

Estimating international risk-sharing in the presence of  
endogeneity.

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## **Abstract**

Over six chapters, this thesis explores how to estimate risk-sharing when output is not exogenous. The thesis starts with a survey of the current literature and how it estimates risk-sharing. This survey is then followed by risk-sharing estimations based on a panel of 24 countries over the period of 1970-2007. The estimation approaches applied include the literature's Classical and Level approaches, as well as alternative estimation approaches that provide robust parameter estimates when the literature commonly assumed output exogeneity is dropped. These alternative estimators consist of procedures using instrumental variables ranging from first differenced two-stage least squares, a dynamic generalized method of moments estimation, and an instrumental variables estimation using an instrument derived from a structural vector autoregressive model. Also, a Monte Carlo Simulation is undertaken to show the severity of the bias inherent in the Classical estimation method, as well as to show the performance of the proposed alternative methods. When output is endogenous, the Classical estimation method is found to underestimate risk-sharing, while the best performing alternative approaches are concluded to be the Level approach and the instrumental variables estimation approach using an instrument derived from a structural vector autoregressive model. This thesis contributes to the risk-sharing literature by discussing and quantifying the bias the Classical estimation approach suffers from due to output endogeneity. It also contributes by adapting estimation methods from other fields that allow consistent estimations of risk-sharing parameters in the presence of endogeneity bias, and by analyzing the performance of these asymptotic panel estimators in the specific context of the panel dimensions commonly found in the risk-sharing literature.

## **Dedication**

In memory of my father Dr. Reiner J. Dunker (1947-2008).

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# Chapter 1

## Introduction

This thesis looks at risk-sharing, which is the extent to which a country's income and thus consumption is subject to that country's individual income shocks versus an aggregate of income shocks across a group of countries. This is of interest to any monetary union as the more harmonized consumption is, or rather the more the member's consumption is decoupled from the country's idiosyncratic income shock, the more appropriate the overarching monetary policy of the monetary union becomes as it increasingly mimics the individual countries' monetary policies when they are not in a monetary union.

In essence, the risk-sharing aspect attempts to identify the extent to which it is a sacrifice to abandon individual monetary policy in favor of one cohesive policy across all member countries. The cost of monetary union by losing country individual monetary policy diminishes the higher the risk-sharing is amongst the group of countries.

The second chapter, provides a detailed introduction to the aspect of risk-sharing and the associated literature, including an overview of the main approaches the literature applies to estimate risk-sharing. This is followed in the third chapter by an application of the common risk-sharing methodologies found in the literature to a panel of 24 Organisation for Economic Co-operation and Development (OECD) countries over the period 1970-2007.<sup>1</sup> The results of these estimations form the benchmark for the subsequent chapters.

The fourth chapter starts by discussing the feasibility of an assumption commonly employed by the literature when estimating risk-sharing: exogeneity of output. The chapter then proceeds to discuss the impact of simultaneity bias on the risk-sharing estimation when the assumption of output exogeneity fails. It proposes

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<sup>1</sup>For the reader's benefit a comprehensive list of abbreviations and symbols that are used in this thesis can be found in appendix (A).

a variety of alternative estimation methodologies that should provide consistent results in the presence of simultaneity bias.

The fifth chapter employs a Monte Carlo Simulation (MCS) to analyze the impact of simultaneity bias on the risk-sharing estimation methodologies in a controlled environment. The MCS is then used to analyze the performance of the alternative estimation methodologies presented in the fourth chapter and subjects them to varying assumptions. This both presents the strength and weakness of the alternative approaches, as well as demonstrates under which conditions which approach performs best in estimating the true extent of risk-sharing. The final chapter, the sixth chapter, is a conclusion which briefly summarizes the key findings.

The main findings are that the Classical approach underestimate the true risk-sharing by ignoring the endogeneity bias. Also, following the application of various Instrumental Variables (IV)-estimation procedures and a MCS, it can be concluded that the IV-estimation utilizing a Structural Vector Autoregressive (SVAR) derived instrument provides the most robust instrument and consequently it provides considerably more reliable risk-sharing estimations than the Anderson and Hsiao (1981, 1982) First-Difference Two Stage Least Square (FD2SLS) or Holtz-Eakin et al. (1988) dynamic Generalized Method of Moments (dGMM) approaches.

The thesis contributes to the literature in several ways. The two main contributions are: i) the explicit discussion of the presence of simultaneity bias that affects the risk-sharing estimation approach as commonly applied in the literature, and accordingly the presentation of alternative approaches that should provide robust estimates, as well as ii) quantifying the bias inherent in the literature's commonly applied risk-sharing estimation approach and investigating the performance of the proposed alternative approaches in estimating the risk-sharing. Amongst the various alternative approaches, the most novel and a contribution in and of itself, as well as one of the best performing approach for consistent risk-sharing estimation in the presence of simultaneity bias, is an instrumental variables estimation that employs an instrument that is derived from a SVAR model.

The identification of a robust estimation methodology allows the appropriate quantification of the extent of risk-sharing of a group of countries and hence contributes to the appropriate identification of a monetary union under the Optimal Currency Area theory based on risk-sharing. More precisely, by ignoring the endogeneity bias the literature, in particular the Classical literature, has over-estimated unshared risk which in turns signaled to, for example, Euro-zone countries that there was a higher cost associated when joining the European Monetary Union than was actually the case. Greater risk-sharing minimizes the cost of monetary union. However, the exact quantification of the optimal level of risk-sharing for a monetary

union is beyond the scope of this thesis, which attempts to provide a consistent risk-sharing estimation methodology in the presence of output endogeneity.

Additionally, the thesis attempts to look at whether risk-sharing has risen. This topic is commonly discussed in the literature and relates to whether or not risk-sharing expanded in the wake of globalization and increased cross-country financial flows. However, the alternative estimation approaches prove to be too imprecise to make any conclusive statement on whether risk-sharing expanded. Future research could establish an estimation approach or enhance the alternative approaches presented here to allow for consistent and more precise estimates, making it possible to identify a shift in risk-sharing that is robust in the presence of endogeneity.

Moreover, although the results of the MCS in this thesis are tailored to the international risk-sharing specific panel dimensions and data characteristics, they have implications for wider empirical research on OECD data. More specifically, the results are informative for estimations concerning a fairly balanced panel consisting of a small cross-section of countries and a small time series. The overall results show that although the Ordinary Least Squares (OLS) estimations provide inconsistent estimates when simultaneity bias is present, these estimates have small dispersion, as well as have small standard errors despite the application of a range of variance-covariance estimation procedures that are robust to varying forms of heteroskedasticity and serial correlation. However, the alternative estimators, which have primarily an asymptotic justification, provide consistent estimate but have wide dispersion, especially in the case of FD2SLS and dGMM. Furthermore, while both the FD2SLS and IV-estimations using instruments derived from a Bayoumi and Eichengreen (1993) style SVAR (SVAR-IV) are exactly identified, the FD2SLS suffers extensively from finite sample bias in comparison to the SVAR-IV. These results reinforce established findings and demonstrate this in the context of a small balanced macro-economic sample. Nonetheless, future research could enhance the MCS by further varying the assumptions and panel dimensions to provide a more comprehensive contribution around more general behaviours of these estimators beyond the restricted risk-sharing estimation environment.

Overall, the results suggest that because the literature, particularly the Classical literature, ignores output's endogeneity bias, its risk-sharing findings will need to be reassessed. That is, this thesis establishes that, in comparison to robust estimates, the traditional Classical estimation procedures are likely to find lower risk-sharing than is actually the case.

# Chapter 2

## An introduction to the literature on international risk-sharing

### 2.1 Introduction

The basic theoretical principle of risk-sharing rests on the idea that people may be able to improve their ability to smooth their consumption over time, and thereby raise their utility, by sharing their risks of time varying consumption. In an international context, the opportunities for risk-sharing by different sets of national households come from idiosyncratic country output shocks. Those opportunities can be exploited either by state-contingent claims on foreigners' output, or cross-government transfers, or international borrowing and lending. Efforts to test the idea that countries will exploit their opportunities for risk-sharing have led to two different empirical approaches in the literature. The first stipulates that consumption patterns should be equal across countries if perfect risk-sharing exists. Therefore it tests for consumption correlation across countries. In this strand Backus et al. (1992) have proposed the consumption correlation puzzle, since they found that, contrary to the hypothesis of risk-sharing, cross-country consumption correlation is lower than the underlying output risk. Papers that found consumption to be less correlated than output, through various methods, include Devereux et al. (1992), Tesar (1993, 1995), Obstfeld (1994), and Stockman and Tesar (1995). Stockman and Tesar (1995) proposed that the difference in correlation can be explained by a preference shock, or taste shock, despite perfect risk-sharing. If countries are subject to country specific taste shocks, they stipulated, then the consumption correlation will naturally be lower than the initial correlation of output shocks.

The second empirical test stipulates that if perfect risk-sharing exists then consumption growth should be independent of country specific, idiosyncratic, output

	Ex ante	Ex post
Consumption smoothing	Domestic insurance against idiosyncratic output shocks	Domestic smoothing of consumption through saving behavior (Private, Corporate, Government saving)
Risk-sharing	Cross-country engagement to share output shock, e.g., cross-ownership of assets and international net income flows	Cross-country (income) flows after output shocks, to counter output shocks. E.g. international net transfers and international borrowing through net exports

Table 2.1: The difference between risk-sharing and consumption smoothing

movement and instead should be dependent on the aggregate output growth. It is this second empirical test of risk-sharing, which assumes a complete financial market, that this chapter and the following chapters are concerned with. When performing this test however, one should be aware that a fine differences exist between four aspects of the empirical application. Table (2.1) presents these aspects in relation to one another.

The fundamental difference lies in two aspects. The first is consumption smoothing which involves no cross-country activity (flow) and is effectively an intertemporal smoothing using domestic savings and reflects the equalization of intertemporal marginal utility. The second is risk-sharing and encompasses cross-country activities to offset idiosyncratic output shocks to income. This can be achieved through trading state contingent assets such as claims on foreign output (and the associated international income flows), prior to observing an output shock, or by flows such as international borrowing and lending through net exports or international net transfers, after the shock has been observed.

In the model presented in the following section, independence from idiosyncratic output shock is achieved for the consumption pattern by trading state contingent assets (claims on foreign output) prior to observing any output shocks and therefore committing to share idiosyncratic output shock risk. To this extent, the model below demonstrates the results of the ex-ante channel, also referred to as consumption insurance.<sup>1</sup>

The first empirical investigations that tested the independence of consumption from idiosyncratic output shock were by Mace (1991), Cochrane (1991), and Townsend (1994). They attempted to test for perfect risk-sharing. This was done by regressing consumption shock on output shocks and testing the statistical significance of the coefficient. In the presence of full risk-sharing, the coefficient would

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<sup>1</sup>See Sørensen and Yosha (1998) for a brief explanation of the difference between full risk-sharing and full consumption-smoothing and how in the case of complete financial markets, they are the same.

be statistically insignificant, which would imply that there is no statistical relationship between country-specific consumption and output movements.<sup>2</sup> However, subsequent work showed that this did not test for perfect risk-sharing but rather a composite of risk-sharing and consumption-smoothing.<sup>3</sup> Baxter and Crucini (1995) presented a possible scenario in the short run where perfect consumption smoothing through borrowing and lending served exclusively after the shock has been observed to mimic the ex-ante perfect risk-sharing outcome and thus rendering consumption independent of idiosyncratic output shock. Subsequently, it has become common to recognize that independence of consumption from country specific output shocks reflects a combination of ex ante risk-sharing and ex post consumption smoothing. This thesis follows the concept in the literature, which has now become common, that risk-sharing encompasses both ex ante risk-sharing and ex post consumption smoothing.

There are two strands to this post-Baxter-Crucini conception in the literature: the first, Classical method, in my terminology, utilizes first differences of variables, and the second, Level method, utilizes levels of variables. The former can be further categorized into two sub-strands: the Classical method based on consumption-output relationship a la Mace (1991), Cochrane (1991), and Townsend (1994), and the second, the Asdrubali et al. (1996)<sup>4</sup> method based on variance decomposition. The Classical or ASY method has found (as standard) relatively low international risk-sharing with little improvement over the years, even after the recent period of globalization and the associated rise in financial flows. On the contrary, the Level approach literature has found that international risk-sharing is relatively high, though not as high as apparent domestic inter-regional risk-sharing. Besides finding higher risk-sharing, the level literature also finds a rise in risk-sharing shortly after the beginning of globalization.

This chapter presents a survey of the literature on the topic of risk-sharing and it is structured as follows: Section (2.2) presents a risk-sharing model upon which the empirical literature rests. Section (2.3) presents the Classical and ASY estimation method literature, section (2.4) presents the Level estimation approach literature.

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<sup>2</sup>The test conducted by Mace (1991), Cochrane (1991), and Townsend (1994) did not find that perfect risk-sharing was taking place as the coefficient was found to be different from zero.

<sup>3</sup>The methods of Mace (1991), Cochrane (1991), and Townsend (1994) for full risk-sharing, assumes, as will be discussed at length later, that all the shocks originate from output. In other words, the estimation does not suffer from simultaneity bias as output is assumed to be exogenous. Although the assumption of output exogeneity has been discussed in the literature, see for example Sørensen and Yosha (1998) page 231, Qiao (2010) pages 9-10, Artis and Hoffmann (2007a) pages 8-9, or Artis and Hoffmann (2008) page 453, the literature has not formally tested for output exogeneity as it has commonly assumed this to be the case. Following the literature, the exogeneity assumption will be adopted for the duration of this and the following chapter. However, for chapter four and five, this assumption will be loosened.

<sup>4</sup>From this point forward, when referring to the work from Asdrubali et al. (1996) the citation will be shortened to the surname initial of the authors Asdrubali, Sørensen and Yosha (ASY).

Finally, section (2.5) will conclude by summarizing the chapter.

## 2.2 The theoretical foundation of international risk-sharing

This section presents a model that illustrates the theoretical foundation for the empirical application of risk-sharing.<sup>5</sup> This model assumes that there are a total of  $N$  countries with identical representative agents in a two period framework. The output of a specific country  $n$  in period one is exogenously given,  $Y_1^n$ , while period two output,  $Y_2^n(s)$ , is subject to an exogenous shock  $s$ , where there are  $\varrho$  possible shocks, with each shock having a  $\pi(s)$  probability of happening.<sup>6</sup> The model allows for the trade of two assets in the first period. The first, a riskless bond,  $B_1^n$ , has a guaranteed return of  $(1+r)$  in the second period. This type of risk-free bond reflects consumption smoothing in the model. The other asset is a claim on period two shock contingent output of country  $n$ ,  $V_1^n$ .<sup>7</sup> Specifically,  $V_1^n$  is the period one market value of the second period state contingent output of country  $n$ .<sup>8</sup> The representative consumer of country  $n$  attempts to maximize her lifetime utility in respect to first and second period consumption  $C_1^n$  and  $C_2^n(s)$ . The utility function has a CRRA functional form of  $u(C_t) = \frac{C_t^{1-\rho}}{(1-\rho)}$ , where  $\rho$  is the relative risk aversion coefficient. This yields the following maximization problem:

$$\max_{C_1^n, C_2^n(s)} U^n = u(C_1^n) + \iota \sum_{s=1}^{\varrho} \pi(s) u(C_2^n(s)) \quad (2.1)$$

where  $\iota$  is a standard time preference factor. The maximization in (2.1) is subject to the first period budget constraint:

$$Y_1^n + V_1^n = C_1^n + B_1^n + \sum_{m=1}^N x_m^n V_1^m \quad (2.2)$$

and the second period budget constraint:

$$C_2^n(s) = (1+r)B_1^n + \sum_{m=1}^N x_m^n Y_2^m(s) \quad (2.3)$$

---

<sup>5</sup>The model is a general risk-sharing model. It is taken from Obstfeld and Rogoff (1996) Ch.5.3. and is presented here for the reader's benefit with some additional steps shown.

<sup>6</sup>Where the possible shocks range from  $-\infty$  to  $\infty$ .

<sup>7</sup> $V_1^n$  being perpetual claims on a country's future output is in fact reminiscent of the assets proposed by Shiller (1993), which are also referred to in the literature as Shiller securities.

<sup>8</sup>This implies a complete financial market in the sense that we have  $N$  possible shocks each period, due to having  $N$  countries experiencing shocks each period, and  $N$  assets, as  $N$  countries sell their claims of state contingent period two output.

where  $x_m^n$  is country  $n$ 's share of country  $m$ 's future output. Rewriting (2.3) in respect to  $B_1^n$  and substituting the resulting expression of  $B_1^n$  in (2.2), one obtains the following new budget constraint:

$$C_1^n = Y_1^n + V_1^n - \left( \frac{1}{(1+r)} (C_2^n(s) - \sum_{m=1}^N x_m^n Y_2^m(s)) + \sum_{m=1}^N x_m^n V_1^m \right) \quad (2.4)$$

Next, after substituting (2.4) into (2.1), one obtains the following first order conditions by maximizing with respect to  $x_m^n$  and  $C_2^n(s)$ :

$$\frac{\partial U^n}{\partial C_2^n(s)} = -\frac{1}{(1+r)} u'(C_1^n) + \iota \pi(s) u'(C_2^n(s)) = 0 \quad (2.5)$$

$$\frac{\partial U^n}{\partial x_m^n} = u'(C_1^n) \left( \frac{1}{(1+r)} Y_2^m(s) - V_1^m \right) = 0 \quad (2.6)$$

Rewriting (2.5) to include the expression of the utility function, one obtains:

$$\frac{1}{1+r} C_1^{m(-\rho)} = \iota \pi(s) C_2^m(s)^{(-\rho)} \quad (2.7)$$

The ratio of consumption in one period to the other is therefore:

$$\frac{C_2^m(s)}{C_1^n} = \left( \frac{1}{(1+r)(\iota \pi(s))} \right)^{-\rho} \quad (2.8)$$

Since it is assumed that the representative agents of each country are identical, (2.8) holds for all countries. When summing (2.8) across countries, where  $\sum_m^N C_2^m(s) = C_2^W(s) = Y_2^W(s)$ , one obtains the equivalent aggregate (global) condition:

$$\frac{Y_2^W(s)}{Y_1^W} = \left( \frac{1}{(1+r)(\iota \pi(s))} \right)^{-\rho} \quad (2.9)$$

Since the right hand sides of (2.9) and (2.8) are equal, the following expression holds:

$$\frac{Y_2^W(s)}{Y_1^W} = \frac{C_2^n(s)}{C_1^n} = \frac{C_2^m(s)}{C_1^m} \quad (2.10)$$

Eq.(2.10) represents the concept of perfect risk-sharing to which we referred to in the previous section: consumption growth is identical across countries and follows global output growth rather than country specific output growth.

Although the model as presented here has only two periods, the model can be extended to multi- or infinite time periods with continued shocks to output. Nonetheless, the conclusion would be the same as in (2.10); the optimal consumption path would be subject to global output growth rather than the country's idiosyncratic output shocks. In essence risk-sharing refers to the extent a country has hedged

itself against its own idiosyncratic output shocks. This means a country has shared the risk of its negative or positive idiosyncratic output shocks with the rest of the world. Perfect risk-sharing, as characterized in (2.10), would be when all risk has been shared to the fullest extent at which point consumption would be subject to global output growth. The empirical risk-sharing literature, including this thesis, attempts to investigate whether this optimal consumption path is followed. More precisely, the literature looks at whether risk-sharing is taking place and to what extent, or rather how far it is from perfect risk-sharing.

However, before proceeding to the empirical approaches derived from (2.10), several steps remain in order to validate the model. Following the principal idea of (2.10), by extension, consumption of country  $n$  is a proportion of aggregate output, so that consumption for first period is  $C_1^n = \mu^n Y_1^W$  and for second period  $C_2^n(s) = \mu^n Y_2^W(s)$ . It remains to be shown that these proportional characterizations of consumption in period one and two represents an equilibrium that maximizes utility. For this, it needs to be shown that the proportional consumption does not violate the budget constraints, and the associated prices of both assets need to be presented (i.e. the prices of the bonds and state contingent claims).

The associated bond price follows from (2.8) and shown in (2.11) below with consumption expressed as a proportion of world output and summed across shocks.

$$\left( \frac{Y_1^W}{\sum_{s=1}^g \iota \pi(s) Y_2^W(s)} \right)^{-\rho} = (1+r) \quad (2.11)$$

The associated share price  $V_1^m$  is obtained from (2.6), summed across shocks in the following way:

$$\sum_{s=1}^g u'(C_1^n) \frac{1}{(1+r)} Y_2^m(s) = u'(C_1^n) V_1^m \quad (2.12)$$

where  $u'(C_1^n) = (1+r)\iota\pi(s)u'(C_2^n(s))$ , so that

$$\iota \sum_{s=1}^g \pi(s) u'(C_2^n(s)) Y_2^m(s) = u'(C_1^n) V_1^m \quad (2.13)$$

After inserting the proportion of world output for consumption, we get:

$$V_1^m = \iota \sum_{s=1}^g \pi(s) \left( \frac{Y_2^W(s)}{Y_1^W} \right)^{-\rho} Y_2^m(s) \quad (2.14)$$

It still remains to be verified that the budget constraints are not violated when

consumption is a proportion of world output. The second period budget constraint

$$\mu^n Y_2^W(s) = (1+r)B_1^n + \sum_{m=1}^N x_m^n Y_2^m(s) \quad (2.15)$$

is not violated if the agents hold no bonds,  $B_1^n = 0$ , and if the proportion of the various countries in the pool of claims on a country's future output is equivalent to the consumption proportion of world output of the various countries,  $x_m^n = \mu^n$ . The first period budget constraint

$$Y_1^n + V_1^n = \mu^n Y_2^W + \sum_{m=1}^N x_m^n V_1^m \quad (2.16)$$

holds when  $\mu^n = \frac{Y_1^n + V_1^n}{\sum_{m=1}^N (Y_2^m(s) + V_1^m)}$ .

## 2.3 The Classical empirical framework literature

Eq.(2.10) above has spawned two different methodologies in the empirical risk-sharing literature. The first assumes that the consumption pattern of any country should be identical to that in any other country belonging to the aggregate area. Subsequently, the first approach derives the following from (2.10) as basis for empirical investigation:  $\log(\frac{C_{n,t}}{C_{n,t-1}}) = \log(\frac{Y_{W,t}}{Y_{W,t-1}}) = \log(\frac{C_{m,t}}{C_{m,t-1}})$ ,  $\forall m \neq n$ . In other words perfect risk-sharing is when the consumption correlation between any two countries of the same integrated area is one.<sup>9</sup> The second empirical approach is based on the idea that, in the case of perfect risk-sharing (and possibly because of perfect consumption smoothing), a country's consumption should be independent of its idiosyncratic output shocks. As distinct to the first approach, the second approach converts (2.10) into the statement:  $\log(\frac{C_{n,t}}{C_{n,t-1}}) = \log(\frac{Y_{W,t}}{Y_{W,t-1}}) \neq \log(\frac{Y_{n,t}}{Y_{n,t-1}}) - \log(\frac{Y_{W,t}}{Y_{W,t-1}})$ . The first empirical test utilizing the second approach of consumption-output correlation, presented by Cochrane (1991), Mace (1991), and Townsend (1994), was a test for perfect risk sharing and was formulated as a regression of consumption on output. The regression had the following functional form:

$$\Delta \log(C_{i,t}) = \eta_t + \beta_u \Delta \log(Y_{i,t}) + \nu_{i,t} \quad (2.17)$$

where  $C$  stands for total consumption per capita,  $\eta_t$  are time dummies to extract the aggregate shocks each period, and  $Y$  is Gross Domestic Product per capita (GDP) as a measure of output.

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<sup>9</sup>Or for the sake of simplicity, in the case of perfect risk-sharing, any country part of the aggregate area should have consumption correlation to an aggregate measure of consumption of one.

The risk-sharing test of Eq.(2.17) tests  $\beta_u = 0$  under the assumption of perfect risk-sharing. This is true because perfect risk-sharing would render consumption independent of idiosyncratic output movement. Asdrubali et al. (1996) proposed that even if  $\beta_u \neq 0$  and the hypothesis of perfect risk sharing can be rejected,  $\beta_u$  can serve as an indication of the extent of risk-sharing. That is,  $1 - \beta_u$  yields the amount of the output shock being shared.<sup>10</sup> Furthermore Asdrubali et al. (1996) (ASY) proposed using an output variance decomposition (derived from an accounting identity) to develop a framework for testing various channels through which risk-sharing can take place. Therefore to some extent, they also proposed an approach for separating risk-sharing from consumption smoothing. The ASY-method will be discussed in greater detail later on, but one should be aware that the Classical method is nested in the ASY-method in the sense that the estimations of unshared risk are equivalent between the Classical and the ASY-method.

Various other formulations derived from Eq.(2.10) serve in the literature. A more commonly used formulation of Eq.(2.10) is:<sup>11</sup>

$$\Delta(\log(C_{i,t}) - \overline{\log(C_t)}) = \beta_u \Delta(\log(Y_{i,t}) - \overline{\log(Y_t)}) + \Delta(\nu_{i,t} - \bar{\nu}_t) \quad (2.18)$$

Where  $\overline{\log(C_t)}$ ,  $\overline{\log(Y_t)}$  and  $\bar{\nu}_t$  are cross-sectional averages, used to demean the respective variables and obtain idiosyncratic terms.

At this point it is necessary to discuss the concept and existence of two-way Fixed Effects, time and cross-section fixed effects, in relation to the above panel estimation, Eq.(2.18). If we start with the following estimation equation as the Data Generating Process (DGP) precursor to Eq.(2.18), that is before first difference and demeaning is applied:

$$\log(C_{i,t}) = \varpi + \log(Y_{i,t})\beta_u + \nu_{i,t} + \xi_i + \eta_t \quad (2.19)$$

then the time fixed effect,  $\eta_t$ , exists as the aggregate area every year is subject to a common (aggregate) shock. This is reflected in Eq.(2.10) as the rise (or fall) in world output. These common shocks need to be filtered to obtain the idiosyncratic shock and thus test for risk-sharing. In Eq.(2.18), time fixed-effects are extracted, by demeaning using the weighted sum, where the weights are derived from the country's relative importance to the overall level of GDP each year. The Eq.(2.18) is equivalent to Eq.(2.17) in that they filter out the common shock and apply first differences. The difference only lies in how the filtering is achieved. While in Eq.(2.17) the filtering is done through the use of time dummies, in Eq.(2.18) it is done through cross-sectional demeaning.

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<sup>10</sup>It follows that  $\beta_u$  reflects the proportion of output shocks that are not shared.

<sup>11</sup>The equation has no constant as the constant drops out when taking first difference unless a time trend is present. Thus, a constant is included in the estimations which in all cases, as should be the case if no time trend is present, is not different from zero.

Time dummies were originally used in the methods applied by Asdrubali et al. (1996), as well as, Mace (1991), Cochrane (1991), and Townsend (1994). Martin and Sachs (1991) proposed using cross-sectional demeaning, and this method is used by, among others, Mélitz and Zumer (1999), Bayoumi and Masson (1995) and Becker and Hoffmann (2006). The cross-section (panel) fixed-effect,  $\xi_i$ , on the other hand are nested in the panel data due to countries having unique features that affect consumption and are potentially correlated with output. If untreated, the panel fixed-effects would cause endogeneity. Therefore these effects need to be extracted to avoid bias issues. The extraction of the cross-section fixed effect is achieved, through using first differences. As a result of filtering out the fixed effects, when one estimates Eq.(2.18), one has to be aware of the serial correlation, introduced by the first difference, and the contemporaneous correlation, introduced through the cross-section demeaning, in the error variance-covariance structure.<sup>12</sup>

Nonetheless, independent of which formulation is chosen, be it Eq.(2.17) or (2.18),  $1 - \beta_u$  captures risk-sharing and consumption smoothing, aka the consumption independence of idiosyncratic output shocks.

For the sake of clarity, the use of lower case letters from here onwards indicates variables which have been demeaned using a weighted sum, with weights being derived from a country's contribution to the overall level of GDP.

### 2.3.1 ASY-method

Asdrubali et al. (1996) extended the framework of perfect risk-sharing testing. They argue that the coefficient in a estimation of consumption on output also provides an indication of the extent of risk-sharing in the absence of perfect risk-sharing. Additionally, Asdrubali et al. (1996) proposed a variance decomposition that allows for testing risk-sharing taking place through several channels: insurance channels (also referred to as income smoothing), consumption smoothing, and federal government transfers. This is done by using an accounting identity. The original objective of the Asdrubali et al. (1996) paper was to look at risk-sharing amongst US-states. For this purpose Asdrubali et al. (1996) proposed an accounting identity based on regional risk-sharing. The accounting identity Eq.(2.20) is based on the international risk-sharing application of Sørensen and Yosha (1998) and Mélitz and Zumer (1999) and follows in principle Asdrubali et al. (1996) proposed regional risk-sharing accounting identity and variance decomposition.<sup>13</sup>  $Y$  is Gross Domestic Product, GNI

<sup>12</sup>Please see the appendix for a formal discussion on the topic of the presence of a two-way fixed-effects model.

<sup>13</sup>Risk-sharing estimation approaches based on an accounting identity and variance decomposition are clustered into one category and are referred to as ASY-method – regardless whether it is for international or regional risk-sharing estimation. This is due to Asdrubali et al. (1996) being

is Gross National Income, GNDI is Gross National Disposable Income, HA is home absorption, and C is total consumption.

$$Y \equiv \frac{Y}{GNI} \frac{GNI}{GNDI} \frac{GNDI}{HA} \frac{HA}{C} C \quad (2.20)$$

What follows are the steps for obtaining the separation of risk-sharing into channels through the use of variance decomposition of output. The first step is to take logs:

$$\begin{aligned} \log(Y) \equiv & [\log(Y) - \log(GNI)] + [\log(GNI) - \log(GNDI)] \\ & + [\log(GNDI) - \log(HA)] + [\log(HA) - \log(C)] + \log(C) \end{aligned} \quad (2.21)$$

where the difference between Y and GNI is international net income, between GNI and GNDI is international net transfers, between GNDI and HA is net exports (effectively capturing international borrowing), and the difference between HA and C is changes in domestic savings – but also includes among other factors, capital depreciation.

The next step is to take first difference on both sides obtaining the change, or rather shock, between periods for international net income, international transfers, international borrowing transfers, and domestic savings. By multiplying both sides by  $\Delta \log(Y)$ , subtracting the means on both sides and taking expectation, one obtains the variance of  $\Delta \log(Y)$  on the left hand side and the covariance terms on the right hand side:

$$\begin{aligned} Var(\Delta \log(Y)) \equiv & Cov([\Delta \log(Y) - \Delta \log(GNI)], \Delta \log(Y)) \\ & + Cov([\Delta \log(GNI) - \Delta \log(GNDI)], \Delta \log(Y)) \\ & + Cov([\Delta \log(GNDI) - \Delta \log(HA)], \Delta \log(Y)) \\ & + Cov([\Delta \log(HA) - \Delta \log(C)], \Delta \log(Y)) \\ & + Cov(\Delta \log(C), \Delta \log(Y)) \end{aligned} \quad (2.22)$$

where the left hand side is the total variance of output and the right hand side decomposes the variance of output based on the accounting identity. Effectively, the right hand side measures the buffering of consumption against output fluctuation through various factors, with the last term showing the extent to which there is a lack of risk-sharing. That is, the last term shows the covariance of consumption with output.

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the first to propose such an approach to risk-sharing estimation.

When one divides by the variance of  $Var(\Delta \log(Y))$  on both sides, one obtains the following accounting identity, which forms the core of the empirical application of Asdrubali et al. (1996):

$$1 \equiv \beta_{k1} + \beta_{k2} + \beta_c + \beta_s + \beta_u \quad (2.23)$$

These  $\beta$ s are the proportional decomposition of output's variance into covariances with a variety of income sources and consumption. They in essence capture the risk-sharing channels that buffer consumption against output fluctuations.  $\beta_{k1}$  captures the covariance of the international net income from abroad with output as a proportion of the overall variance of output and signifies the ex-ante income insurance channel.  $\beta_{k2}$  captures the covariance of international net transfers with output and measures the international country equivalent of federal government transfer payments.<sup>14</sup> In this case, the international net transfers are, for the purpose of risk-sharing analysis, countering output fluctuations. Thus the  $\beta_{k2}$  captures within variation, that is variation over time, and it follows the methodology of Bayoumi and Masson (1995) and Mélitz and Zumer (2002) for regional government transfers, and the international application of Sørensen and Yosha (1998) for capturing the stabilization effect.<sup>15</sup>  $\beta_c$  reflects the covariance of foreign borrowing and lending, or the use of the trade balance, with output to buffer consumption.  $\beta_s$  reflects the covariance of domestic savings behaviour with output capturing domestic movement in savings to buffer consumption against idiosyncratic output shocks. The savings consist of domestic savings and investment, including capital depreciation, by agents, firms, and government. Finally,  $\beta_u$  reflects the covariance of consumption and output as a proportion of overall output variance and accounts for unshared risk. In other words,  $\beta_u$ , reflects the extent to which output are not shared, with all other  $\beta$ 's being risk-sharing channels, measuring a variety of source of income that buffer consumption from being affected by output fluctuations.

These risk-sharing channels are commonly estimated using the following models:<sup>16</sup>

$$\Delta \log(y_{i,t}) - \Delta \log(gni_{i,t}) = \varpi_{k1} + \beta_{k1} \Delta \log(y_{i,t}) + \nu_{i,t}^{k1} \quad (2.24)$$

<sup>14</sup>Sørensen and Yosha (1998) denote  $\beta_{k2}$  as  $\beta_\tau$ .

<sup>15</sup>Hagen (1998) provides an overview of the empirical findings for the US-states when one does not differentiate between stabilization of consumption and redistribution of income. The paper concludes from various empirical findings that the US federal government uses the transfer amongst state primarily for redistribution and to some extent consumption stabilization, so that when one does not separate redistribution and stabilization, one obtains an over estimate of the transfer channel as a risk-sharing channel. Additionally Hagen (1998) discusses the extent of symmetry in the transmission effect of transfers between regions and the potential negative effect this can have on the desirability of a fiscal transfer channel.

<sup>16</sup>For clarity, the nature of the error term has been kept simple here, and is extensively discussed in the following chapters. The nature of the econometric approaches to estimating these models and thus equations are also discussed later on.

$$\Delta \log(gni_{i,t}) - \Delta \log(gndi_{i,t}) = \varpi_{k2} + \beta_{k2} \Delta \log(y_{i,t}) + \nu_{i,t}^{k2} \quad (2.25)$$

$$\Delta \log(gndi_{i,t}) - \Delta \log(ha_{i,t}) = \varpi_c + \beta_c \Delta \log(y_{i,t}) + \nu_{i,t}^c \quad (2.26)$$

$$\Delta \log(ha_{i,t}) - \Delta \log(c_{i,t}) = \varpi_s + \beta_s \Delta \log(y_{i,t}) + \nu_{i,t}^s \quad (2.27)$$

$$\Delta \log(c_{i,t}) = \varpi_u + \beta_u \Delta \log(y_{i,t}) + \nu_{i,t}^u \quad (2.28)$$

To reiterate, the Classical framework of testing for risk-sharing is nested in the ASY method. That is, the Classical Eq.(2.18) is the same as ASY's unshared risk channel estimation, Eq.(2.28), and in large use the same DGP process. This is the reason why the ASY and the Classical approaches are considered together. In essence, ASY further developed the Classical literature approach of testing for risk-sharing to also incorporate the identification of how the risk-sharing is achieved.

### 2.3.2 Classical literature findings

Before proceeding with the presentation of the literature's findings, it is worth highlighting again that the literature commonly assumes that output is exogenous. Although some in the literature acknowledge that this assumptions might not hold, see for example Sørensen and Yosha (1998) page 231, Qiao (2010) pages 9-10, Artis and Hoffmann (2007a) pages 8-9, or Artis and Hoffmann (2008) page 453, this has not been formally tested. This is an important assumption in that if it is not the case, the resulting risk-sharing estimate would be biased due to simultaneity bias. This output endogeneity is at the heart of this thesis and will be extensively discussed in the fourth and fifth chapters, including discussion of how risk-sharing can be consistently estimated in the presence of output endogeneity. For the duration of this and the following chapter, however, we will forgo further discussion of output endogeneity and follow the literature in assuming that output is exogenous.

To enhance the exposition of the literature review, all results are shown in terms of risk shared. This means that in the case of unshared risk parameter estimates the linear transformation of subtracting the unshared risk coefficient from one is applied;  $1 - \beta_u$ . This is done so that all numbers shown are in terms of either total risk-sharing achieved or risk-sharing achieved through specific channels. Nonetheless for completeness, where applicable the unshared risk estimates, standard errors, and a 95% confidence interval are shown in parentheses after the results, e.g. 40% risk-sharing ( $\beta_u=0.6$ , S.E.=0.0503,[0.401, 0.598]). The standard errors and the confidence intervals are shown to give the reader a sense of significance and precision of estimates, although all referenced results are significant unless explicitly stated otherwise. Moreover, as will become evident, most estimates are fairly precisely estimated.

In their paper, Asdrubali et al. (1996) find that the US-states shared on average a total of 75% ( $\beta_u=0.25$ , S.E.=0.06, [0.132, 0.368]) of their idiosyncratic output during 1963-1990, of which 39% (S.E.=0.03, [0.331, 0.449]) percent was through cross-ownership of assets, 23% (S.E.=0.06, [0.112, 0.348]) through intertemporal consumption smoothing, and 13% (S.E.=0.01, [0.110, 0.150]) through federal government transfer payments.<sup>17</sup> However, these results have been criticized for overestimating the risk-sharing between US-States, since the estimated risk-sharing coefficients capture not only between-state, but also within-state shock smoothing, and this is consumption smoothing, not risk-sharing. Still, the literature has widely taken their findings as a benchmark by which to compare international risk-sharing and risk-sharing among monetary union members. Mélitz and Zumer (1999) find similar results, in terms of channel proportion to each other, for US-states between 1964-1990. Their results show an overall risk-sharing of 61% ( $\beta_u=0.39$ , S.E.=-, [- , -]),<sup>18</sup> of which 34% (S.E.=0.013, [0.314, 0.366]) was through income smoothing, 18% (S.E.=0.014, [0.153, 0.207]) through intertemporal consumption smoothing, and 10% (S.E.=0.006, [0.088, 0.112]) through federal government transfers.<sup>19</sup> A similar result of 11% (S.E.=0.006, [0.106, 0.130]) through the federal transfer channel was presented again in another later paper by Mélitz and Zumer (2002).

However, some of the problems with the optimistic results obtained by Asdrubali et al. (1996) can be traced back to limited data available between US-states. Fortunately, for international applications, the current account balances provide detailed data for the application of the output variance decomposition used by Asdrubali et al. (1996) for US-state risk-sharing.<sup>20</sup>

Such an international application has been provided by Sørensen and Yosha (1998). They test for international risk sharing through: 1) net factor income flow, 2) capital depreciation (theoretically providing dis-smoothing), 3) net international transfers, and 4) domestic consumption smoothing (through international borrowing and domestic savings). Beside investigating general risk-sharing internationally,

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<sup>17</sup>Mélitz and Zumer (2002) provide an overview of the empirical literature and the difference in accounting used for estimating the federal transfer system within countries as a stabilization tool for the US, Canada, France and the UK. They find when using the personal income approach that the US government provided 20% (S.E.=0.012, [0.176, 0.224]) stabilization. When using the gross product approach, which is similar to the approach of Asdrubali et al. (1996), they find that the US federal government channels account for 11% (S.E.=0.006, [0.106, 0.130]). Hagen (1998) provides an overview of the literature on fiscal transfer for US states and some other countries, and concludes that the literature finds about 10% of federal transfers consumption stabilization for US states.

<sup>18</sup>Note that hyphens in the S.E. and 95% CI indicate numbers that are not available because either the authors did not provide them, or they are compound measurements.

<sup>19</sup>These results are from Table 1 column (4) on p.160 in Mélitz and Zumer (1999). Similar results were found for Canadian regional risk-sharing.

<sup>20</sup>Since we are interested in international risk-sharing, that is risk-sharing across countries, a deeper discussion of regional risk-sharing findings is omitted. What follows concentrates on risk-sharing in an international context.

they also investigate in more detail the extent to which various components of domestic consumption smoothing through domestic savings (private, corporate and government savings) contribute to risk-sharing. This is done to shed light on institutional barriers. Such an institutional barrier could be a legislation that limits the size of a deficit and thus limits the ability of government to use government deficits for consumption smoothing, which in turn shift the burden from government savings to private or corporate savings. For corporate savings, consumption smoothing is achieved by retaining dividend payments during booms and paying larger dividend ratios during recessions. However, this pattern can be identified and offset by shareholders through counter-movements in private savings.

Sørensen and Yosha (1998) find that for 27 OECD countries during 1966-1990, 35% of output shocks at one year difference are shared, more precisely between 1966-1980 34% ( $\beta_u=0.66$ , S.E.=0.03, [0.601, 0.719]) of output shocks are shared and 35% ( $\beta_u=0.65$ , S.E.=0.04, [0.572, 0.728]) between 1981-1990, with both estimates being significant and fairly precisely estimated. Of the risk-sharing about half is achieved through government savings and half through corporate savings. On the other hand, the net factor income flow channel does not contribute to risk-sharing. This means that risk-sharing is almost exclusively achieved through domestic consumption smoothing for OECD countries. However, from 1966-1980 the EU-8 achieved 43% output shock smoothing ( $\beta_u=0.57$ , S.E.=0.06, [0.451, 0.689]) almost exclusively through savings, while from 1980-1990 output shock buffering dropped to about 22% ( $\beta_u=0.78$ , S.E.=0.07, [0.640, 0.920]) as reflected by a drop in the savings channel.<sup>21</sup> As for the international transfer channel, during 1981-1990 3% (S.E.=0.010, [0.010, 0.050]) to 7% (S.E.=0.03, [0.010, 0.130]) of output shock was smoothed through international transfer flows amongst OECD and EU-8 countries, but during 1966-1980 the international transfer did not provide any significant output buffering to consumption. On the other hand, when using 3 year differences, only 25% ( $\beta_u=0.75$ , s.e.=0.10, [0.554, 0.946]) of risk-sharing takes place almost exclusively through government savings in OECD countries. Given the potential existence of Ricardian equivalence, Sørensen and Yosha (1998) test for full and immediate Ricardian equivalence and find no conclusive evidence for or against the hypothesis.

