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Abstract: This paper estimates the elasticity of intertemporal substitution for U.S. aggregate time series data, taking into account the precautionary savings motive. By making use of a recursive utility function, we estimate an Euler equation, via GMM. This procedure leads consumption growth rate to depend on asset returns, and on a time-varying variance, which captures the precautionary motive. When significant, the elasticity of intertemporal substitution estimates ranges from 0.4 to 1.8, which are higher than most of the results found in the literature. Furthermore, the evidence suggests that consumers react to risk; however, the contribution of precautionary motive to consumption growth seems to be limited.

Keywords: consumption; asset returns; elasticity of intertemporal substitution; precautionary savings; nonexpected utility.

1. Introduction

In modern consumption theory, there are two important sources of adjustment in consumption-savings allocation: the movement in expected asset returns and the level of risk that consumers face. Under the usual CRRA utility, a higher (lower) expected return makes consumers defer (anticipate) consumption, everything held constant, and the elasticity of intertemporal substitution (EIS) measures the magnitude of this adjustment (Hansen and Singleton, 1983; Hall, 1988). Leland (1968) and Sandmo (1970) showed that, whereas the utility function exhibits a positive third derivative, the introduction of uncertainty slows down consumption. Thus, uncertainty generates the so-called precautionary savings.

The majority of the literature has focused on the EIS estimates, ignoring the precautionary motive for saving. However, some studies have shown that precaution seems to be responsible for a large part of consumers' savings. For instance, Kazarosian (1997) and Carroll and Samwick (1998) concluded that the precautionary component of wealth for a typical U.S. household ranges from 20% to 50%.

The empirical strategy commonly employed to estimate the EIS consists of estimating equation (1), which approximates the consumer Euler equation under CRRA utility.

$$\Delta ln(C_t) = \alpha_{1,i} + \psi r_{i,t} + \varepsilon_{i,t}, \;\; i = 1, \dots, N \tag{1}$$

where C_t is the consumption level, $r_{i,t}$ is the return of the *i-th* asset held by the consumer, *N* is the number of assets in the economy, and $\varepsilon_{i,t}$ is the error term. Therefore, the consumption growth rate should move along with consumer portfolio returns. The parameters to be estimated are the EIS, ψ, and the intercept, $\alpha_{1,i} = \psi(ln\beta + 0.5\sigma_i^2)$, where β is the subjective discount factor and σ_i^2 is the variance of $r_{i,t} - \psi^{-1}\Delta ln(C_t)$, as detailed in Section 2.

Several studies have estimated equation (1), finding estimates of EIS below 0.4 for the U.S. aggregate time-series data. Indeed, only some of them found statistically significant values. Among those we can mention Mankiw (1981), Hall (1988), Campbell and Mankiw

(1989), Patterson and Pesaran (1992), Hahm (1998), Campbell (2003), Yogo (2004) and Gomes and Paz (2011, 2013).

In equation (1) the constant variance σ_i^2 cannot be distinguished from the intercept and, as a consequence, the strength of the precautionary motive cannot be evaluated. This situation is reverted if the variance changes over time. However, if the variance is mistakenly assumed to be constant over-time, then equation (1) omits a relevant variable, which endangers the EIS estimation. In order to circumvent these problems, the non-observable variance should be estimated and included in the test equation. For instance, in order to measure a time-varying variance, Yi and Choi (2006) estimated an ARCH model for the consumption growth rate. After that, they estimated a series of reduced-form Euler equations so that no inference was carried out for the structural parameters. Despite that, the variance coefficient was significant in specifications based on Epstein and Zin (1989) preferences. Jorion and Giovannini (1993) also used parametric models to estimate a time-varying variance along with Epstein and Zin (1989) preferences. They estimated the structural-form Euler equation, but the structural parameters estimates were not significant.

Our concern here is with regard to the proper estimation of the EIS estimation for the U.S. aggregate time-series data. On this matter, equation (1) assumes CRRA utility, which implies that the EIS is the reciprocal of the relative risk aversion (RRA) coefficient. In order to avoid such restriction, we adopt Epstein and Zin (1989) preferences and, the resulting Euler equation leads the consumption growth rate to depend on the consumer portfolio return and a single asset return. As uncertainty comes from these variables, there is a need to use a multivariate technique to estimate the time-varying risk. In our case, this approach is applied by means of multivariate GARCH models. After that, we estimate a series of structural-form Euler equations, including the time-varying risk measure. Finally, we assess the performance of the model by both overidentification tests and its ability to provide precise parameter estimates.

