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Cross-country Consumption Risk Sharing, a Long-run Perspective

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Abstract

This paper estimates an empirical nonstationary panel regression model that tests long-run consumption risk sharing across a sample of OECD and emerging market (EM) countries. This is in contrast to the existing literature on consumption risk sharing, which is mainly about risks at business cycle frequency. Since our methodology focuses on identifying cointegrating relationships while allowing for arbitrary short-run dynamics, we can obtain a consistent estimate of long-run risk sharing while disregarding any short-run nuisance factors. Our results show that long-run risk sharing in OECD countries increased more than that in EM countries during the past two decades.

JEL Classification Numbers: E00, E21, F00

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Contents

1 Introduction

The complete market benchmark model on consumption risk sharing across countries predicts that a country's consumption equals a constant portion of current world output that depends on the country's initial share of the world wealth (Obstfeld and Rogoff (1995))[2]. This implies that a country's consumption is independent of or orthogonal to GDP, apart from the global components of its consumption and GDP. Much of the empirical literature has used panel regressions of country specific consumption growth on output growth in testing this orthogonal implication (I call this type of regression "conventional panel regression").[3] [4]

What is puzzling is the indecisiveness of the findings. It is not surprising that the test and estimate results found limited risk sharing considering many factors can limit the level of risk sharing in the real world (Mendoza (1991) and Backus, Kehoe and Kydland (1992) on market frictions and restrictions on market institutions; and Obstfeld and Rogoff (1995) on moral hazard and sovereign risks).[5] It is the indecisiveness that makes people even doubt if risk sharing indeed exists in practice. For example, Canova and Ravn (1996) concluded that the risk sharing is almost complete in the short cycle, but not in the medium and long cycles. This contradicts the claim of Artis and Hoffmann (2006) that there is more risk sharing in the long-run than in the short-run. Moreover, despite the theoretical prediction that globalization should reinforce risk sharing through easier access to more diversified contingency contracts, much of the literature nevertheless did not find increases in risk sharing following the recent increase in global financial integration (Bai and Zhang (2006) and Moser, Pointer and Scharler (2004)).[6] Labhard and Sawichi (2006), based on a factor analysis approach, even find a slight decrease in risk sharing between UK regions and between UK and other OECD countries. For survey papers, please refer to Kose, Prasad and Terrones

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[2]Obstfeld and Rogoff 1995 show that, assuming a framework of two countries, two periods, output uncertainty, complete market, CRRA utility function, the consumer utility maximization leads to "perfectly pooled equilibrium" (Lucas (1982)) or mathematically $C_2(s) = \mu Y_2^W(s)$.

[3]The term of risk sharing is also called ex-ante risk sharing or state contingent insurance (they are interchangable in this paper), distinguishing with the ex-post risk sharing or intertemporal smoothing. For a preview on the regression specification on selected papers, please refer to Appendix I.

[4]Kollmann (1995), using nonstationary time-series technique to test risk sharing, found rejection of the null hypothesis of full risk sharing in all country pairs. However, the method he used, besides the problem of potential low power and high size distortion in time series context, can only do a test of full risk sharing or not, but cannot test the degree of risk sharing.

[5]Backus, Kehoe and Kydland (1992) has documented an important "consumption correlation regularity", i.e., the cross country consumption correlation is no higher than cross country output correlation, contradicting with the benchmark model's prediction. Following Backus, Kehoe and Kydland (1992), many researchers' explanations of the regularity hinge on the idea of relaxing the consumption utility function to allow, for example, non-addictive non-tradable goods (Backus and Smith (1993) and Tesar (1993)), the nonseperability of goods and leisure (Devereux, Gregory and Smith (1992)), and taste shocks (Stockman and Tesar (1995)). The problem is that the models still predict strong consumption correlation, but the empirical tests nevertheless indicate low.

[6]Artis and Hoffmann (2006) and Artis and Hoffmann (2007), among a few papers, found risk sharing increased in the recent financial integration period.

(2007) and Corcoran (2008).

At a basic level, the conventional panel regression requires stationarity of the data in order to avoid spurious regression problem and nonstandard distributions on inference. Therefore, in testing risk sharing, researchers routinely first-difference data on consumption and GDP. As a result of differencing, the estimates measure risk sharing on transitory shocks or risks at business cycle frequency. The welfare gain from risk sharing at business cycle frequency has been found small in the literature, for example, Gourinchas and Jeanne (2006), Lucas (1987) and Cole and Obstfeld (1991). The small welfare gain implies the motivation of risk sharing is low and may be dominated by many other motivations. It is therefore not surprising that only low risk sharing or no increase of risk sharing has been found in the literature.

If the level of output contains information, beyond the information carried through changes in output, that is useful for the decision-making on consumption risk sharing, we should include the level of output into our investigation. Specifically, if output is I(0), i.e. it is mean-reversing, the level of output does not give much additional information beyond the differenced output. If output is I(1), differencing would remove the permanent component of output that drives the nonstationarity.

As discussed below, the welfare gain of risk sharing on the permanent shocks should be much higher than that on the transitory shocks. We therefore think it is important and interesting to test risk sharing on permanent shocks. In this case, the estimated consumption risk sharing, identified by the cointegrating coefficient in a nonstationary panel regression model, is the long-run risk sharing.

Because our methodology focuses on identifying the long-run cointegrating relationship, we can allow for full heterogeneities on the short-run dynamics. This implies that we can obtain a consistent estimate of long-run risk sharing while disregarding any short-run nuisance factors. However, in the conventional panel regression model, without further structure assumption on the model, the dynamics is restricted to be homogeneous.[7] As a result, they omit important factors such as the heterogeneity in short-run dynamics that are caused by intertemporal smoothing, taste shocks, or market frictions. The recent paper by Artis and Hoffmann (2008) offers a similar insight. They argued that the risk sharing has, in fact, increased following the recent financial integration, but both the conventional panel regression and consumption correlation failed to detect this increase due to the change of the output dynamics in the same period.

Athanasoulis and van Wincoop (2001), and a more recent and close cousin of it, Flood, Marion and Matsumoto (2008) are among the recent developments in the literature that have brought us closer to understanding long-run risk sharing. Athanasoulis and van Wincoop (2001) argued "the effect of temporary income shocks on consumption can be buffered through borrowing and lending, but over longer horizons one can

[7]This is essentially because that conventional panel analysis is an extension of cross-sectional analysis where it pools the cross-sectional dimension or averages on the cross-sectional dimension to achieve an estimate. In another word, it relies on the cross-sectional asymptotics for inference. Therefore it cannot allow for country-specific slope coefficients and dynamics.

expect consumption growth to closely follow the growth rate of income after risk sharing." They therefore use the techniques developed in Athanasoulis and van Wincoop (2000) to test income risk sharing at different frequencies between U.S. states. However, the long-run measure of the paper is reliable if the state income data is free of intertemporal consideration.

Artis and Hoffmann (2006) is the closest paper in the literature to this paper. They, as this paper does below, use consumption and GDP levels (instead of growth rates) on testing and estimating risk sharing, which they hope can, in some way, get rid of the effects of short-run confounding factors. However, their regression is essentially under conventional panel framework, without taking the nonstationary properties and full heterogeneity in the short-term dynamics into account. More importantly, they use the OLS or pooled version dynamic OLS which does not give an estimate of cointegrating relationship if the slope coefficient is heterogenous.

Our results indicate that, for the period of 1950 to 2008, the level of long-run risk sharing in the OECD countries is similar to that in the emerging market countries. However, during the financial integration episode of the past two decades, long-run risk sharing in OECD countries has increased much more than that in emerging market countries. Furthermore, we investigate the relationship between various measures of financial integration and cross-country risk sharing, but only find weak evidences on such linkages.

The paper is structured as follows. In section 2, we discuss implication of financial integration on risk sharing and how long-run risk sharing can be estimated in nonstationary panel. Section 3 will illustrate the model specification pertinent to the issues in testing and estimating risk sharing. We will discuss our data and sample selection in section 4. Section 5 will present our cointegration estimating and testing results; we examine the distribution patterns of the risk sharing and link it to some financial integration indicators in section 6. Finally, section 7 will conclude this paper and discuss possible future directions.

2 Theoretical Motivations

In order to estimate long-run risk sharing, we need to understand how risk sharing happens when countries open up and financially integrate with each other. In fact, financial integration influences a country's consumption, given a certain output dynamics, through two functions: state contingent insurance and intertemporal smoothing. In a financially integrated world, countries facing uncertain output streams use the Arrow-Debreu securities or Shiller portfolios to share the idiosyncratic output risks away (Arrow (1964), Debreu (1959) and recently Shiller (1993)). In practice, such securities or portfolios do not exist, so we use the cross-country holding of assets and liabilities as proxies. If the insurance is not complete, the intertemporal smoothing that involves intertemporal reallocation of consumption through borrowing and lending in a risk free bond market comes into play. If the insurance market is complete, this risk free market is redundant (Constantinides and Duffie (1996))[8].

A point that we need to keep in mind is that intertemporal smoothing may be preferable in the case that a shock can also be insured because, considering the sovereign risks and moral hazards, the cost of insurance contracts is higher than the riskless bond contracts (Obstfeld and Rogoff (1995) Chapter 6). We are not considering the sovereign risk and moral hazard explicitly. However, those types of endogenous imperfection of the international capital market can further limit the extent of risk sharing (Becker and Hoffmann (2006)).[9] I will discuss this further when explaining the empirical results.

These two functions are mechanically different and bear different welfare implications. Beveridge and Nelson (1981) has illustrated that any time series which exhibits the kind of homogeneous non-stationarity can be decomposed into two additive components, a weakly dependent stationary series and a pure random walk. Intuitively, if we investigate the fluctuation of the GDP series, the primary source of fluctuation is the growth that is driven by shocks that has persistent or permanent effects, and the transitory fluctuations that surround the trend growth are second-order. Specifically, the transitory shocks only lead the GDP deviating from its current value temporarily and reversing to its current value in the long run. However, the GDP subject to permanent shocks is not mean-reversing and thus perform as a unit root process. We therefore say the transitory fluctuations, which are stationary, are second-order comparing to the first-order nonstationary movement caused by the permanent shocks.

Baxter and Crucini (1995) concludes if output shock has persistent effects, it can only be shared through insurance market, and the risk free bond market can only share the transitory shocks.[10] Therefore, in the context of risk sharing, the deterministic force on a country's consumption trend is state contingent insurance. Given the persistent shock can only be shared in insurance market has been said, then, for the permanent component of output, which has an infinite variance over time, the uncertainty facing individuals is very large and thus the state contingent insurance, comparing to the intertemporal smoothing, bears a much larger welfare gain (van Wincoop (1999); Obstfeld (1994)). We can think of this welfare gain using the following example. Let us imagine the extreme case of complete market with full state contingent insurance. We would expect consumption growth rate in US is the same as in Zimbabwe. Clearly, in terms of a country's long-term development, insurance is more important and constitutes most of the welfare gain. It is for this reason that I think a separate investigation

[8]Another risk sharing institution is government transfer. However, since it is relatively small at the country level (Asdrubali, Sorensen and Yosha (1996)), and also because this paper focus on the financial integration, we do not have it explicitly in the paper. However, we should keep in mind that the estimated risk sharing has a small portion of the government transfer effect.

[9]We call the sovereign risk and moral hazard endogenous incompleteness in order to distinguish them with the other market incompleteness, such as the uninsurable nontradable goods market, the riskless bond along market which can be treated as exogenously given.

[10]That is, if shocks to GDP are transitory, intertemporal smoothing through borrowing and lending in the risk free bond market can act as a close substitute for risk sharing. However, if shocks to GDP are persistent, the ex-post risk sharing, which smooth consumption through intertemporally allocating resources, will not be effective due to the persistent nature of the shocks.

of long-run risk sharing is warranted.

Although we are not focusing on risk sharing at business cycle frequency or on the transitory shocks, it is fully addressed in the serial correlation properties of the nonstationary panel analysis. This is because long-run risk sharing involves I(1) movement of consumption and output while risk sharing on transitory shocks only involves I(0) stationary movements which is an order of magnitude less and therefore can be corrected by using internal instruments.

Specifically, similar as in the literature, we use the relationship between idiosyncratic GDP per capita and idiosyncratic consumption per capita as a measure of long-run risk sharing effect of financial integration. The difference is that we explore the nonstationarity of this relationship. Suppose $c_{it} - c_t^*$, $t = 1, ..., T$ has a unit root for each member $i = 1, ..., N$, and so does for $y_{it} - y_i^*$ ($c_{it} - c_t^*$ and $y_{it} - y_i^*$ index idiosyncratic consumption per capita and idiosyncratic GDP per capita respectively), then $c_{it} - c_t^*$ and $y_{it} - y_t^*$ form a cointegrated panel if some linear combination, $\epsilon_{it} = (c_{it} - c_i^*) - \alpha_i - \beta_i(y_{it} - y_i^*)$ is stationary. The slope coefficient β_i is the steady state cointegrating coefficient which indicates a long-run relationship between two I(1) series that will be maintained forever unless some external shock breaks it. We interpret the estimated β_i as our measure of long-run risk sharing. Since risk sharing on the transitory shocks only involves with short-run fluctuations towards its steady state equilibrium, it is contained into the error term in such a cointegrated system (Phillips (1991)).

In brief, the long-run risk sharing is defined in contrast to the risk sharing on risks at business cycle frequency that dominates the literature, where the series is firstly differenced to render stationarity.[11] The nonstationary panel approach allows us to isolate the long-run steady state relationship from short-run dynamics through wiping out the confounding effect of intertemporal smoothing and other nuisance features.

Another advantage of nonstationary panel analysis is that, the group mean Fully Modified OLS (FMOLS) and the group mean Dynamic OLS (DOLS) estimation can address an important issue in the empirical work on risk sharing, the cross country variation in the steady state of risk sharing. The intuition on this is straightforward. At the practical level, different countries will reasonably choose the level of cross-country holding of assets and liabilities to the extent that the costs equal benefits. Given that the costs and benefits may differ across countries and across different contingencies, the level of risk sharing should be different. While the group-mean nonstationary specification allows heterogeneous slope coefficients, the slope coefficient is forced to be common across countries in the conventional panel specification.[12] As a byproduct of

[11]Depending on the assumption of the data, some literature using detrending method to render stationarity. For example, Stockman and Tesar (1995) detrend output and consumption data through HP filter and underlying assumption is the data are trend stationary. A rather unsatisfactory implication to model economy using this approach is that the long-run evolution of the time series is deterministic and therefore perfectly predictable. There is no macroeconomic theory indicate growth has a deterministic trend for a certain country. Intuitively, if each country has different deterministic trends, then the country has the highest trend should already dominate the world by now. For this reason, we consider stochastic trend.