Sørensen and Yosha (1998) take their findings as evidence that corporate saving does not provide long run smoothing, but governments provide short and long run consumption smoothing. Subsequently, given the lack of evidence for Ricardian equivalence, they argue for relaxing the Maastricht treaty to allow government debt to accumulate. This would in turn allow for government savings to continue

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<sup>21</sup>EU-8 includes to Belgium, Denmark, France, Germany, Ireland, Italy, the Netherlands, and United Kingdom. Also commonly used through the thesis is the abbreviation EU-15 which refers to the pre-2004 15 European Union members (excluding the EU enlargement countries).

to provide consumption smoothing until such a time as when financial and capital markets in the EU have developed and integrated to provide risk-sharing through private consumer channels or until European institutions are in a position to provide extensive risk-sharing through international transfers. Furthermore, they examine consumption smoothing behavior through net exports (also referred to as international borrowing) and domestic net physical investment (domestic savings), and find that little private saving consumption smoothing is done through net exports, but is instead mostly done through domestic investment. Finally, they look at the effect of real exchange rate movement on risk sharing and consumption patterns, and find that there is a relatively small effect on the cross-sectional consumption patterns, since consumption has a relatively low elasticity response to PPP movements.

Arreaza et al. (1998), while finding similar results as Sørensen and Yosha (1998), additionally look at the different government deficit aspects that contribute to domestic consumption smoothing. They find that for EU-8 countries during 1971-1993, 13% (S.E.=0.020, [0.091, 0.169]) of consumption smoothing was through government consumption, 18% (S.E.=0.020, [0.151, 0.229]) through government domestic transfers, 5% (S.E.=0.01, [0.020, 0.060]) through government subsidies, and no consumption smoothing occurred through taxes, that is the estimate is not significantly different from zero. Similar results were found for OECD countries, with the exception that the taxes provided dis-smoothing, since they rose by less than output. Additionally, Arreaza et al. (1998) investigate whether these government channels provide equal or more smoothing for a negative or positive output shock. They find that positive and negative shocks are equally shared in the OECD for all fiscal factors. On the other hand, EU-8 domestic government transfers provide greater smoothing during negative shocks, which potentially generate larger deficits in the EU-8 since greater transfers are not easily reversed during booms. They interpret this observation as a sign of a stronger commitment by the EU-8 to social insurance.

Arreaza et al. (1998) also investigate whether the level of deficit has an impact on consumption smoothing ability. This investigation was prompted by the idea that: i) if during a recession a country is generous with spending and low taxation, it might find it hard to reverse its policy during a boom and will thus accrue a large deficit and provide low consumption smoothing, ii) the country's government borrowing crowds out private borrowing, and iii) if a country has a large deficit, it might find it hard to borrow. They find no evidence that large deficits have an impact on smoothing through government saving or private saving channels.

Arreaza et al. (1998) also investigate whether smoothing through deficits differ according to the type of fiscal budgetary institution that determines government fiscal policy. They find that delegation (e.g. a strong finance minister) and targeting (successful agreement by coalition members on fiscal targets) have higher consump-

tion smoothing via government consumption and government transfers, but lower smoothing through government subsidies. They interpret these findings as “evidence that effective budgetary institutions can accomplish efficient consumption smoothing via government deficit spending and lower average deficits.” However, these gains of consumption smoothing are to a certain extent offset by lower private sector consumption smoothing.

Méltitz and Zumer (1999) find an overall risk-sharing of 20% ( $\beta_u=0.8$ , S.E.=, [-, -]) for OECD countries and 23% ( $\beta_u=0.77$ , S.E.=, [-, -]) between 1960-1994 for EU-15 countries. For OECD countries 5% (S.E.=0.005, [0.040, 0.060]) was through income smoothing, while 14% was through consumption smoothing.<sup>22</sup> For EU-15 countries, 8% (S.E.=0.017, [0.047, 0.113]) was through income smoothing and 15% was through consumption smoothing.<sup>23</sup>

Asdrubali and Kim (2000) look at similar risk-sharing channels structure as Sørensen and Yosha (1998), with the exception that Asdrubali and Kim (2000) do not look at the capital depreciation effect. However unlike Sørensen and Yosha (1998), Asdrubali and Kim (2000) look at the risk-sharing effects of nominal exchange rate and relative commodity prices. Their empirical investigation is done in a structural panel VAR framework, which allows for feedback between output and the risk-sharing channels. They find, for a sample of 23 OECD countries (and 15 EU-countries) that over the period 1960-1990 most risk-sharing took place through domestic consumption smoothing (domestic saving/credit channel). Furthermore, they find that real exchange rate, through nominal exchange rate and relative price adjustment, has a negative smoothing effect, or at least does not affect risk-sharing. From this negative risk-sharing effect they concluded that the Monetary Authority of Euro-zone countries did not lose a tool (exchange rate control) for shock stabilization when they formed the Euro-zone.<sup>24</sup>

Afonso and Furceri (2007) investigate risk-sharing in the EU-25 through net factor income flows from abroad, depreciation of capital, international government transfers, and foreign and domestic savings for the period 1980 to 2005. They find that between 1980-2005, the EMU and EU-15 shared about 43% ( $\beta_u=0.568$ , S.E.=0.049, [0.473, 0.664]) and 39% ( $\beta_u=0.611$ , S.E.=0.043, [0.526, 0.696]) of output shocks. Most was through the savings channels, with 39% (S.E.=0.060, [0.272, 0.508]) for EMU and 37% (S.E.=0.053, [0.265, 0.472]) for EU-15, and a minor

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<sup>22</sup>No standard error and confidence interval for consumption smoothing are shown as it is a compound measure of two estimates, one of which is insignificant  $\beta_c=0.01$  (S.E.=0.007, [-0.003, 0.023]) and one of which is significant  $\beta_{k2}=0.13$  (S.E.=0.007, [0.115, 0.145])

<sup>23</sup>Again no standard error and confidence interval for consumption smoothing are shown as it is a compound measure of two estimates, one of which is insignificant  $\beta_c=0.02$  (S.E.=0.028, [-0.035; 0.075]) and one of which is significant  $\beta_{k2}=0.13$  (S.E.=0.021, [0.089, 0.171])

<sup>24</sup>Asdrubali and Kim (2000) also look at regional risk-sharing in the United States. However, these findings are not discussed here since this thesis is interested in international risk-sharing.

amount was through the international government transfer and income insurance channels, while capital depreciation had a dis-smoothing effect. Risk-sharing increases when they use the sample period from 1992 to 2005. For this period, risk-sharing rose to about 50% for both EMU ( $\beta_u=0.499$ , S.E.=0.047, [0.405, 0.593]) and EU-15 countries ( $\beta_u=0.502$ , S.E.=0.046, [0.412, 0.592]), with 7% (S.E.=0.029, [0.009, 0.124]) risk-sharing for EMU and insignificant 5% (S.E.=0.026, [-0.002, 0.102]) risk-sharing for EU-15 countries achieved through income insurance and government transfer channels. When narrowing the sample period to 1998-2005, risk sharing dropped to 37% for EMU ( $\beta_u=0.6343$ , S.E.=0.056, [0.522, 0.747]) and EU-15 ( $\beta_u=0.6272$ , S.E.=0.060, [0.508, 0.746]), with consumption smoothing accounting for about 25% of it, and there was a significant rise in income insurance to 14% (S.E.=0.048, [0.041, 0.232]) for EMU and 12% (S.E.=0.046, [0.027, 0.208]) for EU-15. For the EU-25 between 1992-2005 and 1998-2005, Afonso and Furceri (2007) find a significant and fairly precisely estimated 36% ( $\beta_u=0.6397$ , S.E.=0.108, [0.427, 0.852]) and 31% ( $\beta_u=0.6937$ , S.E.=0.044, [0.606, 0.781]) respectively for risk-sharing of output shocks, with risk sharing taking place almost exclusively through consumption smoothing.

Demyanyk et al. (2008) investigate risk-sharing among the Euro-zone countries and the Accession countries for the periods 1995-1999 and 2000-2006. In particular, they investigate the effect of diversified financial asset holdings on income insurance channel and the banking consolidation on debt lending behavior. They find that for Euro-zone countries during 1995-1999, the income insurance channel was not significantly different from zero and that in 2000-2006, 15.7% (S.E.=0.078, [0.001, 0.313]) of shocks were smoothed through net factor income flows. For the larger economies of the EU-15 countries, income insurance fell from 11.2% (S.E.=0.044, [0.023, 0.201]) in 1995-1999 to 5.1% (S.E.=0.062, [-0.073, 0.175]) in 2000-2006, which is not significantly different from zero. Demyanyk et al. (2008) believe that recessions have caused this decline even though the underlying income smoothing has increased. They see this increasing difference in income insurance between EU15 and Euro-zone countries as evidence that the EMU has increased risk sharing for Euro-zone members through promoting financial integration. The Accession countries show a positive rise in income insurance risk-sharing from an insignificant 7.7% (S.E.=0.053, [-0.031, 0.185]) in 1995-1999 to a significant 12.6% (S.E.=0.053, [0.019, 0.233]) in 2000-2006. They also found that overall risk-sharing has risen for the EMU from 42.3% ( $\beta_u=0.577$ , S.E.=0.106, [0.361, 0.793]) in 1995-1999 to 52.9% ( $\beta_u=0.471$ , S.E.=0.071, [0.329, 0.613]) in 2000-2006. For the EU-15 countries, risk-sharing fell slightly from 40.5% ( $\beta_u=0.595$ , S.E.=0.056, [0.482, 0.708]) in 1995-1999 to 38.6% ( $\beta_u=0.614$ , S.E.=0.053, [0.508, 0.720]) in 2000-2006. The Accession countries total risk-sharing of 25.1% ( $\beta_u=0.749$ , S.E.=0.087, [0.571, 0.927]) in 1995-1999 fell to 11.5% ( $\beta_u=0.885$ , S.E.=0.064, [0.756, 1.014]) in 2000-2006. Given the drop, to-

tal risk-sharing for Accession countries is lower than the income insurance channel. They believe that this implies that some channels, namely savings, have a negative impact on risk-sharing and cause dis-smoothing. Furthermore, they find that the EMU and the EU have an increased international portfolio diversification, with an increased holding of foreign assets, both of which are associated with increased income smoothing. However, in regard to the effectiveness of investment into assets and liabilities for providing risk sharing, they found that investing outside of the EU provides more risk-sharing, potentially due to the returns on those assets being more disassociated from EU output shocks.

For banking sector consolidation, Demyanyk et al. (2008) find no significant effect of foreign banking consolidation for income smoothing or consumption smoothing. Domestic banking consolidation has a positive impact of 10.9% (S.E.=0.046, [0.017, 0.201]) on income smoothing for EMU, 8.3% (S.E.=0.041, [0.001, 0.165]) for EU-15 countries, and 6.8% (S.E.=0.061, [-0.055, 0.191]) for Accession countries, but is only significantly different from zero for EMU and EU-15 countries. Demyanyk et al. (2008) conclude that EMU countries have experienced benefits from entering into a monetary union and the subsequent financial integration, especially in regard to risk-sharing through income smoothing.

Kose et al. (2009), using a sample of 69 countries over the period from 1969-2004 and applying first difference estimation, do not find a substantial improvement for risk sharing during the years of globalization (1984-2004) for the entire sample. While industrial countries seem to have experienced a rise in risk sharing due to a rise in financial openness/integration, developing and emerging countries did not experience such an increase, despite increased financial integration. Kose et al. (2009) propose that the difference in risk sharing effect during 1984-2004 can be traced to the difference in the composition of financial flows. Risk-sharing increased in industrial countries due to having FDI flows, (portfolio) equity stock, and some debt stock. On the other hand, the emerging markets experienced lower risk sharing due to their financial flow being until recently, mainly in debt stock.

Bai and Zhang (2012) find that, for a sample of 43 countries using first differences estimation, risk-sharing declined from a significant and fairly precisely estimated 24% ( $\beta_u=0.760$ , S.E.=0.030, [0.701, 0.819]) between 1970-1986 to a significant and fairly precisely estimated 16% ( $\beta_u=0.840$ , S.E.=0.020, [0.801, 0.879]) between 1987-2004. For a sample of 21 OECD countries, they find an insignificant increase in risk-sharing from 38% ( $\beta_u=0.620$ , S.E.=0.040, [0.542, 0.698]) between 1970-1986 to 40% ( $\beta_u=0.600$ , S.E.=0.030, [0.541, 0.659]) between 1987-2004. Bai and Zhang (2012) estimate international risk-sharing in the context of increased financial integration. They conclude that liberalized financial markets did not lead to increased international risk-sharing as the financial market integration is limited by incomplete

markets and as sovereign debt repayment cannot be perfectly enforced.

More recently, Balli and Pierucci (2015) investigate risk-sharing for OECD and EMU countries over the period 1970-2010 using first differences.<sup>25</sup> They find that risk-sharing for OECD countries rose from a significant and fairly precisely estimated 18% ( $\beta_u=0.822$ , S.E.=0.033, [0.757, 0.886]) between 1970-1989 to a significant and fairly precisely estimated 28% ( $\beta_u=0.723$ , S.E.=0.030, [0.664, 0.782]) between 1990-2010, while risk-sharing for EMU countries declined from 31% ( $\beta_u=0.688$ , S.E.=0.058, [0.574, 0.802]) to 25% ( $\beta_u=0.748$ , S.E.=0.056, [0.638, 0.858]).<sup>26</sup> Additionally, they also investigate the extent of risk-sharing driven by social and political globalization effects and find that the social and political integration had a positive effect for both OECD and EMU countries.

In short, the majority in the classical literature (including ASY variance decomposition) has commonly found that risk-sharing is lower internationally than between regions within countries and that international risk-sharing did not increase during the early 1990s.<sup>27</sup> Several theoretical reasons have been brought forward to explain the difference between international and regional risk-sharing. One suggestion is that consumption is subject to country specific shocks that are non-diversifiable due to the consumption of non-traded goods. Other reasons that have been brought forward include state-verification, moral hazard, and enforceability. These reasons, affecting strictly ex-post channels, imply that it is hard to determine the kind and the severity of a shock, and that once a positive shock occurs, countries might not be willing to transfer funds abroad. The theoretical stipulations would explain the lower international risk-sharing relative to regional risk-sharing. However, they do not explain why the classical approach literature does not find increased risk-sharing during the period of globalization. As found by Milesi-Ferretti and Lane (2003, 2005, 2006), this period saw an increase in cross-country trade in state contingent assets in the form of higher international capital flows, and therefore a theoretical associated rise in risk-sharing should have occurred.

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<sup>25</sup>Balli and Pierucci (2015) also look at risk-sharing for low and middle income economies. However, for brevity, we forgo to summarizing their findings for these two groups here.

<sup>26</sup>Balli and Pierucci (2015) findings are sensitive to the inclusion of the real exchange rate impact. Again for brevity, Balli and Pierucci (2015) results as presented here are restricted to the findings that exclude the real exchange rate effect, on the grounds that the sample size is bigger when excluding the real exchange rate effect.

<sup>27</sup>Nonetheless there is a minority which do find a rise in risk-sharing. For example Sørensen et al. (2007) find a rise in risk-sharing in conjunction with a decline in home bias during the late 90's for industrial countries. Kose et al. (2009) reinforce this finding as they find a similar results for industrial countries, while failing to find similar improvement in risk-sharing for developing countries. Additionally, Demyanyk et al. (2008) find tentative results that indicate that EMU countries experienced a rise in income risk-sharing but a decline in consumption smoothing as a result of the EMU-membership. Furthermore, Balli and Pierucci (2015) find rising risk-sharing for OECD countries but not for EMU countries.

## 2.4 The Level empirical framework literature

To overcome some of the above mentioned shortcomings, a different approach to the Classical estimation method is becoming increasingly widespread in the literature. This new approach proposes using the level of variables rather than first differences.

One of the first Level method estimation was by Becker and Hoffmann (2006)<sup>28</sup> but Artis and Hoffmann (2007a,b, 2008) (AH) have done more to promote it. AH propose to use this alternative method, the Level method, as they argue that international ex-ante risk-sharing via state contingent assets is in relation to long horizon, or rather via trends in output such as permanent, or highly persistent output shocks. Moreover, they argue that ex-ante risk-sharing has increased in the early 1990's in response to the rise in international state contingent asset trade, as was found by Milesi-Ferretti and Lane (2003) in the late 1980's, but that the Classical and ASY approaches do not find a rise since they relate consumption to the elements of output driven by business cycles, such as short run or transitory output shocks. These shocks can be smoothed using ex-post channels such as borrowing and lending.<sup>29</sup> Thus, AH advocate the estimation of risk-sharing using the level rather than first difference of variables, as it provides an estimate of risk-sharing that captures the long-run relationship between consumption and output, capturing the full extent of international ex-ante risk-sharing that is derived from trade in international state contingent assets.

In other words, while the level estimation is designed to investigate risk-sharing of highly persistent to permanent shocks and therefore capture long run risk-sharing, the Classical and ASY first differences approach investigates shocks without distinguishing between permanent or transitory, subsequently capturing the short run risk-sharing aspect. AH demonstrate in one of their papers, that instead of using levels of variables, a similar result can be achieved by applying trend filter to as-

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<sup>28</sup>Theirs was an estimation of a structural VAR which allowed for differences and level estimation, short run and long run estimation in one approach.

<sup>29</sup>More precisely, in Artis and Hoffmann (2008), AH set out that, as consumption is correlated to permanent output movements, when estimating risk-sharing in first difference the correlation of consumption to output might not show improvements in risk-sharing as volatility of transitory versus permanent output shocks have fallen more dramatically. That is Artis and Hoffmann (2008) on page 449 write "Specifically, we argue that [first difference] risk-sharing regressions have not picked up the effect of financial globalization because the short term volatility of output growth has dropped by more than has its long-term volatility[...]. Since, as we show consumption reacts primarily to permanent changes in relative output, the volatility of relative consumption conditional on *current* relative output growth has not decreased as financial globalization has progressed." supplemented by "We argue that this pattern of decline in volatility indicates a more gradual adjustment of output to permanent idiosyncratic shocks: for a permanent shock of a given size, output today reacts less strongly. Since consumption adjusts directly to the shock in permanent income, it therefore appears more volatile in relation to current output." on page 450. For a more comprehensive derivation and explanation of the permanent versus transitory output impacts on risk-sharing estimation please see Artis and Hoffmann (2008) pages 454-458.

certain the same long run (permanent) consumption-output (income) relationship estimation. But, as AH mention, the use of trend-filters to filter out the permanent effect requires sufficient variation in the trend, as otherwise no within-group estimates would be possible because of the lack of within variation, even if there was enough variation across the cross-section.

The level estimation commonly rests on the following model:

$$\log(c_{i,t}) = \varpi + \beta_u^{LR} \log(y_{i,t}) + \nu_{i,t}^{LR} \quad (2.29)$$

Eq.(2.29) is similar to Eq.(2.19), differing in that no first differences is taken and  $\nu_{i,t}^{LR}$  contain any short term dynamics of  $c_{i,t}$  that are stationary and thus not correlated with non-stationary  $y_{i,t}$ .<sup>30</sup> The estimation of the Eq.(2.29) by AH is based on Kao and Chiang (2001) (pooled) Dynamic OLS:

$$\log(c_{i,t}) = \varpi + \beta_u^{LR} \log(y_{i,t}) + \sum_{p=0}^P (\beta_{p,1} \Delta \log(y_{i,t-p}) + \beta_{p,0} \Delta \log(y_{i,t+p})) + \nu_{i,t}^{LR} \quad (2.30)$$

Eq.(2.30) is the same as (2.29) apart from the fact that (2.30) is enhanced with leads and lags of first differenced  $\log(y_{i,t})$ . This is done to account for bias arising in finite samples. That is, while an OLS estimation of Eq.(2.29) should asymptotically yield superconsistent estimates of  $\beta_u^{LR}$  when output and consumption are non-stationary, in a small sample, due to potential serial correlation between the  $\log(y_{i,t})$  with  $\nu_{i,t}^{LR}$ , estimation of  $\beta_u^{LR}$  can be biased. Leads and lags are included in Eq.(2.30) to avoid this bias. The resulting estimate of  $\beta_u^{LR}$  should have an approximate normal distribution and thus standard t-statics should be applicable as the associated t-value should be asymptotically  $N(0, 1)$ . The appropriate length of the included leads and lags is determined by using information criteria such as Akaike's or Schwarz's Bayesian information criteria.

### 2.4.1 Level literature findings

Artis and Hoffmann (2007a) find for 23 OECD countries between 1960 to 2004, that long-term risk-sharing has increased from less than 10% to between 30% and 40% after 1990.<sup>31</sup> This increase is associated with a particular growth in cross-country asset holdings during the 1990s. Additionally they found that debt asset

<sup>30</sup>We leave for the fourth chapter the issue of unit-root and co-integration surrounding Eq.(2.29).

<sup>31</sup>The unshared risk coefficients and the associated standard errors, as well as the confidence intervals can not be provided in a comprehensive and accessible manner due to the numbers referring to several estimation shown by Artis and Hoffmann (2007a) in Table 1. Nonetheless, the quoted result is based on Artis and Hoffmann (2007a) page 3 “[...] the fraction of long-term idiosyncratic output risk that gets shared internationally by the average OECD country has increased from less than 10 to more than 30 percent.”

holdings have a positive impact on medium-run risk-sharing through consumption smoothing, while cross-holdings of equity have a positive impact on medium-run income smoothing.<sup>32</sup>

Artis and Hoffmann (2007b) find using level estimation that risk-sharing has increased for 23 OECD countries, especially during the 1990s. Furthermore, the EMU countries' main driving force for the increased risk-sharing was insurance channels, which has subsequently gained importance as a risk-sharing channel. During the 1990s the EMU had a 10% increase in risk sharing through the ex-ante channel. For the remaining OECD countries, the main channels and driving force for improvement was the ex-post channel of borrowing and lending.

Artis and Hoffmann (2008) take a different approach by applying a Beveridge-Nelson-type decomposition to output, separating into permanent and transitory output, and then running a standard FD estimation.<sup>33</sup> They find that full risk-sharing of transitory idiosyncratic output shock occurred amongst 22 OECD countries between 1960-2000. On the other hand, they find that risk-sharing for permanent output shock was imperfect. However, risk sharing increased during the period of globalization in the 1980s, and even more so during the period of increased gross international asset positions in the 1990s, from about 30% ( $\beta_u^{LR}=0.7$ , S.E.=0.03, [0.641, 0.759]) –which is significant and fairly precisely estimated, to 60% ( $\beta_u^{LR}=0.39$ , S.E.=0.05, [0.291, 0.489]) –which is still significant but less precise, due to a rise in risk-sharing for permanent idiosyncratic output shocks.

Leibrecht and Scharler (2008) use a different estimation approach than AH with the same objective in mind. What they use is a one and two step error-correction model, which allows them to quantify the risk-sharing in short and long run and gives them the opportunity to obtain the speed of adjustment of short run risk-sharing to the long run. In other words, if risk-sharing increases with time, the speed of adjustment will indicate how long it will take to achieve the higher long run risk-sharing.

Leibrecht and Scharler (2008) investigate the risk-sharing amongst 21 OECD countries over the period of 1951 to 2000. The paper sets out to test the cointegration between consumption and output. To this end both Leibrecht and Scharler (2008) and Pierucci and Ventura (2009) take the existence of cointegration as evidence of imperfect risk-sharing in the long run, for if there was perfect risk-sharing, then idiosyncratic consumption and idiosyncratic output should not be cointegrated.

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<sup>32</sup>AH make a finer point about when one explicitly includes country fixed effect when estimating Eq.2.29 that it doesn't reflect permanent shock risk-sharing and thus term such estimation as medium term risk-sharing estimation. This concept of medium term is presented in the third chapter.

<sup>33</sup>The Beveridge-Nelson-type filter is used instead of standard trend filters in order to obtain a higher variation in the permanent component.

Leibrecht and Scharler (2008) find that 30% ( $\beta_u=0.71$ , S.E.=0.04, [0.632, 0.788]) of risk was shared in the short run, while only 10% ( $\beta_u^{LR}=0.91$ , S.E.=, [-, -]) was shared in the long run. Furthermore, they investigate whether risk sharing depends on the extent to which there is international diversification represented by foreign assets and liability position. On this point they find that countries with above average holdings of foreign assets and liability positions are less exposed to shock in the short and long run. Specifically, they find that countries with greater diversified portfolios achieved both higher long run (34%,  $\beta_u^{LR}=0.66$ , S.E.=0.06, [0.542, 0.778]) and short run (46%,  $\beta_u=0.54$ , S.E.=0.08, [0.383, 0.697]) risk-sharing, while countries with below average portfolios had short run risk-sharing of 21% ( $\beta_u=0.79$ , S.E.=0.04, [0.712, 0.868]) and long run of 2% ( $\beta_u^{LR}=0.98$ , S.E.=0.04, [0.902, 1.058]). Furthermore, the delay of consumption to idiosyncratic shock varies from 1.7 years for a country with below average holdings of foreign assets and liability position to 5.7 years for above average countries, until the shock fully hits in terms of final stage of consumption co-movement level. They interpret this result as evidence for the lack of long run risk-sharing due to the binding constraint of ex-post consumption smoothing channels and limited set of state-contingent assets available, which the financial market can not readily provide.

In common with Leibrecht and Scharler (2008), Pierucci and Ventura (2009) use a two-step Engle-Granger approach for 21 OECD countries between 1951 to 2000, and find that the risk-sharing coefficient for long run (36%,  $\beta_u^{LR}=0.64$ , S.E.=0.06, [0.522, 0.758]) and short run (36%,  $\beta_u=0.64$ , S.E.=0.03, [0.581, 0.699]) were equivalent. They also find that the adjustment coefficient of -0.04 (S.E.=0.01, [-0.060, -0.020]), while being significant, is close to zero and "...suggests that the short run dynamics of idiosyncratic consumption are fairly independent of those of long run idiosyncratic consumption", (Pierucci and Ventura (2009), p.12). Overall, they find that globalization did not increase risk-sharing in both the long run and short run, since most risk-sharing improvement was achieved prior to the 1990s and actually deteriorated some during the 1990s. In effect, these results are in contradiction with AH. Furthermore, the Pierucci and Ventura (2009) finding that risk-sharing is the same in the long run as in the short run is in contradiction with the Leibrecht and Scharler (2008) findings.

Qiao (2010) looks at non-stationary panel estimation of risk-sharing for 26 OECD and 22 emerging countries over the period 1950-2008.<sup>34</sup> He finds that while over the entire sample period nearly 14% of the long run risk is shared by both the OECD countries ( $\beta_u^{LR}=0.88$ , S.E.=0.01, [0.861, 0.899]) and the emerging countries

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<sup>34</sup>While Qiao (2010) follows the general Level-approach, the precise econometric framework is based on Pedroni (2001)'s Group-mean DOLS, which is a minor deviation of the more general pooled DOLS shown in Eq.(2.29). For an explanation of GDOLS and the difference between the DOLS, as well as an application of GDOLS please see the third chapter.

( $\beta_u^{LR}=0.86$ , S.E.=0.01, [0.84, 0.880]), during the period of financial globalization long run risk-sharing rises for the OECD countries to 34% ( $\beta_u^{LR}=0.66$ , S.E.=0.009, [0.643, 0.677]) and for the emerging countries to 23% ( $\beta_u^{LR}=0.77$ , S.E.=0.009, [0.751, 0.789]).<sup>35</sup> Furthermore, he finds that countries with higher financial flow also have higher risk-sharing. However, the positive effect is decreasing with the amount of financial flows.

More recently, Fuleky et al. (2015a) used Pesaran (2006) common correlated effects mean group estimators to estimate short and long run risk-sharing for 158 countries over the period of 1970-2010.<sup>36</sup> They find that for the entire sample the short run risk-sharing with 29% ( $\beta_u=0.71$ , S.E.=0.03, [0.651, 0.769]) was higher than the long run risk-sharing with 17% ( $\beta_u^{LR}=0.83$ , S.E.=0.03, [0.651, 0.769]). They find a similar disparity between short and long run risk-sharing for OECD countries with 32% ( $\beta_u=0.68$ , S.E.=0.04, [0.602, 0.758]) short run risk-sharing and 20% ( $\beta_u^{LR}=0.80$ , S.E.=0.05, [0.702, 0.898]) long run risk-sharing. Furthermore, when applying the estimation to the sub-periods 1970-1989 and 1990-2010 they do not find a significant rise in risk-sharing with short run risk-sharing for the entire cross-section being 30% ( $\beta_u=0.70$ , S.E.=0.03, [0.641, 0.759]) between 1970-1989 and 32% ( $\beta_u=0.68$ , S.E.=0.04, [0.602, 0.758]) between 1990-2010 and the long run risk-sharing being 18% ( $\beta_u^{LR}=0.82$ , S.E.=0.03, [0.761, 0.879]) and 15% ( $\beta_u^{LR}=0.85$ , S.E.=0.04, [0.772, 0.928]). For the OECD sub-sample they find 32% ( $\beta_u=0.68$ , S.E.=0.02, [0.641, 0.719]) short run risk-sharing between 1970-1990 and 36% ( $\beta_u=0.64$ , S.E.=0.02, [0.601, 0.679]) for 1990-2010 and long run risk-sharing being 20% ( $\beta_u^{LR}=0.8$ , S.E.=0.05, [0.702, 0.898]) in both sub-periods. Overall, Fuleky et al. (2015a) estimates are significant and fairly precisely estimated.

## 2.5 Conclusion

In summary, risk-sharing is about consumption hedging against country specific idiosyncratic shocks such as output shocks. This is based on the theoretical model presented in section (2.2) which in Eq.(2.10) shows that when perfect risk-sharing is taking place, a country's consumption growth is independent of idiosyncratic output shocks and instead is identical to consumption in other countries, more specifically it is correlated to the global output movement. This has spawned two empirical methodologies to test risk-sharing: i) the first which tests consumption correlation across countries and ii) the second that investigates the correlation of idiosyncratic consumption with idiosyncratic output. It is this latter that this thesis is interested

<sup>35</sup>All four estimates are both significant and fairly precisely estimated.

<sup>36</sup>Common correlated effects and Pesaran (2006)'s common correlated effects mean group estimators will be explained and discussed at length in the next chapter.

in. It stipulates that if perfect risk-sharing was taking place, the correlation of idiosyncratic consumption with output would be zero. Moreover, if perfect risk-sharing does not take place, a regression of idiosyncratic consumption on idiosyncratic output should yield an unshared risk coefficient that if subtracted from 1 should provide the extent to which risk-sharing is taking place.

To study the correlation of idiosyncratic consumption with output, two distinct empirical approaches have been developed in the literature; the Classical (and ASY) approach and the Level approach. The former, the Classical approach, uses the first difference estimation of idiosyncratic consumption and idiosyncratic output to estimate unshared risk, while the latter, the Level approach, uses the level of idiosyncratic consumption and idiosyncratic output in a regression, labeling the results as medium or long run risk-sharing. The Classical approach literature commonly finds international risk-sharing amongst OECD countries to be around 30% with estimates ranging from around 20% to 40% risk-sharing. Moreover, unshared risk appears to be precisely estimated with a standard error commonly of around 0.03 to 0.04. This is prevalent when comparing estimates undertaken in chapter 4 which have much higher standard errors and thus wider confidence intervals.

Meanwhile, the Level approach literature finds OECD medium and long run risk-sharing to be initially low with values of around 10% to 30%, rising to 20% to 60% post 1990.<sup>37</sup> Again the estimates tend to be fairly precisely estimated with most standard errors being between 0.03 to 0.04.

However, the empirical tests of risk-sharing as commonly employed in the literature, in particular for the Classical literature, rely on output being exogenous. And while at times the exogeneity is discussed, it is commonly assumed, without formal testing, that the assumption of output exogeneity holds. This is an important assumption in that if it is not the case, the resulting risk-sharing estimate would be biased due to simultaneity bias. This output endogeneity is at the heart of this thesis and will be extensively discussed in Chapter 4 and 5, though for now we will follow the literature in assuming that output is exogenous.

Thus, the literature applies two distinctly different approaches to estimating the correlation between consumption and output: first difference and level estimation. The literature finds a varying degree of risk-sharing taking place that ranges from 10% to 40% and tends to be precisely estimated. Moreover, the estimation of the variance-covariance is commonly done to be robust to various forms of heteroskedasticity and serial correlation. Nonetheless, the literature appears to forgo extensive discussion or even testing of simultaneity bias, but rather assumes that all explana-

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<sup>37</sup>The Level literature's first difference risk-sharing estimates range from 30% to 40%, which is similar to the Classical approach. That is the Level approach, akin to the Error Correction Model, in some instances employs both first differences and levels of variables in an estimation.

tory variables are exogenous. It is this lack of consideration and discussion of the presence of exogeneity bias which is at the heart of this thesis, including suggestions of how to robustly estimate risk-sharing in the presence of the output endogeneity.

## Chapter 3

# Empirical applications of risk-sharing estimation methodologies

This chapter presents risk-sharing estimations based on the Classical and Level approaches presented in the second chapter. The estimation results in this chapter form the anchor to the literature and are the benchmark for the subsequent chapters. That is, the results in this chapter show that the results in the literature can be reproduced with the data set used in this and the following chapters. Therefore, any difference in results in comparison to the literature in the subsequent chapters are driven by the methods employed.

In addition to the standard Classical feasible GLS with AR(1) correction estimation a variety of other estimators are presented. These follow the Classical principal of estimating first-differenced unshared-risk based on the models Eq.(2.18) or Eq.(2.28), but they have varying small sample performance properties. Also, in addition to the Classical first differences and Level estimation approaches, the Pesaran et al. (1997, 1999) Pooled Mean Group estimator is presented. This combines the level and first differences methodology into an error correction model using country individual estimations that are averaged to provide a panel parameter estimate. This is similar to the Pedroni (2001) Group-Mean Dynamic OLS estimation which is also applied as part of the Level estimation.

Presenting the Pooled Mean Group estimator is part of a larger discussion tying the risk-sharing literature to the common correlated effects literature.<sup>1</sup> As discussed below, although the risk-sharing literature implicitly corrects for common correlated

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<sup>1</sup>See for example Pesaran et al. (1997, 1999), Pesaran (2006, 2015), or Pesaran and Tosetti (2011).

effects, it does so by imposing strong restrictions on the form the common correlated effects take.

### 3.1 Data

The data used in the estimation is taken from OECD statistics and is for 24 OECD countries over the period of 1970-2007.<sup>2</sup> The data is deflated with 2000 as the base year, is in per capita terms, and in US dollars using the 2000 market exchange rate. This largely ignores the potential effect of the real exchange rate on risk-sharing, which may be important. For example, both Sørensen and Yosha (1998) and Hoffmann (2008) explore how real exchange rate movements provide some form of risk-sharing. While Sørensen and Yosha (1998) find the real exchange rate to have relatively little impact on risk-sharing, Hoffmann (2008) finds that exchange rate movements provide extensive risk-sharing. Here we will follow most of the literature and the results of Sørensen and Yosha (1998) in supposing that the real exchange movements can be ignored.<sup>3</sup>

The period from 2008 onward is deliberately excluded so as to line up with the majority of the time-horizons analyzed in the existing literature, against which this chapter's estimation results are compared. Also, the selected time horizon avoids having to make an assumption on whether the financial crisis that started in 2008 was caused by a structural or temporal economic shock, something that is important from a monetary policy perspective and thus for monetary union and risk-sharing.

The estimation is applied to the entire sample period as well as two sub-samples, 1970-1990 and 1991-2007. Amongst other reasons, the use of sub-periods is based on the attempt to analyze the small sample performance of the estimators in estimating risk-sharing. This is because the properties of some of the estimators lend themselves to use with shorter time periods. It also enables us to investigate whether risk-sharing expanded with the rise in global financial market integration and increased trade of equity found in the late 80s early 90s. Finally, the selected sub-sample periods follow commonly used sub-samples in the literature, allowing us to more easily compare the estimations with the literature.

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<sup>2</sup>The 24 OECD countries are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, South Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

<sup>3</sup>Please note that Sørensen et al. (2007) used PPP adjustment to account for the real exchange rate effect on risk-sharing.

## 3.2 Empirical applications of the Classical approach

The classical empirical framework follows the model of unshared risk as laid out in Eq.(2.18) and Eq.(2.28). No attempt is made to estimate risk-sharing channels, as the interest is limited to overall risk-sharing. Amongst other reasons, ignoring the estimation of separate channels facilitates comparison of performance across estimation methods in estimating risk-sharing, which is the underlying interest in this and following chapters.

In the pursuit of estimating risk-sharing based on the Classical method, a variety of estimators are employed. While they all differ in the approach to the variance-covariance matrix, the estimators use the same risk-sharing estimation equation. Driving the need for using a variety of econometric techniques is the presence of heteroskedasticity and autocorrelated errors, and each estimator has its respective strengths and weaknesses in correcting for the presence of both.<sup>4</sup>

Period	OLS	OLS(HAC)	OLS(cluster)	FGLS	PCSE	DK
1970 to 2007						
$\beta_u$	0.7369***	0.7369***	0.7369***	0.7234***	0.7204***	0.7369***
SE()	(0.0212)	(0.0335)	(0.0620)	(0.0110)	(0.0293)	(0.0312)
95% CI	[0.695, 0.779]	[0.671, 0.803]	[0.609, 0.865]	[0.702, 0.745]	[0.663, 0.778]	[0.674, 0.800]
$R^2$	0.5762	0.5762	0.5762	–	0.5552	0.576
1970 to 1990						
$\beta_u$	0.7291***	0.7291***	0.7291***	0.7030***	0.7080***	0.7291***
SE()	(0.0295)	(0.0391)	(0.0745)	(0.0058)	(0.0395)	(0.0450)
95% CI	[0.671, 0.787]	[0.652, 0.806]	[0.575, 0.883]	[0.692, 0.714]	[0.631, 0.785]	[0.635, 0.823]
$R^2$	0.5604	0.5604	0.5604	–	0.5365	0.5604
1991 to 2007						
$\beta_u$	0.7665***	0.7665***	0.7665***	0.7656***	0.7722***	0.7665***
SE()	(0.0302)	(0.0629)	(0.0911)	(0.0115)	(0.0449)	(0.0342)
95% CI	[0.707, 0.826]	[0.643, 0.890]	[0.578, 0.955]	[0.743, 0.788]	[0.684, 0.860]	[0.694, 0.839]
$R^2$	0.6140	0.6140	0.6140	–	0.6235	0.6140

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Please note that no  $R^2$  is reported for GLS due to the nature that  $R^2$  for GLS is not bound between zero and one and that the  $R^2$  for GLS would not reflect solely the explained total sum of squared. Standard errors are shown in parentheses in rows labeled as SE() and 95% confidence intervals are shown in square brackets in rows labeled as 95% CI.

Table 3.1: FD unshared risk parameter estimates.

The first estimator in Table (3.1) is a standard OLS estimation with no adjustment for heteroskedasticity or serial correlation.<sup>5</sup> The second is an OLS estimation

<sup>4</sup>The various estimators do not correct or even consider the possibility of endogeneity. The topic of risk-sharing and endogeneity is at the heart of the fourth and fifth chapters.

<sup>5</sup>Using the White, Durbin-Watson and the Breusch-Godfrey LM tests, it was found that heteroskedasticity and serial correlation are present. However, the validity of the tests hinges on output being exogenous, something that is extensively discussed in the next chapter.

with standard errors corrected for arbitrary heteroskedasticity and serial correlation using a Bartlet kernel with a bandwidth of 2. The third estimator is a cluster-robust OLS estimation, with the clusters being countries and assumed to be independent across clusters. To account for contemporaneous cross-cluster correlation, the Parks (1967) FGLS cluster robust estimation (also referred to as the Parks method), Beck and Katz (1995) Panel-Corrected Standard Errors (PCSE), and Driscoll and Kraay (1998) standard errors correction (DK) are in columns four, five and six respectively. Beck and Katz (1995) argue that the PCSE is better than FGLS for hypothesis tests, as FGLS standard errors are too optimistic. Furthermore, Beck and Katz (1995) point out that the FGLS estimator requires the time dimension of the data to be relatively large compared to the cross-section, which is hardly the case in the annual macro-economic data used in the risk-sharing literature, and indeed is not the case for the data set employed here. Additionally, Beck and Katz (1995) show that the PCSE, which relies on large T-asymptotics, has good finite-sample performance. However, the PCSE small sample performance, as argued by Hoechle (2007), declines when the cross-section (N) becomes large relative to the time dimension (T), or rather, when the division of the time dimension by cross-section becomes small ( $\frac{T}{N}$ ). The Driscoll and Kraay (1998) method on the other hand does not suffer from the negative effect of a relatively large N compared to T, as the consistency does not rely on large N, but rather on large T-asymptotics. Furthermore, Driscoll and Kraay (1998) allow for errors that are heteroskedastic, autocorrelated, and correlated between cross-sections up to some specified lag – in our case three. Hoechle (2007) and Driscoll and Kraay (1998) show that when one ignores the existence of cross-sectional dependence in the error term it can lead to a severe bias in the standard error estimates. Furthermore, they find that the DK standard errors outperforms various alternatives, even though to some extent it is biased as well. These different methods are different ways of calculating standard errors under different assumptions and reflect advances in econometric techniques that go beyond, for example, the Asdrubali et al. (1996) application of feasible GLS with an AR(1) correction.

