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Common Correlated Effects and International Risk Sharing

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Common Correlated Effects and International Risk Sharing

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Abstract

Existing studies of risk pooling among groups of countries are predicated upon the highly restrictive assumption that all countries have symmetric responses to aggregate shocks. We show that the conventional risk sharing test fails to isolate idiosyncratic fluctuations within countries and produces spurious results. To avoid these problems, we propose an alternative form of the risk sharing test that is robust to heterogeneous country characteristics. In our empirical example, we provide estimates using the proposed approach for various groupings of 158 countries.

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. The underlying theory suggests that if a country has full access to risk sharing opportunities, consumption will be independent of domestic income shocks and follow aggregate consumption in the reference area. With idiosyncratic risk diversified away, consumption growth rates become perfectly correlated across individual countries.

Although countries are only affected by aggregate risk under the risk sharing hypothesis, the impact of global shocks may not have a uniform distribution across across the world. Because of differences in their productive and financial structure, regulations, and their participation in international trade, countries may be affected by aggregate shocks to varying degrees. For example, a country with a disproportionally large export sector may face greater fluctuations caused by aggregate sources than a country that does not participate in international trade. In principle, due to their structure, some countries might not be exposed to aggregate risk at all, or may exhibit an inverse relationship, in that their GDP could react counter-cyclically to common risk factors. A distinguishing feature of our paper is that we take into account such variation in the impact of global shocks across countries.

We propose an alternative approach for testing the risk sharing hypothesis within a heterogeneous set of economies. To be able to determine whether consumption is smoothed by international risk sharing, one first needs to disentangle the common and idiosyncratic shocks affecting individual countries. We argue that the appropriate method for filtering out the unobserved common factors from the observed variables should allow for the heterogeneity of countries in terms of their exposure to aggregate risk. In contrast to the existing literature, we let global factors have country specific effects on the analyzed variables. Consequently, our approach is better able to isolate idiosyncratic shocks than the cross-sectional demeaning method conventionally used in risk sharing tests.

Similarly to other empirical studies, we find little evidence in support of full international risk pooling. Idiosyncratic risk may not be eliminated for a variety of reasons, including incomplete financial or real markets, limited participation in those markets, absence of intra or inter generational transfers, and limited saving opportunities. Still, even though full insurance appears to be a theoretical curiosity in the absence of complete markets, studying the extent to which idiosyncratic risk affects consumption can shed light on the attained degree of diversification. The rest of the paper is organized as follows: Section 2 reviews the theoretical background of risk sharing tests, Section 3 introduces our empirical strategy, Section 4 discusses the results, and Section 5 concludes.

2 Theoretical Background

Regression based risk sharing (or consumption insurance) tests are based on the null hypothesis of market completeness, or the possibility to redistribute wealth (hence, consumption) across all date-event pairs. Under market completeness, the solution to the representative agent's maximization problem ensures that marginal utility growth is equalized across agents, and depends on aggregate factors but not on individual shocks (Cochrane, 1991; Mace, 1991; Obstfeld, 1994). Assuming CRRA utility functions, the risk sharing hypothesis can be based on estimating the following equation

$$c_{it} = \alpha_i + \gamma_i^c \bar{c}_t + \beta_i x_{it} + \varepsilon_{it} \ , \ i = 1 \ldots N, \ t = 1 \ldots T \ , \tag{1}$$

where c_{it} is a consumption measure for country i, $\bar{c}_{\cdot t}$ is an aggregate measure of consumption, and x_{it} is an idiosyncratic variable. Market completeness implies $\gamma_i^c > 0$ and $\beta_i = 0$. If the discount factors and the coefficients of relative risk aversion are assumed to be equal across countries, the coefficients γ_i^c can be shown to take a unit value. However, such homogeneity is unlikely in reality: Obstfeld (1989) found some evidence against the hypothesis of $\gamma_i^c = 1$ even in countries with similar characteristics, such as Germany, Japan and the United States. Nevertheless, most papers in the field have built on these assumptions, under which the test equation becomes

$$c_{it} - \bar{c}_{t} = \alpha_i + \beta_i x_{it} + \varepsilon_{it} \ . \tag{2}$$

The consumption risk sharing test is based on the null hypothesis $H_0 : \beta_i = 0$, where β_i can be regarded as the extent of the departure from perfect risk sharing. The rejection of the null hypothesis implies that agents do not use an insurance mechanism to fully offset idiosyncratic shocks to their endowments, which are consequently transmitted to consumption. Asdrubali et al. (1996); Crucini (1999); Crucini and Hess (2000); Grimard (1997); Jalan and Ravallion (1999) and many others in the last decade have gone even further by suggesting that the relative size of the estimated slope coefficient can be interpreted as a measure of the degree of insurance or risk pooling.

In virtually all macroeconomic implementations of equation (2), the 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

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

where y_{it} is an income measure for country i, and $\bar{y}_{\cdot t}$ 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 can be interpreted as the effect of idiosyncratic real GDP growth on idiosyncratic consumption growth in country i. If the aggregates, $\bar{c}_{\cdot t}$ and $\bar{y}_{\cdot t}$, are cross-sectional means, then the differencing operations in equation (3) will produce cross-sectionally demeaned variables. Other 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) with an implicit one by including a time dummy d_t in the pooled regression

$$c_{it} = \alpha_i + d_t + \beta y_{it} + \varepsilon_{it} \ . \tag{4}$$

Artis and Hoffmann (2007) derive equation (3) by relying on an alternative theoretical framework proposed by Crucini (1999). They model country specific income, y_{it}, as a mixture of the level of pooled real GDP in participating countries and the level of domestic real GDP. They obtain their results for the perfectly symmetric case where each country is assumed to pool the same proportion of its income. However, similarly to the assumption of equal discount factors and coefficients of risk aversion across countries in the classical framework, this assumption is also likely to be overly restrictive when the analysis is carried out with a heterogeneous set of economies.