[12]Without exploring time series asymptotics, it is difficult for the conventional panel model to achieve

allowing the heterogeneity in risk sharing, we can study the cross-country risk sharing distributions and link this distribution patterns to static financial integration indicators.

Another reason for doing this long-run analysis is because, nevertheless the short-run analysis in the literature find no or limited increase in risk sharing during the recent financial integration period, Lane and Milesi-Ferretti (2003), using carefully collated data, has shown dramatic increase in international capital flows accompanying the financial integration. This leaves the puzzle whether the increased financial integration, as indicated by the increase in capital flows, can, in practice, induce the higher risk sharing (Sorensen, Wu, Yosha and Zhu (2007)). Artis and Hoffmann (2008) found that consumption risk sharing has increased during the financial integration period, but the short-run analysis failed to detect it due to the concurrent decline of output volatility in the short-run. We therefore, by splitting the data sample into pre- and after 1990 period, test the changes in risk sharing associated with financial integration using the nonstationary panel techniques.[13]

A branch of the short-run analysis takes advantage of the gross national income (GNI) data available from country national accounts to estimate state-contingent insurance and intertemporal smoothing separately through an output variance decomposition approach initiated by Asdrubali, Sorensen and Yosha (1996). Using GNI, instead of consumption series, to estimate state-contingent insurance seems get rid of the contamination of intertemporal smoothing in the most direct way. In fact, although the contamination is not directly from consumption smoothing in this case, the same arguments apply. The intertemporal consideration can endogenously influence the real level of net factor income recorded in national account, making it different as the potential level of net factor income (Lane (2001)). Therefore, the net factor income can be simultaneous with the output dynamics and thus bias the estimated insurance in the similar way as the estimate on overall risk sharing we argued in the paragraphs above. In addition, it is well known that the factor income from the BOP account is not accounted accurately. This can induce serious measurement problem in conventional panel regression. Furthermore, the capital gains and losses on investment are not captured in GNI, but it will provide some kind of risk sharing. For countries holding large portfolios in equity and FDI, this is especially important since, typically, most of the returns are in the form of capital gains or losses.

In addition, the nonstationary panel analysis allows some other features that turn out to be particular convenient in testing and estimating the long-run risk sharing. For example, at the macro level, everything is depending on everything else, thus it is fair to think that GDP and consumption are interdependent. Just as in the time series nonstationary analysis, we do not need to worry about the simultaneity or endogeneity problem in nonstationary panel analysis simply due to the fact that we are exploring a

reliable estimate on country specific slope coefficient with enough explanatory power except for the case of Hsiao and Pesaran (2004) where some structures are imposed on their random coefficient model.

[13]This data split is aline with the captial flow patterns found in Lane and Milesi-Ferretti 2003 and is consistent with the practice in the literature.

cointegrating relationship that is an order of magnitude greater than the simultaneous and endogenous problem that plague in the conventional panel analysis. For a similar reason, it is also robust to many forms of omitted variables. In the meanwhile, in contrast to the time series analysis that is well-known to be data-demanding with low power and high size distortion in finite sample, the nonstationary panel is able to use relatively short time series to infer the long run while maintaining reliable power and size properties.

3 An Illustration on Conventional Panel and Nonstationary Panel Approaches

3.1 Conventional Panel

In the literature, many researchers used the following equation, or variants of the following equation to measure risk sharing (see Mace (1991), Cochrane (1991), Townsend (1994), Canova and Ravn (1996), Lewis (1996); for survey papers, refer to Corcoran (2008) and Kose, Prasad and Terrones (2007)):

$$\Delta c_{it} - \Delta c_t^* = \alpha_i + \beta(\Delta y_{it} - \Delta y_t^*) + \varepsilon_{it} \tag{1}$$

where Δc_{it} is the consumption change of country i from period t-1 to t, Δc_t^* is the change in world average consumption from period t-1 to t; Δy_{it} and Δy_t^* are defined in the same way on outputs and therefore, the relative changes of output in country i captures its idiosyncratic output risks. ε_{it} is assumed to be uncorrelated with the regressors, and is typically assumed to be $i.i.d.(0, \sigma^2)$ white noise [14]. β is restricted to be the same across countries and is interpreted as a consumption-based measure of the risk sharing effect of financial integration. If all the maintained assumptions hold, we can get consistent estimate of β from equation (1). However, we argue that, empirically, the estimate of β in this model specification is biased for several reasons. For details on how equation (1) is derived and its technical limitations, please refer to Appendix II.

As you can see in the Appendix II, β is the product of λ and α that serve to measure risk sharings through insurance market and risk free bond market respectively. For example, suppose $\lambda = 0.9$ and $\alpha = 0.8$, then $\beta = 0.72$, meaning 72% of risks are not shared. In another word, this implies 10% of risks $(1-\lambda)$ are shared through insurance, and 18% of risks $(\lambda \times (1-\alpha))$ are shared through intertemporal smoothing. The λ and α can be estimated jointly from equation (1) or separately by using Asdrubali, Sorensen and Yosha (1996) output variance decomposition approach.

[14] As illustrated in the Appendix II, the error term is actually a martingale difference process. Strictly speaking, martingale differernce process and white noise process are not the same (see Rachev et. al (2006)). ε_{it} is assumed $i.i.dWN(0, \sigma^2)$ simply because equation (1) is typically estimated by OLS which requires it as a maintained assumption. Certainly, ε_{it} can be relaxed to allow for heteroskydascity and even homogeneous serial correlations, but these would not change the point that we make.

One of the maintained assumption of equation (1) is ε_{it} is an i.i.d. white noise process because permanent income and aggregated income are assumed to be martingale. The martingale process basically assumes the risk free bond market is efficient. Leroy and Samuelson are among the earliest to notify that martingale process mathematically captures the economic notion of efficient market. It is debatable if the bond market of the U.S. can be modeled as efficient, but we turns to believe a more general DGP in a cross-section of countries. For example, it is hard to believe that the markets are well developed in emerging market and can be modeled in the same way as in the market of U.S. In such cases, we have to take the heterogeneous transitional dynamics into account since simply taking first difference of the data will leave some untreated dynamics in the error term.

The conventional panel can deal with serial correlations since the assumption on ε_{it} in equation (1) can be relaxed to allow for dynamics. If ε_{it} is assumed to be serial correlated, it is by construction treating dynamics. However, it is well known that conventional panel approach typically can only deal with homogeneous dynamics (Arellano and Bond (1991)).[15]. A homogeneous dynamics implies that the impulse responses to disturbances are the same across countries in terms of size, shape and covergence speed. Or, in the case of risk sharing, it assumes the returns of consumption to its long-run equilibrium are the same across countries. This is simply not realistic. If the latent true dynamic is heterogeneous but is forced to be homogeneous, we will run into trouble in estimating the β in equation (1) (Smith and Peseran 1995). This problem cannot be easily solved in the conventional panel setting because it basically estimate a high frequency relationship that is at the same order of magnitudes as the transitional dynamics.

Apart from the problems of untreated dynamics and potential misspecification, equation (1) cannot be consistently estimated by OLS/FE (which are the estimates used in the literature) since ε_{it} is differenced martingale and therefore it is correlated with $(\Delta y_{it} - \Delta y_t^*)$. IV can deal with the inconsistency caused through this channel, but we all know that it is hard, if not impossible, to find valid IV in the macroeconomic context. Besides, the IV is not testable.

Some literature treats the differencing data at lower frequency in equation (1) as capturing long-run effect of risk sharing Canova and Ravn (1996). Again, this is only valid under the very strong assumption on the dynamics which is that ε_{it} is i.i.d. white noise after differencing in the equation (1). But for the reason argued above, we tend to believe that we should specify a model that takes as many lags as needed to make sure ε_{it} is white noise, and we believe that this can only be accomplished by using the nonstationary panel that we are turning to shortly.

β can also be biased due to omitted variables. Demand side shocks, for example, the taste shocks, do not get modeled in the above equation, but they influence con-

[15] More specifically, in a conventional panel regression framework, because $N \to \infty$ and T is finite, we can only do something like Arellano and Bond GMM to correct the endogeneity created when dealing with the fixed effect. However, GMM has to assume homogenous serial correlation and does not allow applying typical time series argument to take care of the dynamics.

sumption given a particular output process, and therefore move the estimated β from its hypothetical values. This omitted variable problem can be fixed if we can find reliable measures on it and include them into the equation (1) as separate regressors. However, the taste shocks are remaining as a black box in the literature and therefore very difficult to find quantifiable measures on it.

In general, to summarize the discussion above, under the framework of conventional panel analysis, we have to make restrictive assumptions on how the data are being generated. The problem is, on the one hand, the lack of the unified theoretical model that can completely describe the DGP,[16] and on the other hand, the unmeasurability or unavailability of data, for example, the quantifiable measure on demand shocks, hindered the applicability of such empirical specifications. However, it turns out not the case in using nonstationary panel. In particular, we can be blind on many aspects of the serial correlation properties of the data generating process and still be able to achieve consistent estimates.

3.2 Nonstationary panel

In this paper, we use the following equation to test ex-ante risk sharing.

$$c_{it} - c_t^* = \alpha_i + \beta_i(y_{it} - y_t^*) + u_{it} \tag{2}$$

$$u_{it} = \Psi_i(L) \cdot \varepsilon_{it} \tag{3}$$

where the consumption and output variables are defined the same as those in the first equation. But instead of working on growth, we deal with levels directly (Please refer to Appendix II for detailed steps on deriving equation(2). Noticing that if$y_{it} - y_t^* \sim I(1)$, and $u_{it} \sim I(0)$ following some weakly dependent I(0) process, then $c_{it} - c_t^* \sim I(1)$ by construction.[17] The subscript i on $\Psi_i(L)$ means the dynamics are allowed to be heterogenous across countries, and ε_{it} is $i.i.d.$ white noise true disturbance term. Despite simplicity in form, this equation has surprising nice features that can take care of the problems discussed above.

As discussed, intertemporal smoothing aims at smoothing out the risks at business cycle frequency that are caused by temporary output shocks. It, therefore, only creates second order bias that can be easily fixed in a cointegrating system. Specifically, the impact of intertemporal smoothing is contained in the terms u_{it}. Since u_{it} is a weakly dependent stationary process, the impacts of the dynamics contained in it is an order of magnitude less than the cointegrating relationship β_i that we are estimating in equation (2). We therefore can employ the FMOLS or DOLS method to make adjustment to

[16] Backus, Kehoe and Kydland (1992) had predicted that "five years from now the models that have been developed will differ from this starting point in fundamental ways", unfortunately, the development is not fundamental enough until now

[17] Consumption and output are I(1) processes are necessary conditions to explore the cointegration relationship between them. We will test these in the empirical part.

achieve consistent and unbiased estimate on β_i by using internal instruments that you will as below.

The nonstationary panel analysis essentially applies nonstationary time series properties into panel. Time series analysis is all about how to take care of dynamics that are unknown when you have enough data on T dimension. Although we do not know the form of $\Psi_i(L)$, but the estimation procedure (step-down procedure in ADF specification or kernel in nonparametric specification) will give the best estimates on them. This allows us treat effectively many issues that require strong assumptions in the conventional panel as nuisance features in the nonstationary setting.

For example, the reasoning above applies to demand shocks. The demand shocks are not explicitly specified in equation (2), but they are washed out without biasing the estimation on β since demand shocks are widely regarded as temporary shocks which is captured by the serial correlation of ε_{it}.

A broad class of short-term dynamics of consumption can be accommodated in equation (2). For example, Cavaliere, Fanelli and Gardini (2008) has shown market frictions, which prevent consumption adjust to its optimal instantaneously but instead gradually, can lead to lower consumption correlation than that standard models predict. They proceed to attribute the lack of risk sharing documented in previous research to the misspecification of short-term dynamics, including the speed of converging. In equation (2), the univariants $c_{i,t} - c_t^*$ and $y_{i,t} - y_t^*$ both have complicated dynamics and these can lead to more complicated dynamics in u_{it}, but it is OK since the estimation procedure will provide the best "guess" on it.

An important advantage of nonstationary panel specification is the equation (2) above allows for heterogeneous slope coefficient, β_i, which serves to capture the cross country variations in risk sharing, while in conventional panel approach that involves stationary variables, the slope coefficient, by construction, are forced to be homogeneous, leaving all the heterogeneities into the fixed effect. As we discussed before, the cost and benefit make it hard to believe that the risk sharing in the U.S. and Zimbabwe are in terms of nature, magnitude and even directions, which implies that a heterogeneous β_i is required.

The reason that β_i is allowed to be heterogeneous is because of the way of pooling data in our cointegration test and estimate. There are two ways of pooling the data on cross-sectional dimension and time series dimension based on the commonality explored across sections. One way assume the commonality across sections comes from a common β and produce within estimator on the cointegration relationship. Another way assume β_i is drawn from a common distribution and produce the group mean estimator of cointegration relationship.Pedroni (2000) andPedroni (2001) emphasize the advantages of using group-mean estimators. Also as a by-product of the group-mean estimator, we can compare the properties of the distribution of individual estimate to group mean values.

It is well-known that we face the data limitation when we apply time series analysis on macroeconomic tests. However, it is not the case for nonstationary panel. One of the nice features of nonstationary panel is that it uses the data on cross-sectional dimension to compensate the relatively short data on temporal dimension in order to achieve reliable estimating and testing results (Pedroni (1997)).

So far, we explain the terms of c_t^* and y_t^* in equation (2) as global component of consumption and output. From the theoretical point of view, the risks that is global in nature cannot be shared and thus the subtraction of c_t^* and y_t^* serves to leave only the idiosyncratic component in check. In the meanwhile, from the empirical point of view, this subtraction can be interpreted as accounting for certain forms of cross-sectional dependency that may present in the nonstationary panel. From a pure econometric point of view, the nonstationary panel approach uses the data on cross-sectional dimension to compensate the relatively short data on temporal dimension in order to achieve reliable estimating and testing results. Therefore, we hope the time series data is independent across sections and thus the information in individual cross section can add onto each other. If the data are cross section dependent, that means some information are redundant that reduces the power and introduces size distortion. The effectiveness of c_t^* and y_t^* in eliminating cross-sectional dependency depends on the form of the dependency, but it turns out that this simple form perform reasonable well in many cases, for example, in the case that the data are in part driven by common global business cycles or by a common stochastic trend.