Table (3.1) shows the unshared risk estimation results obtained from the various estimation methods. The DGP behind the regression model shown in Table (3.1) is still given by Eq.(2.19) and (2.28). The first column is the standard OLS estimation with no adjustment for heteroskedasticity or serial correlation, the second column shows the OLS estimation with standard errors corrected for arbitrary heteroskedasticity and serial correlation, the third column contains the cluster-robust OLS estimation where clusters are defined as the cross-sections with the assumption of independent clusters, the fourth column shows FGLS cluster-robust estimation, column five shows the Beck and Katz (1995) Panel-Corrected Standard Errors (PSCE), and column six shows the Driscoll and Kraay (1998) standard errors correction (DK).

The estimates in Table (3.1) are in line with what is generally found in the literature, which is about 27% risk-sharing in the OECD. Moreover, all estimates are significant; more precisely they are significantly different from zero at 1% significance level, which is in line with the literature and suggests that no perfect risk-sharing is taking place. Also, the estimates are fairly precisely estimated with estimated standard errors of similar magnitude as those found in the literature. Furthermore, while the point estimates show that risk-sharing has dropped, the 95% confidence intervals allow for the possibility that risk-sharing has stayed the same between 1970-1990 and 1991-2007 which is also in line with the general findings of the literature.<sup>6</sup> To this extent, one can see that when using a different data set the general findings of the literature can be reproduced. Therefore we can conclude that any different results in the analysis of the subsequent chapters based on the same data are not driven by the particular data set but derived from approaches that are employed.

### 3.3 Empirical application of the Level approach

The empirical framework for the Level approach is laid out in Eq.(2.29), which differs from Eq.(2.18) in that the levels rather than first differences of consumption and output are used.

Before proceeding to the presentation of the Level application it is important to highlight, as briefly observed in the second chapter, that the Level estimation is inherently analyzing a different shock structure than the Classical approach. The Level estimation is predominantly used to investigate risk-sharing of permanent or highly persistent shocks. The focus of the Classical approach is on transitory shocks and their impact on risk-sharing. The ASY approach has been used to investigate persistent shocks by expanding the difference interval. Asdrubali et al. (1996) looked at US-state risk-sharing over larger differences, Sørensen and Yosha (1998) looked at international risk sharing over a differencing span of three years, while Arreaza et al. (1998) looked at the impact of different fiscal components on domestic risk sharing, also over a differencing span of three years. Finally, Mélitz and Zumer (1999) investigated the effect of persistent shocks on risk-sharing by using the Campbell-Mankiw persistence index. Nonetheless, although the permanent output shocks are considered in the Classical literature, by filtering them out using first differences they are treated in the same way as a transitory shocks. So if one wants to estimate the effect of persistent or permanent shocks the level estimation should be used, while if one is interested in transitory shocks or believes relatively few

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<sup>6</sup>As suggested, the reason for the conclusion of no fall in risk-sharing comes from the 95% confidence intervals around the 1991-2007 estimates overlapping with the 95% confidence interval around the 1970-1990 estimates.

permanent shocks occur, then the classical approach should be used.<sup>7</sup>

Also, two different applications of Level estimation with different interpretations exists. The difference is based on the treatment of the country-specific effects that are no longer automatically filtered out when applying first differences. This is part of the larger discussion on the estimation of channels through which risk-sharing can take place in connection with permanent and transitory output shocks. That is, permanent shocks can only be risk-shared using an ex-ante insurance channel (diversification channel), as borrowing is not well adapted in response to offset the permanent shock. On the other hand, transitory shocks can be shared through diversification channels or consumption smoothing channels.<sup>8</sup> In light of the exclusive use of insurance for risk-sharing of permanent output shocks, AH argue that the interpretation of the risk-sharing parameters depends on whether country-fixed effects are explicitly estimated or not. More precisely, AH argue that the estimation which explicitly includes country fixed effects allows risk-sharing through non-net factor income from abroad and thus does not exclusively reflect risk-sharing against permanent output shocks. On the other hand, AH argue that the estimation excluding country fixed effects solely captures the risk-sharing through net factor income from abroad and thus capture the long run risk-sharing of permanent output. Therefore, AH term the Level estimation which includes country fixed effects as ‘medium run’ and the estimation without cross-section fixed effect as ‘long run’.

The table (3.2) shows the estimation of unshared output shocks for the period 1970-2007 in the first row, 1970-1990 in the second and 1991-2007 in the third. Meanwhile, the first column shows the estimation with country fixed effects, that is, the medium run risk-sharing, while second column shows the risk-sharing estimation without country fixed effects, that is, the long run risk-sharing estimates. All estimates in Table (3.2) are significantly different from zero at a 1% significance level. Moreover, the estimates are fairly precisely estimated with consequently fairly tight confidence intervals. Also, standard errors are in line with the literature which has an average standard error for the level estimate of around 0.03 (ranging from approximately 0.008 to 0.06). Given the estimates in Table (3.2), it becomes apparent that when looking at the long run that risk sharing between 1970-1990 and 1991-2007 remained essentially zero. On the other hand, though not shown in this table, the inclusion of a time-trend did lead to an increase in risk-sharing from 4% (or 96% unshared) in 1970-1990 to 5% (or 95% unshared) in 1991-2007. However, when looking at the medium run risk-sharing results, an increase in risk-sharing occurs from about 20% in 1970-1990 to 37% in 1991-2007, which is an increase in

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<sup>7</sup>When pursuing the empirical investigation in respect to an Optimal Currency Area on the basis of risk-sharing, one should consider more transitory shocks since monetary policy is primarily applicable as a smoothing tool for temporary shocks.

<sup>8</sup>This is supported by Mélitz and Zumer (1999)’s finding that for US-States, the more persistent a shock is, the more income smoothing rises relative to consumption smoothing.

	medium run	long run
1970 till 2007		
$\beta_u^{LR}$	0.8017***	0.9774***
SE()	(0.0121)	(0.0029)
95% CI	[0.7779, 0.8255]	[0.9717, 0.9831]
1970 till 1990		
$\beta_u^{LR}$	0.8061***	0.9720***
SE()	(0.067)	(0.0032)
95% CI	[0.7928, 0.8193]	[0.9657, 0.9784]
1991 till 2007		
$\beta_u^{LR}$	0.6304***	1.0007***
SE()	(.0114)	(0.0049)
95% CI	[0.6082, 0.6527]	[0.9911, 1.010]
Dummy estimation		
$\beta_{u,D1}^{LR}$	0.7916***	0.9559***
SE()	(0.0137)	(0.0038)
95% CI	[0.7648, 0.8185]	[0.9485, 0.9634]
$\beta_{u,D2}^{LR}$	-0.1212***	-0.0068***
SE()	(0.0240)	(0.0025)
95% CI	[-0.1683, -0.0742]	[-0.0117, -0.0018]

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors are shown in parentheses and 95% confidence intervals in square brackets.

Table 3.2: Level unshared risk parameter estimates.

risk-sharing of 17 percentage points.<sup>9</sup>

The significance of the expansion in the medium run risk-sharing was tested using an enhanced version of Eq.(2.29) applied to the entire sample:

$$\log(c_{i,t}) = \varpi + \beta_{u,D1}^{LR} \log(y_{i,t}) + \beta_{u,D2}^{LR} D \log(y_{i,t}) + \xi_i + \nu_{i,t} \quad (3.1)$$

where  $D \log(y_{i,t})$  is an interactive dummy term with  $D$  being equal to 0 prior to and including 1990 and 1 thereafter. The rise in risk-sharing is significant if  $\beta_{u,D2}^{LR}$  is found to be different from 0 and if  $\beta_{u,D2}^{LR} < 0$ , with the null hypothesis being  $H_0 : \beta_{u,D2}^{LR} = 0$  versus the alternative that  $H_A : \beta_{u,D2}^{LR} \neq 0$ . Eq. (3.1) allows for differing unshared risk coefficients between the two periods, as is the case in the unshared risk estimations of two separate sub-periods 1970-1990 and 1991-2007 in Table (3.2). However, unlike the separate sub-period estimations shown in Table (3.2) as 1970-1990 and 1991-2007, Eq. (3.1) does account for the joint distribution of  $\beta_{u,D1}^{LR} \log(y_{i,t})$  and  $\beta_{u,D2}^{LR} D \log(y_{i,t})$  when estimating the variance-covariance estimation of the error matrix.<sup>10</sup> Nonetheless, since we are primarily interested in testing  $H_0 : \beta_{u,D2}^{LR} = 0$ , the restriction on the error variance is of no direct concern. Also, if the level of consumption and output in Eq. (3.1) are non-stationary the mean of the error in Eq. (3.1) is not constant and thus the significance test is invalid. Whether consumption and output are non-stationary is extensively discussed in the following chapter as part of the discussion around endogeneity bias. Assuming that consumption and output are stationary, Table (3.2) presents, in the last row, the coefficient, standard error, and 95% confidence interval for both  $\beta_{u,D1}^{LR}$  and  $\beta_{u,D2}^{LR}$ . The  $H_0 : \beta_{u,D2}^{LR} = 0$  is rejected for a two-sided t-test with 5% significance level, with a p-value of 0.000 in both the long and medium run estimation. Thus it can be concluded that the rise in medium-run risk-sharing, assuming that consumption and output are stationary, is found to be both economically significant and significantly different from zero.

One of the reasons why there seems to be a increase in the risk-sharing could be that the estimation with country fixed effects, allows for country specific risk-sharing. For example, the risk-sharing through state contingent asset portfolios becomes dependent on country-specific factors such as the extent of diversification. An additional reason for the medium-run rise in risk-sharing, as argued by AH,

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<sup>9</sup>The estimation with country FE used country-specific dummies,  $\xi_i$ , to capture the country FE, that is  $c_{i,t} - \bar{c}_t = \beta_u(y_{i,t} - \bar{y}_t) + \xi_i$  where  $\bar{c}_t$  is the aggregate shock in each period (filtering out the time FE). However, an equivalent but alternative method, which is computationally not as heavy in the use of parameters, is to demean with average time effect and average cross-section effect, so that  $c_{i,t} - \bar{c}_i - \bar{c}_t + \bar{c} = \beta_u(y_{i,t} - \bar{y}_i - \bar{y}_t + \bar{y})$ . For a more detailed explanation please see Smith and Fuertes (2010) page 16.

<sup>10</sup>Since the estimation of Eq. (3.1) is done using cluster robust standard errors the variance-covariance matrix does not require the errors to be homoskedastic. If, however, the estimation were done using simple OLS the untested assumption of homoskedasticity would be imposed.

could be that the estimation captures country specific consumption smoothing on top of long-run risk-sharing. These conclusions are drawn from contrasting the results of the estimations with and without explicit modeling of country fixed effects. When combining these two arguments it can be postulated that the risk-sharing of permanent shocks through the holding of the common, or rather average, state contingent assets portfolio is low and shows little improvement when compared to country-specific risk-sharing or consumption smoothing.<sup>11</sup> It should be mentioned that consumption-smoothing is more important in the medium run while portfolio diversification remains the same, depends on making the assumption that permanent and transitory shocks are of similar structure, or that the way permanent shocks and transitory shocks are risk-shared through state contingent assets is the same. However, these assumptions need not hold, in which case the difference in the extent of risk-sharing between the medium run and long run can be explained by transitory shocks being more efficiently risk-shared through state contingent assets (insurance) than permanent shocks, without implying that consumption smoothing takes place.

In short, the difference found between medium- and long-run risk-sharing estimates can be driven by: i) country specific consumption smoothing, which provide substantial risk-sharing for transitory shock in the medium run, or ii) the way that a portfolio of state contingent assets (insurance) provides risk-sharing differs between permanent and less permanent output, or iii) countries are widely dispersed in terms of the extent of risk-sharing gained through diverse state contingent asset portfolios.

Regardless of what drives the difference between medium- and long-run risk-sharing, the extent of risk-sharing and the fact that it is rising in the medium run, while being in line with the Level literature, is in contradiction to the Classical literature.

### 3.3.1 Group mean dynamic OLS estimation

An alternative approach to the pooled Dynamic OLS (DOLS) of Eq.(2.29) used by Artis and Hoffmann (2007a,b, 2008) to estimate the Level approach is the procedure proposed by Pedroni (2001) (Group-mean DOLS or short GDOLS) used in the risk-sharing estimation by Qiao (2010).<sup>12</sup> Whereas AH apply (pooled) DOLS, which does not explicitly account for a country's individual risk-sharing parameter, the Group-mean DOLS is an estimator which allows for a country individual risk-

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<sup>11</sup>This would indicate either that consumption smoothing is highly important relative to the state contingent assets risk-sharing factor, which is in line with Classical literature findings when using the ASY decomposition, or that countries vary in the extent of risk-sharing gained through state contingent asset risk-sharing factor as mentioned above.

<sup>12</sup>An application of Pedroni (2001) GDOLS procedure beyond risk-sharing can be found in Chong et al. (2010) and Carlson et al. (2008).

sharing parameter.<sup>13</sup> However, assuming similar risk-sharing amongst the countries in the sample, the DOLS risk-sharing parameter is the average of the time series parameters for individual countries and therefore should be similar to the Group-mean counterpart.

The Pedroni (2001) GDOLS estimator is presented in addition to the pooled DOLS estimator, as it allows for heterogeneous co-integrating relationships by estimating the co-integrating relationship separately for each country and averaging the coefficients and standard errors in order to obtain a mean estimate.<sup>14</sup> Implicitly, the GDOLS includes country-specific fixed effects since each country's estimation includes a constant that should capture the country-specific effect of a pooled DOLS estimation and thus according to Artis and Hoffmann (2007a,b, 2008) is more akin to medium-run risk-sharing.<sup>15</sup>

Variable	1970-2007	1970-1990	1991-2007
$\beta_u$	0.9988	1.0241	0.5607
SE()	(0.1161)	(0.1912)	(0.2207)
95% CI	[0.7712, 1.2264]	[0.6492, 1.3989]	[0.1860, 0.5955]

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors are shown in parentheses and 95% confidence intervals using the mean estimates and standard errors are shown in square brackets.

Table 3.3: GDOLS mean unshared risk parameter estimates.

Table (3.3) shows the mean parameter estimates of the country's individual estimates of unshared risk. Besides having a higher value in 1970-2007 and 1970-1990, the GDOLS estimates show a similar result as the medium run estimation in Table (3.2); risk-sharing was relatively low in 1970-2007, but a large rise in risk-sharing occurred in 1991-2007. Moreover, estimates are less precisely estimated as standard errors are considerably larger leading to wider 95% confidence intervals. Nonetheless, all estimates in Table (3.3) are significantly different from zero.

<sup>13</sup>An alternative estimation method to the DOLS is the Fully Modified OLS, originally proposed by Phillips and Hansen (1990), which (panel) Groups-mean counterpart (GFMOLS) was proposed by Pedroni (2000).

<sup>14</sup>The parameters, as well as, variance-covariance matrix of each country's individual estimations are T consistent. However, the averaged estimate of the joint risk-sharing parameter and variance-covariance matrix are N consistent. See Pedroni (2001) and Qiao (2010) for a more detailed explanation of the asymptotic properties and consistency of the estimator.

<sup>15</sup>For completeness, each country's individual parameter estimates, which are used in the GDOLS to construct the mean panel estimates, can be found in Table (C.1) in the appendix (C.1).

### 3.4 Heterogeneous slope and spatial common correlated effects.

Two aspects which the risk-sharing literature has not explicitly considered, apart from Fuleky et al. (2015a), are heterogeneous slopes and (spatial) common correlated effects (CCE). Let us enhance Eq.(2.19) to the following form:<sup>16</sup>

$$C_{i,t} = \beta_i Y_{i,t} + \varrho_{i,t} + \xi_i \quad (3.2)$$

where  $\varrho_{i,t} = \gamma_i f_t + \nu_{i,t}$ .  $\nu_{i,t}$  is equivalent to the error in Eq.(2.19) and is assumed to be  $\sim i.i.d. (0, V(\nu_{i,t}))$ . Eq.(3.2) raises two issues that are largely ignored in the risk-sharing literature: heterogeneous slopes,  $\beta_{u,i} = \beta + \kappa_i$ , and common (cross-section) correlated effects,  $\gamma_i f_t$ .  $\gamma_i f_t$  is a more flexible version of the  $\eta_t$  in Eq.(2.18) and (2.19). The structure of the common correlated effects as presented in Eq.(3.2) is based on Pesaran (2006).

The risk-sharing literature, driven by the desire to test idiosyncratic consumption's relation with idiosyncratic output, implicitly corrects for CCE.<sup>17</sup> However, unlike the CCE literature, the risk-sharing literature imposes a variety of restriction on the structure the CCE takes.<sup>18</sup> These restrictions arise because of the way the risk-sharing literature corrects for the common shocks to get an estimation of the correlation between idiosyncratic consumption and output. The risk-sharing literature defines the common shock as the shock experienced by all countries in the sample if every country had a perfect portfolio of state contingent assets, i.e. the aggregate shock experienced by all country in the sample if perfect risk-sharing is taking place.

For one, the risk-sharing literature imposes the restriction that there are no heterogeneous slopes,  $\beta_{u,i} = \beta_u = \beta_{u,j}$ . Also, by the virtue of how the risk-sharing literature demeans consumption and output, a certain structure is imposed on the term  $\gamma_i f_t$ . Following the CCE literature,  $f_t$  is defined as:

$$f_t = [\bar{C}_t, \bar{Y}_t] \quad (3.3)$$

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<sup>16</sup>For clarity the log notation has been dropped, with all variables, unless stated otherwise, being in logs. Also, as in the previous chapters, lower case letters indicates variables which have been demeaned using weighted average.

<sup>17</sup>GDOLS as presented above should also be robust in the presence of heterogeneous panel as the GDOLS is the mean of country individual estimations which allow for country individual slopes.

<sup>18</sup>For the interested reader, the following is a non-exhaustively list of papers of the CCE literature: Pesaran (2006, 2015), Pesaran and Tosetti (2011), Chudik et al. (2011), and Bailey et al. (2012).

The CCE literature defines the weighted mean of consumption and production as:

$$\bar{C}_t = \sum_{i=1}^n w_i C_{i,t} \quad (3.4)$$

and

$$\bar{Y}_t = \sum_{i=1}^n w_i Y_{i,t} \quad (3.5)$$

where the CCE literature requires several conditions for the weights,  $w_i$ , to be valid, including that  $\sum_{i=1}^N w_i = 1$ . In addition, the CCE literature has been defined for use with constant weighting matrix. However, the risk-sharing literature differs to the CCE literature by using time varying weights that reflect the relative economic size (in effect, the economic distance from each other) in each period:

$$w_{i,t} = \frac{Y_{i,t}}{\sum_{i=1}^N Y_{i,t}} \quad (3.6)$$

It is important to note that the time-varying nature of the weighting matrix, as used in the risk-sharing literature, does not make the weighting matrix invalid. For example, by design, the risk-sharing literature employs weights that in each period adds to 1. Moreover, the variance of the weights for country  $i$  over time is fairly low making it in a practical sense similar to a time-invariant weight. Driving the choice of the weights in the risk-sharing literature is the desire to filter out the common effect of holding a perfectly balanced portfolio of state contingent assets against which further risk-sharing is not possible. This state contingent portfolio is subject to the relative economic size of a country to the aggregate. However, given that the weights are output, if output is endogenous, which is at the heart of the next two chapters, then the instruments are invalid.

The risk-sharing literature also assumes that the CCE parameter is symmetric across the cross-section, i.e.  $\gamma_i = \gamma = \gamma_j$ . Moreover, since the risk-sharing literature subtracts the  $\bar{C}_t$  on the LHS sides from Eq.(3.2) to get idiosyncratic consumption and subtracts  $\bar{Y}_t$  on the RHS to get idiosyncratic output,  $\gamma_i$  is assumed by the risk-sharing literature to have the following structure:

$$\gamma = [1, -\beta]' \quad (3.7)$$

Putting this all back into Eq.(3.2) it becomes:

$$C_{i,t} = \beta Y_{i,t} + \bar{C}_t - \beta \bar{Y}_t + \nu_{i,t} + \xi_i \quad (3.8)$$

which is equivalent to Eq.(2.18), the traditional risk-sharing estimation equation, and is the same as a CCE structure with restrictions. In essence the  $\bar{C}_t$  and  $\bar{Y}_t$

are the common shocks which the risk-sharing literature would like to extract so as to be able to test the remaining idiosyncratic consumption and output correlation. That is, if perfect risk-sharing existed, there would be no remaining idiosyncratic consumption movement and the correlation between idiosyncratic consumption and output, as captured by  $\beta_u$ , would be zero.

To summarize, the risk-sharing literature applies a CCE structure with strong restrictions on the weighting matrix and on the CCE coefficients. Imposing these restrictions, if false, could lead to the risk-sharing application estimating parameters inconsistently when compared to a CCE estimation with no restriction.

We are able to test whether there is strong spatial dependence caused by CCE is present or even if the risk-sharing imposed CCE structure is correct, using the Pesaran (2015) Cross-section Dependence test (CD).<sup>19</sup> In its most basic interpretation the CD test tests the null hypothesis of weak (spatial) dependence versus the alternative that there is strong spatial dependence caused by common correlated effects (latent factors). More precisely, under the assumption that the cross-section and time dimension (N and T) increase to infinity at the same rate, the null hypothesis interpretation is that the most spatially correlated cross-section has no more than a certain degree of cross-sectional dependence; specifically, pair-wise cross-sectional correlations are less than  $\frac{1}{4}$ . However, it has been argued, amongst others by Pesaran, that this limit could be extended to  $\frac{1}{2}$  as the bias disappears with expanding sample at the rate of N.<sup>20</sup>

Table (3.4) below, shows the p-value for the CD test employed for three models: the first is a simple mean group estimation that does not correct for spatial common correlated effects (MG), the second is a standard risk-sharing estimation that implicitly corrects for restricted spatial common correlated effects (RS), and the last is a standard CCE estimation which does not impose a structure on the spatial CCE. The MG estimation is based on the Pesaran and Smith (1995) MG estimator and is given by the following Eq.:

$$\Delta C_{i,t} = \beta_i \Delta Y_{i,t} + \Delta \nu_{i,t} \quad (3.9)$$

The risk-sharing estimation with the restricted CCE in Table (3.4) is based on Eq.(3.11) in first difference. Finally, the unrestricted CCE estimation follows the Pesaran (2006) CCE estimation and is given by :

$$\Delta C_{i,t} = \beta_i \Delta Y_{i,t} + \gamma_i^c \Delta \bar{C}_t + \gamma_i^y \Delta \bar{Y}_t + \Delta \nu_{i,t} \quad (3.10)$$

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<sup>19</sup>De Hoyos and Sarafidis (2006) have a brief exposition of the CD test and related tests of cross-section effects.

<sup>20</sup>See for example Bailey et al. (2012) and Pesaran (2015), p. 1091, pp. 1195-1104.

with no restriction on  $\gamma_i^c$  and  $\gamma_i^y$  and with the weights being the average calculated relative GDP share of of the aggregate output over the entire period, i.e. time-invariant weights.

p-values	MG	RS	CCE
	2.776e-15	0	.96179298

Table 3.4: Pesaran (2015) CD test

In the case of the MG estimation in Table (3.4), the null hypothesis is rejected, suggesting that there is at least one cross-section pair with strong spatial correlation. This is not surprising if any risk-sharing takes place. However, in the case of the RS estimation the null is rejected too; this means the model is misspecified, and as a result does not filter out all common correlated effects. This appears to be confirmed when looking at the last estimation, the unrestricted CCE estimation, where the null of weak dependence is not rejected. Combining the CD test results for the ME, the RS and the CCE estimations, one interpretation is that risk-sharing does take place but it is not perfect risk-sharing, which the standard RS estimation corrects for. This could, for example, be that the risk-sharing taking place is not based on the optimal portfolio of state contingent assets for the sample, as specified by the risk-sharing literature, but based on some less than optimal make up of the portfolio. That is, the European countries might have stronger spatial correlations (strong risk-sharing) amongst themselves than with the US. However, given the data set used, the US state contingent asset would dominate the risk-sharing propagated weighted portfolio of state contingent assets and thus the US would dominate the risk-sharing propagated common shock for which it would corrects for. Finding that the risk-sharing literature's demeaned variables does not fully capture the CCE is in line with Fuleky et al. (2015a).<sup>21</sup>

The finding of common correlated effects which the traditional risk-sharing application of weighted demeaning might not capture appropriately makes it necessary to employ an estimation approach that is robust to heterogeneous slope parameters and common correlated effects, such as Pesaran et al. (1997, 1999)'s Pooled Mean Group estimator (PMG). The PMG's foundation is Eq.(3.2), and the PMG should therefore be robust to both heterogeneous slopes and spatial common correlated effects. Before proceeding with the estimation, Eq.(3.2) is commonly re-parameterized into an error correction model:

$$\Delta c_{i,t} = \lambda_i(c_{i,t-1} - \beta_u^{LR} y_{i,t}) + \beta_{u,i}^{SR} \Delta y_{i,t} + \nu_{i,t} \quad (3.11)$$

where  $\beta_u^{LR}$  and  $\beta_{u,i}^{SR}$  are the parameters of interest; the long-run and short-run un-

<sup>21</sup>The CD test as applied by Fuleky et al. (2015a) is based on Pesaran (2004) which had some short-comings and since has been replaced by Pesaran (2015), which is the CD statistic used here.

shared risk coefficient,  $\lambda_i$  is the speed of transition from a short- to a long-run risk-sharing relationship. If  $\lambda = 0$  then there is no long-run relationship between idiosyncratic consumption and output, and by extension no unshared risk i.e. perfect risk-sharing. In essence, the PMG combines the Classical short run and Level long run estimation principles. Estimates are obtained for each country and a mean taken to ascertain the average risk-sharing effect. Given that the mean effect is taken, which allows for country individual effects, the level estimate is more akin to the medium run risk-sharing.

To test whether risk-sharing expanded over time, similar to the Level estimation, Eq. (3.11) is enhanced with a interactive dummy term:

$$\Delta c_{i,t} = \lambda_{i,D}(c_{i,t-1} - \beta_{u,D1}^{LR} y_{i,t} - \beta_{u,D2}^{LR} D^* y_{i,t}) + \beta_{u,D1,i}^{SR} \Delta y_{i,t} + \beta_{u,D2,i}^{SR} D^* \Delta y_{i,t} + \nu_{i,t} \quad (3.12)$$

where  $D = 0$  prior to and including 1990 and 1 thereafter. To test the significance of an expansion in risk-sharing, we test the  $H_0 : \beta_{u,D2,i}^{SR} = 0$ , which if not rejected means that the parameter is equal to zero or rather that no change in risk-sharing occurred, versus  $H_A : \beta_{u,D2,i}^{SR} \neq 0$ , that a change occurred.

separate estimation of Eq. (3.11)			dummy estimation of Eq. (3.12)				
(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\beta_u^{SR}$	$\beta_u^{LR}$	$\lambda^{LR}$	$\beta_{u,D1}^{SR}$	$\beta_{u,D1}^{LR}$	$\beta_{u,D2}^{SR}$	$\beta_{u,D2}^{LR}$	$\lambda_D^{LR}$
SE()	SE()	SE()	SE()	SE()	SE()	SE()	SE()
95% CI	95% CI	95% CI	95% CI	95% CI	95% CI	95% CI	95% CI
1970 till 2007			1970 till 2007				
0.5264***	0.7900***	-0.1004***	0.4492***	0.8691***	-0.0392	0.1530***	-0.1712***
(.0504)	(.0157)	(.0177)	(.0487)	(.0232)	(.0615)	(.0383)	(.0210)
[0.428, 0.625]	[0.759, 0.821]	[-0.135, -0.066]	[0.354, 0.545]	[0.824, 0.915]	[-0.160, 0.081]	[0.078, 0.228]	[-0.212, -0.130]
1970 till 1990							
0.4236***	0.8510***	-0.2162***					
(.0556)	(.0156)	(.0389)					
[0.315, 0.533]	[0.820, 0.882]	[-0.292, -0.140]					
1991 till 2007							
0.3527***	1.0774***	-0.1857***					
(0.0599)	(0.0148)	(0.0440)					
[0.235, 0.470]	[1.048, 1.106]	[-0.272, -0.099]					

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors are shown in parentheses while 95% confidence intervals are in square brackets.

Table 3.5: PMG unshared risk estimates

Table (3.5) presents the unshared risk estimation results for the PMG estimation. Column (I) contains the short run parameter coefficients,  $\beta_u^{SR}$ , for the estimation of the unshared risk over the entire sample and the two separate sub-samples 1970-1990 and 1991-2007, column (II) contains the long run unshared risk estimates,  $\beta_u^{LR}$ , and column (III) contains the estimate of the speed of transition,  $\lambda^{LR}$ , from the short to the long run unshared risk level. Columns (IV)-(VIII) contain the short-run, long-run, and transition parameter estimates for the estimation on the entire

sample with an interactive dummy term, specifically the estimates of Eq. (3.12).

The PMG estimation finds short-run risk-sharing over the entire period to be 47% which is well above the Classical finding of 27% (FGLS) in Table (3.1). And although the PMG shows a expansion in risk-sharing from 58% in 1970-1990 to 65% in 1991-2007, one should be cautious of this finding since the the growth in risk-sharing was not found to be significant. The significance of the change in risk-sharing was tested, similar to the case of the Level estimation, by enhancing Eq. (3.11) with a interactive dummy term and running the estimation on the entire time period. The  $H_0 : \beta_{u,D2}^{SR} = 0$  using a two-sided t-test with 5% significance level could not be rejected, with a p-value of 0.913. Apart from  $\beta_{u,D2}^{SR}$ , however, all other estimates in Table (3.5) are found to be significantly different from zero and fairly precisely estimated with fairly narrow 95% confidence intervals and standard errors that are of similar magnitude to those found in the literature. While the PMG estimation found much higher short-run risk-sharing than the Classical method, in terms of long-run risk-sharing the PMG estimates are not only just at or above the medium-run Level results in Table(3.2), but also show falling risk-sharing from 15% over the period 1970-1990 to essentially zero or negative risk-sharing during 1991-2007. Although not impossible, this is highly improbable as it would mean that idiosyncratic consumption would overreact to idiosyncratic output shocks to the extent that it is counter cyclical. For example, as a country experiences a positive idiosyncratic output shock, idiosyncratic consumption would contract. Also, but of less interest, is that the conversion to a long-run relationship is faster for the period 1970-1990 than for 1991-2007. The finding that short-run risk-sharing is higher than long-run is line with Fuleky et al. (2015a).

A variety of factors could cause the difference in results between the PMG estimation and the Classical and Level estimations, but one possibility could be the method by which the estimators correct for the common correlated effects, with PMG imposing no structure while the Classical and Level estimations impose a structure across the common correlated effects.

### 3.5 Conclusion

The preceding chapter introduced the reader to the risk-sharing literature and the two dominant estimation approaches; the Classical and the Level approach. This chapter applied these two estimation approaches to a panel consisting of 24 OECD countries over the period 1970-2007. The Classical and Level approach as applied here find analogous results to the standard findings of the Classical and Level empirical literature. These estimations were undertaken as a stepping stone for the

fourth chapter where the same data will be used to show the impact of endogeneity bias on risk-sharing estimation. Thus it was necessary to show that similar results to those found in the literature can be obtained with the data, and therefore any difference in results in the following chapters are due to the employed estimation approaches and not driven by the data.

Moreover, this chapter supports Fuleky et al. (2015a) in connecting the risk-sharing literature and the common correlated effects literature. The importance of the common correlated effects literature for risk-sharing was reinforced by finding that spatial common correlated effects are present and the standard risk-sharing approaches does not fully capture the common correlated effects. Accordingly, the PMG estimator was applied, which combines the Classical and Level methodologies, and which should be robust in the presence of heterogeneous slopes and common correlated effects. The PMG estimation found two contradictions, firstly, PMG short run finding suggests higher short run risk-sharing than the Classical literature, and secondly the PMG medium run risk-sharing estimates find little to no risk-sharing which is in contradiction with the Level literature.

However, all the estimations and tests, including the CD test and the PMG estimation are invalid in the presence of output endogeneity, which is the focus of the subsequent chapters. To allow for a clear comparison with the risk-sharing literature, the subsequent chapters will follow the prevailing risk-sharing literature in assuming that there are no heterogeneous slopes and that the restricted CCE structure (as outlined above in section 3.4) is correct.

# Chapter 4

## Risk-sharing and exogeneity

### 4.1 Introduction

Chapter three applied the estimation framework used in the literature: the Classical framework and the Level framework. It followed the literature in the assumption that output is exogenous and provided risk-sharing estimates using a panel data set consisting of 24 OECD countries over the period of 1970-2007. The assumption in the literature that output is exogenous in a risk-sharing estimation framework is by no means a trivial one. That is, a shift in output can be caused by shifts in Aggregate Supply (AS) or Aggregate Demand (AD). This in turn would suggest that in an estimation with consumption as regressand, output can be driven by consumption factors, such as taste shocks, and therefore would cause a reciprocal effect in the estimation and an endogeneity issue would arise. This chapter will loosen the assumption that output is driven strictly by supply in a risk-sharing estimation.

Demand shocks can be risk-shared, but demand shocks cause output to be endogenous in a standard risk-sharing estimation, while supply shocks can be risk-shared and are exogenous in a risk-sharing estimation. Supply shock exogeneity is based on the assumption that the causality runs via a change in output to a change in consumption without a reciprocal effect from consumption on output. To determine the extent to which demand shocks can be risk-shared requires an approach to address the endogeneity problem, for instance an instrumental variables estimation with a valid instrument.

This chapter will present a number of alternative estimators to estimate robust risk-sharing parameters. One of these estimators is the Level approach, introduced in chapter two, as this approach should not be subject to endogeneity bias, under the condition of cointegration and associated superconsistency. Superconsistency

implies that a variable with a higher order of integration cannot be correlated with an error that has a lower order of integration. Three alternative estimators that are used in this chapter are based on Instrumental Variable estimation: Anderson and Hsiao (1981, 1982) first difference two stage least square estimator (FD2SLS), Holtz-Eakin et al. (1988) difference General Method of Moment (dGMM) and an IV estimation using instruments derived from a Bayoumi and Eichengreen (1993) style Structural Vector Autoregression (SVAR-IV). These alternative estimators are subsequently used to estimate risk-sharing parameters for the same data set used in chapter three and compared against the Classical results.

This chapter finds that the alternative estimation methods used in order to deal with endogeneity yield different risk-sharing point estimates to the Classical method: the estimated risk-sharing is strong and increasing over time. These alternative parameter estimates are line with the estimates of the Level approach in chapter three, and validate the hypothesis that conventional risk-sharing estimation is biased because it ignores the output endogeneity.

## 4.2 Endogeneity and feedback

In this chapter, we loosen the assumption of output being exogenously determined. First we discuss the impact on parameter estimates of a violation of the assumed exogeneity. For simplicity we will only present the risk-sharing model for the unshared output shocks. All variables are in logs. The estimation of unshared risk in the previous chapter rested on the following model:

$$c_{i,t} = \varpi + \beta y_{i,t} + \eta_t + \delta_i + v_{i,t} \quad (4.1)$$

where the  $c_{i,t}$  is log consumption of country  $i$  in period  $t$ ,  $y_{i,t}$  is log output,  $\varpi$  is a constant,  $\eta_t$  is a time fixed effect,  $\delta_i$  is a country fixed effect, and  $v_{i,t}$  is the idiosyncratic error term which is assumed not to be serially correlated. It was then transformed into the subsequent model Eq.(2.18) used for estimation

$$\Delta \tilde{c}_{i,t} = \beta \Delta \tilde{y}_{i,t} + \Delta \tilde{v}_{i,t} \quad (4.2)$$

Two transformations have been applied: i) first differencing, indicated by a  $\Delta$  sign, to remove the cross-section fixed effect and ii) cross-sectional demeaning, indicated by  $\tilde{x}_{i,t}$  such that  $\tilde{x}_{i,t} \equiv x_{i,t} - \bar{x}_t$  where  $\bar{x}_t = \frac{\sum_{i=1}^N x_{i,t}}{N}$ , to remove the time fixed effect.

For clarity of exposition, the demeaning notations, like the log notation, is dropped from this point onwards and all variables are both logged and cross-sectionally demeaned unless stated otherwise. Eq.(4.2) is the linear form of the model, while

(4.3) below is the matrix notation of model (4.2), (4.4) is the cross-section sub-matrix notation of (4.2), and (4.5) is the sub-matrix notation across time. These model notations will be used interchangeably. Matrices are denoted by bold letters, such that  $\mathbf{c}$  is a  $(NT \times 1)$  vector of which  $\mathbf{c}_i$  and  $\mathbf{c}_t$  are sub-matrices with  $(T \times 1)$  and  $(N \times 1)$  dimensions respectively.

$$\Delta \mathbf{c} = \Delta \mathbf{y} \beta + \Delta \mathbf{v} \quad (4.3)$$

$$\Delta \mathbf{c}_i = \Delta \mathbf{y}_i \beta + \Delta \mathbf{v}_i \quad (4.4)$$

$$\Delta \mathbf{c}_t = \Delta \mathbf{y}_t \beta + \Delta \mathbf{v}_t \quad (4.5)$$

The Classical risk-sharing literature imposes a key assumption on the model (4.2): output is assumed to be exogenous. More precisely, the assumption is that the output of a country is orthogonal to errors including those that originate from the country's consumption, such as demand shocks or taste shocks, as well as in relation to the errors of all other countries.

Given Eq.(4.2), this assumption can be stated as:

$$\mathbf{A1} \quad E(v_{i,t} y_{j,t}) = 0 \quad (i,j=1,\dots,N)$$

**A1** implies that the output of a country is not correlated with the contemporaneous errors of any country, including demand shocks. However, since the Classical approach applies first difference, assumption **A1** needs to be adjusted:

$$\mathbf{A2} \quad E(\Delta v_{i,t} \Delta y_{j,t}) = 0 \quad (i,j=1,\dots,N)$$

**A2** augments **A1** so that output is not only assumed not to be correlated with contemporaneous errors of any country in the present but also previous period. **A2** is sufficient in that the first difference and demeaning transforms the error term in Eq.(4.1) into  $\Delta \tilde{v}_{i,t} = v_{i,t} + \bar{v}_{i,t-1} - (v_{i,t-1} + \bar{v}_{i,t})$ . If **A2** holds, as assumed by the Classical risk-sharing literature, then the model in Eq. (4.2) can be consistently estimated using FGLS with an AR(1) error structure. The AR(1) error structure occurs due to taking first difference which imposes a known serially correlation structure on the errors. More precisely, assuming that  $v_{i,t}$  is not serial correlated and given that  $\Delta v_{i,t} = v_{i,t} - v_{i,t-1}$  then  $E(\Delta v_{i,t} \Delta v_{i,t-1}) = -1$ . In fact, as shown by Arellano (2010) pp.14-17, the first differenced GLS estimation is equivalent to a fixed effect estimation with time and cross-section fixed effects. So in terms of estimation, the risk-sharing coefficient is given by the following equation:

$$\hat{\beta} = \left( \frac{1}{NT} \mathbf{y}' \mathbf{Q} \mathbf{y} \right)^{-1} \frac{1}{NT} \mathbf{y}' \mathbf{Q} \mathbf{c} \quad (4.6)$$

where  $\mathbf{Q} = \mathbf{D}'(\mathbf{D}\mathbf{D}')^{-1}\mathbf{D}$  and  $\mathbf{D}$  is a  $((T - 1) \times T)$  first difference operator matrix. More precisely, as Arellano (2010) highlights on page 15, the  $\mathbf{Q}$  matrix is also known as the deviations-from-time-means or within-group operator as it is the standard symmetric and idempotent panel data transformation matrix that converts the  $(NT \times 1)$  consumption and output vectors into  $(NT \times 1)$  vectors of deviations from panel means. After substituting and taking probability limits Eq.(4.6) becomes

$$plim\hat{\beta} = \beta + plim\left(\frac{1}{NT}\mathbf{y}'\mathbf{Q}\mathbf{y}\right)^{-1} * plim\left(\frac{1}{NT}\mathbf{y}'\mathbf{Q}\mathbf{v}\right) \quad (4.7)$$

in which the second term on the right hand side would be equal to zero if output is exogenous. But, since we now no longer assume that output is exogenous, the estimate of the coefficient will be inconsistent to the extent of  $plim\hat{\beta} - \beta = Var(\Delta y_{i,t})^{-1}Cov(\Delta y_{i,t}, \Delta v_{i,t}) \neq 0$ .

To expand, interpret Eq.(4.3) as a consumption function with  $\Delta c_{i,t}$  being the change in consumption for country  $i$  at time  $t$  and  $\Delta y_{i,t}$  being the change in income such that  $\Delta y_{i,t}\beta$  is the income effect that drives consumption. Then  $\Delta v_{i,t}$  are all the factors outside of income that have an impact on consumption. For simplicity,  $\Delta v_{i,t}$  is split into two factors: demand shocks  $\Delta \epsilon_{i,t}^D$  and other shocks  $\Delta \epsilon_{i,t}^S$ . The other shocks,  $\epsilon_{i,t}^S$ , for simplicity are assumed to be orthogonal to output such that  $Cov(\Delta y_{i,t}, \Delta \epsilon_{i,t}^S) = 0$ . Demand shocks,  $\epsilon_{i,t}^D$ , includes changes in consumption behaviors such as choice between time spent accruing income versus leisure time, change in taste etc. The bias arises due to  $\epsilon_{i,t}^D$  also featuring as a driving factor in output. The consumption factors impacting output include such things as how much time is spent between working and consuming, or what is consumed, etc. The presence of  $\epsilon_{i,t}^D$  in output leads to simultaneity bias in Eq.(4.6). The unshared risk estimation Eq.(4.6) is biased to the extent of the covariance of output and demand shocks:

$$plim\hat{\beta} - \beta = Var(\Delta y_{i,t})^{-1}Cov(\Delta y_{i,t}, \Delta \epsilon_{i,t}^D) \quad (4.8)$$

where Eq.(4.8) is derived from (4.7) by expanding  $\mathbf{v}$  into  $\boldsymbol{\epsilon}^D + \boldsymbol{\epsilon}^S$ .

