Examining Ricardian Equivalence by estimating and bootstrapping a nonlinear dynamic panel model*

Griet Malengier[†]   Lorenzo Pozzi[‡]

Abstract

We examine the Ricardian Equivalence proposition for a panel of OECD countries in the 80s and 90s by estimating a nonlinear dynamic consumption function. We estimate this function with the Generalized Method of Moments (GMM) using moment conditions that allow us to use information from the levels of the variables included in the consumption function. To examine the performance of this nonlinear GMM estimator and to obtain small sample critical values for the test statistics we apply both one-level and two-level bootstraps. Ricardian Equivalence is rejected since we find a significant number of current income consumers and since permanent income consumers seem to consume less in each period than what would be expected under certainty equivalence.

JEL Classifications: E21, E62, C33

Keywords: Ricardian Equivalence, rule-of-thumb, precaution, panel data, GMM, bootstrap

1 Introduction

The Ricardian Equivalence proposition (Barro 1974) states that the government choice to finance a given amount of expenditures with taxes or with debt is irrelevant for the economy. The assumptions under which the proposition holds are that agents are infinitely lived, rational, perfectly informed, and have no precautionary savings motive (i.e. the certainty equivalence result). Further, there are no liquidity constraints for consumers, governments do not engage in Ponzi games and taxes are lump-sum. Under these conditions debt-financed tax cuts, for instance, do not increase private consumption because consumers expect a tax increase sometime in the future if the government is to satisfy its intertemporal budget constraint. Consumers save the tax cut so that total economy-wide savings and thus interest rates do not change. Aggregate demand and output are unaffected. For early overviews of the theoretical and empirical literature on the Ricardian Equivalence proposition we refer to Bernheim (1987) and Seater (1993). As far as the empirical testing of the proposition is concerned, a large number of studies have tested it by estimating consumption functions that are derived from the first-order condition of a maximization problem and that incorporate one or more specific deviations from the theorem (i.e. the Euler equation approach). For instance, Evans (1988) and Haque (1988) use Blanchard's (1985) model to test whether consumers have finite horizons. Campbell and Mankiw (1991) and Evans and Karras (1998) investigate the importance of liquidity constraints. Dalamagas (1994) investigates whether consumers are myopic or irrational. Others like Haque and Montiel (1989) , Rockerbie (1997), Lopez et al. (2000), and Pozzi (2003) investigate two or more deviations from Ricardian Equivalence simultaneously. In most of these studies strict Ricardian Equivalence is rejected. It should be noted that almost all these studies use a time series approach to test the proposition on one or more individual countries. Two panel studies that test for (deviations from) the Ricardian Equivalence proposition are Evans and Karras (1998) and Lopez et al. (2000). In both studies the Ricardian Equivalence proposition is rejected.

In this paper we investigate the Ricardian Equivalence proposition for a panel of OECD

countries in the 1980s and 1990s. We derive and estimate a nonlinear consumption function from a model that allows for the presence of two consumer types: rule-of-thumb current income consumers and optimizing, permanent income consumers who incorporate the government budget constraint. Besides rule-of-thumb consumption (see also Evans and Karras 1998 and Lopez et al. 2000) a second deviation from Ricardian Equivalence is incorporated in the model, namely the possibility that permanent income consumers consume less in each period than what they would consume under certainty equivalence, i.e. they have a lower marginal propensity to consume out of permanent income. This reflects a precautionary savings motive which has, to the best of our knowledge, not been tested before via consumers' marginal propensity.

Methodologically, the focus of the paper lies on avoiding information loss in both the derivation and the estimation of the model and on correct small sample inference. As far as the first issue is concerned, we note that many studies in the Euler equation tradition derive consumption equations that are either in first differences or in growth rates (see Lopez et al. 2000 and Evans and Karras 1998). While this may be desirable in a time-series context because of stationarity concerns, it may be problematic in a panel context.[1] The reason is that panel data estimation in the presence of endogenous or predetermined variables necessitates some kind of transformation to get rid of country-specific heterogeneity. As shown by Nickell (1981) transforming the data in deviations from the country-specific means leads to biased estimates if the time dimension of the panel is modest.[2] Therefore it is common to transform the data in first-differences to get rid of the country-specific effect (i.e. the estimators of Anderson and Hsiao 1982 and Arellano and Bond 1991). If the equation that is estimated is in first-differences or in growth rates to begin with, a first-difference transform implies an equation in second differences or in first differences of growth rates. This implies a large loss of information and potential instrumentation problems (see the problems associated with the first-difference

---

[1] The trend properties of the variables in the estimated equation are irrelevant for the asymptotic properties of large N panel data estimators (where N is the number of cross-sections).

[2] Judson and Owen (1999) use Monte Carlo simulations to show that even for a time dimension as large as 30 biases may be substantial when using the within estimator to estimate a dynamic panel model.

estimators as discussed in for instance Blundell and Bond 1998). To avoid these problems, first, we derive an empirical specification that is in levels and not in first-differences or growth rates. Second, we use an estimation method that gets rid of the unobserved heterogeneity without resorting to a transformation of the data in deviations from country-specific means (as in Evans and Karras 1998) or resorting to a mere transformation of the data in first-differences (as in Lopez et al. 2000). More specifically, we estimate our nonlinear consumption function with the Generalized Method of Moments (GMM) estimator using moment conditions of the type suggested by Arellano and Bover (1995) and Blundell and Bond (1998). Estimation with these moment conditions allows us to use information from the levels of the variables included in the consumption function. To the best of our knowledge, this type of moment condition has not yet been used in a nonlinear GMM framework before. The second methodological issue we focus on is small sample inference. It is well-known that GMM estimation is not without problems when applied to samples typically encountered in practice (see Tauchen 1986). We use both one-level and two-level bootstraps to conduct inference and to check whether point estimates and estimated standard errors are biased.

The main conclusions from estimating our consumption function for 16 to 19 OECD countries are, first, that over the period 1980-1997 the fraction of rule-of-thumb consumers in these economies is around 25%. Second, the remaining 75% forward-looking consumers have a marginal propensity to consume out of permanent income that is somewhat lower than what we would expect in the certainty equivalence case that underlies Ricardian Equivalence. These conclusions also hold for subsamples (i.e. taking the 80s and 90s seperately). Thus, Ricardian Equivalence is rejected. This is in line with most of the literature (see e.g. the recent overview given by Lopez et al. 2000). Third, the specification test we use does not reject the validity of our model. Fourth, we do not reject the moment conditions suggested by Arellano and Bover (1995) and Blundell and Bond (1998) that allow us to use information from the levels of the variables in our estimations. Fifth, our GMM estimates are not biased but the estimated asymptotic standard errors severely understate the small sample standard errors and the asymptotic distributions of the test

statistics prove to be a poor guide for small sample inference. By using appropriate bootstrap standard errors and bootstrap distributions we are able to conduct inference in a more reliable manner.

The paper is structured as follows. In section 2 we derive a consumption function that allows us to estimate the number of rule-of-thumb current income consumers versus the number of optimizing (Ricardian) consumers. In section 3 we extensively discuss the estimation method we think is the most convenient to avoid information loss and to conduct correct inference in a small sample. In section 4 data issues are discussed. In section 5 we present the results of estimating our specification for a panel of OECD countries in the 80s and 90s. Section 6 concludes.

2 Theoretical Framework

In this section we present a theoretical framework in which a group of consumers follows current income. Another group of consumers is fully optimizing and (weakly) Ricardian. We derive a testable consumption function with variables expressed in levels.