Neely et al. (2001) and Campbell (2003) noted that, as asset returns are difficult to predict, weak instrument problems may arise when estimating the EIS. However, researchers tend to ignore such problems.[1] In order to circumvent this problem, we estimate our testing equation by means of the continuous updating estimator (CUE-GMM), which is recommended under weak instruments (Hansen et al., 1996; Stock et al., 2002).[2]

We also deal with another problem in EIS estimations, and this has to do with the consumer portfolio return. Mulligan (2002) and Dacy and Hasanov (2011) argued that a single asset is not able to mimic consumer portfolio return, as consumers invest in different assets. Thus, we check the robustness of our results substituting the habitual stock return by a synthetic mutual fund (SMF) asset return built by Dacy and Hasanov (2011), which is a share-weighted average of the returns on the financial and residential housing assets held by the representative household.

In summary, to estimate the EIS we develop a novel empirical approach composed by: *i)* a structural-form Euler equation estimated by CUE-GMM method, which allows for the identification of the EIS and also for the evaluation of the precautionary savings motive; *ii)* an appropriate identification of sources of risk, estimated by multivariate techniques; *iii)* a proxy for a typical consumer portfolio return, which allows for a robustness analysis.

Our approach leads to significant estimates of the RRA coefficient and the EIS. When significant, the EIS estimates ranged from 0.4 to 1.8, which is higher than most estimates in the literature, while the RRA coefficient varied from 0.6 to 2.2, and no specification led to unreasonable values. Furthermore, while the Hansen-J overidentification test did not reject any

[1] An exception is Yogo (2004), who found that EIS estimates conducted for the U.S. based on equation (1) were plagued by weak instruments, unless the T-bill is used. Gomes and Paz (2011) further scrutinized Yogo's (2004) results by means of different instrument sets, finding similar results.
[2] We also employ the usual two-step and iterated GMM estimators.

of the specifications used, at a 5% significance level, the null hypothesis that RRA is the reciprocal of the EIS was always rejected. In this sense, there is strong evidence against the CRRA utility function. Finally, the results showed that consumers care about risk, but the contribution of precautionary motive to consumption growth seems to be limited.

The paper is structured as follows. In Section 2 the consumption model used to motivate the empirical specification is laid out, as well as the related literature. Section 3 presents the data set and the econometric methodology. Results are presented in Section 4. Finally, Section 5 summarizes our conclusions.

2. Precautionary Motive

The idea that consumers maximize lifetime utility by smoothing consumption is almost undisputable among economists. Indeed, this broad notion leads to a life-cycle model with empirical content only when a particular setup is chosen (Browning and Crossley, 2001). Initially, papers focused on precautionary motive employed exponential (CARA) utility, obtaining closed-form solutions for consumption function. However, as detailed in Section 2.1, such utility led to undesirable features and, as a consequence, the literature moved towards incorporating isoelastic (CRRA) utility. We adopt nonexpected-utility preferences introduced by Epstein and Zin (1989) and, in Section 2.2 we connect this approach with the precautionary motive, and explain how the CRRA utility can be investigated as a special case. After that, in Section 2.3 we detailed previous studies most similar to our work.

2.1 CARA and CRRA preferences

In a seminal paper, Hall (1978) solved the intertemporal consumer problem under quadratic utility, yielding certainty equivalence, the property that optimal behavior depends only on expectations of other variables and not on their higher moments, which rules out precautionary savings. This is not a surprise given that Leland (1968) and Sandmo (1970) showed that the introduction of uncertainty slows down consumption as long as the utility function exhibits a positive third derivative, which is not the case under quadratic utility.

Even if the certainty equivalence was not viewed as an undesirable property, the drawbacks behind the quadratic utility has motivated more appealing utility functions, such as CARA and CRRA.[3] These utilities exhibit a positive third derivative, bringing back the precautionary savings motive.

