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Common correlated effects and international risk sharing

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Abstract

International risk sharing has been among the most actively researched areas of macroeconomics for the last two decades. Empirical contributions in this field make extensive use of so called "consumption insurance" tests evaluating the extent to which idiosyncratic shocks in income get transferred to consumption. A prerequisite of such a test is the isolation of country specific variation in the data. We show that the cross-sectional demeaning technique frequently used in the literature is in general inadequate to eliminate global factors from a panel data set, and can lead to misleading inference. We argue that international risk sharing tests should instead be based on a method that more reliably deals with global factors. We claim and illustrate in our empirical application that the fairly simple common correlated effects estimator for cross-sectionally dependent panels introduced by Pesaran (2006), and Kapetanios et al. (2010) is a tool that satisfies this requirement.

Keywords: Panel data, Cross-sectional dependence, International risk sharing, Consumption insurance

JEL codes: C23, C51, E21, F36

1 Introduction

Since the early contributions by Cochrane (1991), Mace (1991), and Obstfeld (1994), various tests of consumption risk sharing have been presented in the literature. A wide range of theoretical and empirical studies has examined the extent to which idiosyncratic risks are smoothed across regional or national economies through channels such as capital and credit markets, fiscal policies, and others. These tests were also used to assess the role of financial globalization in shaping the degree of risk sharing across nations. A prerequisite for these risk sharing (or consumption insurance) tests is a testable implication derived from the solution of a planner's or competitive agents' maximization problem in complete markets, that is, when it is possible to redistribute wealth or income (hence, consumption) across all date-event pairs. The solution to those problems reveals that under market completeness marginal utility growth is equalized across agents, and therefore may depend on aggregate factors but not on individual shocks. Assuming CRRA utility functions, the risk sharing hypothesis can be tested by estimating the following equation

$$c_{it} = \alpha_i + \gamma_i \bar{c}_t + \beta_i x_{it} + \varepsilon_{it} , \quad i = 1 \dots N, \quad t = 1 \dots T , \quad (1)$$

where c_{it} is a consumption measure for country i , \bar{c}_t is an aggregate measure of consumption, and x_{it} is an idiosyncratic variable. Market completeness implies $\gamma_i > 0$ and $\beta_i = 0$. If the discount factors and the coefficients of relative risk aversion are taken to be equal across countries (quite a heroic assumption), the coefficients γ_i can be shown to take a unit value. That this is generically the case is quite unlikely, and awaits empirical evidence¹. Nevertheless, most papers in the field have built on these assumptions, under which equation (1) becomes

$$c_{it} - \bar{c}_t = \alpha_i + \beta_i x_{it} + \varepsilon_{it} . \quad (2)$$

In virtually all macroeconomic implementations of equation (2), the generic variable x_{it} containing idiosyncratic shocks is replaced by a proxy for idiosyncratic income, which in turn is calculated as a difference between the individual country's income and a measure of aggregate income. With these modifications the tested relationship becomes

$$c_{it} - \bar{c}_t = \alpha_i + \beta_i (y_{it} - \bar{y}_t) + \varepsilon_{it} , \quad (3)$$

where y_{it} is an income measure for country i , and \bar{y}_t is a measure of aggregate income.

Equation (3) is the basis for several recent influential empirical studies, such as Sorensen and Yosha (2000), Giannone and Reichlin (2006), Sorensen et al. (2007), and Kose et al. (2009) among others. In these studies, the consumption and income measures entering the analysis are consumption growth and real gross domestic product (GDP) growth, respectively. Correspondingly, β_i is interpreted as the effect of idiosyncratic real GDP growth on idiosyncratic consumption growth in country i , or as the extent of the departure from perfect risk sharing. If the \bar{c}_t and \bar{y}_t aggregates represent cross-sectional means, then the differencing operations in equation (3) will produce cross-sectionally demeaned variables. Some studies (for example Asdrubali et al. (1996), Lewis (1997), Sorensen and Yosha (1998), and Fratzscher and Imbs (2009)) replace the explicit cross-sectional demeaning in equation (3) by an implicit one by including a time dummy in the pooled regression

$$c_{it} = \alpha_i + d_t + \beta y_{it} + \varepsilon_{it} , \quad (4)$$

where d_t is a time dummy.

¹Notice, however, that Obstfeld (1989) only found weak evidence against this hypothesis with respect to some relatively homogeneous countries, such as Germany, Japan and the United States.

In an alternative approach, Crucini (1999) and Artis and Hoffmann (2007) derive testable implications for the case where individual countries pool part or all of their income (see Shiller, 1995). They model country specific income as a mixture of domestic real GDP level and pooled real GDP level of participating countries, and obtain the test equation

$$c_{it} - \bar{c}_t = \alpha_i + \beta(y_{it} - \bar{y}_t) + \varepsilon_{it} . \quad (5)$$

Because the variables enter their model in levels, their results reflect the scale of long run international risk sharing. Both Crucini (1999) and Artis and Hoffmann (2007), derive their results in the perfectly symmetric case where all countries are equal. By relaxing this restriction and allowing countries to be heterogeneous in terms of their economies' size and in terms of their share of pooled income, we obtain the more general model

$$c_{it} - \gamma_i^c \bar{c}_t = \alpha_i + \beta_i(y_{it} - \tilde{\gamma}_i^y \bar{y}_t) + \varepsilon_{it} , \quad \text{or} \quad c_{it} = \alpha_i + \gamma_i^c \bar{c}_t + \beta_i y_{it} + \gamma_i^y \bar{y}_t + \varepsilon_{it} , \quad (6)$$

where, as before, the β_i coefficient measures the extent to which idiosyncratic shocks to income are channeled into domestic consumption.

We argue in the sequel that consumption insurance tests should be based on estimating equation (6) as opposed to equations (3) or (4) because the latter suffer from inadequate handling of cross-sectional dependence and could produce misleading inference. Specifically, risk sharing tests require separation of idiosyncratic shocks from global ones, but simple cross-sectional differencing with respect to an aggregate measure is insufficient for this purpose because it imposes the overly restrictive assumption of a unit coefficient on the aggregate measure across all countries. In Section 2 we describe the common correlated effects (CCE) estimator of Pesaran (2006), which was shown to be an effective tool for eliminating common factors from linear relationships in heterogeneous panels, and is especially practical for estimating the link between idiosyncratic fluctuations, as in international risk sharing tests. Section 3 introduces our empirical strategy, Section 4 discusses the results, and Section 5 concludes.

