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THE PREDICTABILITY OF AGGREGATE CONSUMPTION GROWTH IN OECD COUNTRIES: A PANEL DATA ANALYSIS

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SUMMARY

We examine aggregate consumption growth predictability. We derive a dynamic consumption equation which encompasses relevant predictability factors: habit formation, intertemporal substitution, current income consumption and non-separabilities between private consumption and both hours worked and government consumption. We estimate this equation for a panel of 15 OECD countries over the period 1972–2007, taking into account parameter heterogeneity, endogeneity and error cross-sectional dependence using a GMM version of the common correlated effects mean group estimator. Small-sample properties are demonstrated using Monte Carlo simulations. The estimation results support income growth as the only variable with significant predictive power for aggregate consumption growth. Copyright © 2013 John Wiley & Sons, Ltd.

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1. INTRODUCTION

The permanent income hypothesis implies that aggregate private consumption follows a random walk (Hall, 1978). Empirical studies show that this random walk hypothesis is not supported by the data since aggregate consumption growth is predictable, at least to some extent. More sophisticated theoretical models capture this fact by introducing various forms of predictability in aggregate consumption growth. Relevant forms are caused by liquidity constraints (Campbell and Mankiw, 1989, 1990, 1991), habit formation (Campbell, 1998; Carroll *et al*., 2011), intertemporal substitution effects in response to real interest rate changes (Campbell and Mankiw, 1989) and non-separabilities in the utility function between private consumption and government consumption (Evans and Karras, 1998) and between private consumption and hours worked (Basu and Kimball, 2002). Empirically, an often reported finding is the positive impact of aggregate disposable income growth on private consumption growth (i.e. the ‘excess sensitivity’ puzzle), which can be rationalized from models incorporating consumers who base consumption on current income due to liquidity constraints (see Jappelli and Pagano, 1989; Campbell and Mankiw, 1990) or myopia (see Flavin, 1985). These current income consumers are often referred to as ‘rule-of-thumb’ consumers. Recent evidence in favour of current income consumption is provided by Kiley (2010). Other studies, such as Basu and Kimball (2002) and Carroll *et al*. (2011), argue that predictability stemming from the impact of current disposable income on consumption growth is less relevant once other forms of predictability are taken into account. As Gali *et al*. (2007) show that different predictability mechanisms have different macroeconomic implications, it is important to correctly identify the relevant forms of predictability. One drawback of all these studies is that they typically focus only on a subset of possible forms of predictability. Moreover, the empirical

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analysis is usually restricted to a single country (mainly the USA). Studies that present international evidence such as Campbell and Mankiw (1991) and Carroll *et al*. (2011) use a country-by-country approach. As a result, the additional information in the cross-sectional dimension of the data is not fully exploited. Evans and Karras (1998) and Lopez *et al*. (2000) use panel data methods but they do not tackle all the complications that arise when estimating aggregate consumption growth equations with macroeconomic data. In particular, they disregard cross-sectional dependence that may stem from the presence of unobserved variables that are common to all countries in the panel.

This paper examines the predictability of aggregate private consumption growth in a panel of OECD countries over the period 1972–2007. The contribution of the paper to the literature is both theoretical and methodological. Theoretically we present a model with consumers who optimize intertemporally. They form habits since their utility also depends on past consumption. They further substitute consumption intertemporally when confronted with real interest rate changes. Finally, their utility is affected by government consumption and also by the number of hours that they work. Following Campbell and Mankiw (1990) we also allow for rule-of-thumb consumers or current income consumers who consume their entire disposable income in each period. This model provides an expression for aggregate consumption growth that can be estimated using macroeconomic data. The five predictability factors incorporated in the model (habits, intertemporal substitution, non-separabilities in utility between consumption and government consumption and between consumption and hours worked, and current income consumption) lead to the dependence of aggregate private consumption growth on its own lag, on the real interest rate, on aggregate government consumption growth, on the growth rate in aggregate hours worked and on aggregate disposable income growth. These predictability factors constitute deviations from perfect consumption smoothing as implied by Hall's (1978) random walk hypothesis. Our specification for aggregate consumption growth encompasses many of the recent developments in consumption theory. And while our specification nests a number of specifications that have been estimated in the literature previously, to the best of our knowledge no study has yet estimated a specification as general as ours.

Methodologically we estimate the dynamic consumption equation derived in our theoretical model for a panel of 15 OECD countries over the period 1972–2007, making full use of the panel structure of the data. First, we estimate country-specific coefficients which are then combined using the mean group (MG) estimator to obtain estimates for the average effects. This avoids obtaining biased and inconsistent parameter estimates when falsely assuming that the regression slope parameters are identical across countries (see, for example, Pesaran and Smith, 1995). Differences across countries in aggregate consumption growth predictability can, for instance, be due to cross-country differences in financial systems, government policies and demographics. The cross-country estimates from Campbell and Mankiw (1991) and Evans and Karras (1998) indeed show considerable disparity in the predictability estimates obtained from regressions of aggregate consumption growth on current income and government expenditures. Second, we exploit the cross-sectional dependence in the data. Recently, the panel literature has emphasized unobserved, time-varying heterogeneity that may stem from omitted common variables that have differential impacts on individual units (see, for example, Coakley *et al*., 2002; Phillips and Sul, 2003). These latent common variables induce error cross-sectional dependence and may lead to inconsistent estimates if they are correlated with the explanatory variables. Especially when studying macroeconomic data, such unobserved global variables or shocks are likely to be the rule rather than the exception (see, for example, Coakley *et al*., 2006; Westerlund, 2008). In the context of aggregate private consumption, common factors may, for instance, be induced by financial liberalization and business cycle synchronization. Rather than treating the resulting cross-sectional correlation as a nuisance, we exploit it to correct for a potential omitted variables bias stemming from unobserved common factors. To this end, we use the common correlated effects (CCE) methodology suggested by Pesaran (2006). The basic idea behind CCE estimation is to capture the unobserved common factors by including cross-sectional averages of the dependent and the explanatory variables as

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additional regressors in the model. We use the mean group (CCEMG) variant to allow for possible parameter heterogeneity. Next, we suggest a generalized method of moments (GMM) version of the CCEMG estimator to account for endogeneity of the explanatory variables. A Monte Carlo simulation shows that in a dynamic panel data model with both endogeneity and error cross-sectional dependence this CCEMG-GMM performs reasonably well, especially when compared to alternative estimators, for the modest sample size $T=35, N=15$ that is available for our empirical analysis.

The estimation results support rule-of-thumb or current income consumption as the only significant form of predictability. We do not find a significant impact of hours worked on consumption growth. Neither do we find support for habit formation, intertemporal substitution effects and non-separabilities between private consumption and government consumption. Taking into account endogeneity and cross-sectional dependence proves to be important as it has a marked effect on the coefficient estimates. The finding of significant cross-sectional dependence in particular suggests that one or more unobserved common factors affect the predictability of aggregate consumption growth. This suggests that the conclusions obtained by existing studies that use only a time series approach or that use a panel approach without allowing for cross-sectional dependence may be less reliable.

The paper is structured as follows. In Section 2 we derive a dynamic equation for aggregate private consumption growth from a model that encompasses most of the relevant predictability factors discussed in the consumption literature. We discuss specification issues that arise when implementing this equation empirically. In Section 3 we review the different estimators that can be used. Section 4 presents the estimation results for a panel of OECD countries. In Section 5, we investigate the small-sample properties of the considered estimators using a Monte Carlo experiment. Section 6 concludes.

2. THEORY

In this section we first derive a dynamic equation for aggregate private consumption growth from a model that encompasses most of the relevant predictability factors discussed in the literature. Then we discuss a number of specification issues that need to be taken into account before this equation can be estimated.

2.1. The Model

Consider an economy with intertemporally optimizing permanent income consumers. The contemporaneous utility function u of each consumer is of the constant relative risk aversion (CRRA) type and is given by

$$u(C_t) = \frac{1}{1-(1/\theta)}\left[C_t C_{t-1}^{-\beta} H_t^{-\gamma} G_t^{-\pi}\right]^{1-(1/\theta)} \tag{1}$$

where C_t is the real per capita consumption level, H_t is the per capita number of hours worked and G_t is real per capita government consumption. The parameter θ is the elasticity of intertemporal substitution for which $\theta > 0$. Under the CRRA utility this parameter is the inverse of the coefficient of relative risk aversion ($1/\theta$). To correctly interpret the other parameters in the utility function (β, γ and π) we also assume that $\theta < 1$ (i.e. the elasticity of intertemporal substitution is smaller than 1 and the coefficient of relative risk aversion is larger than 1). This restriction is supported by the estimation results reported below. The parameter β is the habit parameter for which $\beta \geq 0$ (Campbell, 1998).

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The parameters γ and π capture respectively the impact of hours worked (Campbell and Mankiw, 1990) and government consumption (Evans and Karras, 1998) on the marginal utility of private consumption. When $\gamma > 0$ (< 0) hours worked and private consumption are complements (substitutes). When $\pi > 0$ (< 0) government consumption and private consumption are complements (substitutes). When $\gamma = 0$ and $\pi = 0$ hours worked and government consumption have no impact on the marginal utility of private consumption. Note that $\gamma < 0$ and $\pi > 0$ do not imply that hours worked increase and government consumption decrease total utility of consumption since a function $\phi(H_t, G_t)$ could be added to the utility function (with $\phi_H < 0$ and $\phi_G > 0$) without changing the first-order condition.

