Common Correlated Effects and International Risk Sharing*†

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Abstract

Existing studies of international risk-sharing rely on the highly restrictive assumption that all economies are characterized by symmetric preferences and uniform transmission of global shocks. We relax these homogeneity constraints by modeling aggregate and idiosyncratic fluctuations as unobserved components, and we use Pesaran's (2006) common correlated effects estimator to control for cross-sectional dependence and heterogeneity. We illustrate the robustness of the proposed approach by estimating the extent of risk-sharing across 158 countries. Our results indicate that consumption is only partially smoothed internationally, and the extent of risk-sharing has remained relatively stable during the last four decades.

Keywords: International risk sharing, Consumption insurance, Panel data, Cross-sectional dependence, Heterogeneous effects
JEL codes: C23, C51, E21, F36

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1 Introduction

Since the early contributions by Cochrane (1991), Mace (1991), and Obstfeld (1994), a number of consumption risk sharing tests have been presented in the literature. To maintain analytical tractability, the derivation and implementation of these tests usually relies on several homogeneity assumptions that are unlikely to hold in worldwide panels: all economies are assumed to be characterized by symmetric preferences and uniform transmission of global shocks. The extent of risk sharing is then estimated by a panel data regression of cross-sectionally demeaned consumption on cross-sectionally demeaned income. However, if the homogeneity assumptions underlying the analysis are violated, the results may be biased.

We extend the existing literature by taking into account various sources of heterogeneity. Specifically, we allow for cross-country variation 1) in preferences, 2) in the transmission of global income shocks, and 3) in the sensitivity of consumption to income shocks. Considering these sources of heterogeneity is worthwhile for the following reasons:

1. The underlying theory suggests that if a country has full access to international risk sharing opportunities, consumption will be independent of idiosyncratic income shocks. However, this does not necessarily imply uniform consumption growth around the world. Country-level and global consumption will move in lockstep if preferences are symmetric across countries, but they will diverge if risk aversion or discount factors are heterogeneous (Obstfeld, 1989, 1994). Hence, even under perfect risk sharing, consumption paths can differ from each other due to heterogeneous preferences.

2. If risk sharing is imperfect, consumption will also be affected by idiosyncratic income fluctuations. This in turn raises the question of how to isolate idiosyn-

cratic income shocks from global ones. Due to 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 income fluctuations caused by aggregate sources than a country that does not participate in international trade. Accordingly, idiosyncratic shocks can be obtained by controlling the extent of global shocks transmitted to individual countries; an extent that is unlikely to be uniform throughout the world (Giannone and Lenza, 2010).

3. Finally, because of differences in the quality of smoothing channels, the effects of idiosyncratic income shocks on consumption may also vary across countries.

By taking into account the aforementioned sources of cross-sectional heterogeneity, we can more accurately estimate the extent of international risk sharing.

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 preferences and exposure to aggregate risk. Consequently, and at odds with the existing literature, we let global factors have country specific loading coefficients. In addition, we relax the homogeneity assumption behind pooled or fixed effects estimation and employ a mean-group type estimator that is robust to heterogeneous country characteristics. Due to these refinements, the proposed approach is expected to be better at isolating idiosyncratic fluctuations and be less susceptible to bias than the cross-sectional demeaning method.

We illustrate the performance of the considered methods under cross-sectional dependence and heterogeneity by analyzing 158 countries. While accounting for these features of the data has an up to 20% impact on the estimates, 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. Although 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, which in turn may have sizeable welfare implications, as shown by van Wincoop (1999) and Athanasoulis and van Wincoop (2000).

We contribute to the existing literature in several important ways. First, we highlight the shortcomings of the conventional approach to analyze international risk sharing. Second, we re-evaluate earlier results on the lack of perfect risk sharing using a more flexible econometric model that isolates idiosyncratic fluctuations in the data. Specifically, we are the first ones to apply the common correlated effects (CCE) estimator of Pesaran (2006) to the analysis of international risk sharing. Third, while earlier studies have focused on smaller more homogeneous sets of economies, our large panel of 158 countries allows us to analyze risk sharing along a variety of economic characteristics. Fourth, we look at the change in the extent of risk sharing over the past forty years, but find no evidence to support the notion that globalization has led to an increase in international consumption smoothing.

2 The Conventional Approach

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 tested using 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, $\bar{c}_t$ 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, to maintain tractability of the analysis, many papers in the field have built on these homogeneity 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. For example, and many others in the last decade noted that the relative size of the estimated slope coefficient can be interpreted as a measure of the degree of insurance or risk pooling. 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.

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 $\bar{y}_t$ is a measure of aggregate income. To obtain an overall β coefficient for the analyzed set of countries, most researchers pool the data and estimate the fixed effects regression

$$c_{it} - \bar{c}_t = \alpha_i + \beta(y_{it} - \bar{y}_t) + \varepsilon_{it} \ , \tag{4}$$

which imposes an additional layer of homogeneity on the model.

Equation (4) is the basis for several recent influential empirical studies, such as Sorensen and Yosha (2000), 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 is interpreted as the effect of idiosyncratic real GDP growth on idiosyncratic consumption growth. If the aggregates, $\bar{c}_t$ and $\bar{y}_t$, are cross-sectional means, then the differencing operations in equation (4) 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 (4) with an implicit one by including a time dummy d_t in the fixed effects regression

$$c_{it} = \alpha_i + d_t + \beta y_{it} + \varepsilon_{it} \ . \tag{5}$$

Artis and Hoffmann (2006) derive equation (4) by relying on a different 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 overly restrictive when the analysis is carried out with a heterogeneous set of economies.