We propose to deal with the cross-sectional variation in country characteristics and the estimation of idiosyncratic effects by taking advantage of an unobserved component model. Although neither aggregate nor idiosyncratic shocks are directly measured, a particular country's observed income, y_{it}, can be decomposed into two analogous unobserved components. By definition, pooled income will follow global cycles that can be captured by common factors, $\boldsymbol{f}_t$, and its contribution to a particular country's observed income can be measured by the factor loadings, $\boldsymbol{\lambda}_{i,y}$,

$$y_{it} = \boldsymbol{\lambda}'_{i,y} \boldsymbol{f}_t + \xi^y_{it} \ , \tag{5}$$

where $\boldsymbol{\lambda}_{i,y}$ allows countries to be heterogeneous in terms of their sensitivity to global shocks. The term $\boldsymbol{\lambda}'_{i,y} \boldsymbol{f}_t$ yields the amount of fully diversified income for country i, and the balance, $\xi^y_{it} = y_{it} - \boldsymbol{\lambda}'_{i,y} \boldsymbol{f}_t$, is the idiosyncratic income. Applying a similar logic to the calculation of idiosyncratic consumption, and approximating the common factors with cross-sectional means of the variables, we obtain the more general model

$$c_{it} - \gamma^c_i \bar{c}_t = \alpha_i + \beta_i (y_{it} - \tilde{\gamma}^y_i \bar{y}_t) + \varepsilon_{it} \ , \tag{6}$$

or

$$c_{it} = \alpha_i + \beta_i y_{it} + \gamma_i^c \bar{c}_t + \gamma_i^y \bar{y}_t + \varepsilon_{it} \ , \tag{7}$$

where the β_i coefficient measures the extent to which idiosyncratic shocks to income are channeled into idioscyncratic consumption. The country specific $\gamma_i^y = -\beta_i \tilde{\gamma}_i^y$ and γ_i^c coefficients allow the amount of income and consumption driven by global shocks to vary across countries. A more detailed discussion of this model follows in Section 3.

When countries are heterogeneous in terms of their pooled resources and their sensitivity to aggregate fluctuations, consumption insurance tests based on equations (3) or (4) may suffer from inadequate handling of global shocks and produce misleading inference. Specifically, risk sharing tests require the isolation of idiosyncratic shocks, but simple cross-sectional differencing with respect to an aggregate measure may be insufficient for this purpose if the effect of global shocks varies across countries. In Section 3 we describe in greater detail the proposed approach to deal with cross-sectional dependence among heterogeneous countries. Our method parallels 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.

3 Empirical Strategy

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 the cross-sectional units, and has been shown to have good finite sample properties in heterogeneous panels. If the null hypothesis of cross-sectional independence is rejected, the co-movement of variables across countries may be modeled by common factors, and 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 panels, is an ideal tool for estimating β_i, the effect of idiosyncratic income on idiosyncratic consumption. 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 caused by common factors in the panel regression

$$c_{it} = \alpha_i + \beta_i y_{it} + u_{it} \ , \ i = 1, 2, \ldots, N \ , \ t = 1, 2, \ldots, T \ . \tag{8}$$

The regressor, y_{it}, is assumed to be generated as

$$y_{it} = a_{i,y} + \boldsymbol{\lambda}'_{i,y} \boldsymbol{f}_t + \xi^y_{it} \ , \tag{9}$$

where $a_{i,y}$ is an individual effect, and $\boldsymbol{f}_t$ is an $m \times 1$ vector of unobserved common effects with individual specific loading vector $\boldsymbol{\lambda}_{i,y}$. The idiosyncratic component ξ^y_{it} is distributed independently of the common effects and across i, and is assumed to follow a covariance stationary process. The error term u_{it} is assumed to have the following structure

$$u_{it} = \boldsymbol{\omega}'_i \boldsymbol{f}_t + \varepsilon_{it} \ , \tag{10}$$

where $\boldsymbol{\omega}_i$ is a $m \times 1$ loading vector capturing the individual specific effect of the common factors $\boldsymbol{f}_t$, and ε_{it} are idiosyncratic errors assumed to be distributed independently of y_{it} and $\boldsymbol{f}_t$. The error term, 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,

$$\hat{\beta}_i = (\boldsymbol{y}_i'\bar{\boldsymbol{M}}\boldsymbol{y}_i)^{-1}\boldsymbol{y}_i'\bar{\boldsymbol{M}}\boldsymbol{c}_i \ , \tag{11}$$

where $\boldsymbol{y}_i = (y_{i1}, y_{i2}, \ldots, y_{iT})'$, $\boldsymbol{c}_i = (c_{i1}, c_{i2}, \ldots, c_{iT})'$, and $\bar{\boldsymbol{M}} = \boldsymbol{I}_T - \bar{\boldsymbol{H}}(\bar{\boldsymbol{H}}'\bar{\boldsymbol{H}})^{-1}\bar{\boldsymbol{H}}'$ with $\bar{\boldsymbol{H}} = (\boldsymbol{\iota}, \bar{\boldsymbol{y}}, \bar{\boldsymbol{c}})$. $\boldsymbol{I}_T$ is a $T \times T$ identity matrix, and $\boldsymbol{\iota}$ is a $T \times 1$ vector of ones. $\bar{\boldsymbol{y}}$ is a $T \times 1$ matrix of cross-sectional means of the regressor, and $\bar{\boldsymbol{c}}$ is a $T \times 1$ vector of cross-sectional means of the dependent variable. The term $\bar{\boldsymbol{M}}\boldsymbol{y}_i$ acts as an "instrument" that controls for the unobserved common factors in the variables and the errors.