2 The common correlated effect estimator

The international risk sharing hypothesis postulates that consumption across countries follows a similar pattern, and deviations from this pattern cannot be predicted by idiosyncratic explanatory variables. The presence of a similar pattern across countries can be tested by the cross-sectional dependence (CD) statistic of Pesaran (2004). This test is based on the pairwise correlation of unit-by-unit OLS residuals, and has been shown to have good finite sample properties in heterogeneous panels. If cross-sectional independence is rejected, the co-movement of variables across countries can be modeled through common factors, and the idiosyncratic components can be obtained by an orthogonal projection of the data onto the common factors. These idiosyncratic components can then be tested for predictability. Pesaran's (2006) common correlated effects (CCE) estimator, which he proposed to deal with dependencies across units in heterogeneous panel, is an ideal tool for estimating the idiosyncratic effects, β_i . The CCE estimator lends itself to this task because it accounts for common factors, such as global cycles, allows for individual specific effects of these factors, and produces coefficient estimates based on idiosyncratic fluctuations in the data.

Specifically, the CCE estimator asymptotically eliminates the cross-sectional dependence in the panel regression

$$c_{it} = \alpha_i + \beta_i y_{it} + u_{it} , \quad i = 1, 2, \dots, N , \quad t = 1, 2, \dots, T , \quad (7)$$

where $c_{it} = \log(C_{it})$, $y_{it} = \log(Y_{it})$, with C_{it} and Y_{it} being the level of a consumption measure and the level of an income measure, respectively. The coefficients β_i represent the elasticities of

consumption with respect to income for each country. Alternatively, if the risk sharing hypothesis is tested with growth rates, $c_{it} = \Delta \log(C_{it})$, $y_{it} = \Delta \log(Y_{it})$, the β_i coefficients represent marginal effects. The dynamics and the common unobserved factors are modeled in the error terms u_{it} . In particular, u_{it} is assumed to have the following structure

$$u_{it} = \boldsymbol{\gamma}'_i \mathbf{f}_t + \epsilon_{it} , \quad (8)$$

where \mathbf{f}_t is an $m \times 1$ vector of unobserved common effects with individual specific loading vector $\boldsymbol{\gamma}_i$, and ϵ_{it} are the individual-specific (idiosyncratic) errors assumed to be distributed independently of y_{it} and \mathbf{f}_t . However, the ϵ_{it} are allowed to be weakly dependent across i , and serially correlated over time.

The CCE estimator is based on the assumption that the regressor, y_{it} , is generated as

$$y_{it} = a_i + \boldsymbol{\lambda}'_i \mathbf{f}_t + v_{it} , \quad (9)$$

where a_i is an individual effect, and $\boldsymbol{\lambda}_i$ is a $m \times 1$ loading vector. The idiosyncratic component v_{it} is distributed independently of the common effects and across i , but is assumed to follow a covariance stationary process. The error term in (7), u_{it} , is allowed to be correlated with the regressor, y_{it} , through the presence of the factors in both, and failure to account for this correlation will generally produce biased estimates of the parameters of interest.

Pesaran (2006) suggested using cross section averages of c_{it} and y_{it} to deal with the effects of the unobserved factors. His CCE estimator is defined as,

$$\hat{\beta}_i = (\mathbf{y}'_i \bar{\mathbf{M}} \mathbf{y}_i)^{-1} \mathbf{y}'_i \bar{\mathbf{M}} \mathbf{c}_i , \quad (10)$$

where $\mathbf{y}_i = (y_{i1}, y_{i2}, \dots, y_{iT})'$, $\mathbf{c}_i = (c_{i1}, c_{i2}, \dots, c_{iT})'$, and $\bar{\mathbf{M}} = \mathbf{I}_T - \bar{\mathbf{H}}(\bar{\mathbf{H}}' \bar{\mathbf{H}})^{-1} \bar{\mathbf{H}}'$ with $\bar{\mathbf{H}} = (\boldsymbol{\iota}, \bar{\mathbf{y}}, \bar{\mathbf{c}})$, and $\boldsymbol{\iota}$ is a $T \times 1$ vector of ones. $\bar{\mathbf{y}}$ is a $T \times 1$ matrix of cross-sectional means of the regressor, and $\bar{\mathbf{c}}$ is a $T \times 1$ vector of cross-sectional means of the dependent variable. The CCE estimator is equivalent to ordinary least squares applied to an auxiliary regression that is augmented with the cross-sectional means of the variables

$$c_{it} = \alpha_i + \beta_i y_{it} + \gamma_i^c \bar{c}_t + \gamma_i^y \bar{y}_t + u_{it} , \quad (11)$$

where γ_i^c and γ_i^y are the individual specific loading coefficients of average consumption and average income, respectively. That is, the $\hat{\beta}_i$ coefficient estimates reflect the effect of income on consumption after controlling for common factors in the data.

While Pesaran (2006) derived the CCE estimator for stationary variables and factors, Kapetanios et al. (2010) proved that the CCE estimators are consistent regardless of whether the common factors, \mathbf{f}_t , are stationary or non-stationary. In the latter case, c_{it} , y_{it} , and \mathbf{f}_t are cointegrated if ϵ_{it} (in equation 8) is stationary. The authors also showed that under a random coefficient model, the mean of the CCE slope coefficient estimates is consistent for any number of unobserved factors. The CCE mean group estimator (CCEMG) is a simple average of the individual CCE estimators, β_i ,

$$\hat{\beta}_{CCEMG} = \frac{1}{N} \sum_{i=1}^N \hat{\beta}_i . \quad (12)$$

When the slope coefficients, β_i , are homogeneous, efficiency gains can be achieved by pooling observations over the cross section units. Pesaran (2006) developed such a pooled estimator

$$\hat{\beta}_{CCEP} = \left(\sum_{i=1}^N \mathbf{y}'_i \bar{\mathbf{M}} \mathbf{y}_i \right)^{-1} \sum_{i=1}^N \mathbf{y}'_i \bar{\mathbf{M}} \mathbf{c}_i . \quad (13)$$

Note that in equation (13) the observations are pooled after a unit-by-unit orthogonal projection onto the cross-sectional means. That is, the CCEP estimator allows for idiosyncratic loadings, γ_i^c , γ_i^y , while estimating a common slope coefficient for the variable of interest, β . This can also be seen by breaking down the CCE estimation algorithm into two stages. In the first stage, the common effects are filtered out from the data by regressing each variable on the cross-sectional averages of all variables in the model

$$c_{it} = \alpha_{i,c} + \gamma_{i,c}^c \bar{c}_t + \gamma_{i,c}^y \bar{y}_t + \varepsilon_{it}^c, \quad (14)$$

$$y_{it} = \alpha_{i,y} + \gamma_{i,y}^c \bar{c}_t + \gamma_{i,y}^y \bar{y}_t + \varepsilon_{it}^y. \quad (15)$$