Suppose there are two consumer types in the real economy: rule-of-thumb current income consumers and optimizing permanent income consumers. As a first type, rule-of-thumb consumers base their consumption decisions on current income because of liquidity constraints (see e.g. Campbell and Mankiw 1990, 1991), myopia (see e.g. Flavin 1985), precaution (see e.g. Carroll 1994), finite horizons (see e.g. Gali 1990) or imperfect information (see e.g. Goodfriend 1992) . We assume that these consumers consume their entire disposable income in each period so that their consumption c_{1t} can be written as,

$$c_{1t} = \lambda(y_t - t_t) \tag{1}$$

where y_t is pre-tax labour income in the economy, t_t are net taxes, and the parameter λ $(0 \leq \lambda \leq 1)$ denotes the fraction of disposable income in the economy that goes to rule-of-thumb consumers. The second type, optimizing infinitely lived permanent income

5

consumers, maximize $V = E_t \sum_{j=0}^{\infty}(1 + \rho)^{-j} \log(c_{2t+j})$ where c_{2t} is consumption of this type of consumers, E_t is the expectations operator conditional on information available to consumers in period t, and ρ $(0 < \rho < 1)$ is their subjective rate of time preference. Maximization occurs subject to the budget restriction $c_{2t} + (1+r)^{-1}(w_{t+1} + b_{t+1}) = (1-\lambda)(y_t - t_t) + (w_t + b_t)$ where w_t is private financial wealth (excluding government bonds) at the beginning of period t, b_t is government debt at the beginning of period t, and r is the interest rate in the economy. The first-order condition is $E_t\left(\left(\frac{c_{2t+1}}{c_{2t}}\right)^{-1}\right) = \frac{1+\rho}{1+r}$ $(\forall t)$. We linearize the LHS of this condition by taking a second-order Taylor approximation of $\left(\frac{c_{2t+1}}{c_{2t}}\right)^{-1}$ around $\frac{c_{2t+1}}{c_{2t}} = 1$ where the conditional uncentered second moment of consumption growth is assumed to be constant and is denoted by σ^2 (see Appendix A). We obtain $E_t c_{2t+1} = k c_{2t}$ $(\forall t)$ where $k = (\sigma^2(1 + r) + 2r + 1 - \rho)(1+r)^{-1}$.

Imposing a transversality condition on the budget constraint of the optimizing permanent income consumers, we can write this constraint as $\sum_{j=0}^{\infty}(1 + r)^{-j}E_t c_{2t+j} = w_t + b_t + \sum_{j=0}^{\infty}(1 + r)^{-j}E_t(1 - \lambda)(y_{t+j} - t_{t+j})$. Substituting the linearized first-order condition into this, we obtain (under the assumption that $k(1 + r)^{-1} < 1$),

$$c_{2t} = \beta(\sum_{j=0}^{\infty}(1 + r)^{-j}E_t[(1 - \lambda)(y_{t+j} - t_{t+j})] + w_t + b_t) \qquad (2)$$

where $\beta = (r^2 + \rho - (1 + r)\sigma^2)/(1 + r)^2$ is the marginal propensity to consume out of permanent income.[3] If $\sigma^2 = 0$ and $r = \rho$ we have $\beta = r/(1+r)$. In that case eq.(2) is the textbook permanent income result (i.e. the certainty equivalence case). Given that log utility implies convex marginal utility, there is a "precautionary savings" motive reflected by σ^2 that tends to lower consumption relative to the certainty equivalence case.

Note further that we assume that permanent income consumers discount future disposable income at a rate equal to the interest rate r. Preliminary estimations of a more complicated model in which the discount rate of these consumers may exceed the discount

---

[3] Log utility is basically a special case of the standard CRRA type of utility function with the coefficient of relative risk aversion restricted to be equal to 1. Our analysis can be extended to a more general utility function with unrestricted but constant relative risk aversion in which case β will be a function of risk aversion as well.

rate of the government r by a mark-up that reflects the length of the consumers' horizon (see Blanchard 1985) gave point estimates very close to zero.[4] Note that in most studies that add rule-of-thumb consumers to Blanchard's finite horizon specification, this mark-up is found not to be different from zero (see Haque and Montiel 1989 and Rockerbie 1997 as well as Lopez et al. 2000 who show this result for a panel of OECD countries). We therefore consider the assumption of equal discount rates for consumers and the government to be appropriate.

If permanent income consumers optimize fully, they take the intertemporal government budget constraint into account, i.e. they are Ricardian. Given that, as noted above, our model does not rule out precaution, we say that consumers are weakly Ricardian.[5] The government budget constraint is given by $\sum_{j=0}^{\infty}(1+r)^{-j}t_{t+j} = \sum_{j=0}^{\infty}(1+r)^{-j}g_{t+j}+b_t$ where g_t are government expenditures (government consumption and investment). Substituting this equation into eq.(2), we obtain,

$$c_{2t} = \beta(\sum_{j=0}^{\infty}(1+r)^{-j}E_t[(1-\lambda)(y_{t+j}-g_{t+j})] + w_t + \lambda b_t) \tag{3}$$

Note that in eq.(3) government debt plays a larger role in permanent income if the fraction of income going to rule-of-thumb consumers is larger. The reason is that a part of the future tax implications of debt will be paid for by these consumers so that a fraction λ of b_t will be wealth for Ricardian consumers.

Total consumption c_t can be written as,

$$c_t = c_{1t} + c_{2t} \tag{4}$$

Substituting eqs.(1) and (3) into eq.(4) and using the quasi-difference approach by Hayashi (1982)[6] to remove the unobservables, we obtain the following testable specification

---

[4]These point estimates were obtained while restricting this mark-up to be larger than or equal to zero during estimation. The results for the other parameters are identical whether or not a mark-up is added as an additional parameter.

[5]Strict Ricardian Equivalence rules out precaution. Consumers are strictly Ricardian if $\sigma^2 = 0$.

[6]Note that other solution methods are possible. Himarios (1995) finds that, in models where rule-of-thumb consumers are included, mathematically equivalent ways of solving the consumer Euler equation give similar estimation results in a time series context.

for total private consumption,

$$
\begin{aligned}
c_t \;=\; & (1+r)c_{t-1} + \lambda(y_t - (1+r)y_{t-1}) - \lambda(t_t - (1+r)t_{t-1}) \\
& + \beta(w_t - (1+r)w_{t-1}) + \beta\lambda(b_t - (1+r)b_{t-1}) \\
& - \beta(1-\lambda)(1+r)y_{t-1} + \beta(1-\lambda)(1+r)g_{t-1} + \eta_t
\end{aligned}
\tag{5}
$$

where for the error term η_t we have that $E_{t-j}\eta_t = 0$ ($\forall j > 0$). We refer to the appendix B for the derivation of this equation. Note that the consumption function is in levels.

The rest of the paper deals with the testing of the model and with the estimation of β and λ conditional on values imposed on r (see section 3). Note that (weak) Ricardian Equivalence holds if $\lambda = 0$. If in addition $\beta = r(1+r)^{-1}$, then strict Ricardian Equivalence holds. Note further that $\beta > r(1+r)^{-1}$ implies that impatience has a relatively strong effect on current consumption compared to precaution. The opposite is implied by $\beta < r(1+r)^{-1}$.

3   Estimation issues

In this section we discuss our empirical approach. The focus is on avoiding information loss and on problems of inference in a relatively small sample.

