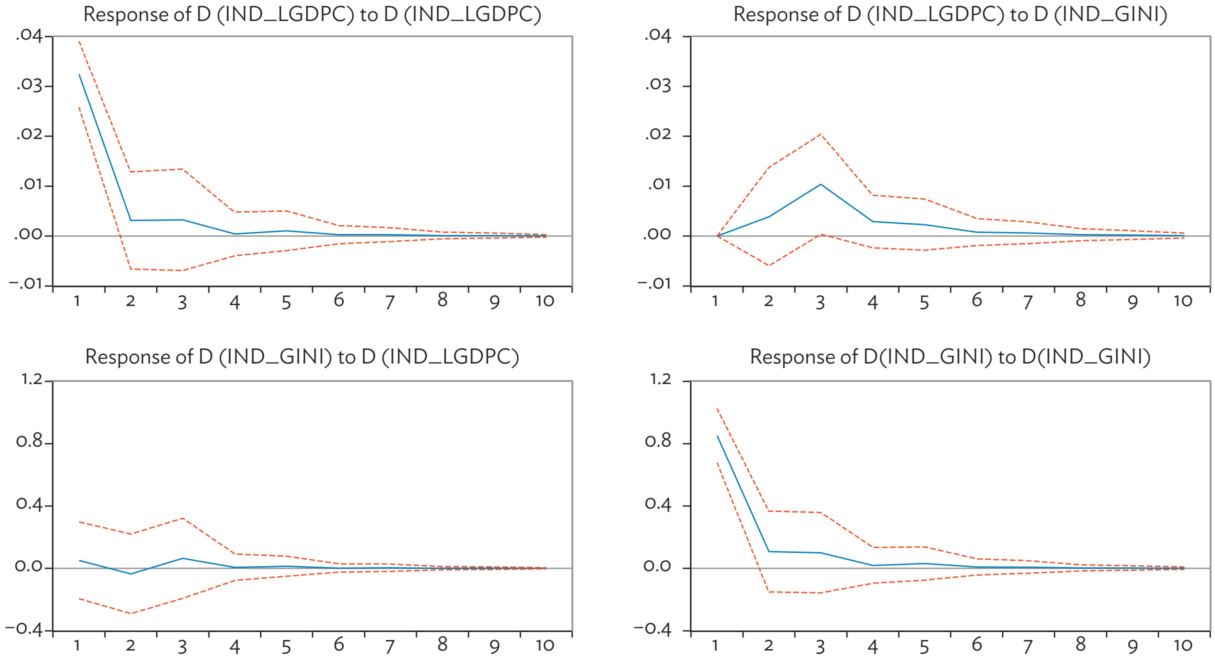
Dependent Variable: D(HKG_LGDPC)				
Sample (adjusted): 1976 2013				
D(HKG_LGDPC) = C(1)*(HKG_LGDPC(−1)−0.00696614197873*HKG_GINI(−1)−9.58243268925)+C(2) *D(HKG_LGDPC(−1))+C(3) *D(HKG_LGDPC(−2))+C(4)*D(HKG_GINI(−1))+ C(5)*D(HKG_GINI(−))+C(6)				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.07211**	**0.01465**	**−4.922385**	**0**
C(2)	−0.11008	0.135733	−0.810968	0.4242
.C(3)	−0.31582	0.133159	−2.371781	0.0248
C(4)	−0.01074	0.003677	−2.921898	0.0068
C(5)	−0.00842	0.004036	−2.085485	0.0463
C(6)	0.059302	0.009188	6.454229	0
R-squared	0.543549	Mean dependent var		0.04101
Adjusted R-squared	0.46204	S.D. dependent var		0.041182



India

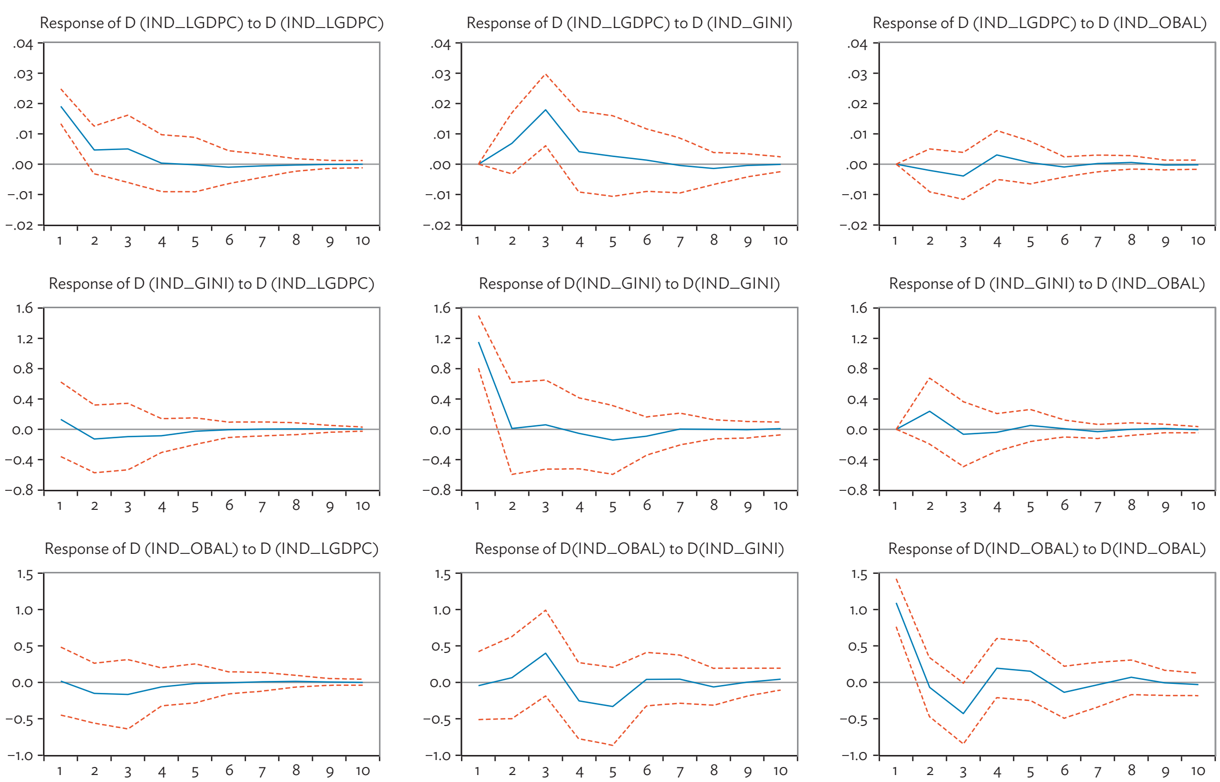
Sample (adjusted): 1962 2010

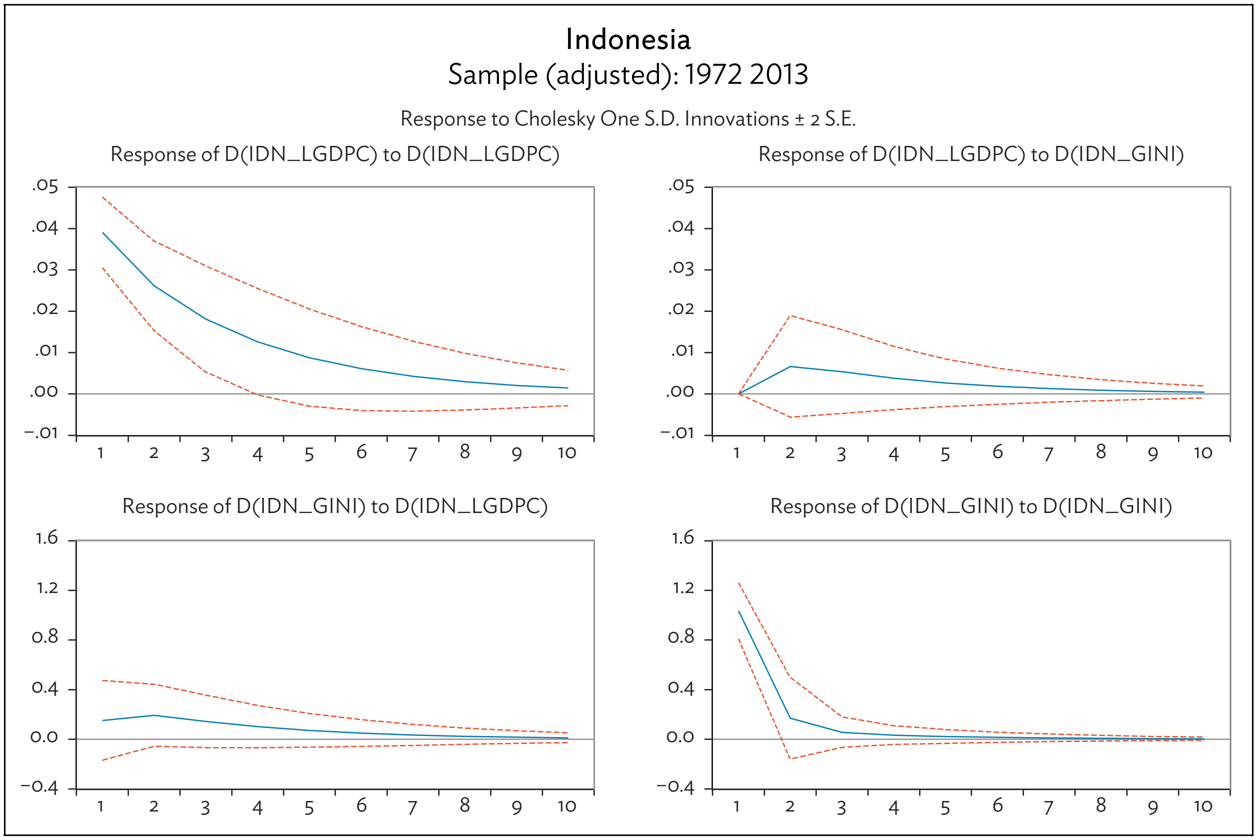
Response to Cholesky One S.D. Innovations ± 2 S.E.



Sample (adjusted): 1988 2010

Response to Cholesky One S.D. Innovations ± 2 S.E.





Vector Error Correction Estimates Sample (adjusted): 1990 2013 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
IDN_LGDPC(−1)	1
IDN_GINI(−1)	−0.08478
	(−0.03313)
	[−2.55909]
IDN_OBAL(−1)	0.143162
	(−0.05952)
	[2.40507]
C	-3.94633

Dependent Variable: D(IDN_LGDPC)
Sample (adjusted): 1990 2013
D(IDN_LGDPC) = C(1)*(IDN_LGDPC(−1) − 0.0847766254754*IDN_GINI(−1)+ 0.143161700069*IDN_OBAL(−1) − 3.94632541353)+C(2) *D(IDN_LGDPC(−1))+C(3)*D(IDN_LGDPC(−2))+C(4)*D(IDN_LGDPC(−3))+C(5)*D(IDN_GINI(−1))+C(6)*D(IDN_GINI(−2))+C(7) *D(IDN_GINI(−3)) + C(8)*D(IDN_OBAL(−1)) + C(9)*D(IDN_OBAL(2)) + C(10)*D(IDN_OBAL(−3)) + C(11)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.09483**	**0.041063**	**−2.30926**	**0.038**
C(2)	−0.23228	0.272755	−0.85162	0.4098
C(3)	−0.49221	0.212065	−2.32103	0.0372
C(4)	0.4017	0.217413	1.847636	0.0875
C(5)	0.017497	0.007788	2.246534	0.0427
C(6)	−0.00536	0.007347	−0.72957	0.4786
C(7)	−0.00308	0.007034	−0.43822	0.6684
C(8)	0.02709	0.008054	3.363505	0.0051
C(9)	0.028257	0.008637	3.271755	0.0061
C(10)	0.001831	0.009639	0.189918	0.8523
C(11)	0.039521	0.01509	2.618936	0.0212
R-squared	0.753839	Mean dependent var		0.034828
Adjusted R-squared	0.564485	S.D. dependent var		0.043673

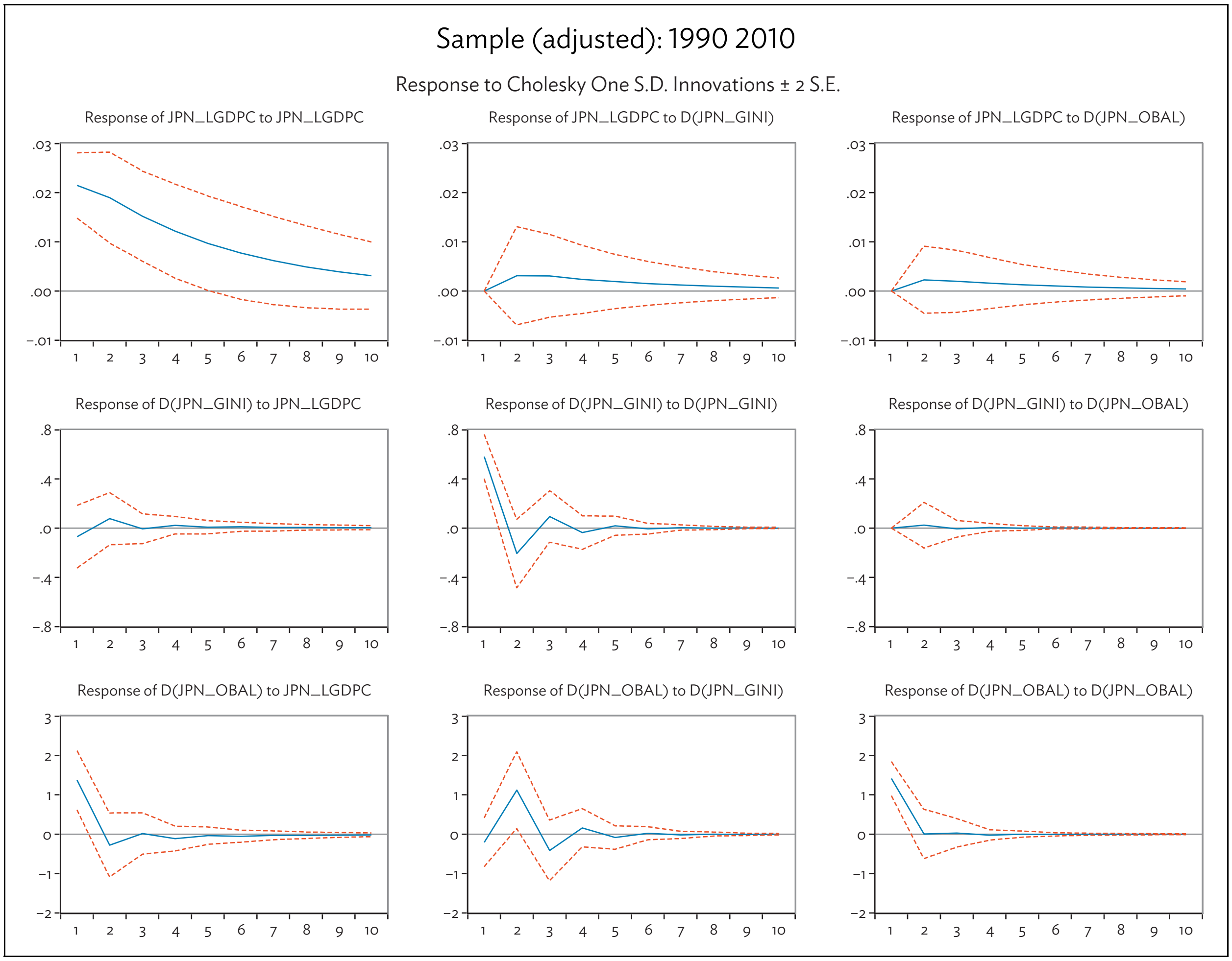
Japan

Vector Error Correction Estimates
Sample (adjusted): 1964 2010
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
JPN_LGDPC(−1)	1
JPN_GINI(−1)	−0.00249
	(−0.02923)
	[−0.08513]
C	−9.99914

Dependent Variable: D(JPN_LGDPC)
Sample (adjusted): 1964 2011
D(JPN_LGDPC) = C(1)*(JPN_LGDPC(−1) −0.00248867650153*JPN_GINI(−1) −9.99913818698) + C(2)*D(JPN_LGDPC(−1)) + C(3) *D(JPN_LGDPC(−2)) + C(4)*D(JPN_LGDPC(−3)) + C(5)*D(JPN_GINI(−1)) + C(6)*D(JPN_GINI(−2)) + C(7)*D(JPN_GINI(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.075691**	**0.017535**	**−4.31646**	**0.0001**
C(2)	0.032614	0.150053	0.217348	0.829
C(3)	−0.209046	0.145323	−1.43849	0.1581
C(4)	0.00968	0.154148	0.062795	0.9502
C(5)	0.007292	0.00445	1.63866	0.1091
C(6)	0.010239	0.004092	2.502069	0.0165
C(7)	0.003282	0.004569	0.718298	0.4767
C(8)	0.033244	0.008622	3.855737	0.0004
R-squared	0.556336	Mean dependent var		0.029107
Adjusted R-squared	0.478695	S.D. dependent var		0.035186



Republic of Korea

Vector Error Correction Estimates
Sample (adjusted): Sample (adjusted): 1970 2013
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
KOR_GINI(−1)	1
KOR_LGDPC(−1)	2.066495
	(−0.27443)
	[7.53016]
C	−50.78486