In the second stage, the CCE estimate of an individual β_i is obtained by regressing the residual $\hat{\varepsilon}_{it}^c$, capturing idiosyncratic consumption, on the residual $\hat{\varepsilon}_{it}^y$, capturing idiosyncratic income. Alternatively, $\hat{\beta}_{CCEP}$ is obtained by a pooled regression of $\hat{\varepsilon}_{it}^c$ on $\hat{\varepsilon}_{it}^y$. The CCE estimator nests the partial pre-filtering discussed by Obstfeld (1994), where each variable is regressed only on its own cross-sectional mean in the first stage. However, the restriction imposed by partial pre-filtering is inappropriate if income or consumption at the country level is affected by both types of global shocks. Therefore, regressing each variable only on its own cross-sectional mean in the first stage may be inadequate to control for cross-sectional dependence.²

The conventional approach for testing the international risk sharing hypothesis is based on subtracting worldwide aggregates from country level variables

$$c_{it} - c_t = \alpha_i + \beta_i(y_{it} - y_t) + \varepsilon_{it}, \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T. \quad (16)$$

However, cross-sectional demeaning imposes unit loading coefficients on the aggregates, which is inappropriate if the impact of global trends varies across countries. As argued in the introduction, even in the presence of full risk sharing, we should expect unit loading factors on aggregate consumption if and only if countries had equal coefficients of risk aversion and equal discount factors.

The CCE estimator admits both simple and weighted cross-sectional averages in the $\bar{\mathbf{M}}$ matrix. However, unequal weights may distort inference if they overstate the importance of outliers in the cross-sectional distribution of the data. For example, if a variable of interest is in per capita terms, each country could be weighted by its population share, so that the aggregate becomes a global per capita measure

$$\sum_{i=1}^N (C_{it} * w_{it}) = \bar{C}_t, \quad w_{it} = \frac{N_{it}}{N_t}, \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T, \quad (17)$$

where C stands for consumption per capita, and N stands for population. This weighting scheme overweighs countries with large population. If some of these countries are atypical, inference will be distorted. Specifically, if the proxies for the common factors are biased towards outliers, the CCE procedure will not be able to eliminate cross-sectional dependence in the panel. Furthermore, most macroeconomic time series, such as consumption and income, require a log-transformation before being fed to linear models. Such non-linear transformation will affect the location of the aggregate measure relative to the distribution of the individual country level variables, and further distort inference. These complications can be avoided if the cross-sectional means entering the $\bar{\mathbf{M}}$ matrix are obtained by applying simple averages to log-transformed country level series.

²Obstfeld (1994) noticed that regressing each country's consumption on aggregate consumption often generated non stationary residuals, but did not impute this to the presence of left over common correlated effects.

Consistent estimation of the model parameters requires that the regression residuals be stationary. The appropriate unit root test should take into account cross-sectional dependence because, if not controlled for, it distorts inference (Banerjee et al., 2004; Gengenbach et al., 2010). Rejection of a unit root in the CCE residuals implies that the non-stationary variables in the model and the unobserved factors are cointegrated. In the next section we describe our empirical model and report estimation results.

3 Data and results

Our analysis is based on annual data that we obtained from the Penn World Tables, version 7.1, released in November 2012 (Heston et al. (2012)). This is a comprehensive dataset, covering more than 170 countries over a fairly long time span, and we selected the period 1970 - 2010, in order to maximize the number of countries with continuously available data in our panel. All values are expressed in real terms in a common currency, so as to make comparisons across countries and time feasible. The analyzed series are comparable to those in other datasets. For example, growth rates of real GDP and real final consumption almost perfectly match those in the last release of the World Bank's World Development Indicators. From the PENN World Tables dataset we use the following variables: purchasing power parity converted GDP per capita and consumption per capita at 2005 constant prices (Laspeyres), and population.

Table 1 and 2 display the cross-sectional mean of β_i across countries and residual diagnostic tests for three approaches of dealing with cross-sectional dependence: CCE estimation, cross-sectional demeaning, and partial pre-filtering. For each method, we perform regressions with data in levels and in first-differences. The results in Table 1 are based on global trend approximations by equally weighted cross-sectional averages, whereas those in Table 2 are based on population weighted cross-sectional averages. The lower panels of the tables illustrate the effect of excluding the Great Recession on the estimates by truncating the sample.

For each regression, we perform residual diagnostics to ensure that the results are not spurious. We test the residuals for cross-sectional dependence using the *CD* statistic proposed by Pesaran (2004). If the *CD* test rejects the null hypothesis of cross-sectional independence, we apply the *CRMA* method of Sul (2009) to test for unit roots in the residual common factors. We also test the idiosyncratic components of the residuals for unit roots using the *CIPS* statistic of Pesaran (2007).

The rejection of the *CD* test for the residuals in all demeaned and pre-filtered regressions indicates that these methods are not able to fully remove cross-sectional dependence from the variables. This also remains the case when the common trends are approximated by population weighted cross-sectional averages. Moreover, the fact that even the CCE residuals are cross-sectionally dependent under the population weighting scheme suggests that some countries with large population are not typical in terms of risk sharing. Therefore, as explained in Section 2, population weights are inappropriate for the approximation of common factors in per capita GDP and consumption.

A quick inspection of Figure 1, illustrating the distribution of $\gamma_{i,c}^c$ and $\gamma_{i,y}^y$ in the first stage regressions (14) and (15), reveals that these loading coefficients vary sharply across countries: they are not equal to one, the value imposed by the demeaning method. Similarly, Figure 2, illustrates the distribution of the cross-loading coefficients $\gamma_{i,c}^y$ and $\gamma_{i,c}^c$; they are not equal to zero, the value imposed by pre-filtering. The constraints imposed by demeaning and pre-filtering leave these estimators misspecified, and as a result these methods are incapable of filtering out the common factors from the panels.

In all cases where the regression is based on variables in levels and the *CD* test rejects cross

sectional independence of the residuals, the *CRMA* test implies that the common factors remaining in the residuals contain unit roots, and therefore the results are spurious. In regressions with stationary, differenced data, residual common factors will cause bias in the estimated coefficients due to the correlation between the residual and the regressors. In general, our diagnostic tests indicate that only the CCE estimator based on simple averaging yields statistically acceptable results.

Figure 3 illustrates the distribution of individual β_i 's across estimation techniques. It is immediately obvious that there is a remarkable heterogeneity among countries in terms of their risk-sharing coefficients, both in levels (long run) and in differences (short run). Correspondingly, the rejection of Pesaran and Yamagata's (2008) test of parameter homogeneity implies that pooled estimation is inappropriate.

In line with earlier studies, our estimation results indicate that, on average, consumption tends to be affected by idiosyncratic risks in both the short and the long-run, but the extent of risk-sharing tends to be higher in the short run. In the long-run, the fraction of unsmoothed cross sectional variation in GDP channelled to consumption is above 0.80, while it is about 0.70 in the short run. However, we should exercise caution in comparing these two figures, as a more appropriate assessment of the long term and the short term risk sharing coefficients should be embedded in an error correction model, as highlighted in Leibrecht and Scharler (2008). We will not pursue this approach here, as it goes beyond the scope of our analysis.

