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A Panel Data Analysis

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The Predictability of Aggregate Consumption Growth in OECD Countries: A Panel Data Analysis*

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Abstract

This paper examines aggregate consumption growth predictability. We first derive a dynamic consumption equation which encompasses relevant predictability factors discussed in the literature: habit formation, intertemporal substitution effects, consumption based on current income, 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 taking into account cross-country parameter heterogeneity, endogeneity issues, and error cross-sectional dependence using a generalised method of moments version of the common correlated effects mean group estimator. Small sample properties are demonstrated using Monte Carlo simulations. The estimation results support current disposable income growth as the only variable with significant predictive power for aggregate consumption growth.

JEL Classification: C23, E21

Keywords: Sticky Consumption, Dynamic Panel, Cross-Sectional Dependence

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 reconcile this stylized fact by introducing various forms of predictability in aggregate consumption growth. Relevant forms are caused by liquidity constraints (Campbell and Mankiw, 1989,

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1990, 1991), habit formation (Campbell, 1998; Carroll et al., forthcoming), 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 is in general obtained 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 like Basu and Kimball (2002) and Carroll et al. (forthcoming) 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 analysis is usually restricted to a single country (mainly the US). Studies that present international evidence such as Campbell and Mankiw (1991) and Carroll et al. (forthcoming) 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 e.g. 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 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 e.g. Coakley et al., 2002; Phillips and Sul, 2003). These latent common variables induce error cross-section 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 (e.g. an international business cycle, oil price shocks, ...) are likely to be the rule rather than the exception (see e.g. Coakley et al., 2006; Westerlund, 2008). In the context of aggregate consumption growth, a common unobserved component might reflect financial liberalization occurring in all OECD countries over the sample period, hence affecting the predictability of aggregate consumption growth. Rather than treating the cross-section 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 additional regressors in the model. We use the mean group (CCEMG) variant to allow for possible parameter heterogeneity. Next, we suggest a generalised method of moments (GMM) version of the CCEMG estimator to account for endogeneity of the explanatory variables. A small-scaled 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. In section 3 we review the different estimators that can be used to estimate this equation in a panel of OECD countries and investigate their small sample properties in a Monte Carlo experiment. Section 4 presents the results from the estimation of the consumption growth equation with the different panel data estimators. Section 5 concludes.

2 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 $CRRA$ 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). 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

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

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 eq.(1) into the first-order condition gives

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

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

$$E_{t-1}\left(X_t\right) = \exp\left[E_{t-1}(\ln X_t) + \frac{1}{2}V_{t-1}(\ln X_t)\right], \tag{3}$$

where the conditional variance $V_{t-1}(\ln X_t)$ is assumed to be constant, i.e. $V_{t-1}(\ln X_t) = \sigma^2_{\ln X}$, implying that the conditional variances of $\Delta\ln C_t$, $\Delta\ln H_t$, and $\Delta\ln G_t$ and the conditional covariances between $\Delta\ln C_t$, $\Delta\ln H_t$, and $\Delta\ln G_t$ are all constant. We then substitute eq.(3) into eq.(2) and take logs of the resulting equality to obtain

$$E_{t-1}(\ln X_t) = \delta - \frac{1}{2}\sigma^2_{\ln X} - \beta(\frac{1}{\theta}-1)\Delta\ln C_{t-1} - R_t, \tag{4}$$

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 $\ln X_t$ derived below eq.(2) into eq.(4) and rearrange terms to obtain

$$\begin{aligned} E_{t-1}\Delta\ln C_t =& \theta(\frac{1}{2}\sigma^2_{\ln X} - \delta) + \beta(1-\theta)\Delta\ln C_{t-1} + \gamma(1-\theta)E_{t-1}\Delta\ln H_t \\ &+ \pi(1-\theta)E_{t-1}\Delta\ln G_t + \theta R_t, \end{aligned} \tag{5}$$

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

or

$$\Delta \ln C_t = \theta(\frac{1}{2}\sigma^2_{\ln X} - \delta) + \beta(1-\theta)\Delta \ln C_{t-1} + \gamma(1-\theta)\Delta \ln H_t + \pi(1-\theta)\Delta \ln G_t + \theta R_t + \omega_t, \qquad (6)$$

where $\omega_t = (\Delta \ln C_t - E_{t-1}\Delta \ln C_t) - \gamma(1-\theta)(\Delta \ln H_t - E_{t-1}\Delta \ln H_t) - \pi(1-\theta)(\Delta \ln G_t - E_{t-1}\Delta \ln G_t)$ with $E_{t-1}\ \omega_t = 0$.

Suppose now that some consumers in the economy are not permanent income optimizing 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,

$$\begin{aligned}\Delta \ln C_t =&(1-\lambda)\left[\theta(\frac{1}{2}\sigma^2_{\ln X} - \delta) + \beta(1-\theta)\Delta \ln C_{t-1} + \gamma(1-\theta)\Delta \ln H_t + \pi(1-\theta)\Delta \ln G_t + \theta R_t + \omega_t\right] \\ &+ \lambda \Delta \ln Y_t, \qquad (7)\end{aligned}$$

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 $0 \leq \lambda \leq 1$). Note that when $\lambda = 0$ eq.(7) collapses to eq.(6).