Assumption **A2** implies that all output shocks originate from supply (output) and not from demand (consumption), including demand shocks which have a delayed or cross-country impact on output. Those are strong assumptions, which can be brought into question simply by looking at a standard AS-AD framework where a change in output, measured by GDP, can be due to a shift in aggregate demand or aggregate supply. Consequently, if an output shift originates in a demand shock, reflecting movement such as a taste shock or a change in saving habits, then consumption drives output, causing output to be endogenous in the risk-sharing estimation.

Given that in Eq.(4.2) the variables were cross-sectionally demeaned and first differencing was applied, bias arising due to  $\Delta\epsilon^D$  encompasses bias arising in this and the previous period, as well as across countries in both periods. The larger is  $Cov(\Delta y_{i,t}, \Delta\epsilon_{i,t}^D)$ , the greater the bias. Assuming  $Cov(\Delta y_{i,t}, \Delta\epsilon_{i,t}^D) > 0$  then the unshared risk would be overstated in estimation by least squares, and consequently risk-sharing understated. An alternative estimator is required that is consistent in the presence of endogeneity.

## 4.3 Level

The preceding potential bias is inherent in the Classical approach. On the other hand, the Level estimation, which utilizes an I(1) assumption, and thus is potentially a cointegration estimation, benefits from superconsistency: an I(1) variable cannot be correlated with an I(0) error. However, for superconsistency to hold, the demeaned consumption and output series must be shown to be co-integrated. Since consumption and output are correlated it is sufficient to show that both consumption and output are integrated to the order of 1. And only if this is the case does the Level-approach benefit from superconsistency and thus leads to risk-sharing estimates that are consistent in the presence of output endogeneity. However, the Level approach and thus the results rely on asymptotics and given the short time series used, finite-sample bias could still be a concern.

### 4.3.1 Unit-Root Test

Following the influential paper by Nelson and Plosser (1982) and subsequent papers refining the findings, it has been widely accepted that GDP is characterized by a unit root process. But nonetheless it is necessary to show that this is the case here, especially since a unit-root process is not necessarily a given, since consumption and output are expressed on a per capita basis and as a ratio to the cross-sectional mean.<sup>1</sup>

But one should also be cautious when interpreting unit-root test results, as it is well documented in the literature that unit-root tests have low power, and that

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<sup>1</sup>For example, based on the two growth theories of unconditional and conditional growth convergence, relative output can be stationary for countries above or below the steady, equilibrium growth rate. A textbook discussion of the unconditional and conditional growth theories and their implications can be found in Romer (2006). See also, for example, Baumol (1986), DeLong (1988), Dowrick and Nguyen (1989), Barro and Sala-i-Martin (1991), Barro and Sala-i-Martin (1992), and Mankiw et al. (1992). However, in this chapter growth convergence is not investigated and is only mentioned as a cautionary example, to show that one should not assume that relative country output and consumption is a unit-root driven process.

various unit-root tests can sometimes have poor finite-sample performance. Several different unit-root tests have been applied below to avoid relying too strongly on the finite-sample performance of one test. The tests employed are: Levin et al. (2002) Levin-Lin-Chu unit-root test (LLC), Im et al. (2003) Im-Pesaran-Shin unit-root test (IPS), Maddala and Wu (1999) unit-root test (MW), Hadri (2000) Lagrange Multiplier unit-root test (HLM), and Pesaran (2007) cross-sectionally augmented Dickey Fuller unit root test (PCADF).

The LLC test null hypothesis is that all panels are  $I(1)$  with the unit root parameter being the same for all panels; if the null hypothesis is rejected, the test assumes that all panels are stationary. The test also assumes that the idiosyncratic errors  $\mathbf{v}$  are independently distributed across the cross-sections, for examples, that the idiosyncratic errors  $v_{i,t}$  and  $v_{j,t}$  are independent of each other. The test's properties are based on  $T$  going to infinity faster than  $N$  and is proposed for a sample of  $N$  10-250 and  $T$  25-250.<sup>2</sup> IPS tests heterogeneous panels, for the null hypothesis of all panels being  $I(1)$  against the alternative hypothesis of some being  $I(1)$ . That is, the IPS test allows for different  $AR(1)$  coefficients for each country. MW tests the null hypothesis of  $I(1)$  for all  $i$ , by testing individual countries. The test does not require a balanced panel, and the alternative hypothesis is that at least one country is  $I(1)$ . HLM tests the  $H_0 : \varphi_i = 0$  for all  $i = 1, 2, 3, \dots, N$  with the alternative hypothesis being that at least one panel contains a unit root. The HLM test allows for heterogeneous panels and country specific deterministic elements. Additionally, the HLM test can be performed for assumed homoskedastic, heteroskedastic, or serially dependent disturbances. However, it does not allow for cross-sectional correlated errors.<sup>3</sup> The HLM is based on asymptotics that  $T$  goes to infinity followed by  $N$  going to infinity, with Hadri (2000) recommending the test for panels consisting of large  $T$  and in comparison moderate sized  $N$ . Finally, PCADF tests for  $H_0 : \varphi_i = 1$  for all  $i = 1, 2, 3, \dots, N$ , while allowing for cross-sectional correlation for heterogeneous panels, with the alternative hypothesis being that some panels are stationary.

For clarity and cross-comparison, all unit-root tests results presented in Table (4.1) are p-values for a restricted uniform functional form: one lag and a deterministic trend.

When looking at Table (4.1), all tests, apart from the LLC test, conclude that relative output and consumption are unit-root processes when using the entire time set of 1970 to 2007.<sup>4</sup> The LLC test rejects the null hypothesis of unit root at the

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<sup>2</sup>The Taylor and Sarno (1998) test, being a comparable test to LLC, was not employed, as it requires the time dimension to be bigger than the cross-section, which is not necessarily the case when testing sub-periods.

<sup>3</sup>The HLM test was run allowing for serial correlated disturbances, but the results for different specifications are the same.

<sup>4</sup>It should be noted that the interpretation of the failures to reject of the null hypotheses is subject to the specification used. Therefore, given the specification used in Table (4.1), rejecting

	<b>c</b>	<b>y</b>
Test with $H_0$ : I(1)		
LLC	0.209	0.019
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i = \varphi_j$		
IPS	0.855	0.872
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
MW	0.846	0.929
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
PCADF	0.980	0.297
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
Test with $H_0$ : I(0)		
HLM	0.000	0.000
$H_0 : \varphi_i < 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		

Table 4.1: Unit-Root tests for OECD 1970 till 2007

5% significance level, but fails to reject the null hypothesis at 1%. The HLM test, unlike the other test, has a null hypothesis of no unit root which it rejects in favor for the alternative of that some panels are I(1).

In addition to their application to the entire time series, the unit root tests have been applied to two sub-samples following Perron (1989), who showed that unit root tests might not reject the I(1) hypothesis over the entire time series when a trend or level change occurs, as Artis and Hoffmann (2007a,b, 2008) (AH) stipulate is the case in the early 90's when a change in level occurred as a result of globalization. Table (4.2) presents the results for the various unit-root tests when applied to the sub-periods 1970-1990 and 1991-2007. In order to facilitate comparison across tests and tables, once again, as in Table (4.1), a uniform specification of one lag and a deterministic trend is applied for all the tests.

While the unit-root tests in Table (4.1), which apply to the entire time series, give the impression of a non-stationary process, the results in Table (4.2), which apply to the sub-periods 1970-1990 and 1991-2007, are less clear. In the case of the sub-period 1970-1990, all tests, except the LLC unit-root test, fail to reject the unit-root hypothesis. However, for the sample period 1991-2007, the unit root hypothesis is rejected except for PCADF (and IPS and MW in the case of output).<sup>5</sup> The rejection of the unit-root hypothesis for the period 1991-2007 suggests that the Level estimation of that sub-period does not have superconsistency and therefore suffers from endogeneity bias. Moreover, while consumption and output over the

<sup>5</sup>The null hypothesis implies that the variable is potentially trend stationary.

<sup>5</sup>The IPS does not reject the null hypothesis in the case of consumption in the sub-period 1991-2007 when looking at a 1% significance level.

	<b>c</b>	<b>y</b>
1970 till 1990		
LLC	0.013	0.004
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i = \varphi_j$		
IPS	0.804	0.443
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
MW	0.583	0.238
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
PCADF	0.147	0.871
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
HLM	0.000	0.000
$H_0 : \varphi_i < 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
1991 till 2007		
LLC	0.000	0.000
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i = \varphi_j$		
IPS	0.020	0.140
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
MW	0.000	0.069
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
PCDAF	0.843	0.956
$H_0 : \varphi_i = 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		
HLM	0.000	0.000
$H_0 : \varphi_i < 1 \forall i$ with $\varphi_i \neq \varphi_j$ possible		

Table 4.2: Unit-Root tests for OECD sub-periods

entire time period might appear to be non-stationary processes, and while over the sub-period they do not, due to a break in the time series as mentioned above, another reason could be that the sub-periods 1970-90 with 21 years and 1991-2007 with 17 years are too short for the unit-root tests. That is, these unit-root tests – as well as, by extension, superconsistency – rely on asymptotics for which the time series might be too short, bringing into question the Level estimation results.

Meanwhile, Group-mean Dynamic OLS (GDOLS), which was briefly presented in chapter three as part of the Level method, is also consistent as long as output and consumption are non-stationary processes. However, unlike Dynamic OLS (DOLS), one needs to test for country individual unit roots, as the method uses individual risk-sharing estimations for individual countries. The results of the country-specific unit-root tests can be found in the appendix (D.1) Tables (D.1) and (D.2). The results of the panel unit-root tests in Tables (4.1) and (4.2) are confirmed, in that not all countries display a unit root process in either the full or sub-periods. This is especially the case in the sub-period 1991-2007 where the most frequent failure of the unit-root hypothesis occurs.

Therefore, the difference found in chapter two and three between the Classical method and the Level method, in addition to AH's explanation, could be due to the level estimation not suffering endogeneity bias. But, the results for the sub-periods 1970-1990 and 1991-2007 need to be interpreted with caution. The unit-root tests do not clearly resolve the question of whether the sub-period 1991-2007 is an  $I(1)$  series or whether the time series are even long enough to justify the asymptotic results and therefore the Level method could also suffer from endogeneity bias.<sup>6</sup> As a result, in the sub-period 1991-2007 the risk-sharing parameter increases, which contradicts the Classical finding, and which could be driven by the point estimate becoming subject to endogeneity bias.<sup>7</sup> However, this would not explain the difference between the long-run and medium-run parameter estimate found in the 1st and 2nd column of Table (3.2) in chapter three, as both would be suffering from bias.

Even though the Level method provides potentially robust parameter estimates, as discussed in preceding chapter, there is a theoretical difference between the shocks being investigated through the Classical and the Level methods. This is especially important when we are interested in the monetary union aspect of risk-sharing of transitory shocks, with the Level method looking at permanent shocks. Therefore, regardless of the econometric validity of the Level method in the presence of endo-

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<sup>6</sup>In chapter five we undertake a Monte Carlo Simulation that looks at the impact of the endogeneity bias on point estimates in a Level estimation environment in the case of close to unit-root processes.

<sup>7</sup>The Level estimation presented in Table (3.2) chapter three estimated unshared risk at 0.8061 in 1970-1990 and 0.6304 for 1991-2007 which is equivalent to 19.39% risk-sharing in 1970-1990 and 36.96% in 1991-2007.

geneity, a different estimator is needed when investigating the extent of risk-sharing of transitory shocks.

## 4.4 FD2SLS and dGMM estimators

Two alternative estimators that could be used are the Anderson and Hsiao (1981, 1982) FD2SLS and the Holtz-Eakin et al. (1988) dGMM estimator. Both estimators are applications of the Instrumental Variable (IV) concept using transformed endogenous regressors as instruments. The dGMM is a GMM estimator whose asymptotics are based on fixed-T and large-N. The dGMM estimator utilizes lagged levels of the endogenous regressors as instruments for the differenced endogenous regressors, with the pool of instruments increasing as the number of time periods available increases. In comparison, the FD2SLS uses the second period lagged level or the second period lagged first differences of the endogenous regressors as instruments in a IV regression, making it less efficient than the dGMM which uses more moment conditions.

Assuming the instruments are valid, the key benefits of the FD2SLS and the dGMM estimators are that, on one hand, they are robust to the presence of endogeneity, and on the other hand, they provide a framework for an IV estimation with no need to obtain an instrument from outside the dataset that is already being used.

### 4.4.1 FD2SLS

To illustrate, the FD2LS runs the following risk sharing estimation:

$$\Delta \mathbf{c} = \Delta \mathbf{y} \beta + \Delta \boldsymbol{\nu} \quad (4.9)$$

which is identical to Eq.(4.3) except that  $\mathbf{y}$  is instrumented by  $\mathbf{Z}$ , a matrix of instruments. These instruments can be considered exogenous if they fulfill the following conditions:<sup>8</sup>

Cond.1  $E(\mathbf{Z}_{it} \Delta \nu_{i,t}) = 0$

Cond.2  $rank E(\mathbf{Z}_{it} \Delta \mathbf{y}_{i,t}) = K$

where the first condition is the standard weak exogeneity condition, i.e. that the instruments are unrelated with the error term, and the second condition is the stan-

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<sup>8</sup> $\mathbf{Z}$  is the matrix containing all instruments for all countries over the entire period.  $\mathbf{Z}_i$  is a subset matrix of  $\mathbf{Z}$  containing the instrument for country  $i$  over the entire period and  $\mathbf{Z}_{it}$  denotes the subset matrix that consists of the instruments for country  $i$  in period  $t$ .

standard full rank condition for identification, i.e. that output is sufficiently correlated with the instrument to be identified.<sup>9</sup> Subsequently, given these conditions, the FD2SLS defines  $\mathbf{Z}$  as a vector consisting of either  $\mathbf{y}_{t-2}$  or  $\Delta\mathbf{y}_{t-2}$ . Due to the structure of the instruments we lose two time dimensions per country on all variables when  $\mathbf{Z} = \mathbf{y}_{t-2}$  such that both  $\mathbf{c}$  and  $\mathbf{y}$  are both  $((T - 2)N \times 1)$  vectors. That is, the first instrument is available in 1972 and consists of the 1970 output. When the instrument is in first differences, we lose three time dimensions, with the vectors being of  $((T - 3)N \times 1)$  dimension. Thus  $\mathbf{Z}$  is the following  $((T - 2)N \times 1)$  or  $((T - 3)N \times 1)$  vector:

$$\mathbf{Z}_i^{level} = \mathbf{y}_{t-2} = \begin{pmatrix} y_{i,1972-2} \\ \vdots \\ y_{i,2007-2} \\ \vdots \\ y_{N,1972-2} \\ \vdots \\ y_{N,2007-2} \end{pmatrix} = \begin{pmatrix} y_{i,1970} \\ \vdots \\ y_{i,2005} \\ \vdots \\ y_{N,1970} \\ \vdots \\ y_{N,2005} \end{pmatrix} \quad (4.10)$$

or

$$\mathbf{Z}_i^{fd} = \Delta\mathbf{y}_{t-2} = \begin{pmatrix} \Delta y_{i,1973-2} \\ \vdots \\ \Delta y_{i,2007-2} \\ \vdots \\ \Delta y_{N,1972-2} \\ \vdots \\ \Delta y_{N,2007-2} \end{pmatrix} = \begin{pmatrix} \Delta y_{i,1971} \\ \vdots \\ \Delta y_{i,2005} \\ \vdots \\ \Delta y_{N,1971} \\ \vdots \\ \Delta y_{N,2005} \end{pmatrix} \quad (4.11)$$

The reason for going back two periods,  $t - 2$ , is to make sure that the instruments are pre-determined relative to the errors,  $\Delta\boldsymbol{\nu}_t = \boldsymbol{\nu}_t - \boldsymbol{\nu}_{t-1}$ , rendering  $\hat{\mathbf{y}}$  orthogonal to demand shock and thus exogenous in Eq. (4.9).

Table (4.3) presents the result for the FD2SLS estimation when using  $\mathbf{Z}^{fd}$ . The estimated unshared risk coefficients are greater than one, implying negative risk-sharing. This would mean that an output shock would lead to a stronger consumption shift. Although not unfeasible, it is unlikely to be the case given the results of the Level, Classical, and subsequent estimation. One possible explanation why the FD2SLS finds negative risk-sharing, while non-IV estimation do not, is that that instrumented output series covariance with consumption can be different to the non-instrumented output used in the Classical or Level approach. Thus the risk-sharing

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<sup>9</sup>Since all variables are demeaned the first condition also implies that  $E(\mathbf{Z}_{it}\Delta\nu_{j,t}) = 0$ . Also,  $K = 1$  as there is only one endogenous regressor and is independent of how many instruments are being used.

Period	1970-2007	1970-1990	1991-2007
$\beta_u$	1.0695***	1.1923***	1.0418***
SE()	(.1842)	(.4400)	(.1694)
95% CI	[0.708, 1.431]	[0.330, 2.055]	[0.710, 1.374]
U-ID KP LM $\chi^2$	10.678	2.741	9.105
U-ID KP p-value	0.0011	0.0978	0.0025
W-ID CD Wald F	25.468	4.535	32.788
W-ID KP Wald F	12.586	3.035	10.926

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors shown are arbitrary heteroskedasticity and autocorrelation-robust standard errors. The estimations were run using the Stata command `xtivreg2` by Schaffer (2010). The critical value for  $\chi^2_{0.01}$  with 1 degree of freedom is 6.635, for  $\chi^2_{0.05}$  is 3.841, and for  $\chi^2_{0.1}$  is 2.706.

Table 4.3: FD2SLS estimation using  $\mathbf{Z}^{fd}$

estimation using instrumented output might not be bound to 1, even though the theoretical risk sharing aspect based on the relations of idiosyncratic output and consumption is bound to 1. Moreover, the risk-sharing coefficient is not estimated very precisely: the 95% confidence interval (labeled as 95% CI in Table (4.3)) is wide and includes values below 1 which allows for the possibility that the true unshared risk is actually less than 1. Overall, it is not clear whether positive, negative, or no risk-sharing is occurring according the FD2SLS in Table (4.3). Regardless, the negative risk-sharing casts a shadow of doubt on the FD2SLS for risk-sharing estimation purposes.

In addition to the point estimates and confidence intervals of unshared risk, Table (4.3) presents a variety of tests that look at the correlation between the endogenous variable, output growth, and the instrument, two period lagged output growth. The correlation between endogenous variables and instruments is important for any IV-estimation. For one thing, if the correlation between the endogenous variable  $\Delta \mathbf{y}$  and the instrument is  $\mathbf{Z}$  is zero, the model would be underidentified and the IV would lead to inconsistent estimates. A zero correlation between  $\Delta \mathbf{y}$  and  $\mathbf{Z}$  would be a violation of the second condition, the rank condition, which explicitly formalizes that the correlation between  $\Delta \mathbf{y}$  and  $\mathbf{Z}$  needs to be non-zero for  $\mathbf{Z}$  to be a valid instrument. In addition to the rank condition, however, for IV to perform satisfactorily in finite samples, it is not enough that the correlation is nonzero; it needs to be "strong". This has been formalized by Bound et al. (1995) and Staiger and Stock (1997) who found that an IV estimation might still suffer from bias due to weak correlation between the endogenous variable and instruments, even when the correlation is found to be statistically significant at conventional significance levels.

The first test is an underidentification test that utilizes the Kleibergen and Paap

(2006) (U-ID KP LM  $\chi^2$ ) Lagrange Multiplier test. The test evaluates the rank condition of the  $E(\mathbf{Z}\Delta\mathbf{y})$  vector. With one endogenous variable and one excluded instrument, the test assesses the correlation between the instrument and the endogenous variables with the null hypothesis being that the two are not correlated versus the alternative that they are correlated. The failure to reject the null hypothesis would mean the IV estimation is inconsistent. The null hypothesis is rejected at a 99% confidence level in two instances; when estimating using the entire sample and when estimating using the sub-period 1991-2007. In the case of the estimation utilizing the sub-period 1970-1990, the null hypothesis can only be rejected at a 90% confidence level. The rejection of the null hypothesis at a lower confidence level is worrisome. In short, the underidentification test for the most part suggests the endogenous variable and instrument are correlated. However, this correlation between the two is surprising if output is actually a unit root process.

An issue with the FD2SLS employed instrument set arises due to the possibility that output is a unit-root process, as discussed in the preceding section.<sup>10</sup> This is a problem due to the functional form of the GDP process and the construction of instruments. For illustration, assume output is generated according to the following functional form:

$$y_{i,t} = y_{i,t-1} + \varepsilon_{i,t} \quad (4.12)$$

such that output is an AR(1) process, or MA( $\infty$ ) since the coefficient of  $y_{i,t-1}$  is 1, subject to shocks. When formulated in first difference it becomes

$$\Delta y_{i,t} = \varepsilon_{i,t} \quad (4.13)$$

Thus an estimation of  $\Delta y_{i,t}$  on  $\Delta y_{i,t-2}$  would yield an uncorrelated regression with a coefficient of zero. This implies that even though the instruments are exogenous, they are not correlated with the first differenced endogenous regressors and therefore the estimator is inconsistent because the rank condition is not satisfied.

In addition to underidentification test, Table (4.3) also presents the results for weak identification tests: the Cragg and Donald (1993) (W-ID CD) and Kleibergen and Paap (2006) (Weak ID KP ) Wald F test statistics.<sup>11</sup> The differences between the weak identification tests and underidentification tests are not in the test statistics used but the small sample correction, the null hypothesis and the critical values employed. The null hypothesis of a weak identification test is that the endogenous variables are weakly identified by the instrument versus the alternative hypothesis that the estimator is not suffering from weak identification bias. In our case of one

<sup>10</sup>This problem applies also to the dGMM approach presented in the next section.

<sup>11</sup>In the special case of exactly identification and a single instrument, the Kleibergen and Paap (2006) statistics and the Olea and Pflueger (2013) statistics are exactly the same as a standard robust first-stage F statistic.

endogenous variable and one instrument, Stock and Yogo (2005) suggest critical values for weak identification tests at 95% confidence level of 16.38 for a rejection rate of 10%, 8.96 for 15%, 6.66 for 20%, and 5.53 for a rejection rate of 25%. The Stock and Yogo (2005) critical values for the Cragg-Donald statistic assume independent and identically distributed (i.i.d.) errors. Alternatively, the Olea and Pflueger (2013) critical values for the Kleibergen and Paap (2006) Wald F test statistics allows for none-i.i.d. errors. Olea and Pflueger (2013) suggest at 95% confidence level the following critical values; 37.418 for a Nagar bias threshold,  $\tau$ , of 5%, 23.109 for  $\tau = 10\%$ , 15.062 for  $\tau = 20\%$ , and 12.039 for  $\tau = 30\%$ .<sup>12</sup>

Looking at Table (4.3), the test statistics of Cragg and Donald (1993) and Kleibergen and Paap (2006) differ widely. When using the Stock and Yogo (2005) suggested critical values with the Cragg and Donald (1993) test statistic, all estimates, apart from the sub-period 1970-1990, in Table (4.3) reject the null hypothesis. This would suggest that only the sub-period 1970-1990 suffers from weak instruments. However, when looking at Olea and Pflueger (2013) critical values together with the Kleibergen and Paap (2006) Wald F test statistics, the estimate fail to reject the null hypothesis at a Nagar bias threshold of 5%, 10%, or 20% suggesting that all three estimations suffer from weak identification bias. Finding weak instrument bias is consistent with output being near I(1).

That is, while Eq. (4.12) and (4.13) highlighted the consequence when output is a unit-root process, i.e. uncorrelated instruments, a potential problem also exists if output is close to non-stationary. If we assume output is generated according to the following functional form:

$$y_{i,t} = \varkappa y_{i,t-1} + \varepsilon_{i,t} \quad (4.14)$$

which when formulated in first difference becomes

$$\Delta y_{i,t} = (\varkappa - 1)y_{i,t-1} + \varepsilon_{i,t} \quad (4.15)$$

and if we than substitute in for  $y_{i,t-1}$  we get

$$\Delta y_{i,t} = (\varkappa - 1)\varkappa y_{i,t-2} + \varepsilon_{i,t} + \varepsilon_{i,t-1} \quad (4.16)$$

If  $\varkappa$  is for example 0.99 then the entire term  $(\varkappa - 1)\varkappa$ , which is equivalent to the covariance between  $\Delta y_{i,t}$  and  $y_{i,t-2}$ , is just  $-0.0099$ . That is, the FD2SLS instruments become increasingly weakly correlated with the endogenous variable as GDP approaches unit-root process.<sup>13</sup> As such, given the finding of unit root (or

<sup>12</sup>For another application of these weak instrument critical values and test statistics please see, for example, Kovandzic et al. (2015).

<sup>13</sup>Again, this is also a problem that dGMM faces in the next section.

close to unit-root) in the sample period 1970-2007 and 1970-1990, the instrument will be insignificantly correlated with the endogenous variable. But, for the period 1991-2007, for which unit-root was not found, the instruments will be significant but potentially weakly correlated with the endogenous variables. However, the reader should keep in mind that although most of the applied unit-root tests indicated a unit root process for consumption and production, some tests did not come to the same conclusion giving grounds for the possibility that neither consumption nor production are I(1). Therefore, the FD2SLS method is presented on the basis that GDP might not be a I(1) but close to a unit-root process, and might serve more as a general method to avoid endogeneity bias in estimates in cases when output is not exactly an I(1), in which case the Level estimation would be suffering from inconsistency.

Period	1970-2007	1970-1990	1991-2007
95% Conf. Inter.	[0.770, 1.719]	[0.269, ...]	[0.753, 1.679]

The Anderson and Rubin (1949) confidence intervals were constructed using the Stata command weakiv by Finlay et al. (2013). A ‘...’ means that the limit, be it upper or lower, was not found to be between -2 and 2.

Table 4.4: Anderson and Rubin (1949) 95% confidence interval for FD2SLS estimation using  $\mathbf{Z}^{fd}$

Given the findings that the estimates in Table (4.3) might suffer from weak identification bias, Tables (4.4) presents the Anderson and Rubin (1949) 95% confidence interval (AR W-ID robust CI) associated with the FD2SLS using  $\mathbf{Z}^{fd}$ . In essence the Anderson and Rubin (1949) statistic does not require the rank condition for the Anderson and Rubin (1949) confidence interval to be valid. In addition, the Anderson and Rubin (1949) statistic can be made to be robust in the presence of heteroskedasticity and autocorrelation.<sup>14</sup> Thus, the Anderson and Rubin (1949) 95% confidence interval provides a range in which the true coefficients could lie, with the range being robust in the presence of weak identification. It is quite clear from Tables (4.4) that all three Anderson and Rubin (1949) confidence intervals are wide, and in the case of the estimation utilizing the sub-period 1970-1990, the upper bound is not found to be below 2. The wide confidence interval makes it virtually impossible to reach firm conclusions about the extent of risk-sharing and whether it has increased.

Table (4.5) presents the FD2SLS results using  $\mathbf{Z}^{level}$ . Unlike the results in Table (4.3), the estimated coefficients in Table (4.5) show a decline in risk-sharing from 25% between 1970-1990 to around 9% risk-sharing between 1991-2007. However, the

<sup>14</sup>For papers that have further evaluated the Anderson and Rubin (1949) statistic please see for example Zivot et al. (1998), Stock and Wright (2000), Dufour and Jasiac (2001), Kleibergen (2002), Moreira (2003), or Dufour and Taamouti (2005) to mention but a few. For a more detailed discussion and survey of weak instrument tests including Anderson and Rubin (1949) please see for example Stock et al. 2002, Andrews and Stock (2005), and Chernozhukov and Hansen (2005).

	1970-2007	1970-1990	1991-2007
$\beta_u$	0.8059	0.7520	0.9124
SE()	(.1466)	(.1839)	(.2227)
95% CI	[0.519, 1.093]	[0.392, 1.113]	[0.476, 1.349]
U-ID KP LM $\chi^2$	9.812	5.555	5.012
U-ID KP LM p-value	0.0017	0.0184	0.0252
Weak ID CD Wald F	28.944	18.206	10.493
Weak ID KP Wald F	11.839	7.333	5.012

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors shown are arbitrary heteroskedasticity and autocorrelated robust standard errors. The estimations were run using the Stata command `ivreg2` by Baum et al. (2010). The critical value for  $\chi^2_{0.01}$  with 1 degree of freedom is 6.635, for  $\chi^2_{0.05}$  3.841, and for  $\chi^2_{0.1}$  2.706.

Table 4.5: FD2SLS estimation using  $\mathbf{Z}^{level}$

confidence interval for each estimate is wide, making it hard to conclude whether risk-sharing declined. In addition, the underidentification test fails to reject the null hypothesis at a 99% confidence level for the both sub-period estimations. Also, looking at Kleibergen and Paap (2006) test statistics for weak identification, the null hypothesis is not rejected given the Olea and Pflueger (2013) critical values for a 30% Nagar bias threshold. The failures to reject the various null hypothesis together with the decline in risk-sharing relative to other findings suggests that the results of the FD2SLS when using the  $\mathbf{Z}^{level}$  as instrument provide inconsistent estimates of unshared risk.

Period	1970-2007	1970-1990	1991-2007
95% Conf. Inter.	[0.463, 1.183]	[0.206, ...]	[-0.131, 1.679]

The Anderson and Rubin (1949) confidence intervals were constructed using the Stata command `weakiv` by Finlay et al. (2013). A ‘...’ means that the limit, be it upper or lower, was not found to be between -2 and 2.

Table 4.6: Anderson and Rubin (1949) 95% confidence interval for FD2SLS estimation using  $\mathbf{Z}^{level}$

For completeness Tables (4.6) presents the Anderson and Rubin (1949) 95% confidence interval (AR W-ID robust CI) associated with the FD2SLS using  $\mathbf{Z}^{level}$ . Much like in the case of Tables (4.4), the confidence intervals in Tables (4.6) are wide and include values above one. In addition, this time, in the case of the sub-period 1991-2007, the confidence interval includes values below 0. Again the sub-period 1970-1990 upper bound is not found to be below 2. Thus, it is again virtually impossible to reach firm conclusions about the extent of risk-sharing and whether it has increased.

Overall, the unshared risk parameter estimates for both the FD2SLS using  $\mathbf{Z}^{fd}$  or

$\mathbf{Z}^{level}$  are dubious and probably suffer from underidentification or weak identification.

#### 4.4.2 dGMM

The dGMM as applied in this chapter follows a standard GMM estimation given by

$$\hat{\beta} = \underset{\hat{\beta}}{\operatorname{argmin}} J(\hat{\beta}) = NT * \bar{g}(\hat{\beta})' \mathbf{W} \bar{g}(\hat{\beta}) \quad (4.17)$$

where  $\bar{g}(\hat{\beta})$  is defined as

$$\bar{g}(\hat{\beta}) = \frac{1}{NT} \mathbf{Z}' (\Delta \mathbf{c} - \Delta \mathbf{y} \hat{\beta}) \quad (4.18)$$

which yields the GMM estimate

$$\hat{\beta} = \left( \frac{1}{NT} \Delta \mathbf{y}' \mathbf{Z} \mathbf{W} \mathbf{Z}' \Delta \mathbf{y} \right)^{-1} \frac{1}{NT} \Delta \mathbf{y}' \mathbf{Z} \mathbf{W} \mathbf{Z}' \Delta \mathbf{c} \quad (4.19)$$

The GMM estimate collapses to the standard IV estimation as laid out in Eq. (4.9) when the model is exactly identified, as the  $\mathbf{W}$  matrix would collapse to an identity matrix. However, in the case when the model is over identified, as is the case with the dGMM,  $\mathbf{W} \neq \mathbf{I}$ , and the GMM estimation of Eq.(4.19) provides a consistent estimate of  $\hat{\beta}$  for any symmetric positive-definite weighting matrix  $\mathbf{W}$ . To obtain an efficient GMM estimator, the residual vector  $\Delta \hat{\mathbf{v}}$  from the estimation of Eq.(4.19) is used to construct the following matrix <sup>15</sup>

$$\hat{\mathbf{S}} = \mathbf{Z}' \Delta \hat{\mathbf{v}} \Delta \hat{\mathbf{v}}' \mathbf{Z} \quad (4.20)$$

with  $\hat{\mathbf{S}}^{-1}$  replacing  $\mathbf{W}$  in an efficient second step GMM estimation:

$$\hat{\beta} = \left( \frac{1}{NT} \Delta \mathbf{y}' \mathbf{Z} \hat{\mathbf{S}}^{-1} \mathbf{Z}' \Delta \mathbf{y} \right)^{-1} \frac{1}{NT} \Delta \mathbf{y}' \mathbf{Z} \hat{\mathbf{S}}^{-1} \mathbf{Z}' \Delta \mathbf{c} \quad (4.21)$$

The dGMM proposes a set of instruments which consist of the lagged levels of the endogenous variable, starting with the second lag and going as far back as possible. This means that the  $\mathbf{Z}_i$  matrix is:

$$\mathbf{Z}_i = \begin{pmatrix} y_{i,0} & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & y_{i,0} & y_{i,1} & & 0 & & 0 \\ \vdots & & & \ddots & & & \vdots \\ 0 & 0 & 0 & \cdots & y_{i,0} & \cdots & y_{i,T-2} \end{pmatrix} \quad (4.22)$$

Consequently, the set of instruments,  $\mathbf{Z}_i$ , consists of any periods prior to and in-

<sup>15</sup>For a more detailed discussion please see Baum et al. (2007)

cluding  $t - 2$ ;  $y_{i,t-2}, y_{i,t-3}, \dots, y_{i,0}$ . Of course, as the number of instruments increases as time expands one could introduce a finite sample bias. Specifically, finite-sample biases could arise due to two factors: firstly due to the IV estimator asymptotic property derived finite sample performance leading to rising finite sample bias as the pool of instruments increases with time to a relative large size compared to the cross-section, and secondly due to the fact that as the lag goes back further, the lagged instrument becomes progressively more weakly correlated with the endogenous variable.

In short, to mitigate the risk of finite sample bias, the instrument set for the dGMM is restricted to  $t - 2$ , which gives us one instrument for each time period or a total of 36 instruments out of 665 possible instruments put forward by the dGMM framework. Hence the  $\mathbf{Z}$  matrix in Eq.(4.17) is a  $((T - 2)N \times 36)$  instrument matrix consisting of two period lagged levels of output. We have 36 instruments as no instrument is available in 1970 or 1971; the first time period with one instrument available is 1972, where the instrumental variable is  $y_{i,1970}$ , and thus we get 36 time periods from 1972 up to and including 2007, where we have the two period lagged output. The dGMM estimation is done using a two-step IV-GMM estimation, which is consistent and efficient in the presence of heteroskedasticity and serial correlation. Furthermore, a finite-sample correction for the two-step covariance error matrix is also applied, as proposed by Windmeijer (2005).

Overall, the risk-sharing estimate results in Table (4.7) are similar to the finding of the Level estimation, with an increase in the dGMM estimates from 24% in 1970-1990 to 43% risk-sharing in 1991-2007. However, caution should be taken when interpreting this increase in risk-sharing as the increase was found to be insignificant.<sup>16</sup> The similarity between the Level and dGMM estimations stems from the use of levels as instruments (and with cross-section fixed effects being specifically modeled). As such, the extent and rise in risk-sharing contradicts the finding of the Classical method, which shows no increase and different point estimates. This lack of increase and the difference of more than 10% in point estimates could amongst other things be due to the Classical estimation set out in the third chapter suffering from bias caused by the violation of output exogeneity. The small difference of about 6% between the Level and dGMM estimation could be due to the presence of a unit-root and the validity of the instruments.

Additionally, the serial correlation test, proposed by Arellano and Bond (1991)

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<sup>16</sup>Similar to the previous chapter, whether the extent of risk-sharing changed was tested by running the estimation on the entire sample with an interactive dummy term where the dummy is 0 prior to and including 1990 and 1 thereafter. The results of this dummy estimation are in the last column of Table (4.7). The test applies to the interactive dummy term's coefficient  $\beta_{u,D2}$  and tests  $H_0 : \beta_{u,D2} = 0$  using a two-sided t-test with 5% significance level. If we fail to reject  $H_0$  it indicates that risk-sharing did not change. But if we reject  $H_0$  and  $\beta_{u,D2} < 0$  then risk-sharing did expand. We fail to reject the null hypothesis with the p-value being 0.291.

	1970-2007	1970-1990	1991-2007	Dummy:1970-2007
$\beta_u$	0.7253***	0.7642***	0.5719***	
$\beta_u$ SE()	(0.1396)	(0.2001)	(0.0986)	
$\beta_u$ 95% CI	[0.452, 0.999]	[0.372, 1.156]	[0.379, 0.765]	
$\beta_{u,D1}$				0.6298
$\beta_{u,D1}$ SE()				(0.0884)
$\beta_{u,D1}$ 95% CI				[0.456, 0.803]
$\beta_{u,D2}$				-0.0198
$\beta_{u,D2}$ SE()				(0.0218)
$\beta_{u,D2}$ 95% CI				[-0.063, 0.023]
N-dimension	24	24	24	24
T-dimension	37	20	17	37
IV-Count	36	19	17	36
AB-AR(1) p-value	0.000	0.018	0.000	0.000
AB-AR(2) p-value	0.795	0.514	0.943	0.884
Hansen p-value	0.945	0.547	0.207	0.924
Sargan p-value	0.000	0.000	0.000	0.00
U-ID KP LM $\chi^2$		22.21	21.35	
U-ID KP LM p-value		0.2738	0.2112	
CLR Weak ID robust CI	[..., ...]	[..., ...]	[..., ...]	

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors shown are arbitrary heteroskedasticity and autocorrelated robust standard errors. The dGMMs and the Moreira (2003) CLR confidence intervals were constructed using the Stata commands `xtabond2` and `weakiv` by Roodman (2006) and Finlay et al. (2013). A ‘...’ means that the limit, be it upper or lower, was not found to be between -2 and 2. Empty cell means the row is not applicable for the respective column.

Table 4.7: dGMM with instrument pool restricted to two period lagged output

–shown in Table (4.7) as AB-AR– shows, as expected, evidence of first-order but not second-order serial correlation. Finding an AR(1) is expected because the first differenced residuals of period  $t$  are correlated with  $t - 1$  by  $-1$ . Consequently, as there is no second-order serial correlation, it can be concluded that our instruments of  $t - 2$  are pre-determined relative to the error term. If there had been serial correlation of a format of an MA(1) process, the IV set would need to start at  $t - 3$ . Or if instead of an MA(1) process it was an AR(1) process in the error, the possible IV would become subject to the autoregressive coefficient, and to how long it takes for the process to approach zero. However, the test is constructed under the assumption of no contemporaneous error correlation, which is not guaranteed to be the case, nor is the assumption necessarily violated in the case of output endogeneity.<sup>17</sup>

Furthermore, the Kleibergen and Paap (2006) underidentification test (U-ID KP rk LM) fails to reject the null hypothesis of  $E(\Delta y_{i,t} Z_{i,t})$  not being full column rank indicating that the dGMM estimations in Table (4.7) might suffer from underidentification and thus be inconsistent. Also, Table (4.7) presents the confidence interval derived using the Moreira (2003) conditional likelihood ratio statistic (CLR).<sup>18</sup> Like the Anderson and Rubin (1949) statistic, the Moreira (2003) conditional likelihood ratio statistic is robust in presence of weak instruments but more powerful when the model is as much overidentified as is the case here. However, the confidence intervals are so wide that the bounds are not found within  $-2$  and  $2$ , making it impossible to reach a conclusion about the extent of risk-sharing and whether it has increased, further casting doubt on the estimates.

Also, the bias that arises from applying too many instruments to the model needs to be considered given that the dGMM’s instrument set expands with time. There are three biases resulting from using too many instruments. Firstly, the number of instruments can impact on the finite sample performance of the asymptotic dGMM estimator. Secondly, using too many instruments can lead to a failure to properly identify the exogenous versus endogenous elements of the endogenous variables, which would lead to inconsistent parameter estimates. In the extreme case this would provide estimates that are as biased as the estimates of a naive OLS regression. And thirdly, using too many instruments impacts the Hansen test, leading it to falsely fail to reject the null hypothesis of joint instruments validity. The general tell-tale signs of using too many instruments, as argued by Roodman (2006) and Windmeijer (2005), are a Hansen p-value very close to 1 and the instrument count

<sup>17</sup>For an explanation and derivation of dGMM and the AB-AR() test, see Roodman (2006). Furthermore, the reader should be aware that the test is designed for large  $N$ , and "large has no precise definition, but applying it to panels with  $N = 20$ , for instance, seems worrisome." (Roodman (2006) p.36)

<sup>18</sup>In fact, the Table (4.7) presents the Kleibergen (2002, 2005) extension of the Moreira (2003) CLR statistic to the non-i.i.d. case.

being larger than the cross-section available.<sup>19</sup> In the case of the estimation utilizing the entire time period (1970-2007), the Hansen p-value is close to one and the instrument count of 36 is larger than the cross-section of 24, suggesting that too many instruments are used. Meanwhile, the value of the Hansen p-value for the sub-period is considerably lower than one and the instrument set is smaller than cross-section, giving some limited confidence that the instruments are valid and that not too many instruments are being used in the sub-period. Since the same IV set is used for the estimation with the entire time-sample, as well as for the sub-samples, it to some extent indicates that the IV set might also be appropriate for the entire time period.