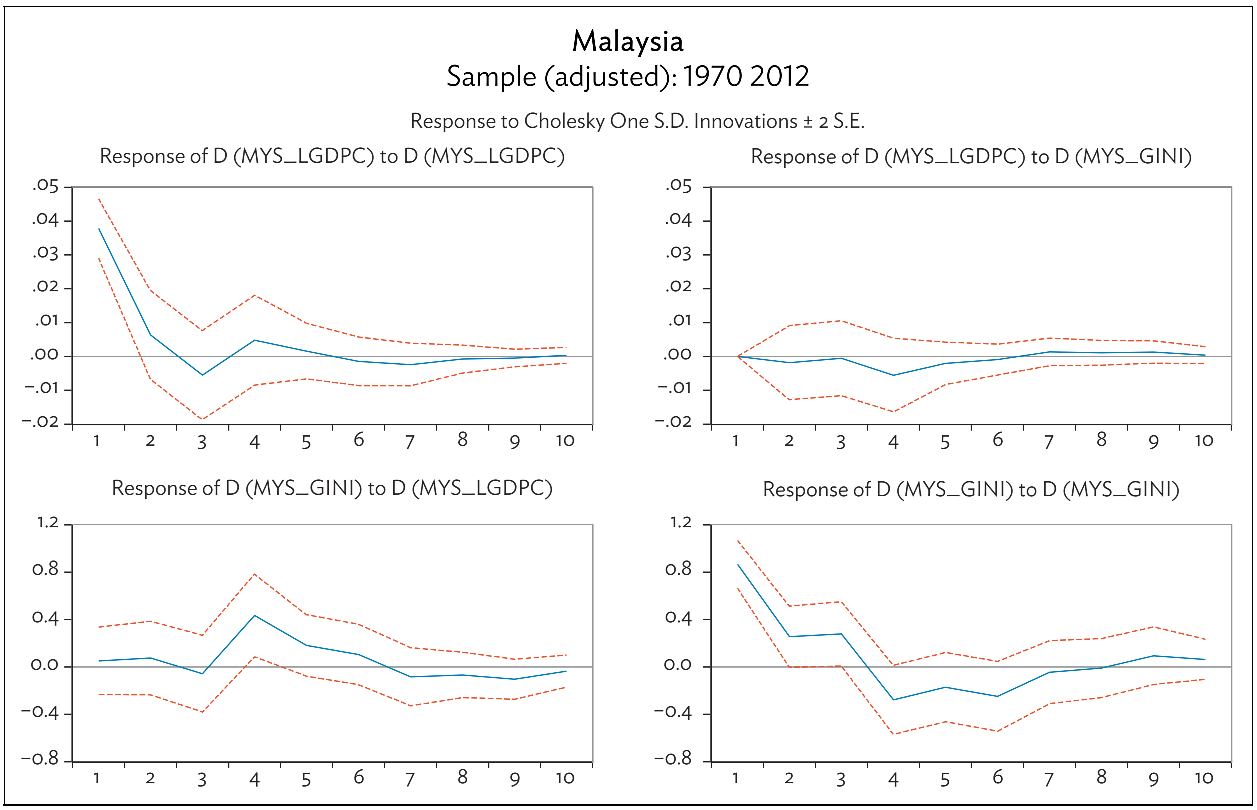
Dependent Variable: D(KOR_GINI)
Sample (adjusted): 1970 2013
D(KOR_GINI) = C(1)*(KOR_GINI(−1) + 2.06649522747*KOR_LGDPC(−1) −50.7848605097) + C(2)*D(KOR_GINI(−1)) + C(3)*D(KOR_GINI(−2)) +C(4)*D(KOR_GINI(−3)) + C(5)*D(KOR_GINI(−4)) + C(6)*D(KOR_GINI(−5)) + C(7)*D(KOR_GINI(−6)) + C(8)*D(KOR_LGDPC(−1)) + C(9) *D(KOR_LGDPC(−2)) + C(10)*D(KOR_LGDPC(−3)) + C(11) *D(KOR_LGDPC(−4)) + C(12)*D(KOR_LGDPC(−5)) + C(13) *D(KOR_LGDPC(−6)) + C(14)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.4421**	**0.072085**	**−6.13302**	**0**
C(2)	0.118667	0.109301	1.085686	0.2863
C(3)	0.329253	0.109918	2.995435	0.0055
C(4)	−0.3537	0.109592	−3.22738	0.003
C(5)	0.051963	0.101047	0.514244	0.6108
C(6)	0.17677	0.095427	1.852402	0.0738
C(7)	−0.19947	0.093617	−2.13072	0.0414
C(8)	−0.90256	3.016545	−0.2992	0.7668
C(9)	1.456644	2.853114	0.510545	0.6134
C(10)	−0.36518	2.840445	−0.12857	0.8986
C(11)	0.233319	2.842364	0.082086	0.9351
C(12)	−2.08607	2.893439	−0.72097	0.4765
C(13)	−0.19238	3.054077	−0.06299	0.9502
C(14)	0.193548	0.323102	0.59903	0.5536
R-squared	0.771186	Mean dependent var		0.080371
Adjusted R-squared	0.672033	S.D. dependent var		1.011665

Vector Error Correction Estimates
Sample (adjusted): 1990 2013
Standard errors in ( ) & t-statistics in [ ]

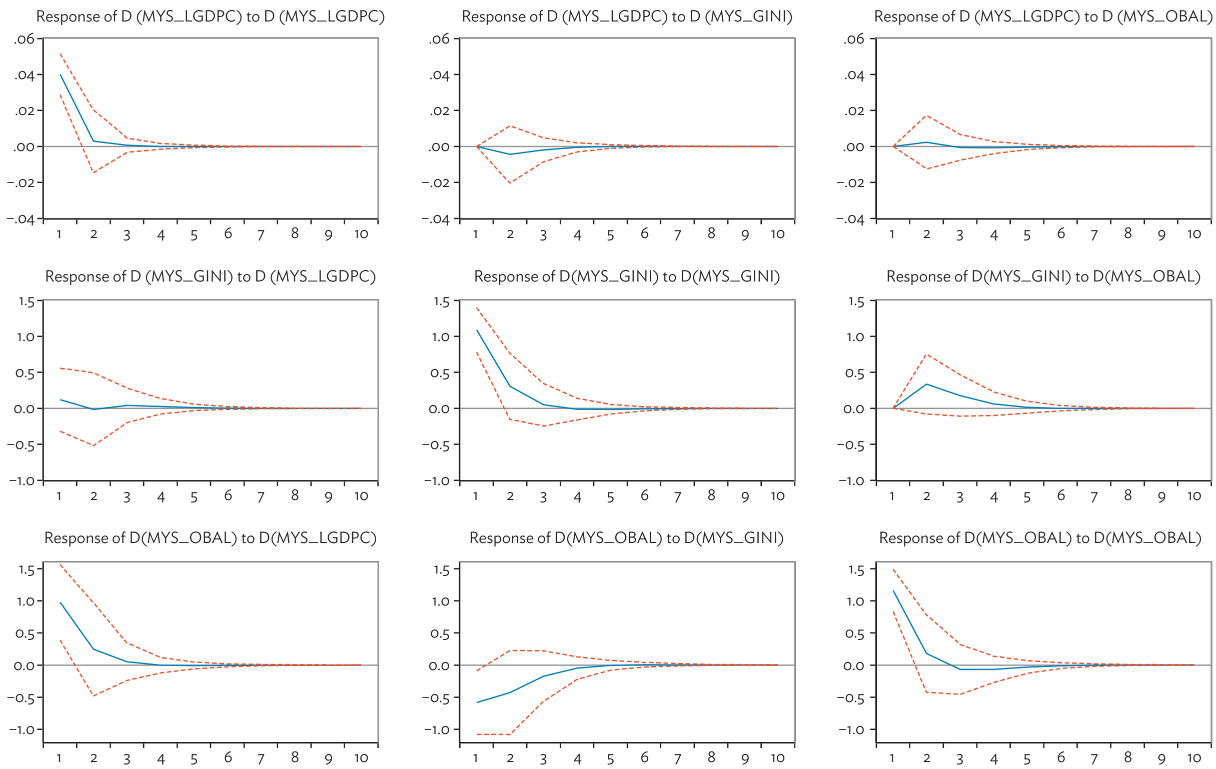
Cointegrating Eq:	CointEq1
KOR_LGDPC(−1)	
KOR_GINI(−1)	−0.11592
	(−0.06174)
	[−1.87760]
KOR_OBAL(−1)	−0.149132
	(−0.02341)
	[−6.37018]
C	−5.943469

Dependent Variable: D(KOR_LGDPC) Sample (adjusted): 1990 2013 D(KOR_LGDPC) = C(1)*(KOR_LGDPC(−1)−0.115920297531*KOR_GINI(−1)− 0.149132113289* KOR_OBAL(−1) − 5.94346919344) + C(2) *D(KOR_LGDPC(−1)) + C(3)*D(KOR_LGDPC(−2)) + C(4) *D(KOR_LGDPC(−3)) + C(5)*D(KOR_GINI(−1)) + C(6)*D(KOR_GINI(−2)) + C(7)*D(KOR_GINI(−3)) + C(8)*D(KOR_OBAL(−1)) + C(9) *D(KOR_OBAL(−2)) + C(10)*D(KOR_OBAL(−3)) + C(11)				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.1052**	**0.04299**	**−2.44695**	**0.0294**
C(2)	−0.75057	0.258738	−2.90089	0.0124
C(3)	−0.49323	0.340967	−1.44655	0.1717
C(4)	−0.25983	0.325733	−0.79768	0.4394
C(5)	−0.03315	0.012198	−2.71745	0.0176
C(6)	−0.03133	0.016749	−1.87023	0.0841
C(7)	−0.03542	0.013375	−2.64811	0.0201
C(8)	−0.01072	0.004983	−2.15162	0.0508
C(9)	−0.01306	0.004599	−2.8386	0.014
C(10)	−0.00586	0.005203	−1.1254	0.2808
C(11)	0.114386	0.035923	3.184249	0.0072
R-squared	0.683326	Mean dependent var		0.044773
Adjusted R-squared	0.439731	S.D. dependent var		0.033255



Sample (adjusted): 1988 2012

Response to Cholesky One S.D. Innovations ± 2 S.E.



New Zealand

Vector Error Correction Estimates
Sample (adjusted): 1981 2013
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
NZL_LGDPC(−1)	1
NZL_GINI(−1)	−0.04145
	(−0.00329)
	[−12.6043]
C	−8.757145

Dependent Variable: D(NZL_LGDPC)
Sample (adjusted): 1981 2013
D(NZL_LGDPC) = C(1)*(NZL_LGDPC(−1) − 0.0414483853635*NZL_GINI(−1) − 8.75714512423) + C(2)*D(NZL_LGDPC(−1)) + C(3) *D(NZL_LGDPC(−2)) + C(4)*D(NZL_LGDPC(−3)) + C(5)*D(NZL_GINI(−1)) + C(6)*D(NZL_GINI(−2)) + C(7)*D(NZL_GINI(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.29648**	**0.059766**	**−4.96062**	**0**
C(2)	−0.4033	0.158477	−2.54481	0.0175
C(3)	−0.41771	0.195203	−2.1399	0.0423
C(4)	−0.49471	0.180573	−2.73968	0.0112
C(5)	−0.02884	0.010556	−2.73187	0.0114
C(6)	−0.03886	0.012738	−3.05102	0.0053
C(7)	−0.03562	0.016796	−2.12082	0.044
C(8)	0.053923	0.009062	5.950127	0
R-squared	0.65165	Mean dependent var		0.014043
Adjusted R-squared	0.554112	S.D. dependent var		0.022621

Vector Error Correction Estimates
Sample (adjusted): 1981 2013
Standard errors in ( ) & t-statistics in [ ]

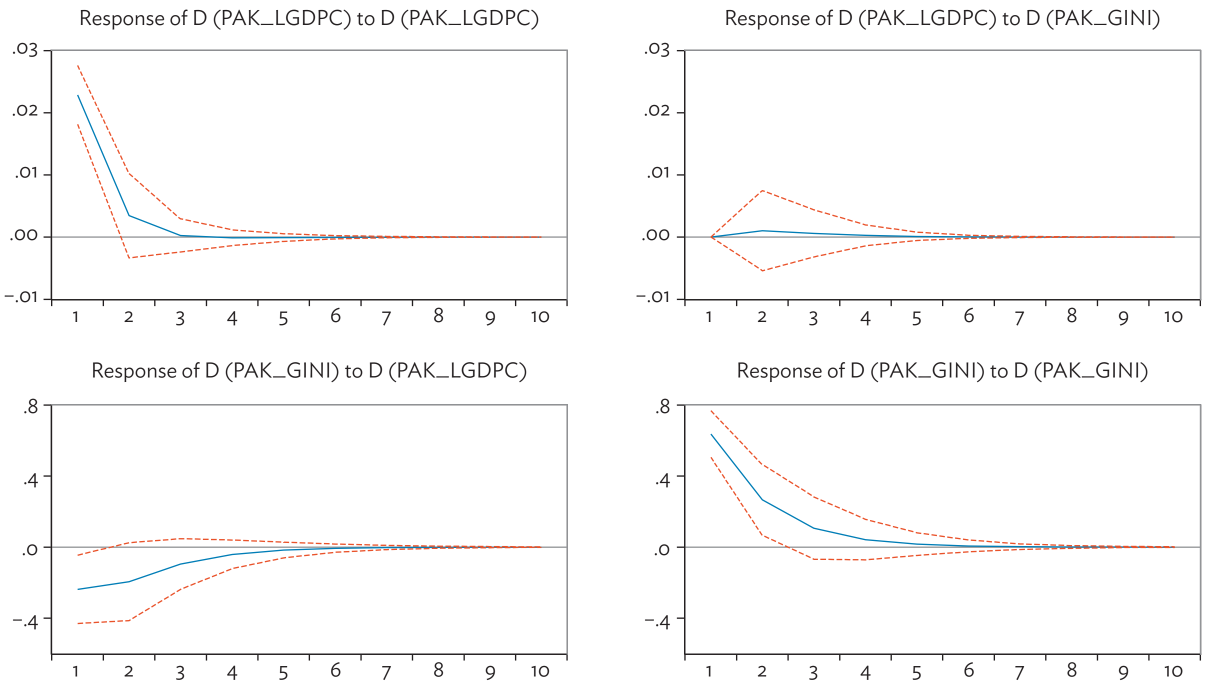
Cointegrating Eq:	CointEq1
NZL_GINI(−1)	1
NZL_LGDPC(−1)	−24.1264 (−1.78953) [−13.4820]
C	211.2783

Dependent Variable: D(NZL_GINI)
Sample (adjusted): 1981 2013
D(NZL_GINI) = C(1)*(NZL_GINI(−1) − 24.1263921678*NZL_LGDPC(−1) +211.278317537) + C(2)*D(NZL_GINI(−1)) + C(3)*D(NZL_GINI(−2)) + C(4)*D(NZL_GINI(−3)) + C(5)*D(NZL_LGDPC(−1)) + C(6) *D(NZL_LGDPC(−2)) + C(7)*D(NZL_LGDPC(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.09733**	**0.045074**	**−2.15926**	**0.0406**
C(2)	0.727612	0.192077	3.788124	0.0009
C(3)	0.855742	0.231771	3.692194	0.0011
C(4)	−0.16839	0.305613	−0.55099	0.5865
C(5)	9.366561	2.883547	3.248277	0.0033
C(6)	3.722431	3.551781	1.048046	0.3046
C(7)	−0.94049	3.285588	−0.28625	0.777
C(8)	−0.2506	0.164894	−1.51976	0.1411
R-squared	0.683945	Mean dependent var		0.218363
Adjusted R-squared	0.59545	S.D. dependent var		0.43211

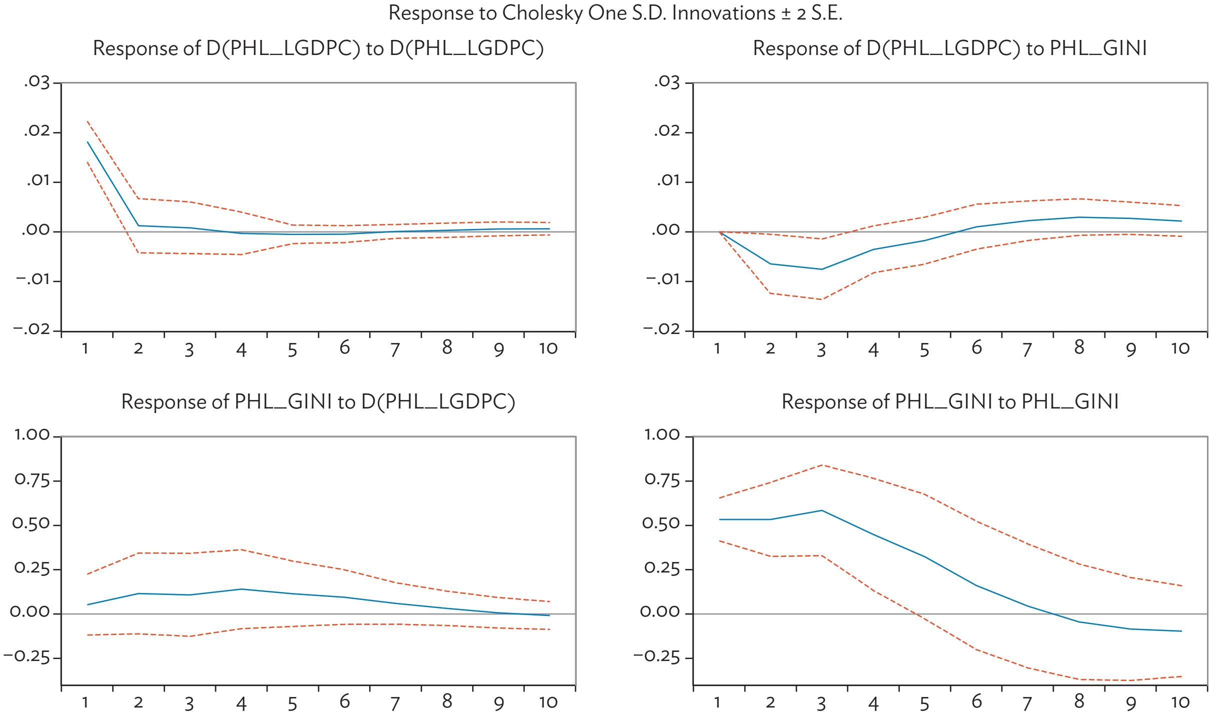
Pakistan
Sample (adjusted): 1965 2011

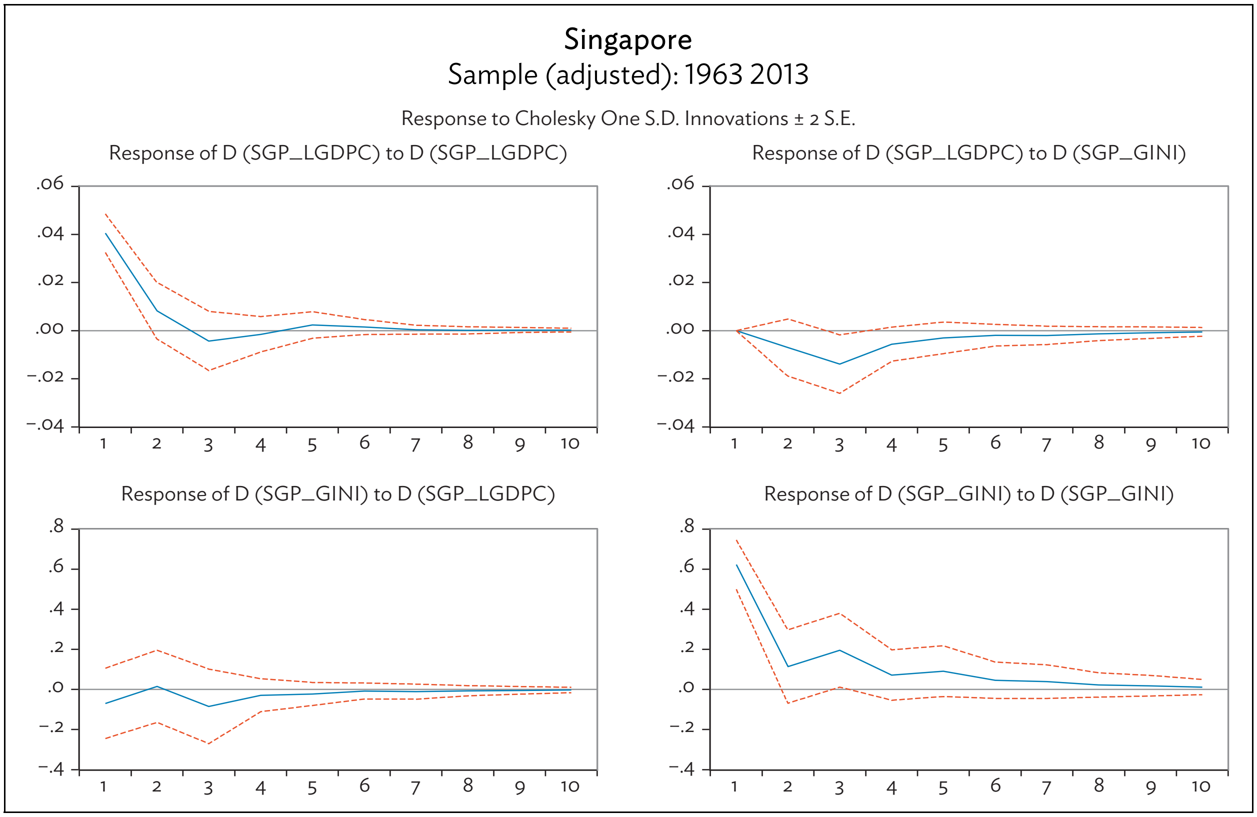
Response to Cholesky One S.D. Innovations ± 2 S.E.