The estimable form of eq.(7) can be written as

$$\Delta \ln C_t = a_0 + a_1 \Delta \ln C_{t-1} + a_2 \Delta \ln H_t + a_3 \Delta \ln G_t + a_4 R_t + a_5 \Delta \ln Y_t + \mu_t, \qquad (8)$$

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

Our consumption eq.(8) encompasses most of the relevant predictability factors discussed in the literature. The "stickiness" parameter $a_1 \geq 0$ reflects habit formation. Its sign is determined by the structural parameter capturing habits, i.e. $\beta \geq 0$. 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 ($0 \leq a_5 \leq 1$) reflects the impact of current income on consumption (liquidity constraints, myopia). It equals the structural parameter λ (where $0 \leq \lambda \leq 1$). 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 eq.(8) 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., forthcoming). 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. Eq.(8) nests however a number of specifications that have been estimated in the literature previously. Campbell and Mankiw (1990) conduct regressions on a version of eq.(8) with restrictions $a_1 = 0$ (with $\Delta \ln Y$ always included and either $\Delta \ln H$, $\Delta \ln G$, or R added as an additional regressor). Evans and Karras (1998) estimate a version of eq.(8) with restrictions $a_1 = a_2 = a_4 = 0$ (with $\Delta \ln Y$ and $\Delta \ln G$ included). Basu and Kimball (2002) estimate a version of eq.(8) with restrictions $a_1 = a_3 = 0$ (with $\Delta \ln H$, $\Delta \ln Y$, and R included). Kiley (2010) estimates a version of eq.(8) with restrictions $a_3 = 0$ (with $\Delta \ln H$, $\Delta \ln Y$, $\Delta \ln C_{t-1}$, and R included). Carroll et al. (forthcoming) estimate a version of eq.(8) with restrictions $a_2 = a_3 = a_4 = 0$ (with $\Delta \ln C_{t-1}$ and $\Delta \ln Y$ included).

The error term μ_t 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 form in the error term μ_t. First, Campbell and Mankiw (1990)

[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.

note that transitory consumption and measurement error can lead to an MA structure of the error term[3]. Second, Working (1960) shows that if consumption decisions are more frequent than observed data then an MA component could be present in consumption growth. Third, if durable consumption components are present in C_t this could induce negative autocorrelation in $\Delta \ln C_t$ 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.

3 Econometric methodology

Our objective is to estimate the model for aggregate consumption growth outlined in section 2 using a panel dataset for 15 OECD countries over the period 1972-2007. Therefore, eq.(8) is written in the form of a first-order autoregressive panel data model

$$y_{it} = \alpha_i + \rho_i y_{i,t-1} + \beta_i' x_{it} + \mu_{it}, \qquad i = 1, 2, \ldots, N, \quad t = 2, \ldots T, \tag{9}$$

where $y_{it} = \Delta \ln C_{it}$ and $x_{it} = (\Delta \ln H_{it}, \Delta \ln G_{it}, R_{it}, \Delta \ln Y_{it})'$. The specification in eq.(9) allows for full heterogeneity in the parameters across countries.

Our estimation approach is outlined in sections 3.1 and 3.2. Section 3.1 starts from the assumption that shocks (μ_{it}) to consumption growth are independent across countries. As this assumption is most likely violated, section 3.2 extends the methodology to control for error cross-sectional dependence using CCE methodology suggested by Pesaran (2006). Given that the proposed estimators all require both N and $T \to \infty$, section 3.3 reports the results of a Monte Carlo experiment which evaluates their small sample performance for the limited sample size of $T = 35$ and $N = 15$ that is available to us for the empirical analysis in section 4.

3.1 Model with cross-sectional independence

As noted in section 2, there are various reasons that could lead to the occurrence of MA type autocorrelation in the error term of eq.(8). Therefore, we allow μ_{it} in the empirical model in eq.(9) to follow an

[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.

$MA(q)$ process

$$\mu_{it} = \phi(L)\,\varepsilon_{it}, \tag{10}$$

where $\phi(L) = 1 + \phi_1 L + \ldots + \phi_q L^q$ is a lag polynomial of order q and ε_{it} is an idiosyncratic error term satisfying the following error condition:

Assumption A1 *(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*.*

A1(a) and **A1**(b) state that ε_{it} is a mean zero error process which is mutually uncorrelated over time and over cross sections. **A1**(c) states that the individual effects are exogenous.

With respect to the explanatory variables we make the following assumptions:

Assumption A2 *(Explanatory variables)*

(a) $E(x_{it}\varepsilon_{js}) = 0$ *for all* i*,* j*,* t *and* $s > t$*,*

(b) $E(x_{it}\alpha_i) =$ *unknown for all* i *and* t*.*

A2(a) allows the variables in x_{it} to be endogenous while **A2**(b) allows x_{it} to be correlated with α_i.

The slope coefficients ρ_i and β_i follow the random coefficient model:

Assumption A3 *(Random slope coefficients)*

$$\rho_i = \rho + \psi_{1i}, \quad \beta_i = \beta + \psi_{2i}, \quad \psi_i = (\psi_{1i}, \psi_{2i}')' \sim iid\,(0, \Omega)\,, \tag{11}$$

where Ω *is a* 5×5 *symmetric nonnegative definite matrix and the random deviations* ψ_i *are distributed independently of* ε_{it} *and* x_{it}*.*

MG estimator

Pesaran and Smith (1995) show that in a dynamic heterogeneous panel data model like in eq.(9), pooled estimators, like for instance the fixed effects estimator, in general provide inconsistent (for large N and T) estimates for the average effects $\overline{\rho} = N^{-1} \sum \rho_i$ and $\overline{\beta} = N^{-1} \sum \beta_i$ if the assumption of homogeneity is violated. To overcome this problem, they suggest using the MG estimator obtained by averaging country-by-country coefficient estimates, i.e. $\widehat{\overline{\rho}} = N^{-1} \sum \widehat{\rho}_i$ and $\widehat{\overline{\beta}} = N^{-1} \sum \widehat{\beta}_i$. This yields consistent estimates for the average effects $\overline{\rho}$ and $\overline{\beta}$ for both $N, T \to \infty$ provided that $\widehat{\rho}_i$ and $\widehat{\beta}_i$ are consistent for $T \to \infty$. Abstracting from a possible $MA(q)$ structure in μ_{it} and endogeneity of x_{it}, country-by-country least squares estimation of the autoregressive model in eq.(9) yields biased but consistent (as $T \to \infty$) estimates for ρ_i and β_i. Therefore, our first estimator MG is the simple average over the N country-specific least squares estimates of eq.(9).