3 An Alternative Approach

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 (Harvey, 1989). 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 modeled by common factors, $\boldsymbol{f}_t$, and its contribution to a particular country's observed income can be captured by the factor loadings, $\boldsymbol{\lambda}_{i,y}$,

$$y_{it} = \boldsymbol{\lambda}'_{i,y}\boldsymbol{f}_t + \xi^y_{it} \ , \tag{6}$$

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

$$c_{it} - \gamma^c_i\bar{c}_t = \alpha_i + \beta_i(y_{it} - \tilde{\gamma}^y_i\bar{y}_t) + \varepsilon_{it} \ , \tag{7}$$

or

$$c_{it} = \alpha_i + \beta_i y_{it} + \gamma_i^c \bar{c}_t + \gamma_i^y \bar{y}_t + \varepsilon_{it} \ , \tag{8}$$

where the β_i coefficient measures the extent to which idiosyncratic shocks to income are channeled into idiosyncratic consumption. The approximation of common factors by cross-sectional averages is advantageous for two reasons: 1) the analysis of risk sharing focuses on consistent estimation of the β coefficient, but it does not concern itself with common factors per se, and 2) Westerlund and Urbain (2015) have shown that this approximation results in lower bias of the β estimate than competing approaches based on direct estimation of the common factors. 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 economies. A more detailed discussion of this model follows in Section 4.

The proposed method for estimating the degree of risk sharing was inspired by the inadequacy of the conventional approach to handle global shocks in a diverse set of countries. When countries are heterogeneous in terms of their preferences, pooled resources, and sensitivity to aggregate fluctuations, consumption insurance tests based on equations (3)-(5) may produce misleading inference. Specifically, risk sharing tests require the isolation of idiosyncratic shocks, but as we subsequently illustrate, cross-sectional differencing with respect to an aggregate measure is insufficient for this purpose if preferences and the transmission of global shocks vary across countries. A similar problem, in the context of the Feldstein-Horioka puzzle, prompted Giannone and Lenza (2010) to use a factor augmented panel regression to isolate idiosyncratic variation in saving and investment. Moreover, if the extent of consumption smoothing is related to the scale of idiosyncratic income shocks, then estimating a single β coefficient in a fixed effects regression will in general produce biased results (see Coakley et al., 2001).

In Section 4 we describe in greater detail our proposed approach to deal with cross-sectional dependence in a diverse set of 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.

4 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. A relationship between idiosyncratic consumption and income can then be estimated and tested for significance.

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

$$c_{it} = \alpha_i + \beta_i y_{it} + u_{it} \ , \ i = 1, 2, \dots, N \ , \ t = 1, 2, \dots, T \ . \tag{9}$$

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

$$y_{it} = a_{i,y} + \boldsymbol{\lambda}'_{i,y} \boldsymbol{f}_t + \xi^y_{it} \ , \tag{10}$$

where $a_{i,y}$ is an individual constant, and $\boldsymbol{f}_t$ is a vector of unobserved common factors 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

$$u_{it} = \boldsymbol{\omega}'_i \boldsymbol{f}_t + \varepsilon_{it} \ , \tag{11}$$

where $\boldsymbol{\omega}_i$ is a 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. The CCE estimator is defined as,

$$\hat{\beta}_i = (\boldsymbol{y}'_i \bar{\boldsymbol{M}} \boldsymbol{y}_i)^{-1} \boldsymbol{y}'_i \bar{\boldsymbol{M}} \boldsymbol{c}_i \ , \tag{12}$$

where $\boldsymbol{y}_i = (y_{i1}, y_{i2}, \dots, y_{iT})'$, $\boldsymbol{c}_i = (c_{i1}, c_{i2}, \dots, c_{iT})'$, 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, (12) applied to (9) produces β_i estimates that are identical to ordinary least squares estimates of β_i in our proposed model (8). The CCE estimator partitions the regression in (8) by projecting consumption and income orthogonally with respect to their cross-sectional means using the $\bar{\boldsymbol{M}}$ matrix. The estimation can also be viewed as a two stage regression. 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

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

$$y_{it} = a_{i,y} + \lambda_{i,y}^{c}\bar{c}_t + \lambda_{i,y}^{y}\bar{y}_t + \xi_{it}^{y} \ . \tag{14}$$

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. While the λ coefficients in (13) and (14) can not be meaningfully interpreted (see Pesaran, 2006; Westerlund and Urbain, 2015), the residuals $\hat{\xi}_{it}^{c}$ and $\hat{\xi}_{it}^{y}$ are valid estimates of the idiosyncratic components and can be compared to cross-sectionally demeaned consumption and income. Note that the latter may not be free of aggregate shocks: if the effect of global cycles differs 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 estimation procedure does not depend on the transformation of the variables: Kapetanios et al. (2011) proved that the CCE estimators are consistent 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 8 and 11) implies that c_{it}, y_{it}, and $\boldsymbol{f}_t$ are cointegrated, and additional information can be obtained about risk sharing within an error correction model (Davidson et al., 1978; Leibrecht and Scharler, 2008; Pierucci and Ventura, 2010).

For an individual country, the deviation from the long run equilibrium relationship between idiosyncratic income and consumption, after controlling for permanent global shocks, is captured by the residual, $\hat{\varepsilon}_{it}$, in equation (8). 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

$$\Delta c_{it} - \gamma_i^{c,SR}\overline{\Delta c}_t = \alpha_i^{SR} + \kappa\hat{\varepsilon}_{it}^{LR} + \beta_i^{SR}(\Delta y_{it} - \tilde{\gamma}_i^{y,SR}\overline{\Delta y}_t) + \varepsilon_{it}^{SR} \ , \tag{15}$$

or

$$\Delta c_{it} = \alpha_i^{SR} + \kappa\hat{\varepsilon}_{it}^{LR} + \beta_i^{SR}\Delta y_{it} + \gamma_i^{c,SR}\overline{\Delta c}_t + \gamma_i^{y,SR}\overline{\Delta y}_t + \varepsilon_{it}^{SR} \ , \tag{16}$$

where $\hat{\varepsilon}_{it}^{LR} = c_{it} - \hat{\alpha}_i^{LR} - \hat{\beta}_i^{LR} y_{it} - \hat{\gamma}_i^{c,LR}\bar{c}_t - \hat{\gamma}_i^{y,LR}\bar{y}_t$. Here, the heterogeneous impact of transitory 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 (see also Holly et al., 2010, Sec. 5.4). The cross-sectional averages also control for potential endogeneity bias arising due to common factors in differenced income and the error term.