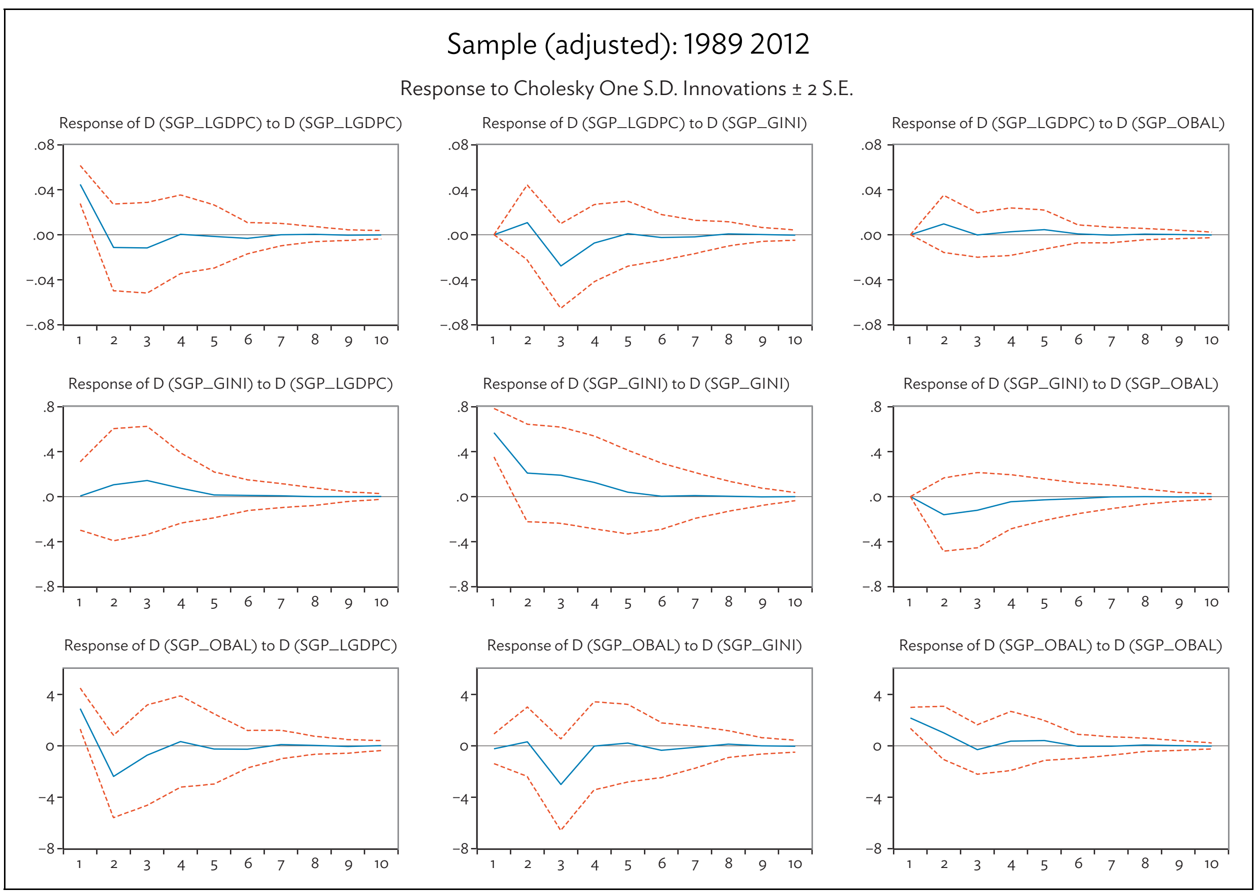


Philippines
Sample (adjusted): 1968 2012

Response to Cholesky One S.D. Innovations ± 2 S.E.



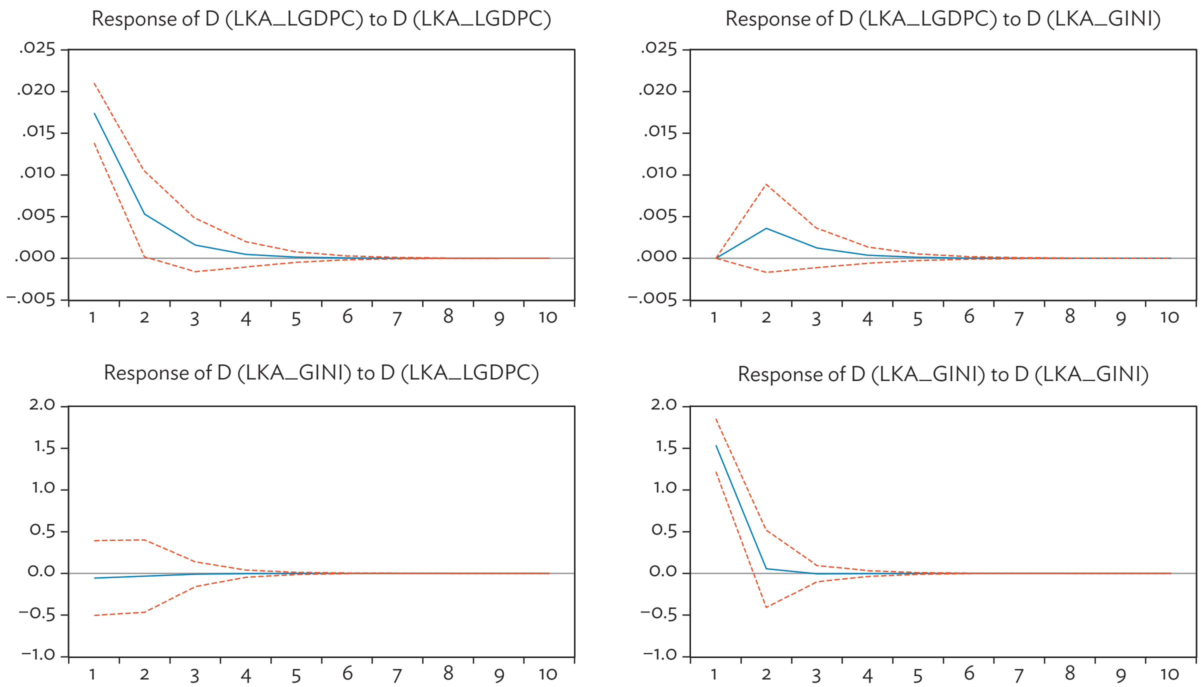

Singapore
Sample (adjusted): 1963 2013
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of D (SGP_LGDPC) to D (SGP_LGDPC)
Response of D (SGP_LGDPC) to D (SGP_GINI)
Response of D (SGP_GINI) to D (SGP_LGDPC)
Response of D (SGP_GINI) to D (SGP_GINI)


Sample (adjusted): 1989 2012
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of D (SGP_LGDPC) to D (SGP_LGDPC)
Response of D (SGP_LGDPC) to D (SGP_GINI)
Response of D (SGP_LGDPC) to D (SGP_OBAL)
Response of D (SGP_GINI) to D (SGP_LGDPC)
Response of D (SGP_GINI) to D (SGP_GINI)
Response of D (SGP_GINI) to D (SGP_OBAL)
Response of D (SGP_OBAL) to D (SGP_LGDPC)
Response of D (SGP_OBAL) to D (SGP_GINI)
Response of D (SGP_OBAL) to D (SGP_OBAL)

Sri Lanka

Sample (adjusted): 1962 2008

Response to Cholesky One S.D. Innovations ± 2 S.E.



Thailand

Vector Error Correction Estimates Sample (adjusted): 1990 2011 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
THA_GINI(−1)	1
THA_LGDPC(−1)	5.918921 (−0.6566) [9.01449]
C	−87.8575

Dependent Variable: D(THA_GINI)
Sample (adjusted): 1990 2011
D(THA_GINI) = C(1)*(THA_GINI(−1) + 5.91892114865*THA_LGDPC(−1) −87.8575008495) + C(2)*D(THA_GINI(−1)) + C(3)*D(THA_GINI(−2)) +C(4)*D(THA_GINI(−3)) + C(5)*D(THA_LGDPC(−1)) + C(6) *D(THA_LGDPC(−2)) + C(7)*D(THA_LGDPC(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.77527**	**0.174636**	**−4.43932**	**0.0006**
C(2)	0.367861	0.145219	2.533151	0.0239
C(3)	0.778477	0.177021	4.397646	0.0006
C(4)	−0.16998	0.213931	−0.79454	0.4401
C(5)	0.399533	2.608915	0.153141	0.8805
C(6)	5.837991	2.87545	2.030288	0.0618
C(7)	6.635775	3.208654	2.068087	0.0576
C(8)	−0.55575	0.177214	−3.13604	0.0073
R-squared	0.773172	Mean dependent var		−0.28672
Adjusted R-squared	0.659758	S.D. dependent var		0.774011

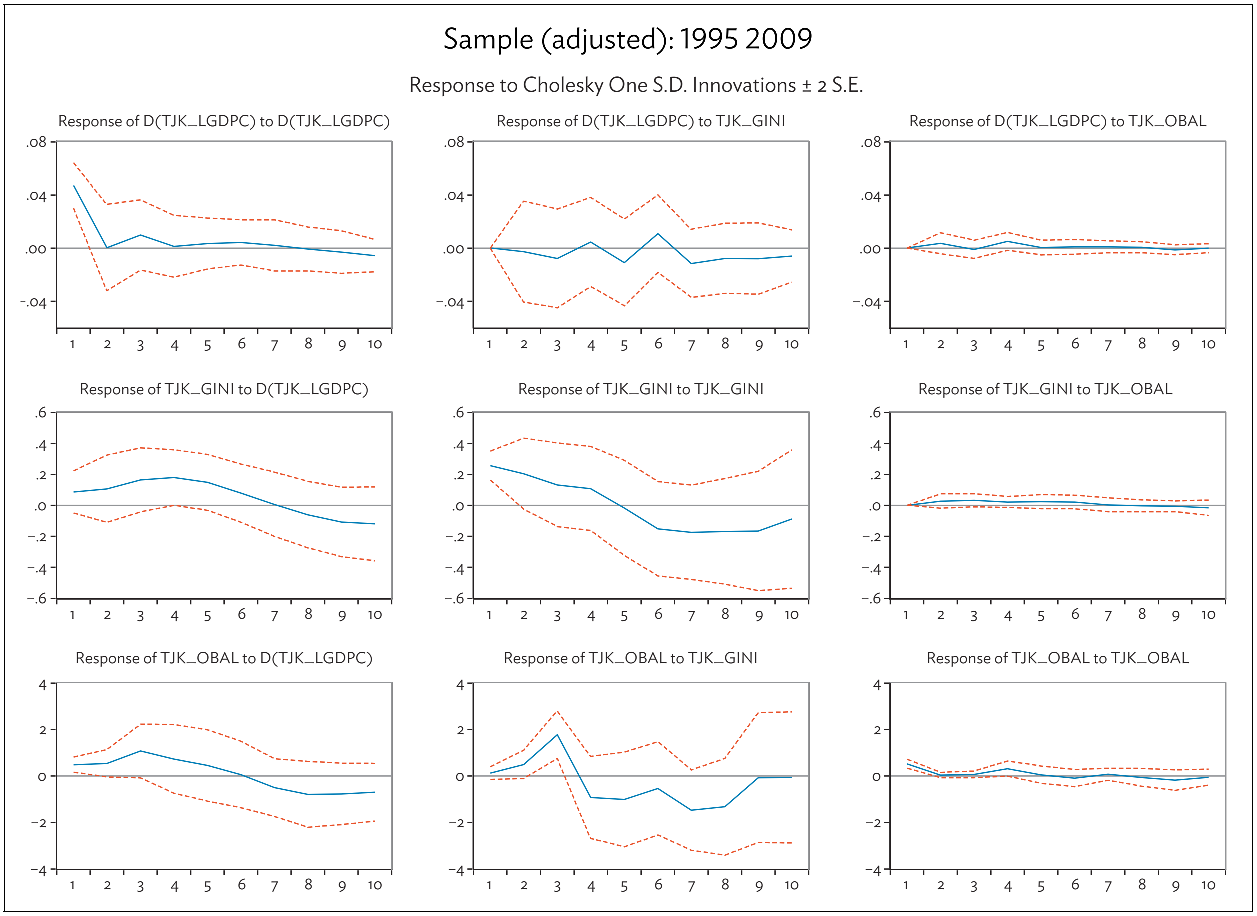
Tajikistan

Vector Error Correction Estimates
Sample (adjusted): 1990 2009
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
TJK_LGDPC(−1)	
TJK_GINI(−1)	−0.1035
	−0.1159
	[−0.89299]
C	−2.439536

Dependent Variable: D(TJK_LGDPC)
Sample (adjusted): 1990 2010
D(TJK_LGDPC) = C(1)*(TJK_LGDPC(−1) − 0.10349712539*TJK_GINI(−1) −2.43953643194) + C(2)*D(TJK_LGDPC(−1)) + C(3)*D(TJK_LGDPC(−2)) + C(4)*D(TJK_LGDPC(−3)) + C(5)*D(TJK_GINI(−1)) + C(6) *D(TJK_GINI(−2)) + C(7)*D(TJK_GINI(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.09714**	**0.035647**	**−2.72499**	**0.0173**
C(2)	0.510744	0.220609	2.315154	0.0376
C(3)	0.41574	0.175208	2.372839	0.0338
C(4)	−0.20467	0.179762	−1.13855	0.2754
C(5)	−0.03809	0.043417	−0.87741	0.3962
C(6)	−0.09624	0.036959	−2.60405	0.0218
C(7)	0.115525	0.044603	2.590052	0.0224
C(8)	−0.01064	0.017471	−0.60884	0.5531
R-squared	0.873101	Mean dependent var		−0.02743
Adjusted R-squared	0.804771	S.D. dependent var		0.129056



Source: Author's calculations.

APPENDIX A.3: REGRESSION RESULTS FOR OECD COUNTRIES

Austria

Vector Error Correction Estimates
Sample (adjusted): 1967 2013
Standard errors in ( ) & t-statistics in [ ]

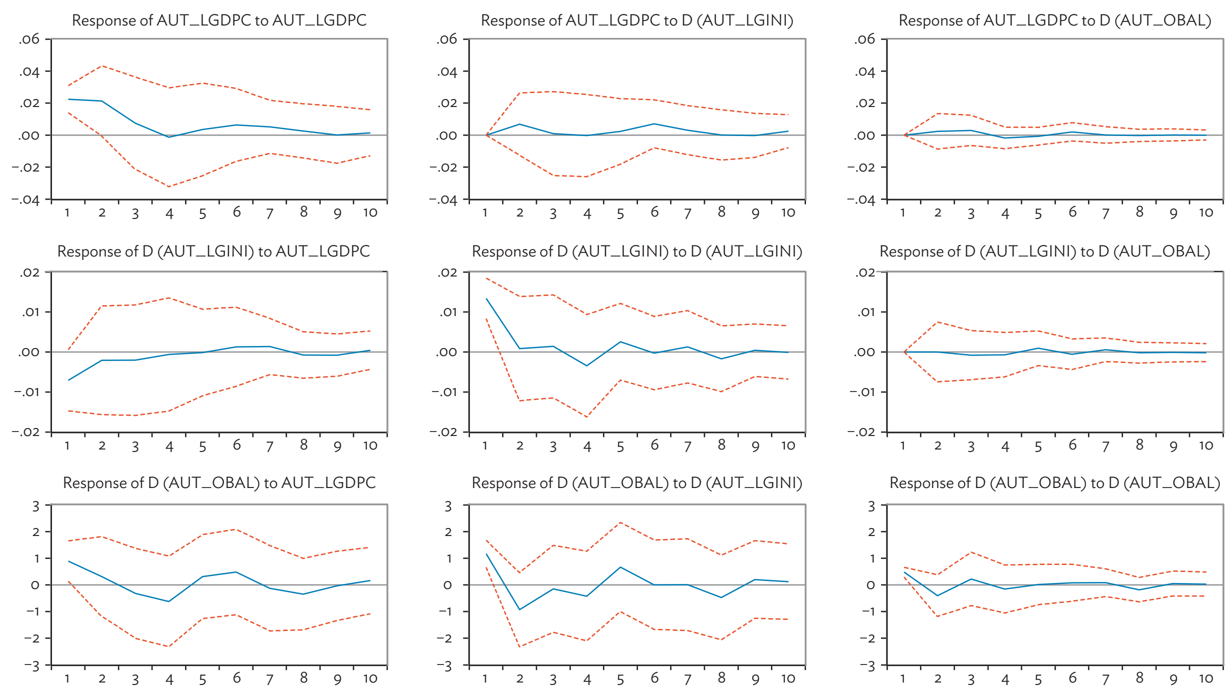
Cointegrating Eq:	CointEq1
AUT_LGDPC(-1)	1
AUT_LGINI(-1)	-1.015909
	(-1.67544)
	[-0.60635]
C	-6.962372

Dependent Variable: D(AUT_LGDPC)
Sample (adjusted): 1967 2013
D(AUT_LGDPC)=C(1)*(AUT_LGDPC(-1)-1.01590865184*AUT_LGINI(-1)-6.96237198739)+C(2)*D (AUT_LGDPC(-1))+C(3)*D(AUT_LGDPC(-2))+C(4)*D(AUT_LGINI(-1))+C(5)*D(AUT_LGINI(-

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**-0.03577**	**0.011004**	**-3.250758**	**0.0029**
C(2)	0.255553	0.171362	1.491304	0.1467
C(3)	-0.148472	0.167314	-0.887383	0.3822
C(4)	-0.007552	0.140197	-0.053864	0.9574
C(5)	-0.120235	0.140059	-0.85846	0.3977
C(6)	0.020592	0.005543	3.714708	0.0009
R-squared	0.464174	Mean dependent var		0.023211
Adjusted R-squared	0.37179	S.D. dependent var		0.020827

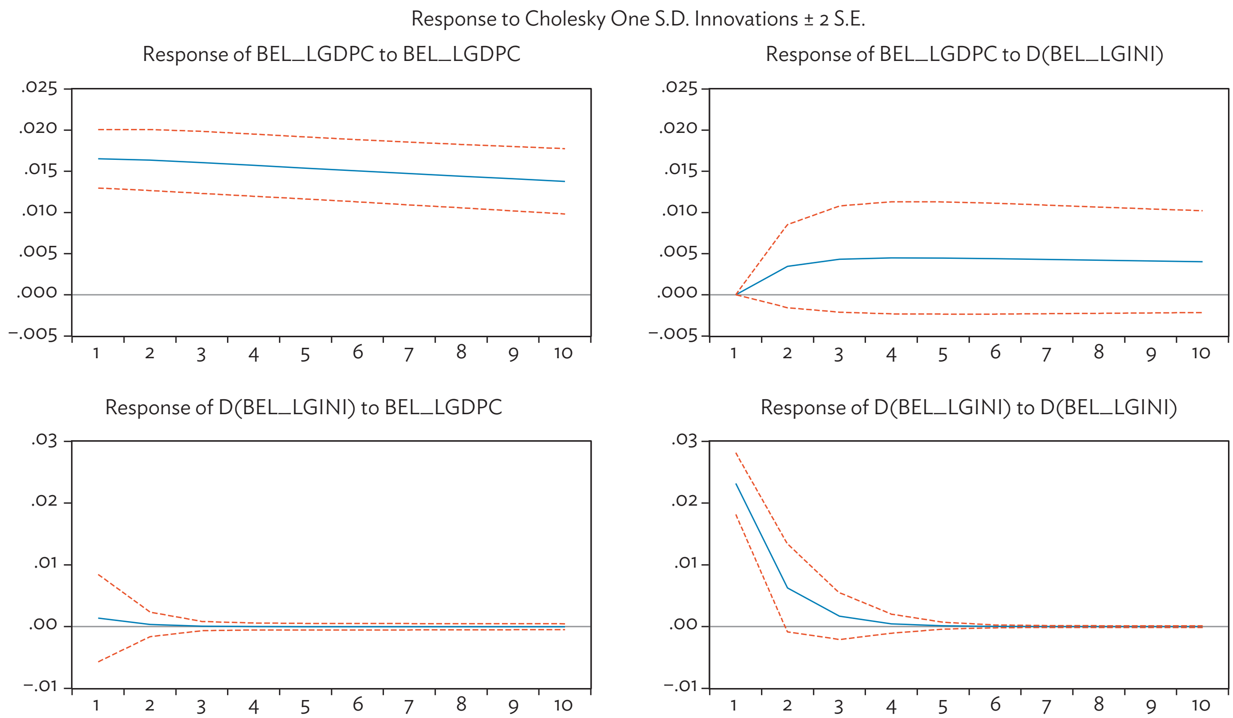
Sample (adjusted): 1999 2012

Response to Cholesky One S.D. Innovations ± 2 S.E.