Following Pesaran (2006) the asymptotic covariance matrix Σ_{MG} of the MG estimator for $b = (\rho, \beta)$ is consistently estimated nonparametrically by

$$\widehat{\Sigma}_{MG} = \frac{1}{N-1} \sum_{i=1}^{N} \left(\widehat{b}_i - \widehat{b}_{MG} \right) \left(\widehat{b}_i - \widehat{b}_{MG} \right)'. \tag{12}$$

Note that, for notational convenience of the GMM estimator presented below, least squares estimation of eq.(9) is equivalent to least squares estimation after eliminating α_i by transforming the model into deviations from individual means

$$\widetilde{y}_{it} = \rho_i \widetilde{y}_{i,t-1} + \beta_i' \widetilde{x}_{it} + \widetilde{\mu}_{it}, \tag{13}$$

where $\widetilde{y}_{it} = y_{it} - \overline{y}_i$ with $\overline{y}_i = T^{-1} \sum_{t=1}^{T} y_{it}$ and similarly for the other variables. For small T, this transformation induces (additional) correlation between the transformed error term $\widetilde{\mu}_{it}$ and the transformed explanatory variables $\widetilde{y}_{i,t-1}$ and $\widetilde{x}_{it}$ but this (additional) correlation disappears for $T \to \infty$ (as $\operatorname*{plim}_{T \to \infty} \overline{\mu}_{it} = 0$ such that $\widetilde{\mu}_{it} \xrightarrow{p} \mu_{it}$).

MG-GMM estimator

Under **A2**, the MG estimator is inconsistent as the variables in x_{it} are allowed to be endogenous while the $MA(q)$ structure in μ_{it} implies that the predetermined $y_{i,t-1}$ is also correlated with μ_{it}. Therefore, we estimate eq.(13) using instrumental variables (IV). More specifically, provided T is sufficiently large, such that $\widetilde{\mu}_{it} \xrightarrow{p} \mu_{it}$, valid orthogonality conditions are

$$E\left(\widetilde{y}_{i,t-l}\widetilde{\mu}_{it}\right) = 0 \quad \text{for each} \quad t = l+1, \ldots, T \text{ and } l \geq q+1, \tag{14a}$$

$$E\left(\widetilde{x}_{i,t-l}\widetilde{\mu}_{it}\right) = 0 \quad \text{for each} \quad t = l+1, \ldots, T \text{ and } l \geq q+1. \tag{14b}$$

The moment conditions suggested in eqs.(14a)-(14b) are valid for each l. Using deeper lags of endogenous variables improves the efficiency of the GMM estimator. However, it also reduces the sample size as observations for which lagged observations are unavailable are dropped. To avoid this trade-off between instrument lag depth and sample depth, we construct instruments by zeroing out missing observations of lags as in Holtz-Eakin et al. (1988). Furthermore, in order to avoid problems related to using too many instruments, we truncate the set of available instruments at the first L available lags. This results in the following reduced set of moment conditions

$$E\left(\widetilde{y}_{i,t-l}\widetilde{\mu}_{it}\right) = 0 \quad \text{for each} \quad q+1 \leq l \leq L+q, \tag{15a}$$

$$E\left(\widetilde{x}_{i,t-l}\widetilde{\mu}_{it}\right) = 0 \quad \text{for each} \quad q+1 \leq l \leq L+q. \tag{15b}$$

Note that in contrast to pooled GMM estimation, where one would typically minimize the magnitude of the empirical moments $\sum_i y_{i,t-l}\mu_{it}$ for each t and l or, for moderately large T, the stacked empirical moments $\sum_i \sum_t y_{i,t-l}\mu_{it}$ for each l, a country-specific GMM estimate for country i is obtained by minimizing $\sum_t y_{i,t-l}\mu_{it}$ for each l. These country-by-country GMM estimates are then averaged over the N countries to obtain the MG-GMM estimate. The covariance matrix can be consistently estimated using the nonparametric estimator given by eq.(12).

3.2 Model with cross-sectional dependence

Following the recent panel literature, we next extend the error process in eq.(10) to allow for a multi-factor structure

$$\mu_{it} = \gamma_i' f_t + \phi(L)\varepsilon_{it}, \tag{16}$$

in which f_t is an $m \times 1$ vector of unobserved common variables and ε_{it} satisfies **A1**. 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). As such, it nests common time effects or time dummies (homogeneous cross-sectional dependence) as a special case.

Assumption A4 *(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,

(c) $E(f_t x_{is}) =$ unknown for all i, t and s,

(d) $E(f_t\alpha_i) =$ unknown for all i and t.

A4 states that the unobserved factors in f_t are exogenous but is quite general as it allows f_t to exhibit rich dynamics[4] and to be correlated with x_{it} and α_i. As **A1** states that ε_{it} is uncorrelated over cross sections, any dependence across countries is restricted to the common factors.[5]

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 eq.(16) is seriously

[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. 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 US, where shocks to consumption growth may lead to international business cycles does not invalidate assumption A4(b) as these will be shocks to f_t and therefore will not show up in ε_{it}.

biased and suffers from large size distortions. Essentially, as the unobserved factors are allowed to be correlated with the explanatory variables (see **A4**), this is an omitted variables bias which does not disappear as $T \to \infty$, $N \to \infty$ or both. So the naive MG estimator is 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.