The first-order condition with respect to consumption C_t is given by

$$u'(C_{t-1}) = \left(\frac{1+R_t}{1+\delta}\right) E_{t-1}\left[u'(C_t)\right] \tag{2}$$

where $0 < \delta < 1$ is the rate of time preference, E_{t-1} the expectations operator conditional on period *t-1* information and R_t the time-varying but risk-free real interest rate for which $E_{t-1}(R_t) = R_t$. Substituting equation (1) into the first-order condition gives

$$E_{t-1}(X_t) = \left(\frac{1+\delta}{1+R_t}\right)\left(\frac{C_{t-1}}{C_{t-2}}\right)^{-\beta\left(\frac{1}{\theta}-1\right)} \tag{3}$$

where $X_t = \left(\frac{C_t}{C_{t-1}}\right)^{-\frac{1}{\theta}} \left(\frac{H_t}{H_{t-1}}\right)^{\gamma\left(\frac{1}{\theta}-1\right)} \left(\frac{G_t}{G_{t-1}}\right)^{\pi\left(\frac{1}{\theta}-1\right)}$ such that $lnX_t = -\frac{1}{\theta}\Delta lnC_t + \gamma\left(\frac{1}{\theta}-1\right)\Delta lnH_t + \pi\left(\frac{1}{\theta}-1\right)\Delta lnG_t$. We assume that the distribution of ΔlnC_t, ΔlnH_t, and ΔlnG_t is jointly normal conditional on period *t-1* information. As a result the distribution of lnX_t is also normal conditional on period *t-1* information. From the log-normal property[1] we then have

$$E_{t-1}(X_t) = exp\left[E_{t-1}(lnX_t) + \frac{1}{2}V_{t-1}(lnX_t)\right] \tag{4}$$

where the conditional variance $V_{t-1}(lnX_t)$ is assumed to be constant, i.e. $V_{t-1}(lnX_t) = \sigma^2_{lnX}$, implying that the conditional variances of ΔlnC_t, ΔlnH_t, and ΔlnG_t and the conditional covariances between ΔlnC_t, ΔlnH_t and ΔlnG_t are all constant. We then substitute equation (4) into equation (3) and take logs of the resulting equality to obtain

$$E_{t-1}(lnX_t) = \delta - \frac{1}{2}\sigma^2_{lnX} - \beta\left(\frac{1}{\theta}-1\right)\Delta lnC_{t-1} - R_t \tag{5}$$

where we have used the approximations $ln(1+\delta) \approx \delta$ and $ln(1+R_t) \approx R_t$. We then substitute the expression for lnX_t derived below equation (3) into equation (5) and rearrange terms to obtain

$$\begin{aligned} E_{t-1}\Delta lnC_t = \theta\left(\frac{1}{2}\sigma^2_{lnX} - \delta\right) &+ \beta(1-\theta)\Delta lnC_{t-1} + \gamma(1-\theta)E_{t-1}\Delta lnH_t \\ &+ \pi(1-\theta)E_{t-1}\Delta lnG_t + \theta R_t \end{aligned} \tag{6}$$

or

[1] The log-normal property says that if y is a normal variable with mean $E(y)$ and variance $V(y)$ then we can write $E(exp(y)) = exp[E(y) + \frac{1}{2}V(y)]$.

$$\Delta lnC_t = \theta\left(\frac{1}{2}\sigma^2_{lnX} - \delta\right) + \beta(1-\theta)\Delta lnC_{t-1} + \gamma(1-\theta)\Delta lnH_t + \pi(1-\theta)\Delta lnG_t + \theta R_t + \omega_t \quad (7)$$

where $\omega_t = (\Delta lnC_t - E_{t-1}\Delta lnC_t) - \gamma(1-\theta)(\Delta lnH_t - E_{t-1}\Delta lnH_t) - \pi(1-\theta)(\Delta lnG_t - E_{t-1}\Delta lnG_t)$ with $E_{t-1}\omega_t = 0$

Suppose now that some consumers in the economy are not optimizing permanent income consumers but are instead rule-of-thumb consumers who consume their entire disposable labour income in each period due to, for instance, myopia (see Flavin, 1985) or liquidity constraints (see Jappelli and Pagano, 1989; Campbell and Mankiw, 1990). In that case the growth rate of real per capita consumption in the economy can be approximated by

$$\Delta lnC_t = (1-\lambda)\left[\theta\left(\frac{1}{2}\sigma^2_{lnX} - \delta\right) + \beta(1-\theta)\Delta lnC_{t-1} + \gamma(1-\theta)\Delta lnH_t + \pi(1-\theta)\Delta lnG_t + \theta R_t + \omega_t\right] + \lambda \Delta lnY_t \quad (8)$$

where Y_t is real per capita disposable labour income (see Campbell and Mankiw, 1991; Kiley, 2010) and where λ approximates the fraction of rule-of-thumb current income consumers (with $0 \le \lambda \le 1$). Note that when $\lambda = 0$ equation (8) collapses to equation (7).

The estimable form of equation (8) can be written as

$$\Delta lnC_t = a_0 + a_1\Delta lnC_{t-1} + a_2\Delta lnH_t + a_3\Delta lnG_t + a_4R_t + a_5\Delta lnY_t + \mu_t \quad (9)$$

where $a_0 = (1-\lambda)\theta\left(\frac{1}{2}\sigma^2_{lnX} - \delta\right)$, $a_1 = (1-\lambda)\beta(1-\theta)$, $a_2 = (1-\lambda)\gamma(1-\theta)$, $a_3 = (1-\lambda)\pi(1-\theta)$, $a_4 = (1-\lambda)\theta$, $a_5 = \lambda$ and where $\mu_t = (1-\lambda)\omega_t$ with $E_{t-1}\mu_t = 0$.

Our consumption equation (equation (9)) encompasses most of the relevant predictability factors discussed in the literature. The 'stickiness' parameter $a_1 \ge 0$ reflects habit formation. Its sign is determined by the structural parameter capturing habits, i.e. $\beta \ge 0$. A non-zero value for a_2 captures the non-separability between private consumption and hours worked. Its sign is determined by the structural parameter γ. When $\gamma > 0$ (< 0) and therefore $a_2 > 0$ (< 0) aggregate hours worked and aggregate private consumption are complements (substitutes). A non-zero value for a_3 captures the non-separability between private consumption and government consumption. Its sign is determined by the structural parameter π. When $\pi > 0$ (< 0) and therefore $a_3 > 0$ (< 0) government consumption and aggregate private consumption are complements (substitutes). The parameter $a_4 > 0$ reflects intertemporal substitution effects in consumption caused by interest rate changes. It is determined by the structural parameter θ (where $0 < \theta < 1$), i.e. the intertemporal elasticity of substitution. The parameter a_5 ($0 \le a_5 \le 1$) reflects the impact of current income on consumption (liquidity constraints, myopia). It equals the structural parameter λ (where $0 \le \lambda \le 1$). It is important to mention that the structural parameters β, γ, π, θ and λ are uniquely identified from the parameters a_1, a_2, a_3, a_4 and a_5. Note further that some of the coefficients in equation (9) could be given other interpretations. A positive coefficient a_1 on lagged aggregate consumption growth could also be the result of the presence of consumers who are inattentive to macro developments (see Reis, 2006; Carroll *et al.*, 2011). Further, a positive coefficient a_5 on current aggregate labour income growth could also be the result of consumers who are imperfectly informed about the aggregate economy (see Goodfriend, 1992; Pischke, 1995).[2]

To the best of our knowledge no study has yet estimated a specification as general as ours. Equation (9) nests, however, a number of specifications that have been estimated in the literature previously.

[2] On the basis of macro data alone—on which the empirical analysis of this paper is based—it is not possible to distinguish the interpretations derived from the model from these alternative possibilities.

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Campbell and Mankiw (1990) conduct regressions on a version of equation (9) with restrictions $a_1 = 0$ (with ΔlnY_t always included and either ΔlnH_t, ΔlnG_t, or R_t added as an additional regressor). Evans and Karras (1998) estimate a version of equation (9) with restrictions $a_1 = a_2 = a_4 = 0$ (with ΔlnY_t and ΔlnG_t included). Basu and Kimball (2002) estimate a version of equation (9) with restrictions $a_1 = a_3 = 0$ (with ΔlnH_t, ΔlnY_t, and R_t included). Kiley (2010) estimates a version of equation (9) with the restriction $a_3 = 0$ (with ΔlnH_t, ΔlnY_t, ΔlnC_{t-1}, and R_t included). Carroll *et al.* (2011) estimate a version of equation (9) with restrictions $a_2 = a_3 = a_4 = 0$ (with ΔlnC_{t-1} and ΔlnY_t included).

2.2. Discussion

2.2.1. Endogeneity

According to the theoretical model the error term in equation (9) depends, by construction, on shocks to the real interest rate and on shocks to the growth rates in aggregate consumption, hours worked and government consumption. Hence the error term μ_t is expected to be contemporaneously correlated with the regressors ΔlnH_t, ΔlnG_t and R_t. Additionally, the error term μ_t is expected to be correlated with the regressor ΔlnY_t because shocks to consumption are basically shocks to permanent income. The latter are correlated with current income growth ΔlnY_t. As such, to estimate the parameters of equation (9) consistently, an instrumental variables approach is necessary. Details will be given in the following sections.