3.1   Empirical specification and moment conditions

Simplifying notation and adding a cross-sectional dimension to eq.(5), we obtain an empirical specification that we can estimate using a panel of countries,

$$
c_{it} = f(c_{it-1}, x_{it}, x_{it-1}, \psi) + \mu_i + \eta_{it}
\tag{6}
$$

where i ($i = 1, ..., N$) refers to cross-section, t ($t = 1, ..., T$) continues to refer to time periods, $f(.)$ is a non-linear function in ψ, μ_i is an unobserved country-specific intercept, ψ is a 2×1 vector given by $\psi = (\beta, \lambda)'$, and x_{it} is a 5×1 vector given by

$x_{it} = (y_{it}, t_{it}, g_{it}, w_{it}, b_{it})'$. To avoid numerical problems given our highly nonlinear specification, the real interest rate r is fixed to a number of values during estimation. This is in line with the literature (see e.g. Evans 1993 , Lopez et al. 2000). The methodology we use to estimate eq.(6) must tackle a number of empirical difficulties. First, it must allow for correlation between the individual effect μ_i and the regressors. Second, it must deal with the endogeneity of (some of the) regressors with respect to private consumption. Third, it must deal with potential problems of heteroskedasticity both in time and across countries. Finally, it must take into account the fact that the error term η_{it} is not necessarily white noise (as derived in the theory in the previous section) but may exhibit autocorrelation of the moving average form of order one (i.e. an MA(1) error) due to time aggregation (Working 1960), the presence of transitory consumption or problems associated with consumer durables (Mankiw 1982). The currently most popular approach to deal with these problems would be to first-difference eq.(6) directly to eliminate μ_i (see Anderson and Hsiao 1982). This gives,

$$\Delta c_{it} = f(\Delta c_{it-1}, \Delta x_{it}, \Delta x_{it-1}, \psi) + \Delta \eta_{it} \tag{7}$$

Valid moment conditions given the potential MA(1) structure of η_{it} are,

$$E\left[c_{it-s}\Delta\eta_{it}\right] = 0 \tag{8}$$

$$E\left[x_{it-s}\Delta\eta_{it}\right] = 0 \tag{9}$$

for $t = 4, ..., T$ and $s \geq 3$. These conditions can be used in a GMM framework to estimate ψ consistently (i.e. the first-difference GMM estimator by Arellano and Bond 1991). Besides the obvious information loss involved in transforming the data, an important shortcoming of estimating a first-difference specification is that, since the macroeconomic series we use are typically persistent, instrumentation may be problematic. With persistent data, lagged levels of the variables are weak instruments for the regression in first-differences. This may lead to imprecise estimates and serious small sample biases (see e.g. Ahn and Schmidt 1995, Blundell and Bond 1998, Blundell, Bond, and Windmeijer 2000). To deal with this, additional moment conditions have been suggested by Arellano

and Bover (1995) and Blundell and Bond (1998) where lagged differences of the variables are used in the levels equation. Additional non-redundant moment conditions for our case then are,

$$E\left[\Delta c_{it-2}(\mu_i + \eta_{it})\right] = 0 \tag{10}$$

$$E\left[\Delta x_{it-2}(\mu_i + \eta_{it})\right] = 0 \tag{11}$$

for $t = 4, ..., T$. As noted by Arellano and Bover (1995) the validity of these additional moment conditions is in many cases an empirical issue.[7] We return to the issue of testing these conditions in the next section.

3.2 Estimation

We use both types of moment conditions discussed in the previous section together to estimate ψ consistently using a nonlinear GMM estimator. Given the relatively large time series dimension and the relatively small cross-sectional dimension of our panel, we avoid using an unmanageable number of moment conditions by choosing a fixed number of moment conditions or instruments per time period. As noted by Tauchen (1986) using too many moment conditions may lead to biased estimates (see below in section 3.3 for more on this). For the moment conditions presented above this implies that s is kept fixed for every value of t. We set $\min(s) = 3$ and $\max(s) = 3$ (instrument set 1) and $\min(s) = 3$ and $\max(s) = 4$ (instrument set 2). For instrument set 1, for example, we can then write eqs.(8)-(11) more compactly as,

$$E(Z_i' v_i) = 0 \tag{12}$$

where v_i is the $2(T-3) \times 1$ vector $(\Delta\eta_{i4}, \Delta\eta_{i5}, ..., \Delta\eta_{iT}, \mu_i + \eta_{i4}, \mu_i + \eta_{i5}, ..., \mu_i + \eta_{iT})'$

---

[7]It is easily seen that these moment conditions are satisfied under the assumption that c_{it} and x_{it} are jointly mean stationary processes. This is a sufficient condition however, not a necessary one. Blundell, Bond, and Windmeijer (2000) give conditions under which for the linear model with exogenous or endogenous regressors the additional moment conditions are valid when regressors (and thus regressand) have time-varying means.

and where Z_i is the $2(T-3) \times 12(T-3)$ matrix given by,

$$Z_i = \begin{bmatrix} c_{i1} & x'_{i1} & 0 & 0 & ... & 0 & 0 & 0 & 0 & 0 & 0 & ... & 0 \\ 0 & 0 & c_{i2} & x'_{i2} & ... & 0 & 0 & 0 & 0 & 0 & 0 & ... & 0 \\ . & . & . & . & ... & . & . & . & . & . & . & ... & . \\ 0 & 0 & 0 & 0 & ... & c_{iT-3} & x'_{iT-3} & 0 & 0 & 0 & 0 & ... & 0 \\ 0 & 0 & 0 & 0 & ... & 0 & 0 & \Delta c_{i2} & \Delta x'_{i2} & 0 & 0 & ... & 0 \\ 0 & 0 & 0 & 0 & ... & 0 & 0 & 0 & 0 & \Delta c_{i3} & \Delta x'_{i3} & ... & 0 \\ . & . & . & . & ... & . & . & . & . & . & . & ... & . \\ 0 & 0 & 0 & 0 & ... & 0 & 0 & 0 & 0 & 0 & 0 & ... & \Delta x'_{iT-2} \end{bmatrix}$$

The GMM estimator we use is $\widehat{\psi} = \arg\min_\psi (v'Z) W_N (Z'v)$ where v is the $2N(T-3) \times 1$ vector $(v_1, ..., v_N)'$, where Z is the $2N(T-3) \times 12(T-3)$ matrix given by $(Z_1, ..., Z_N)'$.[8] The matrix W_N is a positive definite weighting matrix. Hansen (1982) shows that the optimal choice for W_N is the inverse of the variance-covariance matrix of the moment conditions, namely $W_N = (N^{-1} \sum_{i=1}^N Z'_i v_i(\widehat{\psi}_1) v_i(\widehat{\psi}_1)' Z_i)^{-1}$ where $\widehat{\psi}_1$ is an initial consistent estimate of ψ which we obtain by applying our GMM estimator using an initial parameter independent weighting matrix.[9] The optimal GMM estimator is thus obtained in two steps and is robust to heteroskedasticity and autocorrelation. Under regularity conditions, $\sqrt{N}(\widehat{\psi} - \psi)$ has an asymptotic normal distribution (i.e. asymptotics hold for $N \to \infty$). The variance-covariance matrix V can be estimated by $\widehat{V} = (\widehat{D}' \widehat{W_N} \widehat{D})^{-1}$ with the $12(T-3) \times 2$ matrix $\widehat{D} = \left[\frac{\partial(N^{-1} Z'v)}{\partial \psi'} \right]_{\psi = \widehat{\psi}}$. Asymptotic standard errors of $\widehat{\psi}$ then are $sd^a(\widehat{\psi}) = \sqrt{\widehat{V}_{jj}/N}$ for $j = 1, 2$. Since our model is overidentified (i.e. $\dim(Z'v) > \dim(\psi)$), we use the Sargan test for overidentifying restrictions given by $S(\widehat{\psi}) = N^{-1} \left(v(\widehat{\psi})'Z \right) \widehat{W_N} \left(Z'v(\widehat{\psi}) \right)$ (see e.g.