CCEMG estimator

Pesaran (2006) proposes to eliminate the error cross-sectional dependence by projecting out the factors f_t using the cross-sectional averages of y_{it}, $y_{i,t-1}$ and x_{it}. For a model with a single factor[6], inserting eq.(16) in eq.(9) and taking cross-sectional averages yields

$$\overline{y}_t = \overline{\alpha} + \overline{\rho y}_{t-1} + \overline{\beta}' \overline{x}_t + \overline{\gamma} f_t + \phi(L) \overline{\varepsilon}_t, \tag{17}$$

where $\overline{y}_t = N^{-1} \sum_{i=1}^{N} y_{it}$ and similarly for the other variables. Solving eq.(17) for f_t

$$f_t = \frac{1}{\overline{\gamma}} \left(\overline{y}_t - \overline{\alpha} - \overline{\rho y}_{t-1} - \overline{\beta}' \overline{x}_t - \phi(L) \overline{\varepsilon}_t \right), \tag{18}$$

and inserting eq.(18) in eq.(9) with error structure eq.(16) yields

$$\begin{aligned} y_{it} &= \alpha_i + \rho_i y_{i,t-1} + \beta_i' x_{it} + \frac{\gamma_i}{\overline{\gamma}} \left(\overline{y}_t - \overline{\alpha} - \overline{\rho y}_{t-1} - \overline{\beta}' \overline{x}_t - \phi(L) \overline{\varepsilon}_t \right) + \phi(L) \varepsilon_{it}, \\ &= \alpha_i^+ + \rho_i y_{i,t-1} + \beta_i' x_{it} + c_{1i} \overline{y}_t + c_{2i} \overline{y}_{t-1} + c_{3i}' \overline{x}_t + \phi(L) \varepsilon_{it}^+, \end{aligned} \tag{19}$$

with $\alpha_i^+ = \alpha_i - \frac{\gamma_i}{\overline{\gamma}} \overline{\alpha}$, $c_{1i} = \frac{\gamma_i}{\overline{\gamma}}$, $c_{2i} = -\overline{\rho} \frac{\gamma_i}{\overline{\gamma}}$, $c_{3i} = -\overline{\beta}' \frac{\gamma_i}{\overline{\gamma}}$, $\varepsilon_{it}^+ = \varepsilon_{it} - \frac{\gamma_i}{\overline{\gamma}} \overline{\varepsilon}_t$.

The CCEMG estimator proposed by Pesaran (2006) is the simple cross-sectional average of the CCE estimates, with the latter being the country-specific least squares estimates of the augmented regression in eq.(19).[7] As **A1** implies that $\operatorname*{plim}_{N \to \infty} \overline{\varepsilon}_t = 0$, the error made when approximating f_t by $\overline{y}_t$, $\overline{y}_{t-1}$ and $\overline{x}_t$ in eq.(18) becomes negligible for $N \to \infty$ such that $\varepsilon_{it}^+ \xrightarrow{p} \varepsilon_{it}$ in eq.(19). This is the basic result in Pesaran (2006) that the inclusion of cross-sectional averages asymptotically eliminates the error cross-

[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 eq.(19) below, but are not presented here for notational convenience.

[7] Note that the augmented regression in eq.(19) can lead to multicollinearity problems if the explanatory variables are highly correlated with the cross-sectional averages. This would be the case when the explanatory variables are highly correlated over countries. Table 1 shows that there is significant correlation but this is not extremely high.

sectional dependence induced by the unobserved common factors. As such, for $N \to \infty$ eq.(19) is a standard heterogeneous dynamic panel data model with cross-sectional independent error terms. As such, the CCE estimator is biased for fixed T, but this bias disappears as $T \to \infty$. Conditional on x_{it} being predetermined or exogenous and $\phi(L) = 1$, this implies that consistency of the CCEMG estimator requires both N and $T \to \infty$.

Again for notational convenience, note that the CCE estimator can also be obtained as the least squares estimator after projecting out the individual effects and the cross-sectional means from the model in eq.(19), i.e.

$$\breve{y}_{it} = \rho \breve{y}_{i,t-1} + \beta' \breve{x}_{it} + \breve{\mu}_{it}, \tag{20}$$

where $\breve{y}_{it}$ is the residual from a country-by-country regression of y_{it} on a constant, $\overline{y}_t$, $\overline{y}_{t-1}$ and $\overline{x}_t$ and similarly for the other variables. Letting both N and $T \to \infty$ we have that $\breve{\mu}_{it} \xrightarrow{p} \phi(L)\, \varepsilon_{it}$ where $N \to \infty$ is required for the elimination of the unobserved common factors using the cross-sectional averages and $T \to \infty$ is required to avoid correlation between transformed variables and errors[8].

CCEMG-GMM estimator

Endogeneity of x_{it} and $MA(q)$ errors 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 eq.(20). Provided both N and T are sufficiently large, such that $\breve{\mu}_{it} \xrightarrow{p} \phi(L)\, \varepsilon_{it}$, valid moment conditions for each country i are

$$E\left(\breve{y}_{i,t-s}\breve{\mu}_{it}\right) = 0 \quad \text{for each} \quad q+1 \leq s \leq L+q, \tag{21a}$$

$$E\left(\breve{x}_{i,t-s}\breve{\mu}_{it}\right) = 0 \quad \text{for each} \quad q+1 \leq s \leq L+q. \tag{21b}$$

where in line with the discussion in section 3.1 we use a reduced set of instruments by truncating the set of available instruments at the first L available lags. The covariance matrix for both the CCEMG and the CCEMG-GMM estimator can be consistently estimated using the nonparametric estimator given by eq.(12).

[8]Note that in eq.(20) the individual effects α_i have been removed as the inclusion of a country specific constant in the construction of the de-factored variables implies that, as in eq.(13), these variables are all transformed into deviations from individual means.

3.3 Monte Carlo simulation

This section provides Monte Carlo simulation results on the small sample properties of the MG, MG-GMM, CCEMG and CCEMG-GMM estimators under both cross-sectional dependence and endogeneity. 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.