Up to this point, our discussion takes incomplete market as given, but did not explain why the market is incomplete. Explaining why the market is not complete is not the purpose of this paper and please refer to Obstfeld and Rogoff (1995) Chapter 6 for the theoretical reasons on endogenous market incompleteness, such as sovereign risk and moral hazard if you are interested. Our estimated slope coefficient in 2 reflects those endogenous incompleteness. In the meanwhile, I want to point out that it also reflect the impact of exogenous incompleteness, for example, the non-insurability of the nontradable goods and labor incomes. But a fine point is that based on the assumptions on the additivity of the period utility function, we need to be cautious on the interpretation. Taken the nontradable goods as an example. If additivity holds, then we can derive a neat equalized marginal rate of substitutions between countries on the tradable goods and therefore we can interpret our estimate on the slope coefficient of 2 as proportional to the case of tradable goods since the nontradable goods are included into the regression. However, if the additivity does not hold, the introducing of the intratemporal elasticity of substitution and its interaction with the intertemporal elasticity of substitution ruled out a neat relationship between countries on the tradable goods and therefore, the interpretation can be viewed as a proxy at best.[18] In the end, we can view our risk sharing estimate as a "de facto" measure of risk sharing.

Backus, Kehoe and Kydland (1992)'s simulation results show that, in the case of technology spillover, consumption correlation can be high while output correlation is low even between the autarky economies. Does our measure of risk sharing is subject to such

[18]The simulation results in the literature show that the impact of nontradable goods is not large enough to generate the as low consumption correlation as it is in the data without assuming extrame intertemporal and intratemporal elasticity of substitution parameters. A similar finding for the case of leisures. This comforts us in not worrying too much on this fine point.

spillover bias? We justify this from two aspects. One the one hand, our test is a long-run test. If technology spillover is as high as in Backus, Kehoe and Kydland (1992)'s simulation model, we should see GDP convergence, but this is not the case of the data (Pedroni (2008)). On the other hand, we have taken the cross-country dependency of GDP out, and this mutes the impacts of technology spillover or contagions in general on our estimated coefficient.

4 Data and Sample Selection

4.1 Dataset

Our data on GDP and consumption are taken from the Penn World Table (PWT) version 6.2, the latest release in September 2006, and World Economic Outlook (WEO) April 2009 Publication. PWT contains a set of annual national accounts economic time series on many countries. It is widely used in the international risk sharing literature and therefore is convenient for our purpose since it has converted the expenditure entries into international dollars so that real quantity cross-country comparisons can be made (for details, please refer to Heston, Summers and Aten (2006)). However, the PWT only has GDP and consumption data up to 2004, in order to achieve the longest possible temporal dimension information, which is, in practice, important for the nonstationary analysis, we therefore extended the data to 2008 by using the national accounts data from WEO.

PWT and WEO covers 188 countries and 176 countries respectively which are literally almost the whole world. However, before rushing to experiment with all the covered countries, we must pay sufficient regard to empirical limitations to this particular sample. Although the PWT data start from 1950, for many developing countries, especially the least developed countries, the data start only after 1970s and the data quality grades signal the reliability of the estimates is of concern. In the meanwhile, conceptually, the restrictions on capital flows, the high risks associated with those countries, along with the substantial international transfer flows which provides some kinds of de-couple of consumption and GDP through non-financial market mechanism, make it highly debatable if any meaningful risk sharing exists and therefore can be detected on those countries.

Based on those considerations, we picked 45 OECD and emerging market countries for which have data span available from 1950 to 2008. These 45 countries covers all the 26 OECD countries and all the 22 emerging market countries defined by the FTSE Group and the Economist, except the East European transitional economies and Russia.[19] Moreover, these 45 countries consist more than 80 percent of world GDP as of

[19] The OECD countries include United States, United Kingdom, Austria, Belgium, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Norway, Sweden, Switzerland, Canada, Japan, Finland, Greece, Iceland, Ireland, Portugal, Spain, Turkey, Australia, New Zealand, Mexico, Korea. The emerging market countries include Argentina, Brazil, Chile, China, Colombia, Egypt, Hong Kong, India, Indonesia, Israel, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Saudi Arabia, Sin-

2008 and thus we believe they are large enough for us to treat them as a proxy for the whole world. We define idiosyncratic GDP per capita and consumption per capita as the country level GDP per capita and consumption per capita minus the world-wide average of GDP per capita and consumption per capita. Therefore, the higher the risk sharing, the less comovement between idiosyncratic GDP per capita and idiosyncratic consumption per capita. From this point on, when we discuss GDP per capita and consumption per capita, we implicitly mean the idiosyncratic ones, which are the demeaned GDP per capita and consumption per capita.

4.2 Sample Selection

We have made the decision on the data sample that we are going to explore, but before applying the empirical tests on it, I think it is worth to explain the strategies that I used to apply the nonstationary techniques in order to achieve the robust and informative results. Basically, any empirical tests are guided by the theoretical models. Unfortunately, we are facing the real world data limitations. This may hinder our ability to apply a test on a certain theory if the data did not show the pattern predicted by the theory. Therefore, another empirical strategy is to investigate what the data tell us and sort out the useful data information in testing the theories. In the practice of this paper, we compromise between the information carried through data and the prediction made by theories, and use both strategies in our tests and hope we can cover basis by doing both.

The panel unit root tests on GDP per capita and consumption per capita, as shown in table 1, signal very strong sign of non-rejection of the null of unit root for the 45 country sample. The tests of cointegration between GDP per capita and consumption per capita, as shown in table 2, indicate significant rejection of the null of unit root on the error term of equation 2, meaning they are cointegrated. These findings are consistent with the predictions of the neoclassical growth model. The neoclassical growth model tells us that a country's GDP per capita should follow some kind of non-mean-reversing process if a country has experienced permanent changes in technologies or in investment rates, and therefore we can model the GDP per capita as a unit root process. Since we find consistency between data and theory, therefore, our first test strategy is to test and estimate long-run risk sharing on the whole 45 countries.

The panel test results in table 1 and table 2 are constructed by the test results of the individual country. For example, in table 1, we reported the IPS ADF test statistics which are, in its simplest form, an average of the individual ADF test statistics. When taking a closer look at the individual country's unit root test results, reported in table A1, we find, for some countries, the test statistics reject the null of unit root on the GDP per capita and consumption per capita. This may due to the high size distortion when coming to time series nonstationary analysis and we should not trust and pay much attention to it. But, at a practical level, there is nothing restricting the GDP

gapore, South Africa, South Korea, Thailand, Turkey.

per capita of a country has to follow a unit root process within a certain time period. For example, the technology changes or changes in investment rates may not have been significant enough within the sample period to drive the country to move with unit root characteristics. To include those countries won't break the test based on the whole sample down. This is because although those countries with stationary GDP per capita process are not very informative about the risk sharing relationship that we are interested in, they are an order of magnitude less than the cointegration relationship and therefore irrelevant asymptotically. However, for a finite sample, we realize that it increases the noise-to-signal ratio of the long-run risk sharing analysis. We therefore take out those countries with stationary test results on GDP per capita or consumption per capita.

We then proceed to conduct the cointegration test on consumption and GDP per capita. The individual cointegration tests in table A2 show that they are not cointegrated for many countries.[20] Again, this could due to the low power for rejection the null hypothesis on the error terms or due to the high size distortion, but to guard us to be on the safe side, we take those countries out. This leaves our with 21 countries, a country sample which contains rich nonstationary information, even for individual countries, and therefore with significantly reduced noise-to-signal ratio. The test results on the 21 country subsample are used as robust checks on the whole sample results.

5 Interpreting the Risk Sharing Relationship

5.1 FMOLS and DOLS

We estimate the slope coefficient of the cointegrating relationship in equation (2) using the group mean FMOLS and group mean DOLS regressions and interpret it as measured "de facto" risk sharing. Depending on the way of pooling the information on time series and cross sectional dimensions of the panel, and depending on the parametric or nonparametric estimation approaches, the econometricians has developed several different versions of the estimators on the panel cointegrating coefficient. For the details, please refer to Phillips and Moon (1997), Mark and Sue (1999) and Kao (1997) for the pooled estimators, and Pedroni (2000) and Pedroni (2001) for the group mean estimators.

We pick the group mean estimators, instead of the pooled versions because the pooled versions have a maintained assumption which treats the slope coefficient of the cointegrating relationship as common value. This maintained assumption not only restricts the applicability of the pooled estimators for our context of risk sharing, but also restricts the opportunities for us to comparing the cross-country distribution of the slope coefficient. Furthermore, the group mean estimators perform better small sample size properties than the pooled estimators in the monte carlo simulations shown

[20] In table 2A, only the countries passed the individual cointegration tests are reported. But the full results are available from the auther up on request.

in Pedroni (2000). In addition, Pedroni (2001) show that the group mean FMOLS and DOLS both tend to perform well in small sample in terms of size distortion, but since DOLS is a parametric-based test, it does better in terms of power when sample is very short which would be the case of this paper when we apply our test for the period post-1990. Therefore, we do both FMOLS and DOLS in order to cover bases.[21]

The FMOLS estimator was first developed by Phillips and Hansen (1990) in the time series context. Pedroni (2000) extended it into panel context and developed the group mean FMOLS estimator, which allows both heterogeneous dynamics and heterogenous cointegrating vectors. The basic idea of the group mean FMOLS estimator is straightforward and can be interpreted as the cross-country average of the individual country FMOLS estimators, where the individual FMOLS estimator has been corrected for serial correlation and for endogeneity through a long-run covariance matrix. The correction can be achieved because of the fact that the cointegration relationship is an order of magnitude higher than the biases induced by serial correlations and endogeneities and therefore the differentiated regressors can serve as internal instruments to get rid of the biases therein.

In the context of risk sharing, this correction means that the effects of intertemporal smoothing, taste shock and some other serial correlation due to transitional dynamics have been wiped out. Therefore, the estimated slope coefficient in equation 2 represents the long-run steady state relationship between GDP and consumption which survives even with the present of transitional dynamics which temporarily drives away the economies from the steady state.[22] For the asymptotic properties of the group mean FMOLS estimator and the steps on how to construct group mean FMOLS in a context of applied econometrics, please refer to Appendix III. Here, we just lay out the group mean FMOLS estimator to see how it is different as the conventional panel estimator and how it allows us to study the distribution of the individual country estimates:

$$\widehat{\beta}^{GFM} = N^{-1}\sum_{i=1}^{N}((\sum_{t=1}^{T}x_{it}^2)^{-1}\sum_{t=1}^{T}(y_{it}x_{it}^* - T\widehat{\gamma}_i)) \tag{4}$$

where, in order to keep the notation as simple as possible, we use y and x. $x_{it}^* = x_{it} - \widehat{\Omega}_{21i}/\widehat{\Omega}_{22i} \bigtriangleup x_{it}$, indicating the x_{it} has been transformed by an adjusting term which serves as the internal instrument; and $\widehat{\gamma}_i = \widehat{\Gamma}_{21i} + \widehat{\Omega}_{21i}^0 - \widehat{\Omega}_{21i}/\widehat{\Omega}_{22i}(\widehat{\Gamma}_{22i} + \widehat{\Omega}_{22i}^0)$, acting as the long-run covariance matrix.

The point we want to make from equation (4) is that the $\widehat{\beta}^{GFM}$ estimator looks very similar as the OLS estimator of the conventional panel, except for two features. The OLS achieve the estimate on slope coefficient by minimizing the sum of the mean squared errors of x on y. The group mean FMOLS does the same, but on top of a

[21]We only report risk sharing estimates using FMOLS since the estimates are similar using DOLS. The DOLS estimates are available up on request.

[22]We are not discussing the group mean DOLS estimator since the idea is the same. The difference is the econometric technique to achieve the serial correlation and endogeneity biases. The DOLS uses the parametric adjustment, instead of the nonparametric adjustment used by FMOLS.

transformation of x and a long-run adjustment. If looking closer to this transformation and adjustment, we can find this is a specific feature of the nonstationary panel because the transformation and adjustment only survive if the x and y are nonstationary. If, the x and y are $I(0)$ as in the case of conventional data, they are in the same order of magnitude as the transformation and adjustment term which makes such transformation and adjustment infeasible. To summarize, provided x and y are $I(1)$, we can take advantage of the nonstationary panel features to achieve the cointegrating relationship estimate which indicates the level of risk sharing in our context. However, the conventional panel analysis, including the dynamic panel analysis such as Arrellano and Bond GMM, as long as it deals with the $I(0)$ process, is subject to first order bias due to the serial correlations which is hard to correct.

The second feature is that the group mean FMOLS allows us to study the cross-country risk sharing distribution. We mentioned that we can interpret the group mean FMOLS as the cross-country average of the individual country FMOLS estimator. From equation 4, we can clear see that $\widehat{\beta}^{GFM} = N^{-1}\sum_{i=1}^{N}(\widehat{\beta}_i^{FM})$, where $\widehat{\beta}_i^{FM} = (\sum_{t=1}^{T} x_{it}^{s})^{-1}\sum_{t=1}^{T}(y_{it}x_{it}^{*} - T\widehat{\gamma}_i)$ is the individual country FMOLS time series estimator.

5.2 Conventional Panel Regression Results

We first check the estimates on risk sharing using conventional panel regression techniques, both in difference and in level. The results are reported in Table 2 and Table 3 respectively. Column 1 of each table reports pooled OLS estimates and Column 2 of each table reports fixed effect estimates. The results are similar across the two specifications though.

The results are comparable with the findings in the literature. Basically, as shown in the first panel of table 2, for the whole sample period, an estimate of about 32 percent of business cycle frequency risks has been shared. However, this constitutes risk sharing through both insurance and intertemporal smoothing. In the case when risk free bond market can act as a close substitute on insurance market, most of the risk sharing should be carried through intertemporal smoothing because insurance contract is more risky and costly due to the moral hazard or contract enforcement issues, especially at the international level. Therefore, out of the 32 percent, it is fair to reasonably think that only a small portion is through insurance market (for theoretical findings and empirical results on this, please refer toBaxter and Crucini (1995) and Artis and Hoffmann (2006)).

By comparing the estimates before and after 1990 in the 2nd and 3rd columns of table 2, one conclusion that would have been drawn is that we do not find increasing in risk sharing in the recent financial integration period. This is puzzling and counterintuitive to the standard model's prediction. Our explanations, in keeping with the argument of this paper, are on two-fold. One is that the low and no increase in risk-sharing through insurance market on business cycle frequency risks is due to the low welfare gains. Another is that the misspecification and restrictive assumptions in the short-run dynamics hinder the capability to achieve an estimate of true β.

Table 3 reports results on estimates of long-run risk sharing by using pooled OLS and FE. The results indicate that less than 9 percent of long-run risks have been shared when estimated by pooled OLS in the whole 1960 to 2008 period, but around 18 percent when estimated by FE. The higher estimates in the FE specification makes better sense. Some of the country-idoisyncratic features cannot be shared through financial market and we should take them into consideration by using fixed effect.