[8] Note that when we use instrument set 2 ($\max(s) = 4$) the dimension of v_i is $2(T-4) \times 1$ and the dimension of Z_i is $2(T-4) \times 18(T-4)$ (i.e. one additional lag of each variable per time period in the first difference part of the system). Likewise v now has dimension $2N(T-4) \times 1$ and Z has dimension $2N(T-4) \times 18(T-4)$.

[9] As an initial weight matrix we use $W_N^1 = (N^{-1} \sum_{i=1}^N Z'_i H Z_i)^{-1}$ where H is a block diagonal matrix where the upper diagonal block corresponds to the first-difference part of the system and contains "2"'s on its diagonal, "-1" above and below each "2" and "0"'s elsewhere. The lower diagonal block corresponds to the levels part of the system and is an identity matrix.

Blundell, Bond, and Windmeijer 2000). This statistic is asymptotically χ^2 distributed under the null hypothesis that the moment conditions are valid. Degrees of freedom are equal to $\dim(Z'v) - \dim(\psi)$. The final statistic we are interested in makes it possible to test the validity of the additional moment conditions given by eqs.(10) and (11). This is the difference Sargan test (see e.g. Blundell, Bond, and Windmeijer 2000) which is given by $dS(\widehat{\psi}) = S - S^*$ where S^* is the Sargan test that is obtained when estimating ψ by using only the moment conditions in eqs.(8) and (9), i.e. estimating the first-difference part of the system only. It is asymptotically χ^2 distributed under the null that the level moment conditions are correct. Degrees of freedom are equal to $\dim(Z'v) - m$ where m is the number of moment conditions in the restricted first difference case (e.g. m equals $6(T-3)$ for instrument set 1).

Note that even though we restrict the number of moment conditions by using a fixed number of instruments per time period, the number of moment conditions is still relatively large compared to the cross-sectional dimension of the panel. This causes some difficulties to invert the variance-covariance matrix of the moment conditions. Therefore we use a pseudo-inverse of this matrix as weighting matrix instead of the regular inverse (see Arellano and Bover 1995).

Finally, we note that our parameter estimates are insensitive to the choice of the starting values for the numerical optimization procedure for the criterion function.

3.3   Small sample inference

It is well known that GMM estimation may be problematic in samples typically encountered in practice. Problems that may occur are that coefficients and standard errors are biased and that the assumed asymptotic distributions for the test statistics poorly approximate their small sample counterparts. Tauchen (1986) for instance emphasizes the danger of having too many moment conditions in GMM estimation. When the sample size is small, an increase in the number of moment conditions increases efficiency but may also lead to biased estimates. Biases are caused because the optimal set of moment con-

ditions may contain instruments dated far into the past that have low correlation with the instrumented variables (see Nelson and Startz 1990) or because there is a correlation between the sample moments and the sample weight matrix (see Altonji and Segal 1994 and Ziliak 1997). Further, Arellano and Bond (1991) show that the estimated asymptotic standard errors of the efficient two-step GMM estimator used in dynamic panels can be severely (downward) biased in small samples (see also Windmeijer 2000). Recent Monte Carlo simulations by Hall and Horowitz (1996) and Bergström, Dahlberg, and Johansson (1997) show that asymptotic distributions and small-sample distributions of test statistics like t-tests and Sargan tests may differ considerably in small samples. To deal with these problems, we conduct a bootstrap that allows us to check whether our estimates and (asymptotic) standard errors are biased and that allows us to use small sample critical values of (asymptotically pivotal) test statistics instead of asymptotic critical values when testing hypotheses.[10] For an example of an application of GMM bootstrap methods to dynamic (but linear) panels we refer to Dahlberg and Johansson (2000).

We start by drawing a cross-sectional unit with probability N^{-1} (with replacement) and pick out the (complete) time series for that unit. We repeat this until we have a full sample consisting of N cross-sections. Given that changing the drawing order of a given sequence of cross-sections does not affect the bootstrap GMM estimates, the number of different bootstrap samples that we can draw in this way equals $(((N-1)+N)!)((N-1)!N!)^{-1}$. Using this bootstrap sample we construct the bootstrap equivalent of the instrument matrix Z which we name Z^b. Likewise the vector v^b is the bootstrap equivalent of v.

We estimate our specification, eq.(5), using this bootstrap sample. The bootstrap GMM estimator is given by $\widehat{\psi}^b = \arg\min_\psi \left(v^{b\prime} Z^b - g^\prime \right) W_N^b \left(Z^{b\prime} v^b - g \right)$ where $g = Z^\prime v(\widehat{\psi})$ are the sample moment conditions estimated from the original data (where $\widehat{\psi}$ is the second step GMM estimate based on the original sample). We use g to recenter the bootstrap

---

[10] For linear dynamic panels Windmeijer (2000) provides an analytical small sample correction for the asymptotic standard errors obtained with GMM estimation in two steps. In our case, since the moment conditions are highly nonlinear in ψ, a bootstrap approach is necessary to obtain more reliable means of inference.

moment conditions (see Hall and Horowitz 1996). The reason is that the bootstrap treats the original data as the population. Contrary to the population moment conditions given in eq.(12), the sample moments $Z'v(\widehat{\psi})$ are not equal to zero in overidentified models. Therefore, to avoid that the bootstrap imposes moment conditions that do not hold in the population the bootstrap samples from, it is necessary to recenter. Further, note that $W_N^b = \left(N^{-1} \sum_{i=1}^{N} \left(Z_i^{b'} v_i^b(\widehat{\psi}_1^b) - g_1 \right) \left(v_i^b(\widehat{\psi}_1^b)' Z_i^b - g_1' \right) \right)^{-1}$ where $\widehat{\psi}_1^b$ is the first-step GMM estimator based on the bootstrap sample and where $g_1 = Z'v(\widehat{\psi}_1)$ are the bootstrap moments used to recenter in the first step (where $\widehat{\psi}_1$ is the first-step GMM estimate based on the original sample). Besides $\widehat{\psi}^b$, we also calculate asymptotic standard errors $sd^a(\widehat{\psi}^b)$, the Sargan test $S(\widehat{\psi}^b)$ and the difference Sargan test $dS(\widehat{\psi}^b)$ from our bootstrap sample.

We repeat the drawing of a sample and the estimation of coefficients, asymptotic standard errors and test statistics B times where B is the number of bootstrap replications (we set $B = 200$ in all cases). To check whether our estimates are biased we calculate $bias(\widehat{\psi}) = \widehat{\psi} - \overline{\psi}^b$ where $\overline{\psi}^b = B^{-1} \sum_{b=1}^{B} \widehat{\psi}^b$. We calculate the bootstrapped standard errors as $sd(\widehat{\psi}) = \sqrt{(B-1)^{-1} \sum_{b=1}^{B} (\widehat{\psi}^b - \overline{\psi}^b)^2}$. Comparison of these standard errors with $sd^a(\widehat{\psi})$ gives us an idea of whether the asymptotic standard errors are well estimated or not.