Experimental design

The data generating process is given by

$$y_{it} = \alpha_i + \rho_i y_{i,t-1} + \beta_i x_{it} + \mu_{it}, \qquad \mu_{it} = \gamma_i f_t + \varepsilon_{it}, \tag{22}$$

$$x_{it} = \theta x_{i,t-1} + \lambda_i f_t + \varphi \varepsilon_{it} + \nu_{it}, \tag{23}$$

$$f_t = \tau f_{t-1} + \eta_t, \tag{24}$$

where in each replication α_i, ε_{it}, ν_{it} and η_t are all drawn independently from an identical normal distribution, i.e. $i.i.d.N\left(0,1\right)$.[9] The slope coefficients in eq.(22) are heterogeneously drawn as $\rho_i = 0.25 + \psi_{i1}$ and $\beta_i = 1 + \psi_{i2}$ where $\psi_{ij} \sim i.i.d.N\left(0, 0.04\right)$ with $j = 1, 2$. The model for the individual specific regressor in eq.(23) is fairly general as they are allowed to be correlated with the unobserved factors (i.e. $\lambda_i \neq 0$) and to be endogenous (i.e. $\varphi \neq 0$). We further set $\theta = 0.5$ and $\tau = 0.5$[10] and conduct three different experiments:

- Experiment 1: no cross-sectional dependence ($\gamma_i = \lambda_i = 0$) and no endogeneity ($\varphi = 0$)
- Experiment 2: cross-sectional dependence ($\gamma_i \sim i.i.d.U\left(1,4\right)$ and $\lambda_i \sim i.i.d.U\left(1,4\right)$), where $i.i.d.U$ is $i.i.d.$ uniformly distributed, and no endogeneity ($\varphi = 0$)
- Experiment 3: cross-sectional dependence ($\gamma_i \sim i.i.d.U\left(1,4\right)$ and $\lambda_i \sim i.i.d.U\left(1,4\right)$) and endogeneity ($\varphi = 0.5$)

The initial value of y_{it} is set equal to zero and the first 50 observations are discarded before choosing our sample. Each experiment was replicated 5000 times for the (T, N) pairs with $T = 20, 35, 50$ and

[9] Note that it is not necessary to control the relative impact of the two error components α_i and μ_{it} since the considered estimators all use demeaned data such that they are invariant to the ratio $\sigma_\alpha^2 / \sigma_\mu^2$.

[10] Results for alternative parameter values are available from the authors on request.

$N = 15, 50$. The GMM estimators are one-step estimators using $y_{i,t-1}$ and $x_{i,t-1}$ as instruments.

Results

Table A-1 in Appendix A reports median bias, root median squared deviation (RMSD), root median squared error (RMSE) and size at the nominal 5% level of t-tests for the null hypotheses that $\rho = 0.25$ and $\beta = 1$ respectively. The RMSD is defined as the square root of the median deviation of an estimator from its median estimate over the Monte Carlo replications, while the RMSE is the square root of the median deviation of an estimator from its population value. As such, they measure dispersion of the estimators around their median and population value respectively. We use the median instead of the mean to avoid that our summary measures are affected by extreme parameter value estimates, which are found for some of the GMM estimators especially in the low T, low N cases.

The first experiment is a heterogeneous dynamic panel data model with no cross-sectional dependence and no endogeneity. In line with the results for homogeneous dynamic panel data models (see e.g. Judson and Owen, 1999), the bias of the MG estimator is negligibly small for $T = 35$. The CCEMG, which is overparameterized in this case, only has a slightly higher bias and dispersion. As can be expected, the use of instrumental variables results in GMM estimators that are relatively more biased and have a larger dispersion. The size is acceptable for all estimators.

The second experiment adds cross-sectional dependence, with the unobserved factor being correlated with x_{it}. Both the MG and the MG-GMM estimator now exhibit a considerable omitted variable bias and suffer from large size distortions. The CCEMG estimator is now preferred with the bias being negligibly small for $T = 35$ and acceptable size. Again, the CCEMG-GMM estimator is relatively more biased and has a larger dispersion for small values of T.

The third experiment adds endogeneity. This implies that also the CCEMG is inconsistent. The CCEMG-GMM estimator is now the preferred estimator. It is biased for small values of T but this bias disappears as T grows larger. Its size is acceptable for moderate values of T. Important to note is that, over the 3 experiments, the bias of the CCEMG-type estimators is highly similar for $N = 15$ and $N = 50$. This suggests that a relatively low cross-sectional dimension ($N = 15$) is not really a source of concern.

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 reasonably well for the modest sample size $T = 35, N = 15$ that is available for the empirical analysis presented in section 4.

4 Empirical results

The model in eq.(9) 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 Appendix B. Table 2 reports the estimates of the unrestricted parameters a_1 to a_5 in eq.(8) 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 eq.(8).[11] The CCEMG-GMM estimator is our preferred estimator since it corrects for both endogeneity and cross-sectional dependence among the countries in the panel. The latter correction is necessary because Table 1 shows that all variables exhibit moderate to strong cross-sectional correlation. Further, as discussed in our Monte Carlo simulations in section 3.3, the CCEMG-GMM estimator performs reasonably well in samples of modest size.