The dynamic specification of the error-correction model is influenced by the following considerations. For annual data, persistence can largely be captured by the first lag, and even Davidson et al. (1978), who use quarterly observations, find that the model with a single annual lag best describes the data. In fact, since their pathbreaking study, the first order autoregressive distributed lag model and the corresponding error-correction model have become the de-facto tools for empirical analysis. Finally, for each extra lag in the model we would have to estimate four coefficients. In addition to the lags of differenced income and consumption, we would also have to use the cross-sectional averages of those lags to control for their cross-sectional dependence. With a short sample, accommodating the extra lags would lead to over-fitting.

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

$$\hat{\beta}^{LR} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i^{LR} \quad \text{and} \quad \hat{\beta}^{SR} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i^{SR}\ . \tag{17}$$

Coakley et al. (2001) showed that, in contrast to pooled and fixed effects estimators, mean-group estimators are robust to dependence between the coefficients and the regressors along the cross-sectional dimension. Furthermore, Coakley et al. (2006) found that among a variety of mean-group estimators, including one based on a cross-sectionally demeaned regression specified in equation (3), the CCE mean-group estimator is the most robust to general settings, such as regressors and errors sharing common factors with possibly correlated factor loadings.

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

$$\sum_{i=1}^{N}(C_{it} * w_{it}) = \bar{C}_t,\ w_{it} = \frac{N_{it}}{N_t}\ ,\ i = 1, 2, \ldots, N\ ,\ t = 1, 2, \ldots, T\ , \tag{18}$$

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 proxies for unobserved global shocks in the $\bar{\boldsymbol{M}}$ matrix are obtained by simple cross-sectional averaging of previously log-transformed country level series. Having described the correspondence between our proposed analytical approach and the CCE methodology, we now turn to our empirical study and report estimation results in the next section.

5 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 subperiod

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*
$CIPS_{\mu}$	0.32	1.87	-9.72*	-7.78*
$CIPS_{\mu,t}$	0.04	3.85	-5.98*	-4.70*

Note: Pesaran's (2004) cross-sectional independence test statistic (CD) follows a standard normal distribtion. The lag length for Pesaran's (2007) panel unit root test ($CIPS$) is set to $T^{1/3} \approx 4$. The 5 % critical values for $CIPS_{\mu}$ (the model includes an intercept) and $CIPS_{\mu,t}$ (the model includes an intercept and a linear trend) are -2.06 and -2.55, respectively. Statistical significance at the 5% level is denoted by *.

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 focuses on smaller sets of rather homogeneous countries.

From the Penn World Tables we use purchasing power parity converted GDP per capita and consumption per capita at 2005 constant prices.[1] 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 to make comparisons across countries and time feasible. Because these variables tend to exhibit exponential growth, we apply a logarithmic transformation to them in our analysis. The diagnostic statistics displayed in Table 1 indicate that log-consumption and log-income levels are cross-sectionally dependent and follow stochastic trends. The log-differenced series are also cross-sectionally dependent, but they do not contain unit roots.

Table 2 displays the results of diagnostic tests applied to the residuals in equations (3), (4), (8), and (16). The first two regressions are evaluated with both the data in

[1] The basic risk sharing equation can be augmented by additional regressors, such as proxies for financial development, net foreign income flows, etc. However, we did not include extra control variables into the analysis, because we wanted to directly relate our study to fundamental contributions in the literature, such as those cited above, all presenting results for the basic equations (3) and (4).

Table 2: Residual Diagnostic Tests

	Eq. (3)		Eq. (4)			
	Levels	Diffs	Levels	Diffs	Eq.(8)	Eq.(16)
CD	11.28*	22.86*	4.48*	18.91*	0.06	-0.83
$CIPS_{\mu}$	-2.03	—	2.01	—	-5.87*	—

Note: See the notes in Table 1.

log-levels and in log-differences. In each regression, we test the residuals for cross-sectional dependence and, when the data are in log-levels, for non-stationarity. We use the CD statistic proposed by Pesaran (2004) for the former, and the $CIPS$ statistic of Pesaran (2007) for the latter (see also Banerjee and Carrion-i Silvestre, 2014; Holly et al., 2010).

Given their great diversity, the countries in our analysis vary in terms of their susceptibility to global shocks. The rejection of cross-sectional independence for the residuals of equation (3) indicates that the cross-sectionally demeaned regression 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. 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 (13) and (14) are more appropriate to estimate idiosyncratic variation.

The estimated slope 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

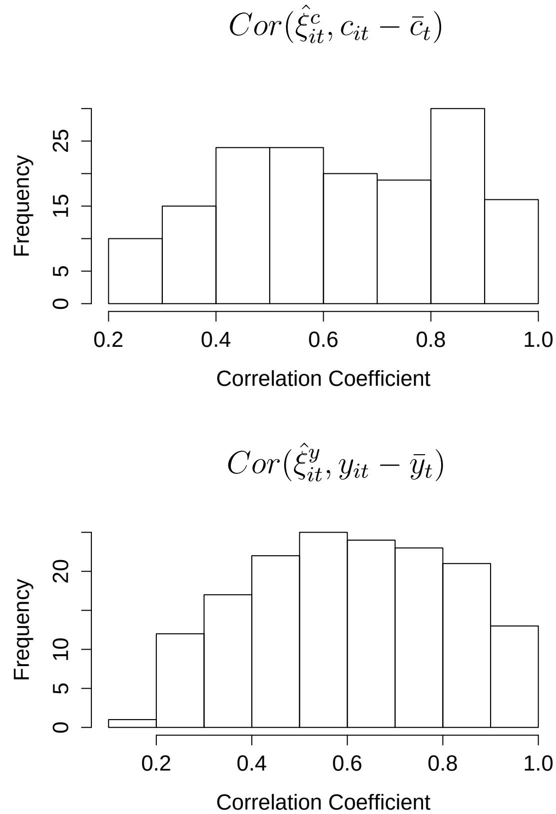

Figure 1: Distribution of correlation coefficients $Cor(\hat{\xi}^c_{it}, c_{it} - \bar{c}_t)$ and $Cor(\hat{\xi}^y_{it}, y_{it} - \bar{y}_t)$. The idiosyncratic components, $\hat{\xi}^c_{it}$ and $\hat{\xi}^y_{it}$, are estimated in (13) and (14), and the cross-sectionally demeaned variables, $c_{it} - \bar{c}_t$ and $y_{it} - \bar{y}_t$, appear directly in (3) and (4). All analyzed series are in log-levels.

essentially lurking variables that confound the relationship between the regressor and the dependent variable. The problem gets exacerbated by the restriction placed on β in model (4), which pushes country specific effects of income shocks into the error term and further distorts the estimates due to the prevalence of unit roots in the residuals. Consequently, the diagnostic tests indicate that only models augmented by cross-sectional averages, that is, equations (8) and (16), yield statistically acceptable results.