In two influential papers, Caballero (1990, 1991) adopted the following CARA utility: $u(c) = (-1/\delta)e^{-\delta c}$, where δ is the constant absolute risk aversion. As a result, a closed-form solution for consumption function was obtained, in which future uncertain decreases current consumption. Following this approach, Hahm and Steigerwald (1999) assumed that the asset return is the reciprocal of the subjective discount factor ($\beta R = 1$), and the consumer Euler equation simplifies to: $\mathrm{E}_{t-1}\left[e^{-\delta \Delta c_t}\right] = 1$. Consequently, consumption normality and homoscedasticity leads to:

$$\Delta c_t = -\frac{\delta}{2}\sigma^2 + \varepsilon_t \tag{2}$$

where ε_t is an innovation, i.e. $\mathrm{E}_{t-1}\left[\varepsilon_{i,t}\right] = 0$, and $\sigma^2 = Var[\Delta c_t] = E[\varepsilon_t^2]$. By using the intertemporal budget constraint, Hahm and Steigerwald (1999) showed yet that

$$c_t = r\left[A_t + \sum_{i=1}^{\infty} R^{-i} E_{t-1}[Y_{t+i}]\right] - r\sum_{i=1}^{\infty} R^{-i}\left(\sum_{j=1}^{i} \frac{\delta}{2} E_t\left[\varepsilon_{t+j}^2\right]\right) \tag{3}$$

where $r = R - 1$. The first term on the right-hand side of equation (3) is the permanent income, while the second term captures the consumption reduction amount under uncertainty. As pointed out by Blanchard and Mankiw (1988), by increasing the variance of consumption, uncertainty leads to a more steeply sloped consumption path (see equation (2)), and as

[3] The quadratic utility has a bliss point, and above it the marginal utility becomes negative. Besides, such utility implies globally increasing absolute risk aversion, which means that wealthier people invest less in risky assets, which contradicts both intuition and empirical evidence (Blanchard and Mankiw, 1988).

uncertainty increases do not affect the budget constraint, any increase in the slope of the consumption function implies a decrease in the initial level of consumption, as showed in equation (3). This reveals the unattractive feature of the exponential utility: uncertainty can lead to negative initial consumption (Blanchard and Mankiw, 1988).

The adoption of CRRA utility rules out negative consumption, at a cost of losing closed-forms solution for consumption function (Guiso et al, 1992). However, as long as $u'''(c) > 0$, the precautionary motive exists, and we still can find an equation similar to (2). The CRRA utility $u(c) = c^{1-\gamma}/(1-\gamma)$, where γ is the constant RRA coefficient, yields the well-known Euler equation given by

$$\mathrm{E}_{t-1}\left[\beta\left(\frac{c_t}{c_{t-1}}\right)^{-\frac{1}{\psi}} R_{i,t}\right] = 1 \tag{4}$$

where $R_{i,t}$, $i = 1, \dots, N$, is the gross return of the *i-th* asset held by the consumer, and $\psi = 1/\gamma$ is the EIS. Assuming that consumption and returns are jointly log-normal and homoskedastic, the Euler equation (4) becomes:

$$\Delta lnc_t = \psi ln\beta + \psi r_{i,t} + \frac{\psi}{2}\sigma^2 + \varepsilon_t \tag{5}$$

where $r_{i,t} \equiv \ln(R_{i,t})$, ε_t is an innovation, and $\sigma^2 = Var[\Delta c_t - \psi lnR_t] = E[\varepsilon_t^2]$. Among other, Carrol (1992, 1997) and Kim (2013) assumed that the return on asset is constant and, consequently, σ^2 simplifies to $Var[\Delta c_t]$. Despite that, as argued by Dynan (1993), the size of the variance coefficient determines the strength of the precautionary saving motive.

2.2 Epstein and Zin's Preferences

Epstein and Zin (1989, 1991) assumed that consumers choose consumption and assets holdings to maximize the lifetime utility, which is defined recursively by

$$\mathrm{U_t} = \left[(1-\beta)\mathrm{C_t}^{\frac{1-\gamma}{\theta}} + \beta\left(\mathrm{E_t}\left(\mathrm{U_{t+1}^{1-\gamma}}\right)\right)^{\frac{1}{\theta}}\right] \tag{6}$$

where $\theta = (1-\gamma)/(1-\psi^{-1})$ and, as before, β is the subjective discount factor, γ is the RRA coefficient, and ψ is the EIS. The consumer budget constraint is described by $W_{t+1} \leq R_{m,t+1}(W_t - C_t)$, where W is the wealth and R_m is the gross return on total wealth. In this framework, Epstein and Zin (1991) derived the following Euler equation:

$$\mathrm{E}_{t-1}\left\{\left[\beta\left(\frac{C_t}{C_{t-1}}\right)^{-\frac{1}{\psi}}\right]^{\theta}\left[\frac{1}{R_{m,t}}\right]^{1-\theta} R_{i,t}\right\} = 1 \tag{7}$$

where the optimal portfolio, $R_{m,t}$, is given by $\sum_{i=1}^{N} a_{i,t} R_{i,t}$, and $a_{i,t}$, $i = 1, \ldots, N$, are the optimal weights chosen by the consumer.