2.2.2. Autocorrelation

The error term μ_t in equation (9) is assumed to be unpredictable based on lagged information. Three features that are not incorporated in the model could lead to a violation of this assumption and to the occurrence of autocorrelation of the moving average (MA) form in the error term μ_t. First, Campbell and Mankiw (1990) note that transitory consumption and measurement error can lead to an MA structure in the error term.[3] Second, Working (1960) shows that an MA component could be present in consumption growth if consumption decisions are more frequent than observed data. Third, if durable consumption components are present in C_t this could induce negative autocorrelation in ΔlnC_t since durable consumption growth tends to be slightly negatively autocorrelated (see Mankiw, 1982). This negative autocorrelation could be reflected in less positive values for a_1 or in negative MA coefficients in the error term.

2.2.3. Cross-Sectional Dependence

When estimating the equation for aggregate consumption growth equation (9) using a panel of OECD countries, it can be expected that the error term μ_t is not independent across countries. Common unobserved shocks or factors can affect all countries simultaneously and induce error cross-sectional dependence. A twofold interpretation can be given to common unobserved factors found in regressions for aggregate consumption growth. First, financial liberalization most likely affects all OECD countries simultaneously over the sample period and could increase the importance of the common factor through increased risk-sharing opportunities between countries. In that case we would expect that countries' aggregate consumption growth rates move more closely with a common ('world') consumption growth rate (i.e. the idiosyncratic country-specific component of consumption growth becomes less important). Over the period 1973–1988, Obstfeld (1994) documents a general rise in the correlations of domestic consumption growth with world consumption growth for G7 countries. Second, increased business cycle synchronization could increase the importance

[3] Sommer (2007) shows that classical measurement error leads to an MA(1) error term in aggregate consumption growth, while general measurement error leads to an MA(2) error term in aggregate consumption growth.

of a common factor in aggregate consumption growth (see, for example, Kose *et al*., 2008, who provide evidence for aggregate consumption).

2.2.4. Long-Run Considerations

While the model presented above provides an expression for aggregate consumption growth which relates variables in the short run, it also implies a long-run relationship. In particular the solution of the optimization problem given by the Euler equation (equation (2)) is a stochastic representation of the permanent income hypothesis (see Hall, 1978). Campbell (1987) shows that the permanent income hypothesis implies that consumption and disposable income are cointegrated. If all consumers are rule-of-thumb consumers instead of permanent income consumers then aggregate consumption equals disposable income in every period and consumption and disposable income are also cointegrated. Hence both models predict a long-run cointegration relationship between income and consumption. However, since no error correction term enters directly into our derived equation for consumption growth—equation (9)—deviations from the equilibrium relationship between consumption and income are not subsequently corrected by changes in aggregate consumption. Then, by necessity, it is income that must adjust to the lagged difference between income and consumption to maintain the long-run equilibrium relationship between both variables (see Deaton, 1992, pp. 124–125). To deal with this cointegration relationship in our estimation of equation (9) we follow the empirical approach outlined for US data by Campbell and Mankiw (1990) and applied subsequently in a large number of papers (see, for example, McKiernan, 1996). The approach consists in imposing structure on the process followed by aggregate income growth when estimating equation (9). This can be done by adding an appropriate lag of $ln(Y_t) - ln(C_t)$ as an error-correction term in the instrument list for income growth (see Campbell and Mankiw, 1990, pp. 267–268). More details on the instruments used in our estimations will be given in the following sections.

3. ECONOMETRIC METHODOLOGY

In this section we outline our econometric methodology to estimate the model for aggregate consumption growth outlined in Section 2.1 using a panel dataset for 15 OECD countries over the period 1972–2007.

3.1. Model and Assumptions

Equation (9) is written in the form of a first-order autoregressive panel data model:

$$y_{it} = \alpha_i + \rho_i y_{i,t-1} + \beta_i' x_{it} + \mu_{it}, \qquad i = 1, 2, \ldots, N, \quad t = 2, \ldots T \tag{10}$$

$$\mu_{it} = \gamma_i' f_t + \phi(L)\varepsilon_{it} \tag{11}$$

where $y_{it} = \Delta lnC_{it}$ and $x_{it} = (\Delta lnH_{it}, \Delta lnG_{it}, R_{it}, \Delta lnY_{it})'$. The individual effect α_i captures unobserved time-invariant heterogeneity, while the heterogeneity in the parameters ρ_i and β_i across countries may, for example, reflect differences across countries in financial market institutions and development, government policies and demographics. Following the recent panel literature, we allow for a multi-factor structure in μ_{it} in which f_t is an $m \times 1$ vector of unobserved common variables. This error structure is quite general as it allows for an unknown (but fixed) number of unobserved common components with heterogeneous factor loadings (heterogeneous cross-sectional dependence).

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As such, it nests common time effects or time dummies (homogeneous cross-sectional dependence) as a special case. As noted in Section 2.2.2, there are various reasons that could lead to the occurrence of MA type autocorrelation in the error term of equation (9). Therefore, we allow μ_{it} in the empirical model in equation (10) to have an MA(q) component where $\phi(L) = 1 + \phi_1 L + \ldots + \phi_q L^q$ is a lag polynomial of order q. We further make the following assumptions.

Assumption 1. (Error condition)

(a) $E(\varepsilon_{it}) = 0$ for all i and t;
(b) $E(\varepsilon_{it}\varepsilon_{js}) = 0$ for either $i \neq j$, or $t \neq s$, or both;
(c) $E(\varepsilon_{it}\alpha_j) = 0$ for all i, j and t.

Assumption 2. (Explanatory variables) $E(x_{i,t-s}\varepsilon_{it}) = 0$ for all i, t and $s > 0$.

Assumption 3. (Random slope coefficients) $\rho_i = \rho + \psi_{1i}$, $\beta_i = \beta + \psi_{2i}$, $\psi_i = (\psi_{1i}, \psi'_{2i})' \sim \text{i. i. d.}\,(0, \Omega)$, where Ω is a 5×5 symmetric non-negative definite matrix and the random deviations ψ_i are distributed independently of ε_{it} and x_{it}.

Assumption 4. (Cross-sectional dependence)

(a) The unobserved factors f_t can follow general covariance stationary processes;
(b) $E(f_t\varepsilon_{is}) = 0$ for all i, t and s.

Assumption 1(a) and (b) states that ε_{it} is a mean zero error process which is mutually uncorrelated over time and over cross-sections. Assumption 1(c) states that the individual effects are exogenous. With respect to the explanatory variables, Assumption 2 allows the variables in x_{it} to be endogenous but implies that appropriately lagged, i.e. depending on the order of the MA component in μ_{it}, values of x_{it} are available as instruments. Note that we do not restrict x_{it} to be uncorrelated with α_i. Assumption 4 states that the unobserved factors in f_t are exogenous but it is quite general as it allows f_t to exhibit rich dynamics[4] and to be correlated with x_{it} and α_i. As Assumption 1 states that ε_{it} is uncorrelated over cross-sections, any dependence across countries is restricted to the common factors.[5]

3.2. Estimation Methodology

3.2.1. Averaging over Country-by-Country Coefficient Estimates

Pesaran and Smith (1995) show that in a dynamic heterogeneous panel data model as in equation (10), pooled estimators such as the fixed effects estimator in general provide inconsistent (for large N and T) estimates for the average effects $\overline{\rho} = N^{-1}\sum_{i=1}^{N} \rho_i$ and $\overline{\beta} = N^{-1}\sum_{i=1}^{N} \beta_i$. To overcome this problem, they suggest averaging over country-by-country coefficient estimates, i.e. $\hat{\rho} = N^{-1}\sum_{i=1}^{N} \hat{\rho}_i$

[4] In case the common factors are persistent, this implies the addition of unobserved predictability factors in aggregate consumption growth which are not accounted for by the theory in Section 2.1. As such, if we can include f_t as an explanatory variable this allows for an empirical extension of the theoretical model.

[5] Note that the occurrence of large countries in the sample, such as the USA, where shocks to consumption growth may lead to international business cycles, does not invalidate Assumption 4(b) as these will be shocks to f_t and therefore will not show up in ε_{it}.

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and $\hat{\bar{\beta}} = N^{-1}\sum_{i=1}^{N}\hat{\beta}_i$. This yields consistent estimates for the average effects $\bar{\rho}$ and $\bar{\beta}$ for both $N, T \to \infty$ provided that $\hat{\rho}_i$ and $\hat{\beta}_i$ are consistent for $T \to \infty$. In the remainder of this section we will outline four alternative estimators for the country-specific coefficients ρ_i and β_i. This will result in four alternative estimators for the average effects. Following Pesaran (2006), the asymptotic covariance matrix Σ for each of these average estimators is consistently estimated nonparametrically by

$$\hat{\Sigma} = \frac{1}{N-1}\sum_{i=1}^{N}\begin{bmatrix}\hat{\rho}_i - \hat{\bar{\rho}} \\ \hat{\beta}_i - \hat{\bar{\beta}}\end{bmatrix}\begin{bmatrix}\hat{\rho}_i - \hat{\bar{\rho}} & \hat{\beta}_i - \hat{\bar{\beta}}\end{bmatrix} \tag{12}$$

3.2.2. Naive Estimators

Direct estimation of ρ_i and β_i in the model in equations (10)–(11) is infeasible as the factors f_t in the error term μ_{it} are unobserved. As a benchmark in the empirical analysis and in the Monte Carlo simulation below, we therefore start with two naive estimators that ignore f_t. The first one estimates ρ_i and β_i using ordinary least squares (OLS) on equation (10) ignoring the error structure in equation (11). The average over the N country-specific OLS estimates is referred to as the mean group (MG) estimator. Abstracting from endogeneity of x_{it}, a possible MA(q) component in μ_{it} and cross-sectional dependence induced by the common factors f_t, country-by-country OLS estimation of the autoregressive model in equation (10) yields biased but consistent (as $T \to \infty$) estimates for ρ_i and β_i. In this case, the MG estimator is consistent for both $N, T \to \infty$.