Instead of using the critical values of the χ^2 distribution to test the validity of the moment conditions, we use the critical values of the small sample distribution of the Sargan test $S(\widehat{\psi}^b)$ $(b = 1, ..., B)$ and of the difference Sargan test $dS(\widehat{\psi}^b)$ $(b = 1, ..., B)$. More specifically, we reject the null hypothesis of valid moment conditions if $S(\widehat{\psi}) > cv \left(S(\widehat{\psi}^b) \right)$ and we reject the null hypothesis of valid level moment conditions if $dS(\widehat{\psi}) > cv \left(dS(\widehat{\psi}^b) \right)$ where cv denotes the critical value of the small sample distribution under investigation. To perform a one-sided test we use the percentiles 90 and 95 of these distributions as respectively the 10% and 5% critical values.

Similarly, instead of using the critical values of the standard normal distribution to test hypotheses on ψ, we could use the critical values of the small sample distribution of t-values $t^a(\widehat{\psi}^b) = \frac{\widehat{\psi}^b - \widehat{\psi}}{sd^a(\widehat{\psi}^b)}$ $(b = 1, ..., B)$. We would then reject the null hypothesis $\psi = \psi_0 = 0$

in favour of $\psi > 0$ if $t^a(\widehat{\psi}) = \frac{\widehat{\psi}-\psi_0}{sd^a(\widehat{\psi})} > cv\left(t^a(\widehat{\psi}^b)\right)$ where cv are the 10% and 5% critical values which, since the test is one-sided, correspond to the 90 and 95 percentiles of the distribution. Note that this method of sampling and this method of constructing t-values and testing hypotheses is the method suggested by Hall and Wilson (1991).[11]

One problem with the application of this method is that it may provide bad results if the estimate of the variance is poor (see Li and Maddala 1996). The results reported below suggest that the estimated asymptotic standard errors are underestimated. Therefore we follow the suggestion by Hartigan (1986) to implement a two-level bootstrap. That is, we calculate bootstrapped standard errors and use these instead of the unreliable asymptotic ones to construct a correct (pivotal) t-value. Then we bootstrap again to obtain a small sample distribution of t-values. Thus we obtain $t(\widehat{\psi}^b) = \frac{\widehat{\psi}^b - \widehat{\psi}}{sd(\widehat{\psi}^b)}$ $(b = 1, ..., B)$ where $sd(\widehat{\psi}^b)$ is the bootstrapped standard error obtained by bootstrapping from the (bootstrap) sample from which $\widehat{\psi}^b$ was estimated. The number of bootstrap replications to compute $sd(\widehat{\psi}^b)$ for $b = 1, ..., B$ is set to B^* (we set $B^* = 200$ in all cases). We now reject the null hypothesis $\psi = \psi_0 = 0$ in favour of $\psi > 0$ if $t(\widehat{\psi}) = \frac{\widehat{\psi}-\psi_0}{sd(\widehat{\psi})} > cv\left(t(\widehat{\psi}^b)\right)$ where cv are the 10% and 5% critical values which, since the test is one-sided, correspond to the 90 and 95 percentile of the distribution.[12]

4 Data issues

In this section we discuss the data and the data sources that we use. Data are annual and mostly taken from OECD (2003). All data are in real terms. For private consumption (c_t) we use real aggregate consumption (code: CPV). For debt b_t we use both gross and net government debt (code: GGFL for gross debt en NGFL for net debt) deflated by the consumer price index (code: CPI). Note that for Australia (gross) nominal debt is not available from OECD before 1988, so we take the gross debt series available from the IMF

---

[11]See sampling scheme S1 with statistic T1 in Li and Maddala (1996) on page 122.

[12]We also test $\beta = r(1+r)^{-1}$ versus $\beta \neq r(1+r)^{-1}$ (two-sided test) by using the percentiles 2.5 and 97.5 of the $t(\widehat{\beta}^b)$ distribution as 5% critical values and percentiles 5 and 95 as 10% critical values.

(IFS, 2000). For government expenditures g_t (consumption and investment) we use real government investment (code: IGV) plus real government consumption (code: CGV). For taxes minus net transfers (t_t) we calculate real government expenditures minus the real primary deficit. The nominal primary deficit (code: NLGX) is deflated by the consumer price index. For pre-tax income (y_t) real GDP (code: GDPV) is used. The advantage of this measure is that it excludes interest income on government bonds as is the case for y_t in the theory. Private sector wealth excluding government bonds (w_t) is proxied through the real capital stock of the business sector (code: KBV) plus real net foreign assets. Net foreign assets are taken from Lane and Milesi-Ferretti (2001a, 2001b) and are first set from USD into local currency through purchasing power parities (code: PPP) after which they are deflated by the consumer price index. For the complications encountered with this series for Belgium we refer to Pozzi (2003). Finally, we divide all series by population (code: POP) to obtain per capita measures and we scale the variables by dividing all observations in one country by that country's real per capita GDP in the first year of the sample.

Data availability determines the sample period which is 1980-1997. The sample contains 19 countries if gross government debt is used: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, UK, and USA. When using net government debt Australia, Greece, and Ireland drop out since no net government debt series is available for these countries.

5 Results

The results from estimating eq.(5) with instrument set 1 using the gross government debt are presented in table 1. We refer to section 3.2 for the description of this instrument set. Interest rates are set respectively to 0.03, 0.05, and 0.07. The point estimates for β and λ have the expected signs and plausible values. Using the critical values of the two-level bootstrapped small sample distribution of the t-values, only in the case $r = 0.07$ we find

16

that β is significantly higher than zero at the 10% level. Further, the point estimates for β are in general smaller than the value of the marginal propensity to consume in the case of certainty equivalence (i.e. the value for $\frac{r}{1+r}$). Interpreting this in terms of our model it implies that forward looking consumers may have a precautionary savings motive that potentially offsets their impatience. We can however not reject the hypothesis $\beta = \frac{r}{1+r}$ at the usual levels of significance (results not reported but available upon request).

The point estimates for λ are significantly positive at the 5% level. Over the period 1980-1997 these results suggest that about 25% of consumers in OECD countries are rule-of-thumb current income consumers. This result is within the range of country-specific estimates found for this fraction in other studies (see e.g. Campbell and Mankiw 1991, Bacchetta and Gerlach 1997). As far as panel studies are concerned, it is more or less in line with the fraction estimated by Evans and Karras (1998) for 66 development and industrial countries over the period 1970-1989. It is however substantially lower than the 40% found by Lopez et al. (2000) for OECD countries over the period 1975-1992. Possibly the difference stems from the different panel methodology employed. Lopez et al. (2000) apply a first difference GMM estimator to a consumption function derived in first differences (thus differencing the data twice before estimation), whereas we avoid differencing by applying the system GMM estimator to an equation with variables expressed in levels.

If we compare the usual GMM asymptotic standard errors with the bootstrapped ones, we can see that the former are considerably lower than the latter for both β and λ in all cases. This result is in accordance with the problem of underestimated standard errors of two-step GMM estimators as reported by Arellano and Bond (1991) and Windmeijer (2000). The observed biases in the point estimates are negligible however. The problems encountered do justify a posteriori the use of (two-level) bootstrapped distributions for the t-values to conduct inference.