The CCE estimator is equivalent to ordinary least squares applied to an auxiliary regression augmented with the cross-sectional means of the variables. In other words, (11) applied to (8) produces β_i estimates that are identical to ordinary least squares estimates of β_i in our proposed model (7). The CCE estimator partitions the regression in (7) by projecting consumption and income orthogonally with respect to their cross-sectional means using the $\bar{\boldsymbol{M}}$ matrix. The estimation can be broken down 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

$$c_{it} = a_{i,c} + \lambda_{i,c}^{c}\bar{c}_t + \lambda_{i,c}^{y}\bar{y}_t + \xi_{it}^{c} \ , \tag{12}$$

$$y_{it} = a_{i,y} + \lambda_{i,y}^{c}\bar{c}_t + \lambda_{i,y}^{y}\bar{y}_t + \xi_{it}^{y} \ . \tag{13}$$

In the second stage, the CCE estimate of an individual β_i is obtained by regressing the residual $\hat{\xi}_{it}^{c}$, capturing idiosyncratic consumption, on the residual $\hat{\xi}_{it}^{y}$, capturing idiosyncratic income. Because the consumption and income aggregates tend to be highly collinear, the λ coefficients in (12) and (13) are estimated imprecisely and therefore can not be meaningfully interpreted. However, as collinearity does not affect the residuals, $\hat{\xi}_{it}^{c}$ and $\hat{\xi}_{it}^{y}$ can be considered valid estimates of the idiosyncratic components and can be compared to cross-sectionally demeaned consumption and income. The latter may not be free of aggregate shocks: if the effect of global cycles varies across countries, cross-sectional demeaning will not be able to isolate the idiosyncratic variation in the data and will therefore lead to biased conclusions about the extent of risk sharing.

Most empirical analyses focus on testing the risk sharing hypothesis with differenced data. However, several recent studies, including Becker and Hoffmann (2006) and Artis and Hoffmann (2012), have examined the implications of risk sharing in the long run by exploiting the information contained in the levels of the variables. Conveniently, our proposed testing procedure does not depend on the transformation of the variables: Kapetanios et al. (2010) proved that the CCE estimators are consistent regardless of whether the common factors, $\boldsymbol{f}_t$, are stationary or non-stationary. However, consistent estimation of the model parameters requires that the regression residuals be stationary. The rejection of a unit root in ε_{it} (in equations 7 and 10) implies that c_{it}, y_{it}, and $\boldsymbol{f}_t$ are cointegrated.

As illustrated by Leibrecht and Scharler (2008) and Pierucci and Ventura (2010), cointegration can be exploited in an error correction model to obtain additional information about risk sharing. For an individual country, the deviation from the long run equilibrium relationship between idiosyncratic income and consumption is captured by the residual, $\hat{\varepsilon}_{it}$, in equation (7). The speed at which this equilibrium error is corrected, κ, can then be estimated along with the extent of risk sharing in the short run, β_i^{SR}, in the following error-correction model

$$\Delta c_{it} - \gamma_i^{c,SR}\overline{\Delta c_t} = \alpha_i^{SR} + \kappa\hat{\varepsilon}_{it}^{LR} + \beta_i^{SR}(\Delta y_{it} - \tilde{\gamma}_i^{y,SR}\overline{\Delta y_t}) + \varepsilon_{it}^{SR} \ , \tag{14}$$

or

$$\Delta c_{it} = \alpha_i^{SR} + \kappa\hat{\varepsilon}_{it}^{LR} + \beta_i^{SR}\Delta y_{it} + \gamma_i^{c,SR}\overline{\Delta c_t} + \gamma_i^{y,SR}\overline{\Delta y_t} + \varepsilon_{it}^{SR} \ , \tag{15}$$

where $\hat{\varepsilon}_{it}^{LR} = c_{it} - \hat{\alpha}_i^{LR} - \hat{\beta}_i^{LR}y_{it} - \hat{\gamma}_i^{c,LR}\bar{c}_t - \hat{\gamma}_i^{y,LR}\bar{y}_t$. Short run risk sharing tests also require the isolation of idiosyncratic effects. Here, the heterogeneous impact of global shocks is filtered out by including in the regression the cross-sectional means of differenced consumption and income, $\overline{\Delta c_t}$ and $\overline{\Delta y_t}$, with country specific coefficients, $\gamma_i^{c,SR}$ and $\gamma_i^{y,SR}$, respectively.

Under a random coefficient model, the simple averages of the individual CCE estimators of β_i^{LR} and β_i^{SR} are consistent estimators of the overall β^{LR} and β^{SR}, respectively. These mean group estimators are defined as

$$\hat{\beta}_{MG}^{LR} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i^{LR} \quad \text{and} \quad \hat{\beta}_{MG}^{SR} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i^{SR} \ . \tag{16}$$

The CCE estimator admits both simple and weighted cross-sectional averages in the $\bar{\boldsymbol{M}}$ 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

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

where C stands for consumption per capita, and N stands for population. This weighting scheme overweights countries with large population. If some of these countries are atypical in terms of their participation in the global pool of resources, inference will be distorted. Specifically, if the proxies for the common factors are biased towards outliers, the CCE procedure will not be able to isolate the idiosyncratic effects in individual countries and eliminate cross-sectional dependence in the panel.

An additional source of bias may be the log-transformation required by most macroeconomic variables, such as consumption and income, before they can be analyzed in linear models. Such non-linear transformation will affect the location of the aggregate measure relative to the cross-sectional distribution of the country level variables, and further distort inference. These complications can be avoided if the cross-sectional means entering the $\bar{\boldsymbol{M}}$ matrix are obtained by applying simple averages to previously log-transformed country level series. Having described the correspondence between our proposed testing approach and the CCE methodology, we now turn to our empirical study and report estimation results in the next section.

4 Data and Results

Our analysis is based on annual data 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. We use the sub-period 1970 - 2010, which yields 158 countries with continuously available annual data. The analysis of such a large heterogeneous panel is a distinguishing feature of our study; the existing literature largely focuses on smaller sets of rather homogeneous countries.