To illustrate the disagreement between the two methods in our heterogeneous data set, we examine the correlation of the idiosyncratic components estimated by the first stage regressions and cross-sectional demeaning. 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 follow 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 factor loadings equal to zero ensure that $\hat{\xi}^c_{it}$ and $\hat{\xi}^y_{it}$ remain void of global shocks.

The discrepancy between the methods is further highlighted using two representative countries in Figure 2. The plots illustrate the evolution of idiosyncratic components and demeaned variables, and it is evident that the latter are trending. Those stochastic trends are either introduced (Central African Republic - not sensitive to global shocks) or not fully removed (China - highly sensitive to global shocks) by cross-sectional demeaning. The stochastic trends show up on both the left and the right hand side of equation (3), which leads to a bias in the individual $\beta^{LR}_{DEM,i}$ estimates for two reasons. First, $\hat{\beta}^{LR}_{DEM,i}$ attributes the trend in demeaned consumption to the trend in demeaned 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 $\beta^{LR}_{DEM,i}$ estimates are spurious. When the model in equation (3) is evaluated with log-differenced series, the $\beta^{SR}_{DEM,i}$ 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

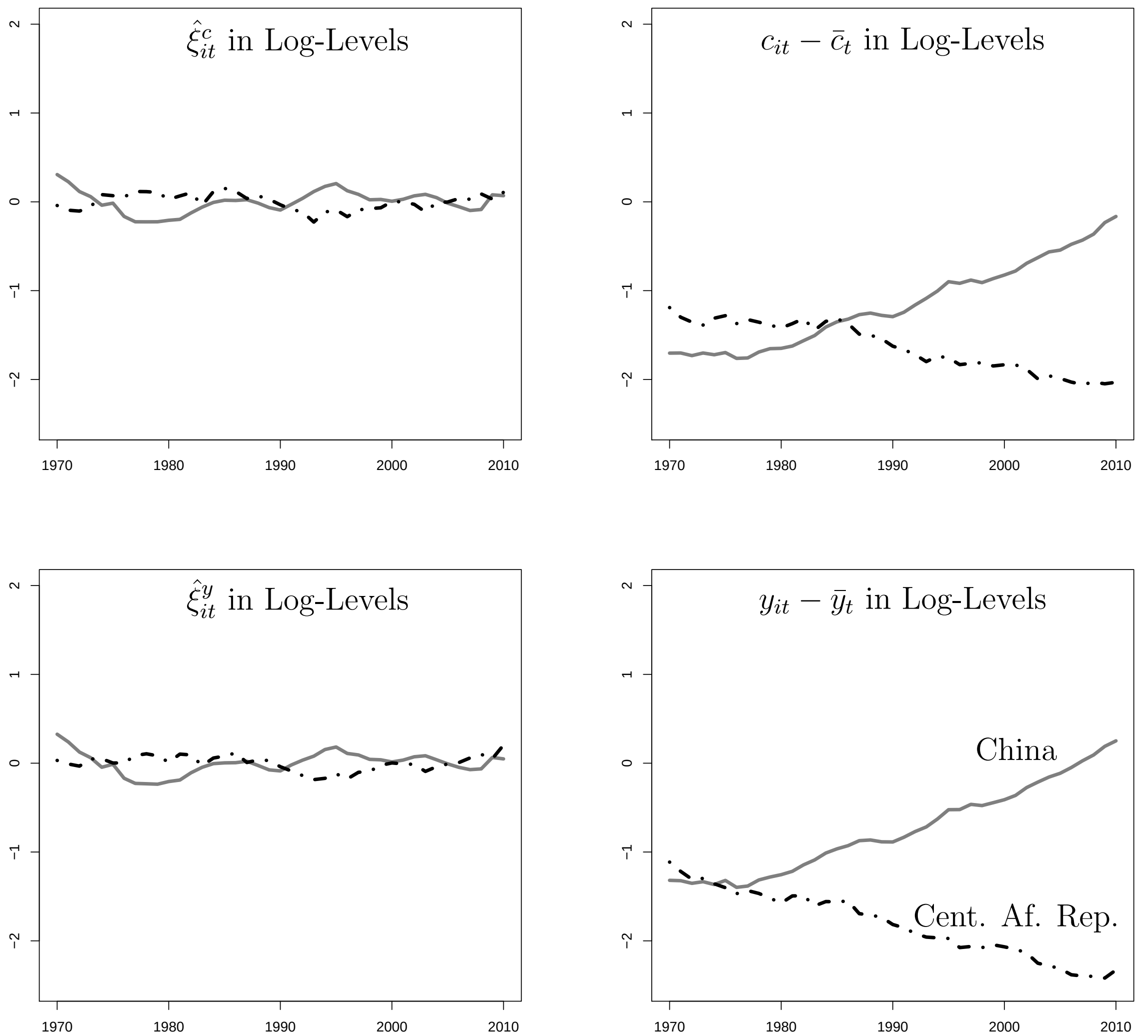

Figure 2: Plots of idiosyncratic components, $\hat{\xi}^c_{it}$ and $\hat{\xi}^y_{it}$, and cross-sectionally demeaned variables, $c_{it} - \bar{c}_t$ and $y_{it} - \bar{y}_t$ for two representative countries: China (solid line) highly sensitive to global shocks and Central African Republic (dash-dotted line) not sensitive to global shocks. All analyzed series are in log-levels.

regression misspecified and incapable of filtering out the common factors from our heterogeneous panels.