Belgium

Sample (adjusted): 1965 2012



Sample (adjusted): 1997 2012

Vector Error Correction Estimates Sample (adjusted): 1997 2012 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
BEL_LGINI(−1)	1
BEL_LGDPC(−1)	0.192761
	(−0.06452)
	[2.98778]
BEL_OBAL(−1)	−0.016194
	(−0.00315)
	[−5.14081]
C	−5.301424

Dependent Variable: D(BEL_LGINI)
Sample (adjusted): 1997 2012
D(BEL_LGINI) = C(1)*(BEL_LGINI(−1) + 0.192760964741*BEL_LGDPC(−1) − 0.0161938925914*BEL_OBAL(−1) − 5.3014238162) + C(2) *D(BEL_LGINI(−1)) + C(3)*D(BEL_LGDPC(−1)) + C(4)*D(BEL_OBAL(−1)) + C(5)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.724963**	**0.237994**	**−3.046139**	**0.0111**
C(2)	0.572964	0.226666	2.527783	0.0281
C(3)	0.047034	0.349198	0.134692	0.8953
C(4)	−0.004987	0.003854	−1.294167	0.2221
R-squared	0.541131	Mean dependent var		−0.00148
Adjusted R-squared	0.374269	S.D. dependent var		0.02037

Canada
Sample (adjusted): 1964 2010

Vector Error Correction Estimates
Sample (adjusted): 1964 2010
Standard errors in ( ) & t-statistics in [ ]

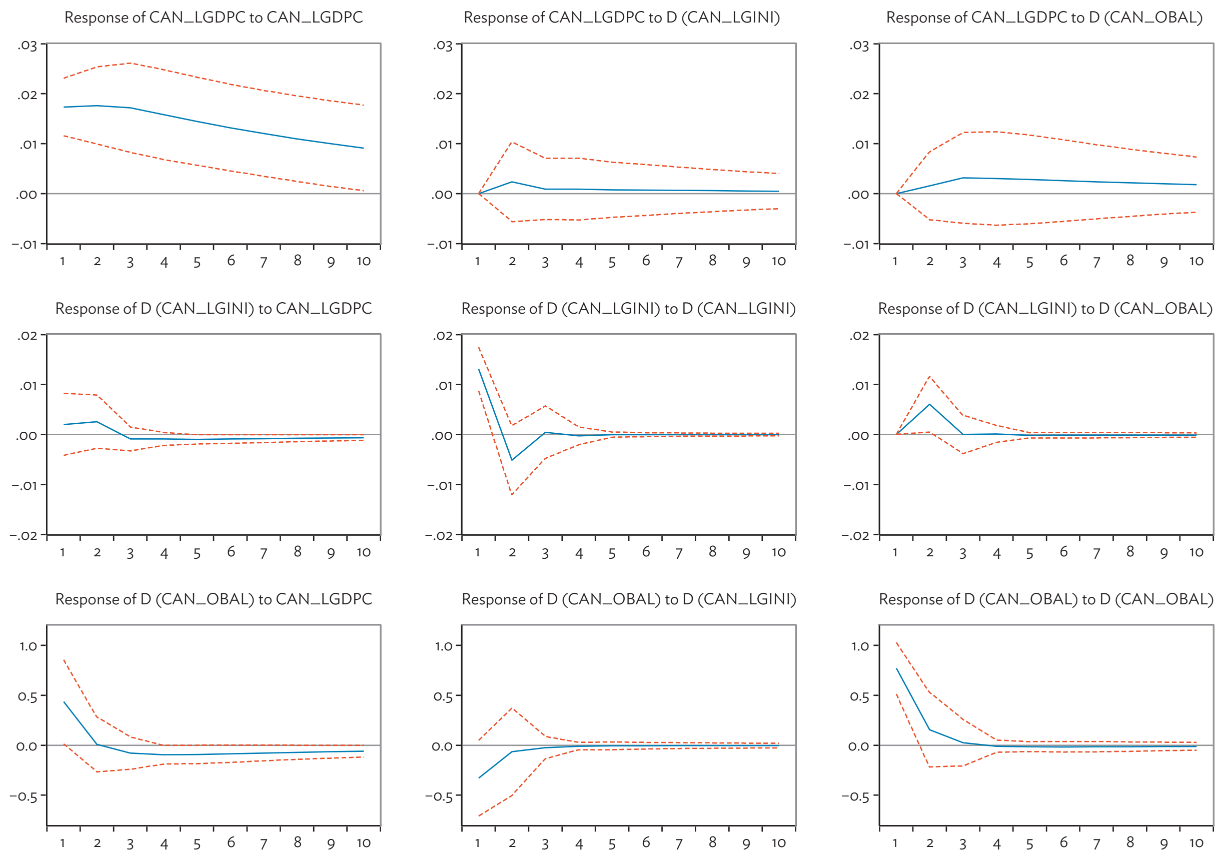
Cointegrating Eq:	CointEq1
CAN_LGINI(−1)	1
CAN_LGDPC(−1)	−0.30228
	−0.03569)
	[−8.46946]
C	−0.28323

Dependent Variable: D(CAN_LGINI)
Sample (adjusted): 1964 2010
D(CAN_LGINI) = C(1)*(CAN_LGINI(−1) − 0.30228257789*CAN_LGDPC(−1)− 0.283228207197) + C(2)*D(CAN_LGINI(−1)) + C(3)*D(CAN_LGINI(−2)) + C(4)* D(CAN_LGINI(−3)) + C(5)*D(CAN_LGDPC(−1)) + C(6)*D(CAN_LGDPC(−2)) + C(7)* D(CAN_LGDPC(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.66436**	0.144689	**−4.59165**	**0**
C(2)	0.240363	0.136415	1.761993	0.0859
C(3)	0.521696	0.139021	3.752642	0.0006
C(4)	0.246574	0.156267	1.577904	0.1227
C(5)	0.025937	0.295836	0.087673	0.9306
C(6)	0.308367	0.323897	0.952054	0.3469
C(7)	−0.03079	0.290546	−0.10597	0.9162
C(8)	−0.00453	0.009805	−0.4615	0.647
R-squared	0.39351	Mean dependent var		0.005805
Adjusted R-squared	0.284652	S.D. dependent var		0.044354

Sample (adjusted): 1993 2010

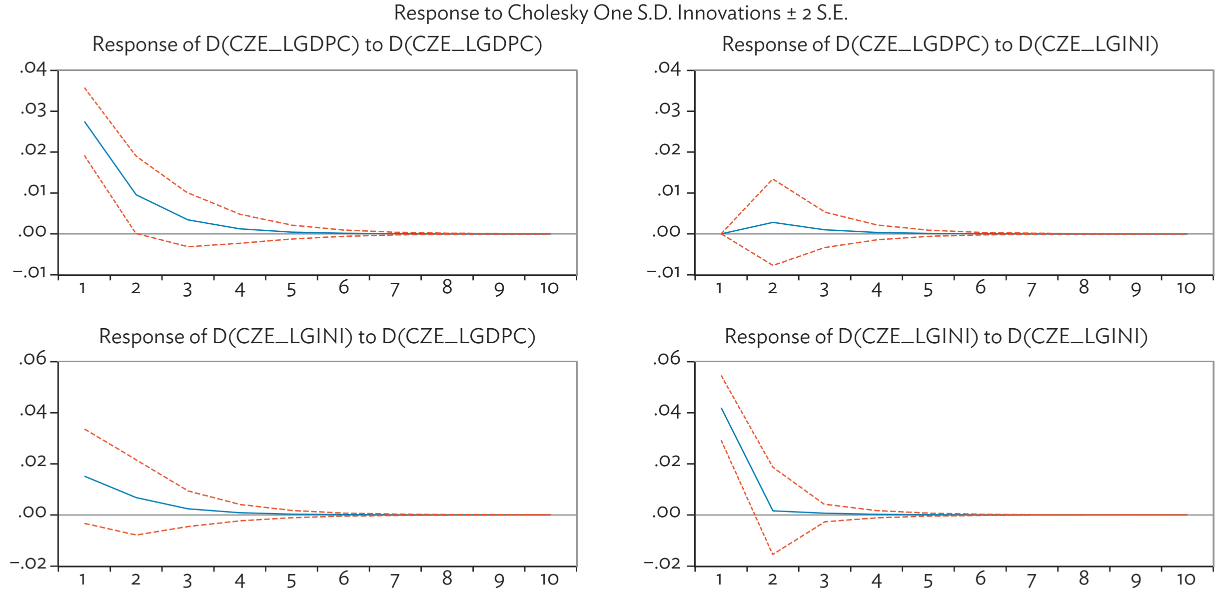
Response to Cholesky One S.D. Innovations ± 2 S.E.

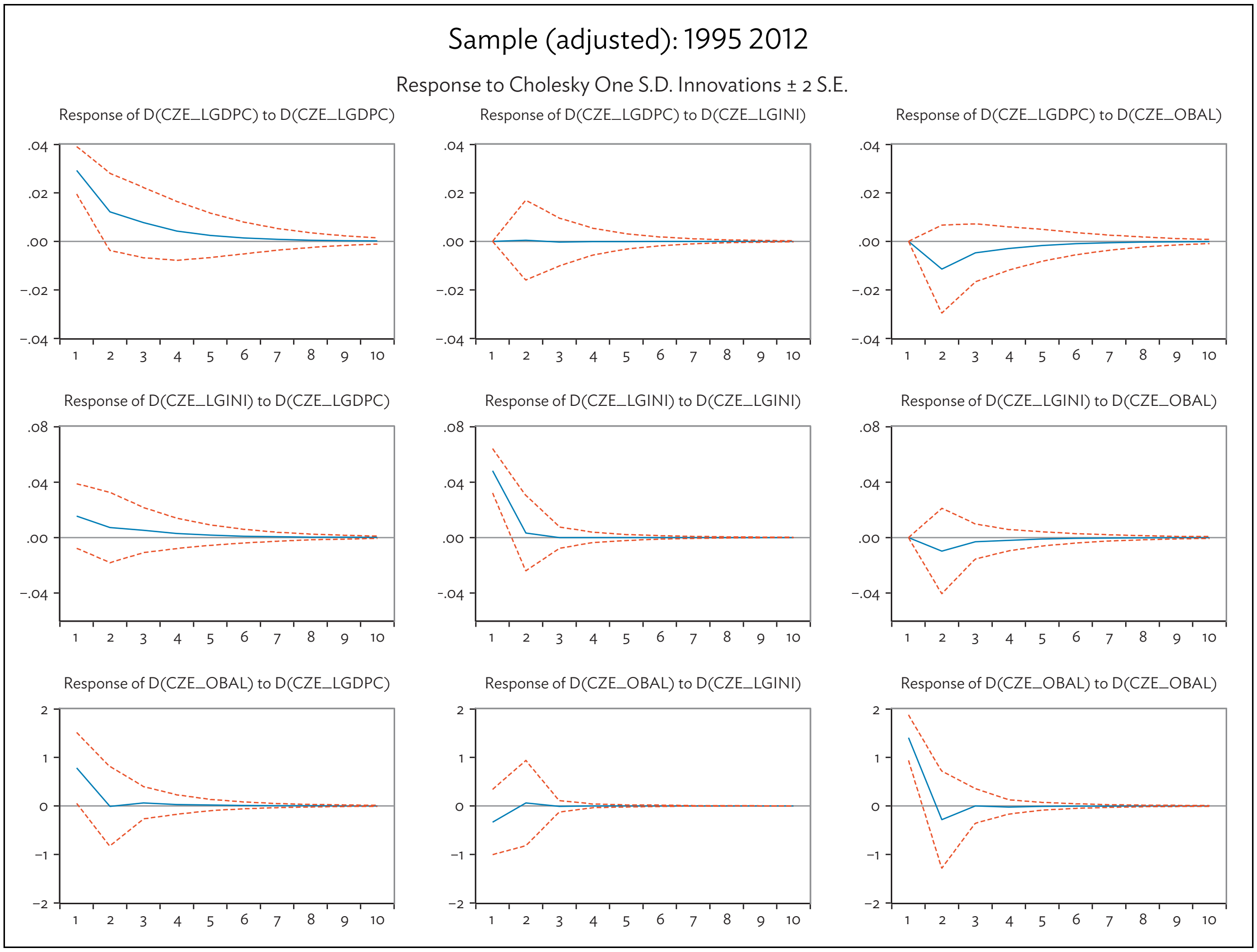


Czech Republic

Sample (adjusted): 1992 2013

Response to Cholesky One S.D. Innovations ± 2 S.E.





Denmark

Vector Error Correction Estimates
Sample (adjusted): 1966 2013
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
DNK_LGDPC(−1)	1
DNK_LGINI(−1)	5.699045
	(−1.23596)
	[4.61105]
C	−28.50959

Dependent Variable: D(DNK_LGDPC)
Sample (adjusted): 1966 2013
D(DNK_LGDPC) = C(1)*(DNK_LGDPC(−1) + 5.699045235*DNK_LGINI(−1) − 28.5095947126) + C(2)*D(DNK_LGDPC(−1)) + C(3)*D(DNK_LGDPC(−2)) + C(4)*D(DNK_LGINI(−1)) + C(5)*D(DNK_LGINI(−2)) + C(6)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.028608**	**0.008482**	**−3.372901**	**0.0016**
C(2)	0.11621	0.14692	0.790971	0.4334
C(3)	−0.232604	0.144738	−1.607073	0.1155
C(4)	−0.016049	0.08817	−0.182027	0.8564
C(5)	0.045547	0.097405	0.467598	0.6425
C(6)	0.018808	0.00439	4.28413	0.0001
R-squared	0.321432	Mean dependent var		0.016464
Adjusted R-squared	0.24065	S.D. dependent var		0.021695

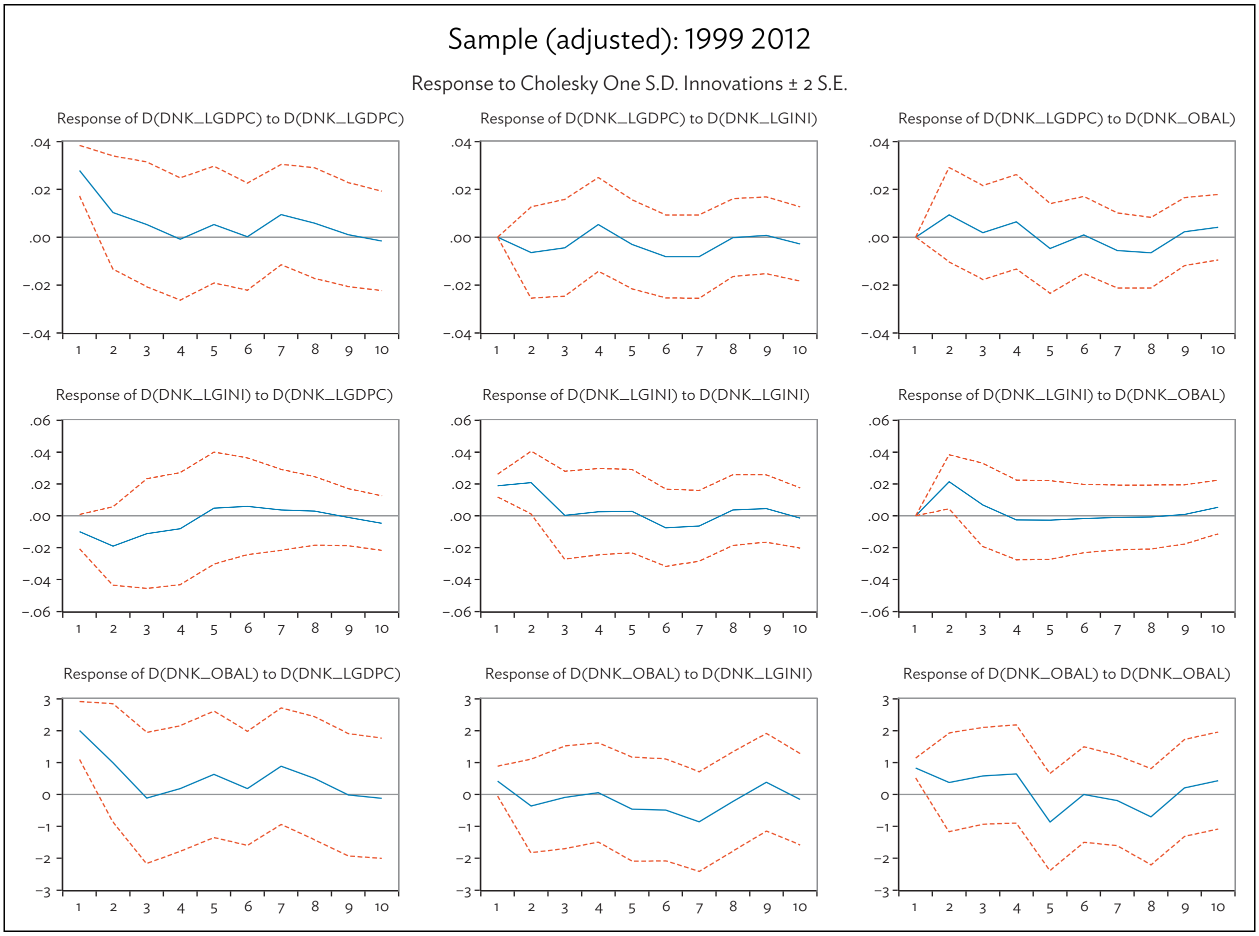
Vector Error Correction Estimates
Sample (adjusted): 1966 2013
Standard errors in ( ) & t-statistics in [ ]