[Insert Table 1 about here]

From the Penn World Tables we use purchasing power parity converted GDP per capita and consumption per capita at 2005 constant prices. The analyzed series are comparable to those in other datasets, such as the World Bank's World Development Indicators. They are expressed in real terms in a common currency, so as to make comparisons across countries and time feasible. Because these variables tend to exhibit exponential growth, we apply a log-transformation to them in our analysis. The diagnostic statistics displayed in Table 1 indicate that the log transformed consumption and income levels are cross-sectionally dependent and non-stationary. The log-differenced series are also cross-sectionally dependent, but they do not contain unit roots.

[Insert Table 2 about here]

Table 2 displays the results of diagnostic tests applied to the residuals in equations (3), (7), and (15). The first two regressions are evaluated with both the data in log-levels and in log-differences. To verify the robustness of the results, we repeat the analysis for a truncated sample excluding the Great Recession. In each regression, we test the residuals for cross-sectional dependence and non-stationarity. For the former, we use the CD statistic proposed by Pesaran (2004). For the latter, we use the $CIPS$ statistic of Pesaran (2007), and if the CD test rejects the null hypothesis of cross-sectional independence, we test the cross-sectional average of the residuals for unit roots using the $CRMA$ test of Sul (2009).

The rejection of the CD test for the residuals of the cross-sectionally demeaned regressions indicates that equation (3) is not able to fully isolate the idiosyncratic fluctuations in the variables. In other words, the unit coefficients imposed on the aggregates do not reflect the true influence of global shocks on country level variables, and they give rise to residual common factors in the regression.[1] The estimated coefficients will be biased if the global shocks are not fully filtered out from the variables because $\hat{\beta}_i$ will, at least in part, attribute aggregate fluctuations in consumption to aggregate fluctuations in income. Global factors are essentially lurking variables that confound the relationship between the regressor and the dependent variable. Moreover, when the regression is based on variables in log-levels and the CD test rejects cross sectional independence, the $CRMA$ test indicates that the common factors remaining in the residuals contain unit roots. Consequently, our diagnostic tests indicate that only models augmented by simple cross-sectional averages, equations (7) and (15), yield statistically acceptable results.

Given their great diversity, the countries in our analysis vary in terms of their susceptibility to global shocks. If the countries were homogeneous, in terms of risk aversion, time preference and endowments, the global shocks would have a unit loading for each country, and cross-sectional demeaning would be an appropriate method to calculate the idiosyncratic components. However, when they are heterogeneous, and the impact of global shocks differs across countries, the first stage regressions (12) and (13) are more appropriate to estimate idiosyncratic variation. To illustrate the disagreement between the two methods in our heterogeneous data set, we examine the correlation of the idiosyncratic components estimated

[1]This also remains the case when the common trends are approximated by population weighted cross-sectional averages. In fact, under the population weighting scheme even the residuals in equations (7) and (15) are cross-sectionally dependent, which suggests that some countries with large population are not typical in terms of risk sharing. Under these circumstances, population weights are inappropriate for the approximation of common factors in per capita GDP and consumption.

by the first stage regressions and cross-sectional demeaning.

[Insert Figure 1 about here]

Figure 1 shows the distribution of the correlation coefficients $Cor(\hat{\xi}^c_{it}, c_{it}-\bar{c}_t)$ and $Cor(\hat{\xi}^y_{it}, y_{it}-\bar{y}_t)$ when the data is in log-levels. The correlation between the two types of estimates of the idiosyncratic components is below 0.80 for over two thirds of the countries. The correlation is close to unity if the country specific income and consumption closely mimic their aggregate counterparts, but close to zero when a country is not influenced by global shocks. In the former case both methods can successfully eliminate the global effects. However, in the latter case, $c_{it} - \bar{c}_t$ and $y_{it} - \bar{y}_t$ introduce mirror images of the global shocks into the demeaned variables, while $\hat{\xi}^c_{it}$ and $\hat{\xi}^y_{it}$ remain void of global shocks.

[Insert Figure 2 about here]

Figure 2 illustrates the evolution of scaled idiosyncratic components and demeaned variables, and it is evident that the latter are trending in many instances. Those trends are either introduced or not fully removed by cross-sectional demeaning. The trends show up on both the left and the right hand side of equation (3), which leads to a bias in the β_i estimates for two reasons. First, $\hat{\beta}_i$ attributes the trend in consumption to the trend in income. Second, the diagnostic tests of the regression residuals in Table 2 imply that cross-sectionally demeaned income and consumption are not cointegrated, and the β_i estimates are spurious. When the model in equation (3) is evaluated with log-differenced series, the β_i estimates do not suffer from the issues related to non-stationarity, but they are influenced by the lingering aggregate effects in the cross-sectionally demeaned data. These illustrations further corroborate our earlier finding that imposing a unit loading coefficient on the aggregates leaves the demeaned regression misspecified and incapable of filtering out the common factors from our heterogeneous panels.

[Insert Table 3 about here]

We now turn to the discussion of the statistically defensible coefficient estimates. Table 3 displays the mean group estimates of risk sharing behavior for a variety of country groups. In line with earlier studies, our overall results based on the whole sample indicate that consumption tends to be affected by idiosyncratic shocks in both the long and the short run, and the extent of risk-sharing tends to be higher in the short run. The fraction of idiosyncratic variation in GDP channelled to consumption is about 0.70 in the short-run, while it is slightly above 0.80 in the long run. Our results reveal a geo-economic pattern that is similar to the one found by Kose et al. (2009) who analyzed 69 countries over the 1960-2004 period. In particular, $\hat{\beta}^{LR}$ and $\hat{\beta}^{SR}$ are inversely related to the level of development, which signals a greater capacity of developed economies to insure against idiosyncratic risk.