The similarity of the mean-group estimates across estimation methods conceals some sizable differences in the country specific estimates across methods. For the data entering the analysis in log-levels, the estimated coefficients under the demeaning method are significantly different from the CCE ones for about 50% of the countries, including Australia, Austria, Belgium, Denmark, Greece, India, Japan, Netherlands, New Zealand, Norway, USA. Thus, the CCE and the traditional demeaning method to assess the degree of risk sharing yields remarkably different conclusions for these countries.

In Table 3 and 4, more than 95% of the country-specific β_{CCE} estimates are significantly different from zero (151 out of 158), which suggests that these countries have incomplete markets. In fact, over one-third of countries exhibits dis-smoothing behavior with $\beta_{CCE} > 1$. By contrast, the β_{DEM} estimates obtained by the widely used demeaning methodology imply that a different set of countries is perfectly insured, and that there is a greater portion of countries with uninsured consumption (155 out of 158). The lack of risk sharing is also apparent when the estimates are obtained from log-differenced data: about 90% (142 out of 158) of $\beta_{CCE\Delta}$ estimates is significantly different from zero, whereas this portion is closer to 87 % (138 out of 158) for $\beta_{DEM\Delta}$. As in the long-run, the set of countries or regions exhibiting dis-smoothing behavior does not perfectly overlap across methods.

Let us now focus on the results obtained from the consistent CCE method only and look at country-specific behavior regarding risk-sharing. First, in terms of the number of countries, the extent of perfect risk sharing is higher in the short run. Also, there is a large group of countries which has over 50 % higher coefficient estimates in the long-run. Second, there are fewer countries with dis-smoothing behavior in the short-run. Still, there are some countries that show dis-smoothing behavior both in the short and the long run, such as the Bahamas, Barbados, Bermuda, Burkina Faso, China, Cuba, Djibouti, El Salvador, Ethiopia, Guinea, Hungary, Nepal, Nigeria, Sudan. Finally, countries such as Panama, Iraq, Tanzania are perfectly insured in both short and long run.

4 Conclusion

International risk sharing tests are usually based on the premise that under complete markets country specific consumption should not be affected by idiosyncratic income shocks. A prerequisite of such a test is the isolation of country specific variation in the data. We show that cross-sectional demeaning, while frequently applied in the literature, is in general insufficient to eliminate cross-sectional dependence and common factors from a panel data set. Inadequate handling of cross-sectional dependence can lead to misleading inference: the correlation of residual common factors with the regressors leaves the least square estimate biased, and if the residual common factor contains a unit root, the regression results are invalid. Our results indicate that a partial pre-filtering of the data suggested by Obstfeld (1994) is also insufficient to eliminate the cross-sectional dependence in the panel. We show that a more statistically appropriate approach is the CCE methodology of Pesaran (2006) and Kapetanios et al. (2010) that controls for global trends, and focuses on the estimation of the coefficients of consumption risk sharing. In our empirical example, we contrast the spurious estimates based on a cross-sectionally demeaned data set with the estimates obtained by the CCE approach. Although the mean group estimates are similar, the country specific estimates vary widely across estimation methods. Because cross-sectional demeaning may yield invalid results and erroneous conclusions, international risk sharing tests should be based on a method that more reliably deals with global factors. We argue and illustrate in our empirical application that the fairly simple CCE estimator is a tool that satisfies this requirement.

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Table 1: Comparison of Results: Common Factors Estimated by Simple Averages

Full Sample: 1970-2010						
	CCE	CCE_{Δ}	DEM	DEM_{Δ}	PPF	PPF_{Δ}
β_{MG}	0.83*	0.71*	0.85*	0.73*	0.83*	0.70*
CD	0.06	-0.53	11.28*	22.86*	15.27*	10.17*
$CRMA$	—	—	-1.74	—	-0.85	—
$CIPS(0)$	-21.19*	—	-9.78*	—	-15.97*	—
$CIPS(1)$	-18.52*	—	-8.16*	—	-14.03*	—
$CIPS(2)$	-12.80*	—	-6.08*	—	-12.82*	—
$CIPS(3)$	-11.15*	—	-5.23*	—	-9.38*	—
$CIPS(4)$	-5.87*	—	-2.03*	—	-5.13*	—

Truncated Sample: 1970-2007						
	CCE	CCE_{Δ}	DEM	DEM_{Δ}	PPF	PPF_{Δ}
β_{MG}	0.83*	0.72*	0.85*	0.73*	0.82*	0.70*
CD	0.36	-0.33	12.68*	23.44*	16.41*	8.74*
$CRMA$	—	—	-1.86	—	-0.80	—
$CIPS(0)$	-20.78*	—	-9.15*	—	-14.53*	—
$CIPS(1)$	-18.39*	—	-7.66*	—	-12.86*	—
$CIPS(2)$	-12.96*	—	-5.33*	—	-11.97*	—
$CIPS(3)$	-11.85*	—	-3.80*	—	-8.39*	—
$CIPS(4)$	-5.75*	—	-0.13	—	-3.96*	—

Note: β_{MG} is the mean group estimator. CCE and CCE_{Δ} are the common correlated effects estimates for the data in log-levels and in log-differences, respectively. DEM and DEM_{Δ} are estimates from a cross-sectionally demeaned regression with the data in log-levels and in log-differences, respectively. PPF and PPF_{Δ} are estimates from a partially pre-filtered regression with the data in log-levels and in log-differences, respectively. CD is Pesaran's (2004) cross-sectional independence test. The null hypothesis is cross-sectional independence. $CRMA$ is Sul's (2009) unit root test for the common factors. $CIPS(p)$ statistics are the cross-sectional averages of cross-sectionally augmented Dickey Fuller ($CADF(p)$) statistics (Pesaran, 2007). The null hypothesis is that all series are non-stationary; the alternative hypothesis is that some series are stationary. Statistical significance at the 5% level or lower is denoted by*.