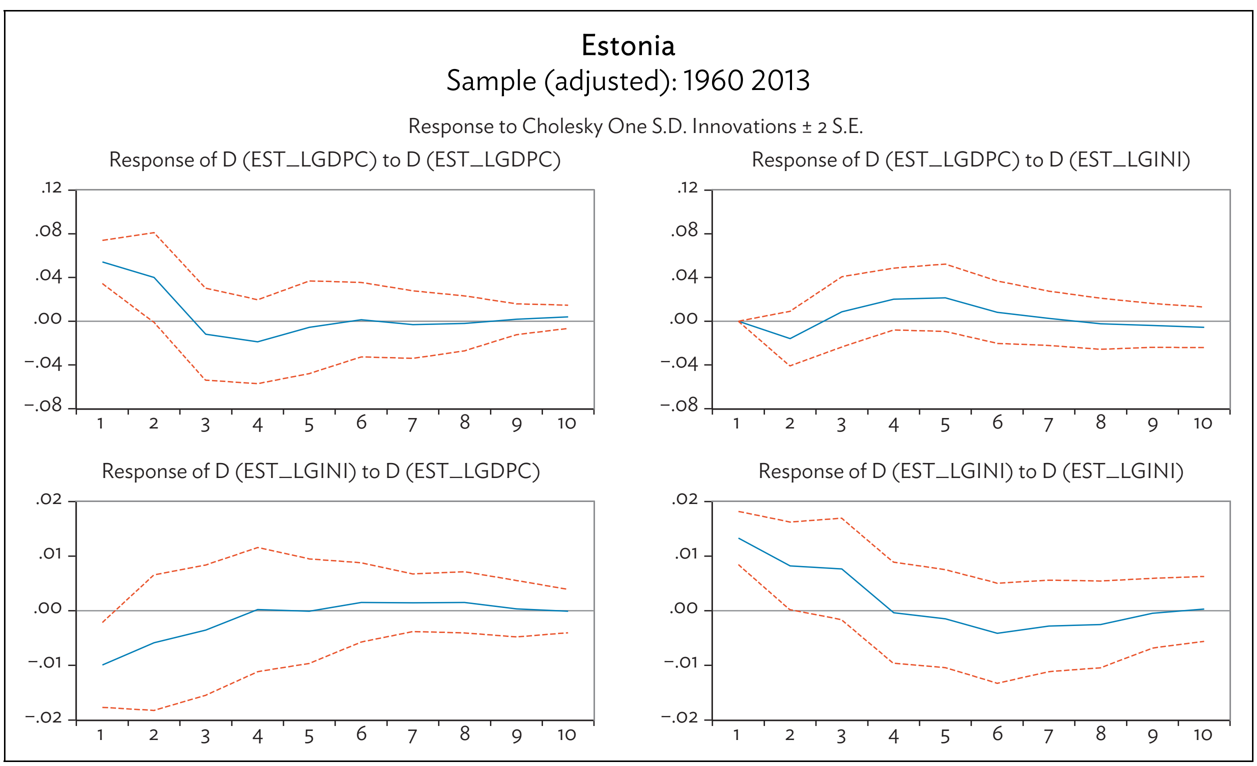
Cointegrating Eq:	CointEq1
DNK_LGINI(−1)	1
DNK_LGDPC(−1)	0.175468
	−0.05353
	[3.27776]
C	−5.002521

Dependent Variable: D(DNK_LGINI)
Sample (adjusted): 1966 2013

D(DNK_LGINI) = C(1)*(DNK_LGINI(−1) + 0.175467987841*DNK_LGDPC(−1) − 5.00252121839) + C(2)*D(DNK_LGINI(−1)) + C(3)*D(DNK_LGINI(−1) − 5.00252121839) + C(2)*D(DNK_LGINI(−1)) + C(3)*D(DNK_LGINI(−2)) + C(4)*D(DNK_LGDPC(−1)) + C(5)*D(DNK_LGDPC(−2)) + C(6)

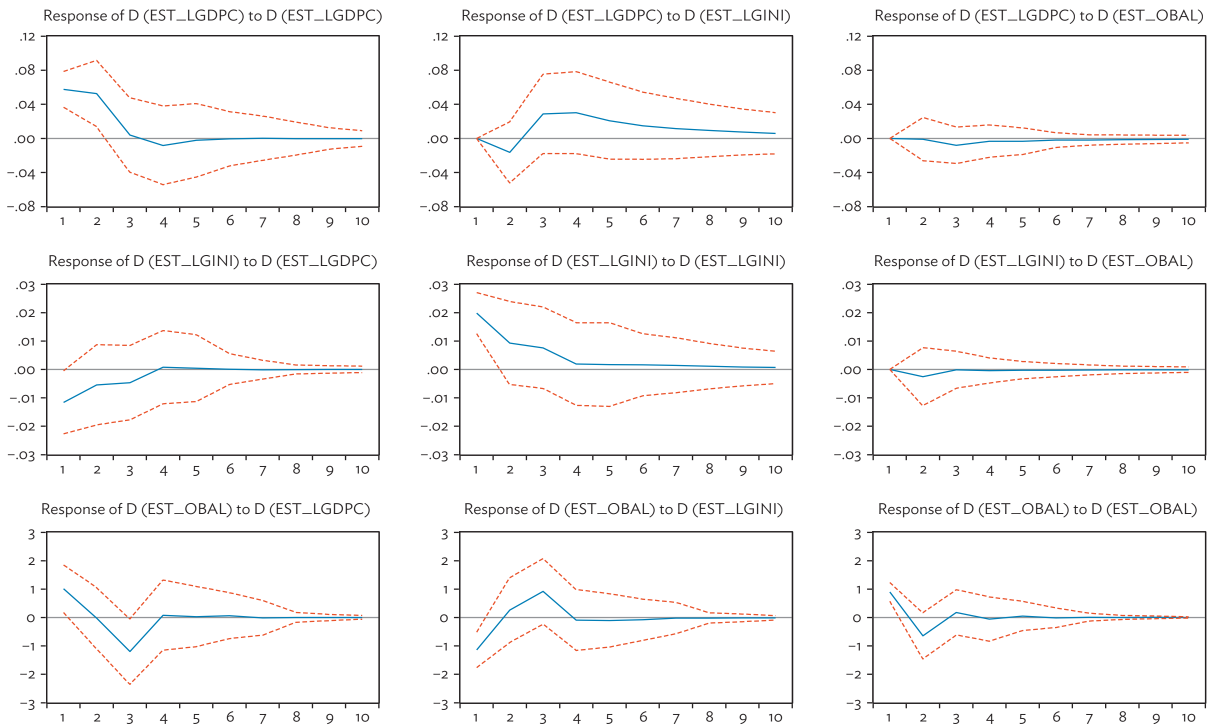
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.238928**	**0.077788**	**−3.071528**	**0.0037**
C(2)	0.615841	0.14189	4.340256	0.0001
C(3)	0.125633	0.156753	0.801473	0.4274
C(4)	−0.21094	0.236436	−0.892164	0.3774
C(5)	−0.111537	0.232923	−0.478857	0.6345
C(6)	0.006531	0.007065	0.924415	0.3606
R-squared	0.428492	Mean dependent var		0.003266
Adjusted R-squared	0.360456	S.D. dependent var		0.038044


Sample (adjusted): 1999 2012
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of D(DNK_LGDPC) to D(DNK_LGDPC)
Response of D(DNK_LGDPC) to D(DNK_LGINI)
Response of D(DNK_LGDPC) to D(DNK_OBAL)
Response of D(DNK_LGINI) to D(DNK_LGDPC)
Response of D(DNK_LGINI) to D(DNK_LGINI)
Response of D(DNK_LGINI) to D(DNK_OBAL)
Response of D(DNK_OBAL) to D(DNK_LGDPC)
Response of D(DNK_OBAL) to D(DNK_LGINI)
Response of D(DNK_OBAL) to D(DNK_OBAL)


Estonia
Sample (adjusted): 1960 2013
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of D (EST_LGDPC) to D (EST_LGDPC)
Response of D (EST_LGDPC) to D (EST_LGINI)
Response of D (EST_LGINI) to D (EST_LGDPC)
Response of D (EST_LGINI) to D (EST_LGINI)

Sample (adjusted): 1998 2012

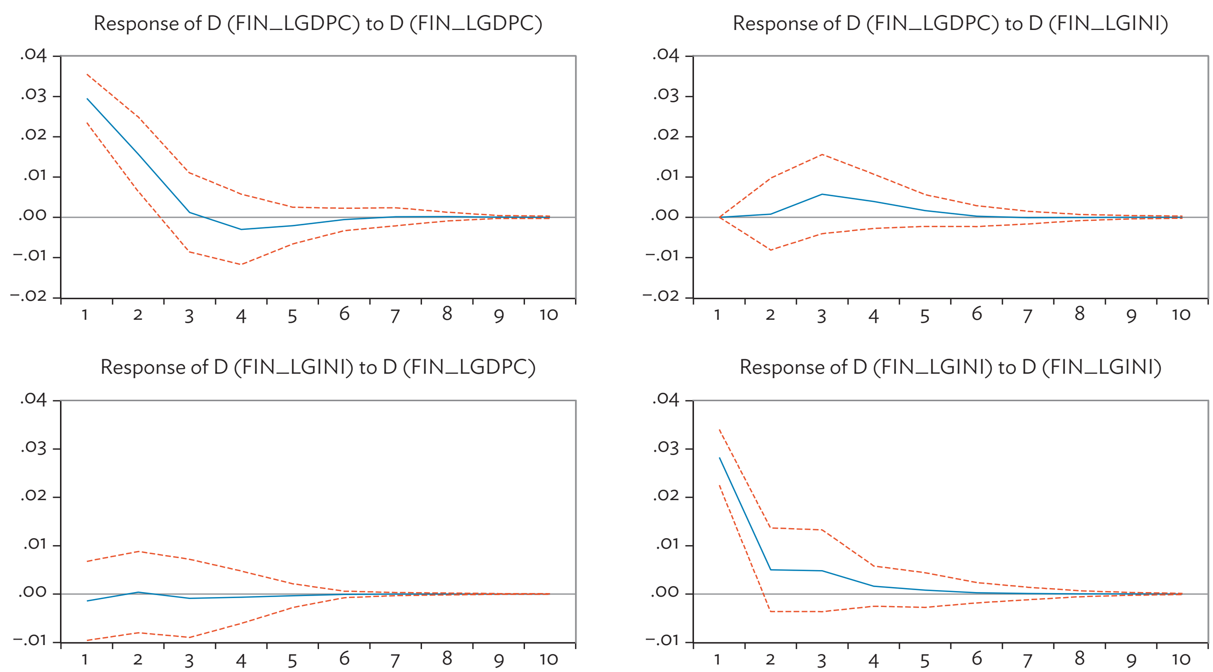
Response to Cholesky One S.D. Innovations ± 2 S.E.



Finland

Sample (adjusted): 1966 2013

Response to Cholesky One S.D. Innovations ± 2 S.E.



Vector Error Correction Estimates Sample (adjusted): 1998 2012 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
FIN_LGINI(−1)	1
FIN_LGDPC(−1)	−0.305218 (−0.08952) [−3.40946]
FIN_OBAL(−1)	0.015594 (−0.0038) [4.10418]
C	−0.060055

Dependent Variable: D(FIN_LGINI)
Sample (adjusted): 1998 2013

D(FIN_LGINI) = C(1)*(FIN_LGINI(−1) − 0.305218275923*FIN_LGDPC(−1) + 0.0155942666705*FIN_OBAL(−1) − 0.0600553314789) + C(2) *D(FIN_LGINI(−1)) + C(3)*D(FIN_LGINI(−2)) + C(4)*D(FIN_LGDPC(−1)) + C(5)*D(FIN_LGDPC(−2)) + C(6)*D(FIN_OBAL(−1)) + C(7) *D(FIN_OBAL(−2)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.265431**	**0.08379**	**−3.167828**	**0.0132**
C(2)	0.274463	0.283822	0.967026	0.3619
C(3)	0.195053	0.299242	0.651825	0.5328
C(4)	0.537921	0.125939	4.2713	0.0027
C(5)	0.429138	0.212228	2.022065	0.0778
C(6)	−0.006564	0.001763	−3.722702	0.0058
C(7)	−0.004018	0.002723	−1.47541	0.1783
C(8)	−0.017279	0.006054	−2.854322	0.0213
R-squared	0.849501	Mean dependent var		0.007318
Adjusted R-squared	0.717813	S.D. dependent var		0.015034

France

Vector Error Correction Estimates Sample (adjusted): 1966 2012 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
FRA_LGDPC(−1)	1
FRA_LGINI(−1)	2.416335 (−0.54312) [4.44900]
C	−18.39334

Dependent Variable: D(FRA_LGDPC)
Sample (adjusted): 1966 2013
D(FRA_LGDPC) = C(1)*(FRA_LGDPC(−1) + 2.41633531274*FRA_LGINI(−1) − 18.3933449212) + C(2)*D(FRA_LGDPC(−1)) + C(3) *D(FRA_LGDPC(−2)) + C(4)*D(FRA_LGDPC(−3)) + C(5)*D(FRA_LGINI(−1)) + C(6)*D(FRA_LGINI(−2)) + C(7)*D(FRA_LGINI(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.035995**	**0.016911**	**−2.128534**	**0.0395**
C(2)	0.395368	0.149303	2.64809	0.0115
C(3)	−0.082278	0.161184	−0.510461	0.6125
C(4)	0.159098	0.153734	1.034891	0.3069
C(5)	0.032387	0.06838	0.47363	0.6383
C(6)	0.055243	0.068039	0.811942	0.4216
C(7)	0.121067	0.075663	1.600076	0.1175
C(8)	0.010522	0.004702	2.237879	0.0309
R-squared	0.407405	Mean dependent var		0.019805
Adjusted R-squared	0.303701	S.D. dependent var		0.018887

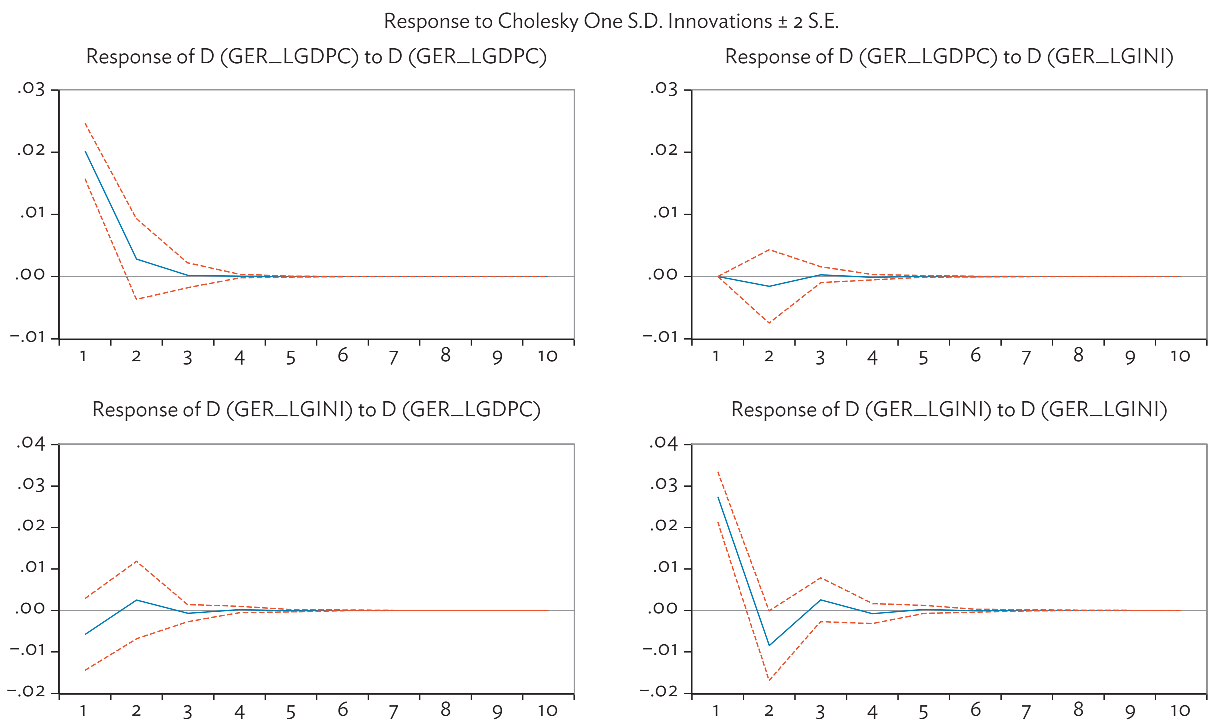
Vector Error Correction Estimates
Sample (adjusted): 1966 2012
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
FRA_LGINI(−1)	1
FRA_LGDPC(−1)	0.41385
	−(0.06616)
	[6.25550]
C	−7.612083

Dependent Variable: D(FRA_LGINI)
Sample (adjusted): 1966 2013
D(FRA_LGINI) = C(1)*(FRA_LGINI(−1) + 0.413849847216*FRA_LGDPC(−1) − 7.61208298543) + C(2)*D(FRA_LGINI(−1)) + C(3)*D(FRA_LGINI(−2)) + C(4)*D(FRA_LGINI(−3)) + C(5)*D(FRA_LGDPC(−1)) + C(6) *D(FRA_LGDPC(−2)) + C(7)*D(FRA_LGDPC(−3)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.292567**	**0.079976**	**−3.658206**	**0.0007**
C(2)	0.162718	0.128783	1.263503	0.2139
C(3)	0.374954	0.128126	2.926436	0.0057
C(4)	−0.130083	0.142511	−0.912793	0.367
C(5)	−0.240713	0.283113	−0.850236	0.4004
C(6)	−0.35406	0.304823	−1.161525	0.2525
C(7)	−0.392767	0.290498	−1.352048	0.1841
C(8)	0.022026	0.008853	2.488049	0.0172
R-squared	0.419335	Mean dependent var		0.000251
Adjusted R-squared	0.315113	S.D. dependent var		0.035855

Germany
Sample (adjusted): 1972 2012



Greece
Sample (adjusted): 1967 2012

Vector Error Correction Estimates Sample (adjusted): 1967 2012 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
GRC_LGINI(−1)	1
GRC_LGDPC(−1)	0.154322 (−0.05255) [2.93679]
C	−5.025474

Dependent Variable: D(GRC_LGINI)
Sample (adjusted): 1967 2012
D(GRC_LGINI) = C(1)*(GRC_LGINI(−1) + 0.154321579679*GRC_LGDPC(−1) − 5.02547396088) + C(2)*D(GRC_LGINI(−1)) + C(3)*D(GRC_LGINI(−2)) + C(4)*D(GRC_LGDPC(−1)) + C(5)*D(GRC_LGDPC(−2)) + C(6)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.161174**	**0.064524**	**−2.497896**	**0.0167**
C(2)	0.078874	0.149506	0.527565	0.6007
C(3)	0.22726	0.142352	1.596465	0.1183
C(4)	0.010263	0.077187	0.132958	0.8949
C(5)	0.044458	0.083265	0.533928	0.5963
C(6)	−0.001438	0.00306	−0.469921	0.641
R-squared	0.213198	Mean dependent var		−3.55E−05
Adjusted R-squared	0.114848	S.D. dependent var		0.018091

Vector Error Correction Estimates
Sample (adjusted): 1998 2012
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
GRC_LGINI(−1)	1
GRC_LGDPC(−1)	0.292765
	(−0.00682)
	[42.9014]
GRC_OBAL(−1)	0.003957
	(−0.00061)
	[6.51023]
C	−6.391287