Under Assumption 2, the MG estimator is inconsistent as the variables in x_{it} are allowed to be endogenous, while the MA(q) component in μ_{it} implies that the predetermined $y_{i,t-1}$ is also correlated with μ_{it}. Therefore, our second estimator for ρ_i and β_i is a GMM estimator using an appropriate number of periods lagged values of $y_{i,t-1}$ and x_{it} as instruments. The appropriate lag depth depends on the order q of the MA component in μ_{it}, i.e. the first available lags are $y_{i,t-1-q}$ and $x_{i,t-1-q}$. Adding deeper lags improves the efficiency of the GMM estimator. However, in order to avoid problems related to using too many instruments, we only use the first two available lags. This results in the following instrument set: $(y_{i,t-1-q}, y_{i,t-2-q}, x_{i,t-1-q}, x_{i,t-2-q}, z_{it})$; where z_{it} is a set of additional instruments which will be defined in the next section. The country-by-country GMM estimates are then averaged over the N countries to obtain the MG-GMM estimator.

3.2.3. Common Correlated Effects Estimators

The most obvious implication of ignoring error cross-sectional dependence is that it increases the variation of standard panel data estimators. Phillips and Sul (2003), for instance, show that if there is high cross-sectional correlation there may not be much to gain from using the cross-sectional dimension of the panel dataset. However, cross-sectional dependence can also introduce a bias and even result in inconsistent estimates. For a static panel data model, the Monte Carlo simulations in Pesaran (2006) reveal that the MG estimator ignoring the error component structure proposed in equation (11) is seriously biased and suffers from large size distortions. Essentially, as Assumption 4 allows the unobserved factors to be correlated with the explanatory variables, this is an omitted variables bias which does not disappear as $T \to \infty$, $N \to \infty$ or both. Thus the naive estimators presented above are biased and even inconsistent in this case. Second, Phillips and Sul (2007) show that in a dynamic panel data model cross-sectional dependence introduces additional small-sample bias.

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Pesaran (2006) shows that the cross-sectional averages of y_{it}, $y_{i,t-1}$ and x_{it} are suitable proxies for f_t. For a model with a single factor,[6] this can be seen by inserting equation (11) in equation (10) and taking cross-sectional averages to obtain

$$\overline{y}_t = \overline{\alpha} + \overline{\rho}\,\overline{y}_{t-1} + \overline{\beta}'\overline{x}_t + \overline{\gamma}f_t + \phi(L)\overline{\varepsilon}_t \tag{13}$$

where $\overline{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$ and similarly for the other variables. Solving equation (13) for f_t yields

$$f_t = \frac{1}{\overline{\gamma}}\left(\overline{y}_t - \overline{\alpha} - \overline{\rho}\,\overline{y}_{t-1} - \overline{\beta}'\overline{x}_t - \phi(L)\overline{\varepsilon}_t\right) \tag{14}$$

such that from using Assumption 1, which implies that $\operatorname*{plim}_{N\to\infty} \overline{\varepsilon}_t = 0$ for each t, we have

$$\hat{f}_t = 1/\overline{\gamma}\left(\overline{y}_t - \overline{\alpha} - \overline{\rho}\,\overline{y}_{t-1} - \overline{\beta}'\overline{x}_t\right) \xrightarrow{p} f_t \tag{15}$$

This is the main result in Pesaran (2006) that the cross-sectional averages $(\overline{y}_t, \overline{y}_{t-1}, \overline{x}_t)$ can be used as observable proxies of f_t. Although the construction of $\overline{f}_t$ as a consistent estimator of f_t requires knowledge of the unknown underlying parameters, the individual coefficients (ρ_i, β_i) and their means can be consistently estimated from an augmented form which is obtained by inserting equation (14) in equation (10):

$$\begin{aligned} y_{it} &= \alpha_i + \rho_i y_{i,t-1} + \beta'_i x_{it} + \frac{\gamma_i}{\overline{\gamma}}\left(\overline{y}_t - \overline{\alpha} - \overline{\rho}\,\overline{y}_{t-1} - \overline{\beta}'\overline{x}_t - \phi(L)\overline{\varepsilon}_t\right) + \phi(L)\varepsilon_{it} \\ &= \alpha_i^+ + \rho_i y_{i,t-1} + \beta'_i x_{it} + c_{1i}\overline{y}_t + c_{2i}\overline{y}_{t-1} + c'_{3i}\overline{x}_t + \phi(L)\varepsilon_{it}^+ \end{aligned} \tag{16}$$

with $\alpha_i^+ = \alpha_i - \frac{\gamma_i}{\overline{\gamma}}\overline{\alpha}$, $c_{1i} = \frac{\gamma_i}{\overline{\gamma}}$, $c_{2i} = -\overline{\rho}\frac{\gamma_i}{\overline{\gamma}}$, $c_{3i} = -\overline{\beta}'\frac{\gamma_i}{\overline{\gamma}}$, and $\varepsilon_{it}^+ = \varepsilon_{it} - \frac{\gamma_i}{\overline{\gamma}}\overline{\varepsilon}_t$. As $\operatorname*{plim}_{N\to\infty} \overline{\varepsilon}_t = 0$ implies that $\varepsilon_{it}^+ \xrightarrow{p} \varepsilon_{it}$ for $N \to \infty$, equation (16) is a standard heterogeneous dynamic panel data model with cross-sectional independent error terms as $N \to \infty$. Country-by-country least squares estimation of equation (16) is the CCE estimator suggested by Pesaran (2006). The CCEMG estimator is then the simple average of the individual CCE estimators. Given the dynamic nature of the model, the individual CCE estimator is biased for finite T, but conditional on x_{it} being predetermined or exogenous and $\phi(L) = 1$ this bias disappears as $T \to \infty$. This implies that consistency of the CCEMG estimator requires both N and $T \to \infty$.

Endogeneity of x_{it} and/or an MA(q) component in μ_{it} imply that the CCEMG estimator is inconsistent even for both N and $T \to \infty$. Therefore, we use GMM in the country-by-country estimation of equation (16). As $N \to \infty$, such that $\varepsilon_{it}^+ \xrightarrow{p} \varepsilon_{it}$, the cross-sectional averages $\overline{y}_t$, $\overline{y}_{t-1}$ and $\overline{x}_t$ are exogenous, while appropriate instruments for $y_{i,t-1}$ and x_{it} are as before $(y_{i,t-1-q}, y_{i,t-2-q}, x_{i,t-1-q}, x_{i,t-2-q}, z_{it})$. Also, letting $T \to \infty$, this will yield consistent country-by-country CCE-GMM estimates. These CCE-GMM estimates are then averaged over the N countries to obtain the CCEMG-GMM estimator.

[6] Multiple factors can be treated in the same way (see Phillips and Sul, 2007), and yield the same (unrestricted) model as the one presented in equation (16), but are not presented here for notational convenience.

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4. EMPIRICAL RESULTS

The model in equations (10)–(11) is estimated using aggregate yearly data for 15 OECD countries over the period 1972–2007. The selection of the countries and the sample period is determined by data availability and the aim to have as many time periods as possible for a reasonably large set of countries. The data are described in Section A of the online Appendix (supporting information).[7]

As motivated in the previous section, the GMM estimators are constructed using $y_{i,t-1-q}$, $y_{i,t-2-q}$, $x_{i,t-1-q}$, $x_{i,t-2-q}$ and z_{it} as instruments for the endogenous variables $y_{i,t-1}$ and x_{it}, where z_{it} is a set of additional instruments. We report results for three alternative instrument sets, which differ according to the assumed MA(q) component in the error term μ_{it}. Instrument set (a) assumes $q=0$, (b) assumes $q=1$ and (c) assumes $q=2$. We include the appropriately lagged error correction term $lnY_{i,t-1-q}-lnC_{i,t-1-q}$ as an additional instrument in z_{it}. As noted in Section 2.2.4, this serves to take into account the cointegration relationship that—according to our theoretical framework—exists between consumption and income. We have further experimented with other additional instruments in z_{it} like the lagged inflation rate (see, for example, Kiley, 2010) but these had little or no impact on the results, which we therefore do not report. We use a two-step procedure with a consistent estimate for the optimal weighting matrix constructed from a White type of estimator, allowing for heteroscedasticity when using instrument set (a) and from a Newey–West type of estimator allowing for both heteroscedasticity and *MA(1)* or *MA(2)* errors when using instrument sets (b) and (c) respectively.

Table I reports the average effects of the unrestricted parameters a_1 to a_5 in equation (9) as well as the estimates of the structural parameters β, θ, λ, γ, and π, since they are uniquely identified from the parameters a_1 to a_5 as indicated by the parameter restrictions reported below equation (9).[8] The estimation results for the individual countries can be found in Table B-1 of the online Appendix. In order to save space, individual country results for the GMM estimators are only reported for instrument set (b).