Going beyond the Hansen test's signal that too many instruments are used, both the Hansen and Sargan methods test the joint null hypothesis that the instruments are valid, in other words that the instruments are exogenous to the error term. The Hansen and Sargan test come to opposite conclusions; the Hansen test fails to reject that the instruments are valid, while the Sargan test rejects the null hypothesis. Although the Sargan test has better finite sample performance than the Hansen test, the Hansen test is robust and consistent in cases of heteroskedasticity and serially correlated disturbances while the Sargan test is not. Together, the Hansen signal that too many instruments are being used and the Sargan test's rejection of the instruments' validity raise doubts about the validity of the dGMM estimation results, which is not surprising given that the dGMM method is designed for panel samples consisting of large N and small T. As such, the estimator lends itself to being applied to smaller but more numerous sub-sample period estimations.<sup>20</sup>

Alternatively, to avoid instrument proliferation and potentially using too many instruments, the dGMM instrument set can be collapsed such that each lag used is collapsed into a single instrument, i.e. all instruments that are at the second lag level of the endogenous variable are collapsed into one instrument of  $\mathbf{y}_{t-2}$ .<sup>21</sup> Collapsing the dGMM instrument when only using t-2 would make the dGMM equivalent to the FD2SLS with  $\mathbf{Z}^{level} = \mathbf{y}_{t-2}$  in Table (4.5). Accordingly, to gain efficiency, Table (4.8) shows the estimation results when the collapsed instrument pool is limited to the two and three period lagged level of output.<sup>22</sup>

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<sup>19</sup>For completeness, the estimation was also done with up to  $t - 3$  instruments, and the result remained largely the same, except for the standard error being lower. The difference in the standard error is due to the gains in efficiency through having more instruments. Meanwhile, given the tell-tale signs of using too many instruments, they imply with Hansen p-value close to one that the IV set utilizing up to  $t - 3$  lags, rather than just  $t - 2$ , is an unwise choice.

<sup>20</sup>However, such sub-sample estimations are not of direct interest, as they are not commonly done in the risk-sharing literature and thus they are not shown here.

<sup>21</sup>See Roodman (2009) for a more in depth discussion of the proliferation of instruments and the appropriate use and implementation of collapsed instruments and limited lag length.

<sup>22</sup>For completeness, appendix (D.2) shows the result of dGMM using only collapsed two period lagged output as instrument.

	1970-2007	1970-1990	1991-2007	Dummy:1990-2007
$\beta_u$	0.7249***	0.7951***	0.7815***	
$\beta_u$ SE()	(.0979)	(.2107)	(.0447)	
$\beta_u$ 95% CI	[0.533, 0.917]	[0.382, 1.208]	[0.694, 0.869]	
$\beta_{u,D1}$				0.6794***
$\beta_{u,D1}$ SE()				(.0606)
$\beta_{u,D1}$ 95% CI				[0.561, 0.798]
$\beta_{u,D2}$				-0.0393
$\beta_{u,D2}$ SE()				(.0321)
$\beta_{u,D2}$ 95% CI				[-0.102, 0.024]
IV-Count	2	2	2	2
AB-AR(1) p-value	0.000	0.030	0.000	0.001
AB-AR(2) p-value	0.796	0.431	0.822	0.554
Hansen p-value	0.421	0.633	0.052	0.078
Sargan p-value	0.493	0.650	0.000	0.402
U-ID KP LM $\chi^2$	2.24	1.67	3.85	7.72
U-ID KP LM p-value	0.3270	0.4337	0.1460	0.0522
AR Weak ID robust CI	[..., ...]	[..., ...]	[0.693, 0.915]	

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors shown are arbitrary heteroskedasticity and autocorrelated robust standard errors. The critical value for  $\chi^2_{0.01}$  with 2 degree of freedom is 9.210, for  $\chi^2_{0.05}$  5.991, and for  $\chi^2_{0.1}$  4.605. The dGMMs and the Anderson and Rubin (1949) confidence intervals were constructed using the Stata commands `xtabond2` and `weakiv` by Roodman (2006) and Finlay et al. (2013). A ‘...’ means that the limit, be it upper or lower, was not found to be between -2 and 2. Empty cell means the row is not applicable for the respective column.

Table 4.8: dGMM estimation with collapsed instrument set limited to two and three period lagged output

Contrary to Table (4.7), Table (4.8) appears to suggest that risk-sharing stayed essentially flat. However, the 95% confidence interval for the unshared risk estimate using the sub-period 1970-1990 ranges from 0.3820 to 1.2083, which is much wider than the confidence interval for the estimates using the sub-period 1991-2007, which ranges from 0.694 to 0.869.<sup>23</sup> Thus there is a possibility that the actual risk-sharing could also have expanded between the two sub-periods in the case of the dGMM using a collapsed instrument set of t-2 and t-3. The estimations in Table (4.8) also differ from the dGMM estimations in Table (4.7), in that the Hansen and Sargan tests both fail to reject the null hypothesis of valid instruments, except for the estimation on sub-period 1991-2007 where only the Hansen test fails to reject null hypothesis. Adding further doubt, the Kleibergen and Paap (2006) underidentification test fails to reject the null hypothesis of  $E(\Delta y_{i,t} Z_{i,t})$  not being full column rank, where  $\mathbf{Z} = [y_{i,t-2} \ y_{i,t-3}]$ , bringing into question the estimates as they appear to suffer from underidentification and consequently are potentially inconsistent.

As discussed in the case of FD2SLS, the dGMM estimator face an issue if output is a unit-root process. That is, if output is a unit root process, the endogenous variable and the instrument set would be uncorrelated. This implies that even though the instruments are exogenous, they are not correlated with the endogenous regressors and therefore the estimator is inconsistent because the rank condition is not satisfied.<sup>24</sup> Also, like in the case of the FD2SLS, the instruments become weaker as output approaches a unit-root process. Thus again, as in the case of the FD2SLS, the dGMM method is presented on the basis that GDP might not be a I(1) but close to a unit-root process, and might serve more as a general method to avoid endogeneity bias in estimates in cases when output is not exactly an I(1), in which case the Level estimation would be suffering from inconsistency. Along this line of thought, an interesting observation, given the finding of 1991-2007 not being I(1) while 1970-1990 being I(1), is that the results of dGMM and Level are similar, implying that to some extent the point estimates are valid, as at least one of the estimators should be valid in each sub-period.

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<sup>23</sup>Also, using the same approach as before for testing a change in risk-sharing between 1970-1990 and 1991-2007, we fail to reject the  $H_0 : \beta_{u,D2} = 0$  using a two-sided t-test with 5% significance level, with the p-value being 0.221. This means risk-sharing did not increase nor decrease between the two sub-period. The dGMM results for the interactive dummy estimation using collapsed instruments set consisting out of two and three period lagged output are shown in the last column of Table (4.8).

<sup>24</sup>Alternative estimators which could be used and which are similar to the dGMM estimator include the estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998), referred to as system GMM. However, the system GMM, similar to dGMM, would also suffer under the unit-root and it is more like to suffer under instrument proliferation and potential weak identification than dGMM. Also, the system GMM employs a different methodology by instrumenting a level estimation with first difference, bringing the system GMM closer to a Level risk-sharing estimation. For a detailed discussion of the system GMM and its assumptions please see Roodman (2006). Given these conditions, the system GMM will not be further discussed. Nonetheless, for completeness the preliminary results of the system GMM estimator can be found in the appendix.

## 4.5 SVAR-IV approach

While not requiring the researcher to provide instruments beyond lags of the regressor, the FD2SLS and the dGMM require the series to be stationary, which is not necessarily the case as discussed above. In this case, while following the concept of instrumenting endogenous output, one could construct an instrument on the basis of identifying aggregate demand and aggregate supply shocks. Bayoumi and Eichengreen (1993) proposed an identification process, based on Blanchard and Quah (1989) and Bayoumi (1992), for the separation of output's aggregate supply from aggregate demand shocks. This process is based on theoretical assumptions derived from an AS-AD framework to separate output's supply from demand shocks using the information contained in prices and output. Whereas aggregate demand shocks are driven by consumption shocks, and thus render an output series endogenous in the regression of consumption on output, aggregate supply shock drive output exogenously.

Although demand shocks can be risk-shared, they are driven by consumption and thus render output series endogenous in a standard risk-sharing estimation of consumption on output. On the other hand, aggregate supply shock drive output exogenously and can be risk-shared in a similar way to demand shocks. This means the identification of supply shocks will provide an exogenous instrument to estimate consistently the overall risk-sharing of output shocks, especially when output is mainly composed of supply shocks. The novelty of the approach used here is not with the identification of the supply shock, which is wholly based on Bayoumi and Eichengreen (1993), but in using the derived supply shock as an exogenous instrument in an IV estimation and in this particular context in estimating risk-sharing.

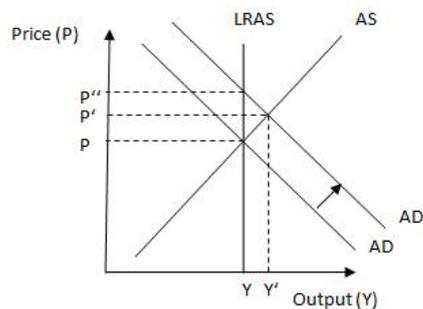


Figure 4.1: Aggregate Demand shift

The identification of aggregate demand shocks is derived from the effects on price and output associated with a demand shock. These effects can be seen in Fig.(4.1), where a positive demand shock, shifting aggregate demand from  $AD$  to  $AD'$ , causes prices to rise to  $P'$  and output to  $Y'$  in the short run equilibrium in which  $AS$  equals  $AD'$ . However, this shift reflects the short run and as the time span moves to the

long run and the aggregate supply shifts to its long run vertical LRAS position, as determined by the production possibility frontier, the price further rises to  $P''$  while output shifts back to  $Y$ . This shows that a positive aggregate demand shock when causing a positive price rise, also causes a temporary increase in output but not a permanent rise in output. Of course, this impact separation assumes that shocks that shift the  $AD$  curve to  $AD'$  curve are permanent, an assumption that is also held in the case of supply shocks shifting the  $AS$  curve below.

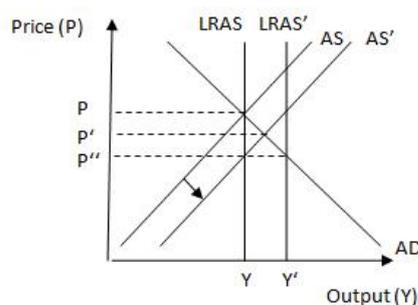


Figure 4.2: Aggregate Supply shift

Fig.(4.2) shows the argument used for the identification of aggregate supply shocks. A positive supply shock shifts the aggregate supply  $AS$  to  $AS'$  with an associated drop in prices from  $P$  to  $P'$  and a rise in output from  $Y$  to  $Y'$ . The identification assumption further stipulates that the  $AS$  shock will have a permanent output rise associated with a shift in the  $LRAS$  supply, or the production possibility frontier, as well. This permanent effect implies that, unlike in the  $AD$  shock, output has permanently increased and prices have permanently fallen.<sup>25</sup> Of course, this effect separation of impacts assumes that shocks that shift the  $AD$  and  $AS$  curve are permanent.

#### 4.5.1 Estimation method

This section presents the method used for the identification and separation of demand and supply shocks via a Structural Vector Autoregression (SVAR) approach. It then goes on to describes the subsequent use of the derived supply shock to estimate risk-sharing in an one step IV-GMM regression that is similar to the FD2SLS and dGMM estimations except instead of using lagged output the derived supply shocks are used as an instrument. The notation is different in this section as it follows the general notation used in the SVAR estimation method presented by Bayoumi and Eichengreen (1993). For example, one of the difference in notation in

<sup>25</sup>Similar SVAR estimations have been done by Funke (1998) and Funke and Hall (1998), but for the purpose of analyzing the importance of structural supply and demand shocks for UK regions and German regions.

this section (4.5.1) compared to others is that  $\mathbf{x}_t$  does not refer to a vector containing all countries at time  $t$ , but a vector of variables at time  $t$ , e.g.  $\mathbf{x}_t = [x_{i,t}^1, x_{i,t}^2]'$ .

Before proceeding to the estimation, it is necessary to differentiate between the SVAR and its risk-sharing use in this chapter and the SVAR application by Bayoumi and Eichengreen (1993) and Asdrubali and Kim (2000). Although the SVAR estimation follows the SVAR as applied by Bayoumi and Eichengreen (1993), the application here goes beyond their original use by employing the derived supply shock to instrument GDP in an IV-regression to estimate risk-sharing. Meanwhile, the approach based on SVAR for the purpose of estimating risk-sharing presented here differs from the SVAR presented in Asdrubali and Kim (2000), as here we explicitly assume that GDP shocks are not exclusively exogenous but contain an endogenous element, i.e. demand shocks. By contrast, the SVAR application by Asdrubali and Kim (2000) allows for GDP to be endogenous, but assumes that GDP shocks are exogenous. Subsequently, the SVAR is used to extract the exogenous elements, which are then used as IVs in a estimation which Asdrubali and Kim (2000) refer to as static risk-sharing estimation.

Firstly the method used for the identification and separation of demand and supply shocks is presented. The method used is a SVAR as in Bayoumi and Eichengreen (1993) with the following structural model:

$$\mathbf{x}_t = \sum_{i=0}^{\infty} L^i \mathbf{A}_i \boldsymbol{\omega}_t \quad (4.23)$$

In Eq.(4.23)  $\mathbf{x}_t$  is a vector of variables, which in our case contains the logarithmic change in output  $\Delta y_t$  and prices  $\Delta p_t$ , and these are an MA( $\infty$ ) of a vector of shocks,  $\boldsymbol{\omega}_t$ , consisting of aggregate demand shocks  $\omega_{D,t}$  and aggregate supply shocks  $\omega_{S,t}$ . Therefore  $\mathbf{x}'_t = [\Delta y_t \ \Delta p_t]$  and  $\boldsymbol{\omega}'_t = [\omega_{D,t} \ \omega_{S,t}]$ .  $A_i$ , the impulse response function, represents the parameters of the reaction of output and prices to the demand and supply shocks. While the underlying macroeconomic theoretical impact of aggregate demand and supply shocks was shown in the previous section, we can use the derived impact to formalize the structure of the impulse response matrix:

$$\sum_{i=0}^{\infty} L^i \mathbf{A}_i = \sum_i L^i \begin{bmatrix} a_{11,i} & a_{12,i} \\ a_{21,i} & a_{22,i} \end{bmatrix} \boldsymbol{\omega}_t \quad (4.24)$$

From our theoretical model, we expect that aggregate demand shocks will have no permanent impact on output, so that

$$\sum_{i=0}^{\infty} a_{11,i} = 0 \quad (4.25)$$

where  $a_{11,i}$  is the parameter of demand shocks in the output equation. In addition to the exclusion of the permanent effect of demand shocks on output, the theoretical model implies that demand and supply shocks have opposite effects on price. However, in the application of the SVAR, these restrictions are not imposed on the structural parameters. They could serve instead to see if the shocks have been appropriately identified. However, we do not know the parameter values of  $A_i$  or  $\omega_t$ , but need to extract this information from the information we have, which is the realization of output and prices in the sample period. Subsequently, based on these realizations, we can construct a reduced form of the model

$$\mathbf{x}_t = \mathbf{B}_1\mathbf{x}_{t-1} + \mathbf{B}_2\mathbf{x}_{t-2} + \dots + \mathbf{B}_i\mathbf{x}_{t-i} + \mathbf{e}_t \quad (4.26)$$

which rewritten in the form of a MA process using lag polynomial become

$$\mathbf{x}_t = \sum_{i=0}^{\infty} \mathbf{D}_i\mathbf{e}_{t-i} \quad (4.27)$$

where  $\mathbf{e}_t$  is a vector of true output and price shocks. The invertible MA representation, as pointed out by Funke (1998) and Funke and Hall (1998), assumes that nonfundamental representation does not exist, which therefore circumvents the issue raised by Lippi and Reichlin (1993) on the topic on noninvertible process.

Eq.(4.26) represents the reduced form of our structural model on which the VAR estimation will be run to obtain estimates of the demand and supply shocks, with  $\hat{\mathbf{e}}_{t-i}$  being the residual vector of the (4.26) VAR estimation consisting of the estimated output and price shocks.<sup>26</sup> For simplicity, it is assumed that  $\mathbf{e}_{t-i} = \hat{\mathbf{e}}_{t-i}$ , i.e. that the true output and price shocks have been appropriately identified and represented by the output and price shocks derived by the VAR estimation.

However, a further step is necessary since,  $\mathbf{e}_t$ , the residual of the estimated output and price equations, does not allow us to differentiate aggregate demand from supply shocks. To do so, we stipulate that

$$\mathbf{e}_t = \mathbf{C}\omega_t \quad (4.28)$$

and we say the variance

$$\mathbf{e}_t\mathbf{e}_t' = \mathbf{C}\omega_t\omega_t'\mathbf{C}' \quad (4.29)$$

While we already know the elements on the left hand side (since the residual was obtained from the estimated VAR), we do not know the elements on the right hand side. This means we know three elements on the left hand side, whereas the right

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<sup>26</sup>The appropriate lag length of the VAR given by the length of  $\mathbf{B}_i\mathbf{x}_{t-i}$  and other aspects of estimating the actual SVAR will be discussed later on.

hand side includes seven unknown elements from the  $\mathbf{C}$  matrix and  $\boldsymbol{\omega}_t$  vector. This means the system can not be identified in its current form. To be able to identify it we need to impose restrictions; to be precise, we need at least four restrictions to identify the system. A common and to some extent obvious restriction is that we assume that the demand and supply shocks are independent of each other. Furthermore, we assume the common restriction of the variance of demand and the variance of supply shocks to be 1, effectively meaning that the demand and supply shocks are *i.i.d.*  $N(0, 1)$ . Effectively, the  $2 \times 2$  variance-covariance matrix of  $\boldsymbol{\omega}_t$  is an identity matrix whose variance's diagonal is equal to 1:

$$\boldsymbol{\omega}_t \boldsymbol{\omega}'_t = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (4.30)$$

This imposes three restrictions, and we need one more restriction to identify the system. In this case we come back to the theoretical conclusion that demand shocks have no permanent effect on output. Consequently, when inserting for  $\mathbf{e}_t = \mathbf{C}\boldsymbol{\omega}_t$ , we stipulate that:<sup>27</sup>

$$\sum_{i=0}^{\infty} \mathbf{D}_i \mathbf{C} = \begin{bmatrix} d_{11,i} & d_{12,i} \\ d_{21,i} & d_{22,i} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} = \begin{bmatrix} 0 & \cdot \\ \cdot & \cdot \end{bmatrix} \quad (4.31)$$

With these four restrictions the system is just-identified and the SVAR can be estimated. Specifically, these four restrictions allows us to uniquely identify the  $\mathbf{C}$  matrix in  $\mathbf{e}_t \mathbf{e}'_t = \mathbf{C} \boldsymbol{\omega}_t \boldsymbol{\omega}'_t \mathbf{C}'$  as we need solve

$$\begin{bmatrix} e_{y,t} e_{y,t} & e_{y,t} e_{p,t} \\ e_{p,t} e_{y,t} & e_{p,t} e_{p,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} c_{11} & c_{21} \\ c_{12} & c_{22} \end{bmatrix} \quad (4.32)$$

where the left hand side is the known variance and covariance of the residual from the estimated VAR, output and price shocks, and where  $c_{11,i}$  is known based on the linear restriction imposed in Eq(4.31). Having uniquely identified the  $\mathbf{C}$  matrix then allows us to solve Eq. (4.28),  $\mathbf{C}^{-1} \mathbf{e}_t = \boldsymbol{\omega}_t$ , for demand and supply shocks,  $\boldsymbol{\omega}'_t = [\omega_{D,t} \ \omega_{S,t}]$ , which written out is:

$$\begin{bmatrix} c_{11} & c_{21} \\ c_{12} & c_{22} \end{bmatrix}^{-1} \begin{bmatrix} e_{y,t} \\ e_{p,t} \end{bmatrix} = \begin{bmatrix} \omega_{D,t} \\ \omega_{S,t} \end{bmatrix} \quad (4.33)$$

In this entire process, we did not impose any restriction on the parameters of demand and supply shocks on price. This allows us to use impulse response functions to test whether the impact of shocks on price follow the predicted effect, i.e. demand

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<sup>27</sup>In essence, this translates into saying that a demand shock has no permanent impact on output. However, it allows for some impact which, over time, approaches zero.

shocks have a positive effect and supply shocks have a negative effect. If this is the case, one can take it as a sign that one has correctly identified aggregate demand and supply shocks. Furthermore, to appropriately specify the reduced form model and estimate the residuals, it is necessary to find the appropriate lag length. The lag length for the underlying VAR is chosen to be 2 for each country. We have followed Bayoumi and Eichengreen (1993) in applying a uniform lag length to preserve the symmetry of estimation and to allow a more natural comparison and the use of the obtained structural errors. The actual lag length is based on the Akaike and Schwarz IC, which identifies either one or two lags to be used for the countries in the sample.

Before proceeding with the actual risk-sharing estimation, the structure of the derived demand and supply shocks will be described. Table (4.9) and Fig. (4.3) show the properties of the above SVAR derived demand and supply shocks for the 24 OECD countries. Table (4.9) demonstrates that both demand and supply shocks have a mean of 0 and a variance of 1. These properties are further supported by Fig. (4.3), which shows that the shocks are well approximated by the density function of a normal distribution with a mean of 0 and a variance of 1, indicated by the solid black line. Additionally, a range of normality tests failed to reject the hypothesis of normal distribution. However, this should not come as much of a surprise, since the underlying reduced errors were estimated by SVAR methods which imposes the errors to be *i.i.d.*  $N(0, 1)$ . And so when calculating the structural errors from reduced errors using scalar and linear transformation, the structural errors should have a similar distribution as the underlying reduced form errors.

Shock	Mean	Std. Dev.	Min	Max
Ag.Demand	0.000	1.0006	-3.6598	4.1029
Ag.Supply	0.000	1.0006	-3.7876	3.2659

Supply and demand shock derived from the SVAR for 24 OECD countries over the period 1970-2007.

Table 4.9: Estimated aggregate supply and demand shocks descriptive statistics

Now that we have obtained the supply shocks we can move to estimating the risk-sharing. This is done using a standard IV-estimation. The estimation relies for its asymptotic properties on fixed  $N$  and large  $T$ . The underlying estimation is the same Eq. (4.17) or Eq. (4.19) except that  $\Delta \mathbf{y}$  is instrumented with  $\mathbf{Z}$ , an  $NT * 1$  vector consisting of the derived supply shocks  $\boldsymbol{\varepsilon}_S$ . This is exactly identified IV as there is one endogenous variable,  $\mathbf{y}$ , and one instrument,  $\boldsymbol{\varepsilon}_S$ .<sup>28</sup>

<sup>28</sup>While using this process provides one IV, the supply shock, to test the exogeneity of regressors requires over-identification – i.e. the amount of IVs has to exceed the amount of endogenous regressors which in this case means at least two IVs are needed for over-identification. One solution, is to use the same instruments as in the FD2SLS, either  $\Delta \mathbf{y}_{t-2}$  or  $\mathbf{y}_{t-2}$ , which would provide a

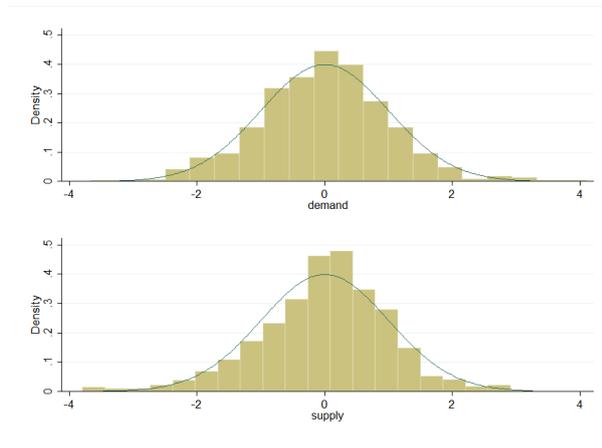


Figure 4.3: Distribution of aggregate demand and supply shocks

## 4.5.2 Estimation results

The results of the risk-sharing estimation using derived supply shocks in an IV-GMM estimation are displayed below in Table (4.10). The standard errors shown in Table (4.10) are arbitrary heteroskedasticity and autocorrelated robust standard errors. Additionally, as the shocks might have lower variance around zero towards the 1990's and onwards as a result of active business cycle management, separate estimates of aggregate supply shocks were done: one in which the supply shocks were derived from one SVAR on the entire sample period and one in which the supply shocks for 1970-1990 and 1991-2007 were derived from two SVARs on these sub-periods. Whereas the top half of Table (4.10) refers to the risk-sharing estimates using aggregate supply shocks obtained from the SVAR over the entire sample period, the bottom half refers to the risk-sharing estimates utilizing aggregate supply shocks obtained from the two sub-sample SVARs.

It is apparent from Table (4.10) that risk-sharing has risen by about 8 percentage points from 28% in 1973-2007 to 36% in 1991-2007. However, caution should be taken as the risk-sharing expansion is found to be not significant.<sup>29</sup> Nonetheless, the risk-sharing estimates obtained from instrumenting using aggregate supply shocks

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second instrument without the instrument proliferation of the dGMM. The estimation using both the supply shocks and FD2SLS style instrument can be found in appendix (D.4).

<sup>29</sup>The test whether risk-sharing changed between 1973-1990 and 1991-2007 follows the same methodology as introduced in the previous chapter and used throughout this chapter. The test is based on testing the parameter of an interactive dummy term from a estimation over the entire period, with the dummy being 0 prior to and including 1990 and 1 thereafter. Specifically, the parameter of interest is  $\beta_{u,D2}$  as shown in the last column of Table (4.10). The test tests  $H_0 : \beta_{u,D2} = 0$  using a two-sided t-test with 5% significance level. If  $H_0$  is not rejected than risk-sharing did not change between 1973-1990 and 1991-2007 –up nor down. The  $H_0$  of no change is not rejected in case of the IV-estimation where the supply shocks are derived from one SVAR over the entire period with the p-value being 0.555. In case of the IV-estimation where the supply shocks are derived from sub-period SVAR estimations the  $H_0$  is rejected at a 5% significance level but not at a 1% significance level.

Variable	1973-2007	1973-1990	1991-2007	Dummy:1973-2007
$\beta_u$	0.6848***	0.7151***	0.6363***	
$\beta_u$ SE()	(0.0591)	(0.0753)	(0.1106)	
$\beta_u$ 95% CI	[0.569, 0.801]	[0.568, 0.863]	[0.420, 0.853]	
$\beta_{u,D1}$				0.7151***
$\beta_{u,D1}$ SE()				(0.0753)
$\beta_{u,D1}$ 95% CI				[0.568, 0.863]
$\beta_{u,D2}$				-0.0789
$\beta_{u,D2}$ SE()				(0.1335)
$\beta_{u,D2}$ 95% CI				[-0.341, 0.183]
U-ID KP LM $\chi^2$	85.541	55.480	27.837	27.837
U-ID KP LM p-value	0.0000	0.0000	0.0000	0.0000
W-ID CD Wald F	295.840	152.283	136.470	140.503
W-ID KP Wald F	140.130	96.405	45.199	22.603
AR weak-iv robust CI	[0.565, 0.800]	[0.569, 0.867]	[0.352, 0.816]	
subperiod SVARs				
$\beta_u$	0.9410***	1.1442***	0.6810***	
$\beta_u$ SE()	(0.0902)	(0.1553)	(0.1184)	
$\beta_u$ 95% CI	[0.764, 1.118]	[0.840, 1.449]	[0.449, 0.913]	
$\beta_{u,D1}$				1.1442***
$\beta_{u,D1}$ SE()				(0.1553)
$\beta_{u,D1}$ 95% CI				[0.840, 1.449]
$\beta_{u,D2}$				-0.4632**
$\beta_{u,D2}$ SE()				(0.1956)
$\beta_{u,D2}$ 95% CI				[-0.847 -0.080]
U-ID KP LM $\chi^2$	44.667	20.884	28.119	20.884
U-ID KP LM p-value	0.0000	0.0000	0.0000	0.0000
W-ID CD Wald F	74.688	30.220	53.854	29.337
W-ID KP Wald F	59.323	25.204	48.414	12.60
AR weak-iv robust CI	[0.773, 1.137]	[0.8920, 1.581]	[0.4044, 0.8920]	

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. The IV estimations and the Anderson and Rubin (1949) confidence intervals were constructed using the Stata commands ivreg2 and weakiv by Baum et al. (2010) and Finlay et al. (2013). Empty cell means the row is not applicable for the respective column.

Table 4.10: IV-Estimation using aggregate supply shocks

are of a similar extent to the Level-approach estimates of 20% for 1970-2007, 19% for 1970-1990, and 37% for 1991-2007, and the dGMM estimates of 27% for 1970-2007, 24% for 1970-1990, and 43% for 1991-2007. Of course there are differences in the point estimates, but the results from Level estimation, dGMM and SVAR-IV show the same outcome: a similar increase in risk-sharing from 1970-1990 to 1990-2007 with a similar albeit different extent of risk-sharing. Caution should be exercised here in concluding an increase in risk-sharing occurred as the increase wasn't found to be substantial. However, the rejection of a substantial increase in risk sharing is because the change is very imprecisely estimated with a change anywhere from -0.8 to +0.2. This wide range makes it difficult to draw a strong conclusion about the extent and significance of the change in risk-sharing between the two sub-periods.

Also, it is very important to recognize that both the underidentification and weak identification tests are clear that the estimations in Table (4.10), unlike the FD2SLS, neither suffer from under- nor weak identification. In addition, the Anderson and Rubin (1949) confidence interval is clearly defined within the -2 and 2 range and, with the exception of two instances, is clearly defined by values near or between 0 and 1 and is much narrower than in the case of the dGMM or FD2SLS. In short, it appears that the SVAR-IV estimates are consistent as they, unlike the FD2SLS or dGMM, do not suffer from under- nor from weak identification, despite output being unit-root or being close to it. Thus, as the results from the SVAR-IV appear more reliable than the FD2SLS or dGMM results, it could be concluded that the strategy of constructing instruments via an SVAR estimation was more successful in generating more reliable instruments than was FD2SLS or dGMM.

## 4.6 Conclusion

This chapter has set out to ease the assumption of exogeneity in case of risk-sharing model estimation. In that attempt the chapter has looked at various estimators on top of the methods employed in literature; Anderson and Hsiao (1981, 1982) FD2SLS estimator, Holtz-Eakin et al. (1988) dGMM estimator and a instrumental variable estimation based on Bayoumi and Eichengreen (1993) SVAR. These additional estimators were presented based on the underlying endogeneity of output and the subsequent bias in risk-sharing point estimates. That is, these additional estimators should, under certain circumstances, be robust to endogeneity bias that arises due to the causality of demand shocks originating in consumption running to output. Also an extensive part of the discussion of robust estimates centered on the Level approach, which should be robust if non-stationary.

When comparing the results to the Classical approach, where no rise in risk-

sharing is found, the alternative approaches indicate some rise in risk-sharing. While the Level approach is potentially inconsistent, the presence of similar results in the dGMM and SVAR-IV method, gives further credence to the conclusion that risk-sharing has indeed increased. However, both the FD2SLS and the dGMM appear to suffer either from under- or from weak identification, which is likely related to output being close to a unit root process or being  $I(1)$ , and therefore their estimates are potentially inconsistent. The SVAR-IV on the other hand does not appear to suffer from under- nor from weak identification and its results in comparison to the Level estimation appear reasonable. Overall, this supports the conclusion that the SVAR-IV approach is more successful -in that it generates a much stronger instrument- in providing consistent risk-sharing parameter that are considerably more reliable than the FD2SLS and dGMM in the context of risk-sharing estimates.

# Chapter 5

## Risk-sharing and endogeneity: a Monte Carlo Study

### 5.1 Introduction

The previous chapter presented various alternative risk-sharing estimation methods that under certain circumstances are robust to the endogeneity of output. These alternative estimators led to the conclusion that risk-sharing was higher and increasing compared to the findings of the Classical approach estimated in the third chapter. However, it should be noted that the coefficients for the two subsamples were not precisely estimated, and in most cases the null that no change in risk-sharing could not be rejected. In this chapter a Monte Carlo simulation (MCS) is employed to analyse the risk-sharing estimation performance of the various approaches introduced in the preceding chapters. On the one hand this will demonstrate to what extent the Classical approach is biased when output is endogenous, and on the other hand identify which alternative approach performs best in estimating risk-sharing.

The various risk-sharing estimation methodologies have unique strengths and weaknesses which affect their ability to estimate risk-sharing. For example, besides suffering from endogeneity, the small sample has implications for the use of the Classical method. In estimating using the Classical method, the third chapter applied a correction for cluster-based heteroskedasticity and autocorrelation-consistent errors. This approach in estimating the cluster-robust covariance relies for its asymptotic properties on the number of clusters, determined by the cross-section of the panel data, to go to infinity. However, in our panel data the cross section with 24 countries is not close to infinity, or even large. Meanwhile, the Level method requires a non-stationary output and consumption series for consistency. In contrast, the dGMM method requires stationarity and suffers from increasingly weak instrument bias as

output approaches  $I(1)$ . Therefore, while both the Level and dGMM methods display similar results in the previous chapters, only one can be valid. Furthermore, dGMM is an asymptotic estimator designed for a large cross-section and a short time period. However, in our case the panel consist of similar seized time series and cross-section with both being far from infinity. Lastly, the IV estimation using derived supply shocks requires an intermediate estimation in which the supply shocks are derived, leaving this approach more prone to mis-specifications, of which the likeliest is that demand shocks are falsely identified as supply shocks.

The panel structure of the MCS will be the same as panel structure of the data used in the preceding chapters: a cross-section of 24 and time series of 37. In addition, the endogeneity of output in the risk-sharing estimation will be explicitly modeled.

The results presented below show that in the case of endogeneity bias the Classical estimation method underestimates risk-sharing by about 23% and more, while the alternative methods tend to generate estimates that are closer to the true risk-sharing parameter. Also, as the severity of the endogeneity bias increases, almost all the methods diverge from the true parameter with exception of the level and the supply shock based IV methods.

## 5.2 Data generating processes

This section presents underlying structure common to all the data generating processes (DGPs) which underlie the MCS. The DGPs discussion starts with outlining the underlying common structure to all DGPs.

To reflect the data set used in the previous chapters, the DGPs are defined in terms of a panel data set with a cross-section of 24 and a time series of 37. The DGPs define three variables for the MCS to be applied to for each of the proposed risk-sharing estimation methodologies: consumption per capita ( $\mathbf{c}$ ), output per capita ( $\mathbf{y}$ ), and price ( $\mathbf{p}$ ). All three variables will be modeled in logs. Also, as in in the fourth chapter, all variables are defined as matrices and vectors such that, for example,  $\mathbf{c}$  is a  $(24 * 37 \times 1)$  vector of consumption, with  $\mathbf{c}_t$  being a  $(24 \times 1)$  sub-vector of  $\mathbf{c}$  that contains all the cross sections in time period  $t$  and  $\mathbf{c}_i$  being a  $(37 \times 1)$  sub-vector of  $\mathbf{c}$  that contains all the time periods for cross-section  $i$ .

The variation in the DGPs is driven by two exogenous shocks: supply ( $\epsilon_{i,t}^S$ ) and demand shocks ( $\epsilon_{i,t}^D$ ).<sup>1</sup> The supply and demand shocks, based on the fourth chapter's

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<sup>1</sup> $\epsilon^S$  and  $\epsilon^D$  are the  $(24 * 37 \times 1)$  vectors containing the stacked  $\epsilon_{i,t}^S$  and  $\epsilon_{i,t}^D$  respectively.

SVAR estimation, will be modeled as:

$$\epsilon_{i,t}^D, \epsilon_{i,t}^S \sim i.i.d. N(0, 1) \quad (5.1)$$

### 5.2.1 Output

Given the supply and demand shocks, the functional form of output is defined as:

$$\mathbf{y}_t = \mathbf{y}_{t-1}\alpha + \epsilon_t^D\psi + \epsilon_t^S \quad (5.2)$$

which states that output is an AR(1) process driven by demand and supply shocks. In its current form, Eq. (5.2) excludes a time trend. However, for reasons that will become clear later, including a time trend is a trivial matter as it does not affect the risk-sharing estimates beyond whether to include or exclude an intercept in the risk-sharing estimation, or in the case of the Level methodology whether to include a time trend. The starting value of each cross section,  $y_{i,0}$ , is randomly chosen from a normal distribution with a mean of 9.25079 and variance of 0.3117286 which reflects the first period distribution of the panel data used in the previous chapters.<sup>2</sup>

Since output is modeled as an AR(1) process, supply and demand shocks have a contemporaneous effect on output and continue to impact output subject to the nature of the AR(1) coefficient,  $\alpha$ . To see this Eq. (5.2) could be expressed as an MA( $\infty$ ):

$$\mathbf{y}_i = \mathbf{\Gamma}(\epsilon_i^D\psi + \epsilon_i^S) \quad (5.3)$$

where  $\mathbf{\Gamma}$  is the following matrix

$$\mathbf{\Gamma} = \begin{bmatrix} \alpha & \alpha^2 & \cdots & \alpha^T \\ 0 & \alpha & \cdots & \alpha^{T-1} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha \end{bmatrix} \quad (5.4)$$

Eq. (5.3) highlights that output in any period is the sum of all the preceding shocks subject to  $\alpha$ . If  $|\alpha| = 1$  output is a unit root process and Eq. (5.3) and Eq. (5.2) would be a random walk, i.e. output in any period is the unweighted sum of all preceding supply and demand shocks. In short, output is modeled as the equilibrium realization of aggregate supply and aggregate demand driven by supply and demand shocks.

As a word of caution: as discussed by Chesher and Peters (1994) and Davidson

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<sup>2</sup>Although the choice has little impact on the dynamics of output and therefore has no meaningful impact on the results of the risk-sharing estimation.

and MacKinnon (1993), the estimators examined and the associated (finite-sample) results rely on the regressor's distribution, specifically whether or not the regressors are symmetrically distributed around a mean. Therefore, the results might have special properties that might not hold in general.<sup>3</sup> This applies to output as defined in Eq. (5.2), when  $|\alpha| < 1$  as output gravitates toward the demand and supply shock distributions which are defined as being symmetrically distributed around a mean of zero. However, in the fourth chapter, it was discussed at length that a symmetric distribution of  $\epsilon^D$  and  $\epsilon^S$  is an appropriate choice.

Two conceptually distinct versions of the DGPs will be constructed: one in which output is explicitly assumed to be exogenous and one in which output is endogenous. When modeling output as exogenous,  $\psi$  in Eq. (5.2) will be zero, which implies that output is solely driven by supply shocks. That does not mean demand shocks are not occurring, but rather that they are not affecting output. This exogenous output scenario is used to provide a base case for a risk-sharing estimation in which output is not exogenous.

When output is modeled as endogenous,  $\psi$  in Eq. (5.2) will take a value above zero and up to and including one,  $0 < \psi \leq 1$ . In other words,  $\psi$  captures the severity of the endogeneity and limits the contemporaneous impact of a demand shock on output. The closer  $\psi$  is to zero, the less severe the endogeneity bias, and vice versa when  $\psi$  approaches one. Combined with the autoregressive coefficient  $\alpha$  in Eq. (5.2),  $\psi$  implies that demand shocks die out faster than supply shocks if  $\alpha$  and  $\psi$  are smaller than one. In case where  $\alpha = 1$  but  $\psi < 1$  then, for similar demand and supply shocks, output varies more strongly with supply than demand shocks.

Also,  $\psi$  is defined as being constant across the panel series, i.e.  $\psi_i = \psi_j \forall i \neq j$ . This is done to avoid unnecessary complexity, especially since the panel estimation would reflect the average of the country individual time-series with the point estimates being equivalent to the mean of the chosen distribution if  $\psi$  is symmetrically distributed. At the same time however, it would increasingly obscure the conclusion as the results would become subject to an additional changing factor, which would increase the combinations of MCS results. Furthermore, the variance of the point estimates would be increased beyond the variance due to the asymptotic properties of the estimators employed. In other words, the point estimates are expected to be the same with greater variance. Therefore, since we are interested in the point estimate, there is no gain in introducing this additional complexity. Note that  $\psi \neq 0$  by itself does not imply output is endogenous but the presence of demand shocks in consumption directly creates the simultaneity bias in the risk-sharing estimation.

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<sup>3</sup>That is, if the MSC regressors are symmetrically distributed around a mean, the employed estimator tends to have special properties which do not hold for most other distributions. This means the results of a MCS using symmetrically distributed random regressors could be misleading, especially if the real world regressors are not symmetrical distributed around a mean.

		Autoregressive parameter $\alpha$	
		$\alpha < 1$	$\alpha = 1$
Endogeneity parameter $\psi$	$\psi = 0$	stationary exogenous	unit-root exogenous
	$\psi > 0$	stationary endogenous	unit-root endogenous

Table 5.1: Individual DGPs

In summary, each DGP's output time series is driven by supply and demand shocks, and by two parameters: output autocorrelations parameter  $\alpha$  and demand shock parameter  $\psi$ . Table (5.1) summarizes the properties of output for the various combinations of  $\alpha$  and  $\psi$ . If  $\alpha < 1$  output is stationary, and unit-root when  $\alpha = 1$ . Meanwhile, if  $\psi = 0$  output is exogenous, and if  $\psi > 0$  output is endogenous. This creates four possible states: i) output is stationary and exogenous when  $\alpha < 1$  and  $\psi = 0$ , ii) output is unit-root and exogenous when  $\alpha = 1$  and  $\psi = 0$ , iii) output is stationary and endogenous when  $\alpha < 1$  and  $\psi = 1$ , iv) output is unit-root and endogenous when  $\alpha = 1$  and  $\psi = 1$ .<sup>4</sup>

## 5.2.2 Consumption and price

Consumption will be driven by output and demand shocks:

$$\mathbf{c} = \beta_u \mathbf{y} + \boldsymbol{\epsilon}^D \quad (5.5)$$

where  $\beta_u$  measures to what extent consumption is driven by output. In other words,  $\beta_u$  is the unshared risk coefficient we want to compare across the various risk-sharing estimation approaches. Demand shocks,  $\boldsymbol{\epsilon}^D$ , appear both in consumption Eq. (5.5) and in output Eq. (5.2) and are the element that causes output to be endogenous in Eq. (5.5). In effect, Eq. (5.5) is the MCS basic risk-sharing model to be estimated and is equivalent to Eq. (2.18) and (4.2) in the preceding chapters.