Table 1: Diagnostic tests for cross-sectional independence

	Sample period: 1972-2007, 15 countries				
	$\Delta \ln C_{it}$	$\Delta \ln H_{it}$	$\Delta \ln G_{it}$	R_{it}	$\Delta \ln Y_{it}$
$\overline{\widehat{\rho}}$	0.275	0.259	0.328	0.675	0.306
CD	17.11	16.12	20.42	42.04	19.07
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Notes: The average cross correlation coefficient $\overline{\widehat{\rho}} = (2/N(N-1)) \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho}_{ij}$ is the simple average of the pair-wise country cross correlation coefficients $\widehat{\rho}_{ij}$. CD is the Pesaran (2004) test defined as $\sqrt{2T/N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho}_{ij}$, which is asymptotically normal under the null of cross-sectional independence. p-values are in square brackets

The instrument sets used for the GMM estimators are determined by setting $q = 2$ and $L = 2$. From the Sargan/Hansen overidentifying restrictions test S_2 reported in Table 2 we note that the used moment conditions are not rejected by the data. This contrasts with the cases $q = 0$ / $L = 4$ and $q = 1$ / $L = 3$

[11]Note that in principle we could also identify the parameter δ from the fixed effects α_i $(= a_0)$ and from $\sigma^2_{\ln X}$ 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 e.g. Loayza et al., 2000) which will make the correct identification of δ unfeasible.

for which the moment conditions are rejected at the 5% level by the Sargan/Hansen tests S_0 respectively S_1. While these results suggest that there is MA(2) serial correlation in the error term it should be noted that the point estimates and significance levels are very similar across these three cases (results not reported).

Table 2: Panel data estimation results

Dependent variable: $\Delta \ln C_{it}$				Sample period: 1972-2007, 15 countries		
	MG	MG-GMM		CCEMG	CCEMG-GMM	
		one-step	two-step		one-step	two-step
Linear coefficient estimates ($q = 2, L = 2$)						
$\Delta \ln C_{i,t-1}$	-0.02	-0.02	-0.11	-0.01	0.07	0.08
	(0.03)	(0.07)	(0.11)	(0.04)	(0.07)	(0.10)
$\Delta \ln H_{it}$	0.31^{***}	0.34^{***}	0.33^{**}	0.21^{***}	0.20	0.13
	(0.05)	(0.13)	(0.16)	(0.05)	(0.20)	(0.22)
$\Delta \ln G_{it}$	0.05	-0.02	0.01	0.02	-0.03	-0.01
	(0.04)	(0.07)	(0.08)	(0.05)	(0.08)	(0.08)
R_{it}	0.01	0.07	0.09	0.08	0.14	0.10
	(0.03)	(0.05)	(0.05)	(0.07)	(0.10)	(0.11)
$\Delta \ln Y_{it}$	0.49^{***}	0.47^{***}	0.46^{***}	0.34^{***}	0.37^{***}	0.43^{***}
	(0.04)	(0.12)	(0.13)	(0.05)	(0.10)	(0.13)
Implied non-linear coefficient estimates						
β	-0.04	-0.05	-0.25	-0.02	0.15	0.17
	(0.07)	(0.23)	(0.31)	(0.07)	(0.15)	(0.19)
γ	0.62^{***}	0.74^{**}	0.74^{**}	0.36^{***}	0.40	0.29
	(0.14)	(0.30)	(0.31)	(0.11)	(0.42)	(0.48)
π	0.11	-0.05	0.01	0.03	-0.05	-0.03
	(0.07)	(0.16)	(0.18)	(0.09)	(0.16)	(0.18)
θ	0.02	0.14	0.17	0.12	0.22	0.18
	(0.06)	(0.10)	(0.10)	(0.10)	(0.14)	(0.18)
λ	0.49^{***}	0.47^{***}	0.46^{***}	0.34^{***}	0.37^{***}	0.43^{***}
	(0.04)	(0.12)	(0.13)	(0.05)	(0.10)	(0.13)
Sargan/Hansen overidentifying restrictions tests						
S_0 ($q = 0, L = 4, df = 15$)		50.63	42.53		49.73	41.62
		[0.00]	[0.00]		[0.00]	[0.00]
S_1 ($q = 1, L = 3, df = 10$)		20.31	21.25		18.06	24.50
		[0.03]	[0.02]		[0.05]	[0.01]
S_2 ($q = 2, L = 2, df = 5$)		6.08	6.76		7.34	9.90
		[0.30]	[0.24]		[0.20]	[0.08]

Notes: Standard errors are in parentheses. For the linear estimates they are calculated from eq.(12) for all estimators while for the non-linear estimates they are calculated from the covariance matrix of the linear estimates using the delta method. p-values are in square brackets. One-step GMM uses the 'two stage least squares' suboptimal choice of weighting matrix while two-step GMM uses a consistent estimate for the optimal weighting matrix constructed from a Newey-West type of estimator allowing for heteroscedasticity and $MA(2)$ errors. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

The Sargan/Hansen test of overidentifying restrictions is χ^2 distributed under to null of joint validity of all moment conditions defined in eqs.(15) or (21) for given choice of q and L.

From Table 2 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. Only when estimated with our preferred CCEMG-GMM estimator they are positive with a t-value around 1. Carroll et al. (forthcoming) 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.[12]

We further find that the impact of the growth rate in hours worked and the estimates for γ are positive and significant for all but our preferred CCEMG-GMM estimators. While in the latter case 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 US cannot be refuted completely.

The impact of government consumption growth on private consumption growth is never significant and its magnitude is low. As a result, the estimate for π reported in the table is 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).

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 real interest rate has an insignificant impact on aggregate consumption growth in all cases (see e.g. Campbell and Mankiw, 1990). This result is confirmed by the estimates for the elasticity of intertemporal substitution θ reported in the table which are all insignificant even though they have economically sensible values and their t-values are often above 1.

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. Our parameter estimates are in line with studies by Campbell and Mankiw (1990) and Kiley (2010)

[12] The lower significance of lagged consumption growth may also partially be caused by the use aggregate total consumption instead of consumption of non-durables and services (which Carroll et al. use for about half their countries). Durable components in our consumption measure may bias our habit parameter estimate downward since durable consumption growth tends to be somewhat negatively autocorrelated (see Mankiw, 1982).

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. (forthcoming) we do not find that rule-of-thumb or current income consumption is less important once other forms of predictability are taken into account.