Comparing the estimates before and after 1990 in the 2nd and 3rd columns of table 3, there is still no much increase in risk sharing. However, an issue is how much we can trust the estimates in table 3 in general. We know that OLS can achieve consistent estimate on the cointegrating coefficient, but there is a second-order bias associated with it. The second order-bias does not appear even asymptotically. In finite sample, we suspect that the second-order bias may turn out to be first-order bias, which seriously influence the reliability of these estimates.

5.3 Nonstationary Panel Regression Results

We report the long-run risk sharing estimates on the 45 country sample and its sub-groups in table 4A. For the panel of 45 countries on the period of 1950-2008, the point estimate shows about 14 percent of long-run risks has been shared. The t-statistics on testing the null hypothesis of full risk sharing is 112.92, which indicates far from complete risk sharing; on the other hand, the t-statistics on testing the null of no risk sharing points to the existence of economically and statistically significant risk sharing. We also performed estimates by splitting our sample into two periods. In the recent financial integration period, long-run risk sharing among the 45 countries more than doubled that in the pre-1990 period, reaching to 27 percent from 12 percent.

The estimate and test results on sub-country groups confirm our main message and offer more insights. The risk sharing of OECD countries are at a similar level as the risk sharing of emerging market on the whole sample period. However, in the financial integration period, about 34 percent of risks are shared for OECD countries, while only about 23 percent of risks are shared for emerging market countries. More importantly, the benefit of risk sharing are evenly enjoyed within OECD country groups. This is not the case for emerging markets. It seems that most of the benefit of financial integration are enjoyed by the advanced emerging markets. (interesting to FDI insurance (not as much as expected to be paid back as debt, debt vulnerability)

It looks a bit puzzling that the risk sharing of EU countries is only about 10 percent for the whole sample period, and only about 6 percent for the pre-1990 period. We therefore have done a intra-region risk sharing analysis. The results appear in the memorandum panel of Table 4A. When testing risk sharing only between OECD countries, it shows that risk sharing is higher than risk sharing between OECD countries and the rest of the world for the whole sample period and the pre-1990 period, but the level of risk sharing are similar in the post-1990 period. This indicates that the market between OECD and emerging markets are more isolated before the financial integration. A comparison of risk sharing within EU 15 countries and the risk sharing between EU15 and the rest of the world, however indicates that EU15 countries used to share risks mostly between themselves, but more risks are shared with the rest of the world in the post-1990 period (risk sharing is about 24 percent within EU15 after 1990, but about 36 percent with rest of the world). A similar story applies to other advanced countries. They used to share more risks within themselves, but now share more risks with EU countries and emerging market.

As a robust check, table 4B shows the long-run risk sharing estimates on the 21 country sample. Since we do not have enough countries on the cross-section to do a detailed breakdown on country groups, we only estimate the risk sharing on a sample of 21 countries, a sample of 11 OECD countries and 10 emerging market countries. The results basically show the same picture as the tests on the full sample of 45 countries. Basically, we find that the risk sharing estimate on the panel of 21 countries is 14 percent for the whole sample period and increases to 39 percent in the financial integration period. The increase is entirely due to more risk sharing in the OECD countries though.

6 Cross-country risk sharing patterns

The group mean FMOLS does not restrict the slope coefficient to be homogeneous, and we therefore can look into the heterogenous cross-country patterns of risk sharing, by looking into the estimates of cointegrating coefficients on individual countries. We know that the estimates are not reliable individually, i.e. each of them is a poor estimate of the true cointegrating relationship due to the high size distortion of our short sample, but each of them are asymptotically consistent estimate, and so the pooling of the individual estimates should show some consistent pattern. We report in the Appendix Table A3a and A3b on the estimates of cointegrating coefficients of individual countries. The difference between Table A3a and Table A3b is attribute to the different strategy we used on data sampling.

The measures on financial integration is from the updated and extended version of dataset constructed by Lane and Milesi-Ferretti (2007). It contains data for the period 1970-2007 and for 178 economies plus the euro area as an aggregate. For each of the countries, it reports total external assets and liabilities and the associated breakdowns. We constructed our measure of financial integration by first split the data into pre and after 1990 period. We then calculate the average of total assets and liabilities, average of portfolio equity assets and liabilities, average of FDI assets and liabilities and average of Debt assets and liabilities on the splitted periods for each country of our sample. The panel figure shows the linkage of risk sharing pattern with such calculated financial integration measures.

The first chart in the panel show that long-run risk sharing is positively correlated with gross asset and liability to GDP ratio in the pre-1990 period. This is as expected from the theoretical model's prediction. The second chart shows a weaker positive relationship for the post-1990 period. As you can see from the x-axis, the gross capital flow, on average, quadrupled compared to the pre-1990 period. If taking out the observation of Ireland as an outlier, then it is about tripled. However, as we have seen in our tables, long-run risk sharing, on average, only doubled than before. This indicate the pace of increase in long-run risk sharing does not catch up with the pace of increase in financial flows. It is therefore too strong to claim that risk sharing and financial flows are not twins separated from the birth. Financial integration is the necessary condition for risk sharing, but it is not sufficient, i.e., more liberal financial flows does not necessarily carry out proportionally more risk sharing. As pointed out by **?**, threshold effect can be a potential explanation.

The middle two charts in the panel show the relationship between long-run risk sharing and gross FDI and portfolio to GDP ratio. The bottom two charts show the relationship with debt to GDP ratio. Two features worth pointing out. One is most of the increase in financial flows in the post-1990 period is driven by the increase of FDI and portfolio. FDI and portfolio as percent of GDP is, no doubt, quadrupled in post-1990 period than the pre-1990 period. But the debt to GDP ratio is only doubled if taking out Ireland. The second feature is they both confirmed the relationship of the top two charts, with post-1990 showing a less positive relationship.

7 Conclusion

In this paper, we specify an empirical nonstationary panel regression model that tests long-run risk sharing and allows for richer data generating processes. This is in contrast to the literature on consumption risk sharing which is mainly about risks at business cycle frequency. Since our methodology focuses on identifying cointegrating relationships while allowing for arbitrary short-run dynamics, we can obtain a consistent estimate of long-run risk sharing while disregarding any short-run nuisance factors. Furthermore, the combination of a focus on the long-run low frequency relationship and the dimensionality of the panel allows us to study the distribution pattern of cross-country risk sharing. We therefore can link the distribution pattern to various measures of financial integration.

Our results show that, for the period of 1950-2008, about 14 percent of long-run risk has been shared in the OECD countries and in the emerging market countries. However, during the financial integration episode of the past two decades, long-run risk sharing in OECD countries increased more than that in emerging market countries, with about 34 percent of risks shared in the OECD countries and about 23 percent of risks shared in the emerging market countries. These results are robust to us sample selection.

When investigating the relationship between various measures of financial integration and cross-country risk sharing, we find evidence of positive relationships, i.e. more capital flows is associated with more long-run risk sharing. However, the positive relationship is less in the recent financial integration period, indicating that the increase of risk sharing is not proportional to the increase in capital flows.

The approach used in this paper provided the opportunities to study long-run risk sharing, but the risk sharing at the business cycle frequency is an important and interesting question to be fully addressed. As a future research, we can use nonstationary vector autoregressive models to address this question. Long-run risk sharing identified in this paper could be used to decompose GDP and consumption processes into trends and cycles. We can then estimate the impulse-response to cyclical disturbances to analyze short-run risk sharing.

Table 1. Panel Unit Root and Cointegration Test Results (45 countries)

Unit root	GDP	Consumption	
IPS ADF (large sample adjustment values)	3.21***	1.09***	
IPS ADF (Bootstrapped)	0.84***	-0.01***	
MW (Bootstrapped)	84.73***	89.42***	
Cointegration	ADF	PP	Rho
Group mean panel	-2.71***	-4.24***	-3.74***
Pooled Panel	-1.16	-2.67***	-2.06***

Note: Lag truncation: K=4

Table 2: Conventional Panel Regression Results under Different Specifications

	(1)	(2)	(3)	(4)
1960-2008	Pooled OLS	Pooled OLS	FE OLS	FE OLS
GDP growth	0.680	0.681	0.669	0.669
	(0.055)***	(0.059)***	(0.062)***	(0.067)***
Constant	0.001	0.017	0.001	0.018
	(0.001)*	(0.007)**	(0.001)*	(0.007)***
Observations	2535	2535	2535	2535
R-squared	0.31	0.33	0.29	0.31
Pre 1990				
GDP growth	0.641	0.642	0.624	0.621
	(0.070)***	(0.076)***	(0.079)***	(0.087)***
Constant	0.002	0.011	0.002	0.020
	(0.001)	(0.008)	(0.001)	(0.007)***
Observations	1680	1680	1680	1680
R-squared	0.27	0.28	0.25	0.26
Post 1990				
GDP growth	0.809	0.807	0.803	0.800
	(0.045)***	(0.045)***	(0.061)***	(0.060)***
Constant	0.001	0.003	0.001	0.003
	(0.001)	(0.003)	(0.001)	(0.003)
Observations	855	855	855	855
R-squared	0.50	0.51	0.46	0.46
Year dummy	No	Yes	No	Yes
Number of countries	45	45	45	45

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Level Panel Regression Results under Different Specifications

	(1)	(2)	(3)	(4)
1960-2008	Pooled OLS	Pooled OLS	FE OLS	FE OLS
GDP growth	0.912	0.912	0.796	0.794
	(0.006)***	(0.006)***	(0.012)***	(0.013)***
Constant	0.009	0.022	-0.023	-0.056
	(0.004)**	(0.031)	(0.004)***	(0.021)***
Observations	2580	2580	2580	2580
R-squared	0.95	0.95	0.78	0.78
Pre 1990				
GDP growth	0.912	0.912	0.801	0.797
	(0.007)***	(0.007)***	(0.024)***	(0.026)***
Constant	0.011	0.022	-0.022	-0.061
	(0.005)**	(0.031)	(0.007)***	(0.021)***
Observations	1725	1725	1725	1725
R-squared	0.95	0.95	0.65	0.66
Post 1990				
GDP growth	0.911	0.911	0.826	0.824
	(0.009)***	(0.009)***	(0.024)***	(0.025)***
Constant	0.006	0.005	-0.015	-0.023
	(0.006)	(0.032)	(0.006)***	(0.009)**
Observations	855	855	855	855
R-squared	0.95	0.95	0.71	0.71
Year dummy	No	Yes	No	Yes
Number of countries	45	45	45	45

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4A. Country Group Cointegration Coefficient Estimates

Group	Whole sample period			Before 1990			After 1990		
	Coefficient	t-statistic (b=0)	t-statistic (b=1)	Coefficient	t-statistic (b=0)	t-statistic (b=1)	Coefficient	t-statistic (b=0)	t-statistic (b=1)
Full Panel (45)	**0.86**	**112.92**	**-17.81**	**0.88**	**119.56**	**-13.84**	**0.73**	**108.55**	**-26.56**
OECD (26)	0.88	89.07	-11.04	0.90	105.84	-7.43	0.66	77.08	-26.53
EU15	0.91	55.41	-4.59	0.94	80.33	0.54	0.64	56.17	-20.42
Euro area 12	0.88	56.51	-5.79	0.94	82.14	1.11	0.66	55.61	-22.65
Other advanced countries (11)	0.84	72.23	-11.61	0.84	68.92	-12.06	0.68	52.91	-16.94
Emerging market (22)	**0.86**	**86.24**	**-16.22**	**0.86**	**69.86**	**-14.92**	**0.77**	81.36	-11.92
Advanced emerging markets (8)	0.79	72.22	-12.85	0.79	57.69	-9.87	0.65	21.63	-9.72
Other emerging markets	0.90	52.96	-10.54	0.91	43.53	-11.23	0.84	86.44	-7.53
Memorandum									
Intra region risk sharing									
OECD (26)	0.80	112.99	-22.67	0.86	121.79	-15.2	0.65	69.79	-30.29
EU15	0.84	94.96	-10.02	0.92	97.29	-3.15	0.76	80.65	-24.07
Advanced emerging markets (8)	0.73	48.40	-10.84	0.55	28.57	-9.93	0.71	18.44	-8.78

Note 1: Advanced emerging markets includes all the countries defined by the Economist and Morgan Stanley Capital International (MSCI),
which are South Africa, Brazil, Mexico, Israel, Saudi Arabia, Hong Kong, Korea and singapore, except the two transitional economies: Hungary and Poland.
Note 2: the high coefficients on OECD, esp. on EU 15 and Euro 12 indicate that before financial integration, EU countries did very small risk sharing with rest of the world.

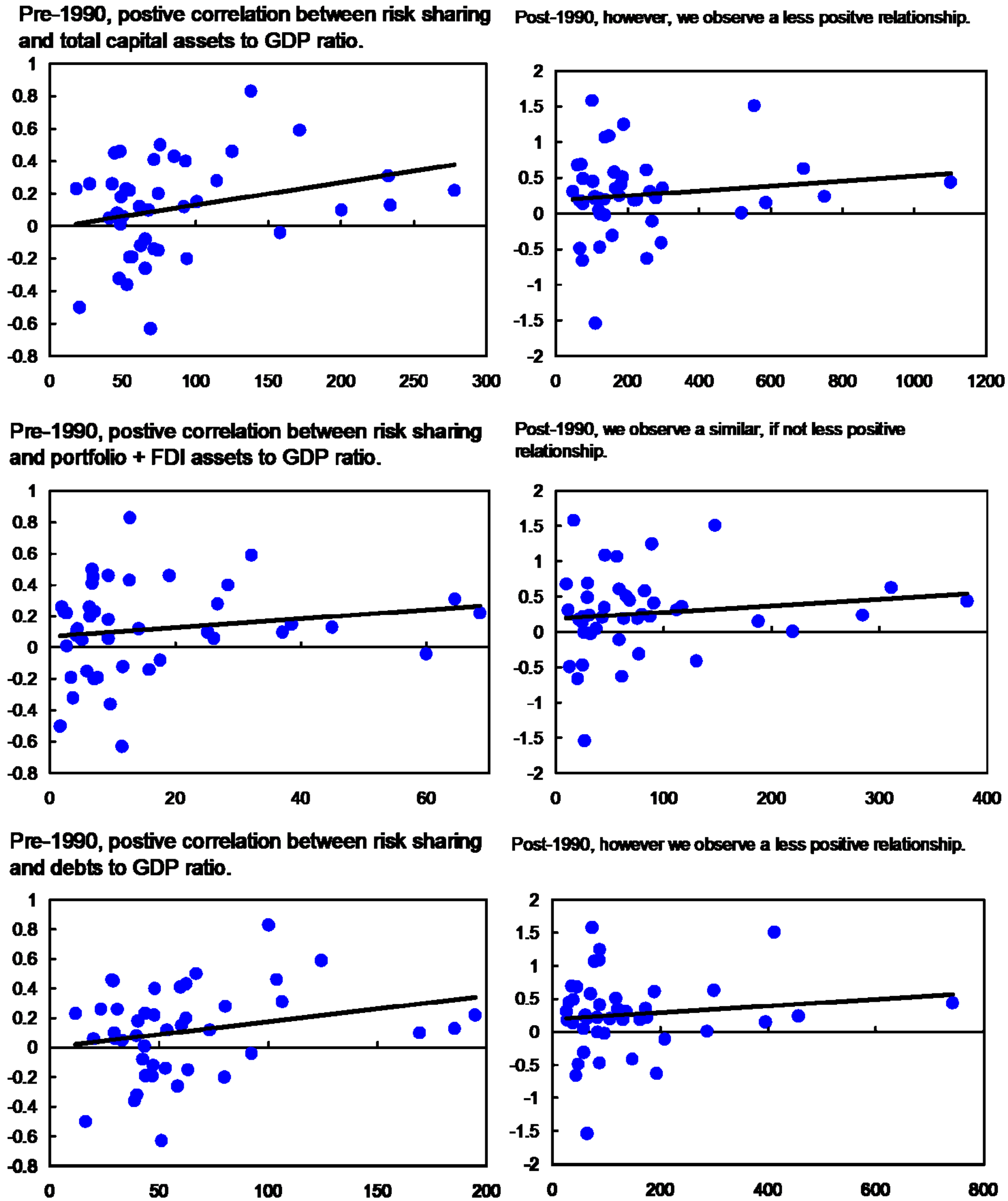
Table 4B. Country Group Cointegration Coefficient Estimates (Countries passed individual tests)