We now turn to the discussion of the statistically defensible CCE coefficient estimates, which we also contrast with the estimates obtained by the demeaning methodology. Table 3 displays the estimates of risk sharing behavior for a variety of country categories. In line with earlier studies (such as Becker and Hoffmann, 2006), our overall CCE 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 CCE results reveal a geo-economic pattern that is similar to the one found by Kose et al. (2009) who analyzed 69 developing and developed countries over the 1960-2004 period. In particular, $\hat{\beta}^{LR}_{CCEMG}$ and $\hat{\beta}^{SR}_{CCEMG}$ are roughly inversely related to the level of development, which signals a greater capacity of developed economies to insure against idiosyncratic risk as they tend to have better access to well functioning credit and capital markets. Quite remarkably, this geo-economic pattern is either absent or reversed under restrictions imposed by the conventional fixed effects estimation technique.

The conventional estimates are affected by various biases, and as the $\pm$ columns in Table 3 indicate, the gap between the conventional estimates and the CCE estimates can reach 20%. The fixed effects estimator in (4) will produce different results than the mean group estimator in (3) if $\hat{\beta}_{DEM,i}$ is correlated with the variance of demeaned income, $S_i = Var(y_{it} - \bar{y}_t)$ (see Coakley et al., 2001). We find that the correlation $Cor(\hat{\beta}^{LR}_{DEM}, S)$ across i is negative, and consequently $\hat{\beta}^{LR}_{DEMFE}$ is lower than $\hat{\beta}^{LR}_{DEMMG}$, within all groups except low income countries. In the short run, this negative bias dominates in β^{LR}_{DEMFE} estimates for lower income and less developed countries. The

Table 3: Coefficient Estimates

Country Group	$\hat{\beta}^{LR}_{DEMFE}$	$\pm$	$\hat{\beta}^{LR}_{DEMMG}$	$\pm$	$\hat{\beta}^{LR}_{CCEMG}$	$\hat{\beta}^{SR}_{DEMFE}$	$\pm$	$\hat{\beta}^{SR}_{DEMMG}$	$\pm$	$\hat{\beta}^{SR}_{CCEMG}$	$\hat{\kappa}$	$\hat{\mu}$
WholeSample[1]	*0.78*	*-6%*	*0.85*	*2%*	0.83 (0.03)	*0.68*	*-4%*	*0.73*	*3%*	0.71 (0.03)	-0.39	0.37
HighIncome[1,2,3,4]	*0.66*	*-20%*	*0.91*	*11%*	0.82 (0.06)	*0.74*	*14%*	*0.72*	*11%*	0.65 (0.04)	-0.33	0.63
UpperMidIncome[2]	*0.87*	*2%*	*0.92*	*8%*	0.85 (0.05)	*0.78*	*7%*	*0.74*	*1%*	0.73 (0.07)	-0.41	0.34
LowerMidIncome[1,2,3]	*0.76*	*-8%*	*0.77*	*-7%*	0.83 (0.05)	*0.54*	*-23%*	*0.67*	*-4%*	0.70 (0.05)	-0.42	0.37
LowIncome	*0.81*	*-1%*	*0.80*	*-2%*	0.82 (0.08)	*0.71*	*-8%*	*0.77*	*0%*	0.77 (0.07)	-0.44	0.14
OECD[3,4]	*0.81*	*1%*	*0.87*	*9%*	0.80 (0.05)	*0.78*	*15%*	*0.76*	*12%*	0.68 (0.04)	-0.31	0.48
Non-OECD[1]	*0.77*	*-8%*	*0.85*	*1%*	0.84 (0.03)	*0.68*	*-6%*	*0.72*	*0%*	0.72 (0.03)	-0.42	0.34
Developed[1,2,3,4]	*0.85*	*9%*	*0.87*	*12%*	0.78 (0.05)	*0.74*	*14%*	*0.73*	*12%*	0.65 (0.04)	-0.32	0.52
Developing[1,3]	*0.78*	*-10%*	*0.88*	*1%*	0.87 (0.04)	*0.66*	*-11%*	*0.73*	*-1%*	0.74 (0.03)	-0.41	0.36
EU[4]	*0.87*	*5%*	*0.88*	*6%*	0.83 (0.05)	*0.74*	*7%*	*0.76*	*10%*	0.69 (0.04)	-0.34	0.50

Note: Country group definitions follow those used by the World Bank and OECD (see also the Appendix). $\hat{\beta}^{LR}_{DEMFE}$ and $\hat{\beta}^{SR}_{DEMFE}$ are obtained by estimating equation (4) with data in log-levels and in log-differences, respectively. $\hat{\beta}^{LR}_{DEMMG}$ and $\hat{\beta}^{SR}_{DEMMG}$ are obtained by estimating equation (3) with data in log-levels and in log-differences, respectively, and aggregating the $\hat{\beta}_i$ using equation (17). $\hat{\beta}^{LR}_{CCEMG}$ is obtained by estimating equation (8) with data in log-levels, $\hat{\beta}^{SR}_{CCEMG}$ is obtained by estimating the error-correction model in equation (16), and aggregating the $\hat{\beta}_i$ using equation (17). Standard errors in parentheses. Full international risk sharing implies H_0: $\beta = 0$. All β estimates are different from 0 at the 5% level of marginal significance, but only inference based on the CCE methodology is valid. [1] indicates that the 90% confidence interval around $\hat{\beta}^{LR}_{CCEMG}$ excludes $\hat{\beta}^{LR}_{DEMFE}$. [2] indicates that the 90% confidence interval around $\hat{\beta}^{LR}_{CCEMG}$ excludes $\hat{\beta}^{LR}_{DEMMG}$. [3] indicates that the 90% confidence interval around $\hat{\beta}^{SR}_{CCEMG}$ excludes $\hat{\beta}^{SR}_{DEMFE}$. [4] indicates that the 90% confidence interval around $\hat{\beta}^{SR}_{CCEMG}$ excludes $\hat{\beta}^{SR}_{DEMMG}$. $\pm$ indicates the percentage difference between the estimate in the preceding column and the respective $\hat{\beta}^{LR}_{CCEMG}$ or $\hat{\beta}^{SR}_{CCEMG}$ estimate. $\hat{\kappa}$ denotes the estimated speed-of-adjustment coefficient in the error-correction model. $\hat{\mu}$ denotes the mean adjustment lag computed as $\hat{\mu} = (1 - \frac{\hat{\beta}^{SR}}{\hat{\beta}^{LR}})/(-\hat{\kappa})$ based on Hendry (1995).