If we look at the Sargan test and the difference Sargan test we find no evidence against our model and instruments. Using the reported p-values we cannot reject the null hypothesis that the moment conditions are correct (for the Sargan test) and that the level moment conditions are correct (for the difference Sargan test). Thus, our approach of

using a first-difference specification combined with a levels specification to avoid information loss seems justified. We also note that the bootstrapped distributions (and thus the critical values) for both these test statistics differ considerable from the asymptotic ones so that, again, our bootstrap approach is appropriate and necessary.

In table 2 we present the results of estimating eq.(5) with the net government debt. Though net government debt may be a more appropriate measure for debt in a Ricardian model, data are now only available for sixteen OECD countries instead of nineteen. The cross-sectional dimension is now somewhat smaller than the time dimension. The conclusions regarding the point estimates and the significance of β and λ are identical to those reported in table 1. The Sargan and the difference Sargan test do not reject the moment conditions. The only exception is the case $r = 0.03$ where the difference Sargan test reveals some evidence of misspecification when using the level moment conditions.

As a robustness check we estimate eq.(5) using a different instrument set (instrument set 2 which is explained in section 3.2). The results for gross government debt are reported in table 3, those for net government debt in table 4. The conclusions reached are largely identical to those reported for tables 1 and 2.

Finally, we note that the estimation of eq.(5) for the 80s and 90s seperately does not reveal significant differences in the point estimates for λ and β between these two periods or between these subperiods and the full sample period (results not reported but available upon request). Thus, for the OECD countries as a whole, there is no indication of shifts in time of the fraction of current income consumers during the 80s versus the 90s. Since the evidence on time-variation in the excess sensitivity of private consumption to current income in individual country studies is mixed (see e.g. Campbell and Mankiw 1991, Bacchetta and Gerlach 1997), this result is not inconsistent with the existing literature.

6 Conclusions

In this paper we investigate the Ricardian Equivalence proposition for a panel of OECD countries in the 1980s and 1990s. We use a model with two consumer types. One type of consumers is rule-of-thumb and follows current income, the other type is a permanent income consumer who incorporates the government budget constraint. The presence of the first type constitutes a deviation from the Ricardian Equivalence proposition. We also allow for a second deviation from Ricardian Equivalence, a precautionary savings effect, by allowing that permanent income consumers consume less out of permanent income than what they would consume in the case of certainty equivalence. Methodologically, we focus on the problems of information loss and small sample inference when estimating dynamic panels. As far as the first issue is concerned, we avoid the loss of information that comes with first-difference transformations by deriving a testable consumption function that is in levels to begin with. Then, we use a nonlinear GMM estimator that uses moment conditions that exploit information from the levels of the variables that appear in the consumption function. As for the second issue, we use both one-level and two-level GMM bootstraps to conduct inference and to check whether our estimates and asymptotic standard errors are biased.

Our results suggest that about 25% of the consumers in OECD countries over the period 1980-1997 are rule-of-thumb consumers and that the remaining fraction are permanent income consumers who incorporate the government budget constraint. This remaining 75% of consumers may not be strictly Ricardian however since the marginal propensity to consume out of permanent income of these consumers is lower (though not significantly so) than what we would expect in the certainty equivalence case which underlies Ricardian Equivalence. We conclude that Ricardian Equivalence is rejected. Our model and each type of moment conditions we use in the estimations is supported by the data. This justifies the use of information from the levels of the variables to obtain estimates. Further, our point estimates are not biased, but the asymptotic standard errors are, as exptected, underestimated. The asymptotic distributions of the test statistics poorly approximate

their small sample counterparts justifying our bootstrap approach to conduct inference.

References

AHN, S., AND P. SCHMIDT (1995): "Efficient estimation of models for dynamic panel data," *Journal of Econometrics*, 68, 5–28.

ALTONJI, J., AND L. SEGAL (1994): "Small sample bias in GMM estimation of covariance structures," *NBER Technical Working Paper*, 156.

ANDERSON, T., AND C. HSIAO (1982): "Formulation and estimation of dynamic models using panel data," *Journal of Econometrics*, 18, 47–82.

ARELLANO, M., AND S. BOND (1991): "Some tests of specification for Panel Data: Monte Carlo evidence and an application to Employment Equations," *Review of Economic Studies*, 58, 277–297.

ARELLANO, M., AND O. BOVER (1995): "Another look at the Instrumental Variable estimation of Error-Components Models," *Journal of Econometrics*, 68, 29–51.

BACCHETTA, P., AND S. GERLACH (1997): "Consumption and Credit Constraints: International Evidence," *Journal of Monetary Economics*, 40, 207–238.

BARRO, R. (1974): "Are government bonds net wealth ?," *Journal of Political Economy*, 82(6), 1095–1117.

BERGSTRÖM, P., M. DAHLBERG, AND E. JOHANSSON (1997): "GMM bootstrapping and testing in dynamic panels," *Uppsala University, Department of Economics, Working paper*, 1997/10.

BERNHEIM, B. (1987): "Ricardian Equivalence: an evaluation of the theory and evidence," in *NBER Macroeconomics Annual*, ed. by S. Fischer, pp. 263–304. MIT Press.

BLANCHARD, O. (1985): "Debt, deficits and finite horizons," *Journal of Political Economy*, 93(2), 223–247.

BLUNDELL, R., AND S. BOND (1998): "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, 87, 115–143.

BLUNDELL, R., S. BOND, AND F. WINDMEIJER (2000): "Estimation in Dynamic Panel Data Models: Improving on the Performance of the Standard GMM Estimator," in *Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, ed. by B. Baltagi, vol. 15 of *Advances in Econometrics*. Elsevier Science, Amsterdam.

CAMPBELL, J., AND N. MANKIW (1990): "Permanent Income, Current Income and Consumption," *Journal of Business and Economic Statistics*, 8, 265–279.

CAMPBELL, J., AND N. MANKIW (1991): "The Response of Consumption to Income. A Cross Country Investigation," *European Economic Review*, 35, 723–767.

CARROLL, C. (1994): "How does future income affect current consumption ?," *Quarterly Journal of Economics*, pp. 111–147.

DAHLBERG, M., AND E. JOHANSSON (2000): "An examination of the dynamic behaviour of local governments using GMM bootstrapping methods," *Journal of Applied Econometrics*, 15, 401–416.

DALAMAGAS, B. (1994): "The tax versus debt controversy in a multivariate cointegrating framework," *Applied Economics*, 26, 1197–1206.

EVANS, P. (1988): "Are Consumers Ricardian ? Evidence for the United States," *Journal of Political Economy*, 96(5), 983–1004.

——— (1993): "Consumers are not Ricardian: evidence from nineteen countries," *Economic Inquiry*, 31, 534–548.

EVANS, P., AND G. KARRAS (1998): "Liquidity Constraints and the substitutability between Private and Government Consumption," *Economic Inquiry*, 36, 203–214.

FLAVIN, M. (1985): "Excess Sensitivity of Consumption to Current Income: Liquidity Constraints or Myopia?," *Canadian Journal of Economics*, 38, 117–136.

GALI, J. (1990): "Finite Horizons, Life Cycle Savings and time series evidence on Consumption," *Journal of Monetary Economics*, 26, 433–452.

GOODFRIEND, M. (1992): "Information-Aggregation bias," *American Economic Review*, 82, 508–519.

HALL, P., AND J. HOROWITZ (1996): "Bootstrap critical values for tests based on generalized method of moments estimators," *Econometrica*, 64(4), 891–916.

HALL, P., AND S. WILSON (1991): "Two guidelines for bootstrap hypothesis testing," *Biometrics*, 47, 757–762.