Before looking at the specific coefficient estimates, we perform some diagnostic tests. The panel test results are reported at the bottom of Table I. The cross-sectional independence test CD is from Pesaran (2004). Cross-sectional independence is rejected when applying the test to the residuals of the regressions estimated with the MG and MG-GMM estimators but not for the regressions estimated with the CCEMG-GMM estimator. This result suggests that cross-sectional dependence is an issue and that, to err on the side of caution, more weight should be given to the results obtained from the CCE type estimators.

For the GMM estimators, the Hansen (1982) overidentifying restrictions J test is first calculated for each country individually. The results are reported in Table B-1 of the online Appendix. Next, the panel version *F(J)* is obtainedby combining the country-specific p-values using the Fisher (1925) combined probability test. From the panel results in Table I we see that the used moment conditions are rejected by the data only when instrument set (a) is used. For instrument sets (b) and (c) the moment conditions are not rejected. This suggests that the order of the MA component in the residuals is at most $q=1$.

---

[7] Note that we use aggregate total consumption instead of consumption of non-durables and services, which from a strict theoretical point of view may be a better measure (see, for example, Carroll *et al.*, 2011, who use this measure for about half their countries). Unfortunately, over our sample period a complete time series for household expenditures on non-durables and services is only available from OECD National Accounts for five out of the 15 countries included in our analysis: Australia, Canada, France, Italy and the USA. Obviously five countries is too little to apply the CCE estimators. However, for the standard mean group estimators (MG, MG-GMM) it is possible to estimate our consumption equation with this alternative consumption measure on a per country basis. Our results suggest that the country-specific point estimates of the parameters in the consumption equation are very similar to the country-specific estimates reported in Table B-1 of the online Appendix with total consumption as a consumption measure. Hence we do not expect that the conclusions from our paper would be very different if we could use non-durables and services as a measure of consumption for all countries.

[8] Note that in principle we could also identify the parameter δ from the fixed-effects α_i (=a_0) and from σ^2_{lnX}, which could be calculated from the data. However, it can be expected that the fixed effects are contaminated by country-specific but time-invariant measurement error (see, for example, Loayza *et al.*, 2000), which will make the correct identification of δ unfeasible.

Table I. Panel data estimation results. Dependent variable: ΔlnC_{it}; sample period: 1972–2007, 15 countries

	MG	MG-GMM			CCEMG	CCEMG-GMM		
		(a)	(b)	(c)		(a)	(b)	(c)
Linear coefficient estimates								
$\Delta lnC_{i,t-1}$	−0.02	−0.02	0.01	0.02	−0.01	0.02	0.06	0.17
	(0.03)	(0.05)	(0.08)	(0.08)	(0.04)	(0.04)	(0.09)	(0.10)
ΔlnH_{it}	0.31***	0.28***	0.23	0.25**	0.21***	0.17	0.27*	0.17
	(0.05)	(0.09)	(0.14)	(0.09)	(0.05)	(0.10)	(0.14)	(0.14)
ΔlnG_{it}	0.05	0.09	0.05	0.13*	0.02	0.06	−0.05	0.00
	(0.04)	(0.07)	(0.07)	(0.07)	(0.05)	(0.08)	(0.09)	(0.07)
R_{it}	0.01	0.05	0.13***	0.06	0.08	0.05	0.09	−0.01
	(0.03)	(0.04)	(0.04)	(0.06)	(0.07)	(0.10)	(0.10)	(0.08)
ΔlnY_{it}	0.49***	0.48***	0.45***	0.34***	0.34***	0.32***	0.46***	0.35***
	(0.04)	(0.12)	(0.07)	(0.10)	(0.05)	(0.08)	(0.15)	(0.10)
Implied nonlinear coefficient estimates								
β	−0.04	−0.03	0.03	0.04	−0.02	0.04	0.12	0.26
	(0.07)	(0.15)	(0.17)	(0.12)	(0.07)	(0.05)	(0.17)	(0.15)
γ	0.62***	0.60**	0.55*	0.42**	0.36***	0.26	0.59	0.26
	(0.14)	(0.28)	(0.33)	(0.16)	(0.11)	(0.19)	(0.36)	(0.21)
π	0.11	0.19	0.11	0.22	0.03	0.10	−0.11	0.00
	(0.07)	(0.14)	(0.16)	(0.12)	(0.09)	(0.13)	(0.21)	(0.11)
θ	0.02	0.09	0.23***	0.09	0.12	0.07	0.16	−0.01
	(0.06)	(0.09)	(0.08)	(0.09)	(0.10)	(0.15)	(0.17)	(0.13)
λ	0.49***	0.48***	0.45***	0.34***	0.34***	0.32***	0.46***	0.35***
	(0.04)	(0.12)	(0.07)	(0.10)	(0.05)	(0.08)	(0.15)	(0.10)
Diagnostics								
Residual cross-sectional independence tests								
$\bar{\hat{\rho}}$	0.14	0.06	0.09	0.08	−0.04	−0.03	−0.01	−0.02
CD	8.82	3.35	5.26	4.88	−2.45	−1.59	−0.44	−1.09
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.11]	[0.66]	[0.27]
Autocorrelation								
MG- MA_1	−0.03	−0.07	−0.00	0.03	−0.16***	−0.08	−0.25***	−0.26***
	(0.04)	(0.05)	(0.06)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)

MG- MA_2	−0.08	−0.10	−0.03	0.11*	−0.06	−0.06	−0.07	−0.08
	(0.08)	(0.08)	(0.06)	(0.06)	(0.09)	(0.06)	(0.06)	(0.07)
F ($l_{0,1}$)	34.54	21.08	28.59	28.62	52.67***	40.60*	40.23*	42.06*
	[0.26]	[0.89]	[0.54]	[0.54]	[0.01]	[0.09]	[0.10]	[0.07]
F ($l_{1,2}$)	18.82	25.22	23.78	18.73	32.05	25.77	29.60	27.53
	[0.94]	[0.71]	[0.78]	[0.95]	[0.37]	[0.69]	[0.49]	[0.60]
Instrument strength								
MG-CrDo		0.44	0.46	0.33		0.40	0.30	0.31
Instrument validity								
F(*J*)		40.95*	12.65	20.93		44.90**	19.16	27.60
		[0.09]	[1.00]	[0.89]		[0.04]	[0.94]	[0.59]
Exogeneity								
F (ΔJ)		46.93**	37.45	19.80		40.81*	35.06	14.38
		[0.03]	[0.16]	[0.92]		[0.09]	[0.24]	[0.99]

Note: Standard errors are in parentheses. For the linear estimates they are calculated from equation (12) for all estimators, while for the nonlinear estimates they are calculated from the covariance matrix of the linear estimates using the delta method. *p*-values are in square brackets. Asterisks indicate significance at *10%, **5% and ***1% level, respectively. For the GMM estimators, '(a)', '(b)' and '(c)' refer to instrument sets assuming MA(0), MA(1) and MA(2) errors respectively. The reported results are for a two-step procedure using a consistent estimate for the optimal weighting matrix constructed from a White type of estimator allowing for heteroscedasticity when using instrument set (a) and from a Newey–West type of estimator allowing for both heteroscedasticity and MA(1) or MA(2) errors when using instrument sets (b) and (c) respectively. The average cross-correlation coefficient $\bar{\hat{\rho}} = (2N(N-1))\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}$ is the simple average of the pair-wise country cross-correlation coefficients ρ_{ij}. CD is the Pesaran (2004) test defined as $\sqrt{2T/N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}$, which is asymptotically normal under the null of cross-sectional independence. *p*-values are in square brackets. MG- MA_1 and MG- MA_2 are the mean group results from estimating an MA(2) model on the estimated residuals. F ($l_{q,s}$) is a Fisher test combining the *p*-values of the individual countries' Cumby and Huizinga (1992) autocorrelation test, with (i) $l_{0,1}$ testing the null of no autocorrelation against the alternative of *MA(1)* errors and (ii) $l_{1,2}$ testing the null of MA(1) errors against the alternative of MA(2) errors. MG-CrDo is the mean of the individual countries' Cragg–Donald test statistics for weak instruments. F (*J*) is a Fisher test combining the *p*-values of the individual countries' Hansen (1982) *J*-tests of overidentifying restrictions, which tests the joint validity of all the instruments used. F (ΔJ) is a Fisher test combining the *p*-values on the individual countries' difference-in-Hansen ΔJ -tests which tests whether the alleged endogenous variables ΔlnH_{it}, ΔlnG_{it}, R_{it} and ΔlnY_{it} are actually exogenous. See notes to Table B-1 in the online Appendix for how the ΔJ -test is executed.

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The difference-in-Hansen test, denoted ΔJ, tests whether the regressors $(\Delta H_{it}, \Delta G_{it}, R_{it}, \Delta Y_{it})$ are actually exogenous by adding their contemporaneous values to the set of instruments and testing whether the resulting increase in the J statistic is significant. Individual country p-values are again combined using the Fisher test to obtain panel results. These show that exogeneity of the regressors can be rejected when using instrument set (a) but not when using instrument sets (b) and (c).

The results of the J and ΔJ tests may, however, not be very informative due to weak instruments. When comparing the average Cragg–Donald test statistic for weak instruments (Cragg and Donald, 1993) reported in Table I for the GMM estimators with the appropriate critical values from Stock and Yogo (2004), we cannot reject the null hypothesis that the instruments are weak. We find this result for all GMM estimators and for all instrument sets considered.