Dependent Variable: D(GRC_LGINI)
D(GRC_LGINI) = C(1)*(GRC_LGINI(−1) + 0.292765459431*GRC_LGDPC(−1) + 0.00395653484898*GRC_OBAL(−1) − 6.39128705679) + C(2) *D(GRC_LGINI(−1)) + C(3)*D(GRC_LGINI(−2)) + C(4)*D(GRC_LGDPC(−1)) + C(5)*D(GRC_LGDPC(−2)) + C(6)*D(GRC_OBAL(−1)) + C(7) *D(GRC_OBAL(−2)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−1.904153**	**0.589951**	**−3.227647**	**0.0145**
C(2)	0.696449	0.332744	2.093048	0.0746
C(3)	0.240566	0.259008	0.928797	0.3839
C(4)	0.19727	0.172105	1.146217	0.2894
C(5)	0.281907	0.194545	1.449062	0.1906
C(6)	0.001908	0.002067	0.922846	0.3868
C(7)	−0.000922	0.0013	−0.709775	0.5008
C(8)	−0.008637	0.003962	−2.18019	0.0656
R-squared	0.792187	Mean dependent var		0.007318
Adjusted R-squared	0.584375	S.D. dependent var		0.015034

Hungary

Vector Error Correction Estimates	
Sample (adjusted): 1995 2013	
Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
HUN_LGDPC(−1)	1
HUN_LGINI(−1)	−1.282833
	(−1.79681)
	[−0.71395]
C	−4.89003

Dependent Variable: D(HUN_LGDPC)
Sample (adjusted): 1995 2013

D(HUN_LGDPC) = C(1)*(HUN_LGDPC(-1) - 1.2828329897*HUN_LGINI(-1) - 4.89002995119) + C(2)*D(HUN_LGDPC(-1)) + C(3) *D(HUN_LGDPC(-2)) + C(4)*D(HUN_LGDPC(-3)) + C(5) *D(HUN_LGINI(-1)) + C(6)*D(HUN_LGINI(-2)) + C(7)*D(HUN_LGINI(-3)) + C(8)

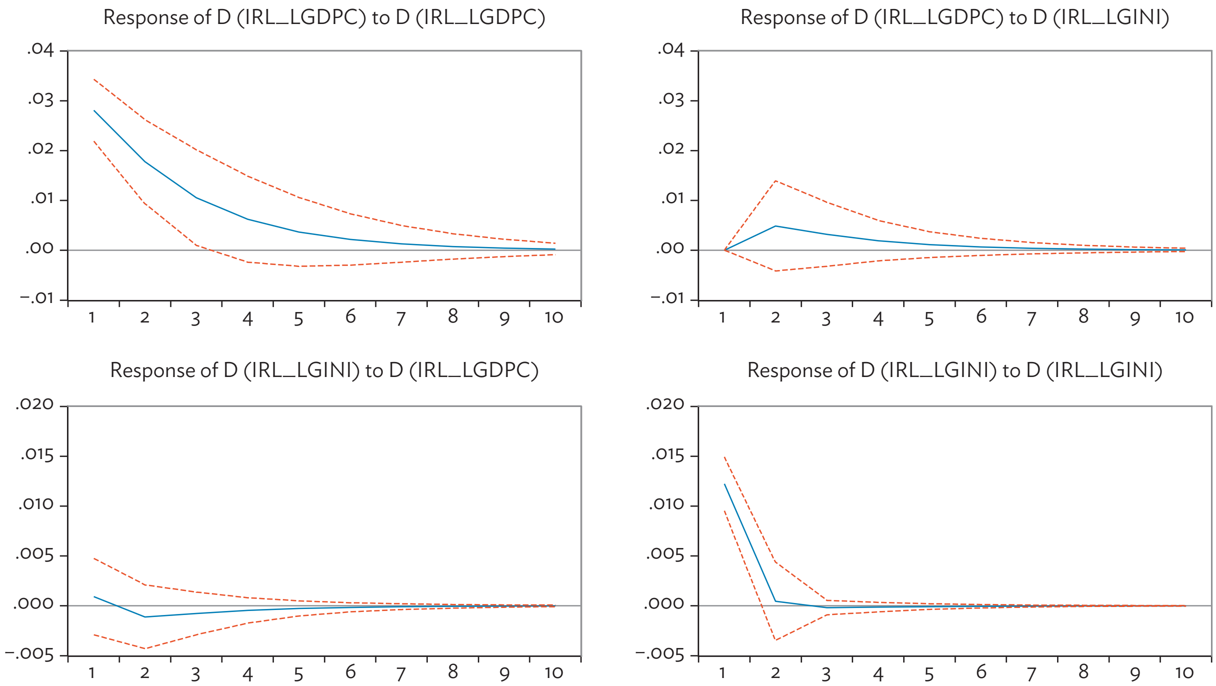
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**-0.065158**	**0.0296**	**-2.201271**	**0.05**
C(2)	0.201955	0.25016	0.807301	0.4366
C(3)	0.108334	0.255971	0.423229	0.6803
C(4)	0.468426	0.25798	1.815745	0.0967
C(5)	0.593243	0.248969	2.382804	0.0363
C(6)	-0.208746	0.255527	-0.816924	0.4313
R-squared	0.56608	Mean dependent var		0.022342
Adjusted R-squared	0.289949	S.D. dependent var		0.027685

Sample (adjusted): 1999 2012

Ireland

Sample (adjusted): 1972 2012

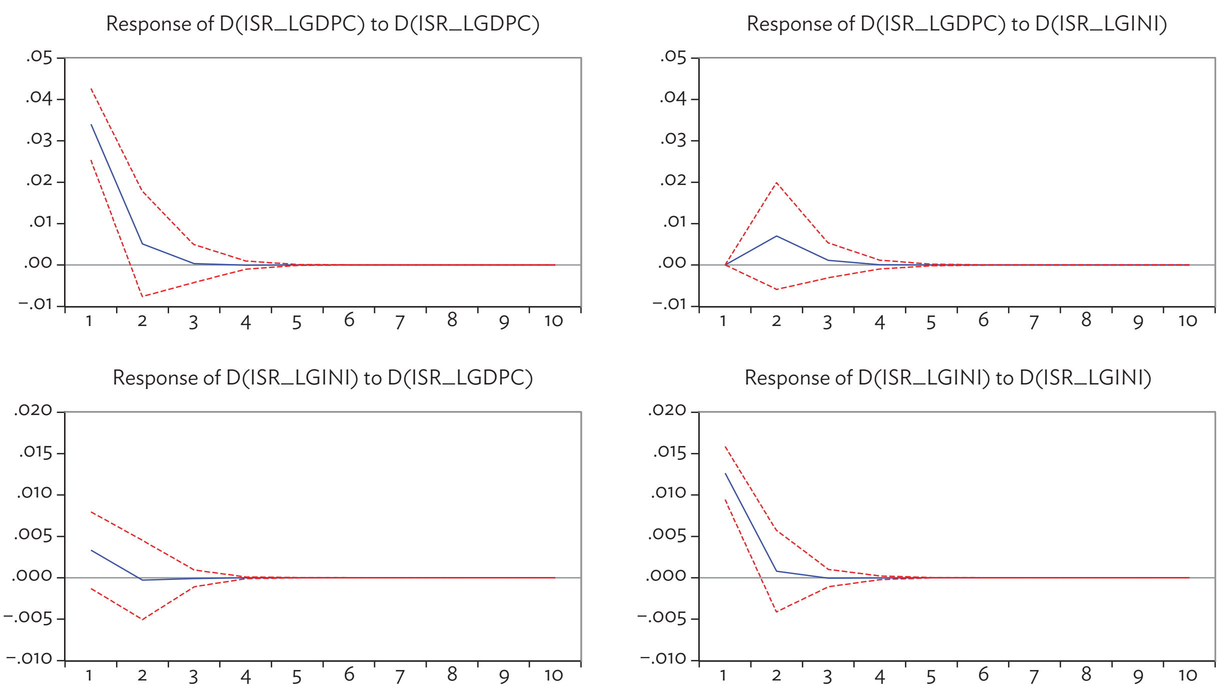
Response to Cholesky One S.D. Innovations ± 2 S.E.



Israel

Sample (adjusted): 1981 2011

Response to Cholesky One S.D. Innovations ± 2 S.E.



Italy
Sample (adjusted): 1969 2013

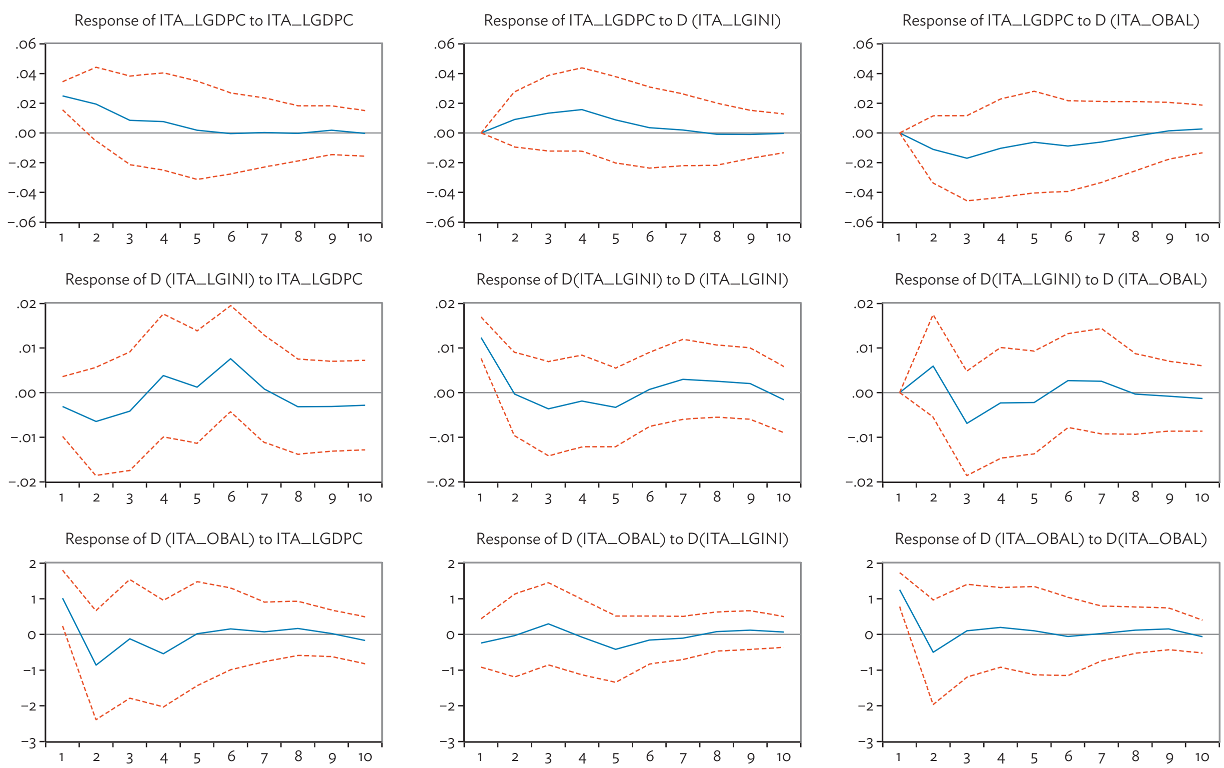
Vector Error Correction Estimates	
Sample (adjusted): 1969 2013	
Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
ITA_LGDPC(−1)	1
ITA_LGINI(−1)	−0.489016
	(−1.05608)
	[−0.46305]
C	−8.375658

Dependent Variable: D(ITA_LGDPC)
Sample (adjusted): 1969 2013
D(ITA_LGDPC) = C(1)*(ITA_LGDPC(−1) − 0.489016446297*ITA_LGINI(−1) − 8.37565830573) + C(2)*D(ITA_LGDPC(−1)) + C(3)*D(ITA_LGINI(−1)) + C(4)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.054144**	**0.013935**	**−3.885471**	**0.0004**
C(2)	0.055931	0.153437	0.364519	0.7173
C(3)	0.068417	0.108827	0.628673	0.5331
C(4)	0.016676	0.004365	3.820231	0.0004
R-squared	0.371886	Mean dependent var		0.017573
Adjusted R-squared	0.325926	S.D. dependent var		0.026124

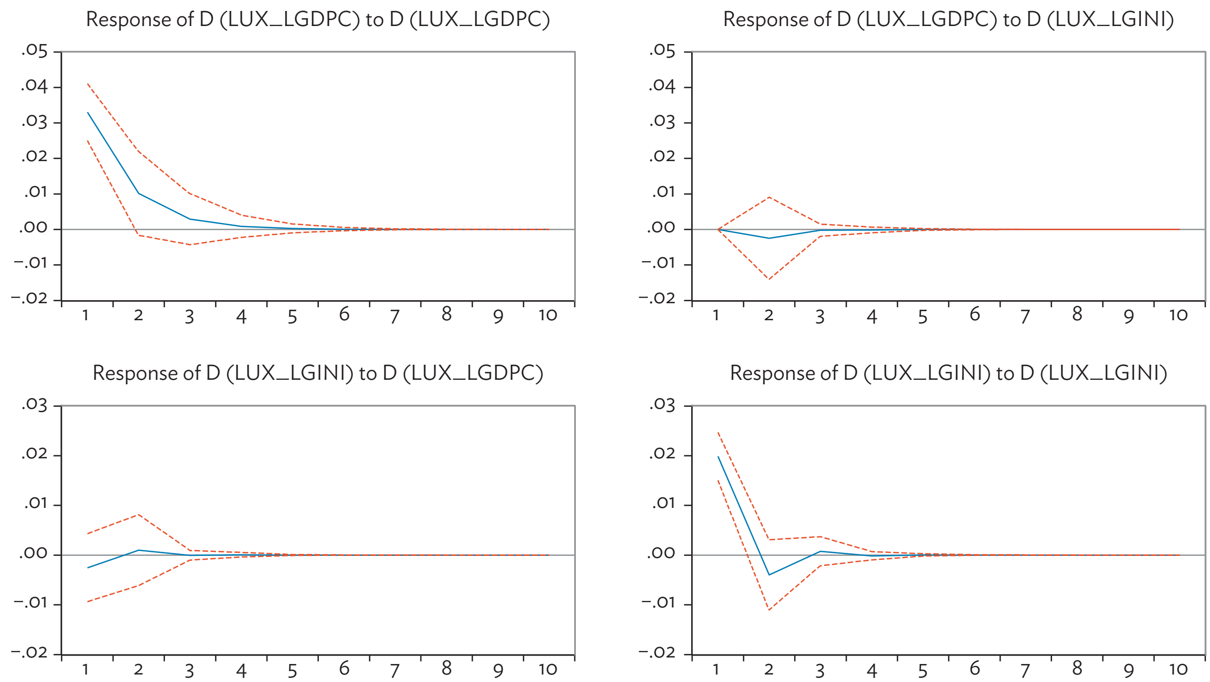
Sample (adjusted): 1999 2012

Response to Cholesky One S.D. Innovations ± 2 S.E.



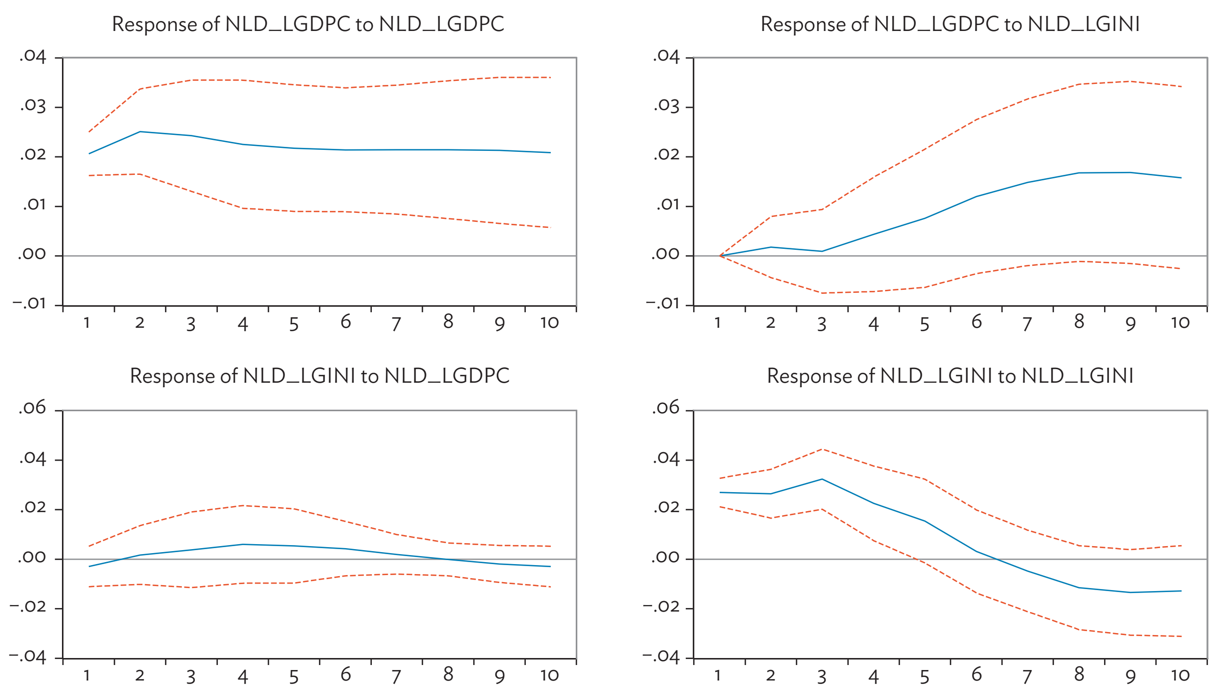
Luxembourg
Sample (adjusted): 1972 2012

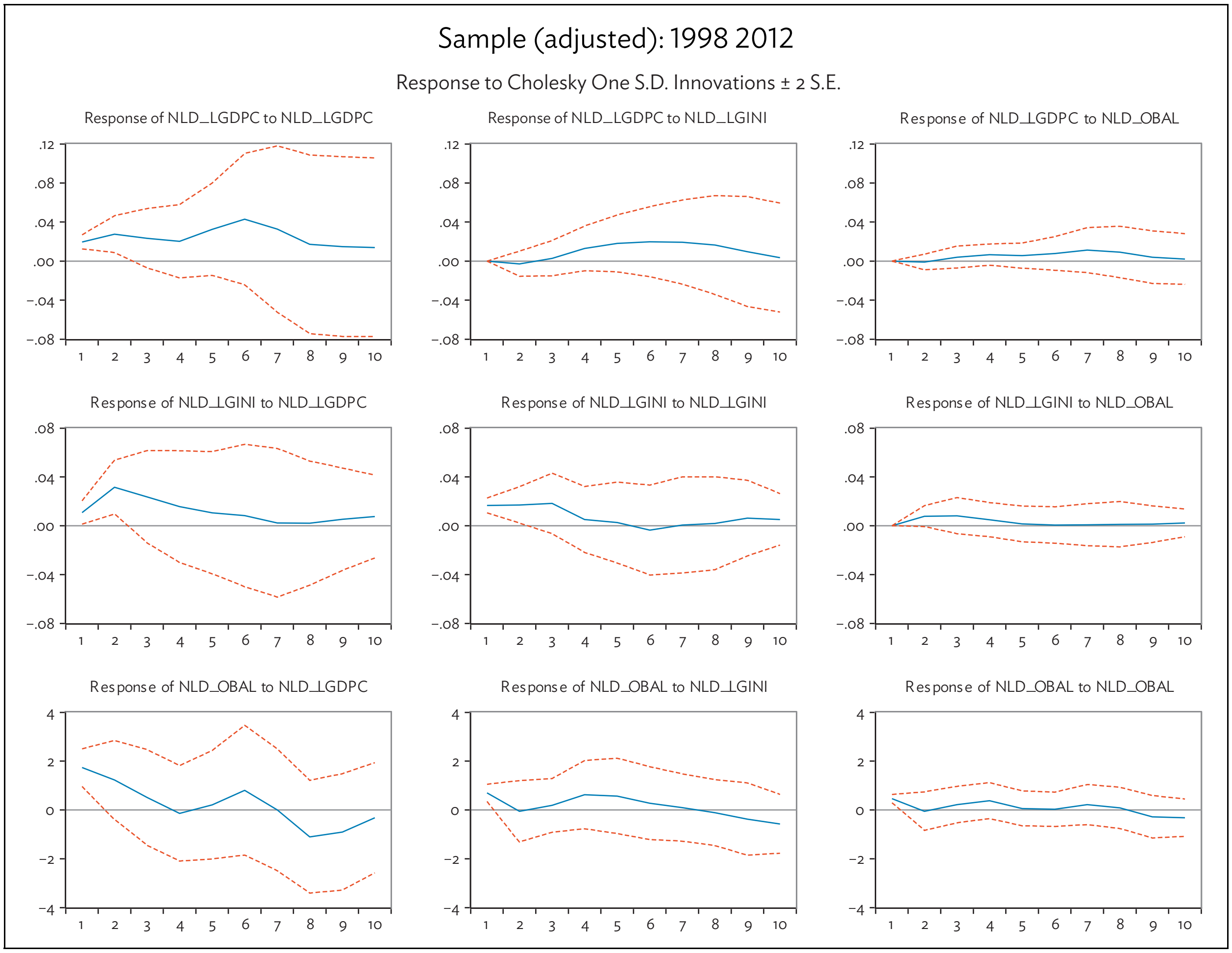
Response to Cholesky One S.D. Innovations ± 2 S.E.