Table 2: Comparison of Results: Common Factors Estimated by Weighted Averages

Full Sample: 1970-2010						
	<i>CCE</i>	<i>CCE</i> $_{\Delta}$	<i>DEM</i>	<i>DEM</i> $_{\Delta}$	<i>PPF</i>	<i>PPF</i> $_{\Delta}$
β_{MG}	0.85*	0.71*	0.88*	0.75*	0.84*	0.70*
<i>CD</i>	5.06*	3.80*	10.11*	17.24*	6.76*	9.12*
<i>CRMA</i>	-1.45	—	-1.62	—	-1.57	—
<i>CIPS</i> (0)	-20.64*	—	-9.52*	—	-17.33*	—
<i>CIPS</i> (1)	-17.62*	—	-8.76*	—	-17.15*	—
<i>CIPS</i> (2)	-13.28*	—	-5.34*	—	-13.89*	—
<i>CIPS</i> (3)	-10.45*	—	-4.04*	—	-11.49*	—
<i>CIPS</i> (4)	-7.39*	—	-3.31*	—	-9.67*	—

Truncated Sample: 1970-2007						
	<i>CCE</i>	<i>CCE</i> $_{\Delta}$	<i>DEM</i>	<i>DEM</i> $_{\Delta}$	<i>PPF</i>	<i>PPF</i> $_{\Delta}$
β_{MG}	0.85*	0.71*	0.88*	0.74*	0.84*	0.70*
<i>CD</i>	5.55*	4.14*	11.00*	14.60*	7.58*	6.33*
<i>CRMA</i>	-1.15	—	-1.78	—	-1.45	—
<i>CIPS</i> (0)	-20.85*	—	-10.33*	—	-16.00*	—
<i>CIPS</i> (1)	-17.72*	—	-9.27*	—	-15.79*	—
<i>CIPS</i> (2)	-12.69*	—	-6.37*	—	-12.61*	—
<i>CIPS</i> (3)	-9.89*	—	-5.19*	—	-10.29*	—
<i>CIPS</i> (4)	-6.35*	—	-4.25*	—	-8.83*	—

Note: β_{MG} is the mean group estimator. *CCE* and *CCE* $_{\Delta}$ are the common correlated effects estimates for the data in log-levels and in log-differences, respectively. *DEM* and *DEM* $_{\Delta}$ are estimates from a cross-sectionally demeaned regression with the data in log-levels and in log-differences, respectively. *PPF* and *PPF* $_{\Delta}$ are estimates from a partially pre-filtered regression with the data in log-levels and in log-differences, respectively. *CD* is Pesaran's (2004) cross-sectional independence test. The null hypothesis is cross-sectional independence. *CRMA* is Sul's (2009) unit root test for the common factors. *CIPS*(*p*) statistics are the cross-sectional averages of cross-sectionally augmented Dickey Fuller (*CADF*(*p*)) statistics (Pesaran, 2007). The null hypothesis is that all series are non-stationary; the alternative hypothesis is that some series are stationary. Statistical significance at the 5% level or lower is denoted by*.

Table 3: Comparison of country-specific coefficient estimates

id	country	β_{CCE}	β_{DEM}	$\beta_{CCE\Delta}$	$\beta_{DEM\Delta}$	id	country	β_{CCE}	β_{DEM}	$\beta_{CCE\Delta}$	$\beta_{DEM\Delta}$
1	AFG ¹	0.87*	0.77*	0.94*	0.93*	41	DOM	0.90*	0.72*	0.98*	0.98*
2	AGO	2.00*	1.86*	0.00	0.34	42	DZA	1.48*	1.86*	0.07	0.04
3	ALB	0.18*	0.25	0.28*	0.25*	43	ECU	0.71*	0.72*	0.50*	0.50*
4	ARG	0.97*	0.82*	1.28*	1.30*	44	EGY	0.68*	0.63*	0.33*	0.40*
5	ATG ¹	0.99*	0.60*	1.83*	1.84*	45	ESP ¹	0.89*	0.98*	0.85*	0.96*
6	AUS ¹	0.42*	0.75*	0.09	0.14	46	ETH ¹	1.10*	0.97*	1.00*	1.02*
7	AUT ¹	1.11*	0.87*	0.68*	0.78*	47	FIN	0.81*	0.87*	0.47*	0.46*
8	BDI	0.86*	0.87*	1.00*	0.97*	48	FJI ¹	0.64*	-0.26	0.52*	0.66*
9	BEL ^{1,2}	0.98*	0.79*	0.37*	0.70*	49	FRA ²	1.02*	1.08*	0.69*	0.90*
10	BEN	0.80*	0.79*	0.67*	0.71*	50	FSM ¹	1.03*	1.11*	0.97*	1.00*
11	BFA	1.96*	2.13*	1.16*	1.28*	51	GAB ¹	0.34*	1.03*	-0.16	-0.19
12	BGD ¹	1.61*	1.23*	0.99*	1.02*	52	GBR ¹	1.13*	1.21*	0.94*	1.04*
13	BGR	1.01*	1.08*	0.67*	0.68*	53	GER ²	1.16*	1.13*	0.54*	0.78*
14	BHR ¹	0.64*	1.34*	0.72*	0.71*	54	GHA	1.00*	1.02*	0.80*	0.89*
15	BHS ¹	1.42*	1.15*	1.27*	1.28*	55	GIN	1.56*	1.40*	1.32*	1.10*
16	BLZ ¹	1.22*	0.96*	0.96*	0.98*	56	GMB	0.85*	1.01*	0.95*	0.86*
17	BMU	1.47*	1.51*	1.00*	0.95*	57	GNB ¹	0.99*	0.59*	0.65*	0.71*
18	BOL ¹	0.64*	0.97*	0.81*	0.82*	58	GNQ ¹	0.67*	0.40*	0.73*	0.83*
19	BRA	0.83*	0.74*	0.93*	0.96*	59	GRC ¹	0.20	1.14*	0.49*	0.48*
20	BRB	1.59*	1.51*	1.25*	1.19*	60	GRD ¹	0.46*	0.97*	0.81*	0.80*
21	BRN ¹	-0.90*	-0.24*	0.67	0.51	61	GTM ¹	0.86*	0.75*	0.73*	0.64*
22	BTN	0.56*	0.52*	0.60*	0.56*	62	GUY	1.15*	1.08*	0.97*	0.94*
23	BWA ¹	0.40*	0.58*	0.25*	0.29*	63	HKG ¹	1.22*	1.07*	0.93*	0.93*
24	CAF ¹	0.92*	0.73*	0.78*	0.78*	64	HND ¹	1.00*	0.78*	-0.20	-0.14
25	CAN	0.41*	0.38*	0.52*	0.69*	65	HTI ¹	0.97*	0.62*	1.22*	1.19*
26	CHE ¹	0.23*	0.71*	0.22*	0.35*	66	HUN	1.02*	0.91*	1.02*	0.96*
27	CHL ¹	0.96*	0.81*	0.88*	0.88*	67	IDN ¹	1.09*	1.34*	0.62*	0.68*
28	CHN ¹	1.00*	0.96*	1.01*	1.01*	68	IND ¹	0.95*	0.80*	0.62*	0.64*
29	CIV	0.76*	0.93*	0.86*	0.89*	69	IRL	0.64*	0.66*	0.60*	0.64*
30	CMR	0.97*	0.96*	0.73*	0.74*	70	IRN ¹	0.59*	0.14	0.47*	0.43*
31	COG ¹	0.46*	1.08*	0.31*	0.26	71	IRQ	-0.08	-0.28	0.27	0.20
32	COL	0.92*	0.86*	0.80*	0.78*	72	ISL	1.25*	1.26*	0.90*	0.91*
33	COM	0.40*	0.43*	0.22	0.23	73	ISR	1.08*	1.21*	0.91*	0.97*
34	CPV	0.99*	1.02*	0.63*	0.68*	74	ITA	1.00*	1.01*	0.68*	0.83*
35	CRI ¹	0.93*	1.26*	1.13*	1.14*	75	JAM	0.88*	0.73*	1.06*	0.88*
36	CUB ¹	1.16*	1.04*	1.13*	1.10*	76	JOR	1.34*	1.37*	0.59*	0.58*
37	CYP ¹	0.87*	1.05*	0.78*	0.79*	77	JPN ¹	0.86*	0.92*	0.62*	0.68*
38	DJI	1.25*	1.06*	1.08*	0.84*	78	KEN	1.08*	0.76*	1.53*	1.47*
39	DMA ¹	0.62*	0.93*	0.48	0.42	79	KHM	0.94*	0.90*	1.00*	0.99*
40	DNK ¹	0.53*	0.44*	0.66*	0.78*	80	KIR ¹	0.67*	0.36*	0.42*	0.38*