Group	Whole sample period			Before 1990			After 1990		
	Coefficient	t-statistic (b=0)	t-statistic (b=1)	Coefficient	t-statistic (b=0)	t-statistic (b=1)	Coefficient	t-statistic (b=0)	t-statistic (b=1)
Full Panel (21)	**0.86**	**126.14**	**-19.11**	**0.83**	**107.12**	**-16.63**	**0.71**	**94.62**	**-22.87**
OECD (11)	0.90	97.78	-10.62	0.86	89.53	-7.28	0.63	65.36	-22.25
Emerging market (10)	**0.80**	**102.06**	**-21.69**	**0.80**	**72.73**	**-20.55**	**0.82**	**73.55**	**-10.03**

Advanced emerging markets includes all the countries defined by the Economist and Morgan Stanley Capital International (MSCI),
which are South Africa, Brazil, Mexico, Israel, Saudi Arabia, Hong Kong, Korea and singapore, except the two transitional economies: Hungary and Poland.

Note: the high coefficients on OECD, esp. on EU 15 and Euro 12 indicate that before financial integration, EU countries did very small risk sharing with rest of the world.
OECD: Austria, Belgium, Luxembourg, Sweden, Switzerland, Canada, Japan, Ireland, Spain, Australia, New Zealand and Korea.
Emerging markets: South Africa, Argentina, Chile, Hong Kong, China, Korea, Malaysia, Pakistan, singapore, Thailand.

Figure: Cross-country Risk Sharing and Financial Assets



Source: PWT , WEO and EWN II

Table A1. Individual and Panel Unit Root Test Results 1950-2008 (45 countries)

	GDP			Consumption		
Country	**ADF**	**pval**	**lags**	**ADF**	**pval**	**lags**
United States	0.21	0.953	8	-0.98	0.714	8
United Kingdom	-0.94	0.723	8	-0.76	0.777	8
Austria	-1.11	0.676	3	-1.36	0.578	3
Belgium	-1.90	0.304	8	-1.48	0.486	6
Denmark	0.31	0.942	8	0.14	0.937	6
France	-1.23	0.595	8	-1.86	0.328	8
Germany	-0.80	0.737	3	-1.66	0.451	3
Italy	-0.85	0.139	6	-1.42	0.548	3
Luxembourg	-0.92	0.709	5	-1.22	0.628	8
Netherlands	0.18	0.963	6	-1.15	0.666	5
Norway	-1.47	0.505	8	-5.2	0.001	0
Sweden	0.27	0.952	8	0.64	0.98	8
Switzerland	0.25	0.946	7	0.29	0.93	8
Canada	0.41	0.971	8	-0.44	0.855	8
Japan	-1.69	0.426	2	-1.39	0.56	3
Finland	-1.59	0.477	2	-5.25	0.001	0
Greece	-2.38	0.156	8	-1.69	0.417	8
Iceland	-3.75	0.003	0	-1.45	0.519	5
Ireland	-1.87	0.244	8	-2.42	0.112	0
Portugal	-4.35	0.004	0	-1.99	0.251	8
Spain	-1.93	0.300	7	-2.37	0.141	8
Turkey	-4.39	0.001	6	-1.82	0.325	5
Australia	0.59	0.972	8	-0.5	0.835	8
New Zealand	-0.50	0.855	2	-1.33	0.544	8
South Africa	-0.47	0.794	8	-1.54	0.517	1
Argentina	-0.62	0.882	0	-0.81	0.813	0
Brazil	-1.34	0.551	8	-1.64	0.475	2
Chile	-1.93	0.347	5	-2.57	0.099	0
Colombia	-0.63	0.803	8	-0.31	0.907	4
Mexico	-0.27	0.927	2	-2.37	0.15	0
Peru	-0.93	0.762	1	-1.36	0.594	7
Israel	-1.80	0.353	8	-0.23	0.878	7
Saudi Arabia	-1.28	0.562	5	-0.94	0.649	7
Egypt	-0.92	0.740	6	-0.97	0.696	8
Hong Kong	-0.98	0.720	3	-1.69	0.454	1
India	0.38	0.930	8	-2.18	0.202	6
Indonesia	-0.97	0.751	1	-0.88	0.671	8
Korea	-1.00	0.610	5	-0.72	0.688	5
Malaysia	-1.08	0.679	3	-0.74	0.813	1
Pakistan	-1.27	0.575	8	-2.64	0.088	7
Philippines	-1.14	0.673	4	-1.58	0.437	8
Singapore	-1.37	0.563	1	-1.02	0.743	1
Thailand	-0.79	0.694	7	-0.42	0.881	3
Morocco	-3.29	0.025	0	-2.06	0.284	2
China	0.00	0.803	6	0.23	0.898	4
IPS ADF (large sample adjustment values)	3.21	0.999	8	1.09	0.999	8
IPS ADF (Bootstrapped)	0.84	0.800	8	-0.01	0.495	8
MW (Bootstrapped)	84.73	0.637	8	89.42	0.498	8

Note: Lag truncation: K=8

Table A2. Indiviudal and Panel Cointegrated Test Results 1960-2008

Country	ADF	P value	lags	PP	P value
Austria	-3.50	0.012	3	-4.56	0.001
Belgium	-2.06	0.239	3	-2.7	0.07
Luxembourg	-2.86	0.058	1	-4.24	0.002
Sweden	-3.11	0.035	0	-3.15	0.03
Switzerland	-3.24	0.021	0	-3.15	0.027
Canada	-3.18	0.027	1	-2.44	0.139
Japan	-2.84	0.053	1	-3.91	0.006
Ireland	-3.51	0.013	0	-3.71	0.01
Spain	-2.73	0.070	0	-3.04	0.041
Australia	-3.35	0.016	0	-3.57	0.012
New Zealand	-2.79	0.060	0	-2.95	0.04
South Africa	-3.04	0.041	1	-2.6	0.101
Argentina	-3.96	0.003	1	-3.35	0.018
Chile	-2.67	0.091	0	-2.61	0.107
Hong Kong	-5.34	0.002	2	-3.46	0.017
Korea	-3.97	0.004	0	-3.87	0.005
Malaysia	-3.82	0.007	1	-2.93	0.055
Pakistan	-2.81	0.063	3	-2.56	0.11
Singapore	-4.49	0.002	1	-2.84	0.064
Thailand	-3.68	0.010	0	-3.87	0.008
China, P. R.: Ma	-3.22	0.029	2	-3.44	0.013
Group mean panel	-7.25	0.000	4	-7.36	0.0000
Pooled panel	-6.32	0.000	4	-7.02	0.0000

Note: the symblos *, **, *** indicate 10%, 5% and 1% rejection repectively.

Table A3a. Cointegration coefficient estimates

Country	1950-2008			Before 1990			After 1990		
	Coefficient	t-statistic (b=0)	t-statistic (b=1)	Coefficient	t-statistic (b=0)	t-statistic (b=1)	Coefficient	t-statistic (b=0)	t-statistic (b=1)
United States	0.33	1.26	-2.59	0.54	3.27	-2.82	-0.07	-0.58	-9.00
United Kingdom	0.46	1.58	-1.88	0.87	11.63	-1.81	-0.51	-1.54	-4.56
Austria	1.20	53.97	9.17	1.20	59.75	9.98	1.11	25.24	2.44
Belgium	0.88	16.82	-2.19	0.90	18.00	-2.05	0.85	20.98	-3.71
Denmark	1.18	5.44	0.85	0.88	6.22	-0.87	0.78	6.46	-1.86
France	1.03	19.44	0.64	1.14	53.63	6.76	0.64	10.67	-6.03
Germany	0.98	5.17	-0.10	1.63	13.97	5.40	0.81	44.10	-10.03
Italy	1.05	6.35	0.31	1.19	28.09	4.46	0.65	20.89	-11.25
Luxembourg	0.49	3.29	-3.46	0.33	0.98	-2.02	-0.04	-0.20	-5.88
Netherlands	1.13	7.01	0.78	1.04	6.34	0.26	0.99	17.92	-0.14
Norway	0.41	6.89	-9.83	0.57	16.64	-12.44	0.81	7.82	-1.86
Sweden	1.39	11.85	3.31	1.12	8.70	0.95	1.41	19.96	5.77
Switzerland	0.88	24.48	-3.24	0.78	14.55	-4.02	0.76	63.06	-19.87
Canada	1.01	12.29	0.16	0.85	10.19	-1.78	0.59	5.26	-3.73
Japan	0.95	57.09	-2.89	0.95	72.85	-4.06	0.78	35.13	-9.99
Finland	0.85	13.63	-2.43	0.88	25.84	-3.49	0.69	6.45	-2.88
Greece	0.77	5.39	-1.59	0.82	15.53	-3.37	0.80	7.30	-1.86
Iceland	1.20	14.51	2.41	1.19	20.12	3.23	1.63	6.35	2.45
Ireland	0.48	13.11	-14.04	0.41	3.72	-5.47	0.56	26.38	-20.47
Portugal	0.79	15.68	-4.29	0.80	14.85	-3.64	0.39	9.43	-15.03
Spain	0.93	35.88	-2.86	0.94	43.87	-2.98	0.49	3.49	-3.61
Turkey	1.01	4.63	0.03	0.74	6.56	-2.27	1.49	26.34	8.66
Australia	0.83	10.86	-2.29	0.94	14.02	-0.82	0.42	3.53	-4.95
New Zealand	0.96	15.66	-0.65	1.08	14.26	1.07	-0.25	-1.84	-9.08
South Africa	0.75	13.46	-4.46	0.90	9.31	-0.99	0.55	3.30	-2.65
Argentina	0.90	39.29	-4.58	0.92	31.57	-2.70	1.02	24.85	0.57
Brazil	1.05	5.35	0.24	1.36	18.16	4.76	0.31	2.52	-5.56
Chile	0.80	5.04	-1.26	0.72	5.59	-2.18	1.31	36.29	8.58
Colombia	1.40	9.84	2.81	0.74	10.57	-3.79	1.66	33.88	13.42
Mexico	0.82	8.45	-1.81	0.77	6.90	-2.05	0.51	5.00	-4.81
Peru	0.84	6.88	-1.31	0.59	1.69	-1.16	0.76	4.21	-1.32
Israel	0.57	2.64	-1.98	0.54	5.51	-4.63	-0.09	-0.72	-8.45
Saudi Arabia	0.44	2.47	-3.11	0.17	0.66	-3.10	1.47	8.21	2.64
Egypt	0.36	4.64	-8.40	0.50	4.86	-4.89	2.54	19.07	11.56
Hong Kong	1.10	55.80	4.85	1.07	48.47	3.29	1.24	13.24	2.59
India	0.45	2.27	-2.77	1.50	6.01	2.01	0.69	41.58	-18.81
Indonesia	1.67	10.95	4.38	1.32	6.71	1.64	-0.58	-2.01	-5.49
Korea	0.82	83.44	-17.81	0.78	49.24	-14.01	0.86	25.41	-3.99
Malaysia	0.67	18.43	-8.98	0.60	10.19	-6.93	0.75	6.96	-2.35
Pakistan	0.76	4.85	-1.52	0.99	6.39	-0.06	0.32	2.58	-5.45
Philippines	0.72	6.77	-2.59	1.15	6.97	0.93	1.00	9.20	0.01
Singapore	0.73	32.64	-12.25	0.69	24.93	-11.19	0.37	4.23	-7.23
Thailand	0.70	29.55	-12.55	0.55	32.89	-26.88	0.95	18.83	-1.01
Morocco	1.03	12.20	0.37	1.26	20.39	4.24	0.79	12.03	-3.20
China	0.80	40.23	-10.03	0.77	11.43	-3.34	0.82	96.92	-20.75
Panel	0.86	112.92	-17.81	0.88	119.56	-13.84	0.73	108.55	-26.56

Source: PWT and WEO.
We select our countries based on the sample coverage and data justification. Specifically, we select the OECD countries and the emerging market countries which are a total of 51 countries. Then we take out the East European transitional economies Czech. Rep. Hungary, Poland and Slovak Rep. This leaves us with 47 countries in our data sample (25 OECD and 22 emerging markets). we selected countries has data coverage at least from year 1967.