To summarize, our newly introduced CCEMG-GMM estimator - which corrects for endogeneity and error cross-sectional dependence - indicates that aggregate consumption growth in a panel of OECD countries over the period 1972-2007 depends significantly only on the growth rate in aggregate disposable labour income. The coefficient estimates on 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) are insignificant at the conventional 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 however.

5 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 $N, T \to \infty$ jointly. A Monte Carlo experiment shows that the CCEMG-GMM estimator performs reasonably well even for the modest sample size $T = 35, N = 15$ that is available for our empirical analysis. 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 aggregate disposable labour income. Current disposable income growth 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 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 however.

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Appendix A Results Monte-Carlo simulation

Table A-1: Monte Carlo results heterogeneous DGP ($\rho = 0.25$, $\beta = 1$, $\theta = 0.5$, $\tau = 0.5$)

	MG				CCEMG				MG-GMM				CCEMG-GMM			
(T, N)	Bias	RMSD	RMSE	Size	Bias	RMSD	RMSE	Size	Bias	RMSD	RMSE	Size	Bias	RMSD	RMSE	Size
Experiment 1: $\gamma_i = \lambda_i = 0$ and $\varphi = 0$																
Results for ρ																
(20,15)	−0.038	0.041	0.048	0.110	−0.052	0.044	0.059	0.159	−0.066	0.124	0.139	0.069	−0.078	0.142	0.159	0.078
(35,15)	−0.017	0.038	0.040	0.081	−0.024	0.039	0.041	0.107	−0.046	0.084	0.093	0.072	−0.060	0.097	0.112	0.085
(50,15)	−0.013	0.039	0.040	0.074	−0.016	0.039	0.040	0.091	−0.036	0.065	0.072	0.074	−0.049	0.072	0.082	0.096
(20,50)	−0.036	0.022	0.037	0.192	−0.053	0.023	0.054	0.339	−0.070	0.117	0.136	0.082	−0.080	0.139	0.162	0.098
(35,50)	−0.020	0.021	0.025	0.103	−0.028	0.021	0.030	0.157	−0.049	0.072	0.088	0.093	−0.070	0.084	0.110	0.121
(50,50)	−0.013	0.021	0.022	0.077	−0.018	0.021	0.024	0.103	−0.038	0.048	0.059	0.096	−0.053	0.055	0.074	0.129
Results for β																
(20,15)	0.017	0.047	0.048	0.081	0.018	0.050	0.052	0.093	0.167	0.457	0.500	0.067	0.182	0.572	0.606	0.061
(35,15)	0.009	0.041	0.041	0.071	0.010	0.042	0.042	0.086	0.129	0.264	0.291	0.066	0.172	0.358	0.386	0.083
(50,15)	0.007	0.039	0.040	0.079	0.008	0.040	0.040	0.092	0.098	0.160	0.184	0.072	0.149	0.210	0.251	0.091
(20,50)	0.016	0.025	0.028	0.075	0.018	0.027	0.030	0.081	0.196	0.470	0.508	0.060	0.217	0.578	0.634	0.055
(35,50)	0.011	0.022	0.023	0.065	0.013	0.022	0.024	0.072	0.129	0.257	0.288	0.074	0.201	0.333	0.398	0.090
(50,50)	0.005	0.021	0.022	0.060	0.007	0.022	0.022	0.065	0.098	0.145	0.172	0.095	0.144	0.182	0.229	0.119
Experiment 2: $\gamma_i = i.i.d.U[1,4]$, $\lambda_i = i.i.d.U[1,4]$ and $\varphi = 0$																
Results for ρ																
(20,15)	−0.146	0.046	0.146	0.657	−0.042	0.042	0.052	0.159	−0.132	0.208	0.249	0.123	−0.048	0.132	0.141	0.067
(35,15)	−0.135	0.043	0.135	0.616	−0.013	0.037	0.038	0.120	−0.040	0.233	0.231	0.052	−0.030	0.089	0.093	0.059

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	MG				CCEMG				MG-GMM				CCEMG-GMM			
(T, N)	Bias	RMSD	RMSE	Size	Bias	RMSD	RMSE	Size	Bias	RMSD	RMSE	Size	Bias	RMSD	RMSE	Size
(50,15)	−0.131	0.043	0.131	0.594	−0.005	0.039	0.039	0.119	0.028	0.239	0.241	0.049	−0.020	0.065	0.068	0.070
(20,50)	−0.145	0.029	0.145	0.959	−0.052	0.022	0.052	0.373	−0.139	0.206	0.250	0.148	−0.067	0.124	0.141	0.078
(35,50)	−0.136	0.025	0.136	0.961	−0.023	0.020	0.027	0.151	−0.041	0.242	0.242	0.051	−0.046	0.085	0.093	0.073
(50,50)	−0.131	0.025	0.131	0.961	−0.012	0.020	0.021	0.098	0.015	0.246	0.246	0.050	−0.031	0.056	0.064	0.075
Results for β																
(20,15)	0.746	0.087	0.746	1.000	0.014	0.052	0.053	0.082	0.692	0.666	0.946	0.253	0.106	0.661	0.667	0.042
(35,15)	0.738	0.078	0.738	1.000	0.005	0.042	0.042	0.079	0.438	0.662	0.787	0.144	0.109	0.398	0.407	0.051
(50,15)	0.732	0.071	0.732	1.000	0.002	0.040	0.040	0.088	0.240	0.671	0.713	0.093	0.087	0.232	0.249	0.057
(20,50)	0.750	0.066	0.750	1.000	0.013	0.028	0.029	0.071	0.704	0.687	0.970	0.250	0.144	0.646	0.662	0.034
(35,50)	0.740	0.053	0.740	1.000	0.010	0.023	0.024	0.066	0.402	0.722	0.818	0.132	0.130	0.394	0.422	0.048
(50,50)	0.735	0.046	0.735	1.000	0.005	0.021	0.022	0.055	0.276	0.689	0.722	0.079	0.103	0.222	0.252	0.070
Experiment 3: $\gamma_i = i.i.d.U[1,4]$, $\lambda_i = i.i.d.U[1,4]$ and $\varphi = 0.5$																
Results for ρ																
(20,15)	−0.162	0.045	0.162	0.730	−0.084	0.040	0.085	0.365	−0.159	0.194	0.246	0.155	−0.090	0.120	0.147	0.125
(35,15)	−0.151	0.042	0.151	0.701	−0.062	0.037	0.063	0.295	−0.067	0.243	0.250	0.063	−0.045	0.093	0.103	0.067
(50,15)	−0.148	0.043	0.148	0.681	−0.057	0.039	0.059	0.278	−0.002	0.270	0.271	0.046	−0.025	0.080	0.084	0.061
(20,50)	−0.160	0.027	0.160	0.987	−0.095	0.021	0.095	0.846	−0.158	0.189	0.248	0.188	−0.102	0.108	0.145	0.177
(35,50)	−0.153	0.025	0.153	0.986	−0.074	0.020	0.074	0.704	−0.062	0.241	0.252	0.069	−0.061	0.089	0.107	0.111
(50,50)	−0.149	0.024	0.149	0.989	−0.066	0.020	0.066	0.622	−0.021	0.268	0.268	0.046	−0.036	0.070	0.079	0.071
Results for β																
(20,15)	0.784	0.080	0.784	1.000	0.220	0.048	0.220	0.869	0.763	0.621	0.984	0.298	0.246	0.584	0.646	0.072