Our estimates for OECD countries are quite similar to those obtained by Leibrecht and Scharler (2008) who also used an error correction model: our $\hat{\beta}^{LR} = 0.68$ and $\hat{\beta}^{SR} = 0.80$ fall somewhat below their estimates of about 0.7 and 0.9, respectively. However, our estimated speed of equilibrium-error correction, $\hat{\kappa} = -0.31$, deviates from their -0.1 estimate by a larger margin[2]. Consequently, the mean adjustment lag (computed as $\hat{\mu} = (1 - \hat{\beta}^{SR})/(-\hat{\kappa})$ based on Hendry, 1995) indicates that in OECD countries an income shock exerts its full effect on consumption within about a year according to our study and in about three years according to the results of Leibrecht and Scharler (2008). In Table 3 the mean adjustment lag is also inversely related to the level of development, and it is the shortest in low income countries, where consumption appears to react to income shocks faster, perhaps due to a weaker institutional framework, fewer consumption smoothing opportunities, or a lack of access to financial markets.

[Insert Figure 3 about here]

[2]Notice, however, that the time period analyzed by Leibrecht and Scharler (2008) is different from ours.

Figure 3 illustrates the distribution of individual β_i's. It is immediately obvious that there is a remarkable heterogeneity among countries in terms of their risk-sharing coefficients, both in the long run and in the short run.

[Insert Table 4 and 5 about here]

Table 4 and 5 list the values of the country specific β_i^{LR} and β_i^{SR} estimates. As expected, full insurance is extremely rare. More than 95% of the β_i^{LR} and almost 90% of the β_i^{SR} estimates are significantly different from zero, which indicates a widespread lack of consumption risk sharing. The degree of risk sharing tends to be lower in the long run for most countries. In fact, 33 of the analyzed countries have 50% higher coefficient estimates in the long run than in the short run, and over 45 of them appear to exhibit dis-smoothing behavior ($\beta_i > 1$) in the long run, whereas only 27 do so in the short run.

5 Conclusion

International risk sharing tests are based on the premise that under complete markets country specific consumption should not be affected by idiosyncratic income shocks. A prerequisite for these tests is the isolation of idiosyncratic fluctuations in the variables. The existing literature typically employs cross-sectional demeaning to filter out global shocks from consumption and income panels, but the validity of that method relies on the restrictive assumption of symmetric country characteristics. In general, demeaning is not capable of eliminating cross-sectional dependence from a heterogeneous data set. And inadequate handling of common factors can lead to misleading inference because the estimated coefficient will attribute aggregate fluctuations in consumption to aggregate fluctuations in income.

We suggest that a statistically more appropriate technique is to control for global factors by allowing for heterogeneous loading coefficients within an unobserved components framework that parallels the *CCE* methodology of Pesaran (2006) and Kapetanios et al.

(2010). In our empirical example, we illustrate the inadequacy of cross-sectional demeaning and provide estimates for 158 countries and various country groupings using the proposed approach. Our results largely confirm the findings of the existing literature that full risk sharing is almost never achieved, and that the degree of risk sharing tends to be lower in the long run.

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Table 1: Tests for Individual Variables

	Levels		Differences	
	$\log C$	$\log Y$	$\Delta \log C$	$\Delta \log Y$
CD	253.45*	239.37*	22.93*	43.33*
$CRMA$	2.11	2.08	-3.92*	-3.21*
$CIPS$	-0.32	1.87	-9.72*	-7.78*

Note: Pesaran's (2004) cross-sectional independence test (CD) follows a standard normal distribtion. The 5 % critical value for Pesaran's (2007) panel unit root test ($CIPS$) is -2.06. The lag length for the $CIPS$ test is set to $T^{1/3} = 4$. The 5 % critical value for Sul's (2009) unit root test for the cross-sectional means ($CRMA$) is -1.88. The lag length for the $CRMA$ test is determined by the Bayesian Information Criterion. Statistical significance at the 5% level or lower is denoted by *.

Table 2: Residual Diagnostic Tests

Full Sample (1970-2010)

	Levels		Differences		ECM
	Eq. (3)	Eq. (7)	Eq. (3)	Eq. (7)	Eq. (15)
CD	11.28*	0.06	22.86*	-0.53	-0.83
$CRMA$	-1.74	—	-6.02*	—	—
$CIPS$	-2.03	-5.87*	-8.66*	-10.09*	-10.03*

Truncated Sample (1970-2007)

	Levels		Differences		ECM
	Eq. (3)	Eq. (7)	Eq. (3)	Eq. (7)	Eq. (15)
CD	12.68*	0.36	23.44*	-0.33	-0.48
$CRMA$	-1.86	—	-5.56*	—	—
$CIPS$	-0.13	-5.75*	-5.34*	-8.36*	-11.02*

Note: Pesaran's (2004) cross-sectional independence test (CD) follows a standard normal distribtion. The 5 % critical value for Pesaran's (2007) panel unit root test ($CIPS$) is -2.06. The lag length for the $CIPS$ test is set to $T^{1/3} = 4$. The 5 % critical value for Sul's (2009) unit root test for the cross-sectional means ($CRMA$) is -1.88. The lag length for the $CRMA$ test is determined by the Bayesian Information Criterion. Statistical significance at the 5% level or lower is denoted by *.

Table 3: Mean Group Coefficient Estimates for Sub-Samples

Country Group	$\hat{\beta}^{LR}$	$\hat{\beta}^{SR}$	$\hat{\kappa}$	$\hat{\mu}$
Whole sample	0.83*	0.71*	-0.39*	0.74
High Income	0.87*	0.67*	-0.33*	1.00
UpperMid Income	0.85*	0.73*	-0.41*	0.66
LowerMid Income	0.83*	0.70*	-0.42*	0.71
Low Income	0.82*	0.77*	-0.44*	0.52
OECD	0.80*	0.68*	-0.31*	1.03
Non-OECD	0.84*	0.72*	-0.42*	0.67
Developed	0.78*	0.65*	-0.32*	1.09
Developing	0.87*	0.74*	-0.41*	0.63
Europe	0.79*	0.67*	-0.34*	0.97
Asia	0.88*	0.70*	-0.40*	0.75
Africa	0.83*	0.70*	-0.43*	0.70

Note: Country group definitions follow those used by the World Bank and OECD. $\hat{\beta}^{LR}$ is obtained by estimating equation (7) with data in log-levels. $\hat{\beta}^{SR}$ is obtained by estimating the error-correction model in equation (15). $\hat{\kappa}$ denotes the estimated speed-of-adjustment coefficient in the error-correction model. $\hat{\mu}$ denotes the mean adjustment lag computed as $\hat{\mu} = (1 - \hat{\beta}^{SR})/(-\hat{\kappa})$ based on Hendry (1995). Statistical significance at the 5% level or lower is denoted by *.