negative correlation between $\hat{\beta}$ and S implies that, within a particular group, countries with high income variation tend to smooth their consumption more than countries with low income variation, which is consistent with the conclusion put forth by Browning and Collado (2001). In turn, the mean group β^{LR}_{DEMMG} estimates tend to exhibit an upward bias due to lingering global shocks shared by $c_{it} - \bar{c}_t$ and $y_{it} - \bar{y}_t$. Although income level is not necessarily a good approximation to the degree of openness, the conventional long run mean-group estimates, $\hat{\beta}^{LR}_{DEMMG}$, counterintuitively imply that low income countries enjoy a greater degree of risk sharing than high income countries do, whereas the CCE results, $\hat{\beta}^{LR}_{CCEMG}$, remain fairly similar across income groups.

Our CCE estimates for OECD countries, $\hat{\beta}^{LR}_{CCE} = 0.80$ and $\hat{\beta}^{SR}_{CCE} = 0.68$, fall somewhat below the respective conventional estimates of about 0.9 and 0.7 obtained by Leibrecht and Scharler (2008), who—albeit relying on homogeneity assumptions—also used an error correction model. However, our estimated speed of equilibrium-error correction, $\hat{\kappa} = -0.31$, deviates from their -0.1 estimate by a larger margin. Consequently, the mean adjustment lag (computed as $\hat{\mu} = (1 - \frac{\hat{\beta}^{SR}_{CCE}}{\hat{\beta}^{LR}_{CCE}})/(-\hat{\kappa})$ based on Hendry, 1995) indicates that in OECD countries an idiosyncratic income shock exerts its full effect on consumption within about half a year according to our study as opposed to about two years according to the results of Leibrecht and Scharler (2008). The last column of Table 3 illustrates the direct relationship between the mean adjustment lag and the level of development. It is the shortest in low income countries, where consumption appears to react to idiosyncratic income shocks faster, perhaps due to a weaker institutional framework, fewer consumption smoothing opportunities, or a lack of access to financial markets.

Table 4 allows us to contribute to the debate on whether increased financial globalization, an impressive surge in flows of real and financial assets across countries, has brought about more, or better, insurance opportunities. Economic theory does not

Table 4: CCEMG Coefficient Estimates for Subsamples, in Subperiods

	$\hat{\beta}^{LR}_{CCEMG}$		$\hat{\beta}^{SR}_{CCEMG}$	
Country Group	1970-1989	1990-2010	1970-1989	1990-2010
Whole Sample	0.82 (0.03)	0.85 (0.04)	0.70 (0.03)	0.68 (0.04)
High Income	0.82 (0.07)	0.83 (0.07)	0.66 (0.02)	0.62 (0.03)
UpperMid Income	0.88 (0.05)	0.85 (0.06)	0.75 (0.03)	0.75 (0.04)
LowerMid Income	0.77 (0.06)	0.85 (0.06)	0.66 (0.03)	0.66 (0.04)
Low Income	0.78 (0.09)	0.87 (0.10)	0.76 (0.04)	0.70 (0.03)
OECD	0.80 (0.05)	0.80 (0.05)	0.68 (0.02)	0.64 (0.02)
Non-OECD	0.82 (0.04)	0.86 (0.04)	0.71 (0.03)	0.69 (0.04)
Developed	0.76 (0.03)	0.80 (0.05)	0.65 (0.02)	0.63 (0.02)
Developing	0.85 (0.03)	0.89 (0.05)	0.72 (0.03)	0.73 (0.03)
EU	0.78 (0.03)	0.86 (0.05)	0.64 (0.02)	0.69 (0.02)

Note: See also the notes in Table 3. The hypothesis that the extent of risk sharing has not increased in the 1990-2010 subperiod relative to the 1970-1989 one ($H_0 : \hat{\beta}_{1970-1989} = \hat{\beta}_{1990-2010}$, $H_1 : \hat{\beta}_{1970-1989} > \hat{\beta}_{1990-2010}$) cannot be rejected for any country group at the 5% level of marginal significance.

necessarily imply that this should be the case. Whether asset trading fosters risk sharing, crucially depends on the co-movements of domestic and foreign asset returns. The benefit will be limited if, due to geographic, political or cultural proximity, countries only engage in asset trading with partners that are affected by similar shocks. Neither will procyclical foreign credit—abundant in booms and scarce in busts—contribute to international risk sharing. On the other hand, asset trading between countries that experience asymmetric shocks is expected to result in a greater degree of insurance.

Empirical evidence in favor of a diversification motive in asset trading is mixed. For example, Lane and Milesi-Ferretti (2008) found little evidence that gains from diversification drive bilateral cross-country asset holdings. Instead, they observed that investors tend to hold equity in destinations with similar business cycle and stock market behavior. On the other hand, Pericoli et al. (2013), using the same data but resorting to a (panel) fractional regression model for investment shares, concluded that asset trading does appear to be affected by an incentive to diversify risk. Also, Sorensen et al. (2007) documented that during the 1990s a decline in home bias was associated with an increase in risk sharing in OECD countries. Kose et al. (2009) found that, while industrial countries have attained higher levels of risk sharing during the recent period of globalization, developing countries have been mostly shut out of these benefits. They attributed this result to the composition of capital flows, with external debt preventing many emerging economies to efficiently share risks. Similarly to Bai and Zhang (2012), they suggested that the dichotomy can be explained by the existence of threshold mechanisms, whereby only countries reaching a certain level of financial development reap the benefits of financial globalization.