Note: Statistical significance at the 5% level or lower is denoted by *. β_{CCE} and β_{DEM} denote the CCE estimates and estimates from cross-sectionally demeaned panels, respectively, with the data in log-levels. $\beta_{CCE\Delta}$ and $\beta_{DEM\Delta}$ denote the CCE estimates and estimates from cross-sectionally demeaned panels, respectively, with the data entering estimation in log-differenced form. The superscripts next to the country code indicates that: (1) the 95% confidence interval around β_{CCE} does not contain β_{DEM} , (2) the 95% confidence interval around $\beta_{CCE\Delta}$ does not contain $\beta_{DEM\Delta}$.

Table 4: Comparison of country-specific coefficient estimates (continued)

id	country	β_{CCE}	β_{DEM}	$\beta_{CCE\Delta}$	$\beta_{DEM\Delta}$	id	country	β_{CCE}	β_{DEM}	$\beta_{CCE\Delta}$	$\beta_{DEM\Delta}$
81	KNA	0.80*	0.76*	-0.13	-0.12	121	PRT ¹	0.81*	0.91*	0.58*	0.67*
82	KOR	0.84*	0.82*	0.81*	0.89*	122	PRY	0.77*	0.67*	0.40	0.29
83	LAO	0.85*	0.67*	1.07*	1.01*	123	ROM ¹	0.50*	0.71*	0.68*	0.77*
84	LBN	0.84*	0.85*	0.89*	0.89*	124	RWA ¹	0.59*	1.08*	0.17*	0.16*
85	LBR ¹	1.15*	0.83*	0.86*	0.94*	125	SDN	1.01*	0.98*	1.44*	1.41*
86	LCA ¹	0.70*	0.49*	0.70*	0.71*	126	SEN ¹	0.88*	1.10*	0.47*	0.45*
87	LKA	1.10*	1.03*	0.25	0.25	127	SGP	0.73*	0.66*	0.43*	0.46*
88	LSO ¹	1.05*	0.55*	0.51*	0.51*	128	SLB	1.04*	0.94*	0.53	0.45
89	LUX	0.69*	0.58*	0.25*	0.36*	129	SLE ¹	0.67*	1.17*	0.70*	0.73*
90	MAC	1.00*	0.74*	0.29*	0.26*	130	SLV	1.32*	1.25*	1.19*	1.28*
91	MAR ¹	0.34*	0.12	0.51*	0.47*	131	SOM	0.95*	1.01*	0.97*	0.89*
92	MDG	1.17*	1.15*	0.06	0.07	132	STP ¹	1.19*	0.88*	1.32*	1.31*
93	MDV	0.96*	0.89*	0.64*	0.63*	133	SUR ¹	1.30*	2.33*	2.10*	2.21*
94	MEX	0.80*	0.76*	0.85*	0.86*	134	SWE	0.67*	0.57*	0.64*	0.78*
95	MHL ¹	1.34*	0.64*	0.22	0.23	135	SWZ	0.40*	0.53*	0.29	0.31
96	MLI ¹	-0.17	-0.60*	0.02	-0.04	136	SYC ¹	1.08*	0.89*	0.83*	0.86*
97	MLT ¹	0.75*	0.93*	0.68*	0.68*	137	SYR	0.78*	0.79*	0.98*	0.95*
98	MNG	0.67*	0.68*	1.45*	1.33*	138	TCD ¹	0.47*	0.67*	0.53*	0.55*
99	MOZ ¹	0.89*	0.74*	0.80*	0.76*	139	TGO ¹	0.33*	0.60*	0.80*	0.75*
100	MRT	0.80*	0.75*	0.88*	0.91*	140	THA	0.78*	0.80*	0.66*	0.70*
101	MUS	0.84*	0.97*	0.70*	0.76*	141	TON	0.92*	0.89*	0.65*	0.67*
102	MWI ¹	0.44*	0.63*	0.56*	0.56*	142	TTO	0.93*	0.86*	0.53*	0.58*
103	MYS ¹	0.54*	0.74*	0.94*	0.94*	143	TUN ¹	0.64*	1.65*	0.31*	0.32*
104	NAM	1.03*	1.16*	0.94*	0.89*	144	TUR	0.72*	0.66*	1.09*	1.07*
105	NER ¹	0.32*	0.57*	1.17*	1.05*	145	TWN ¹	1.12*	0.99*	0.63*	0.74*
106	NGA	1.13*	1.22*	1.33*	1.23*	146	TZA ¹	-0.04	-0.41	0.08	0.14
107	NIC	0.72*	0.86*	0.38*	0.35*	147	UGA ¹	0.97*	1.05*	0.99*	1.02*
108	NLD ¹	0.72*	0.57*	0.77*	0.94*	148	URY	1.00*	0.99*	0.96*	0.95*
109	NOR ¹	0.38*	0.72*	0.61*	0.61*	149	USA ^{1,2}	0.91*	1.05*	0.72*	0.86*
110	NPL	1.10*	0.93*	1.20*	1.23*	150	VCT	0.74*	0.87*	1.14*	1.13*
111	NZL ¹	0.95*	1.18*	0.82*	0.86*	151	VEN ¹	1.02*	0.36*	0.68*	0.57*
112	OMN ¹	1.26*	1.97*	0.32	0.55	152	VNM ¹	0.55*	0.65*	0.80*	0.75*
113	PAK	0.59*	0.64*	0.99*	0.91*	153	VUT	0.78*	0.76*	0.79*	0.81*
114	PAN	0.15	0.27*	0.06	0.09	154	WSM	0.95*	0.82*	0.90*	0.90*
115	PER ¹	0.95*	1.14*	0.96*	0.97*	155	ZAF	0.67*	0.66*	0.71*	0.59*
116	PHL	0.29*	0.26*	0.29*	0.29*	156	ZAR ¹	0.63*	0.83*	0.19	0.17
117	PLW	0.45	0.64*	-0.97*	-0.91*	157	ZMB	0.88*	0.77*	1.34*	1.29*
118	PNG	0.96*	0.93*	0.58*	0.48	158	ZWE ¹	0.24	0.70*	0.73*	0.73*
119	POL ¹	0.93*	1.02*	1.08*	1.07*						
120	PRI ¹	0.55*	0.65*	0.35*	0.43*						