Netherlands
Sample (adjusted): 1965 2012

Response to Cholesky One S.D. Innovations ± 2 S.E.





Norway

Vector Error Correction Estimates
Sample (adjusted): 1963 2012
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
NOR_LGINI(−1)	1
NOR_LGDPC(−1)	−0.032526
	(−0.03489)
	[−0.93220]
C	−2.804722

Dependent Variable: D(NOR_LGINI)				
Method: Least Squares				
Sample (adjusted): 1963 2012				
D(NOR_LGINI) = C(1)*(NOR_LGINI(−1) − 0.0325262650672*NOR_LGDPC(−1) − 2.8047219673) + C(2)*D(NOR_LGINI(−1)) + C(3)*D(NOR_LGINI(−2)) + C(4)*D(NOR_LGDPC(−1)) + C(5)*D(NOR_LGDPC(−2)) + C(6)				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.294662**	**0.097633**	**−3.018051**	**0.0042**
C(2)	0.108807	0.150641	0.722294	0.4739
C(3)	0.208715	0.14444	1.444992	0.1555
C(4)	−0.033652	0.243964	−0.13794	0.8909
C(5)	−0.308435	0.239682	−1.286849	0.2049
C(6)	0.01078	0.006714	1.605735	0.1155
R-squared	0.192228	Mean dependent var		0.002354
Adjusted R-squared	0.100436	S.D. dependent var		0.026501

Poland

Vector Error Correction Estimates	
Sample (adjusted): 1994 2013	
Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
POL_LGDPC(−1)	1
POL_LGINI(−1)	−6.473937
	(−0.86531)
	[−7.48164]
C	13.14266

Dependent Variable: D(POL_LGDPC)				
Sample (adjusted): 1994 2013				
D(POL_LGDPC) = C(1)*(POL_LGDPC(−1) − 6.47393749955*POL_LGINI(−1) + 13.1426626684) + C(2)*D(POL_LGDPC(−1)) + C(3) *D(POL_LGDPC(−2)) + C(4)*D(POL_LGDPC(−3)) + C(5)*D(POL_LGINI(−1)) + C(6)*D(POL_LGINI(−2)) + C(7)*D(POL_LGINI(−3)) + C(8)				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.075556**	**0.038146**	**−1.98069**	**0.071**
C(2)	0.022188	0.300523	0.073832	0.9424
C(3)	−0.646177	0.301106	−2.146011	0.053
C(4)	−0.086606	0.145011	−0.597235	0.5615
C(5)	−0.350115	0.201519	−1.737382	0.1079
C(6)	0.007779	0.173414	0.044856	0.965
C(7)	−0.084146	0.176677	−0.476272	0.6424
C(8)	0.075402	0.023116	3.261939	0.0068
R-squared	0.686101	Mean dependent var		0.041907
Adjusted R-squared	0.502993	S.D. dependent var		0.018148

Portugal

Vector Error Correction Estimates Sample (adjusted): 1979 2012 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
PRT_LGINI(−1)	1
PRT_LGDPC(−1)	−0.344003
	−0.05962
	[−5.77006]
C	−0.178705

Dependent Variable: D(PRT_LGINI)
Sample (adjusted): 1979 2012
D(PRT_LGINI) = C(1)*(PRT_LGINI(−1) − 0.344002525028*PRT_LGDPC(−1) − 0.17870456122) + C(2)*D(PRT_LGINI(−1)) + C(3)*D(PRT_LGINI(−2)) + C(4)*D(PRT_LGDPC(−1)) + C(5)*D(PRT_LGDPC(−2)) + C(6)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.213683**	**0.060969**	**−3.504814**	**0.0016**
C(2)	0.556334	0.165691	3.35767	0.0023
C(3)	0.346846	0.18102	1.916069	0.0656
C(4)	0.007432	0.152345	0.048785	0.9614
C(5)	−0.175747	0.157189	−1.118062	0.273
C(6)	0.003157	0.004219	0.748288	0.4605
R-squared	0.617309	Mean dependent var		0.003091
Adjusted R-squared	0.548971	S.D. dependent var		0.025045

Slovak Republic

Vector Error Correction Estimates Sample (adjusted): 1994 2013 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
SVK_LGINI(−1)	1
SVK_LGDPC(−1)	0.185574
	−0.08127
	[2.28351]
C	−4.946045

Dependent Variable: D(SVK_LGINI)
Sample (adjusted): 1994 2013
D(SVK_LGINI) = C(1)*(SVK_LGINI(−1) + 0.185573588574*SVK_LGDPC(−1)) − 4.94604536316) + C(2)*D(SVK_LGINI(−1)) + C(3)*D(SVK_LGDPC(−1)) + C(4)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.262028**	**0.042571**	**−6.155067**	**0**
C(2)	0.153639	0.128541	1.195257	0.2494
C(3)	−0.278255	0.1494	−1.862484	0.081
C(4)	0.023373	0.008032	2.910014	0.0102
R-squared	0.787578	Mean dependent var		0.014497
Adjusted R-squared	0.747749	S.D. dependent var		0.042939

Spain

Vector Error Correction Estimates
Sample (adjusted): 1967 2013
Standard errors in ( ) & t-statistics in [ ]

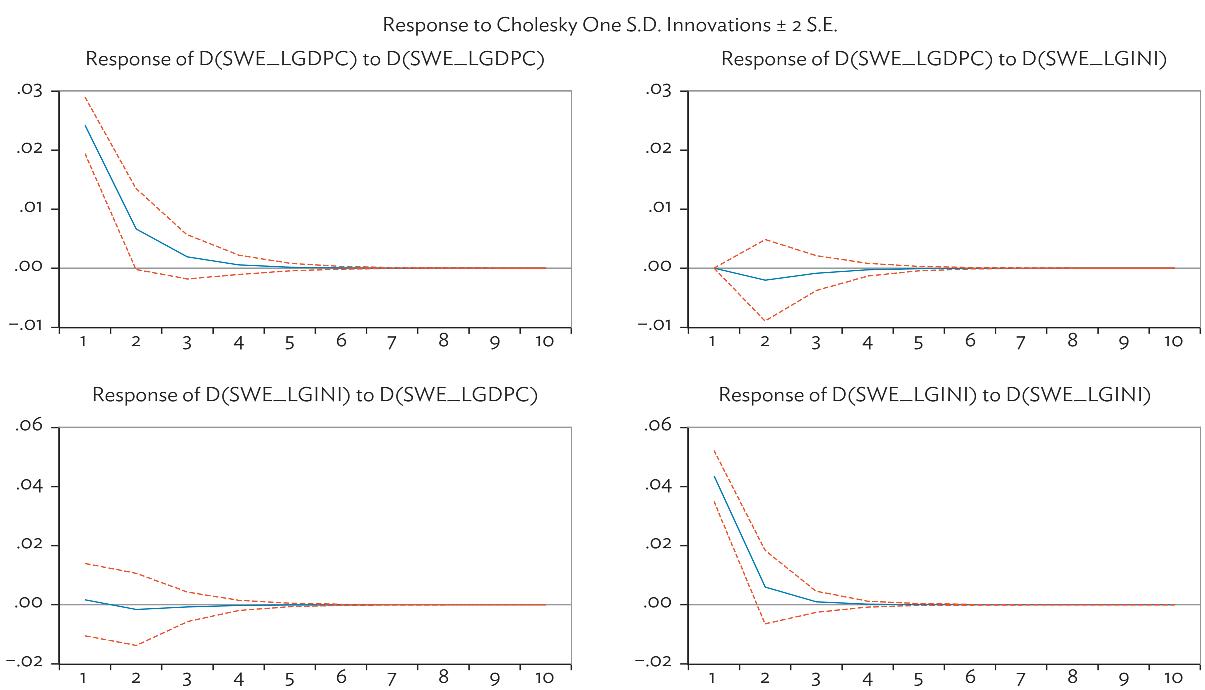
Cointegrating Eq:	CointEq1
ESP_LGINI(−1)	1
ESP_LGDPC(−1)	−0.042857
	(−0.0597)
	[−0.71785]
C	−3.029582

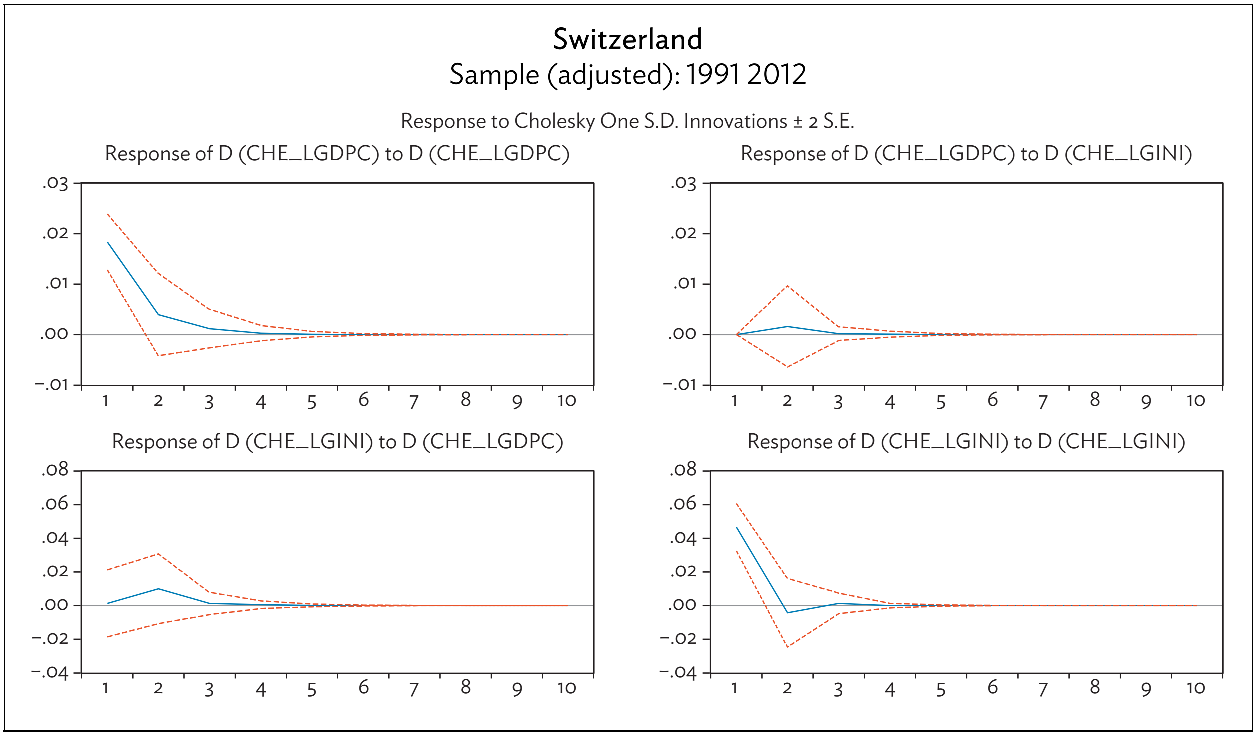
Dependent Variable: D(ESP_LGINI)
Sample (adjusted): 1967 2013
D(ESP_LGINI) = C(1)*(ESP_LGINI(−1)−0.0428572048438*ESP_LGDPC(−1)−3.02958167079) +C(2)*D(ESP_LGINI(−1))+C(3)*D(ESP_LGINI(−2))+C(4) *D(ESP_LGINI(3))+C(5) *D(ESP_LGDPC(−1))+C(6) *D(ESP_LGDPC(−2))+C(7) *D(ESP_LGDPC(−3))+C(8)

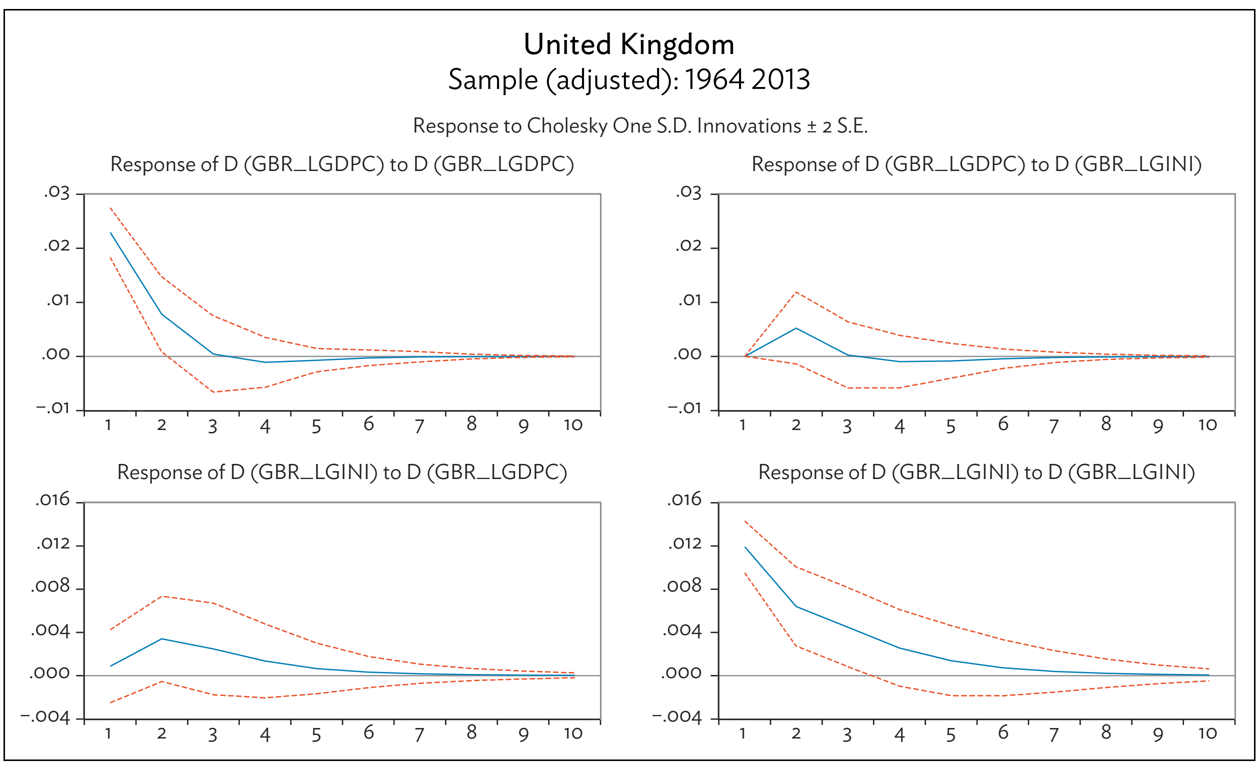
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.260291**	**0.059695**	**−4.360348**	**0.0002**
C(2)	0.1869	0.096545	1.935881	0.0647
C(3)	0.197692	0.061255	3.227368	0.0036
C(4)	0.050846	0.073971	0.687382	0.4984
C(5)	−0.243	0.196745	−1.235103	0.2287
C(6)	0.245339	0.250244	0.980396	0.3367
C(7)	−0.082403	0.218014	−0.377973	0.7088
C(8)	0.011735	0.005455	2.151216	0.0417
R-squared	0.769483	Mean dependent var		0.01736
Adjusted R-squared	0.702248	S.D. dependent var		0.031455

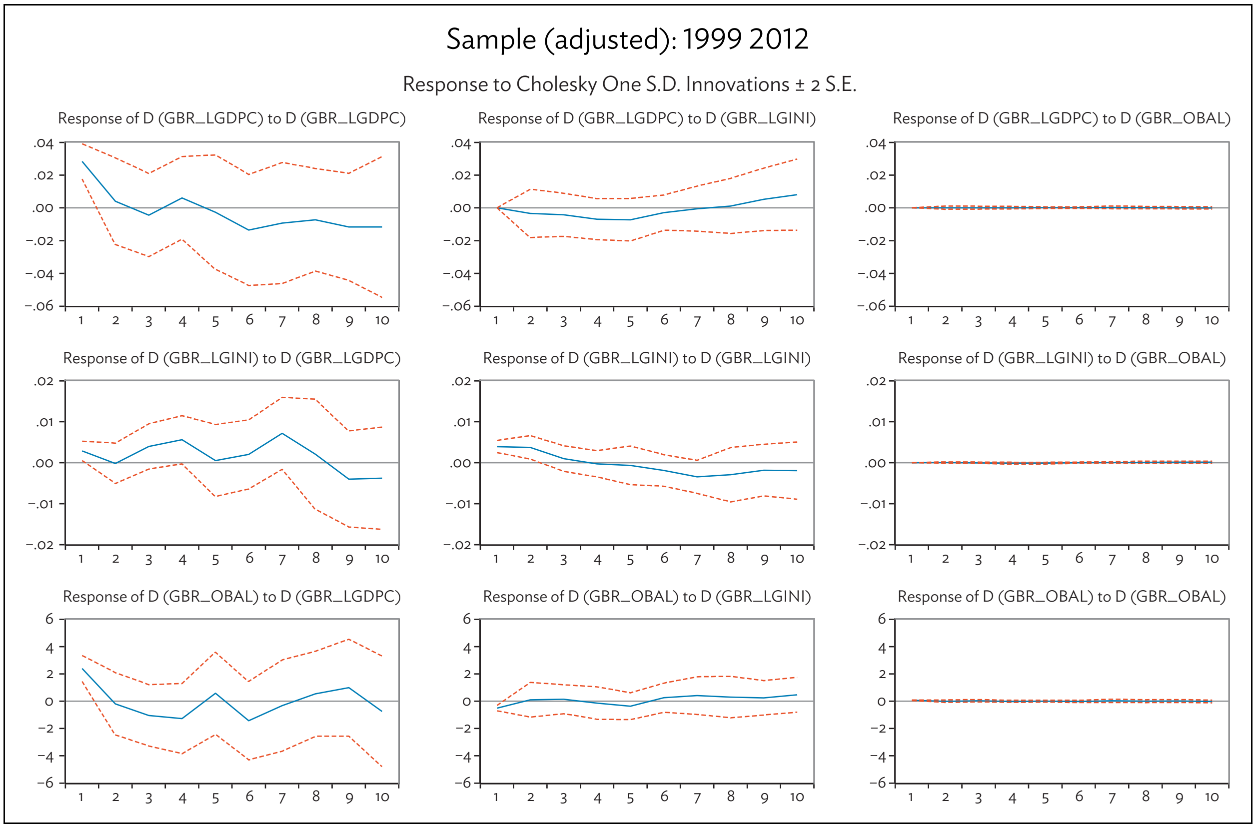
Sweden

Sample (adjusted): 1962 2012




Switzerland
Sample (adjusted): 1991 2012
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of D (CHE_LGDPC) to D (CHE_LGDPC)
Response of D (CHE_LGDPC) to D (CHE_LGINI)
Response of D (CHE_LGINI) to D (CHE_LGDPC)
Response of D (CHE_LGINI) to D (CHE_LGINI)