Table A3b. Cointegration coefficient estimates

Country	1950-2008 Coefficient	1950-2008 t-statistic (b=0)	1950-2008 t-statistic (b=1)	Before 1990 Coefficient	Before 1990 t-statistic (b=0)	Before 1990 t-statistic (b=1)	After 1990 Coefficient	After 1990 t-statistic (b=0)	After 1990 t-statistic (b=1)
Austria	1.20	53.97	9.17	1.20	59.75	9.98	1.11	25.24	2.44
Belgium	0.88	16.82	-2.19	0.90	18.00	-2.05	0.85	20.98	-3.71
Luxembourg	0.49	3.29	-3.46	0.33	0.98	-2.02	-0.04	-0.20	-5.88
Sweden	1.39	11.85	3.31	1.12	8.70	0.95	1.41	19.96	5.77
Switzerland	0.88	24.48	-3.24	0.78	14.55	-4.02	0.76	63.06	-19.87
Canada	1.01	12.29	0.16	0.85	10.19	-1.78	0.59	5.26	-3.73
Japan	0.95	57.09	-2.89	0.95	72.85	-4.06	0.78	35.13	-9.99
Ireland	0.48	13.11	-14.04	0.41	3.72	-5.47	0.56	26.38	-20.47
Spain	0.93	35.88	-2.86	0.94	43.87	-2.98	0.49	3.49	-3.61
Australia	0.83	10.86	-2.29	0.94	14.02	-0.82	0.42	3.53	-4.95
New Zealand	0.96	15.66	-0.65	1.08	14.26	1.07	-0.25	-1.84	-9.08
South Africa	0.75	13.46	-4.46	0.90	9.31	-0.99	0.55	3.30	-2.65
Argentina	0.90	39.29	-4.58	0.92	31.57	-2.70	1.02	24.85	0.57
Chile	0.80	5.04	-1.26	0.72	5.59	-2.18	1.31	36.29	8.58
Hong Kong	1.10	55.80	4.85	1.07	48.47	3.29	1.24	13.24	2.59
Korea	0.82	83.44	-17.81	0.78	49.24	-14.01	0.86	25.41	-3.99
Malaysia	0.67	18.43	-8.98	0.60	10.19	-6.93	0.75	6.96	-2.35
Pakistan	0.76	4.85	-1.52	0.99	6.39	-0.06	0.32	2.58	-5.45
Singapore	0.73	32.64	-12.25	0.69	24.93	-11.19	0.37	4.23	-7.23
Thailand	0.70	29.55	-12.55	0.55	32.89	-26.88	0.95	18.83	-1.01
China	0.80	40.23	-10.03	0.77	11.43	-3.34	0.82	96.92	-20.75
Panel	**0.86**	**126.14**	**-19.11**	**0.83**	**107.12**	**-16.63**	**0.71**	**94.62**	**-22.87**

Source: PWT and WEO.
We select our countries based on the sample coverage and data justification. Specifically, we select the OECD countries and the emerging market countries which are a total of 51 countries. Then we take out the East European transitional economies Czech. Rep. Hungary, Poland and Slovak Rep. This leaves us with 47 countries in our data sample (25 OECD and 22 emerging markets). we selected countries has data coverage at least from year 1967.

8 Appendix

Appendix I: Studies using Conventional Panel Analysis

Kose et al. 2007

$\Delta c_{it} - \Delta c_t^* = \alpha_i + \delta_t + (\beta_0 + \beta_1 fo_{it})(\Delta y_{it} - \Delta y_t^*) + \varepsilon_{it}$

Sorensen et al 2007

$\Delta c_{it} - \Delta c_t^* = \alpha_i + (\beta_0 + \beta_1(EHB_{it} - EHB_t^*) + \beta_2(t - \bar{t})(\Delta y_{it} - \Delta y_t^*) + \varepsilon_{it}$

Bai and Zhang 2005

$\Delta c_t = \alpha_i + \gamma \Delta y_t + \varepsilon_{it}$

$\Delta c_{it} = \alpha_i + \eta \Delta c_t^* + \gamma \Delta y_{it} + \varepsilon_{it}$

Moser et al 2004

$\Delta c_{it} = \alpha_i + \eta_i \Delta c_t^* + \gamma_i(\Delta y_{it} - \Delta y_t^*) + \varepsilon_{it}$

Crucini 1999

$\Delta c_{it} = \eta_i \Delta c_t^* + (1 - \eta_i) \Delta yp_{it} + \varepsilon_{it}$

Lewis 1996

$\Delta c_{it}^{T-D} = v_t + \eta_1 \Delta y_{it}^N + \eta_2 \Delta y_{it}^D + \eta_3 \Delta y_{it}^{T-D} + \varepsilon_{it}$

Obstfeld 1995

$\Delta c_t = \alpha + \eta \Delta c_t^* + \gamma(\Delta y_t - \Delta i_t - \Delta g_t) + \varepsilon_{it}$

Appendix II: Technically Illustration on Conventional and Non-stationary Panel

Deriving Testing Equation (1)

Taking incomplete risk sharing as the point of departure, we assume two groups of consumers in country i. One group, who does not pool its income in the world market, consumes its permanent income, y_t^p, following the permanent income hypothesis (PIH). The other group pools its income and therefore consume the income after risk sharing y_t^*. Thus, $c_{1t} = \lambda y_t^p$ and $c_{2t} = (1 - \lambda) y_t^*$, where λ and $1 - \lambda$ are the proportion of group 1 and group 2 consumers in country i. Putting the two groups together, we have $c_t = c_{1t} + c_{2t} = \lambda y_t^p + (1 - \lambda) y_t^*$. Since the risk sharing is pertinent to the idiosyncratic consumption and output, we take out the global components and get $c_t - c_t^* = \lambda(y_t^p - y_t^*)$, where $c_t^* = y_t^*$. y_t^p is not observable or directly measurable, we take the first difference of the above equation and get $\triangle c_t - \triangle c_t^* = \lambda(\triangle y_t^p - \triangle y_t^*)$. So far, we assume group 1 consumes permanent income, but there are many reasons, for example, liquidity constraints, make us believe this is a too strong assumption. We therefore follow Campbell and Mankiw (1990, 1991) assuming that there are two sub-groups of consumers in group 1. The first sub-group consumes its current income while the second sub-group consumes its permanent income. Rewrite the last equation above by substituting $\triangle y_t^p$ with $\alpha \triangle y_t + (1 - \alpha) \triangle y_t^p$, where α is the proportion of sub-group 1 consumer in group 1, we get $\triangle c_t - \triangle c_t^* = \lambda(\alpha \triangle y_t + (1 - \alpha) \triangle y_t^p) - \lambda \triangle y_t^*$ or $\triangle c_t - \triangle c_t^* = \alpha\lambda(\triangle y_t - \triangle y_t^*) + (1 - \alpha)\lambda(\triangle y_t^p - \triangle y_t^*)$.

The literature consequently assumes that the permanent income and the world aggregate (or average) income are martingale and derive the testable equation $\triangle c_t - \triangle c_t^* = \beta(\triangle y_t - \triangle y_t^*) + \varepsilon_t$, where $\beta = \alpha\lambda$, and ε_t is a martingale difference so that $E_{t-1}(\varepsilon_t|\zeta_{t-1}) = 0$, where ζ_{t-1} is the information set formed by the past values available at time $t-1$. ε_t is typically assumed to be $i.i.d.(0, \sigma^2)$ white noise, although, strictly speaking, martingale difference process and white noise process are not the same (see Rachev et. al (2006)). However, to make such difference is not essential and would not change the point that we make, since ε_t can be relaxed to allow for heteroskydascity and even arbitrary serial correlations. The equation above is the single country counterpart of the equation (1). By imposing common β across countries and including a constant fixed effect term, we get equation (1): $\Delta c_{it} - \Delta c_t^* = \alpha_i + \beta(\Delta y_{it} - \Delta y_t^*) + \varepsilon_{it}$, where ε_{it} is assumed $i.i.d.(0, \sigma^2)$ across i.[23]

In the literature, equation (1) is consequently estimated by using panel pooled OLS or fixed effect techniques. If the maintained assumptions of exogenous regressors (in the case of pooled OLS) or strictly exogenous regressors (in the case of FE) and the rank condition both hold, consistent estimate of β can be achieved when $N \to \infty$ and T is fixed.[24] Certain assumptions can be relaxed in equation (1), for example, to allow for endogeneity of $(\Delta y_{it} - \Delta y_t^*)$, and consistent estimator can still be achieved by using IV or GMM approaches. However, even after relaxing, we still turned to believe a more DGP since there are two restrictions in conventional panel cannot be relaxed by construction.

First, in equation (1), the asymptotic properties depend on $N \to \infty$ and fixed T, therefore, the series correlation across i required to be the same. A homogeneous series correlation assumption is reasonable in micro panel. However, at country level, we believe non-trivial heterogeneous serial correlations (taste shocks, market frictions, etc.). Or more generally, it is just not possible that the dynamics of US and Zimbabwe are the same in terms of level, length and even directions. Second, β is assumed to be homogeneous in equation (1). For the reason discussed in the main text, we turned to believe a heterogeneous coefficient. If the true DGP is heterogeneous in nature but forced to be homogeneous in regression models, then the estimated β will not capture the average risk sharing effect. Actually, all the arguments of Peseran and Smith (1995) will apply and $\beta \to 1$ no matter what the true value is.

In a broader sense, permanent income follows a martingale process only when the

[23]Deriving equation (1) is helpful to understand the setting of nonstationary panel below. However, we can come up with equation (1) from the orthogonality condition of the benchmark model: $E(\Delta c_{it} - \Delta c_t^*|X_{it}) = 0$ where X_{it} is a vector of idiocyncratic risk factors of country i. This orthogonality condition implies a testable condition $\beta = 0$. However, it is well-known that the real world financial market is incomplete. This led researchers to adopt a pragmatic approach to interpret the estimated β from regression model as a measure of the degree of risk sharing.

[24]Equation (1) cannot be consistently estimated by POLS/FE since the assumption $E((\varepsilon_{it}(\triangle y_{it} - \triangle y_t^*)) = 0$ can not hold. Specifically, ε_{it} is differenced martigale and therefore it is correlated with $(\Delta y_{it} - \Delta y_t^*)$ by construction. IV can deal with the inconsistency caused through this channel, but we all know that it is hard, if not impossible, to find valid IV in the macroeconomic context. Besides, the IV is not testable.

riskless bond market is efficient with no arbitrage (Steve LeRoy and Paul Samuelson are among the earliest who recognized that the martingale process mathematically captures the economic notion of efficient markets). It is debatable if the riskless bond market can be modeled as efficient. However, if we buy the argument of inefficient markets, we cannot ignore the heterogeneities induced by intertemporal smoothing across countries.

Moreover, equation (1) estimate risk sharing of transitory shocks. Durlauf and Quah 1999 argued that conventional panel estimated a high frequency relationship by forcing all the low frequency relationship into the fixed effect. In contrast, despite the use of deterministic terms, the slope coefficient in cointegrating panel picks up long-run relationship. This is particularly convenient for isolating long-run risk sharing from short-run nuisance factors.

Deriving equation (2) and nonstationary panel

Given the above has been said, we turn to nonstationary panel analysis. We know that nonstationarity is typical in macro panel. The presence of nonstationary provides us the opportunity to take advantage of its nice properties in analyzing risk sharing.

To see this, let's first derive the test equation (2). The test equation (2) can be derived following the same procedure in deriving equation (1) above, except for making a distinction of temporary component (y_t^T) and permanent component (y_t^p) of y_t, where y_t^p is I(1) and y_t^T is I(0). We know that $c_t = \lambda(\alpha y_t + (1-\alpha)y_t^p) + (1-\lambda)y_t^*$. By realizing that the $y_t = y_t^p + y_t^T$, we can rewrite it into $c_t = \lambda(y_t^p + \alpha y_t^T) + (1-\lambda)y_t^*$. By removing the global common component, we get $c_t - c_t^* = \lambda(y_t^p - y_t^*) + \alpha\lambda y_t^T$.[25] This is the theoretical model on which the testing equation (2) based. Empirically, the I(0) term $\alpha\lambda y_t^T$ is absorbed into the short-term dynamics of the error term; the term $\lambda(y_t^p - y_t^*)$ is not directly observable, however, due to the fact that it is I(1), we can substitute y_t^p by y_t since the effect of the difference between y_t^p and y_t is again I(0) which are absorbed into the error term. By taking this into panel, again attaching the true disturbance term and fixed effect terms, we get equation (2): $c_{it} - c_t^* = \alpha_i + \beta_i(y_{it} - y_t^*) + u_{it}$.

Noticing that now $\beta_i = \lambda_i$, since the intertemporal smoothing effect is isolated into the error term $u_{it.}$ So far, we have pushed data generating features into the error term and simply hope that the error term can accommodate them. Again, as we allow full heterogeneities in the short-run dynamics of the error term and we essentially explore the time-series properties that are all about how to take care of unknown dynamics, we can achieve consistent estimate on the long-run behavior of cross-country risk sharing that are invariant with respect to finely detailed structure assumption. In another word, different as the case of the conventional panel, we are not making assumptions on restricting the DGP, but hoping that the full heterogeneities can be rich enough to include the true data generating mechanism as a special case.

[25] We made an unnecessary assumption so far in deriving equation (2). We do not any more need to restrict α proportion of consumer to consume current income. Since the nonstationary panel can accommodate almost any type of ARMA process, we can allow different stochastic responses of intertemporal smoothing to output shocks across countries.

Appendix III: Group mean FMOLS estimator: its model specifications, estimation recipes, theorems of consistency and limiting distribution

To simplify the notations used in this appendix, we use y_{1it} to denote $c_{it} - c_t^*$, y_{2it} to denote $y_{it} - y_t^*$, and equation *(2)* can be rewrite into

$$y_{1it} = \alpha_i + \beta_i y_{2it} + \varepsilon_{it} \qquad t = 1, ..., T;\ i = 1, ..., N \tag{5}$$

where, as defined in the main text, β_i is the slope parameter that we are interested in, $\{\varepsilon_{it}\}$ are the I(0) weakly dependent disturbance terms, and y_{2it} is I(1). Noticing that y_{2it} is I(1) and ε_{it} is I(0), y_{1it} is I(1) by construction.

Equation (5) is our regression model. We assume that the true model can be expressed into the following equation system or (even more general case which we will discuss[26]) using Phillips triangular representation

$$\begin{aligned} y_{1it} &= \alpha_i + \beta_i y_{2it} + \varepsilon_{it} && (6)\\ y_{2it} &= y_{2it-1} + \upsilon_{it} \qquad t = 1, ..., T;\ i = 1, ..., N && (7) \end{aligned}$$

where $\mu_{it} = (\varepsilon_{it}, \upsilon_{it})'$ is the I(0) stationary weakly dependent disturbance terms.