Table 4: Country-Specific Coefficient Estimates

id	country	β^{LR}	β^{SR}	id	country	β^{LR}	β^{SR}
1	AFG	0.87 *	0.95 *	41	DOM	0.90 *	1.01 *
2	AGO	2.00 *	0.62	42	DZA	1.48 *	0.24
3	ALB	0.18 *	0.29 *	43	ECU	0.71 *	0.57 *
4	ARG	0.97 *	1.26 *	44	EGY	0.68 *	0.37
5	ATG	0.99 *	1.58 *	45	ESP	0.89 *	0.80 *
6	AUS	0.42 *	0.12	46	ETH	1.10 *	1.03 *
7	AUT	1.11 *	0.74 *	47	FIN	0.81 *	0.46 *
8	BDI	0.86 *	0.79 *	48	FJI	0.64 *	0.57 *
9	BEL	0.98 *	0.53 *	49	FRA	1.02 *	0.73 *
10	BEN	0.80 *	0.66 *	50	FSM	1.03 *	0.98 *
11	BFA	1.96 *	1.27 *	51	GAB	0.34 *	-0.09
12	BGD	1.61 *	1.10 *	52	GBR	1.13 *	0.95 *
13	BGR	1.01 *	0.85 *	53	GER	1.16 *	0.62 *
14	BHR	0.64 *	0.78 *	54	GHA	1.00 *	0.88 *
15	BHS	1.42 *	1.29 *	55	GIN	1.56 *	1.53 *
16	BLZ	1.22 *	1.11 *	56	GMB	0.85 *	0.92 *
17	BMU	1.47 *	0.90 *	57	GNB	0.99 *	0.74 *
18	BOL	0.64 *	0.86 *	58	GNQ	0.67 *	0.72 *
19	BRA	0.83 *	0.90 *	59	GRC	0.20	0.49 *
20	BRB	1.59 *	1.29 *	60	GRD	0.46 *	0.69 *
21	BRN	-0.90 *	0.04	61	GTM	0.86 *	0.75 *
22	BTN	0.56 *	0.57 *	62	GUY	1.15 *	0.93 *
23	BWA	0.40 *	0.19 *	63	HKG	1.22 *	0.85 *
24	CAF	0.92 *	0.83 *	64	HND	1.00 *	0.19
25	CAN	0.41 *	0.48 *	65	HTI	0.97 *	1.12 *
26	CHE	0.23	0.23 *	66	HUN	1.02 *	1.00 *
27	CHL	0.96 *	0.79 *	67	IDN	1.09 *	0.56 *
28	CHN	1.00 *	1.01 *	68	IND	0.95 *	0.71 *
29	CIV	0.76 *	0.78 *	69	IRL	0.64 *	0.62 *
30	CMR	0.97 *	0.79 *	70	IRN	0.59 *	0.39 *
31	COG	0.46 *	0.30 *	71	IRQ	-0.08	0.27 *
32	COL	0.92 *	0.75 *	72	ISL	1.25 *	1.01 *
33	COM	0.40 *	0.27	73	ISR	1.08 *	0.83 *
34	CPV	0.99 *	0.67 *	74	ITA	1.00 *	0.76 *
35	CRI	0.93 *	1.13 *	75	JAM	0.88 *	0.80 *
36	CUB	1.16 *	1.18 *	76	JOR	1.34 *	0.68 *
37	CYP	0.87 *	0.72 *	77	JPN	0.86 *	0.63 *
38	DJI	1.25 *	0.96 *	78	KEN	1.08 *	1.41 *
39	DMA	0.62 *	0.47 *	79	KHM	0.94 *	0.97 *
40	DNK	0.53 *	0.67 *	80	KIR	0.67 *	0.47 *

Note: $\hat{\beta}^{LR}$ is obtained by estimating equation (7) with data in log-levels. $\hat{\beta}^{SR}$ is obtained by estimating the error-correction model in equation (15). Inference is based on heteroskedasticity and autocorrelation consistent robust standard errors. Statistical significance at the 5% level or lower is denoted by *.

Table 5: Comparison of country-specific coefficient estimates (continued)