United Kingdom
Sample (adjusted): 1964 2013
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of D (GBR_LGDPC) to D (GBR_LGDPC)
Response of D (GBR_LGDPC) to D (GBR_LGINI)
Response of D (GBR_LGINI) to D (GBR_LGDPC)
Response of D (GBR_LGINI) to D (GBR_LGINI)



United States

Vector Error Correction Estimates
Sample (adjusted): 1964 2012
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
USA_LGDPC(−1)	1
USA_LGINI(−1)	−2.390181
	(−0.53685)
	[−4.45221]
C	−1.897841

Dependent Variable: D(USA_LGDPC)
D(USA_LGDPC) = C(1)*(USA_LGDPC(-1)-2.3901810227*USA_LGINI(-1)-1.89784059001)
+C(2)*D(USA_LGDPC(-1))+C(3)*D(USA_LGDPC(-2))+C(4)*D(USA_LGDPC(-3))+C(5)*
D(USA_LGINI(-1))+C(6) *D(USA_LGINI(-2))+C(7)*D(USA_LGINI(-3))+C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**-0.049375**	**0.016996**	**-2.905149**	**0.0058**
C(2)	0.245824	0.14256	1.724358	0.092
C(3)	-0.209342	0.144726	-1.446469	0.1555
C(4)	-0.158506	0.138266	-1.146385	0.2581
C(5)	-0.061527	0.258314	-0.238186	0.8129
C(6)	0.022262	0.247549	0.089931	0.9288
C(7)	0.34907	0.245405	1.422424	0.1623
C(8)	0.021946	0.005043	4.351889	0.0001
R-squared	0.310642	Mean dependent var		0.019639
Adjusted R-squared	0.195749	S.D. dependent var		0.020845

Vector Error Correction Estimates Sample (adjusted): 1964 2012 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
USA_LGINI(−1)	1
USA_LGDPC(−1)	−0.418378
	−0.06885
	[−6.07680]
C	0.794015

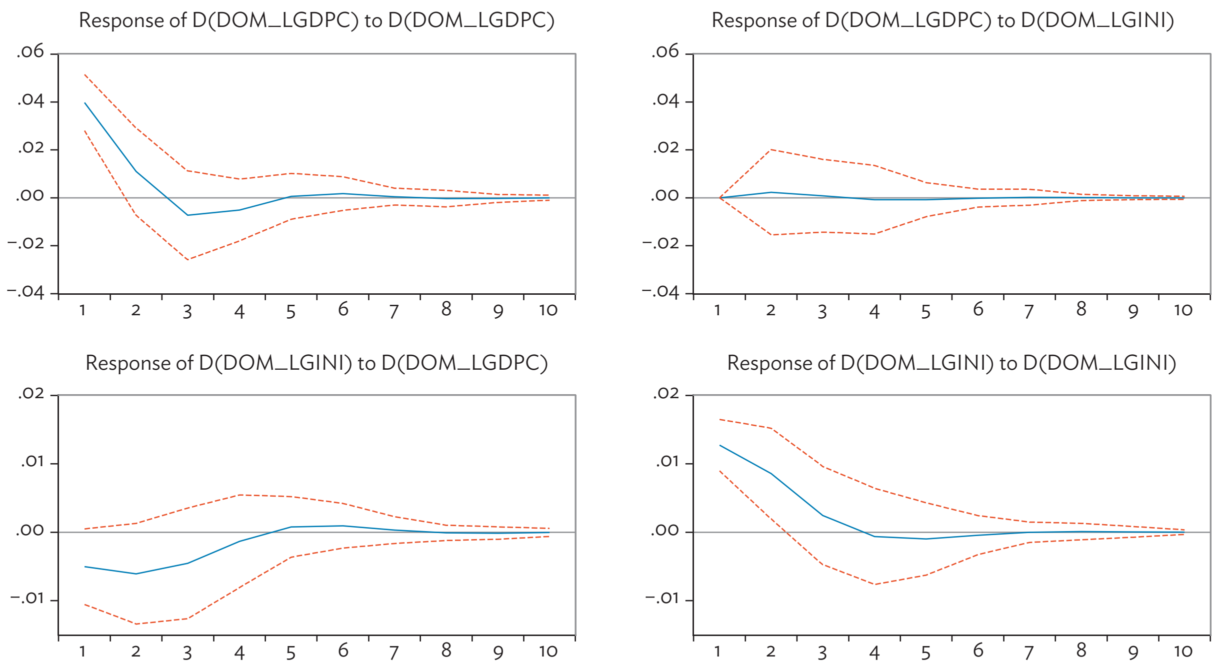
Dependent Variable: D(USA_LGINI) DD(USA_LGINI) = C(1)*(USA_LGINI(−1)−0.418378353147*USA_LGDPC(−1)+0.794015420584)+C(2)*D(USA_LGINI(−1))+C(3)*D(USA_LGINI(−2))+C(4)*D(USA_LGINI(−3))+C(5)*D(USA_LGDPC(−1))+C(6) *D(USA_LGDPC(−2))+C(7)*D(USA_LGDPC(−3))+C(8)				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.045189**	**0.022026**	**−2.051668**	**0.0466**
C(2)	0.255207	0.139208	1.833274	0.074
C(3)	0.361052	0.133421	2.706105	0.0099
C(4)	−0.173324	0.132414	−1.30895	0.1978
C(5)	−0.005465	0.07685	−0.071118	0.9436
C(6)	0.006266	0.078088	0.080242	0.9364
C(7)	−0.164115	0.07453	−2.202002	0.0333
C(8)	0.004347	0.002727	1.594204	0.1186
R-squared	0.516269	Mean dependent var		0.00158
Adjusted R-squared	0.433681	S.D. dependent var		0.013387

Source: Author’s calculations.

APPENDIX A.4: REGRESSION RESULTS FOR LATIN AMERICAN COUNTRIES

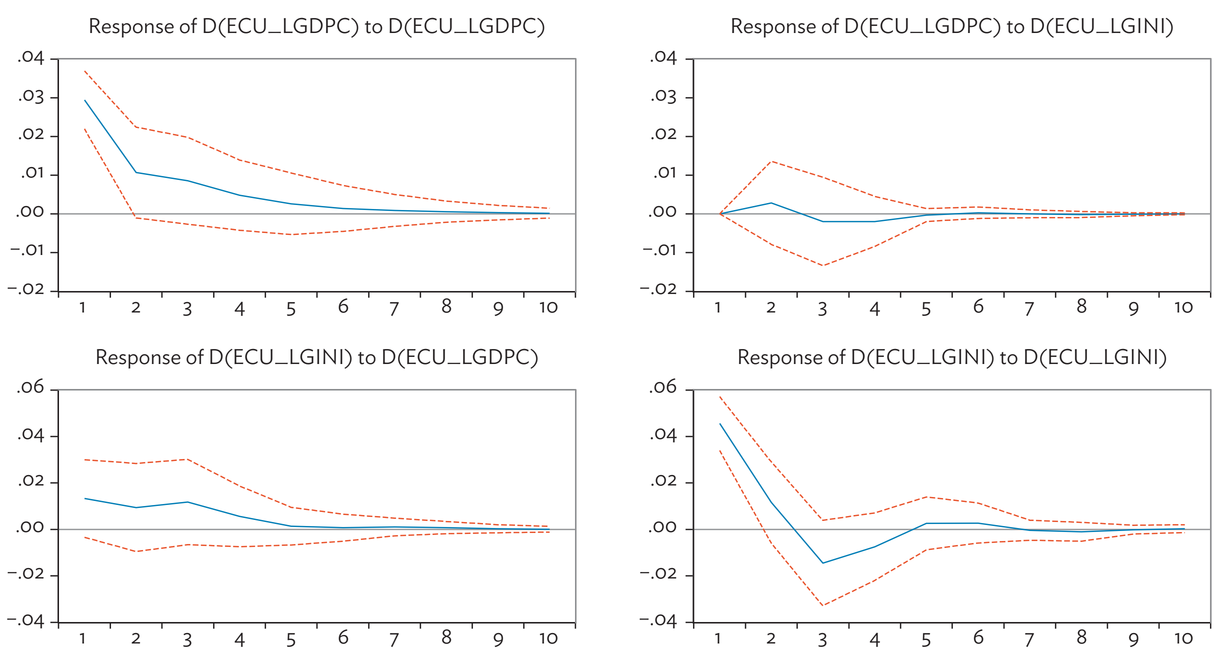
Dominican Republic
Sample (adjusted): 1989 2011

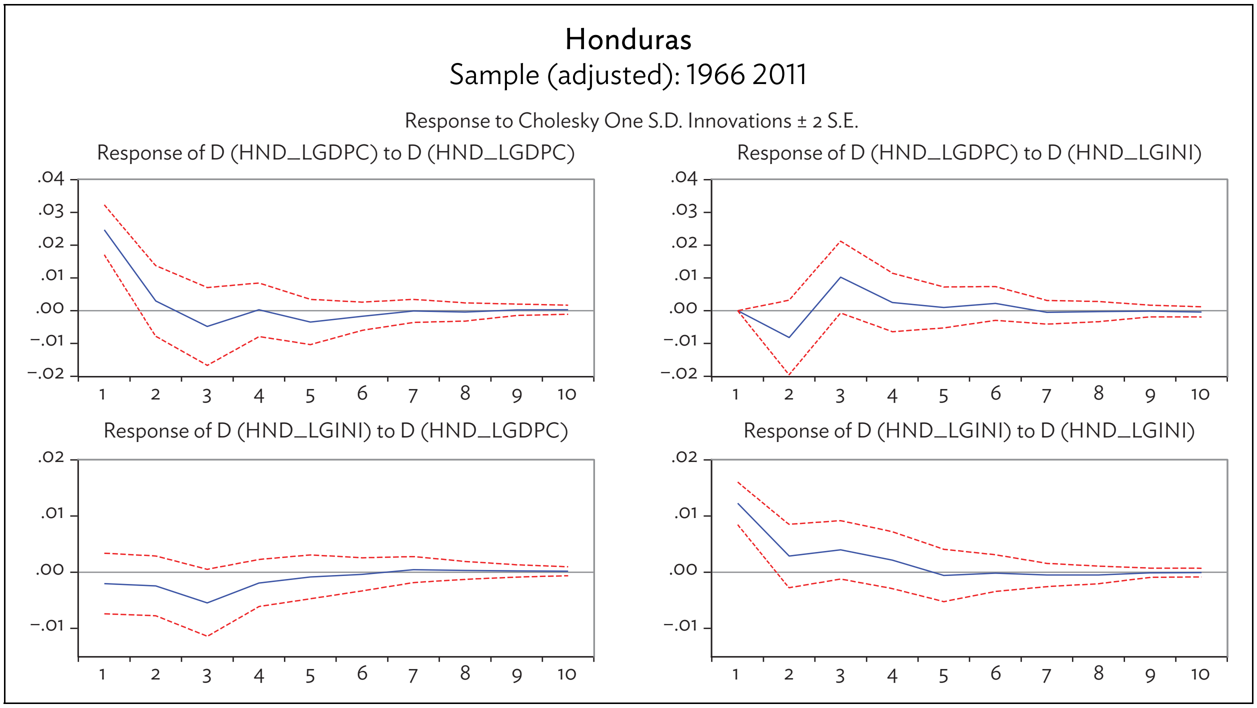
Response to Cholesky One S.D. Innovations ± 2 S.E.



Ecuador
Sample (adjusted): 1966 1996

Response to Cholesky One S.D. Innovations ± 2 S.E.





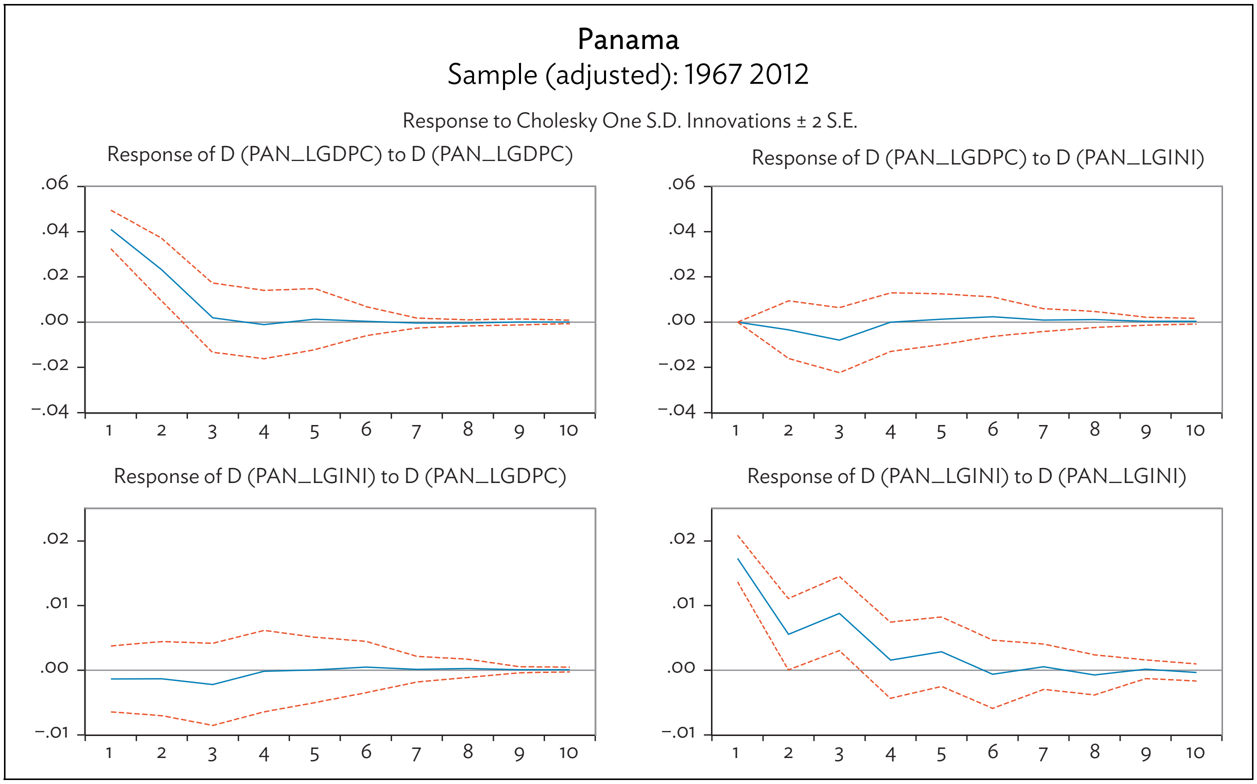
Mexico

Vector Error Correction Estimates Sample (adjusted): 1972 2012 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
MEX_LGINI(−1)	1
MEX_LGDPC(−1)	0.290429
	(−0.05856)
	[4.95918]
C	−6.42135

Dependent Variable: D(MEX_LGINI)

D(MEX_LGINI) = C(1)*(MEX_LGINI(−1)+0.290428995099*MEX_LGDPC(−1)−6.42135053285) +C(2)*D(MEX_LGINI(−1))+C(3)*D(MEX_LGINI(−2))+C(4)*D(MEX_LGINI(−3))+C(5) *D(MEX_LGDPC(−1))+C(6) *D(MEX_LGDPC(−2))+C(7)*D(MEX_LGDPC(−3))+C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**−0.322023**	**0.09666**	**−3.331491**	**0.0021**
C(2)	0.032781	0.1346	0.243544	0.8091
C(3)	0.405211	0.110748	3.65885	0.0009
C(4)	0.034764	0.125726	0.276508	0.7839
C(5)	0.318512	0.091277	3.489522	0.0014
C(6)	0.000911	0.102562	0.008878	0.993
C(7)	−0.121254	0.096428	−1.257449	0.2174
C(8)	−0.00383	0.003674	−1.042303	0.3048
R-squared	0.540032	Mean dependent var		−0.003044
Adjusted R-squared	0.442463	S.D. dependent var		0.02322



Paraguay

Vector Error Correction Estimates Sample (adjusted): 1994 2011 Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
PRY_LGINI(–1)	1
PRY_LGDPC(–1)	–0.185403
	(–0.16984)
	[–1.09166]
C	–2.526782

Dependent Variable: D(PRY_LGINI)
D(PRY_LGINI) = C(1)*(PRY_LGINI(–1)–0.185402743509*PRY_LGDPC(–1)–2.52678226917)+C(2)*D(PRY_LGINI(–1))+C(3)*D(PRY_LGINI(–2))+C(4)*D(PRY_LGINI(–3))+C(5)*D(PRY_LGDPC(–1))+C(6) *D(PRY_LGDPC(–2))+C(7)*D(PRY_LGDPC(–3))+C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	**–0.404096**	**0.087763**	**–4.604427**	**0.001**
C(2)	0.089798	0.193293	0.464571	0.6522
C(3)	0.136964	0.182995	0.748459	0.4714
C(4)	0.325057	0.164506	1.97596	0.0764
C(5)	–0.17797	0.068311	–2.605266	0.0263
C(6)	–0.215566	0.078596	–2.742711	0.0207
C(7)	–0.076085	0.109889	–0.692379	0.5045
C(8)	–0.000298	0.002367	–0.125851	0.9023
R-squared	0.895823	Mean dependent var		0.003459
Adjusted R-squared	0.822898	S.D. dependent var		0.021107

Source: Author's calculation

Interrelation between Growth and Inequality

The paper highlights the importance of “broad-based growth” as a framework to support economic growth and inclusiveness at the same time. Different countries show different dynamics between economic growth and inequality depending on diverse development, social, and economic contexts. If a growth pattern worsens inequality, renewed attention should be paid to curbing inequality. Those countries showing an inclusive growth pattern are encouraged to further promote growth with a lower risk of sacrificing equity.

About the Asian Development Bank

ADB’s vision is an Asia and Pacific region free of poverty. Its mission is to help its developing member countries reduce poverty and improve the quality of life of their people. Despite the region’s many successes, it remains home to the majority of the world’s poor. ADB is committed to reducing poverty through inclusive economic growth, environmentally sustainable growth, and regional integration.

Based in Manila, ADB is owned by 67 members, including 48 from the region. Its main instruments for helping its developing member countries are policy dialogue, loans, equity investments, guarantees, grants, and technical assistance.

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