Since the cointegration testing and cointegrating coefficients estimation and hypothesis test in the time series context has been well established, we review some of the Propositions in the time series context first. The time series counter-part of equation (6) and (7) is as following:

$$\begin{aligned} y_{1t} &= \alpha + \beta y_{2t} + \varepsilon_t && (8)\\ y_{2t} &= y_{2t-1} + \upsilon_t \qquad t = 1, ..., T && (9) \end{aligned}$$

We assume that the equation (8) and (9) satisfy the assumptions and therefore the results in the Proposition 19.2 of Hamilton 1994, which I quoted below (Note the notation in the proposition is self-contained and should not be confused with the notation outside the proposition):

Proposition 19.2: Let y_{1t} be a scalar and y_{2t} be a $(g \times 1)$ vector. Let $n = g + 1$, and suppose that the $(n \times 1)$ vector $(y_{1t},\ y_{2t}')'$ is characterized by exactly one cointegrating relation $(h = 1)$ that has a nonzero coefficient on y_{1t}. Let that triangular representation for the system be

$$y_{1t} = \alpha + \gamma' y_{2t} + z_t^* \tag{[19.2.9]}$$

[26]The structure system below is typical of more general models which can have multiple regressors, multidimensional cointegrationships and with deterministic trends in equation *7. (*Phillips (1991)). Nevertheless, the discussion remains essentially the same.

$$\triangle y_{2t} = u_{2t} \qquad ([19.2.10])$$

Suppose that

$$\begin{bmatrix} z_t^* \\ u_{2t} \end{bmatrix} = \Psi^*(L)\varepsilon_t \qquad ([19.2.11])$$

where ε_t is an $(n \times 1)$ $i.i.d.$ vector with mean zero, finite fourth moments, and positive variance-covariance matrix $E(\varepsilon_t\varepsilon_t^{'}) = PP'$. Suppose further that the sequence of $(n\times n)$ matrices $\{s \cdot \Psi_s^*\}_{s=0}^{\infty}$ is absolutely summable and that the rows of $\Psi^*(1)$ are linearly independent. Let $\widehat{\alpha}_T$ and $\widehat{\gamma}_T$ be estimated based on OLS estimation of [19.2.9],

$$\begin{bmatrix} \widehat{\alpha}_T \\ \widehat{\gamma}_T \end{bmatrix} = \begin{bmatrix} T & \sum y_{2t}^{'} \\ \sum y_{2t}^{'} & \sum y_{2t}y_{2t}^{'} \end{bmatrix} \begin{bmatrix} \sum y_{1t} \\ \sum y_{2t}y_{1t} \end{bmatrix} \qquad ([19.2.12])$$

where $\sum$ indicates summation over t from 1 to T. Partition $\Psi^*(1) \cdot P$ as

$$\Psi^*(1) \cdot P = \begin{bmatrix} \underset{(1\times n)}{\lambda_1^*} \\ \underset{(g\times n)}{\Lambda_2^*} \end{bmatrix}$$

Then

$$\begin{bmatrix} T^{1/2}(\widehat{\alpha}_T - \alpha) \\ T(\widehat{\gamma}_T - \gamma) \end{bmatrix} \xrightarrow{L} \begin{bmatrix} 1 & \{\int[W(r)^{'}dr\} \cdot \Lambda_2^{*\prime} \\ \Lambda_2^* \cdot \{\int[W(r)dr\} & \Lambda_2^* \cdot \{\int[W(r) \cdot W(r)^{'}dr\} \cdot \Lambda_2^{*\prime} \end{bmatrix}^{-1} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} \qquad ([19.2.13])$$

where $W(r)$ is n-dimensional standard Brownian motion, the integral sign denote integration over r from 0 to 1, and

$$\begin{aligned} h_1 &= \lambda_1^{*'} \cdot W(1) \\ h_2 &= \Lambda_2^* \cdot \{\int_0^1 [W(r) \cdot W(r)^{'}dr\} \cdot \lambda_1^* + \sum_{v=0}^{\infty} u_{2t}z_{t+v}^* \end{aligned}$$

The holding of [19.2.13] involves the Beveridge and Nelson decomposition on $(y_{1t}$ $y_{2t}^{'})^{'}$and the multivariate functional limiting theorem on $(z_t^* \ u_{2t}^{'})^{'}$. In order to better understand this OLS estimator, let's consider a simplified case. If we assume y_{2t} is a random walk, z_t^* is white noise and $(z_t^* \ u_{2t}^{'})^{'}$ are Gaussian disturbance processes, the regression model [19.2.9] satisfy the case where the error term is $i.i.d.$ Gaussian and is independent of explanatory variables, and under these standard assumptions, the OLS estimator is normal distributed conditional on X and the t and F statistics have the exact t and F distributions for inference. If the error term is non-Gaussian, OLS estimator is normal distributed and we can use its associated asymptotic t and F statistics for inference.

What happen if $\left[z_t^*, u_{2t}^{'}\right]^{'}$ is autocorrelated and/or z_t^* correlated with $\triangle y_{2t}$. The estimated $\widehat{\gamma}_T$ by OLS in [19.2.9] is still superconsistent, but now it has a second-order bias. Actually, although $\triangle y_{2t}$ is mean zero in Proposition 19.2, the superconsistency property survives even in the case $E(\triangle y_{2t}) = \delta_2 \neq 0$. Hansen (1992) has given the generalized result through rotating of variables. This generalization is also applied to the case of FMOLS that we will discuss below. However, the second-order bias, which does not go away asymptotically, may hinder our ability to infer our testing result in finite sample, so the task remains is how to correct the second order bias created by the serial correlation and endogeneity caused by feedback effect between $\triangle y_{2t}$ and z_t^*, which we are now turning into.

Given there are different representations on the equation (8) and (9), it is not surprising on lack of consensus on the best empirical estimating approach. Phillips and Loretan (1991) has shown the many different representations and the transformations and interchanges among them in the time series context. The asymptotic theory of their paper concluded that the full systems maximum likelihood method (FSML) in the situation where the unit roots are imposed is the optimal approach. In the meanwhile, they have also shown that the FMOLS developed by Phillips and Hansen (1990) is optimal as well since FMOLS estimator are asymptotically the same as FSML estimator. Given the limitation of spaces and also for the reason that we will give the recipe for panel FMOLS estimator, please refer to Chapter 19.3 (Hamilton 1994) for the exact formula on the asymptotic distribution of the FMOLS estimator and associated test statistics. But we can intuitively know that, after the corrections, the FMOLS estimator becomes well behaved and we can use the standard asymptotic t and F statistics for inference.

Empirically, in the time series context, the inference based on FMOLS estimator suffers from the low power and high size distortion in finite sample. Pedroni (2000) basically extended Phillips and Hansen (1990) FMOLS approach into panel and developed panel group mean FMOLS estimator of (5). Nonstationarity is typical in macro panel. As stated in Baltagi and Kao 2000, "the focus of panel data econometrics has shifted towards studying the asymptotics of macro panels with large N (number of countries) and large T (length of the time series) rather than the usual asymptotics of micro panel with large N and small T...(t)he hope of the econometrics of non-stationary panel data is to combine the best of both worlds: the method of dealing with non-stationary data from the time-series and the increased data and power from the cross-section. The addition of the cross-section dimension, under certain assumptions, can act as repeated draws from the same distribution. Thus as the time and cross-section dimension increase panel test statistics and estimators can be derived with converge in distribution to normally distributed random variables."

In the context of double indexed process where both N and T $\rightarrow \infty$, three approaches (sequential limit, diagonal limit and joint limit) are possible, depending on the passage to infinity of the two indexes. Phillips and Moon (2000) has given a generalization on when the sequential limit is equivalent to joint limit. Specifically, they first derived the sequential limit of a double index sequence and then verified the joint limit theory applies when $T, N \to \infty$ and $T/N \to \infty$. For the macroeconomic series, in most of the cases, we can think them as T is potentially growing while N is relatively constant, so they fit into the scenario where $T, N \to \infty$ and $T/N \to \infty$. For this reason, the sequential limit theory is used to develop the asymptotics for the panel group mean FMOLS estimators. This is also consistent with the claim in Baltagi and Kao 2000 that cross section can act as repeated draws from the same distribution. Therefore, we can think the group mean FMOLS estimator below as $T \to \infty$ being in a sense the true asymptotic feature.

Let's firstly look at the recipes on how to compute the group mean FMOLS estimator and hypothesis test statistics. We will then see why the short term dynamics in a cointegrating system can be allowed to be heterogeneous across countries and the regressors can be allowed for complete endogeneity. This is basically in keep with the discussion of Phillips (1991) on why optimal estimation on cointegrating coefficients can be achieved without a finely detailed specification on the short-run dynamics and how the endogeneity bias of the OLS estimation of the time series counterpart of equation 5 can be adjusted. These arguments can be directly applied into panel context.[27]

Step 1: Estimate by OLS the time series cointegration regression for each country and collect estimated residuals $\widehat{\varepsilon}_{it}$.

Step 2: For each country i, using estimated residuals from step 1, form the time series vectors $\xi_{it} = (\widehat{\varepsilon}_{it}, \Delta y_{2it})'$. We can then use these vectors to compute the country specific long-run covariance matrix $\Omega_i = \sum_{j=-\infty}^{\infty} \Psi_{ij}$, where Ψ_{ij} is the jth autocovariance for ξ_i. The matrix Ω_i can be thought of as $\Omega_i = \Sigma_i + \Gamma_i + \Gamma_i^{'}$, where Σ_i is contemporaneous covariance matrix; Γ_i and $\Gamma_i^{'}$ are the forward and backward spectrum respectively. We can use the Newey-West estimator to estimate Ω_i nonparametrically and get $\widehat{\Omega}_i = \widehat{\Sigma}_i + \widehat{\Gamma}_i + \widehat{\Gamma}_i^{'}$ where $\widehat{\Sigma}_i = 1/T \sum_{t=1}^{T} \xi_{it}\xi_{it}^{'}$, $\widehat{\Gamma}_i = +1/T \sum_{s=1}^{K_i} [1 - s/(K_i + 1)] \sum_{t=s+1}^{T} \xi_{it}\xi_{it-s}^{'}$. The bandwidth K_i is typically chosen as a fraction of the sample, such as $K_i = 4(T_i/100)^{2/9}$ (Newey and West (1994).

Step 3: For each country i, compute the adjustment terms $\widehat{\gamma}_i = \widehat{\Gamma}_{21i} + \widehat{\Sigma}_{21i} - \widehat{\Omega}_{21i}/\widehat{\Omega}_{22i}(\widehat{\Gamma}_{22i} + \widehat{\Sigma}_{22i})$ to correct for country specific serial correlation dynamics; compute $y_{1it}^{*} = (y_{1it} - \overline{y_{1i}}) - \widehat{\Omega}_{21i}/\widehat{\Omega}_{22i} \triangle y_{2it}$ to correct for country specific endogeneity where the difference in y_{2it} are used as "internal instruments". The terms in $\widehat{\gamma}_i$ and y_{1it}^{*} are indirectly from the estimates of the long-run covariance matrix Ω_i. To see this, in partition form:

$$\Omega_i = \begin{bmatrix} \Omega_{11i} & \Omega_{12i} \\ \Omega_{21i} & \Omega_{22i} \end{bmatrix}$$

where $\Omega_{11i} = \sigma^2$ is scalar long-run variance of $\widehat{\varepsilon}_{it}$; $\Omega_{12i} = \Omega_{21i}$ is the scalar long-run covariance between $\widehat{\varepsilon}_{it}$ and $\triangle y_{2it}$;[28] Ω_{22i} is the scalar long-run covariance among $\triangle y_{2it}$.

[27] The illustration below on computing step is based on a seminar at the IMF by Peter Pedroni.

[28] In the general case when y_{2it} is not a scalar, but a $M \times 1$ vector, then $\Omega_{12i} = \Omega_{21i}^{'}$ is $M \times 1$ vector

Step 4: Compute the country specific FMOLS estimator using the adjustment terms from Step 3:

$$\widehat{\beta}^*_{FMi} = [\sum_{t=1}^{T}(y_{2it} - \overline{y_{2i}})^2]^{-1}[\sum_{t=1}^{T}(y_{2it} - \overline{y_{2i}})y^*_{1it} - T\widehat{\gamma}_i]$$

and the associated t-statistic is:

$$t_{\widehat{\beta}^*_{FMi}} = (\widehat{\beta}^*_{FMi} - \beta_{oi})[\widehat{\Omega}_{11i}\sum_{t=1}^{T}(y_{2it} - \overline{y_{2i}})^2]^{1/2}$$

where β_{oi} is the value of the coefficient being tested under the null hypothesis.

Step 5: Compute the group mean FMOLS estimator as

$$\widehat{\beta}^*_{GFM} = N^{-1}\sum_{n=1}^{N}\widehat{\beta}^*_{FMi}$$

and the associated t-statistic is:

$$t_{\widehat{\beta}^*_{GFM}} = N^{-1/2}\sum_{n=1}^{N} t_{\widehat{\beta}^*_{FMi}} = N^{1/2}\overline{t_{\widehat{\beta}^*_{FM}}}$$

where $\overline{t_{\widehat{\beta}^*_{FM}}} = N^{-1}\sum_{n=1}^{N} t_{\widehat{\beta}^*_{FMi}}$ is the group mean.

Step 6: Compare panel statistic from step 5 to critical values of tails of N(0, 1) distribution to reject. Specifically, under $H_0 : \beta_i = \beta_0$ (for all i, or, for most i)

$$t_{\widehat{\beta}^*_{GFM}} \Longrightarrow N(0,1)$$

Under $H_A : \beta_i \neq \beta_0$ (for all i, or, for some i)

$$t_{\widehat{\beta}^*_{GFM}} \rightarrow \pm\infty$$

So this is a two sided test and large absolute values imply rejection of null.

The Step 1 and Step 6 above provide the recipes on calculating the group mean FMOLS estimator and test statistics on it. I am now explaining the theorems of consistency and limiting distribution of the panel group mean FMOLS estimator. Please note that the following relies heavily on Phillips and Moon (1997) and Pedroni (2000), and I include the material here only to make my paper self-contained. In this appendix, we only work on FMOLS since the DOLS is just the parametric counterpart of the FMOLS and therefore the same principle applies. Please refer to Pedroni 2001 for the group mean DOLS estimator.

of long-run covariance between $\widehat{\varepsilon}_{it}$ and $\triangle y_{2it}$,The analysis remain essentially the same.

Pedroni (2000) has illustrated that well-behaved estimators in the context of FMOLS can be achieved under two assumptions.[29]

The first assumption is that the multivariate functional central limit theorem that we mentioned above holds for every i of the panel as T grows large. If we define the error terms in equation (6) and (7) as $\xi_{it} = (\varepsilon_{it}\ v_{it})'$, then the theorem can be defined as following

Assumption 1.1 in Pedroni (2000): *The process of ξ_{it} satisfies a multivariate functional central limit theorem such that the convergence as $T \to \infty$ fro the partial sum $1/\sqrt{T}\sum_{t=1}^{[Tr]} \xi_{it} \to B_i(r, \Omega_i)$ holds for any given member, i, of the panel, where $B_i(r, \Omega_i)$ is Brownian motion defined over the real interval $r \in (0, 1]$, with asymptotic covariance Ω_i.*

This is the key assumption which allows the asymptotic analysis differ from the conventional panel since now the asymptotics relies on $T \to \infty$, as well as $N \to \infty$, instead of fix T and only allowing $N \to \infty$. As stated in Pedroni (2000) that I quote, "this [assumption] places very little restriction on the temporal dependency and heterogeneity of the error process and encompasses for example a broad class of stationary ARMA processes. It also allows the serial correlation structure to be different for individual members of the panel" and the long-run variance and covariance matrix "capture the endogenous feedback effect, which is also permitted to vary across individual members of the panel."