As a more direct test of the order of the MA component, we therefore also use the estimated error terms for each country and for each estimator to (i) estimate an MA(2) model and (ii) perform a Cumby and Huizinga (1992) (CH) autocorrelation test. The CH test is particularly suited as it allows the model to have MA errors and to be estimated by a variety of GMM estimators, including those used in this paper. The country-specific results are reported in Table B-1 of the online Appendix and summarized in Table I by reporting mean group estimates for the MA(1) and MA(2) parameters and combining the p-values of the CH autocorrelation test using a Fisher test. The results confirm, in particular for the CCEMG-GMM estimator, the above conclusion that the order of the MA component in the residuals is $q = 1$.

Given the finding of significant cross-sectional dependence, an MA(1) component in the error terms and possible endogeneity of the regressors, the CCEMG-GMM estimator with instrument set (b) is our preferred estimator.

When looking at the point estimates reported in Table I, we note that the coefficient on lagged aggregate consumption growth is either insignificant or its significance is very low. In some cases it is estimated with a negative sign. The structural estimates for β are in line with this since the estimates for β are generally found to be insignificant. Carroll *et al*. (2011) find significant and positive values for this parameter in quarterly data. The lower significance of our estimates may be due to data frequency, i.e. habit formation may be an important predictability mechanism at the quarterly frequency but is probably less relevant in annual data.

We further find that the impact of the growth rate in hours worked and the estimates for γ are positive and often significant. For the CCEMG-GMM estimator with instrument set (b) the impact of hours worked on consumption is significant (but only at the 10% level), while the parameter γ is not—even when the estimates are insignificant their magnitude is rather high. So it seems that the results of Basu and Kimball (2002), who argue in favour of complementarity between consumption and labour in the USA, cannot be refuted completely.

The impact of government consumption growth on private consumption growth is never significant and the magnitude of the estimated impact is low. As a result, the estimates for π reported in the table are never significant. We conclude that there is no evidence to support the existence of non-separabilities between private consumption and government consumption. This stands in contrast to results reported, for instance, by Evans and Karras (1998) for a large sample of countries.

When looking at potential intertemporal substitution effects, i.e. the impact of the real interest rate on aggregate consumption growth, our results are in line with the literature in the sense that the evidence to support intertemporal substitution is not very strong (see, for example, Campbell and Mankiw, 1990). This result is confirmed by the estimates for the elasticity of intertemporal substitution θ reported in the table, which are insignificant even though they tend to have economically sensible values. There is one exception though. When the estimation is conducted with the MG-GMM estimator using instrument set (b) we find a positive and strongly significant impact of the real interest rate on aggregate consumption growth.

We finally find that the impact of aggregate disposable income growth on aggregate consumption growth—which equals the structural parameter λ —is positive and strongly significant across all estimators and instrument sets. Our parameter estimates are in line with studies by Campbell and Mankiw (1990) and Kiley (2010), who also find that current disposable income growth has a positive and significant impact on aggregate consumption growth. Contrary to Basu and Kimball (2002) and Carroll *et al.* (2011), we do not find that rule-of-thumb or current income consumption is less important once other forms of predictability are taken into account. Given the significance of the rule-of-thumb result and its robustness, it makes sense to check the individual country estimates of this parameter, which are reported in Table B-1 of the online Appendix. From that table we note that, across all estimators, for the majority of the countries considered a positive and significant impact of aggregate disposable income growth on aggregate consumption growth is found. With respect to the well-documented case of the USA we find point estimates for λ that lie between 0.5 and 0.66 —a result which is in accordance with the range of values for this parameter reported in the literature (see, for example, Campbell and Mankiw, 1990).

To summarize, the results that we obtain with our newly introduced CCEMG-GMM estimator—which we consider to be the most appropriate for the question at hand—suggest that aggregate consumption growth in a panel of OECD countries over the period 1972–2007 depends significantly (at the 1% level) only on the growth rate in aggregate disposable labour income. The impact of the growth rate in hours worked (non-separability between consumption and hours worked) is positive and significant at the 10% level but the coinciding structural model parameter is not significant. The coefficient estimates on lagged aggregate consumption growth (habit formation) and the interest rate (intertemporal substitution) are insignificant at the conventional significance levels, while their signs and magnitudes are economically meaningful. There is no evidence in favour of non-separabilities between private consumption and government consumption.

Our estimations may be hampered by two important complications. First, as noted by Stock and Yogo (2004), the weak instruments problem reported above can lead to biased estimates and to unreliable inference. Second, all of the estimators used are consistent for $N, T \to \infty$. Since our sample size ($T = 35$ and $N = 15$) is relatively small—especially in the N dimension—small-sample biases might make our estimation results less reliable. To investigate the potential biasedness and reliability of inference of the estimators—in particular the CCEMG-GMM estimator—under both weak instruments and a relatively small sample size we conduct a Monte Carlo simulation in the next section.

5. MONTE CARLO SIMULATION

In this section we use a Monte Carlo experiment to examine the small-sample properties of the MG, MG-GMM, CCEMG and CCEMG-GMM estimators. To make sure that the Monte Carlo results are relevant for putting our empirical results in Section 4 into perspective, the data-generating process (DGP) and population parameters are chosen such that the properties of the simulated data match with those of the observed data as much as possible. Although we are mainly interested in the setting $T = 35$ and $N = 15$, we also present results for a range of alternative sample sizes to illustrate the more general properties of the estimators.

5.1. Experimental Design

The DGP is assumed to be

$$\Delta lnC_{it} = \rho_i \Delta lnC_{i,t-1} + \beta_i \Delta lnY_{it} + \gamma_{1i} f_{1t} + \xi_{it} \tag{17}$$

$$\Delta lnY_{it} = \theta_{1i} \Delta lnY_{i,t-1} + \theta_{2i} \Delta lnC_{i,t-1} + \gamma_{2i} f_{1t} + \gamma_{3i} f_{2t} + \delta_i \left(lnY_{i,t-1} - lnC_{i,t-1} \right) + \zeta_{it} \tag{18}$$

with

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$$
\begin{aligned}
f_{1t} &= \tau_1 f_{1,t-1} + \eta_{1t}, \quad \eta_{1t} \sim \text{i.i.d.}N\left(0, \sigma^2_{\eta_1}\right) \\
f_{2t} &= \tau_2 f_{2,t-1} + \eta_{2t}, \quad \eta_{2t} \sim \text{i.i.d.}N\left(0, \sigma^2_{\eta_2}\right) \\
\xi_{it} &= \varepsilon_{it} + \phi_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim \text{i.i.d.}N\left(0, \sigma^2_{\varepsilon}\right) \\
\zeta_{it} &= v_{it} + \varphi \xi_{it}, \qquad v_{it} \sim \text{i.i.d.}N\left(0, \sigma^2_{v}\right)
\end{aligned}
$$

The DGP for ΔlnC_{it} is a restricted version of the model in equations (10)–(11). First, for the sake of simplicity of the MC simulation, we restrict the set of explanatory variables to include only lagged consumption growth $\Delta lnC_{i,t-1}$ and income growth ΔlnY_{it}. $\Delta lnC_{i,t-1}$ is included to maintain the dynamic panel structure, while ΔlnY_{it} is included as this appears to be the only variable which is (robustly) significant in the empirical analysis. Second, we consider a single common factor (i.e. we restrict $m = 1$). This is without loss of generality as the CCE-type estimators are robust to multiple common factors. Third, as the empirical results suggest that the order of the MA component in the errors is at most 1, we restrict ξ_{it} to be an MA process of order 1. Finally, we also set the individual effects $\alpha_i = 0$. As all regressions include a country-specific constant, such that the individual effects are cancelled out exactly, this is without any loss of generality.

The DGP for the explanatory variable ΔlnY_{it} is fairly general as it allows for correlation with the unobserved common factor in ΔlnC_{it} (i.e. when $\gamma_{2i} \neq 0$), endogeneity (i.e. when $\varphi \neq 0$) and, as explained in Section 2.2.4, error correction to the long-run relationship between lnC_{it} and lnY_{it} (i.e. when $\delta_i > 0$). It is important to note that the addition of $\Delta lnC_{i,t-1}$ to the DGP of ΔlnY_{it} can also be given a theoretical justification. As noted by Campbell and Mankiw (1990), the permanent income hypothesis implies that current consumption summarizes consumers' information about the future process for income. Then, assuming that consumers have better information about future income than that which is contained in the history of income growth, lagged values of consumption growth will help to predict income growth.