HANSEN, L. (1982): "Large sample properties of generalized method of moment estimators," *Econometrica*, 50, 1029–1054.

HAQUE, N. (1988): "Fiscal policy and private sector behaviour in developing economies," *IMF Staff Papers*, 35(2), 316–335.

HAQUE, N., AND P. MONTIEL (1989): "Consumption in developing countries: tests for liquidity constraints and finite horizons," *Review of Economics and Statistics*, 71, 408–415.

HARTIGAN, J. (1986): "Comment on the paper by Efron and Tibshirani," *Statistical Science*, 1, 75–76.

HAYASHI, F. (1982): "The Permanent Income Hypothesis: estimation and testing by instrumental variables," *Journal of Political Economy*, 90(5), 895–916.

HIMARIOS, D. (1995): "Euler equation tests of Ricardian Equivalence," *Economics Letters*, 48, 165–171.

JUDSON, A., AND A. OWEN (1999): "Estimating Dynamic Panel Data Models: A Guide for Macroeconomists," *Economics Letters*, 65, 9–15.

LANE, P., AND G. MILESI-FERRETTI (2001): "The external wealth of nations: measures of foreign assets and liabilities for industrial and developing countries," *Journal of International Economics*, 55(2), 263–294.

———— (2001b): "Revised data set for the paper "The external wealth of nations" on URL website http://econserv2.bess.tcd.ie/plane/data.html," .

LI, H., AND G. MADDALA (1996): "Bootstrapping time series models," *Econometric Reviews*, 15(2), 115–158.

LOPEZ H.J, SCHMIDT-HEBBEL, K., AND L. SERVÉN (2000): "How effective is fiscal policy in raising national saving ?," *Review of Economics and Statistics*, 82(2), 226–238.

MANKIW, N. (1982): "Hall's consumption hypothesis and durable goods," *Journal of Monetary Economics*, 10, 417–426.

NELSON, C., AND R. STARTZ (1990): "The distribution of the instrumental variables estimator and its t-ratio when the instrument is a poor one," *Journal of Business*, 63, 125–140.

NICKELL, S. (1981): "Biases in dynamic models with fixed effects," *Econometrica*, 49(6), 1417–1426.

POZZI, L. (2003): "Tax discounting in a high debt economy," *Oxford Bulletin of Economics and Statistics*, 65(3), 261–282.

ROCKERBIE, D. (1997): "Are consumers Ricardian when some are liquidity constrained ?," *Applied Economics*, 29, 821–827.

SEATER, J. (1993): "Ricardian Equivalence," *Journal of Economic Literature*, 31, 142–190.

TAUCHEN, G. (1986): "Statistical properties of GMM estimators of structural parameters obtained from financial market data," *Journal of Business and Economic Statistics*, 4, 397–416.

Windmeijer, F. (2000): "A finite sample correction for the variance of linear two-step GMM estimators," *Institute for Fiscal Studies Working Paper*, 00/19.

Working, H. (1960): "Note on the correlation of first differences of averages in a random chain," *Econometrica*, 28, 916–918.

Ziliak, J. (1997): "Efficient estimation with panel data when instruments are predetermined: an empirical comparison of moment-condition estimators," *Journal of Business and Economic Statistics*, 14(4), 419–431.

Appendix A: derivation of linearized first-order condition

Consider the first-order condition,

$$E_t\left(\left(\frac{c_{2t+1}}{c_{2t}}\right)^{-1}\right) = \frac{1+\rho}{1+r} \tag{A1}$$

A second-order Taylor approximation of $\left(\frac{c_{2t+1}}{c_{2t}}\right)^{-1}$ around $\frac{c_{2t+1}}{c_{2t}} = 1$ gives,

$$\left(\frac{c_{2t+1}}{c_{2t}}\right)^{-1} = 1 - \left(\frac{c_{2t+1}}{c_{2t}} - 1\right) + \left(\frac{c_{2t+1}}{c_{2t}} - 1\right)^2 \tag{A2}$$

Furthermore, we assume a constant conditional uncentered second moment of consumption growth equal to σ^2, i.e.,

$$E_t\left(\frac{c_{2t+1}}{c_{2t}} - 1\right)^2 = E_t\left(\frac{c_{2t+1} - c_{2t}}{c_{2t}}\right)^2 = \sigma^2 \tag{A3}$$

Substituting eqs. (A2) and (A3) into eq.(A1), we obtain,

$$E_t\left(1 - \left(\frac{c_{2t+1}}{c_{2t}} - 1\right)\right) + \sigma^2 = \frac{1+\rho}{1+r}$$

or,

$$E_t c_{2t+1} = \left(\sigma^2 + 2 - \frac{1+\rho}{1+r}\right) c_{2t}$$

24

This corresponds to the linearized first-order condition given in the text, namely,

$$E_t c_{2t+1} = k c_{2t}$$

with

$$k = \frac{\sigma^2 (1 + r) + 2r + 1 - \rho}{1 + r}$$

Appendix B: derivation of eq.(5)

Suppose we have a variable x_t and a discount rate m, so that we can write,

$$\sum_{j=0}^{\infty} (1 + m)^{-j} x_{t+j} \equiv (1 + m) \left(\sum_{j=0}^{\infty} (1 + m)^{-j} x_{t+j-1} - x_{t-1} \right)$$

After taking expectations at time t of both sides and adding and subtracting the term $(1 + m) \sum_{j=0}^{\infty} (1 + m)^{-j} E_{t-1} [x_{t+j-1}]$ at the RHS, following equation is obtained,

$$\sum_{j=0}^{\infty} (1 + m)^{-j} E_t [x_{t+j}] = (1 + m) \left[\sum_{j=0}^{\infty} (1 + m)^{-j} E_{t-1} [x_{t+j-1}] - x_{t-1} \right] + e_{xt}$$

where

$$e_{xt} = \sum_{j=0}^{\infty} (1 + m)^{-j+1} \left(E_t [x_{t+j-1}] - E_{t-1} [x_{t+j-1}] \right)$$

Replace x_t with y_t and g_t and m with r to obtain,

$$\sum_{j=0}^{\infty} (1 + r)^{-j} E_t [y_{t+j}] = (1 + r) \left[\sum_{j=0}^{\infty} (1 + r)^{-j} E_{t-1} [y_{t+j-1}] - y_{t-1} \right] + e_{yt} \qquad \text{(B1)}$$

$$\sum_{j=0}^{\infty} (1 + r)^{-j} E_t [g_{t+j}] = (1 + r) \left[\sum_{j=0}^{\infty} (1 + r)^{-j} E_{t-1} [g_{t+j-1}] - g_{t-1} \right] + e_{gt} \qquad \text{(B2)}$$

with expectation revisions (thus uncorrelated to lagged information sets),

$$e_{yt} = \sum_{j=0}^{\infty} (1 + r + \rho)^{-j+1} \left(E_t [y_{t+j-1}] - E_{t-1} [y_{t+j-1}] \right)$$

$$e_{gt} = \sum_{j=0}^{\infty} (1 + r + \rho)^{-j+1} \left(E_t [g_{t+j-1}] - E_{t-1} [g_{t+j-1}] \right)$$

Substituting eqs.(1) and (3) into eq.(4), we obtain,

$$c_t = \lambda(y_t - t_t) + \beta(\sum_{j=0}^{\infty}(1+r)^{-j}E_t[(1-\lambda)(y_{t+j} - g_{t+j} + w_t + \lambda b_t)] \qquad \text{(B3)}$$