Given Eq. (5.5), the endogeneity of output can be stated as the covariance of the shock experienced by GDP and consumption. If we define  $e_{i,t}^{gdp}$  as the error in the GDP Eq. (5.2), such that  $e_{i,t}^{gdp} = \epsilon_{i,t}^S + \psi \epsilon_{i,t}^D$ , and  $e_{i,t}^c$  to be the error in the consumption Eq. (5.5), such that  $e_{i,t}^c = \epsilon_{i,t}^D$ , then we can state that  $\begin{pmatrix} e_{i,t}^{gdp} \\ e_{i,t}^c \end{pmatrix} \sim \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \mathbf{V} \right)$ . It follows that  $\mathbf{V}$ , the variance-covariance matrix, is equal to  $\begin{pmatrix} \sigma_{gdp}^2 & \sigma_{sd} \\ \sigma_{sd} & 1 \end{pmatrix}$ , where  $\sigma_{sd}$  is the  $Cov(e_{i,t}^{gdp}, e_{i,t}^c)$  and  $\sigma_{sd} = 0$  if output is exogenous. Otherwise, if output is endogenous then  $\sigma_{sd} \equiv Cov(\epsilon_{i,t}^D, \epsilon_{i,t}^S + \psi \epsilon_{i,t}^D) = \psi$ .  $\sigma_{gdp}^2$  is the variance of the output shock, which is a composite of the variance of demand and supply shocks, that is

<sup>4</sup>The actual values of  $\alpha$  and  $\psi$  and the various DGP which arise from the choices is discussed later on.

$$\sigma_{gdp}^2 = Var(\epsilon_{i,t}^s + \psi\epsilon_{i,t}^d) = Var(\epsilon_{i,t}^s) + Var(\epsilon_{i,t}^d) + Cov(\epsilon_{i,t}^s, \epsilon_{i,t}^d) = 1 + 1 + 0.^5$$

The price variable is needed to identify the supply shocks in the SVAR estimation approach. Following the analysis of the fourth chapter, price is modeled with demand shocks having a permanent positive impact on price, and supply shocks having a permanent negative impact:

$$\mathbf{p}_t = \mathbf{p}_{t-1} + \epsilon_t^D - \epsilon_t^S \quad (5.6)$$

In Eq. (5.6) price is defined as random walk, but since the SVAR estimation is exclusively in first differences, Eq. (5.6) collapses to

$$\Delta\mathbf{p}_t = \epsilon_t^D - \epsilon_t^S \quad (5.7)$$

### 5.2.3 Time and cross-section fixed effects

The previous chapters used cross-sectional demeaned and first differenced variable to account for the time and cross-section fixed effects.

Cross-section fixed effects have not been explicitly modeled given that the various risk-sharing estimation approaches, apart from the Level approach, are in first differences, which makes it redundant to model cross-section fixed effects explicitly. To see this take Eq. (5.5) and add cross-section fixed effects such that we get

$$\mathbf{c}_t = \mathbf{a}_t + \mathbf{y}_t\beta_u + \epsilon_t^D \quad (5.8)$$

where  $\mathbf{a}$  is the vector containing the cross-section fixed effects which vary over the cross-section,  $\mathbf{a}_i \neq \mathbf{a}_j$ , but do not vary over time,  $\mathbf{a}_t = \mathbf{a}_{t-1}$ . When taking first difference Eq. (5.8) collapses to

$$\Delta\mathbf{c}_t = \Delta\mathbf{y}_t\beta_u + \Delta\epsilon^D \quad (5.9)$$

because  $\Delta\mathbf{a}_t = 0$ . For the Level estimation, since this estimation relies on non-stationary variables and the associated superconsistency, modeling cross-section fixed effects has no impact on the unshared risk estimate as cross-section fixed effects are stationary and therefore unrelated to the non-stationary variables.

Like cross-section fixed effects, time fixed effects have not been explicitly mod-

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<sup>5</sup>The endogeneity of output from abroad is reflected in the aggregate demand shocks which capture consumption shifts abroad via export shifts. As will be discussed below, since consumption and output are demeaned in the risk-sharing regression using aggregate measure of consumption and output based on weighted sum of country individuals consumption and output, a measurement of aggregate area demand shock will be featured, as part of the demeaning process, in the risk-sharing regression.

eled. This is because the variables in the estimation, apart from the SVAR, have to be demeaned, regardless of whether or not time fixed effects are present. Thereby, any time fixed effects are filtered out regardless of whether or not they are modeled. The demeaning is applied to account for the mean output shift in each period, which with a balanced portfolio cannot be insured against. In other words, mean output variation needs to be filtered out to ascertain a country's idiosyncratic shocks.

The demeaning is done using a weighted sum, as the theoretical standard risk-sharing model stipulates that a country's share in a balanced portfolio of state contingent assets is subject to the country's GDP size relative to the aggregate area. Consequently, the weights provide an indication of the relative size of the country's output, with the weights summing to one ( $\sum_{i=1}^N w_{i,t} = 1 \forall t = 1, 2, 3, \dots, T$ ). Since output in our DGPs is a randomly generated measurement of GDP per capita, the output variable does not contain a distinguishable measurement of countries' relative size of GDP. In other words, the actual weights assigned to the countries in this MCS can be randomly assigned to reflect relative size with the only requirement being that the weights sum to one. Subsequently, the weights used in the actual empirical estimation can be used in the DGPs without impacting the MCS results. This means that the weights are generated by

$$\mathbf{w}_i = \frac{\mathbf{GDP}_i}{\sum_{i=1}^N \mathbf{GDP}_i} \quad (5.10)$$

where  $\mathbf{GDP}$  denotes the actual GDP of the 24 OECD countries used in the previous chapters, while  $\mathbf{w}_i$  is a  $(37 \times 1)$  vector of weights which varies both over time and cross-section.<sup>6</sup> The mean measure is therefore given by

$$\bar{\mathbf{x}} = \sum_{i=1}^N \mathbf{w}_i \mathbf{x}_i \quad (5.11)$$

such that a demeaned variable is

$$\tilde{\mathbf{x}} = \mathbf{x} - \bar{\mathbf{x}} \quad (5.12)$$

To see why the demeaning would have filtered out time fixed effects take once again Eq. (5.5) and this time add a time fixed effect vector such that we get the following

$$\mathbf{c}_i = \mathbf{q} + \mathbf{y}_i \beta_u + \boldsymbol{\epsilon}_i^D \quad (5.13)$$

where  $\mathbf{q}$  is the  $37 \times 1$  time fixed effect vector that is constant across cross-section,  $\mathbf{q}_i =$

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<sup>6</sup>It is worth highlighting that in the previous chapters, when output per capita was endogenous, than the weights, constructed using output, were endogenous too. However, for simplicity, and given that the weights are determined exogenously to the DGPs, the weights in the MCS are exogenous.

$\mathbf{q}_j$ , but varies over time,  $\mathbf{q}_t \neq \mathbf{q}_{t-1}$ . If we apply the demeaning from Eq. (5.12) to Eq. (5.13) we get

$$\mathbf{c}_i - \sum_{i=1}^N \mathbf{w}_i \mathbf{c}_i = \mathbf{q} - \sum_{i=1}^N \mathbf{w}_i \mathbf{q} + (\mathbf{y}_i - \sum_{i=1}^N \mathbf{w}_i \mathbf{y}_i) \beta_u + \boldsymbol{\epsilon}_i^D - \sum_{i=1}^N \mathbf{w}_i \boldsymbol{\epsilon}_i^D \quad (5.14)$$

which collapses to

$$\mathbf{c}_i - \sum_{i=1}^N \mathbf{w}_i \mathbf{c}_i = \mathbf{y}_i - \sum_{i=1}^N \mathbf{w}_i \mathbf{y}_i \beta_u + \boldsymbol{\epsilon}_i^D - \sum_{i=1}^N \mathbf{w}_i \boldsymbol{\epsilon}_i^D \quad (5.15)$$

because  $\sum_{i=1}^N \mathbf{w}_i \mathbf{q} = \mathbf{q}$ . In short, time fixed effects are implicitly nested in the DGPs in the non-demeaned consumption-output functional relationship, but since the relationship is stated in demeaned form, they drop out. Going forward we will drop the demeaning notation and treat all variables as demeaned except when explicitly stated otherwise, or in the case of the SVAR estimation where output and price are not demeaned.

To summarize, the general set up of the DGP for consumption and production is structured in the demeaned and first differences form, which is equivalent to modeling both consumption and output with both fixed effects explicitly and demeaning them and taking first difference in every draw. For the DGP to be equivalent between both options and applicable for our purpose – since the Level application does not take first differences, the only requirements are that the cross-section fixed effects are stationary.

## 5.2.4 Data Generating Processes verification

It is essential to confirm that the common underlying structure of DGPs generates the needed information for the various risk-sharing estimation approaches. More precisely, we must confirm whether the three data formats used in the empirical estimation are supported by the DGPs: first differences, levels, and SVAR.

For the risk-sharing estimation in first differences, since output and consumption are generated in levels, we need to verify that the conversion from level into first difference does not alter the outcome of the risk-sharing estimation by showing that the estimation equation in first difference in the MCS is the same as Eq. (2.18) and (4.2). To do so, we start with taking first difference of Eq. (5.5), which gives us

$$\Delta \mathbf{c} = \Delta \mathbf{y} \beta_u + \Delta \boldsymbol{\epsilon}^D \quad (5.16)$$

Eq. (5.16) is essentially the same as Eqs. (2.18) and (4.2) except for the general

error in Eqs. (2.18) and (4.2),  $\mathbf{v}$ , that could contain various factors that directly influence consumption. Essentially, in Eq. (5.16) the general error which is  $\mathbf{v}$  in Eqs. (2.18) and (4.2) is limited to demand shocks,  $\epsilon^D$ . Nonetheless, estimating Eq. (5.16) using OLS would yield the same consistent unshared risk estimate of  $\beta_u$ , the variance covariance of output and consumption, if there is no endogeneity, and an inconsistent estimate if endogeneity is present, as when estimating Eqs. (2.18) and (4.2) using OLS. In addition, the common structure of DGPs also allows for endogeneity bias in first difference. To see this take Eq. (5.2) and apply first difference such that we get

$$\Delta \mathbf{y} = \mathbf{y}(\alpha - 1) + (\epsilon^D \psi + \epsilon^S) \quad (5.17)$$

Given that  $\epsilon^D$  is still present in Eq. (5.17), output is still not independent of the error,  $\epsilon^D$ , in Eq. (5.16) such that  $E(\mathbf{y}\epsilon^D) \neq 0$ .

In regards to the Level-method, we need to verify that in Eq. (5.5) both  $\mathbf{c}$  and  $\mathbf{y}$ , even after having being demeaned, have the potential to be non-stationary. To verify that unit root is possible we start with the output Eq. (5.2):

$$\mathbf{y}_t = \mathbf{y}_{t-1}\alpha + \epsilon^y \quad (5.18)$$

where, for simplicity, demand and supply shocks are combined in  $\epsilon^y$  such that  $\epsilon^y = \psi\epsilon^D + \epsilon^S$ . The equivalent of Eq. (5.18) for the mean output is given by

$$\bar{\mathbf{y}}_t = \mathbf{w}\mathbf{y}_t = \mathbf{w}(\mathbf{y}_{t-1}\alpha + \epsilon^y) \quad (5.19)$$

such that if we demean Eq. (5.18) by subtracting Eq. (5.19) we get

$$\mathbf{y}_t - \bar{\mathbf{y}}_t = (\mathbf{y}_{t-1} - \bar{\mathbf{y}}_{t-1})\alpha + \epsilon^y - \bar{\epsilon}^y \quad (5.20)$$

so that if  $|\alpha| = 1$ , the question becomes how  $(\mathbf{y}_t - \bar{\mathbf{y}}_{t-1})$  behaves. In other words, the question is whether the demeaned consumption and output term for individual countries converges to zero or whether it diverges from zero.

The answer to the question lies in the weighting process. Let us start, for simplicity, by assuming that the weights are identical for all countries:  $\mathbf{w}_i = \mathbf{w}_j$ . Also, given that  $\epsilon^y = \psi\epsilon^D + \epsilon^S$  and both  $\epsilon^D$  and  $\epsilon^S$  are i.i.d.  $N(0,1)$  then it follows that  $\epsilon^y \sim i.i.d. N(0,1)$ . So that when taking the average across the countries, the weighted mean tends to converge, as the sample of countries is increased, to the chosen mean of the symmetrically distributed errors, the supply and demand shocks, which is zero, i.e.  $\lim_{N \rightarrow \infty} N^{-1} \sum_{i=1}^N \epsilon^y = E(\epsilon^y) = 0$ . This implies that the aggregate of output shocks is close to zero in each period. Thus  $\bar{\mathbf{y}}_t$  grows potentially more slowly than output for individual countries, as in each period the weighted mean

shock tends more towards zero compared to country individual shocks, and thereby providing potential for unit-root in the demeaned variable for some of the 24 countries. On the other hand, the weights in the DGPs are not identical for each country and the panel dimension is limited to 24, which means that the weighted mean of the shocks does not have to be equal or converge to the mean of the symmetric distribution from which the supply and demand shocks are randomly chosen, but rather be close to the shocks experienced by the largest countries.<sup>7</sup> Nonetheless unit roots can exist for some countries as the common structure of the DGPs does not prohibit some countries growing faster or more slowly than the mean growth rate. This implies that if we ran country individual level estimation, the possibility exists that some countries would have unit roots and thus we could get consistent country individual level estimates, while for other countries there wouldn't be a unit root and thus least square estimation using the levels of variables would provide inconsistent risk-sharing parameter estimates. Thus the panel Level estimate can, but does not have to, give consistent estimates when  $|\alpha| = 1$ . Alternatively, if  $|\alpha| \neq 1$ , then there is no potential for a unit root, whether in ratio or not.

Last but not least, we need to verify that output allows for the SVAR to identify supply and demand shocks. To see whether the SVAR identifies the shocks, we need to ensure that the contemporaneous impact of supply and demand shocks can be appropriately identified, subject to the long run restriction and the impact of lagged endogenous variables. Thus we need to verify:<sup>8</sup>

$$\mathbf{C} = (\mathbf{I} - \mathbf{A}_1 - \mathbf{A}_2)^{-1} \mathbf{A}_0^{-1} \mathbf{B}$$

where  $\mathbf{A}_1$  and  $\mathbf{A}_2$  are the  $(2 \times 2)$  coefficient matrices of the lagged endogenous variables,  $\mathbf{A}_0$  is the  $(2 \times 2)$  matrix of contemporaneous effect of the endogenous variables (which we assumed is a I-matrix in the empirical application), and  $\mathbf{B}$  is the contemporaneous impact of supply and demand shock on output and price matrix  $(2 \times 2)$ . Even though we know that all countries will be an AR(1) process (given the DGPs), the reason that we have an AR(2), is that an AR(2) process has been uniformly applied to capture the serial correlation for all countries in the actual empirical application in the previous chapter. Therefore, the application of an AR(2) process reflects the empirical application, and it is in this spirit that the MCS applies an AR(2) condition. Rewritten, we get<sup>9</sup>

$$(\mathbf{I} - \mathbf{A}_1 - \mathbf{A}_2)\mathbf{C} = \mathbf{B}$$

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<sup>7</sup>This does not mean that as  $N$ , the sample of countries, increases and the weight of each country drops that the mean would not converge to zero, although in our case  $N$  is not large enough for that to hold.

<sup>8</sup>A good overview and derivation of the long run restriction matrix can be found in Lütkepohle (2005).

<sup>9</sup>As  $\mathbf{A}_0^{-1} = \mathbf{I}$ , it follows that  $\mathbf{A}_0^{-1}\mathbf{B} = \mathbf{I}\mathbf{B} = \mathbf{B}$

when writing out the matrices

$$\left( \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} a_{11}^1 & a_{12}^1 \\ a_{21}^1 & a_{22}^1 \end{bmatrix} - \begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{21}^2 & a_{22}^2 \end{bmatrix} \right) \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} = \mathbf{B}$$

where, given the long-run restriction of demand shocks having no impact on output,  $c_{11} = 0$ , we get

$$\left( \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} a_{11}^1 & a_{12}^1 \\ a_{21}^1 & a_{22}^1 \end{bmatrix} - \begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{21}^2 & a_{22}^2 \end{bmatrix} \right) \begin{bmatrix} 0 & c_{12} \\ c_{21} & c_{22} \end{bmatrix} = \mathbf{B}$$

which implies that

$$\mathbf{B} = \begin{bmatrix} c_{21}(-a_{12}^1 - a_{12}^2) & c_{12}(1 - a_{11}^1 - a_{11}^2) + c_{22}(-a_{12}^1 - a_{12}^2) \\ c_{21}(1 - a_{22}^1 - a_{22}^2) & c_{12}(-a_{21}^1 - a_{21}^2) + c_{22}(1 - a_{22}^1 - a_{22}^2) \end{bmatrix}$$

where  $b_{11}$ , the contemporaneous effect of demand shocks on output, is equal to  $c_{21}(-a_{12}^1 - a_{12}^2)$ .

Effectively, the contemporaneous effect of demand shock on output depends on the coefficient of price in the output estimation and the long run impact of demand shock on price. However, as output was defined independently of price, the coefficients  $a_{12}^1$  and  $a_{12}^2$  will be equal to zero, and so that  $b_{11} = 0$ .<sup>10</sup> This implies that demand shocks do not affect output contemporaneously, or rather that demand shocks cannot be separately identified from supply shocks. So, given the common structure of the DGPs process, the SVAR would not be able to properly identify supply and demand shocks due to the lack of interaction of output and price in the DGPs.

This leaves two options: re-define the DGPs or use a B-model SVAR. The first option entails making the common structure of the DGPs more dynamic by introducing greater interaction between the price and output, rendering the interpretation of the MCS more elusive.<sup>11</sup> Alternatively, since we know the actual interaction between the supply and demand with output and price, we could define the contemporaneous relationship matrix  $B$ . It should be noted that when using the C-SVAR, as we do when choosing matrix  $B$ , we choose a  $C$  matrix with imposed restrictions that, based on theoretical conclusion, are assumed to be true. While the first option would allow the estimator to be tested along the lines of the empirical application in the fourth chapter, the second option does not increase the complexity of the

<sup>10</sup>Actually, all AR(2) coefficients, including  $a_{12}^2$ , will be zero, as neither output nor price were modeled as AR(2) processes.

<sup>11</sup>If the interaction of price and output were explicitly modeled, this would impact on the performance of the remaining estimators which do not account for price in the risk-sharing estimate. On the other hand, if a specific output process is used solely for the SVAR-IV estimation, this would prohibit the cross-comparison of the estimators performance.

dynamics behind the DGPs which facilitates the interpretation of the MCS results. And so, the SVAR will be a B-model structure, where the true B matrix is known and supplied to the estimator, which in turn allows us, with the DGP's at hand, to run SVARs that appropriately identify and separates output shocks into supply and demand shocks.<sup>12</sup> The B-matrix is defined as

$$\mathbf{B} = \begin{bmatrix} \psi & 1 \\ 1 & -1 \end{bmatrix} \quad (5.21)$$

### 5.2.5 Summary of the employed DGPs

Before proceeding with the MCS findings it is worth summarizing the DGPs. There are several key underlying assumptions that are common to each DGP. Firstly, demand and supply shocks drive consumption, output, and price. They are assumed to be identically and independently normally distributed. This distribution was chosen to mimic the characteristic of the supply and demand shocks that were derived using the SVAR in chapter 4 and essentially means that we do not have heteroskedasticity, serial correlation, or cross-sectional dependence. Output is both driven by demand and supply shocks and is modeled as an AR(1) with the same AR parameter across all cross-sections. Moreover, the unshared risk parameter is identical for all cross-sections. Consumption is modeled as being driven by output and demand shocks. No time fixed or cross-section fixed effects have been explicitly modeled. The aggregate shock is calculated using a weighted average with the weights being the same as those used in chapters 3 and 4. Also, the cross-section dimension has been fixed to 24 countries, while the time series is limited to 37. A relatively small and balanced panel was chosen to mimic the data used in chapter 3 and 4. And while this means the MCS is primarily geared towards risk-sharing, it does have wider implication for literature that deals with simultaneity bias in a relatively small balanced panel, as is common in many dimensions of annual international cross-country empirical analysis.

So far the discussion has been around the general structure that underlies each DGP, and before preceding with the MCS, it is also worth highlighting the various individual DGPs. There are three parameters that vary and therefore uniquely identify each DGP:  $\beta_u$  the unshared risk parameter,  $\alpha$  output's autocorrelation parameter, and  $\psi$  the parameter which sets out the extent demand shocks feed into output.

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<sup>12</sup>The SVAR allows for the construction of three different valid supply shock instruments; non-demeaned supply shock, unweighted cross-sectionally demeaned supply shock, and weighted cross-sectionally demeaned supply shock. All three would be exogenous and correlated with output. We use weighted cross-section demeaned supply shock as it is more intuitively in line with the risk-sharing literature which uses weighted cross-sectionally demeaned output.

$\beta_u$	$\alpha$	$\psi$	DGP	Y I(1)	Y endogenous	Biased estimators	Weak instruments or underidentified
0.8	0.5	0	1	No	No		
		0.5	2	No	Yes	Classical, Level	
		1	3	No	Yes	Classical, Level	
	0.95	0	4	No	No		FD2SLS, dGMM
		0.5	5	No	Yes	Classical, Level	FD2SLS, dGMM
		1	6	No	Yes	Classical, Level	FD2SLS, dGMM
	1	0	7	Yes	No		FD2SLS, dGMM
		0.5	8	Yes	Yes	Classical	FD2SLS, dGMM
		1	9	Yes	Yes	Classical	FD2SLS, dGMM
0.6	0.5	0	10	No	No		
		0.5	11	No	Yes	Classical, Level	
		1	12	No	Yes	Classical, Level	
	0.95	0	13	No	No		FD2SLS, dGMM
		0.5	14	No	Yes	Classical, Level	FD2SLS, dGMM
		1	15	No	Yes	Classical, Level	FD2SLS, dGMM
	1	0	16	Yes	No		FD2SLS, dGMM
		0.5	17	Yes	Yes	Classical	FD2SLS, dGMM
		1	18	Yes	Yes	Classical	FD2SLS, dGMM

Table 5.2: Individual DGPs

In terms of actual parameter values chosen,  $\alpha$  is varied between 0.5, 0.95, and 1. The values for  $\alpha$  that are bordering 1 are interesting because in that region both the dGMM and FD2SLS suffers from weak instruments and the Level-method is not consistent.  $\psi$  will be varied between 0, 0.5, and 1. This wide range is chosen to show how the estimators perform under a wide range of degree of endogeneity, while the wide steps of 0.5 are chosen to keep the MCS of a manageable size. The unshared risk coefficient,  $\beta_u$ , will take the values of 0.6 and 0.8 so that 40% and 20% of risk-sharing is taking place respectively. These values roughly correspond to the range of risk-sharing estimated by the alternative estimation methods in the fourth chapter and the medium run Level estimation in the third chapter.

Table (5.2) lays out each individual DGP as a combination of the three parameters. In total there are 18 individual DGPs. In addition, in the column labeled as ‘Y I(1)’, Table (5.2) summarizes the extent to which DGP is believed to have the possibility of non-stationary output and by extension consumption, and in the column labeled as ‘Y endogenous’ the extent to which DGP’s output is endogenous. The second to last column labeled as ‘Biased estimators’, Table (5.2) highlights for each DGP which estimation approach suffers from endogeneity bias. In the final column labeled as ‘Weak instruments or underidentified’, Table (5.2) summarizes which estimation approach is expected to suffer from weak or uncorrelated instruments for each DGP .

In summary, the Classical approach should be inconsistent in each DGP except when  $\psi = 0$ , because in that particular case output is not affected by demand shocks and thus should be exogenous. The Level approach, when  $\psi > 0$ , should only be consistent when  $\alpha = 1$ . Finally the FD2SLS and the dGMM suffer from weak instruments when  $\alpha = 0.95$  and from uncorrelated instruments when  $\alpha = 1$ .

## 5.3 Monte Carlo Simulation results

Before proceeding with the detailed presentation of the MCS findings, the four main findings that emerge from the MCS are highlighted and summarized:

### Main findings

- 1** The Classical approach over-estimates unshared risk by 23 to 48 percentage points when  $\psi > 0$ . This finding relates to Table (5.3), although similar findings are presented in Tables (5.4), (5.7), (5.8), (E.2), and (E.3).
- 2** The Classical approaches together with the Level approach have the lowest standard deviation of unshared risk parameter estimates. This relates to the results presented in Tables (5.5), (5.9), (5.13) and (E.4), with similar results presented in Tables (E.1), (E.5), and (E.7).
- 3** Overall, the SVAR-IV is the best performing alternative approach, for the following reasons:
  - a** The SVAR-IV mean and median estimate of the unshared risk parameter is close to the true value for higher values of  $\alpha$ , output's autocorrelation parameter, in particular when  $\alpha = 1$ . This relates to Tables (5.3), (5.4), (5.7), (5.8), (E.2), and (E.3).
  - b** The SVAR-IV's standard deviation of estimated unshared risk parameters, together with Classical and Level approaches, is one of the lowest. This finding relates to Tables (5.5), (5.9), (5.13) and (E.4.)
  - c** The SVAR-IV estimator is the best performing estimator in terms of test size, i.e. correctly not rejecting the true unshared risk value. This finding relates to the results presented in Tables (5.6), (5.10), (5.14), and (E.6).
  - d** Apart from the Classical and Level approaches, the SVAR-IV is also one of the best performing estimator in terms of test power, i.e. rejecting the false hypothesis of no rise in risk-sharing, making it one of the best performing estimator in identifying whether risk-sharing changed. This finding relates to Table (5.15).
- 4** The FD2SLS and dGMM perform poorly, especially the FD2SLS which appears to suffer from being exactly identified. This is a reoccurring theme throughout the MCS results below.

The first key finding is that for varying degrees of output autocorrelation and endogeneity bias, the Classical approach overestimates unshared risk by anywhere from 23 to 48 percentage points. Applying this finding to the Classical estimation of

around 27% risk-sharing in Table (3.1), this would suggest that actual risk-sharing could be between 50% to 75%. The second key finding confirms the fourth chapter in the conclusions that the alternative approaches for the most part are imprecisely estimated compared to the Classical approach. The third and fourth key finding confirm the fourth chapter in the conclusion that the SVAR-IV approach is more successful in generating a stronger instrument and thus in providing consistent risk-sharing parameters that are considerably more reliable than the FD2SLS and dGMM.

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.8007	0.8003	0.8001	0.7993	0.7948	0.7982	0.8002	0.9915
$\psi = 0.5$	1.1747	1.1814	1.0002	0.7939	0.7564	0.9295	0.8003	0.9530
$\psi = 1$	1.2753	1.2836	1.0503	0.7927	0.7149	0.9620	0.8002	0.9284
$\alpha = 0.95$								
$\psi = 0$	0.8007	0.8003	0.7999	0.7994	0.6749	0.7994	0.8004	0.8343
$\psi = 0.5$	1.0519	1.0795	0.8200	0.7947	-0.9117	0.8673	0.7988	0.8241
$\psi = 1$	1.1511	1.1811	0.8251	0.7937	1.3819	0.8846	0.7982	0.8205
$\alpha = 1$								
$\psi = 0$	0.8007	0.8003	0.8000	1.3302	5.5998	0.8010	0.8229	0.8000
$\psi = 0.5$	1.0277	1.0603	0.8000	1.0961	-0.3554	0.9369	0.9127	0.7992
$\psi = 1$	1.1262	1.1608	0.8001	0.9119	1.6519	0.9716	0.9280	0.7985

The MCS is based on 10,000 simulations.

Table 5.3: Mean estimated unshared risk parameters when  $\beta_u = 0.8$ .

Table (5.3) presents the mean of the estimated  $\beta_u$ , the unshared risk coefficients, over 10,000 simulations for a selection of risk-sharing estimation approaches. The true  $\beta_u$  in Table (5.3) is 0.8 which is equivalent to 20% risk-sharing. The first two column (I)-(II) present two variations of the Classical estimation; the first is the standard Classical estimation using a feasible GLS with an AR(1) correction (I) and the second is the Classical estimation using the panel corrected standard errors (PCSE) estimation approach (II). The next column is the Level approach without (III) country fixed effects.<sup>13</sup> This is followed by the two versions of the FD2SLS estimation, one using a two period lagged level of output as an instrument (IV)

<sup>13</sup>Given that no country fixed effects were modeled in the level of output or consumption, the Level estimation of unshared risk with fixed effects, referred to in the 3<sup>rd</sup> chapter as the medium run risk-sharing estimation, and the estimation without fixed effects, referred to as long run risk-sharing estimation in the 3<sup>rd</sup> chapter, would be the same. That is, the Level approach with country fixed effects would contain N-1 insignificant coefficients, the impact of which is that it has fewer degrees of freedom and thus is less efficient. Since we are more interested in the bias of the estimators and as the parameter estimates should be the same between the two Level approaches, we only present the Level estimates without country fixed effects.

and one where the instrument is a two period lagged first differenced output (V). This is then followed by two dGMM estimations with one using a non-collapsed two period lagged output (VI), and one using a collapsed two and three period lagged output (VII). The final column (VIII) shows the results for the SVAR derived IV risk-sharing estimation.

The first three rows present the results when the autocorrelation parameter,  $\alpha$ , is equal to 0.5, the next three rows present the results when output is close to a unit-root,  $\alpha = 0.95$ , and the last three rows present the results when output is a unit root process,  $\alpha = 1$ . In each case the endogeneity parameter,  $\psi$ , takes a different value: the first case is when output is exogenous,  $\psi = 0$ , the second and third allow output to be affected by demand with  $\psi$  taking values of 0.5 and 1 respectively. The first row for each autocorrelation value, when  $\psi = 0$ , represents the benchmark, in which the Classical approach provides consistent estimates because output is exogenous.

It is hardly surprising that when  $\psi = 0$  the Classical approach provides an approximately unbiased estimate of the unshared risk parameter of 0.8. However, as output becomes endogenous, the mean of the Classical approach parameter estimates quickly deviate from 0.8. The Classical GLS estimation, for example, overestimates unshared risk by 23 percentage points on average in the case of  $\alpha = 1$  and  $\psi = 0.5$ , and by 48 percentage points on average in the case of  $\alpha = 0.5$  and  $\psi = 1$ . For a given endogeneity parameter, the bias is negatively correlated with  $\alpha$ , the output autocorrelation parameter.

The Level, FD2SLS and dGMM also have mean point estimates close to 20% risk-sharing when  $\psi = 0$  and  $\alpha = 0.5$ . The Level approach, although clearly suffering from bias when  $\psi > 0$  and  $\alpha < 1$ , obtains a mean point estimate of 20% risk-sharing when output is a unit-root process. This is unsurprising as the Level approach benefits from superconsistency when output is a unit-root process.

The FD2SLS in (V), which uses first differenced two period lagged output, provides close to unbiased results of 0.8 when  $\alpha$  is low and  $\psi = 0$ . However, when  $\alpha$  is high, the instrument of the FD2SLS in (V) become inappropriate because the instrument becomes white noise which is uncorrelated with the endogenous variable, the first differenced output. Meanwhile, the instrument used in FD2SLS in column (IV), which is the level of lagged two period output, continues to provide reasonably unbiased estimates of  $\beta_u$  when  $\alpha$  is high, as the instruments remain correlated with first differenced output. However, both FD2SLS perform terribly in estimating  $\beta_u$  when  $\alpha = 1$ , as both the level and first differenced two period outputs are no longer valid instruments due to lack of correlation with the endogenous variable.

The non-collapsed two period lagged output dGMM in column (VI) suffers from bias as output is allowed to be endogenous regardless of the value  $\alpha$  takes. This

could potentially be due to over-fitting as the instruments falsely pick up elements of output that are actually endogenous.<sup>14</sup>

In contrast, the dGMM using the second and third collapsed lagged level of output in column (VII) performs adequately in providing unbiased estimates of  $\beta_u$  when  $\alpha < 1$ , but suffers from bias as  $\alpha = 1$ . Again this is expected as the instruments become increasingly weakly and eventually uncorrelated with the endogenous variable as  $\alpha$  approaches or is equal to 1.

Meanwhile, the SVAR-IV estimation performs poorly when  $\alpha = 0.5$ , with the mean estimate being greater than 0.8. However, the performance of SVAR-IV improves as  $\alpha$  increases. This indicates that for the SVAR to work we need persistence in output, i.e. if  $\alpha$  is very low, the SVAR has limited explanatory power as all the shocks appear as white noise and the SVAR cannot split demand from supply shocks. To this end the question is how high does  $\alpha$  have to be for the SVAR-IV estimation to perform well in providing unbiased estimate of  $\beta_u$ . Table (5.3) shows that in the case of  $\alpha = 0.95$ , the SVAR-IV still provides biased estimates, but when  $\alpha = 1$ , the SVAR appears to provide unbiased estimates, indicating that  $\alpha$  has to be very close to 1 for the SVAR to work.<sup>15</sup>

For completeness, but also because IV estimators like FD2SLS have no moments, including the mean, when, as is the case here, they are exactly identified, Table (5.4) presents the median of the estimated unshared risk parameters.<sup>16</sup> For the most part, the results in Table (5.4) mirror those in Table (5.3). Interestingly the median for the FD2SLS is closer to 0.8. For one, the FD2SLS in (IV) does have a median estimate close to 0.8 when  $\alpha = 1$  but  $\psi = 0$ . Furthermore, the FD2SLS in (V), while still suffering bias when  $\alpha$  is high, appears to have a median that is more in

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<sup>14</sup>The large amount of instruments used relative to the sample dimension can have an impact on the point estimate. More precisely, as presented in Davidson and MacKinnon (1993) (page 222-223), as the number of instruments increases, holding the sample size fixed, the finite-sample bias in the IV estimator approaches that of the biased OLS estimator. This occurs as the instrumented variables increasingly resembles the endogenous variable due to the instrumented variable increasingly also including the endogenous elements as more is explained of the endogenous variables. Hahn and Hausman (2002) provide an explicit expression for the finite-sample bias of the IV estimator including the case where the bias is increasing in the number of instruments.

<sup>15</sup>Further impacting the performance of the SVAR is the autoregressive process imposed on the underlying VAR. That is, an AR(2)-process is uniformly imposed for all countries, even though the actual DGPs is an AR(1). Furthermore, price is used to estimate output and vice versa, even though neither price nor output have an impact on each other in the DGP. Combined with that, since both price and output are driven by same normal distributed shocks, the VAR, therefore, might pick up a spurious relationship. These effects cause the reduced form residual to be incorrectly identified and thus provide an imperfect identification of the structural residual based on the correct B-matrix. That is, as  $\mathbf{e}$ , the reduced form residuals, are not correctly estimated, then because  $\mathbf{e} = \mathbf{B}\boldsymbol{\omega}$  the structural  $\boldsymbol{\omega}$  are not appropriately estimated either. In short, the SVAR is being over-fitted which can have an impact on the risk-sharing point estimates. Similar, Lütkepohl (1985) and Lütkepohl (2005) found that over-fitting an AR-process causes the forecasting error to increase.

<sup>16</sup>For a more detailed exposition of 2SLS estimator including its properties when exactly identified please see Davidson and MacKinnon (1993) chapter 7.5

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.8006	0.8002	0.8000	0.7989	0.7983	0.7976	0.7985	0.9913
$\psi = 0.5$	1.1748	1.1816	1.0000	0.7978	0.7997	0.9315	0.8025	0.9536
$\psi = 1$	1.2754	1.2834	1.0504	0.7997	0.8022	0.9653	0.8047	0.9294
$\alpha = 0.95$								
$\psi = 0$	0.8011	0.8003	0.7999	0.7989	0.7882	0.7988	0.8003	0.8346
$\psi = 0.5$	1.0511	1.0789	0.8199	0.7975	1.0010	0.8681	0.8024	0.8252
$\psi = 1$	1.1507	1.1805	0.8251	0.7984	1.0594	0.8853	0.8018	0.8223
$\alpha = 1$								
$\psi = 0$	0.8007	0.8004	0.8000	0.8002	0.8159	0.8020	0.8006	0.8004
$\psi = 0.5$	1.0269	1.0594	0.7999	0.8227	1.1897	0.9287	0.8472	0.8004
$\psi = 1$	1.1259	1.1601	0.8001	0.8280	1.2907	0.9643	0.8548	0.8004

The MCS is based on 10,000 simulations.

Table 5.4: Median of estimated unshared risk parameters when  $\beta_u = 0.8$ .

line with other estimators. In fact, that the results for the FD2SLS in the Table (5.4) appear more reasonable than in Table (5.3) is in line with the FD2SLS being exactly identified. That is, since the mean for the FD2SLS does not exist, large outliers can make the mean behave erratically. Meanwhile, the FD2SLS median exists and in the MCS results appears sensible. In fact, exactly identified IV estimators are median-unbiased which means that the median is approximately unbiased.<sup>17</sup>

The findings in Table (5.3) are reinforced by Table (5.5) which shows the corresponding standard deviation of the estimated unshared risk parameters. In line with the instrument of the FD2SLS in column (V) becoming weak- or uncorrelated with the endogenous variable when  $\alpha$  approaches or is equal to 1, the standard deviations of the estimated unshared risk parameter increases with  $\alpha$ , and are amongst the highest in Table (5.5) when  $\alpha = 0.95$  or  $\alpha = 1$ . Meanwhile, the instrument of the FD2SLS in column (IV), which is the level of lagged two period output, continues to provide reasonable estimates of unshared risk with limited standard deviation when  $\alpha = 0.95$ . However, both FD2SLS estimations show a very large degree of dispersion in estimating  $\beta_u$  when  $\alpha = 1$ , as both the level and first differenced lagged two period outputs are no longer valid instruments due to lack of correlation with the first differenced output, leading to high standard deviation in estimated unshared risk parameters. This is not surprising because, as previously mentioned the FD2SLS is exactly identified and has no moments. This would suggest that the FD2SLS estimator would have poor finite-sample properties when exactly identified,

<sup>17</sup>For a more detailed exposition see Angrist and Pischke (2009) section 4.6.4.

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.04091	0.03978	0.04935	0.12792	0.49559	0.11663	0.10268	0.04021
$\psi = 0.5$	0.03464	0.03325	0.03919	0.11519	1.74061	0.09779	0.09205	0.03472
$\psi = 1$	0.02383	0.02231	0.02457	0.09169	0.89016	0.06776	0.07293	0.03129
$\alpha = 0.95$								
$\psi = 0$	0.03604	0.03663	0.01535	0.11630	54.30505	0.10186	0.09557	0.03991
$\psi = 0.5$	0.03499	0.03358	0.01242	0.10531	238.1200	0.08737	0.08606	0.03938
$\psi = 1$	0.03000	0.02728	0.00773	0.08373	31.75176	0.06470	0.06823	0.03897
$\alpha = 1$								
$\psi = 0$	0.03438	0.03561	0.00988	27.30229	377.6000	0.15269	1.79173	0.04035
$\psi = 0.5$	0.03470	0.03330	0.00803	28.67869	137.6437	0.13746	1.57278	0.04040
$\psi = 1$	0.03090	0.02794	0.00500	28.03776	40.74899	0.11108	1.09527	0.04057

The MCS is based on 10,000 simulations.

Table 5.5: Standard deviation of the estimated unshared risk parameters when  $\beta_u = 0.8$ .

as found by Nelson and Startz (1990a,b).<sup>18</sup>

Both dGMMs tend to have some of the largest variances in estimating  $\beta_u$  apart from the FD2SLS estimators. This is not surprising given that the dGMM is an asymptotic estimator intended for a panel with a large cross-section and a small time dimension. In the case in which  $\alpha = 1$  both dGMMs have their highest standard deviation in estimating unshared risk parameters due to underidentification, because the instruments are no longer correlated with first differenced output.

Meanwhile, the Classical, the Level, and the SVAR-IV estimators have low standard deviations, with the Level unshared risk parameter standard deviation falling as  $\alpha$  increases. For completeness, the Table containing the mean squared error for the estimated unshared risk parameters when  $\beta_u = 0.8$  can be found in appendix E.1. It echoes the results found in Table (5.5).

Table (5.6) shows the test size for each estimator: the rejection rate for a two sided t-test with a 5% significance level when the  $H_0 : \beta_u = 0.8$  versus  $H_A : \beta_u \neq 0.8$ . The rejection of  $H_0$  implies that the estimator falsely concludes that  $\beta_u \neq 0.8$  although  $\beta_u = 0.8$  in the underlying DGPs, i.e. the higher the rejection rate the worse the estimator is in estimating the unshared risk. Given that the chosen significance level is 5%, a correctly-sized test implies that the  $H_0$  should be rejected around 5% of the times.

The GLS estimator has a poor performance, with its rejection rate remaining

<sup>18</sup>For a more detailed exposition see Davidson and MacKinnon (1993) (pages 221-222).