id	country	β^{LR}	β^{SR}	id	country	β^{LR}	β^{SR}
81	KNA	0.80 *	-0.06	121	PRT	0.81 *	0.50 *
82	KOR	0.84 *	0.78 *	122	PRY	0.77 *	0.23
83	LAO	0.85 *	0.98 *	123	ROM	0.50 *	0.61 *
84	LBN	0.84 *	0.84 *	124	RWA	0.59 *	0.20 *
85	LBR	1.15 *	0.90 *	125	SDN	1.01 *	1.43 *
86	LCA	0.70 *	0.89 *	126	SEN	0.88 *	0.50 *
87	LKA	1.10 *	0.49 *	127	SGP	0.73 *	0.46 *
88	LSO	1.05 *	0.66 *	128	SLB	1.04	0.44 *
89	LUX	0.69 *	0.31 *	129	SLE	0.67 *	0.79 *
90	MAC	1.00 *	0.25 *	130	SLV	1.32 *	1.16 *
91	MAR	0.34	0.44 *	131	SOM	0.95 *	1.01 *
92	MDG	1.17 *	0.12	132	STP	1.19 *	1.31 *
93	MDV	0.96 *	0.66 *	133	SUR	1.30 *	1.83 *
94	MEX	0.80 *	0.83 *	134	SWE	0.67 *	0.58 *
95	MHL	1.34 *	0.56 *	135	SWZ	0.40 *	-0.08
96	MLI	-0.17	0.00	136	SYC	1.08 *	0.89 *
97	MLT	0.75 *	0.67 *	137	SYR	0.78 *	0.96 *
98	MNG	0.67 *	1.09 *	138	TCD	0.47 *	0.51 *
99	MOZ	0.89 *	0.70 *	139	TGO	0.33 *	0.54 *
100	MRT	0.80 *	0.83 *	140	THA	0.78 *	0.61 *
101	MUS	0.84 *	0.60 *	141	TON	0.92 *	0.65 *
102	MWI	0.44 *	0.54 *	142	TTO	0.93 *	0.81 *
103	MYS	0.54 *	0.96 *	143	TUN	0.64 *	0.28 *
104	NAM	1.03 *	0.88 *	144	TUR	0.72 *	0.94 *
105	NER	0.32 *	0.67 *	145	TWN	1.12 *	0.63 *
106	NGA	1.13 *	1.28 *	146	TZA	-0.04	0.37 *
107	NIC	0.72 *	0.51 *	147	UGA	0.97 *	0.94 *
108	NLD	0.72 *	0.71 *	148	URY	1.00 *	0.95 *
109	NOR	0.38 *	0.57 *	149	USA	0.91 *	0.74 *
110	NPL	1.10 *	1.13 *	150	VCT	0.74 *	0.98 *
111	NZL	0.95 *	0.79 *	151	VEN	1.02 *	0.77 *
112	OMN	1.26 *	0.53	152	VNM	0.55 *	0.77 *
113	PAK	0.59 *	0.90 *	153	VUT	0.78 *	0.76 *
114	PAN	0.15	0.14	154	WSM	0.95 *	0.92 *
115	PER	0.95 *	0.93 *	155	ZAF	0.67 *	0.62 *
116	PHL	0.29 *	0.30 *	156	ZAR	0.63 *	0.21
117	PLW	0.45	-0.89 *	157	ZMB	0.88 *	1.34 *
118	PNG	0.96	0.57	158	ZWE	0.24	0.67 *
119	POL	0.93 *	1.08 *				
120	PRI	0.55 *	0.34 *				

Note: $\hat{\beta}^{LR}$ is obtained by estimating equation (7) with data in log-levels. $\hat{\beta}^{SR}$ is obtained by estimating the error-correction model in equation (15). Inference is based on heteroskedasticity and autocorrelation consistent robust standard errors. Statistical significance at the 5% level or lower is denoted by *.

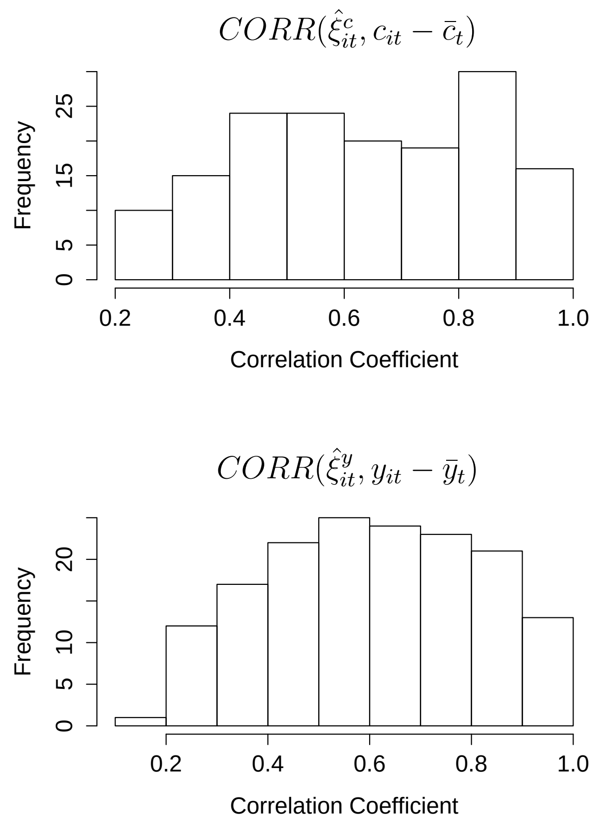

Figure 1: Distribution of correlation coefficients $Corr(\hat{\xi}^c_{it}, c_{it} - \bar{c}_t)$ and $Corr(\hat{\xi}^y_{it}, y_{it} - \bar{y}_t)$. The idiosyncratic components, $\hat{\xi}^c_{it}$ and $\hat{\xi}^y_{it}$, are estimated in (12) and (13), and the cross-sectionally demeaned variables, $c_{it} - \bar{c}_t$ and $y_{it} - \bar{y}_t$, appear directly in (3). All analyzed series are in log-levels.