We have discussed, under the multivariate functional limit theorem, the asymptotics of the OLS estimator and the FMOLS estimator in the time series context. From the recipe Step 5, we can see that the group mean FMOLS estimator is just a cross-section average of the individual i's FMOLS estimator. So, the next assumption we need is

Assumption 1.2 in Pedroni (2000): *(cross sectional independence): The individual processes are assumed to be independent cross sectionally, so that $E(\xi_{it}, \xi_{jt}) = 0$ for all $i \neq j$. More generally, the asymptotic covariance matrix for a panel of dimension $N \times T$ is block diagonal with the ith diagonal block given by the asymptotic covariance for member i.*

Cross sectional independence is used to derive the asymptotic distribution of the slope coefficient estimators when pooling different cross-sections. This assumption is easy to make theoretically, but it is hard to meet in practice. There are some recent development on how to taking care of different types of cross-sectional dependencies. See Mark and Sul (1999) on dealing with contemporaneous dependencies in the case of pooled DOLS; Pedroni 1997 on transitory dynamic dependencies; Bai and Ng (2004), Moon and Perron (2004) and Pesaran (2007) on common factor dependencies; and Pedroni, Vogelsang, Wagner and Westerlund (2007) on general form of dependencies. As shown in the text of the paper, we are assuming simple form of cross-sectional dependency which can be taken cared of through taking out the terms c_t^* and y_t^* and all the properties of group mean FMOLS and DOLS estimators apply after that[30].

[29]Please note that the following analysis rely heavely on Pedroni (2000) and I include the material here only to make my paper self-contained.

[30]The reason why we did not try to deal with other form of cross-sectional dependencies is really the

Under these two assumptions, Pedroni (2000) developed the asymptotic properties of panel OLS, pooled FMOLS and group mean FMOLS estimators. The Proposition 1.1, 1.2 and 1.3 of Pedroni (2000) define each of the estimators. The panel OLS estimator is, like the time series OLS estimator, asymptotically biased and the asymptotic distribution depends on the nuisance parameters associated with the dynamics of the underlying process. Both panel pooled and group mean FMOLS estimators converges to the true value, distributed normally, free of the nuisance parameters; the t-statistics associated are both standard normal which is true regardless whether the true model includes a heterogeneous intercept term or not and regardless the dimensionality of the regressors. However, in line with the difference between Levin Lin and Chu and Im, Peseran and Smith unit root tests, the group mean FMOLS estimator pools the cross-sectional by allowing the cointegrating coefficient is heterogeneous drawn from a distribution $\beta_i \backsim f(\beta, \sigma^2)$ under the alternative hypothesis, while the pooled FMOLS pools the cross-sectional by $\beta_i = \beta_a$, a homogeneous parameter for each individual i. We know from Phillips and Moon (2000) that is the true β is heterogeneous but forced to be homogeneous in our regression model, the pooled FMOLS does not give a cointegrating relationship which is economically meaningful, but instead, measures a long-run statistical correlationship. Furthermore, Pedroni has shown, through Monte Carlo simulation, the group mean FMOLS estimator behaves well even in relatively small samples which is not the case of pooled FMOLS estimator. Therefore, the group mean FMOLS is recommended in empirical analysis.

Moreover, the panel FMOLS estimators preserves the superconsistency properties of the time series FMOLS estimators developed by Phillips and Hansen (1990). Since it is superconsistent and converge at rate $T\sqrt{N}$, we can get extremely precise estimate even for relatively small sample.

In addition, along with the process of illustrating the asymptotic properties of panel FMOLS estimator, both pooled and group mean versions, other advantages of nonstationary panel we claimed in the paper become clear. In equation (1), we need to find external instruments to consistently estimate slope coefficient if y_{it} is endogenous; This is not only true if y_{it} is economically endogenous, but also true for the case that the endogeneity is created by econometric transformation of the data (For example, the difference GMM approach of Arelleno and Bond (1995) on correcting the endogeneity created by first differencing of data). However, this is not the case of nonstationary panel. Since in a cointegrating system, the endogenous bias becomes to be second order which can be corrected using internal instruments. For similar reasons, just as the case of time-series analysis, the estimates on slope coefficient are robust to simultaneity and many forms of omitted variables.

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data limitation. All the techniques in the papers dealing with other form cross-sectional dependencies requires the T dimension is signficantly larger than N dimension in order to avoid large size distortion in finite sample. But on the other hand, taking account of other form of cross-sectional dependencies does not considerably change the results in many empirical research (Pedroni (1997) and Pedroni (2007)). The simulation results in Banerjee, Marcellino and Osbat (2004) show that method of extracting of common time trends works well in practice.

References

Arellano, Manuel and Stephen Bond, Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, Review of Economic Studies, Vol. 58(2), 1991

Arrow, Kenneth J., The role of Securities in the Optimal Allocation of Risk Sharing, Review of Economic Studies, Vol. 29, 1964

Artis, Michael J. and Mathias Hoffmann, The Home Bias and Capital Income Flows between Countries and Regions, CEPR Discussion Papers 5691, C.E.P.R. Discussion Papers, 2006

Artis, Michael and Mathias Hoffmann, Declining Home Bias and the Increase in International Risk Sharing: Lessons from European Integration, in Lars Jonung, Christoph Walker and Max Watson (eds.) Building the Financial Foundations of the Euro: Experiences and Challenges, 2007

Artis, Michael and Mathias Hoffmann, Financial Globalization, International Business Cycles, and Consumption Risk Sharing, Scandinavian Journal of Economics, Vol. 110(3), 2008

Asdrubali, Pierfederico, Bent E. Sorensen and Oved Yosha, Channels of Interstate Risk Sharing: United States 1963-1990," The Quarterly Journal of Economics, Vol. 111(4), 1996

Athanasoulis, Stefano G. and Eric van Wincoop, "Growth Uncertainty and Risk- sharing," Journal of Monetary Economics Vol. 45(3), 2000

Athanasoulis, Stefano G. and Eric van Wincoop, Risk Sharing Within The United States: What Do Financial Markets And Fiscal Federalism Accomplish?, The Review of Economics and Statistics, vol. 83(4), 2001

Backus, David K., Patrick j. Kehoe, and Finn E. Kydland, Internaitonal Real Business Cycles, Journal of Political Economy, Vol. 100, 1992

Backus, David K.; Smith, Gregor W., "Consumption and real exchange rates in dynamic economies with non-traded goods", Journal of International Economics Vol. 35, 1993

Bai, Yan and Jing Zhang, Financial Integration and International Risk Sharing, 2006 Society for Economic Dynamics Meeting Papers 371, 2006

Baxter, Marianne and Mario J. Crucini, Business Cycles and the Asset Structure of Foreign Trade, International Economic Review, Vol. 36, 1995

Banerjee, Anindya, Massimiliano Marcellino and Chiara Osbat, Some cautions on the use of panel methods for integrated series of macroeconomic data, Econometrics Journal, Vol. 7, 2004

Becker, Sascha O. & Mathias Hoffmann, Intra- and international risk-sharing in the short run and the long run, European Economic Review, Elsevier, vol. 50(3), 2006

Beveridge, S. and C. R. Nelson, A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the Business Cycle, Journal of Monetary Economics, Vol. 7, 1981

Canova, Fabio and Morten O. Ravn, International Consumption and Risk Sharing, International Economic Review, Vol 37, 1996

Cavaliere Ciuseppe, Luca Fanelli and Attilio Gardini, International dynamic risk sharing Journal of Applied Econometrics, vol. 23(1), 2008

Cochrane, H. John, A Simple Test of Consumption Insurance, Journal of Political Economics, 1991

Cole, Harold L. and Maurice Obstfeld, Commodity Trade and International Risk Sharing: How Much Do Financial Markets Matter?, Journal of Monetary Economics, Vol. 28(1), 1991

Constantinides, George M. and Darrell Duffie, Asset Pricing with Heterogeneous Consumers, Journal of Political Economy, Vol. 104(2), 1996

Corcoran, Aidan, International Financial Integration and Consumption risk sharing, IIIS Discussion Paper No. 241, 2008

Debreu, Angus, Theory of Value, New Haven, CT: Yale University Press, 1959

Deaton, Angus, Understanding Consumption, Oxford, UK: Clarendon Press, 1992

Devereux, Michael B., Allan W. Gregory and Gregor W. Smith, Realistic Cross-country Consumption Correlations in a two-country, Equilibrium, Business cycle model," Journal of International Money and Finance, vol. 11(1), 1992

Flood, Robert P., Nancy P. Marion and Akito matsumoto, International Risk Sharing During the Globalization Era, the IMF memo, 2008

Gourinchas, Pierre-Olivier and Olivier Jeanne, The Elusive Gains from International Financial Integration, Review of Economic Studies, Vol. 73(3), 2006

Hall, Robert, Stochastic Implications of the Life Cycle-Permanent Income Hypothesis: Theory and Evidence, Journal of Political Economy, Vol. 86, 1978

Heston, Alan, Robert Summers and Bettina Aten, Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, September 2006

Hsiao, Cheng and Hashem M. Pesaran, Random Coefficient Panel Data Models, Cambridge Working Papers in Economics 0434, 2004

Labhard, Vincent and Michael Sawicki, International and Intranational Consumption Risk Sharing: The Evidence for the United Kingdom and OECD, Bank of England Working Paper No. 302, 2006

Lane, P. D., Do International Investment Income Flows Smooth Income?, Weltwirtschaftliches Archiv 137(4), 714-736, 2001

Lane, P. D. and G. M. Milesi-Ferretti, International Financial Integration, International Monetary Fund Staff Papers, 2003

Lewis, Karen K., What can Explain the Apparent Lack of International Consumption Risk Sharing?, Journal of Political Economy, Vol. 104, 1996

Lucas, Robert E., Interest Rates and Currency Prices in a Two-Country World, Journal of Monetary Economics, Vol. 10(3), 1982

Lucas, Robert E., Models of business cycles, Oxford: Blackwell, 1987

Kao, M. Chiang, On the Estimation and Inference of a Cointegrated Regression in Panel Data, Department of Economics, Syracuse University, 1997

Kollmann, Robert, Consumption, real exchange rates and the structure of international asset markets, Journal of International Money and Finance, Vol. 14(2), 1995

Kose, M. Ayhan, Eswar Prasad, and Marco Terrones, How Does Financial Globalization Affect Risk-Sharing? Patterns and Channels," IMF Working Paper, 2007

Mace, Barbara, Full Insurance in the Presence of Aggregate Uncertainty, Journal of Political Economy, Vol. 99, 1991

Mark, N.C., Sul, D., A computationally simple cointegration vector estimator for panel data. Mimeo, Ohio State University, 1999

Mendoza, Enrique, G., Real Business Cycles in a Small Open Economy, The American Economic Review, Vol. 81(4), 1991

Moser, Gabriel, Wolfgang Pointer, and Johann Scharler, International Risk Sharing in Europe: Has Anything Changed? In Liebscher, K., P. Mooslechner and D. Ritzberger-Grunwald, eds., The Economic Potential of a Greater Europe. Edward Elgar Publishing, 2004

Obstfeld, Maurice, Risk-Taking, Global Diversification, and Growth, The American Economic Review, Vol. 84(5), 1994

Obstfeld, Maurice and Kenneth S. Rogoff, Foundations of International Macroeconomics, The MIT Press, 1995

Pedroni, Peter, On the Role of Cross Sectional Dependency in Dynamic Panel Unit Root and Panel Cointegration Exchange Rate Studies, Working paper, Department of Economics, Indiana University, 1997

Pedroni, Peter, Fully Modified OLS for Heterogeneous Cointegrated Panels, Advances in Econometrics: "Nonstationary Panels, Panel Cointegration and Dynamic Panels", Vol. 15, 2000

Pedroni, Peter, Purchasing Power Partiy Tests in Cointegrated Panels, Review of Economics and Statistics, Vol. 83, 2001

Pedroni, Peter, Social Capital, Barriers to Production and Capital shares: Implications for the Importance of Parameter Heterogeneity from a Nonstationary Panel Approach, Journal of Applied Econometrics, Vol. 22, 2007

Pesaran, M Hashem and Ronald P. Smith, Estimating long-run relationships from dynamic heterogeneous panels, Journal of Econometrics, Vol. 68, 1995

Phillips Peter C. B., Optimal Inference in Cointegrated Systems, Econometrica, Vol. 59, 1991

Phillips Peter C. B., Fully Modified Least Squares and Vector Autoregression, Econometrica, Vol. 63, 1995

Phillips, Peter C. B. and Bruce E. Hansen, Statistical Inference in Instrumental Variables Regression with I(1) Processes, Review of Economic Studies, Vol. 57(1), 1990

Phillips, Peter C. B. and Mico Loretan, Estimating Long-run Economic Equilibria, Review of Economic Studies, Vol. 58, 1991

Phillips, Peter C. B. and Hyeonjoon Moon, Linear Regression Limit Theory for Nonstationary Panel Data, Econometrica, Vol. 67, 1997

Phillips, Peter C. B. and Hyeonjoon Moon, Nonstationary Panel Data Analysis: An Overview of Some Recent Developments, Econometric Reviews, Vol. 19, 2000

Rachev, Svetlozar T., Stefan Mittnik, Frank J. Fabozzi, Sergio M. Focardi, Teo Jai, Financial Econometrics: From Basics to Advanced Modeling Techniques, Wiley, John and Sons Incorporated, 2006

Shiller, Robert J., Macro Markets: Creating Institutions for Managing Society's Largest Economic Risks (Oxford: Oxford University Press), 1993

Shiller, Robert J., The New Financial Order: Risk in the 21^{st} Century, (Princeton, New Jersey: Princeton University Press), 2003

Sorensen, Bent E., Yi-Tsung Wu, Oved Yosha and Yu Zhu, Home Bias and International Risk Sharing: Twin Puzzles Separated at Birth" Journal of International Money and Finance Vol. 26(4), 2007

Sorensen, Bent E. and Oved Yosha, International risk sharing and European monetary unification, Journal of International Economics, Vol. 45(2), 1998

Stockman Alan C. and Linda L. Tesar, Tastes and Technology in a Two-Country Model of the Business Cycle: Explaining International Co-Movements, American Economic Review, Vol. 85, 1995

International Risk-sharing and Non-traded Goods, Journal of International Economics, Vol. 35, 1993

Townsend, Robert M, Risk and Insurance in Village India, Econometrica, Vol. 62(3), 1994

van Wincoop, Eric, How big are potential welfare gains from international risksharing?, Journal of International Economics, Vol. 47(1), 1999