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	40.29%	7.58%	37.22%	1.67%	2.83%	3.57%	7.44%	99.02%
$\psi = 0.5$	100%	100%	100%	2.11%	4.87%	23.21%	7.38%	95.95%
$\psi = 1$	100%	100%	100%	2.48%	7.2%	54.69%	7.79%	91.41%
$\alpha = 0.95$								
$\psi = 0$	32.58%	4.57%	35.52%	0%	.03%	3.29%	6.23%	4.49%
$\psi = 0.5$	100%	100%	76.65%	0%	.75%	9.39%	6.42%	3.32%
$\psi = 1$	100%	100%	98.73%	0%	3.08%	19.6%	6.46%	3.23%
$\alpha = 1$								
$\psi = 0$	30.85%	4.08%	34.74%	0%	.02%	2.93%	1%	1.15%
$\psi = 0.5$	100%	100%	34.64%	0%	.23%	11.46%	1.38%	1.16%
$\psi = 1$	100%	100%	34.56%	0%	1.78%	26.31%	2.37%	1.19%

The MCS is based on 10,000 simulations. Two-sided t-test with 5% significance level.

Table 5.6: Test size: rejection rate for 5% significance level when testing  $H_0 : \beta_u = 0.8$ .

well above 5% in every case, even when it provides unbiased parameter estimates in the case of  $\psi = 0$ . This could be due to the GLS over fitting the errors given that the GLS, as applied here, adjusts for an AR(1) even though the errors are not AR(1) which can impact the standard errors.<sup>19</sup>

Meanwhile, the PCSE in (II) performs well when  $\psi = 0$ , with the nominal rejection rate close to 5%. Even though the PCSE, like the GLS, corrects for elements in the error which are not present in the DGP, it does it in a way that allows the PCSE to reduce the error to the correct form of homoskedasticity and no serial correlation. As  $\psi \neq 0$  the rejection rate of the PCSE estimator increases in line with its estimates becoming biased.

The rejection rate of the Level estimation is too high as it remains well above 5% in every case, even when it provides unbiased estimate in case of  $\alpha = 1$ . However, caution needs to be taken when considering the rejection rate of the Level estimator as the hypothesis test in Table (5.6) is not valid if consumption and output are unit root.

The rejection rate of the FD2SLS estimators are too low, as they under reject the  $H_0$ . This is due to the FD2SLS standard error being so large that the 95% confidence ranges are sufficiently large to continuously include 0.8. This is not surprising,

<sup>19</sup>A reminder, when  $\psi > 0$ , the GLS and PCSE estimation approaches provide biased parameter estimates.

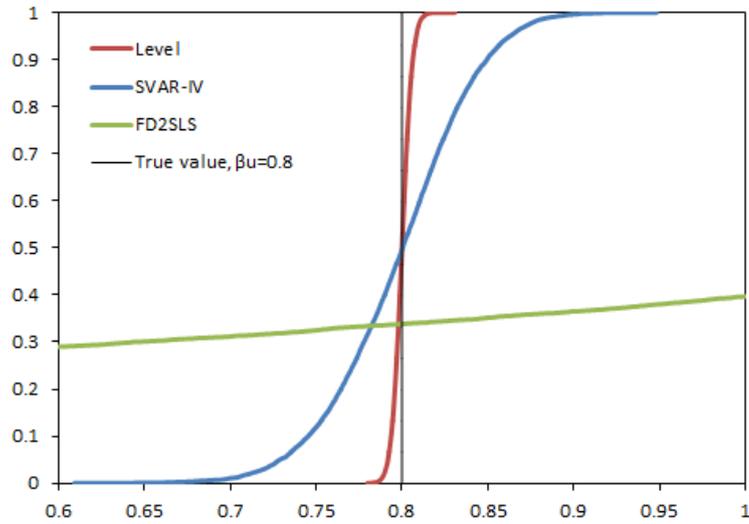


Figure 5.1: Distribution function of the FD2SLS, Level, and SVAR-IV estimators

since, as mentioned above, the FD2SLS is exactly identified and accordingly suffers from poor finite-sample properties. Furthermore, in the case of  $\alpha = 0.95$  or  $\alpha = 0.1$ , the FD2SLS estimators suffer from weak identification and underidentification respectively.

The dGMM estimations have a low rejection rate, especially when  $\alpha$  is high, which is not surprising given that like FD2SLS, dGMM should suffer from weak identification or underidentification and consequently have large standard errors. Meanwhile, the SVAR-IV performs best in Table (5.6) when  $\alpha = 0.95$  with a rejection rate close to 5%. However, the SVAR-IV performs best in providing unbiased estimates when  $\alpha = 1$ .

Looking at all the tables combined, it is quite clear that the FD2SLS suffers from extreme outliers, which as mentioned above, is related to poor small sample performance combined with weak identification when  $\alpha = 0.95$  or underidentification when  $\alpha = 1$ . To visualize the extent of the poor performance, Fig. (5.1) shows the distribution function of the FD2SLS  $\mathbf{Z}^{fd}$  estimator and in comparison those of the SVAR-IV and Level when  $\beta_u = 0.8$ ,  $\alpha = 1$ , and  $\psi = 1$ . In the 10,000 replications, the FD2SLS estimator estimated a maximum coefficient of 3108 and a minimum of -1362. Consequently, the view is limited to the range of  $0.8 \pm 0.2$  as otherwise the extreme values of the FD2SLS estimator would dominate the scale, rendering it largely unreadable for the SVAR-IV and Level distribution. From Fig. (5.1) it is quite clear that FD2SLS suffers from extreme outliers and is fairly imprecise, while both the Level and SVAR-IV estimators suffer less from extreme outliers than FD2SLS and are tightly grouped around 0.8, the value of  $\beta_u$ .

The MCS was also run for the entire time period with  $\beta_u = 0.6$ . For the most part the results were similar to the MCS with  $\beta_u = 0.8$ . Also, the bias of the

estimators in over-estimating unshared risk in percentage points was also similar to the  $\beta_u = 0.8$  case. For example the Classical GLS over-estimated unshared risk by 23% on average in the case of  $\alpha = 1$  and  $\psi = 0.5$ , and by 48% on average in the case of  $\alpha = 0.5$  and  $\psi = 1$ .<sup>20</sup> The tables for the MCS with 40% risk-sharing can be found in Appendix (E.2).

### 5.3.1 MCS and sub-period estimation

In addition to the MCS for the entire time series, the MCS was also run using a shorter period of 20 time periods; this is equivalent to the 1970-1990 sub-period in the previous chapters.<sup>21</sup> Given that some of these alternative estimators rely on asymptotic properties, running the estimation approaches on smaller samples highlights to what extent the estimators performance is impacted on by a shorter sample. The DGP, for the 20 time period MCS, have a true unshared risk parameter of 0.8,  $\beta_u = 0.8$ .

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.8008	0.8007	0.7990	0.8005	0.7682	0.7968	0.8004	0.9923
$\psi = 0.5$	1.1818	1.1849	1.0000	0.7880	0.6522	0.9301	0.8004	0.9528
$\psi = 1$	1.2842	1.2881	1.0502	0.7845	0.6176	0.9627	0.8004	0.9276
$\alpha = 0.95$								
$\psi = 0$	0.8003	0.8004	0.7994	0.8447	-0.6767	0.7999	0.8087	0.8348
$\psi = 0.5$	1.0724	1.0885	0.8198	0.7942	-8.4303	0.9056	0.8042	0.8238
$\psi = 1$	1.1737	1.1916	0.8249	0.7697	-4.7786	0.9328	0.8062	0.8193
$\alpha = 1$								
$\psi = 0$	0.8003	0.8004	0.7995	0.1976	-60.404	0.7997	0.7981	0.8002
$\psi = 0.5$	1.0483	1.0681	0.7999	1.0469	0.2387	0.9927	0.9402	0.7986
$\psi = 1$	1.1498	1.1702	0.7999	1.6185	3.0652	1.0432	0.9975	0.7970

The MCS is based on 10,000 simulations.

Table 5.7: Mean estimated unshared risk parameters for when  $\beta_u = 0.8$  and time is limited to 20 periods.

Following the same structure as Table (5.3), Table (5.7) shows the results when the time dimension is limited to 20 and  $\beta_u = 0.8$ . Unsurprisingly, when output is

<sup>20</sup>That is when  $\alpha = 1$  and  $\psi = 1$ , and  $\beta_u = 0.8$  the Classical GLS has a mean estimate of 1.1262, and 0.9262 when  $\beta_u = 0.6$ . In both case unshared risk is overestimated by around 0.33.

<sup>21</sup>We forgo presenting results for MCS that like the sub-period 1990-2007 has 18 period as the conclusions are the same as for 20 periods.

exogenous, the Classical approach, together with most other estimators, appropriately finds on average unshared risk to be 0.8. And much like the case in Table (5.3), as output becomes endogenous the Classical approach overestimates unshared risk. This time the Classical approach overestimates the unshared risk by 25 percentage points on average in the case of  $\alpha = 1$  and  $\psi = 0.5$ , and by 49 percentage points on average in the case of  $\alpha = 0.5$  and  $\psi = 1$ , which is around 3 percentage points higher at the lower end than in Table (5.3). This could be an effect of the shorter time period.

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.8011	0.8005	0.7990	0.7993	0.7998	0.7966	0.8013	0.9912
$\psi = 0.5$	1.1821	1.1852	0.9998	0.8007	0.8141	0.9352	0.8082	0.9539
$\psi = 1$	1.2842	1.2880	1.0508	0.8013	0.8122	0.9693	0.8111	0.9298
$\alpha = 0.95$								
$\psi = 0$	0.8002	0.8003	0.7993	0.8043	0.7972	0.8002	0.8022	0.8350
$\psi = 0.5$	1.0717	1.0877	0.8197	0.8033	1.0932	0.9021	0.8114	0.8249
$\psi = 1$	1.1734	1.1908	0.8251	0.7987	1.1519	0.9282	0.8123	0.8223
$\alpha = 1$								
$\psi = 0$	0.8002	0.8002	0.7997	0.7870	0.8089	0.8011	0.7924	0.8000
$\psi = 0.5$	1.0476	1.0672	0.8000	0.8339	1.2040	0.9788	0.8780	0.8000
$\psi = 1$	1.1490	1.1698	0.8001	0.8492	1.3098	1.0305	0.8986	0.8001

The MCS is based on 10,000 simulations.

Table 5.8: Median of estimated unshared risk parameters when  $\beta_u = 0.8$  and time is limited to 20 periods.

For completeness, Table (5.8) presents the median and Table (5.9) the standard deviations of the estimated unshared risk parameter when  $\beta_u = 0.8$  and time is limited to 20 periods. Table (5.8) and Table (5.9) in line with Table (5.7), show similar results to the MCS run for  $\beta_u = 0.8$  and over 38 periods with differences being driven by the shorter time period. The associated mean squared error Table can be found in appendix E.3.

Table (5.10) shows the percentage share of t-tests rejecting the  $H_0 : \beta_u = 0.8$  in favor of  $H_A : \beta_u \neq 0.8$  for the sub-period MCS restricted to 20 time periods. For the most part, the findings in Table (5.10) are the same as in Table (5.6), apart from the fact that the rejection rates are higher, which reflects the shorter time period of 20 units in comparison to 38 in Table (5.6), leading to larger standard errors.

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.05611	0.05650	0.06961	0.19269	2.78145	0.16700	0.15490	0.06787
$\psi = 0.5$	0.04691	0.04707	0.05561	0.17495	3.52830	0.14216	0.13945	0.05937
$\psi = 1$	0.03189	0.03171	0.03521	0.14101	7.24057	0.09998	0.11063	0.05412
$\alpha = 0.95$								
$\psi = 0$	0.05052	0.05262	0.02521	2.88327	94.2059	0.18503	0.55620	0.06926
$\psi = 0.5$	0.04863	0.04793	0.02045	1.87699	936.6776	0.16273	0.33709	0.06846
$\psi = 1$	0.04122	0.03863	0.01283	0.40674	492.0937	0.12352	0.34850	0.06796
$\alpha = 1$								
$\psi = 0$	0.04798	0.05086	0.01964	24.24639	5892.612	0.26654	1.77714	0.06995
$\psi = 0.5$	0.04878	0.04738	0.01598	166.1939	123.8111	0.23713	1.85229	0.07007
$\psi = 1$	0.04288	0.03956	0.00995	50.35804	108.8950	0.18450	1.64953	0.07055

The MCS is based on 10,000 simulations.

Table 5.9: Standard deviation of estimated unshared risk parameters when  $\beta_u = 0.8$  and time is limited to 20 periods.

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	70.09%	8.14%	48.61%	1.34%	1.3%	8.02%	6.96%	77.7%
$\psi = 0.5$	100%	100%	99.7%	1.99%	4.78%	22.9%	7.38%	67.42%
$\psi = 1$	100%	100%	100%	2.85%	8.87%	45.32%	8.18%	60.23%
$\alpha = 0.95$								
$\psi = 0$	65.21%	5.31%	45.44%	0%	.06%	7.6%	3.43%	5.67%
$\psi = 0.5$	100%	100%	62.97%	.02%	.84%	13.93%	3.51%	5.13%
$\psi = 1$	100%	100%	87.91%	.02%	2.97%	24.6%	4.34%	5.19%
$\alpha = 1$								
$\psi = 0$	62.99%	4.69%	44.51%	0%	.01%	6.38%	1.21%	3.34%
$\psi = 0.5$	100%	100%	45.04%	0%	.31%	14.67%	1.73%	3.27%
$\psi = 1$	100%	100%	45.11%	0%	1.76%	27.62%	2.79%	3.4%

The MCS is based on 10,000 simulations. Two-sided t-test with 5% significance level.

Table 5.10: Sub-period Test seize: rejection rate for 5% significance level when testing  $H_0 : \beta_u = 0.8$ .

### 5.3.2 MCS and identifying an increase in risk-sharing

To validate the finding of increasing risk-sharing in previous chapters, in this section we look at how well the alternative estimation approaches perform in estimating increasing risk-sharing.

Specifically, to test how each estimator performs in estimating a increase in risk-sharing, Eq. (5.5) was modified to have 0.8 unshared risk for the first 20 periods and 0.6 unshared risk thereafter such that Eq. (5.5) was modified to have the format:

$$\mathbf{c} = \beta_{u,1}\mathbf{y} + \beta_{u,2}\mathbf{d}\mathbf{y} + \boldsymbol{\epsilon}^D \quad (5.22)$$

where  $\beta_{u,1} = 0.8$ ,  $\beta_{u,2} = -0.2$ , and  $\mathbf{d}$  is a vector consisting of 0 when  $t < 21$  and 1 when  $t > 20$ .

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	-0.2009	-0.2013	-0.1980	-0.2016	0.0696	-0.2007	-0.1980	-0.2008
$\psi = 0.5$	-0.2048	-0.2051	-0.1992	-0.2056	0.4756	-0.1950	-0.1963	-0.2007
$\psi = 1$	-0.2069	-0.2066	-0.1994	-0.2060	-0.4457	-0.1930	-0.1966	-0.2007
$\alpha = 0.95$								
$\psi = 0$	-0.2001	-0.2002	-0.1993	-0.2012	0.1470	-0.1983	-0.1995	-0.2008
$\psi = 0.5$	-0.2165	-0.2143	-0.1997	-0.2042	-9.0001	-0.1875	-0.1970	-0.2006
$\psi = 1$	-0.2217	-0.2178	-0.1999	-0.2052	2.9339	-0.1847	-0.1961	-0.2004
$\alpha = 1$								
$\psi = 0$	-0.1999	-0.1998	-0.1996	-0.2519	0.6584	-0.1993	-0.1983	-0.2003
$\psi = 0.5$	-0.2189	-0.2151	-0.1998	-0.5061	-2.3954	-0.2014	-0.1921	-0.2001
$\psi = 1$	-0.2242	-0.2190	-0.2000	-0.1440	1.1050	-0.2017	-0.1880	-0.1999

The MCS is based on 10,000 simulations.

Table 5.11: Mean of estimated unshared risk parameter  $\beta_{u,2}$ .

Table (5.11) presents the mean estimated  $\beta_{u,2}$  parameters. For the most part results are similar to the results in preceding sections. The Classical estimators in (I) and (II) perform well in estimating unbiased parameter when  $\psi = 0$ , but provide biased estimates as  $\psi$  increases. The Level estimator in (III) performs best in estimating unbiased  $\beta_{u,2}$  when  $\alpha = 1$ . The FD2SLS in (V) appears yet again to perform badly in any case, while the FD2SLS in (IV) performs reasonably well till  $\alpha = 1$ . Interestingly, the dGMM in (VI) performs better than the dGMM in (VII) when  $\alpha = 1$ . Also interesting to note, the SVAR-IV, beside having its best performance in providing unbiased parameter estimates when  $\alpha=1$ , in almost all case it is also the best performing estimator.

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	-0.2010	-0.2020	-0.1985	-0.2032	-0.2069	-0.2024	-0.1959	-0.2027
$\psi = 0.5$	-0.2040	-0.2048	-0.1979	-0.2004	-0.1993	-0.1935	-0.1946	-0.2024
$\psi = 1$	-0.2068	-0.2064	-0.1987	-0.1991	-0.2057	-0.1934	-0.1942	-0.2022
$\alpha = 0.95$								
$\psi = 0$	-0.2000	-0.2003	-0.1994	-0.1988	-0.2248	-0.1995	-0.1992	-0.2011
$\psi = 0.5$	-0.2165	-0.2144	-0.1999	-0.1997	-0.1359	-0.1886	-0.1961	-0.2012
$\psi = 1$	-0.2221	-0.2180	-0.1997	-0.1995	-0.1435	-0.1856	-0.1942	-0.2012
$\alpha = 1$								
$\psi = 0$	-0.1999	-0.1995	-0.1998	-0.1988	-0.2088	-0.2001	-0.1991	-0.2012
$\psi = 0.5$	-0.2189	-0.2149	-0.2001	-0.1963	-0.1779	-0.2011	-0.1968	-0.2011
$\psi = 1$	-0.2242	-0.2188	-0.1999	-0.1967	-0.2094	-0.2012	-0.1953	-0.2009

The MCS is based on 10,000 simulations.

Table 5.12: Median of estimated unshared risk parameter  $\beta_{u,2}$ .

Table (5.12) presents the median for estimated  $\beta_{u,2}$  parameters. As is the case in the previous section, although still biased, the FD2SLS appears more in line with the the other estimators. Also in comparison, the dGMM in (VI) and the SVAR-IV appear to perform equally well when  $\alpha = 1$  and  $\psi > 0$ . Moreover, the Level estimator, when  $\alpha$  is equal to 0.95 and 1, is the best performing estimator.

For completeness, Table (5.13) presents the standard deviation of the estimated  $\beta_{u,2}$  parameters. The findings in Table (5.13) are in line with the standard deviations in the previous section; for example, the FD2SLSs and dGMMs estimators have the largest variances.

Table (5.14) presents the rejection rate for a two-sided t-test with a 5% significance level and  $H_0 : \beta_2 = -0.2$  versus  $H_A : \beta_{u,2} \neq -0.2$ . The findings in Table (5.14) are the same as in the previous section apart from the PCSE performing well with rejection rate near the acceptable 5%, despite providing biased estimates of  $\beta_{u,2}$  when  $\psi > 0$ . Moreover, the SVAR-IV is one of the best performing estimators in all cases with near 5% rejection rate, although still performing the best when  $\alpha = 0.95$ .

Finally, Eq. (5.22) allows us to test the performance of the estimators in identifying increases in risk-sharing by testing  $\beta_{u,2}$  with the  $H_0 : \beta_{u,2} = 0$ . This is in line to the parameter test introduced in the 3<sup>rd</sup> chapter to test whether the unshared risk parameter changed between 1970-1990 and 1991-2007 period. Given that we know  $H_0 : \beta_{u,2} = 0$  is false, we are testing whether the estimators falsely do not reject the null hypothesis, and thus do not identify an expansion in risk-sharing.

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.08194	0.07846	0.10112	0.27180	19.61504	0.23401	0.22000	0.10604
$\psi = 0.5$	0.06748	0.06458	0.08118	0.24669	63.48419	0.19655	0.19888	0.09379
$\psi = 1$	0.04559	0.04264	0.05082	0.19845	14.95547	0.13856	0.15819	0.08612
$\alpha = 0.95$								
$\psi = 0$	0.05467	0.05493	0.03296	0.29718	277.1697	0.10472	0.12586	0.11080
$\psi = 0.5$	0.05021	0.04853	0.02692	0.13748	1186.235	0.09210	0.10755	0.10952
$\psi = 1$	0.04071	0.03746	0.01686	0.12314	255.4530	0.07170	0.08726	0.10919
$\alpha = 1$								
$\psi = 0$	0.04187	0.04265	0.02270	11.51990	267.5036	0.09839	0.17712	0.11245
$\psi = 0.5$	0.03947	0.03834	0.01857	33.13100	211.9364	0.08540	0.14574	0.11292
$\psi = 1$	0.03288	0.03035	0.01166	5.80391	167.7534	0.06904	0.15483	0.11418

The MCS is based on 10,000 simulations.

Table 5.13: Standard deviation of estimated unshared risk parameter  $\beta_{u,2}$ .

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	41.1%	7.76%	36.71%	1.53%	1.46%	3.25%	7.08%	6.39%
$\psi = 0.5$	38.93%	7.19%	36.27%	1.3%	1.28%	2.98%	6.78%	6.35%
$\psi = 1$	36.36%	5.67%	37.06%	.72%	.51%	2.73%	6.32%	5.96%
$\alpha = 0.95$								
$\psi = 0$	33.24%	5.08%	35.69%	.01%	.04%	3.02%	6.02%	6.04%
$\psi = 0.5$	32.95%	5.47%	37.5%	0%	.01%	3.27%	6.07%	5.93%
$\psi = 1$	32.2%	5.57%	37.18%	0%	.05%	3.76%	6.56%	5.72%
$\alpha = 1$								
$\psi = 0$	30.67%	4.96%	36.54%	0%	0%	2.74%	2.12%	6.14%
$\psi = 0.5$	32.63%	5.91%	37.55%	0%	0%	2.76%	2.09%	6.02%
$\psi = 1$	34.83%	7.03%	36.89%	0%	.01%	3.26%	2.52%	5.58%

The MCS is based on 10,000 simulations.

Table 5.14: Test size: rejection rate for 5% significance level when testing  $H_0 : \beta_{u,2} = -0.2$ .

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	96.12%	85.67%	88.08%	12.29%	5.58%	16.71%	26.47%	63.16%
$\psi = 0.5$	99%	95.05%	95.29%	13.22%	4.79%	19.62%	29.83%	71.48%
$\psi = 1$	99.98%	99.89%	99.88%	18.26%	4.63%	30.84%	40.35%	77.44%
$\alpha = 0.95$								
$\psi = 0$	99.65%	97.39%	100%	5.58%	.44%	61.63%	62.55%	59.28%
$\psi = 0.5$	99.93%	99.53%	100%	7.18%	.53%	65.49%	68.84%	60.18%
$\psi = 1$	100%	100%	100%	15.25%	.79%	75.38%	82.92%	60.77%
$\alpha = 1$								
$\psi = 0$	99.95%	99.61%	100%	3.95%	.15%	75.09%	59.22%	58.29%
$\psi = 0.5$	100%	100%	100%	7.44%	.27%	76.12%	62.58%	57.99%
$\psi = 1$	100%	100%	100%	18.87%	.46%	81.09%	71.05%	57.6%

The MCS is based on 10,000 simulations. One-sided t-test with 5% significance level.

Table 5.15: Test power: rejection rate for a 5% significance level.

Table (5.15) presents the rejection rate for a one sided t-test with 5% significance level testing the  $H_0 : \beta_{u,2} \geq 0$  versus the  $H_A : \beta_{u,2} < 0$ . The higher the rejection rate the better the estimation approach is in validating an increase risk-sharing. Both the GLS in (I) and the PCSE in (II) have a high rejection rate which means they appropriately identify an increase in risk-sharing, which is in line with the test size which suggest these they reject practically everything, all the time, whether true or not, including rejecting a false null. However, one needs to be cautious in that the estimates for both GLS and PCSE are biased when  $\psi > 0$ . Meanwhile, the Level approach also tends to reject the  $H_0$ , especially when  $\alpha$  is high. However, once again one needs be cautious when considering the Level hypothesis test. The Level approach only provides consistent estimate when consumption and output are non-stationary in which case the hypothesis tests are invalid. The low rejection rate for the FD2SLS to reject the  $H_0 : \beta_{u,2} \geq 0$  is not surprising given the wide confidence intervals. Meanwhile, the dGMMs tends to have more than 50% rejection rate but only when  $\alpha = 0.95$  or  $\alpha = 1$ . However, when  $\alpha = 0.95$  or  $\alpha = 1$  the dGMMs suffer from weak identification or underidentification respectively. The SVAR-IV performance meanwhile shows high rejection of the  $H_0 : \beta_{u,2} \geq 0$  when  $\alpha = 0.5$  and even though the rejection rate falls as  $\alpha$  increases it remains above 50%.

Combining the results in Table (5.14) and (5.15) it can be concluded that the best performing estimator for estimating an change in risk-sharing is the SVAR-IV estimator. The SVAR-IV nominal rejection rate in Table (5.14) is close to 5% for all values of  $\alpha$  and  $\psi$ , while having a decent rejection rate of a false null hypothesis

in Table(5.15). Additionally, SVAR-IV provides means and medians that are close to the appropriate -0.2 in Tables (5.11) and (5.12).

## 5.4 Conclusion

This chapter set out to consolidate the hypothesis of the third and fourth chapters that the Classical approach suffers from bias due to endogeneity while validating the alternative approaches, and in so doing confirming the second, third, and fourth chapters that an actual rise in risk-sharing occurred.

The following conclusions can be drawn from the MCS. Firstly, based on Tables (5.3), (E.2), (5.7), and (5.11), the performance of the estimators across varying  $\psi$  and  $\alpha$  is independent of the value of  $\beta_u$ . For one this would indicate that the risk-sharing findings in the Classical literature, which do not account and correct for the endogeneity, are equally bias and independent of the extent of the risk-sharing. This would also suggest that some correction mechanisms can be developed to correct for the bias in the Classical literature results.

Furthermore, the MCS highlights that the Classical estimation is prone to underestimating the actual risk-sharing by 23 to 48 percentage point when output is endogenous and where the bias is positively correlated with the  $\psi$ , and negatively correlated with  $\alpha$ . Moreover, based on Table (5.15), the Classical approach even though provides bias estimates when  $\psi > 0$ , it does in most cases identify an increase in risk-sharing.

In regards to the performance of the alternative approaches, when  $\alpha$  is high and  $\psi > 0$ , the Level and SVAR-IV estimators in general perform the best in estimating unshared risk, while the FD2SLS performs the worst.<sup>22</sup> However, for the SVAR-IV to provide an unbiased estimates of  $\beta_u$ ,  $\alpha$  needs to be very close to 1, and SVAR-IV best performance in test size is when  $\alpha = 0.95$ . This bring us to the key question of whether the Level or SVAR-IV is the best suited to estimate risk-sharing. The SVAR-IV looks at current shocks regardless of their permanent nature, while the Level estimation, as argued in the second and third chapters, looks at long run relationships between consumption and output. The DGPs did not explicitly distinguish between permanent and temporal supply and demand shocks beyond whether demand and output has perfect or diminishing memory. However, for the sake of monetary union and aspect of risk-sharing, the interest would be with the

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<sup>22</sup>That is the FD2SLS mean appears erratic. However, this is a consequence of FD2SLS being exactly identified and having no mean and having large tails in distribution of the parameter estimate. However, as the FD2SLS is exactly identified it does benefit from approximate median unbiasedness.

aspect of the extent to which temporal shocks are insured which makes the SVAR-IV the optimal choice for risk-sharing estimation. Furthermore, in case of identifying changing risk-sharing, the SVAR-IV performed the best based on one of the best combination of size and power properties. That is, the SVAR-IV nominal rejection rate close to 5% and has a decent rejection rate of the false null hypothesis of no increase in risk-sharing.

The general structure of the DGPs offers opportunities for future research expansions. For one, the interactivity between output and price can be enhanced to allow for the C-Matrix SVAR to be used. The modeling of the interactivity would not directly impact the results of the Classical, Level, FD2SLS, or dGMM, as the relationship would not impact the relationship between consumption and output on which the risk-sharing estimation depends. So, while adding more complexity, it would be a marginal extension to the current DGPs. The second opportunity is to explore the concept of memory in the output process. In the current setup, shocks are modeled as i.i.d. This can be extended to allow shocks to be correlated across time and cross-section. That is, a positive shock in the previous period would increase the probability of a positive shock the current period, and similarly a positive shock in a neighboring country increases the probability of a positive shock at home. However, this was not done as it would increasingly obscure the DGPs process and thus would lose the clarity of interpretation.

Moreover, the MCS has been set up with the express purpose of simulating the circumstances that the international risk-sharing literature, including this thesis, commonly face. For example, the dimensions of the cross-section and time series were chosen to reflect the time dimension of the data used in chapter 3 and 4. Future research can allow for wider varying sample sizes to allow for greater in-depth analysis of the performance of the asymptotic estimators in smaller or greater samples or differently balanced time series versus cross-sections. However, that is not to say that the MCS as applied here does not have applications beyond the risk-sharing literature. For one, it reinforces the finding that the exactly identified IV-estimation –FD2SLS, is subject to wide dispersion in estimating parameters, but is still median-unbiased. It also contributes to the wider literature that uses similar data, that is research looking at estimation using OECD data, and relatively small and balanced panel data. In this context the MCS reinforces the fact that while asymptotic estimators can provide consistent results in the presence of simultaneity bias, this comes at the cost of increasingly imprecise estimation which hinders the interpretation of shifts in parameters. Moreover, the MCS supports the interpretation that in relatively small and balanced panels, the SVAR-IV with one good instrument, the supply shock, is a better choice compared to the many, but potentially weak instruments put forward by the dGMM.

# Chapter 6

## Conclusion

Risk-sharing looks at the correlation between a country's idiosyncratic output fluctuations and its idiosyncratic consumption movements. The importance of risk-sharing for any monetary union is that a high risk-sharing renders a collective monetary policy more appropriate as it increasingly mimics the country's individual monetary policies. The literature has developed two distinct empirical approaches to quantify the extent of risk-sharing amongst a group of countries: the Classical (or ASY) approach and the Level approach. Both approaches have their differences but essentially investigate the correlation of idiosyncratic consumption with idiosyncratic output. The third chapter applied these two approaches to a sample of 24 OECD countries and found that between 1970-1990 and 1991-2007 the Classical approach yielded no rise in risk-sharing with risk-sharing of around 27% between 1970-1990 and 23% between 1991-2007. This result is analogous to the findings of the Classical empirical literature. However, when the Level method was applied we found rising risk-sharing, as is common in the Level literature, going from 19% in 1970-1990 to 37% for 1991-2007. The estimations in the third chapter were undertaken as a stepping stone for the fourth chapter where the same data was used. That is, it was important to show that similar results to those found in the literature can be obtained with the data, such that any difference in results in the fourth chapter are due to the methods employed.

The fourth chapter set out to ease the commonly imposed assumption of exogeneity in case of risk-sharing estimation. In addition to a discussion of the impact on risk-sharing estimation when output is endogenous, the fourth chapter presented various estimators that should provide consistent results in the presence of simultaneity bias. The alternative estimators presented were: Anderson and Hsiao (1981, 1982) FD2SLS estimator, Holtz-Eakin et al. (1988) dGMM estimator and an IV-estimation based on instruments derived from Bayoumi and Eichengreen (1993) SVAR (SVAR-IV). The fourth chapter found that when comparing the results to

the Classical approach, where no rise in risk-sharing was found, the dGMM and the SVAR-IV approaches, like the Level approach in the third chapter, estimated rising risk-sharing. However, for the most part, the SVAR-IV and dGMM risk-sharing parameters were estimated imprecisely, leading to the increase in risk-sharing being found to be insignificantly different from zero. This makes it impossible to provide a conclusive argument for or against a rise in risk-sharing. This is interesting since the literature's Classical estimates presented in the second chapter tend to be precisely estimated, supporting the idea that the robustness comes at a price; estimates can either be imprecise but consistent estimate or precise but inconsistent. In addition, the fourth chapter concluded that the SVAR-IV risk-sharing estimates are considerably more reliable than FD2SLS and dGMM, mainly because the strategy of constructing an instrument using the SVAR approach generated a much stronger instrument.

The fifth chapter set out to consolidate the findings of the fourth chapter by using a Monte Carlo Simulation (MCS) to demonstrate the extent of the bias the Classical approach estimates suffer when output is endogenous, and identify, under various condition, which alternative approach is the best suited for risk-sharing estimation. The fifth chapter concluded that the Classical approach can underestimate risk-sharing by 23 to 48 percentage points, which if applied to the Classical findings for the period 1970-2007 in the third chapter, means that risk sharing could be between 51% and 76% instead of the 28%. Furthermore, the fifth chapter concluded that the Level estimation performed well, but due to differences in the nature of the shock the Level methodology investigates, as discussed in the second, third and fourth chapters, that the SVAR-derived IV estimation is the best suited for risk-sharing estimation.

Overall, the thesis makes two main contributions to the literature. The first is the explicit discussion of the presence of simultaneity bias that affects the risk-sharing estimation approach as commonly applied in the literature, and accordingly the presentation of alternative approaches from other parts of the economic literature that should provide robust estimates. Of these alternative approaches, the most novel approach and a unique contribution to the literature, as well as best performing estimator in estimating risk-sharing, is an IV-estimation that utilizes an instrument derived from a SVAR model.

The second contribution is the quantification of the bias inherent in the risk-sharing approaches commonly applied in the literature, and in the investigation of the performance of the proposed alternative approaches in estimating the risk-sharing. As mentioned above, the bias inherent in the Classical approach due to the ignoring of output endogeneity could lead to underestimating of risk-sharing by 23 to 48 percentage points, while the best alternative estimator is found to be the

## SVAR-IV.

Furthermore, the MCS results provide a wider contribution to the empirical analysis of fairly balanced panels consisting of small cross-sections and small time series, as are common for studies using OECD data. The overall results show that even though OLS estimations provide inconsistent estimates when simultaneity bias is present, they do provide precise estimates. Meanwhile, the alternative estimators, which have primarily an asymptotic justification, provide consistent estimates but are widely dispersed, especially in the case of FD2SLS and dGMM. Moreover, while both the FD2SLS and SVAR-IV estimation are exactly identified, the FD2SLS suffers extensively from finite sample bias in comparison to the SVAR-IV estimation. These results reinforce established findings and provide it in the context of small balanced macro-economic samples. Nonetheless, the MCS was geared towards to the circumstance this thesis faced in estimating risk-sharing in the third and fourth chapters and thus the MCS could be enhanced to provide a more comprehensive contribution around more general estimators behaviors beyond the restricted risk-sharing estimation; this is left to future research. Such improvements could include a wider variance in the small sample and in the relative sizes of the cross-section and time series, as well as a loosening of the assumption of standard normal symmetric distribution of the errors that underlined the MCS. The latter assumption is particularly potent and provides significant future research opportunities on that grounds that the results, subject to the regressors being symmetrically distributed around a mean, might have special properties that might not hold in general, as discussed by Chesher and Peters (1994) and Davidson and MacKinnon (1993).

Lastly, the thesis contributes to the literature's debate around whether risk-sharing has expanded or not. However, the precision of the estimates were too poor to make any conclusion around rising risk-sharing. Hence, a future research opportunity lies in improving the precision of estimates, in particular around the estimation of the variance-covariance matrix.

Overall, the aim of the thesis was to contribute to the conversation around monetary union by consistently estimating risk-sharing in the presence of simultaneity bias. That is, by ignoring the endogeneity bias the risk-sharing literature has over-estimated unshared risk which in turn has signaled to, for example, Euro-zone countries, that there is a higher cost associated with joining the European Monetary Union than was actually the case. In terms of how much risk-sharing is sufficient for joining a monetary union under the Optimal Currency Area theory, the answer is the higher the risk-sharing the better as it minimizes the cost of monetary union. However, the exact quantification of the optimal level of risk-sharing for a monetary union is left to others to stipulate as this is beyond the scope of this thesis.

# Appendices

# Appendix A

## (Chapter 1)

### A.1 List of Abbreviations

This appendix contains a comprehensive list of abbreviations used in the entire thesis.

#### **AB-AR**

Arellano and Bond (1991)'s serial correlation test

#### **AD**

Aggregate Demand

#### **ADF**

Augmented Dickey Fuller test (Dickey and Fuller (1979) and Hamilton (1994))

#### **AH**

Artis and Hoffmann (2007a,b, 2008)

#### **AR(x)**

x order Autoregressive model/process

#### **AS**

Aggregate Supply

#### **ASY**

Asdrubali et al. (1996)

#### **C**

Total consumption

**CCE**

(spatial) Common Correlated Effects

**CD**

Pesaran (2015) Cross-section Dependence test

**CI**

Confidence Interval

**CLR**

Conditional Likelihood Ratio

**CLR Weak ID robust CI**

Weak Identification robust Confidence Interval using the Kleibergen (2002, 2005) extension of the Moreira (2003)'s Conditional Likelihood ratio statistic to the non-i.i.d. case

**Conf. Inter.**

see CI

**CRRA**

Constant Relative Risk Aversion

**dGMM**

Holtz-Eakin et al. (1988) dynamic Generalized Method of Moments

**DGP**

Data Generating Process

**DOLS**

(pooled) Dynamic Optimal Least Squares

**EMU**

European Monetary Union

**Eq.**

Equation

**EU**

European Union

**EU-25**

see EU

**EU-8**

Belgium, Denmark, France, Germany, Ireland, Italy, the Netherlands, and United Kingdom

**EU-15**

The pre-2004 15 European Union members (excluding the EU enlargement countries)

**FD**

First Difference

**FD2SLS**

Anderson and Hsiao (1981, 1982) First-Difference Two Stage Least Square

**FDI**

Foreign Direct Investment

**FE**

Fixed Effect(s)

**FGLS**

Parks (1967) Feasible Generalized Least Squares

**FMOLS**

Fully Modified Optimal Least Squares

**GDOLS**

Group-mean Dynamic Optimal Least Squares

**GDP**

Gross Domestic Production (per capita)

**GFMOLS**

Group-mean Fully Modified Optimal Least Squares

**GLS**

Generalized Least Squares

**GMM**

Generalized Method of Moments

**GNDI**

Gross National Disposable Income

**GNI**

Gross National Income

**H<sub>0</sub>**

Null Hypothesis

**H<sub>A</sub>**

Alternative Hypothesis

**HA**

Home Absorption

**HLM**

Hadri (2000) Lagrange Multiplier unit-root test

**I(1)**

Integrated of order 1

**i.i.d.**

Independent and Identically Distributed

**IC**

Information Criterion

**IPS**

Im et al. (2003) Im-Pesaran-Shin unit-root test

**IV**

Instrumental Variables

**LHS**

Left Hand Side

**LLC**

Levin et al. (2002) Levin-Lin-Chu unit-root test

**LR**

Long Run

**LRAS**

Long Run Aggregate Supply

**MA(x)**

Moving Average of order x

**Max**

Maximum

**MCS**

Monte Carlo Simulation

**MG**

Mean Group

**Min**

Minimum

**MW**

Maddala and Wu (1999) unit-root test

**OECD**

Organisation for Economic Co-operation and Development

**OLS**

Ordinary Least Squares

**OLS(cluster)**

cluster-robust Optimal Least Squares estimation

**OLS(HAC)**

Optimal Least Squares estimation with standard errors corrected for arbitrary heteroskedasticity and serial correlation

**P**

Price

**PCADF**

Pesaran (2007) cross-sectionally augmented Dickey Fuller unit root test

**PCSE**

Beck and Katz (1995) Panel-Corrected Standard Errors estimation

**plim**

probability limit

**PMG**

Pesaran et al. (1997, 1999)'s Pooled Mean Group estimator

**PPeron**

Phillips and Perron (1988) unit root test

**PPP**

Purchasing Power Parity

**RHS**

Right Hand Side

**RS**

Risk-Sharing

**SE**

Standard Error(s)

**SR**

Short Run

**Std.Dev.**

Standard Deviation

**SVAR**

Structural Vector Autoregressive

**SVAR-IV**

IV-estimations using instruments derived from a Bayoumi and Eichengreen (1993) style SVAR

**U-ID KP p-value**

Kleibergen and Paap (2006) underidentification Lagrange Multiplier p-value

**U-ID KP LM  $\chi^2$** 

Kleibergen and Paap (2006) underidentification Lagrange Multiplier  $\chi^2$  test statistics

**UK**

United Kingdom

**US**

United States of America

**VAR**

Vector Autoregressive

**W-ID KD Wald F**

Kleibergen and Paap (2006)'s Wald F weak identification test statistics

**W-ID CD Wald F**

Cragg and Donald (1993)'s Wald F weak identification test statistics

**Y**

see GDP

## **A.2 List of Symbols**

This appendix contains a comprehensive list of symbols used in the thesis.

$(1 - \beta_u)$

The proportion of idiosyncratic output shocks that are shared, i.e. the risk-sharing.

$\mathbf{A}_i$

Vector of the coefficients for aggregate demand and supply shocks.

$\alpha$

Output's AR(1) coefficient in Chapter 5.

$\mathbf{B}_t$

Vector of the coefficients for output and price in period  $t$ .

$\beta_c$

Captures the covariance of foreign borrowing and lending, or the use of the trade balance, with output to buffer consumption.

$\beta_{k1}$

Captures the covariance of the international net income from abroad with output as a proportion of the overall variance of output and signifies the ex-ante income insurance channel.

$\beta_{k2}$

Captures the covariance of international net transfers with output and measures the international country equivalent of federal government transfer payments. What Sørensen and Yosha (1998) cite as  $\beta_\tau$ .