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	MG				CCEMG				MG-GMM				CCEMG-GMM			
(T, N)	Bias	RMSD	RMSE	Size	Bias	RMSD	RMSE	Size	Bias	RMSD	RMSE	Size	Bias	RMSD	RMSE	Size
(35,15)	0.779	0.074	0.779	1.000	0.208	0.042	0.208	0.929	0.494	0.707	0.857	0.167	0.113	0.432	0.439	0.059
(50,15)	0.775	0.069	0.775	1.000	0.205	0.040	0.205	0.935	0.337	0.757	0.826	0.111	0.059	0.306	0.309	0.045
(20,50)	0.789	0.058	0.789	1.000	0.222	0.026	0.222	1.000	0.750	0.644	0.999	0.280	0.279	0.571	0.644	0.069
(35,50)	0.781	0.048	0.781	1.000	0.215	0.022	0.215	1.000	0.485	0.714	0.862	0.152	0.153	0.423	0.444	0.066
(50,50)	0.776	0.043	0.776	1.000	0.209	0.021	0.209	1.000	0.362	0.772	0.851	0.098	0.079	0.291	0.301	0.044

Notes: Bias is the median bias, RMSD is the square root of the median deviation of an estimator from its median estimate over the Monte Carlo replications, RMSE is the square root of the median deviation of an estimator from its population value and Size is the empirical size a the nominal 5% level for a t-test for the null hypotheses that $\rho = 0.25$ and $\beta = 1$ respectively.

Appendix B Data

Data are annual. All data are taken from OECD Economic Outlook (different years) except population data which are taken from OECD National Accounts Volume II Population and Employment (2009) and hours worked data which are taken from the Conference Board and Groningen Growth and Development Centre (2009). Data availability determines the sample period which is 1972-2007. The sample contains 15 countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Spain, Sweden, the United Kingdom, and the United States. All data used are country-specific. To calculate aggregate private consumption (C) we deflate private final consumption expenditures by the consumer price index.[13] To calculate the real interest rate (R) we subtract from the short-term nominal interest rate[14] the inflation rate which is calculated as the growth rate of the consumer price index. To calculate government consumption (G) we deflate government final consumption expenditures by the consumer price index. For aggregate hours worked (H) we use the series total hours worked as reported by the Conference Board. To calculate aggregate disposable labour income (Y) we first add the following three components. The first component is compensation of employees (a) which contains wages of the private sector as well as government wages and the social security contributions paid by private employers. The second component is the labour income of the self-employed (b) which we calculate as in Fiorito and Padrini (2001) by multiplying wages and salaries by the ratio of the number of self-employed to total employees. The third component is net social security transfers paid by the government (c), i.e. social security transfers paid by the government minus social security contributions received by the government. From (a)+(b)+(c) we then subtract taxes. To calculate taxes we follow Carey and Rabesona (2004) and make a distinction between countries where households cannot deduce their social security contributions from their tax base (Australia, Canada, United Kingdom, United States) and

[13]For a few countries we use the deflator of private final consumption expenditures instead.

[14]For most countries we use the treasury bill rate. In some instances we use the money market rate or the discount rate.

countries where households can deduce their social security contributions (all other countries). For the first group of countries the tax rate (d1) can be calculated as direct taxes on households divided by the sum of wages and salaries, property income received by households and total income of the self-employed. For the first group of countries the tax base (e1) is the sum of wages and salaries and labour income of the self-employed. Total taxes for the first group then equal (d1) x (e1). For the second group of countries the tax rate (d2) can be calculated as direct taxes on households divided by compensation of employees plus property income received by households plus total income of the self-employed minus social security contributions received by the government. For the second group of countries the tax base (e2) is compensation of employees plus labour income of the self-employed minus social security contributions received by the government. Total taxes for the second group then equal (d2) x (e2). Aggregate disposable labour income (Y) for the first group then equals (a)+(b)+(c)-(d1) x (e1) deflated by the consumer price index. For the second group it equals (a)+(b)+(c)-(d2) x (e2) deflated by the consumer price index. The variables C, G, H and Y are all divided by population to obtain per capita figures.