To get some insight as to whether the level of risk sharing has changed over time, we have repeated our analysis for two subperiods, one running from 1970 to 1989, the other covering the period 1990 to 2010. Because the reduction in sample size affects the statistical properties of the two subperiods about equally, the estimates corresponding to each subsample can be compared to each other, revealing some interesting results.[2] Specifically, none of the country groups experienced a significant improvement in international consumption risk sharing in the financial globalization era, whether in the long or in the short run.

These conclusions stand in stark contrast with those of Artis and Hoffmann (2012), who estimated the fixed effects regression (4) using a subset of OECD countries that excluded Chile, Hungary, Israel, Korea, Mexico, Poland, and Turkey, and found a significant increase in long-run risk sharing. Using the dataset and estimator in their

[2]Our results do not materially change if we eliminate the impact of the Great Recession by limiting the time horizon to 2007.

study, we replicated the results of Artis and Hoffmann (2012), which were $\hat{\beta}^{LR}_{DEMFE} = 0.98$ for 1960-1990 and $\hat{\beta}^{LR}_{DEMFE} = 0.63$ for 1990-2004. However, once we allowed for general heterogeneity in the model, their conclusions suggesting an increase in risk sharing broke down: we obtained $\hat{\beta}^{LR}_{CCEMG} = 0.93$ for 1960-1990 and $\hat{\beta}^{LR}_{CCEMG} = 0.94$ for 1990-2004. Our results appear to support the view that while there has been an increase in the volume of financial transactions across the world, as of now, globalization has not triggered an increase in international consumption risk sharing.

6 Conclusion

We study the impact of cross-sectional heterogeneity on conventional international risk sharing tests. Relying on the restrictive assumption of symmetric country characteristics, the existing literature typically employs cross-sectional demeaning to filter out global shocks from the consumption and income panels. We find that the conventional method is not able to eliminate cross-sectional dependence and common factors from a heterogeneous data set. Inadequate handling of common factors results in misleading inference because the estimated coefficient attributes aggregate fluctuations in consumption to aggregate fluctuations in income. Moreover, imposing pooled estimation also produces bias in the coefficient estimates due to a positive correlation between the extent of consumption smoothing and the variation in income.

Inspired by the inadequacy of the conventional approach to isolate idiosyncratic fluctuations in a diverse set of 158 countries, we propose an alternative approach. We control for global factors via heterogeneous loading coefficients within an unobserved components framework that parallels the CCE methodology of Pesaran (2006) and Kapetanios et al. (2011). The estimates based on the conventional and the proposed approaches differ by up to 20% for various country groupings. Our results largely confirm the lack of evidence for full risk sharing, with the degree of risk sharing being lower in the long run. Furthermore, we show that developing economies are affected by idiosyncratic shocks quicker and to a greater extent than developed economies. In contrast to some earlier empirical findings, however, we do not detect any evidence of a recent increase in international risk sharing—either for developed or for developing countries—once we appropriately control for cross-sectional heterogeneity in the data.

References

Artis, M. and Hoffmann, M. (2006). The home bias and capital income flows between countries and regions. *CEPR Discussion Papers No. 5691*.

Artis, M. and Hoffmann, M. (2012). The home bias, capital income flows and improved long-term consumption risk sharing between industrialized countries. *International Finance*, 14(3):481–505.

Asdrubali, P., Sorensen, B. E., and Yosha, O. (1996). Channels of interstate risk sharing: United States 1963-1990. *The Quarterly Journal of Economics*, 111(4):1081–1110.

Athanasoulis, S. G. and van Wincoop, E. (2000). Growth uncertainty and risksharing. *Journal of Monetary Economics*, 45(3):477–505.

Bai, Y. and Zhang, J. (2012). Financial integration and international risk sharing. *Journal of International Economics*, 86(1):17–32.

Banerjee, A. and Carrion-i Silvestre, J. L. (2014). Testing for panel cointegration using common correlated effects estimators. *Working paper*.

Becker, S. O. and Hoffmann, M. (2006). Intra- and international risk-sharing in the short run and the long run. *European Economic Review*, 50(3):777–806.

Browning, M. and Collado, M. D. (2001). The response of expenditures to anticipated income changes: Panel data estimates. *American Economic Review*, 91(3):681–692.

Coakley, J., Fuertes, A.-M., and Smith, R. (2001). Small sample properties of panel time-series estimators with I(1) errors. In Baum, C. F., editor, *Computing in Economics and Finance 2001*, number 191. Society for Computational Economics.

Coakley, J., Fuertes, A.-M., and Smith, R. (2006). Unobserved heterogeneity in panel time series models. *Computational Statistics & Data Analysis*, 50(9):2361–2380.

Cochrane, J. H. (1991). A simple test of consumption insurance. *Journal of Political Economy*, 99(5):957–976.

Crucini, M. J. (1999). On international and national dimensions of risk sharing. *The Review of Economics and Statistics*, 81(1):73–84.

Davidson, J. E., Hendry, D. F., Srba, F., and Yeo, S. (1978). Econometric modelling of the aggregate time-series relationship between consumers' expenditure and income in the united kingdom. *The Economic Journal*, pages 661–692.

Fratzscher, M. and Imbs, J. (2009). Risk sharing, finance, and institutions in international portfolios. *Journal of Financial Economics*, 94(3):428–447.

Giannone, D. and Lenza, M. (2010). The Feldstein-Horioka fact. In *NBER International Seminar on Macroeconomics 2009*, pages 103–117. University of Chicago Press.

Harvey, A. (1989). *Forecasting, structural time series models and the Kalman filter*. Cambridge: Cambridge University Press.

Hendry, D. F. (1995). *Dynamic Econometrics*. Oxford: Oxford University Press.

Heston, A., Summers, R., and Aten, B. (2012). Penn world table version 7.1. *Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania*.

Holly, S., Pesaran, M., and Yamagata, T. (2010). A spatio-temporal model of house prices in the usa. *Journal of Econometrics*, 158(1):160–173.