$\beta_s$

Captures the covariance of domestic savings behavior with output, i.e. the consumption buffer against idiosyncratic output shocks achieved via variation in domestic savings.

$\beta_u$

The proportion of idiosyncratic output shocks that are not shared, i.e. the unshared risk.

$\beta_{u,D1}$  **and**  $\beta_{u,D2}$

The proportion of idiosyncratic output shocks that are not shared, i.e. the unshared risk, when the estimation includes an interactive dummy term.

$\beta_u^{LR}$

The proportion of idiosyncratic output shocks that are not shared, i.e. the unshared risk, in the Level estimation.

$\beta_{u,D1}^{LR}$  **and**  $\beta_{u,D2}^{LR}$

The proportion of idiosyncratic output shocks that are not shared, i.e. the unshared risk, in the Level estimation when the estimation includes an interactive dummy term.

$\beta_{p,1}$  **and**  $\beta_{p,0}$

The coefficients of the leads and lags of output in the Level estimation.

$B_1^n$

Risk-less bond.

$C_{i,t}$

The consumption of country  $i$  in period  $t$ .

$\overline{\log(C_t)}$

The cross-sectional average of consumption in period  $t$ .

$C_{m,t}$

The consumption of country  $m$  in period  $t$ .

$C_1^n$

The consumption of country  $n$  in period one. This notation is used in section 2.2 and is done to align the notation with Obstfeld and Rogoff (1996) Ch.5.3. In subsequent part of the thesis, the equivalent is stated by  $C_{i,1}$ .

$C_2^m(s)$

The consumption of country  $n$  in period two, subject to exogenous shock  $s$ . This notation is used in section 2.2 and is done to align the notation with Obstfeld and Rogoff (1996) Ch.5.3. In subsequent part of the thesis, the equivalent is stated by  $C_{i,2}$ .

$C_{n,t}$

The consumption of country  $n$  in period  $t$ .

$C$

Long run restriction matrix of an SVAR.

$D_i$

Vector of coefficient for output and price shocks.

$\delta_i$

Are cross-section fixed effects, also referred to as country fixed effects.

$\epsilon^D$

The demand shocks in the Chapter 5.

$\epsilon^S$

The supply shocks in the Chapter 5.

$\epsilon^Y$

The output shocks in the Chapter 5.  $\epsilon^Y$  consists of supply and demand shocks.

$\eta_t$

Are time fixed effects, also referred to as time dummies.

$f_{i,t}$

The term consisting of weighted regressors and regressand. Together with  $\gamma_i$ ,  $f_{i,t}$  forms the common correlated effects.

$\gamma_i$

The coefficients of the variables in  $f_{i,t}$ . Together with  $f_{i,t}$ ,  $\gamma_i$  forms the common correlated effects.

$GNDI_{i,t}$

Gross National Disposable Income of country  $i$  in period  $t$ .

$GNI_{i,t}$

Gross National Income of country  $i$  in period  $t$ .

$HA_{i,t}$

Home Absorption of country  $i$  in period  $t$ .

$\iota$

The standard time preference factor.

$\mu^n$

Country  $n$ 's consumption as a proportion of aggregate output.

$\nu_{i,t}$

The disturbance or error term.  $\nu_{i,t}$  appears with various subscripts or superscripts to differentiate between the error term of various equations.

$\bar{\nu}_t$

The cross-sectional average of the error in period  $t$ .

$\omega_t$

Vector of aggregate demand and supply shocks.

$\omega_{D,t}$

Aggregate demand shocks.

$\omega_{S,t}$

Aggregate supply shocks.

$\pi(s)$

The probability of shock  $s$  occurring.

$\varpi$

Is used to denote a constant or intercept term.

$L^i$

Lag polynomial.

$p_t$

Price in period  $t$ . Another variation is  $p_{i,t}$  which is price of country  $n$  in period  $t$ .

$\psi$

The parameter which sets out the extent to which demand shocks feed into output in Chapter 5.

$(1 + r)$

Return on riskless bond in the second period.

$\rho$

The relative risk aversion coefficient.

**S**

Efficient GMM weighting matrix.

$U^n$

Country  $n$ 's lifetime utility.

$u(C_1^n)$

The utility of consumption of country  $n$  in period one.

$u(C_2^n(s))$

The utility of consumption of country  $n$  in period two subject to exogenous shock  $s$ .

$V_1^n$

Period one market value of the second period state contingent output of country  $n$ .

$\varkappa$

Output's AR(1) coefficient.

$\varrho_{i,t}$

The disturbance or error term in the Common Correlated Effect estimation which contains both the standard error  $\nu_{i,t}$  and the common correlated effects  $\gamma_i f_t$ .

**W**

Potentially inefficient GMM weighting matrix.

$\mathbf{X}_t$

Vector consisting of output and price in period t.

$\mathbf{e}_t$

Vector consisting of output and price shocks.

$\xi_i$

Are cross-section fixed effects, also referred to as cross-section dummies.

$x_m^n$

Country  $n$ 's share of country  $m$ 's future output.

$Y_{i,t}$

The output of country i in period t.

$\overline{\log(Y_t)}$

The cross-sectional average of output in period t.

$Y_2^m(s)$

The output of country m in period two subject to exogenous shock s. This notation is used in section 2.2 and is done to align the notation with Obstfeld and Rogoff (1996) Ch.5.3. In subsequent parts of the thesis, the equivalent is stated by  $Y_{i,2}$ .

$Y_1^n$

The output of country n in period one. This notation is used in section 2.2 and is done to align the notation with Obstfeld and Rogoff (1996) Ch.5.3. In subsequent parts of the thesis, the equivalent is stated by  $Y_{i,1}$ .

$Y_2^n(s)$

The output of country n in period two subject to exogenous shock s. This notation is used in section 2.2 and is done to align the notation with Obstfeld and Rogoff (1996) Ch.5.3. In subsequent parts of the thesis, the equivalent is stated by  $Y_{i,2}$ .

$Y_1^W$

The global output in period one. This notation is used in section 2.2 and is done to align the notation with Obstfeld and Rogoff (1996) Ch.5.3. In subsequent parts of the thesis, the equivalent is stated by  $Y_{W,1}$ .

$Y_2^W(s)$

The global output in period two subject to exogenous shock  $s$ . This notation is used in section 2.2 and is done to align the notation with Obstfeld and Rogoff (1996) Ch.5.3. In subsequent parts of the thesis, the equivalent is stated by  $Y_{W,2}$

$Y_{W,t}$

The global output in period  $t$ .

**Z**

Set of instrumental variables. For example,  $\mathbf{Z}^{level}$  is the instrument set for the FD2SLS consisting of two period lagged level of the endogenous variable, while  $\mathbf{Z}^{FD}$  is the instrument set for the FD2SLS using two period lagged first differences of the endogenous variable.

# Appendix B

## (Chapter 2)

### B.1 Fixed-Effects

Here we illustrate in more depth the existence of the two-way fixed effect model in the (panel) Eq.(2.18) and how the fixed effects are dealt with.

The time fixed effect is present as every year the whole economic-zone experiences a common shock (the weighted sum of individual country shocks). This common shock is, as the name suggests, common to all countries and should be accounted for to obtain the country's idiosyncratic output movement and thus risk-sharing. This follows from Eq.(2.10), where consumption movement, in the presence of perfect risk-sharing, is subject only to the world output movement and independent of country idiosyncratic output movement. The cross-section fixed effect, or country fixed effect, is based on the idea that each country has certain unique characteristics, such as the way capital is raised and its impact on consumption smoothing. For identification of cross-section and time fixed effects, it is necessary to assume that they are constant either over time and vary over cross-section (cross-section FE), or constant over countries and vary over time (time FE). That is, we start with an estimation equation of:

$$\log(C_{i,t}) = \log(Y_{i,t})\beta_u + \nu_{i,t} + \xi_i + \eta_t$$

where  $\xi_i$  is a country specific effect which is constant over time, and  $\eta_t$  is a time fixed effect and is constant for all countries in period  $t$  (the common shock of the aggregate economic area). Now if one takes the first difference, the unobserved cross-section fixed effect drops out,  $\xi_i - \xi_i = 0$ , and for that matter, any variable

which is constant over time drops out, be it observed or unobserved.<sup>1</sup>

$$\Delta \log(C_{i,t}) = \Delta \log(Y_{i,t})\beta_u + \Delta(\nu_{i,t}) + \Delta(\eta_t)$$

The time fixed effect (common shock) is still present in the equation. One possible step to avoid the time-fixed effect entering the error term is to use time dummies. However, this requires the estimation of  $T$  coefficients, where  $T$  stands for the time span in the panel. Alternatively, the variables can be cross-sectionally demeaned, which is constant for each cross-section and varies over time:

$$\Delta \log(C_{i,t} - \bar{C}_t) = \Delta \log(Y_{i,t} - \bar{Y}_t)\beta_u + \Delta(\nu_{i,t} - \bar{\nu}_t)$$

where  $\bar{X}_t$  denotes the cross-section average in period  $t$ . This demeaning filters out the time fixed effect since the time fixed effect is the same across countries. Therefore, the cross-section average for the time fixed effect is the same as the time fixed effect experienced by each country and subsequently the demeaned time fixed effect is zero.

In the empirical application, the construction of the average to demean the output and consumption variable was done using a weighted sum of the countries in the sample. The weight used is based on the annual proportional share of each country of the summed real GDP. When one demeans, the  $\beta_u$  is still the weighted average of panel units. However, an exception does occur since due to the application of weight, greater importance is given to the proportionally larger OECD countries' output shock as being part of the common shock.<sup>2</sup> It should also be noted that when demeaning, the degrees of freedom need to be adjusted to account for estimating the cross-sectional mean, which is not commonly done by the statistical program.<sup>3</sup> As demeaning is done by weights, with the sum of weights equal to one, the time fixed effect is still filtered out and achieves the equivalent result to the unconditional/unweighted mean being taken.

As mentioned above, one obtains the formulation of Eq.(2.18) relative to Eq.(2.17) as the result of how the filtering out the fixed effects is done. The approach used in Eq.(2.17) is referred to as the 'Least Square Dummy Variables' estimator and the approach in Eq.(2.18) as 'Fixed-Effect' or 'Within' estimator. Effectively the  $\beta_u$  is an equally weighted average of each time series of the panel.

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<sup>1</sup>It should be noted that if one is content with assuming, or has already tested, that the cross-section fixed effects are orthogonal to the included exogenous regressors, one could use a Random Effects estimator.

<sup>2</sup>The implication being that less of a shock is counted as idiosyncratic shock. Where as a small country's consumption has to be uncorrelated with output in level for risk-sharing, larger countries to some extent gain risk-sharing by having less of their output counted as idiosyncratic shocks.

<sup>3</sup>For a more intuitive and detailed explanation please refer to Angrist and Pischke (2009).

# Appendix C

## (Chapter 3)

### C.1 GMDOLS individual country risk-sharing parameter estimates.

This appendix contains the country individual estimates used for the GMDOLS unshared risk estimate presented in chapter 3. Table (C.1) contains the individual country estimates which are used to compile the mean estimate of the GMDOLS in chapter 3. Interesting to note is the wide range of parameter estimates, including some estimates that are above 1, implying negative risk-sharing. As mentioned before, though it is not impossible to find negative risk-sharing, it is very unlikely and cast doubt about the estimates. This doubt is compounded by the wide 95% confidence intervals, given large standard error estimates, which make it hard to reach a conclusion on the extent of risk-sharing taking place in individual countries. Moreover, some country estimates are found to be insignificant, for example Canada's 1991-2007 estimate. However, it is important to keep in mind that the standard errors might be invalid since this estimation utilizes, potentially, non-stationary output and consumption.

Country	1970-2007	1970-1990	1990-2007	Country	1970-2007	1970-1990	1990-2007
Australia	.791*** (.077)	.783*** (.133)	.771*** (.105)	Japan	1.053*** (.079)	1.106*** (.074)	.701*** (.093)
Austria	.821*** (.302)	1.319*** (.133)	-2.083*** (.503)	S. Korea	.800*** (.019)	.686*** (.029)	.596*** (.040)
Belgium	1.473*** (.210)	1.371*** (.166)	-1.911*** (.708)	Mexico	.950*** (.037)	.911*** (.041)	1.625*** (.230)
Canada	1.292*** (.147)	1.817*** (.284)	-.002 (.105)	Netherlands	1.062*** (.117)	1.173*** (.123)	0.399*** (.082)
Denmark	1.718*** (.232)	.480 (.435)	1.050 (.962)	New Zealand	.969*** (.043)	1.097*** (.078)	.823*** (.179)
Finland	.576*** (.117)	1.415*** (.135)	.380*** (.047)	Norway	.572*** (.059)	.650*** (.059)	.746*** (.157)
France	.727*** (.097)	.755*** (.252)	.493 (.700)	Portugal	1.258*** (.096)	1.561*** (.459)	0.824*** (.116)
Germany	1.896*** (.206)	1.640*** (.287)	1.964*** (.287)	Spain	1.080*** (.122)	.828*** (.101)	.940*** (.066)
Greece	.154 (.107)	.894*** (.265)	.525*** (.152)	Sweden	1.133*** (.116)	1.173*** (.167)	-.156* (.084)
Iceland	.863*** (.088)	.934*** (.118)	.898*** (.095)	Switzerland	1.014*** (.032)	1.082*** (.111)	1.163*** (.343)
Ireland	.454*** (.034)	-.167 (.457)	.601*** (.024)	UK	.967*** (.200)	.681*** (.237)	1.132*** (0.033)
Italy	1.367*** (.140)	1.293*** (.214)	1.211*** (.090)	US	.980*** (.111)	1.095*** (.231)	.772*** (.094)

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Each country was estimated using country specific lag-length. Standard errors are in parentheses.

Table C.1: GMDOLS individual country risk-sharing parameter estimates.

# Appendix D

## (Chapter 4)

### D.1 Country individual unit-root tests.

This appendix presents in Tables (D.1) and (D.2) the results of the country individual consumption and output unit-root tests. Two unit-root tests have been applied: the Augmented Dickey Fuller test (Dickey and Fuller (1979) and Hamilton (1994)) and the Phillips and Perron (1988) unit root test. Both tests were done using a country's individual selected lag length and include a trend. Tests without a trend were also done but are not presented here as the results remained similar. The lag length selection was done based on IC. For most countries the appropriate lag length was identified to be 1, although in some cases the appropriate lag length was identified to be 3. In both Tables, the second column contains for each country the lag length that was used. For simplicity of exposition, a one in the last six columns indicates that the null hypothesis of unit-root is not rejected and a zero means the null hypothesis is rejected at a 5% significance level.

For the most part, the two tests fail to reject the null hypothesis of unit-root.<sup>1</sup> However, there are some instances where the two tests come to the opposite conclusion or in the case of German and Canadian output over the period 1991 to 2007, Australian and US consumption over 1991-2007, and Swiss consumption over 1970-2007 both the ADF and PPeron test reject the null of a unit-root process.

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<sup>1</sup>Note that some rejections of a null hypothesis that is true is what is expected for a test that is correctly sized.

Variable	Lag()	1970-2007		1970-1990		1990-2007	
		ADF	PPerron	ADF	PPerron	ADF	PPerron
Austria	1	1	1	0	1	1	0
Australia	1	1	1	1	1	1	1
Belgium	1	1	1	1	1	1	1
Canada	1	1	1	1	1	0	0
Denmark	1	1	1	1	1	1	1
Finland	1	1	1	0	1	0	1
France	1	1	1	1	1	1	1
Germany	1	1	1	1	1	0	0
Greece	3	1	1	1	1	1	1
Iceland	1	1	1	1	1	1	1
Ireland	1	1	1	1	1	1	1
Italy	1	1	1	1	1	1	1
Japan	1	1	1	1	1	1	1
S. Korea	1	1	1	1	1	1	1
Mexico	1	1	1	1	1	1	1
Netherlands	1	1	1	1	1	1	1
New Zealand	1	1	1	1	1	0	1
Norway	1	1	1	1	1	1	1
Portugal	1	1	1	1	1	1	1
Spain	1	1	1	1	1	1	1
Sweden	1	1	1	0	1	0	1
Switzerland	3	1	1	1	1	1	1
United Kingdom	2	1	1	1	1	1	0
United States	1	1	1	1	1	1	1

Table D.1: Country individual GDP unit-root tests

Variable	Lag()	1970-2007		1970-1990		1990-2007	
		ADF	PPerron	ADF	PPerron	ADF	PPerron
Austria	1	1	1	1	1	1	0
Australia	1	1	1	1	1	0	0
Belgium	1	1	0	1	1	0	1
Canada	1	1	1	1	1	1	1
Denmark	1	1	1	1	1	1	1
Finland	1	1	1	0	1	0	1
France	1	1	1	1	1	1	1
Germany	1	1	1	1	1	0	1
Greece	3	1	1	1	1	1	1
Iceland	1	1	1	1	1	1	1
Ireland	1	1	1	1	1	1	1
Italy	1	1	1	1	1	1	1
Japan	1	1	1	1	1	1	1
S. Korea	1	1	1	1	1	1	1
Mexico	1	1	1	1	1	1	1
Netherlands	1	1	1	1	1	1	1
New Zealand	1	1	1	0	1	0	1
Norway	1	1	1	1	1	1	1
Portugal	1	1	1	1	1	1	1
Spain	1	1	1	1	1	0	1
Sweden	1	1	1	1	1	1	1
Switzerland	3	0	0	1	1	1	1
United Kingdom	2	1	1	1	1	1	1
United States	1	1	1	1	1	0	0

Table D.2: Country individual consumption unit-root tests

## D.2 dGMM with collapsed two period lagged output level as instrument

This appendix presents the dGMM results for the case when the instruments set  $\mathbf{Z}$  in Eq. (4.19) is limited to the collapsed instrument of two period lagged output,  $\mathbf{y}_{t-2}$ . The risk-sharing estimates in Table (D.3), like the results in Table (4.7), show

	1970-2007	1970-1990	1991-2007	Dummy:1970-2007
$\beta_u$	0.7846***	0.8745***	0.7058***	
$\beta_u$ SE()	(0.1230)	(0.2823)	(0.0962)	
$\beta_u$ 95% CI	[0.543, 1.026]	[0.321, 1.428]	[0.517, 0.894]	
$\beta_{u,D1}$				0.6389
$\beta_{u,D1}$ SE()				(0.1034)
$\beta_{u,D1}$ 95% CI				[0.436, 0.842]
$\beta_{u,D2}$				-0.0442
$\beta_{u,D2}$ SE()				(0.0257)
$\beta_{u,D2}$ 95% CI				[-0.094, 0.006]
AB-AR(1) p-value	0.000	0.035	0.000	0.001
AB-AR(2) p-value	0.681	0.287	0.769	0.613
U-ID KP LM $\chi^2$	1.48	0.67	3.64	6.66
U-ID KP LM p-value	0.2234	0.4117	0.0566	0.0099
AR Weak ID robust CI	[..., ...]	[..., ...]	[..., 0.955]	

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors shown are arbitrary heteroskedasticity and autocorrelated robust standard errors. The dGMMs and the Anderson and Rubin (1949) confidence intervals were constructed using the Stata commands `xtabond2` and `weakiv` by Roodman (2006) and Finlay et al. (2013). A ‘...’ means that the limit, be it upper or lower, was not found to be between -2 and 2. The critical value for  $\chi^2_{0.01}$  with 1 degree of freedom is 6.635, for  $\chi^2_{0.05}$  3.841, and for  $\chi^2_{0.1}$  2.706. Empty cell means the row is not applicable for the respective column.

Table D.3: dGMM with collapsed instrument set limited to two period lagged output

rising risk-sharing from 13% in the period of 1970-1990 to 29% during 1991-2007. However, like in the case Table (4.7), a significant change in risk-sharing could not be confirmed.

The change in risk-sharing was tested using a interactive dummy term in an estimation spanning the entire time period, where the dummy is 0 prior to and including 1990 and 1 thereafter. The results of this dummy estimation is shown in the last column of Table (D.3). The test applies to the parameter of the interactive dummy term,  $\beta_{u,D2}$ , with the null hypothesis testing whether the parameter is equal to zero  $H_0 : \beta_{u,D2} = 0$  using a two sided t-test with 5% significance level. The null hypothesis in effect states that there is no significant rise in risk-sharing between

1970-1990 and 1991-2007. The  $H_0$  fails to be rejected with the p-value being 0.085.

Furthermore, apart from the dummy estimation, the Kleibergen and Paap (2006) underidentification test fails to reject the null hypothesis of full column rank of  $E(\Delta\mathbf{y}_t\mathbf{Z})$ , where  $\mathbf{Z} = \mathbf{y}_{t-2}$ , suggesting that the results suffers from underidentification and thus might be inconsistent. As discussed in the fourth chapter, this should not be surprising if output is in fact integrated of the order 1.

Finally, the Anderson and Rubin (1949) confidence interval has been applied since the model is exactly identified; however the confidence intervals were not found to be in the bounds of -2 and 2 –apart from the upper bound of the 1991-2007 sub-period estimation–, further supporting the conclusions that the results in Table (D.3) suffer some bias and thus no clear conclusion can be drawn on the extent of risk-sharing taking place nor whether it has expanded over time.

### D.3 System GMM

The system GMM and dGMM estimators are similar in their approach to estimating risk-sharing. Both use lagged values of output as an exogenous instrument for output in a risk-sharing estimation. The system GMM, much like dGMM, creates an instrument for each time period. The difference from the dGMM approach, which uses lagged levels of the endogenous variable as the instruments in a first differenced regression, is that in addition the system GMM utilizes lagged differenced endogenous variables as instruments in a level regression.

Table (D.4) presents the non-collapsed system GMM estimation when the pool of instruments is restricted to a two period lagged output, while Table (D.5) presents the system GMM using the collapsed instrument limited to a two period lagged output. Both show an unshared risk parameter of larger than or close to 1 and their standard confidence intervals span wide ranges. In essence, these results look very much like the inconsistent FD2SLS estimations. And much like the FD2SLS both the collapsed and non-collapsed instruments appear to suffer from various misspecifications. All three system GMM estimations in Table (D.4) appear to suffer from too many instruments as the Hansen p-value is close to one, and the instrument sets are bigger than the respective cross-section. Meanwhile, the system GMMs in the Table (D.5) appear to suffer from under-identification as in all three cases the null hypothesis of the Kleibergen and Paap (2006) Lagrange Multiplier test (U-ID KP LM  $\chi^2$ ) of under-identification is not rejected. This is not unexpected as, given the similarity in constructing the system GMM instrument set to dGMM and FD2SLS, the system GMM should also suffer from under- or from weak identification, as output is or is close to being a unit root process. Finally, the Anderson and Rubin

	1970-2007	1970-1990	1991-2007
$\beta_u$	1.0472***	0.9926***	1.1579***
SE()	(0.0793)	(0.0566)	(0.1036)
95% CI	[0.892, 1.203]	[0.882, 1.104]	[0.955, 1.361]
N-dimension	24	24	24
T-dimension	38	21	17
IV-Count	73	39	35
AB-AR(1) p-value	0.005	0.065	0.008
AB-AR(2) p-value	0.807	0.196	0.459
Hansen p-value	1.000	0.957	0.875
Sargan p-value	0.000	0.000	0.000
U-ID KP LM $\chi^2$			
U-ID KP LM p-value			
CLR Weak ID robust CI	[..., ...]	[..., ...]	[..., ...]

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors shown are arbitrary heteroskedasticity and autocorrelated robust standard errors. The dGMMs and the Moreira (2003) CLR confidence intervals were constructed using the Stata commands `xtabond2` and `weakiv` by Roodman (2006) and Finlay et al. (2013). A ‘...’ means that the limit, be it upper or lower, was not found to be between -2 and 2.

Table D.4: system GMM with the instrument pool restricted to two period lagged output

	1970-2007	1970-1990	1991-2007
$\beta_u$	1.2840***	1.2286***	0.9187***
SE()	(0.2775)	(.2447)	(.2540)
95% CI	[0.740, 1.828]	[0.749, 1.708]	[0.421, 1.417]
N-dimension	24	24	24
T-dimension	38	21	17
IV-Count	3	3	3
AB-AR(1) p-value	0.011	0.042	0.037
AB-AR(2) p-value	0.708	0.425	0.910
Hansen p-value	0.105	0.501	0.128
Sargan p-value	0.000	0.000	0.000
U-ID KP LM $\chi^2$	3.02	0.97	4.52
U-ID KP LM p-value	0.2205	0.6166	0.1042
AR Weak ID robust CI	[..., ...]	[..., ...]	[..., ...]

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. Standard errors shown are arbitrary heteroskedasticity and autocorrelated robust standard errors. The dGMMs and the Anderson and Rubin (1949) confidence intervals were constructed using the Stata commands `xtabond2` and `weakiv` by Roodman (2006) and Finlay et al. (2013). A ‘...’ means that the limit, be it upper or lower, was not found to be between -2 and 2.

Table D.5: system GMM with the instrument pool restricted to collapsed two period lagged output

(1949) confidence interval for all six system GMM estimations is not found within the range of -2 and 2, making it virtually impossible to draw weak identification robust conclusions about the extent of risk-sharing.

## **D.4 IV-estimation using supply shocks and FD2SLS as instruments.**

This appendix presents the risk-sharing estimation when output is instrumented using both SVAR derived supply shocks and FD2SLS style instruments. Similar to Table (4.10), the estimations are done once for supply shocks derived from the entire sample, as well as supply shocks derived from sub-sample specific intervals estimations. The standard errors shown below are arbitrary heteroskedasticity and autocorrelated consistent standard errors.

Table (D.6) presents the risk-sharing estimation when output is instrumented using both derived supply shocks and a two period lagged level of output. In line with results in Table (4.10), Table (D.6) shows rising risk-sharing in both these cases. However, the gain in risk-sharing between 1973-1990 and 1991-2007 is slightly smaller in the case of Table (D.6), rising by roughly 7 percentage points from 28% to 34%, compared to Table (4.10), where risk-sharing rose around 8 percentage points from 28% to 36%. Moreover, in all three cases, the null hypothesis of underidentification is rejected. Also, the null hypothesis of weak identification is rejected in all instances when using Kleibergen and Paap (2006) Wald F test statistics (Weak ID KP Wald F) together with Olea and Pflueger (2013) suggested critical values. This includes the estimation of 1973-1990 when using sub-period derived supply shocks for higher Nagar bias threshold. However, while the Anderson and Rubin (1949) confidence interval for this estimate includes values above one, it also clearly includes values below one, suggesting the possibility of a reasonable level in the interval  $[0.758, 1]$ . Finally, in all instances the Hansen test fails to reject the null hypothesis that the instruments are valid.

Unlike in Table (D.6), the estimations in Table (D.7) are less harmonious in their conclusion of rising risk-sharing. When using supply shocks derived from VAR on the entire sample, risk-sharing remains essentially flat, similar to the dGMM with a collapsed instrument set limited to two and three period lagged outputs in Table (4.8). However, when using supply shocks derived from VAR estimations on sub-periods, the estimations in Table (D.7) show risk-sharing expanding by roughly 18 percentage points between 1973-1990 and 1990-2007, when one restricts the unshared risk in the 1973-1990 sub-period to 1 rather than allowing negative risk-sharing. The increase in risk-sharing was tested for its significance by running an estimation with

Variable	1973-2007	1973-1990	1991-2007
$\beta_u$	0.7000***	0.7246***	0.6560***
SE()	(0.0553)	(0.0746)	(0.0946)
95% CI	[0.592, 0.808]	[0.578, 0.871]	[0.471, 0.841]
IV-Count	2	2	2
Hansen p-values	0.3701	0.7015	0.3876
U-ID KP LM $\chi^2$	91.069	57.337	34.155
U-ID KP LM p-value	0.0000	0.0000	0.0000
W-ID CD Wald F	169.781	91.665	73.316
W-ID KP Wald F	82.816	57.533	25.719
AR weak-iv robust CI	[0.575, 0.829]	[0.544, 0.911]	[0.480, .855]
subperiods estimates			
$\beta_u$	0.9110***	0.9762***	0.7210***
SE()	(0.0763)	(0.1190)	(0.0962)
95% CI	[0.761, 1.061]	[0.743, 1.210]	[0.532, 0.909]
IV-Count	2	2	2
Hansen p-values	0.5571	0.4594	0.4304
U-ID KP LM $\chi^2$	51.964	24.828	30.080
U-ID KP LM p-value	0.0000	0.0000	0.0000
W-ID CD Wald F	52.921	23.352	33.103
W-ID KP Wald F	38.462	16.231	27.391
AR weak-iv robust CI	[0.745, 1.132]	[0.758, 1.424]	[0.451, 0.946]

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. The IV estimations and the Anderson and Rubin (1949) confidence interval were constructed using the Stata commands ivreg2 and weakiv by Baum et al. (2010) and Finlay et al. (2013).

Table D.6: IV-Estimation using aggregate supply shocks and FD2SLS- $\mathbf{Z}^{level}$

Variable	1973-2007	1973-1990	1990-2007
$\beta_u$	0.7225***	0.7329***	0.7290***
SE()	(0.0556)	(0.0761)	(0.0761)
95% CI	[0.613, 0.832]	[0.584, 0.882]	[0.580, 0.878]
IV-Count	2	2	2
Hansen p-values	0.0234	0.1803	0.0488
U-ID KP LM $\chi^2$	92.162	57.910	33.620
U-ID KP LM p-value	0.0000	0.0000	0.0000
W-ID CD Wald F	169.190	79.830	97.798
W-ID KP Wald F	75.506	49.219	28.228
AR weak-iv robust CI	[0.676, 0.773]	[0.567, 0.875]	[0.666, 0.853]
subperiod SVARs			
$\beta_u$	0.9744***	1.1502***	0.8224***
SE()	(0.0820)	(0.1501)	(0.0795)
95% CI	[0.814, 1.135]	[0.856, 1.444]	[0.667, 0.978]
IV-Count	2	2	2
Hansen p-values	0.5056	0.9134	0.0814
U-ID KP LM $\chi^2$	50.283	22.020	34.555
U-ID KP LM p-value	0.0000	0.0000	0.0000
W-ID CD Wald F	51.287	17.040	49.491
W-ID KP Wald F	36.841	14.510	28.223
AR weak-iv robust CI	[0.796, 1.198]	[0.848, 1.758]	[0.674, .952]

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. The IV estimations and the Anderson and Rubin (1949) confidence intervals were constructed using the Stata commands `ivreg2` and `weakiv` by Baum et al. (2010) and Finlay et al. (2013).

Table D.7: IV-Estimation using aggregate supply shocks and FD2SLS- $\mathbf{Z}^{fd}$

an interactive dummy term where the dummy is 0 prior to 1990 and 1 thereafter. The results of this estimation are presented in Table (D.8). More specifically, the rise in risk sharing was tested using the null hypothesis that no change in risk-sharing occurred based on the interactive dummy term parameter being equal to zero,  $H_0 : \beta_{u,D2} = 0$ . Based on a two sided t-test with 5% significance level, the null is not rejected, but when the significance level is chosen to be 10% the null is rejected in favor of the alternative hypothesis which is that a change in risk-sharing occurred.

Moreover, much like in Table (D.6), all six estimations in Table (D.7) reject the null of underidentification, while the 1973-1990 estimation using sub-period derived supply shocks fails to reject the null hypothesis of weak-identification at higher levels of precision. But as in Table (D.6), the Anderson and Rubin (1949) 95% confidence interval allows for the possibility that unshared risk lies in the reasonable range of [0.848;1]. Also interesting to note is that in some instances, contrary to the unanimous conclusion in Table (D.6), the Hansen test in Table (D.7) rejects the null hypothesis of valid instruments at 95% confidence level –apart from the 1991-2007 sub period estimation using supply shocks derived from a SVAR on the entire sample.

Variable	1973-2007
subperiod SVARs	
$\beta_{u,D1}$	1.1502***
$\beta_{u,D1}$ SE()	(0.1501)
$\beta_{u,D1}$ 95% CI	[0.8559, 1.444]
$\beta_{u,D2}$	-0.3277*
$\beta_{u,D2}$ SE()	(.1699)
$\beta_{u,D2}$ 95% CI	[-0.661, 0.005]
IV-Count	2
Hansen p-values	0.2174
U-ID KP LM $\chi^2$	
U-ID KP LM p-value	
W-ID CD Wald F	
W-ID KP Wald F	

Significance levels: \* denotes 10%, \*\* 5%, and \*\*\* 1%. The IV estimations were constructed using the Stata commands ivreg2 and weakiv by Baum et al. (2010).

Table D.8: IV-Estimation with interactive dummy term and using aggregate supply shocks and FD2SLS- $\mathbf{Z}^{fd}$

# Appendix E

## (Chapter 5)

### E.1 Mean squared error of the estimated unshared risk parameter when $\beta_u = 0.8$

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.00167	0.00158	0.00244	0.01636	0.24561	0.01361	0.01054	0.03830
$\psi = 0.5$	0.14163	0.14661	0.04161	0.01330	3.03133	0.02634	0.00847	0.02463
$\psi = 1$	0.22652	0.23438	0.06327	0.00846	0.79955	0.03084	0.00532	0.01747
$\alpha = 0.95$								
$\psi = 0$	0.00130	0.00134	0.00024	0.01352	2948.759	0.01037	0.00913	0.00277
$\psi = 0.5$	0.06466	0.07925	0.00055	0.01112	56698.41	0.01216	0.00741	0.00213
$\psi = 1$	0.12420	0.14594	0.00069	0.00705	1008.412	0.01134	0.00466	0.00194
$\alpha = 1$								
$\psi = 0$	0.00118	0.00127	0.00010	745.6217	142590.5	0.02331	3.21049	0.00163
$\psi = 0.5$	0.05304	0.06886	0.00006	822.4726	18945.22	0.03764	2.48610	0.00163
$\psi = 1$	0.10735	0.13098	0.00003	786.0499	1661.04	0.04177	1.21589	0.00165

The MCS is based on 10,000 simulations.

Table E.1: Mean squared error of the estimated unshared risk parameter when  $\beta_u = 0.8$ .

## E.2 MCS when unshared risk is 0.6

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.6007	0.6003	0.6001	0.5993	0.5948	0.5982	0.6002	0.7915
$\psi = 0.5$	0.9747	0.9814	0.8002	0.5939	0.5564	0.7295	0.6003	0.7530
$\psi = 1$	1.0753	1.0836	0.8503	0.5927	0.5149	0.7620	0.6002	0.7284
$\alpha = 0.95$								
$\psi = 0$	0.6007	0.6003	0.5999	0.5994	0.4749	0.5994	0.6004	0.6343
$\psi = 0.5$	0.8519	0.8795	0.6200	0.5947	-1.1117	0.6673	0.5988	0.6241
$\psi = 1$	0.9511	0.9811	0.6251	0.5937	1.1819	0.6846	0.5982	0.6205
$\alpha = 1$								
$\psi = 0$	0.6007	0.6003	0.6000	1.1302	5.3998	0.6010	0.6229	0.6000
$\psi = 0.5$	0.8277	0.8603	0.6000	0.8961	-0.5554	0.7369	0.7127	0.5992
$\psi = 1$	0.9262	0.9608	0.6001	0.7119	1.4519	0.7716	0.7280	0.5985

The MCS is based on 10,000 simulations.

Table E.2: Mean estimated unshared risk parameters for when  $\beta_u = 0.6$ .

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.6006	0.6002	0.6000	0.5989	0.5983	0.5976	0.5985	0.7913
$\psi = 0.5$	0.9748	0.9816	0.8000	0.5978	0.5997	0.7315	0.6025	0.7536
$\psi = 1$	1.0754	1.0834	0.8504	0.5997	0.6022	0.7653	0.6047	0.7294
$\alpha = 0.95$								
$\psi = 0$	0.6011	0.6003	0.5999	0.5989	0.5882	0.5988	0.6003	0.6346
$\psi = 0.5$	0.8511	0.8789	0.6199	0.5975	0.8010	0.6681	0.6024	0.6252
$\psi = 1$	0.9507	0.9805	0.6251	0.5984	0.8594	0.6853	0.6018	0.6223
$\alpha = 1$								
$\psi = 0$	0.6007	0.6004	0.6000	0.6002	0.6159	0.6020	0.6006	0.6004
$\psi = 0.5$	0.8269	0.8594	0.5999	0.6227	0.9897	0.7287	0.6472	0.6004
$\psi = 1$	0.9259	0.9601	0.6001	0.6280	1.0907	0.7643	0.6548	0.6004

The MCS is based on 10,000 simulations.

Table E.3: Median of estimated unshared risk parameters when  $\beta_u = 0.6$ .

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.04091	0.03978	0.04935	0.12792	0.49559	0.11663	0.10268	0.04021
$\psi = 0.5$	0.03464	0.03325	0.03919	0.11519	1.74061	0.09779	0.09205	0.03472
$\psi = 1$	0.02383	0.02231	0.02457	0.09169	0.89016	0.06776	0.07293	0.03129
$\alpha = 0.95$								
$\psi = 0$	0.03604	0.03663	0.01535	0.11630	54.30504	0.10186	0.09557	0.03991
$\psi = 0.5$	0.03499	0.03358	0.01242	0.10531	238.1201	0.08737	0.08606	0.03938
$\psi = 1$	0.03 000	0.02728	0.00773	0.08373	31.75176	0.06470	0.06823	0.03897
$\alpha = 1$								
$\psi = 0$	0.03438	0.03561	0.00988	27.30229	377.6001	0.15269	1.79173	0.04035
$\psi = 0.5$	0.03470	0.03330	0.00803	28.67869	137.6437	0.13746	1.57278	0.04040
$\psi = 1$	0.03090	0.02794	0.00500	28.03776	40.74901	0.11108	1.09527	0.04057

The MCS is based on 10,000 simulations.

Table E.4: Standard deviation of the estimated unshared risk parameters when  $\beta_u = 0.6$ .

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.00167	0.00158	0.00244	0.01636	0.24561	0.01361	0.01054	0.03830
$\psi = 0.5$	0.14163	0.14661	0.04161	0.01330	3.03133	0.02634	0.00847	0.02463
$\psi = 1$	0.22652	0.23438	0.06327	0.00846	0.79955	0.03084	0.00532	0.01747
$\alpha = 0.95$								
$\psi = 0$	0.00130	0.00134	0.00024	0.01352	2948.758	0.01037	0.00913	0.00277
$\psi = 0.5$	0.06466	0.07925	0.00055	0.01112	56698.46	0.01216	0.00741	0.00213
$\psi = 1$	0.12420	0.14594	0.00069	0.00705	1008.412	0.01134	0.00466	0.00194
$\alpha = 1$								
$\psi = 0$	0.00118	0.00127	0.00010	745.6219	142590.6	0.02331	3.21049	0.00163
$\psi = 0.5$	0.05304	0.06886	0.00006	822.4726	18945.22	0.03764	2.48610	0.00163
$\psi = 1$	0.10735	0.13098	0.00003	786.0500	1661.042	0.04177	1.21589	0.00165

The MCS is based on 10,000 simulations.

Table E.5: Mean squared error of the estimated unshared risk parameter when  $\beta_u = 0.6$ .

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	40.29%	7.58%	37.22%	1.67%	2.83%	3.57%	7.44%	99.02%
$\psi = 0.5$	100%	100%	100%	2.11%	4.87%	23.21%	7.38%	95.95%
$\psi = 1$	100%	100%	100%	2.48%	7.2%	54.69%	7.79%	91.41%
$\alpha = 0.95$								
$\psi = 0$	32.58%	4.57%	35.52%	0%	.03%	3.29%	6.23%	4.49%
$\psi = 0.5$	100%	100%	76.65%	0%	.75%	9.39%	6.42%	3.32%
$\psi = 1$	100%	100%	98.73%	0%	3.08%	19.6%	6.46%	3.23%
$\alpha = 1$								
$\psi = 0$	30.85%	4.08%	34.74%	0%	.02%	2.93%	1%	1.15%
$\psi = 0.5$	100%	100%	34.64%	0%	.23%	11.46%	1.38%	1.16%
$\psi = 1$	100%	100%	34.56%	0%	1.78%	26.31%	2.37%	1.19%

The MCS is based on 10,000 simulations.

Table E.6: Test size: rejection rate for 5% significance level when testing  $H_0 : \beta_u = 0.6$ .

### E.3 Mean squared error of the estimated unshared risk parameter when $\beta_u = 0.8$ and time series is 20 periods

	Classical		Level	FD2SLS		dGMM		SVAR-IV
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\alpha = 0.5$								
$\psi = 0$	0.00315	0.00319	0.00485	0.03712	7.73668	0.02790	0.02399	0.04158
$\psi = 0.5$	0.14800	0.15038	0.04311	0.03075	12.46951	0.03715	0.01944	0.02689
$\psi = 1$	0.23542	0.23923	0.06382	0.02012	52.45387	0.03647	0.01224	0.0192
$\alpha = 0.95$								
$\psi = 0$	0.00255	0.00277	0.00064	8.31440	8876.045	0.03423	0.30940	0.00600
$\psi = 0.5$	0.07655	0.08555	0.00081	3.52278	877362.4	0.03763	0.11363	0.00525
$\psi = 1$	0.14132	0.15485	0.00079	0.16634	242163.1	0.03288	0.12148	0.00499
$\alpha = 1$								
$\psi = 0$	0.00230	0.00259	0.00039	588.1914	34700000	0.07104	3.15790	0.00489
$\psi = 0.5$	0.06402	0.07412	0.00026	27617.71	15327.96	0.09336	3.45030	0.00491
$\psi = 1$	0.12417	0.13865	0.00010	2536.348	11862.06	0.09317	2.75969	0.00499

The MCS is based on 10,000 simulations.

Table E.7: Mean squared error of the estimated unshared risk parameter when  $\beta_u = 0.8$  and time is limited to 20 periods.

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