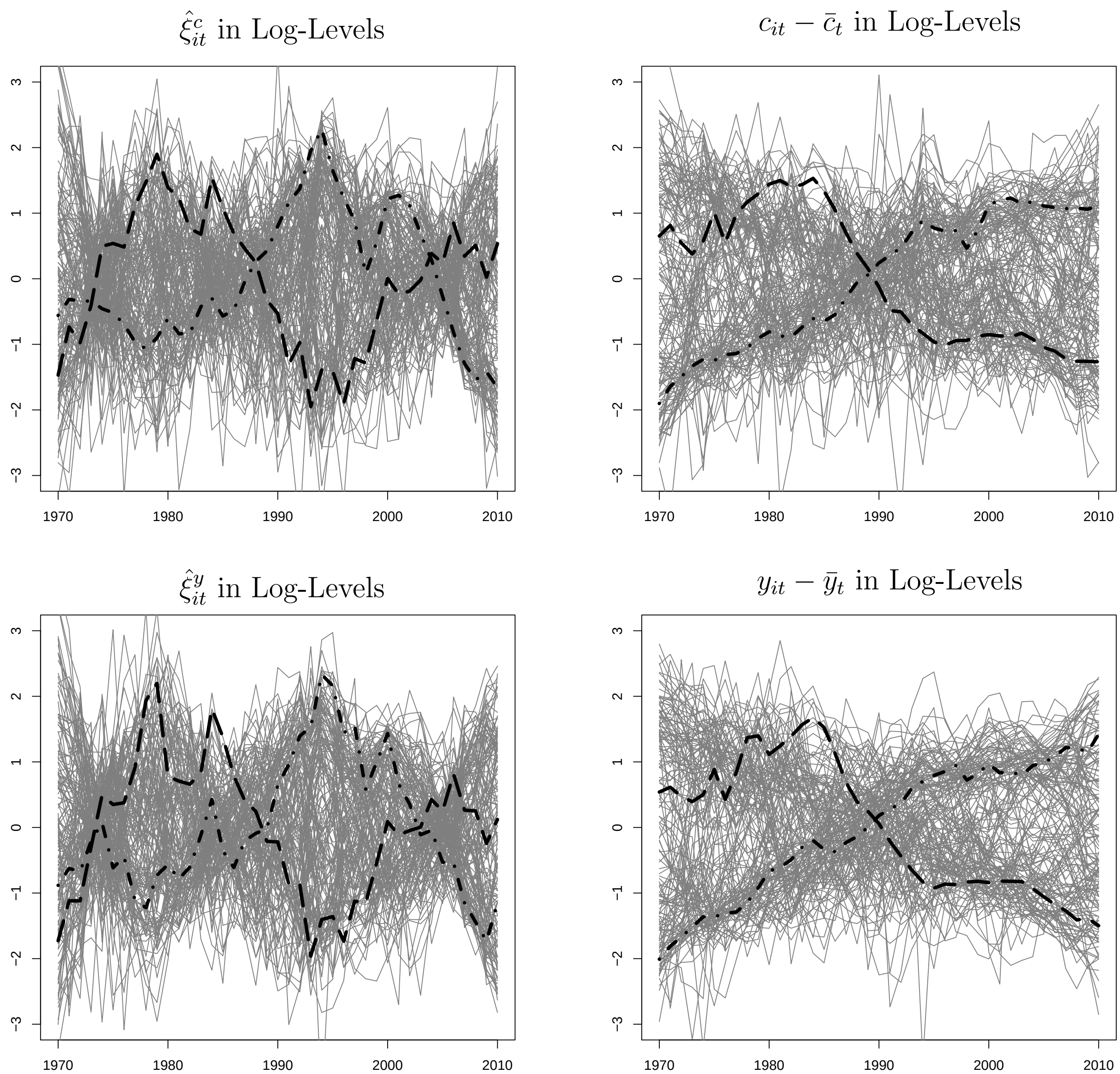

Figure 2: Scaled (standardized) estimates of idiosyncratic components (left), $\hat{\xi}^c_{it}$ and $\hat{\xi}^y_{it}$, estimated in (12) and (13), and the cross-sectionally demeaned variables (right), $c_{it} - \bar{c}_t$ and $y_{it} - \bar{y}_t$, appearing in (3). All analyzed series are in log-levels. The estimates are highlighted for two representative countries: Singapore (dash-dotted line) and Cameroon (long-dashed line).

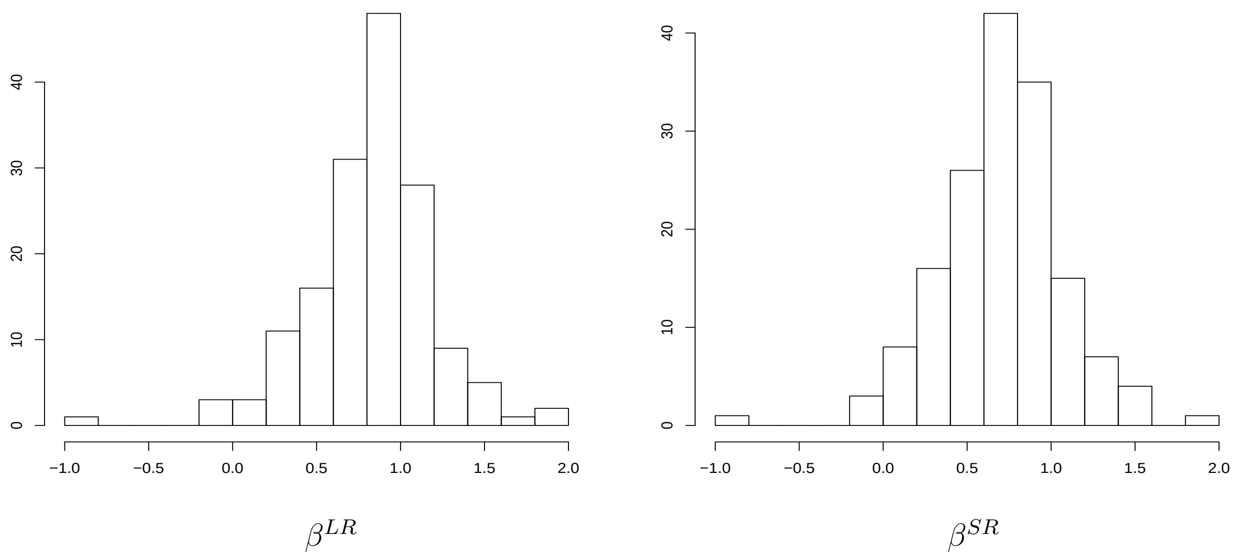

Figure 3: Distribution of country specific coefficient estimates. $\hat{\beta}^{LR}$ is obtained by estimating equation (7) with data in log-levels. $\hat{\beta}^{SR}$ is obtained by estimating the error-correction model in equation (15).