Kapetanios, G., Pesaran, M. H., and Yamagata, T. (2011). Panels with non-stationary multifactor error structures. *Journal of Econometrics*, 160(2):326–348.

Kose, M. A., Prasad, E. S., and Terrones, M. E. (2009). Does financial globalization promote risk sharing? *Journal of Development Economics*, 89(2):258–270.

Lane, P. R. and Milesi-Ferretti, G. M. (2008). International investment patterns. *The Review of Economics and Statistics*, 90(3):538–549.

Leibrecht, M. and Scharler, J. (2008). Reconsidering consumption risk sharing among oecd countries: some evidence based on panel cointegration. *Open Economies Review*, 19(4):493–505.

Lewis, K. K. (1997). Are countries with official international restrictions 'liquidity constrained'? *European Economic Review*, 41(6):1079–1109.

Mace, B. J. (1991). Full insurance in the presence of aggregate uncertainty. *Journal of Political Economy*, 99(5):928–956.

Obstfeld, M. (1989). How integrated are world capital markets? Some new tests. In Calvo, G., Findley, R., Kouri, P., and Braga de Macedo, J., editors, *Debt, Stabilization and Development: Essays in memory of Carlos Diaz-Alejandro.*, pages 134–155. Oxford: Basil Blackwell.

Obstfeld, M. (1994). Are industrial-country consumption risks globally diversified? In Leiderman, L. and Razin, A., editors, *Capital Mobility: The Impact on Consumption, Investment and Growth*, pages 13–47. Cambridge: Cambridge University Press.

Pericoli, F., Pierucci, E., and Ventura, L. (2013). Cross-border equity portfolio choices and the diversification motive: A fractional regression approach. *Economics Letters*, 121(2):282–286.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. *CESifo Working Paper Series No. 1229; IZA Discussion Paper No. 1240.*

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4):967–1012.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2):265–312.

Pierucci, E. and Ventura, L. (2010). Risk sharing: a long run issue? *Open Economies Review*, 21(5):705–730.

Sorensen, B. E., Wu, Y.-T., Yosha, O., and Zhu, Y. (2007). Home bias and international risk sharing: Twin puzzles separated at birth. *Journal of International Money and Finance*, 26(4):587–605.

Sorensen, B. E. and Yosha, O. (1998). International risk sharing and European monetary unification. *Journal of International Economics*, 45(2):211–238.

Sorensen, B. E. and Yosha, O. (2000). Is risk sharing in the United States a regional phenomenon? *Economic Review-Federal Reserve Bank of Kansas City*, 85(2):33–47.

van Wincoop, E. (1999). How big are potential welfare gains from international risksharing? *Journal of International Economics*, 47(1):109–135.

Westerlund, J. and Urbain, J.-P. (2015). Cross-sectional averages versus principal components. *Journal of Econometrics*, 185(2):372–377.

Appendix: List of countries by subgroup[3]

High Income: Australia, Austria, Bahamas, Bahrain, Barbados, Belgium, Bermuda, Brunei, Canada, Cyprus, Denmark, Equatorial Guinea, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, Republic of Korea, Luxembourg, Macao, Malta, Netherlands, New Zealand, Norway, Oman, Poland, Portugal, Puerto Rico, Singapore, Spain, St. Kitts & Nevis, Sweden, Switzerland, Trinidad & Tobago, United Kingdom, United States.

Upper Mid-Income: Algeria, Angola, Antigua & Barbuda, Argentina, Botswana, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, Gabon, Grenada, Iran, Jamaica, Jordan, Lebanon, Malaysia, Maldives, Mauritius, Mexico, Namibia, Palau, Panama, Peru, Romania, Seychelles, South Africa, St. Lucia, St.Vincent & Grenadines, Suriname, Thailand, Tunisia, Turkey, Uruguay, Venezuela.

Lower Mid-Income: Albania, Belize, Bhutan, Bolivia, Cameroon, Cape Verde, Republic of Congo, Cote d'Ivoire, Djibouti, Egypt, El Salvador, Fiji, Ghana, Guatemala, Guyana, Honduras, India, Indonesia, Iraq, Kiribati, Lesotho, Marshall Islands, Fed. Sts. Micronesia, Mongolia, Morocco, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Paraguay, Philippines, Samoa, Sao Tome & Principe, Senegal, Solomon Islands, Sri Lanka, Sudan, Swaziland, Tonga, Vanuatu, Vietnam, Zambia.

Low Income: Afghanistan, Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Central African Republic, Chad, Comoros, Dem. Rep. Congo, Ethiopia, Gambia, The, Guinea, Guinea-Bissau, Haiti, Kenya, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Nepal, Niger, Rwanda, Sierra Leone, Somalia, Tanzania, Togo, Uganda, Zimbabwe.

OECD: Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Republic of Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.

OECD-AH: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States.

Developed: Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Israel, Ireland, Italy, Japan, Luxembourg, Malta,

[3] Our conclusions are robust to the presence of small countries in the sample. The results do not materially change when countries with population below 1 million are excluded from the analysis.

Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Spain, Sweden, Switzerland, United Kingdom, United States.

Developing: Algeria, Angola, Argentina, Bahrain, Bangladesh, Barbados, Benin, Bermuda, Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Chile, China, Colombia, Comoros, Dem. Rep. Congo, Republic of Congo, Costa Rica, Cote d'Ivoire, Cuba, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Ethiopia, Gabon, The Gambia, Ghana, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong, India, Indonesia, Iran, Iraq, Israel, Jamaica, Jordan, Kenya, Republic of Korea, Lebanon, Lesotho, Liberia, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Morocco, Mozambique, Namibia, Nepal, Nicaragua, Niger, Nigeria, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Singapore, Somalia, South Africa, Sri Lanka, Sudan, Taiwan, Tanzania, Thailand, Togo, Trinidad & Tobago, Tunisia, Turkey, Uganda, Uruguay, Venezuela, Vietnam, Zambia, Zimbabwe.

EU: Austria, Belgium, Bulgaria, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Spain, Sweden, United Kingdom.