The heterogeneous slope coefficients are drawn as

$$
\begin{aligned}
\rho_i &= \rho + \psi_{1i}, \quad \psi_{1i} \sim \text{i.i.d.}N\left(0, \sigma^2_{\rho}\right), \qquad \beta_i = \beta + \psi_{2i}, \quad \psi_{2i} \sim i.i.d.N\left(0, \sigma^2_{\beta}\right) \\
\theta_{1i} &= \theta_1 + \psi_{3i}, \quad \psi_{3i} \sim \text{i.i.d.}N\left(0, \sigma^2_{\theta_1}\right), \quad \theta_{2i} = \theta_2 + \psi_{4i}, \quad \psi_{4i} \sim i.i.d.N\left(0, \sigma^2_{\theta_2}\right) \\
\phi_i &= \phi + \psi_{5i}, \quad \psi_{5i} \sim \text{i.i.d.}N\left(0, \sigma^2_{\phi}\right), \qquad \delta_i = \delta + \psi_{6i}, \quad \psi_{6i} \sim i.i.d.N\left(0, \sigma^2_{\delta}\right)
\end{aligned}
$$

In order to obtain realistic parameter values, we calibrate the DGP outlined above to our observed sample of OECD data. More specifically, the parameter values are chosen such that the moments (standard deviations, cross-correlations, autocorrelations, cross-sectional dependence) of the simulated data match with those of the observed data as much as possible. We do this by first estimating the restricted consumption equation (17) and the income equation (18) to get an idea about the parameter values and their heterogeneity over countries. The value for the MA(1) parameter ϕ_i is inspired by country-by-country auxiliary estimations of an MA(1) process on the estimated residuals of the consumption equation (17) (also see the country-specific estimation results in Table B-1 of the online Appendix). As the CCE-type of estimators do not provide direct estimates for the common factors, we further calibrate the parameters (τ_1,τ_2) governing the AR process of the common factors, the factor loadings (γ_{1i},γ_{2i},γ_{3i}) and the error variances $\left(\sigma^2_{\eta_1}, \sigma^2_{\eta_2}, \sigma^2_{\varepsilon}, \sigma^2_{v}\right)$ to the observed data. To shed light on the impact of cross-sectional dependence and endogeneity on the considered estimators, we conduct the following four experiments with parameter values given by

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Table II. Calibration of the Monte Carlo experiments

	Actual	Experiment 1		Experiment 2		Experiment 3		Experiment 4	
	data	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Standard deviations									
stdv (ΔlnC_{it})	0.021	0.021	0.020	0.021	0.021	0.021	0.021	0.021	0.021
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
stdv (ΔlnY_{it})	0.024	0.024	0.024	0.025	0.024	0.025	0.024	0.025	0.024
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Autocorrelation structure									
cor ($\Delta lnC_{it}, \Delta lnC_{i,t-1}$)	0.377	0.301	0.128	0.317	0.144	0.383	0.279	0.388	0.283
	(0.188)	(0.211)	(0.227)	(0.206)	(0.224)	(0.189)	(0.208)	(0.187)	(0.206)
cor ($\Delta lnY_{it}, \Delta lnY_{i,t-1}$)	0.463	0.355	0.331	0.371	0.342	0.421	0.408	0.428	0.415
	(0.198)	(0.180)	(0.178)	(0.178)	(0.177)	(0.168)	(0.167)	(0.167)	(0.166)
cor ($\Delta lnC_{it}, \Delta lnC_{i,t-2}$)	0.098	0.109	0.069	0.108	0.065	0.145	0.124	0.144	0.121
	(0.176)	(0.201)	(0.188)	(0.199)	(0.187)	(0.195)	(0.184)	(0.194)	(0.183)
cor ($\Delta lnY_{it}, \Delta lnY_{i,t-2}$)	0.219	0.116	0.093	0.116	0.090	0.151	0.138	0.151	0.138
	(0.265)	(0.202)	(0.196)	(0.200)	(0.195)	(0.195)	(0.192)	(0.195)	(0.192)
Cross-correlation structure									
cor ($\Delta lnC_{it}, \Delta lnY_{it}$)	0.686	0.491	0.457	0.685	0.660	0.627	0.609	0.707	0.692
	(0.128)	(0.176)	(0.179)	(0.124)	(0.128)	(0.151)	(0.154)	(0.125)	(0.128)
cor ($\Delta lnC_{it}, \Delta lnY_{i,t-1}$)	0.361	0.232	0.232	0.275	0.225	0.315	0.318	0.332	0.314
	(0.167)	(0.201)	(0.193)	(0.198)	(0.199)	(0.192)	(0.187)	(0.190)	(0.189)
cor ($\Delta lnC_{i,t-1}, \Delta lnY_{it}$)	0.448	0.357	0.332	0.370	0.304	0.418	0.405	0.424	0.394
	(0.200)	(0.192)	(0.183)	(0.189)	(0.187)	(0.181)	(0.175)	(0.179)	(0.176)
Cross-sectional dependence									
cor ($\Delta lnC_{it}, \Delta lnC_{jt}$)	0.275	0.000	0.000	0.000	0.000	0.320	0.331	0.314	0.327
	(0.217)	(0.201)	(0.184)	(0.202)	(0.184)	(0.192)	(0.179)	(0.192)	(0.179)
cor ($\Delta lnY_{it}, \Delta lnY_{jt}$)	0.306	0.000	0.000	0.000	0.000	0.260	0.266	0.258	0.266
	(0.191)	(0.206)	(0.202)	(0.208)	(0.203)	(0.200)	(0.196)	(0.200)	(0.197)
cor ($\Delta lnC_{it}, \Delta lnY_{jt}$)	0.230	0.000	0.000	0.000	0.000	0.260	0.267	0.256	0.265
	(0.198)	(0.203)	(0.189)	(0.204)	(0.190)	(0.198)	(0.189)	(0.199)	(0.189)
cor ($\Delta lnC_{it}, \Delta lnC_{j,t-1}$)	0.150	−0.001	−0.001	−0.001	0.000	0.169	0.177	0.165	0.174
	(0.220)	(0.204)	(0.187)	(0.205)	(0.187)	(0.195)	(0.181)	(0.196)	(0.182)
cor ($\Delta lnY_{it}, \Delta lnY_{j,t-1}$)	0.259	0.000	0.000	0.000	0.001	0.155	0.159	0.153	0.158
	(0.197)	(0.209)	(0.205)	(0.211)	(0.206)	(0.204)	(0.201)	(0.205)	(0.202)
cor ($\Delta lnC_{it}, \Delta lnY_{j,t-1}$)	0.147	0.000	0.000	0.000	0.000	0.139	0.144	0.137	0.142
	(0.207)	(0.206)	(0.193)	(0.208)	(0.194)	(0.202)	(0.192)	(0.203)	(0.193)
cor ($\Delta lnC_{i,t-1}, \Delta lnY_{jt}$)	0.207	0.000	0.000	0.000	0.000	0.169	0.174	0.166	0.173
	(0.195)	(0.206)	(0.192)	(0.208)	(0.193)	(0.199)	(0.189)	(0.200)	(0.190)

(Continues)

Table II. (Continued)

	Actual	Experiment 1		Experiment 2		Experiment 3		Experiment 4	
	data	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Persistence error correction term									
cor ($lnC_{i,t-1} - lnY_{i,t-1}$, $lnC_{i,t-2} - lnY_{i,t-2}$)	0.907	0.834	0.789	0.840	0.812	0.847	0.816	0.851	0.829
	(0.100)	(0.101)	(0.125)	(0.097)	(0.113)	(0.093)	(0.111)	(0.091)	(0.104)
Instrument strength (Cragg–Donald statistic)									
MG-GMM(a)	2.24	2.52	2.34	2.07	2.06	2.38	2.26	2.18	2.15
MG-GMM(b)	1.03	0.92	0.83	0.89	0.80	1.03	0.94	1.00	0.91
CCEMG-GMM(a)	2.00	2.60	2.11	2.20	1.90	2.50	2.03	2.27	1.92
CCEMG-GMM(b)	1.15	0.96	0.78	0.93	0.75	0.94	0.83	0.93	0.81

- All experiments (common parameter values): $\rho = 0.20$, $\beta = 0.40$, $\theta_1 = 0.30$, $\theta_2 = 0.20$, $\delta = 0.10$, $\tau_1 = 0.25$, $\tau_2 = 0.25$, $\sigma_\rho = 0.10$, $\sigma_\beta = 0.10$, $\sigma_{\theta_1} = 0.06$, $\sigma_{\theta_2} = 0.08$, $\sigma_\delta = 0.03$, $\sigma_{\eta_1} = 0.007$ and $\sigma_{\eta_2} = 0.007$.
- Experiment 1 (no cross-sectional dependence, no endogeneity): $\gamma_{ji} = 0$ for $j = 1, 2, 3$, $\varphi = 0.4$, $\sigma_\varepsilon = 0.0175$ and $\sigma_v = 0.0210$.
- Experiment 2 (no cross-sectional dependence, endogeneity): $\gamma_{ji} = 0$ for $j = 1, 2, 3$, $\varphi = 0.4$, $\sigma_\varepsilon = 0.0155$ and $\sigma_v = 0.0210$.
- Experiment 3 (cross-sectional dependence, no endogeneity): $\gamma_{ji} \sim$ i. i. d. $U(0.25,1.75)$ for $j = 1, 2, 3$, $\varphi = 0$, $\sigma_\varepsilon = 0.0135$ and $\sigma_v = 0.0175$.
- Experiment 4 (cross-sectional dependence, endogeneity): $\gamma_{ji} \sim$ i. i. d. $U(0.25,1.75)$ for $j = 1, 2, 3$, $\varphi = 0.25$, $\sigma_\varepsilon = 0.0125$ and $\sigma_v = 0.0175$.

For each of these four experiments, we consider two versions:

i. MA(0) errors: $\phi_i = 0$.
ii. MA(1) errors: $\phi = -0.25$ and $\sigma_\phi = 0.10$.

For each cross-section i, we generate data for ΔlnC_{it} and ΔlnY_{it} using the above DGP over the period $t = -49, \ldots, 1, \ldots, T$ with initial values $\Delta lnC_{i,-49} = 0$ and $\Delta lnY_{i,-49} = 0$. Data for lnC_{it} and lnY_{it} are obtained by simple accumulation of ΔlnC_{it} and ΔlnY_{it} with initial values $lnC_{i,-49} = 0$ and $lnY_{i,-49} = 0$. The actual sample is then obtained by discarding the first 50 observations.