Note: Statistical significance at the 5% level or lower is denoted by *. β_{CCE} and β_{DEM} denote the CCE estimates and estimates from cross-sectionally demeaned panels, respectively, with the data in log-levels. $\beta_{CCE\Delta}$ and $\beta_{DEM\Delta}$ denote the CCE estimates and estimates from cross-sectionally demeaned panels, respectively, with the data entering estimation in log-differenced form. The superscripts next to the country code indicates that: (1) the 95% confidence interval around β_{CCE} does not contain β_{DEM} , (2) the 95% confidence interval around $\beta_{CCE\Delta}$ does not contain $\beta_{DEM\Delta}$.

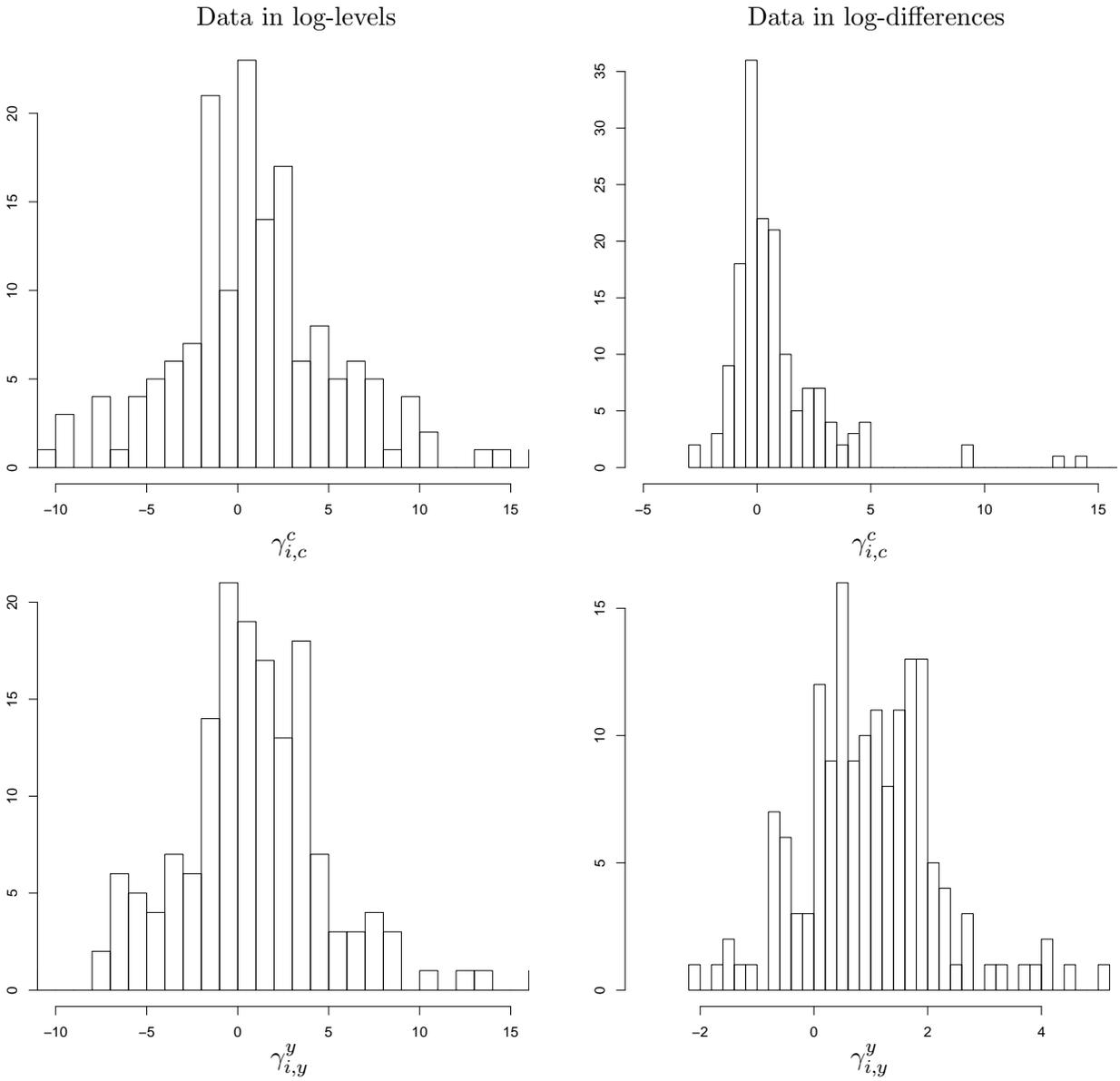


Figure 1: Distribution of the $\gamma_{i,c}^c$ and $\gamma_{i,y}^y$ loading coefficient estimates in equations (14) and (15).