Lagging eq.(B3) one period and rearranging leads to,

$$\beta(1-\lambda)\sum_{j=0}^{\infty}(1+r)^{-j}E_{t-1}[y_{t+j-1}] = c_{t-1} - \lambda(y_{t-1} - t_{t-1}) \qquad \text{(B4)}$$

$$+\beta(1-\lambda)\sum_{j=0}^{\infty}(1+r)^{-j}E_{t-1}[g_{t+j-1}] - \beta w_{t-1} - \beta\lambda b_{t-1}$$

Moreover, using eqs.(B1)-(B2) into eq.(B3), we obtain,

$$c_t = \lambda(y_t - t_t) + \beta(1-\lambda)(1+r)\left[\sum_{j=0}^{\infty}(1+r)^{-j}E_{t-1}[y_{t+j-1}] - y_{t-1}\right] \qquad \text{(B5)}$$

$$+\beta(1-\lambda)e_{yt} - \beta(1-\lambda)(1+r)\left[\sum_{j=0}^{\infty}(1+r)^{-j}E_{t-1}[g_{t+j-1}] - g_{t-1}\right]$$

$$-\beta(1-\lambda)e_{gt} + \beta w_t + \beta\lambda b_t$$

Plugging eq.(13) into eq.(13) leads to eq.(5) with,

$$\eta_t = \beta(1-\lambda)(e_{yt} - e_{gt})$$

26

Tables

Table 1. Estimation results for eq.(5) with instrument set 1 and gross government debt (19 OECD countries, annual data, 1980-1997).

		(1)	**(2)**	**(3)**
		r=0.03	r=0.05	r=0.07
β	est	0.014	0.025	0.034*
	sd^a	0.009	0.009	0.008
	sd	0.039	0.044	0.040
	$bias$	0.006	0.003	0.000
λ	est	0.258**	0.254**	0.250**
	sd^a	0.017	0.017	0.017
	sd	0.054	0.057	0.052
	$bias$	-0.002	0.005	0.003
S	$pval$	0.430	0.435	0.455
	df	178	178	178
dS	$pval$	0.315	0.320	0.310
	df	90	90	90

Notes: we refer to section 3.2 for details on instrument sets. est is the second step GMM point estimate, sd^a is the asymptotic standard error, sd is the bootstrapped standard error, $bias$ is the bias in the point estimate, S is the Sargan test, dS is the difference Sargan test, $pval$ (p-value) is calculated from the bootstrapped distributions of the Sargan test statistic and difference Sargan test statistic. It equals 1 minus the percentile that coincides with the value found for these tests in the estimation. The null hypothesis is that the moment conditions are correct for S and that the level moment conditions are correct for dS. df are the degrees of freedom. * (**) indicates that the estimate is significantly larger than zero at the 10% (5%) level of confidence. This one-sided test uses the 90 and 95 percentiles of the bootstrapped distribution of t-values (two-level bootstrap). We refer to sections 3.2 and 3.3 for details.

Table 2. Estimation results for eq.(5) with instrument set 1 and net government debt (16 OECD countries, annual data, 1980-1997).

		(1)	**(2)**	**(3)**
		r=0.03	r=0.05	r=0.07
β	est	0.014	0.025	0.034*
	sd^a	0.011	0.009	0.008
	sd	0.052	0.054	0.048
	$bias$	0.000	0.004	0.005
λ	est	0.262**	0.257**	0.251**
	sd^a	0.020	0.020	0.020
	sd	0.056	0.057	0.055
	$bias$	-0.011	-0.010	-0.004
S	$pval$	0.150	0.160	0.175
	df	178	178	178
dS	$pval$	0.040	0.110	0.120
	df	90	90	90

Notes: we refer to section 3.2 for details on instrument sets. est is the second step GMM point estimate, sd^a is the asymptotic standard error, sd is the bootstrapped standard error, $bias$ is the bias in the point estimate, S is the Sargan test, dS is the difference Sargan test, $pval$ (p-value) is calculated from the bootstrapped distributions of the Sargan test statistic and difference Sargan test statistic. It equals 1 minus the percentile that coincides with the value found for these tests in the estimation. The null hypothesis is that the moment conditions are correct for S and that the level moment conditions are correct for dS. df are the degrees of freedom. * (**) indicates that the estimate is significantly larger than zero at the 10% (5%) level of confidence. This one-sided test uses the 90 and 95 percentiles of the bootstrapped distribution of t-values (two-level bootstrap). We refer to sections 3.2 and 3.3 for details.

Table 3. Estimation results for eq.(5) with instrument set 2 and gross government debt (19 OECD countries, annual data, 1980-1997).

		(1)	(2)	(3)
		r=0.03	r=0.05	r=0.07
β	est	0.014	0.025	0.035*
	sd^a	0.013	0.013	0.012
	sd	0.041	0.035	0.034
	$bias$	0.006	0.004	0.006
λ	est	0.263**	0.259**	0.255**
	sd^a	0.013	0.014	0.015
	sd	0.057	0.054	0.049
	$bias$	-0.005	-0.001	-0.002
S	$pval$	0.310	0.355	0.290
	df	250	250	250
dS	$pval$	0.395	0.465	0.390
	df	84	84	84

Notes: we refer to section 3.2 for details on instrument sets. est is the second step GMM point estimate, sd^a is the asymptotic standard error, sd is the bootstrapped standard error, $bias$ is the bias in the point estimate, S is the Sargan test, dS is the difference Sargan test, $pval$ (p-value) is calculated from the bootstrapped distributions of the Sargan test statistic and difference Sargan test statistic. It equals 1 minus the percentile that coincides with the value found for these tests in the estimation. The null hypothesis is that the moment conditions are correct for S and that the level moment conditions are correct for dS. df are the degrees of freedom. * (**) indicates that the estimate is significantly larger than zero at the 10% (5%) level of confidence. This one-sided test uses the 90 and 95 percentiles of the bootstrapped distribution of t-values (two-level bootstrap). We refer to sections 3.2 and 3.3 for details.

Table 4. Estimation results for eq.(5) with instrument set 2 and net government debt (16 OECD countries, annual data, 1980-1997).

		(1)	**(2)**	**(3)**
		r=0.03	r=0.05	r=0.07
β	est	0.015	0.026	0.035
	sd^a	0.018	0.016	0.015
	sd	0.047	0.046	0.048
	$bias$	0.009	0.006	0.005
λ	est	0.270**	0.264**	0.259**
	sd^a	0.017	0.016	0.016
	sd	0.056	0.061	0.053
	$bias$	-0.009	-0.011	-0.010
S	$pval$	0.165	0.160	0.185
	df	250	250	250
dS	$pval$	0.240	0.165	0.130
	df	84	84	84

Notes: we refer to section 3.2 for details on instrument sets. est is the second step GMM point estimate, sd^a is the asymptotic standard error, sd is the bootstrapped standard error, $bias$ is the bias in the point estimate, S is the Sargan test, dS is the difference Sargan test, $pval$ (p-value) is calculated from the bootstrapped distributions of the Sargan test statistic and difference Sargan test statistic. It equals 1 minus the percentile that coincides with the value found for these tests in the estimation. The null hypothesis is that the moment conditions are correct for S and that the level moment conditions are correct for dS. df are the degrees of freedom. * (**) indicates that the estimate is significantly larger than zero at the 10% (5%) level of confidence. This one-sided test uses the 90 and 95 percentiles of the bootstrapped distribution of t-values (two-level bootstrap). We refer to sections 3.2 and 3.3 for details.