Each experiment is replicated 5000 times for the (T,N) pairs with $T = 20, 35, 50$ and $N = 15, 50$. In each experiment, we compute the MG, MG-GMM, CCEMG and CCEMG-GMM estimators. The GMM estimators are two-step estimators using the instrument sets (a) and (b) defined above. In order to save space, instrument set (c) is not used as the order of the MA process in the simulated data is at most 1.

To shed some light on the relevance of the Monte Carlo design, Table II compares some of the moments of the observed data with those of the simulated data for the sample size $T = 35, N = 15$ in each of the four experiments. The moments of the simulated data are averages over the 5000 iterations. The results show that the moments of the data simulated using Experiment 4, which is the most general, are very much in line with the observed data. Experiments 1 and 2, which do not model cross-sectional dependence, fail to match the observed correlation in both ΔlnC_{it} and ΔlnY_{it} across countries. Experiments 1 and 3, which do not model endogeneity, fail to match the observed contemporaneous correlation between ΔlnC_{it} and ΔlnY_{it} within countries, although this is to a lesser degree the case in Experiment 3, as part of this contemporaneous correlation is captured by the common factor f_{1t}, which shows up in both ΔlnC_{it} and ΔlnY_{it}. At the bottom of Table II we also report Cragg–Donald statistics for the various GMM estimators when applied to the observed and to the simulated data. This is very important for the relevance of our Monte Carlo simulation as instrument strength is an important determinant of the size of the bias of the considered GMM estimators and of the reliability of inference based on these estimators. The results show that the instrument strength in the simulated data is highly similar to that in the observed data.

5.2. Results

Tables B-2–B-5 in the online Appendix report results for the four MC experiments. The estimators are compared in terms of mean bias (bias), mean of the estimated standard errors (stde), standard deviation (stdv), root mean squared errors (rmse) and size at the nominal 5% level of t-tests for the null hypotheses that $\rho = 0.20$ and $\beta = 0.40$ respectively.

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Before looking more closely at the results for each of the four experiments, some important, more general results can be noted. First, the performance of the CCEMG-type estimators in the experiments with no cross-sectional dependence is not much worse compared to their standard MG counterparts both in terms of bias and dispersion. This shows that there is no high cost involved in unnecessarily adding cross-sectional averages to account for possible cross-sectional dependence. Second, the bias of the CCEMG-type estimators is highly similar for $N = 15$ and $N = 50$. This suggests that our relatively low cross-sectional dimension ($N = 15$) is not really a source of concern. Third, the mean of the estimated standard errors is in most cases fairly close to the actual standard deviation of the estimates. This shows that the nonparametric estimator defined in equation (12) is reasonably accurate. At least, the weak instruments problem for our GMM estimators does not result in a severe underestimation of the standard errors, which is a well-known problem when using parametric estimates. The size distortions observed for some of the estimators, especially for larger values for T and N, are therefore driven mainly by the bias of the estimators. Fourth, despite a weak instruments problem, the bias and dispersion of the GMM estimators are not unacceptably high, especially when compared to the population values $\rho = 0.20$ and $\beta = 0.40$.

We now turn to some more specific results. Experiment 1(i) is for a heterogeneous dynamic panel data model with no cross-sectional dependence, no endogeneity and no MA component in the errors. As expected, the MG estimator outperforms the other estimators. This is especially the case for estimating β, for which the MG estimator shows almost no bias. Given the accurate estimation of the standard errors, the size of the MG estimator for β is close to its nominal level of 5%. In line with the results for homogeneous dynamic panel data models, the MG estimator for ρ is downward biased but this bias decreases in T and is fairly small for $T = 35$ (see, for example, Judson and Owen, 1999). Note that, given this bias, the MG is severely oversized, especially for larger values of N. Despite the weak instruments problem, the GMM estimators for ρ have a slightly smaller bias and when using instrument set (a) their dispersion, as measured by the stdv, is not much higher compared to the MG estimator. As such, they tend to outperform the MG estimator for ρ also in terms of rmse and size. Only when using instrument set (b), the stdv more or less doubles. The weak instruments problem shows up more clearly when estimating β, though. The GMM estimators are now relatively more biased and have a higher dispersion, irrespective of whether instrument set (a) or (b) is used. However, neither the bias nor the stdv is unacceptably high. Experiment 1(ii) adds an MA(1) component to the errors of the consumption equation. As this implies that lagged consumption growth $\Delta lnC_{i,t-1}$ is endogenous, only the GMM estimators using instrument set (b) are consistent in this case. This shows up very clearly in the estimation results, which show a relatively high bias for ρ that does not disappear for higher values for T and N for all estimators but the GMM estimators using instrument set (b). Surprisingly, all estimators are more or less unbiased for β.

Experiment 2 adds endogeneity of ΔlnY_{it} to the above experiment. The main implication of this is that the MG and CCEMG estimators become inconsistent in both Experiment 2(i) and 2(ii). In the simulation results, this shows up as a much bigger bias and a considerable size problem for these estimators for all sample sizes. With respect to the GMM estimators, both instrument sets are valid in 2(i) but only instrument set (b) is valid in 2(ii). The simulation results now show a relatively higher bias for both ρ and β when using instrument set (a) in experiment 2(ii).

Experiment 3 adds cross-sectional dependence, with the unobserved factor in ΔlnC_{it} being correlated with ΔlnY_{it}, but again assumes ΔlnY_{it} to be exogenous with respect to ε_{it}. Both the MG and the MG-GMM estimators should now suffer from an omitted variables bias. In Experiment 3(i), the CCEMG estimator should now be the preferred estimator. In the simulation results, this shows up especially when estimating β for which the CCEMG estimator has no bias, the smallest stdv and no big size problem. When estimating ρ, the MG estimator tends to have a smaller bias but a bigger stdv, resulting in slightly smaller rmse. In Experiment 3(ii), the CCEMG-GMM(b) should be the preferred estimator. When estimating ρ, the CCEMG-GMM(b) estimator indeed has the smallest rmse for larger values of T, while for smaller values of T the MG-GMM(b) estimator has a slightly smaller rmse. As ΔlnY_{it} is exogenous in this experiment, the CCEMG estimator still clearly has the smallest rmse when estimating β, though.

Experiment 4 includes both endogeneity and cross-section dependence. The CCEMG-GMM estimator is now the only consistent estimator. The simulation results show that the CCEMG-GMM(a) and the CCEMG-GMM(b) estimators for β indeed clearly outperform the other estimators in terms of bias and size for all sample sizes in Experiments 4(i) and 4(ii) respectively. Interestingly, for the sample size ($T = 35, N = 15$) that is available to us in the empirical analysis, the bias is negligibly small and the real sizes of 7.3% and 12.1% respectively are sufficiently close to the nominal level of 5%. Note that the CCEMG estimator has a much smaller dispersion, resulting in a smaller rmse compared to the CCEMG-GMM(a) estimator for smaller values of T, but its relatively larger bias, which does not decrease for larger values of T or N, results in very poor size properties. When estimating ρ, the MG-GMM estimators tend to show up as the preferred estimators in terms of bias and size but the CCEMG-GMM estimators are not lagging behind too much. Note that for the sample size ($T = 35$, $N = 15$) there is a moderate downward bias for ρ which results in a size problem. This problem decreases for larger values of T.

To summarize, in a heterogeneous dynamic panel data model with both endogeneity and error cross-sectional dependence the CCEMG-GMM is the preferred estimator, both in terms of bias and size. Especially when compared to the alternative estimators, it performs relatively well for the modest sample size $T = 35, N = 15$ that is available for the empirical analysis presented in Section 4. However, it should be noted that weak instruments may still imply a small to moderate bias and size distortions. These conclusions should be taken into account when reading the empirical results presented in Section 4.

6. CONCLUSIONS

This paper examines the sources of predictability in aggregate private consumption growth. We first derive a dynamic consumption equation which nests most of the relevant predictability factors discussed in the literature: rule-of-thumb or current income consumption, habit formation, intertemporal substitution effects and non-separabilities between private consumption and both hours worked and government consumption. Next, we estimate this dynamic consumption equation for a panel of 15 OECD countries over the period 1972–2007. We follow recent developments in panel data econometrics by allowing for unobserved common factors which have heterogeneous impacts on the countries in the panel. We develop a CCEMG-GMM estimator by combining the CCEMG estimator advanced by Pesaran (2006) to account for error cross-sectional dependence and the GMM estimator to account for endogeneity of the regressors. The moment conditions imposed by this CCEMG-GMM estimator are valid as $N, T \rightarrow \infty$ jointly. A Monte Carlo experiment shows that the CCEMG-GMM estimator performs reasonably well, taking into account both that the instruments used in the estimations are not strong and that the sample size is relatively small. In our dynamic panel data setting with both endogeneity and error cross-sectional dependence, it is preferred over standard MG, MG-GMM and CCEMG estimators both in terms of bias of the estimated coefficients and in terms of inference.

Taking into account endogeneity and cross-sectional dependence proves to be important as it has a marked effect on our estimation results. These suggest that the growth rate in aggregate private consumption depends positively on the growth rate in current disposable income, which is found to be the only variable with significant predictive power for aggregate consumption growth. The estimates of the impact of lagged aggregate consumption growth (habit formation), the interest rate (intertemporal substitution), and the growth rate in hours worked (non-separability between consumption and hours worked) on aggregate consumption growth are insignificant at the conventional

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significance levels but their signs and magnitudes are economically meaningful. There is no evidence in favour of non-separabilities between private consumption and government consumption.

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