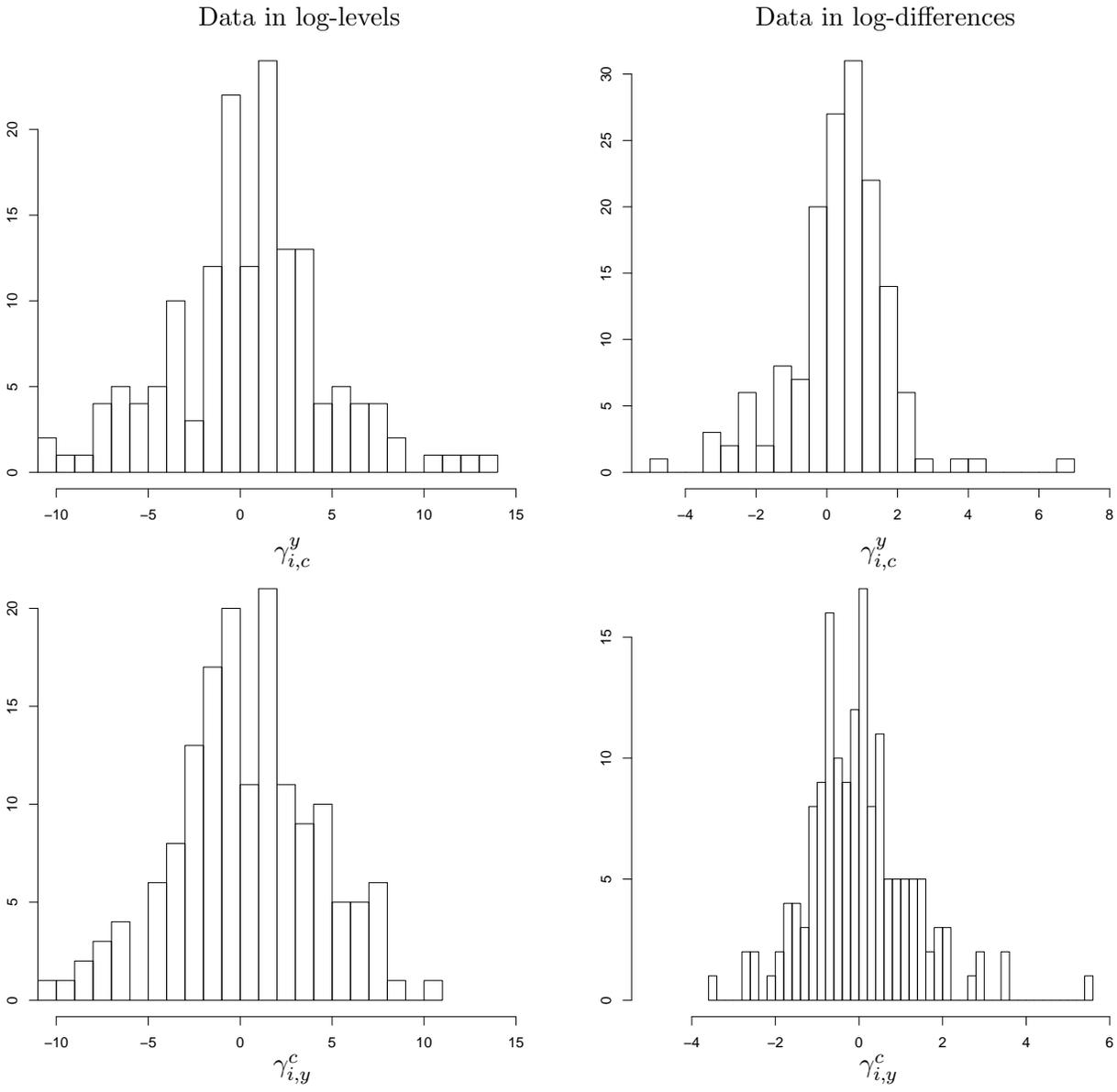


Figure 2: Distribution of the $\gamma_{i,c}^y$ and $\gamma_{i,y}^c$ loading coefficient estimates in equations (14) and (15).

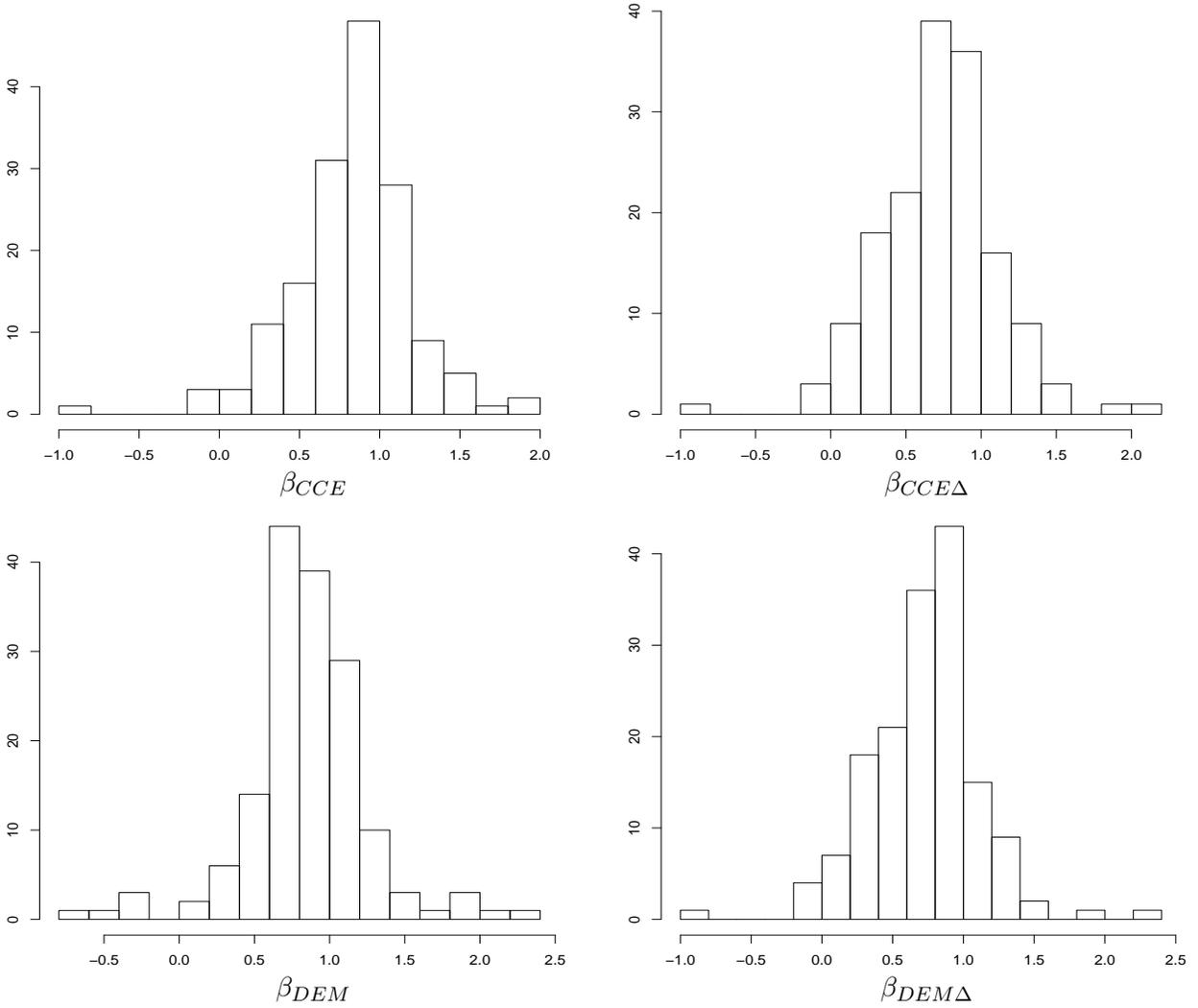


Figure 3: Distribution of country specific coefficient estimates. β_{CCE} and β_{DEM} denote the CCE estimates and estimates from cross-sectionally demeaned panels, respectively, with the data in log-levels. $\beta_{CCE\Delta}$ and $\beta_{DEM\Delta}$ denote the CCE estimates and estimates from cross-sectionally demeaned panels, respectively, with the data entering estimation in log-differenced form.