Equation (7) is a generalization of the standard Euler equation (4) based on the CRRA utility. The novelty is the presence of the household's total portfolio return. A remarkable feature of the CRRA utility is the link between the EIS and the RRA coefficient: one is the reciprocal of the other. However, this automatic connection may not be desirable. The EIS measures an agent's willingness to substitute consumption over time, and it is well defined in the absence of risk. On the other hand, risk aversion measures the agent's willingness to substitute across states of nature, and it is well defined in the absence of any intertemporal dimension (Hall, 1988). Epstein and Zin's approach is more flexible because the EIS is the reciprocal of the RRA coefficient only when $\theta = 1$. Indeed, under this restriction, the household's total portfolio return disappears in equation (7), and the standard Euler equation (4) can be viewed as a special case of Euler equation (7). In this vein, by testing $\theta = 1$ we investigate whether the CRRA utility is suitable or not.

Euler equation (7) can be approximated by the following expression

$$\Delta lnc_t = \psi ln\beta + \frac{\psi(\theta-1)}{\theta} r_{m,t} + \frac{\psi}{\theta} r_{i,t} + \frac{\psi}{2\theta}\sigma^2_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

where $r_{m,t} \equiv \ln(R_{m,t})$, $r_{i,t} \equiv \ln(R_{i,t})$, $\sigma^2_{i,t-1}$ is the conditional variance of $(\theta - 1)r_{m,t} + r_{i,t} - (\theta/\psi)\Delta lnc_t$ based on the information set available in period $t - 1$, and $\varepsilon_{i,t}$ is an innovation.[4] As discussed by Yi and Choi (2007), the precautionary motive leads consumers to decrease current consumption, while increasing current saving in order to raise future consumption, an effect captured by $\sigma^2_{i,t-1}$ in equation (8).

Notice that, when $\theta = 1$ and the variance term is constant, Euler equation (8) becomes equation (1) again. Moreover, some authors argue that equation (1) is compatible with the Epstein and Zin (1989) approach even when $\theta \neq 1$ (see Yogo (2004) and Gomes and Paz (2013)). Assuming homoskedasticity, this happens if the portfolio return is proxied by a single asset return and, as a result, equation (8) becomes

$$\Delta lnc_t = \alpha_{1,i} + \psi r_{i,t} + \varepsilon_{i,t} \tag{9}$$

where $\alpha_{1,i} = \psi(ln\beta + \sigma^2_i/2\theta)$. Notice that equation (9) is identical to equation (1). However, even if precautionary savings were not a concern, we would not adopt equation (9) for two reasons. Firstly, as discussed by Epstein and Zin (1991), in order to distinguish between the empirical predictions of CRRA and Epstein and Zin's preferences, at least two assets are needed, and one of them is the consumer portfolio. Indeed, equation (9) uses the same asset return to represent $r_{i,t}$ and $r_{m,t}$ and, as a result, the parameter θ is no longer identified. Secondly, there is still the critique of the conceptual difference between any particular asset and the representative consumer portfolio, as argued by Mulligan (2002) and Dacy and Hasanov (2011). For those reasons, our empirical strategy is based on equation (8), which enables us to identify the structural parameters and test the CRRA utility, taking into account the precautionary motive.

[4] As detailed in Appendix A, this approximation is exact if we assume that asset returns and consumption are jointly log-normally distributed. Furthermore, the variance term depends on Δlnc_t, $r_{m,t}$ and $r_{i,t}$, $i = 1, \dots, N$. Thus, for each *i* there is a specific variance, and for this reason, $\sigma^2_{i,t-1}$ has the subscript *i*.

As mentioned previously, in equation (8) the precautionary motive is captured by the variance term, $\sigma^2_{i,t-1}$, which is the conditional variance of $(\theta - 1)r_{m,t} + r_{i,t} - (\theta/\psi)\Delta lnc_t$. The variance of $r_{m,t}$, $r_{i,t}$ and Δlnc_t, as well as their covariance terms, are sources of risk that should be taken into account. Hence, the variance term in the testing equation (8) is defined in equation (10).

$$\sigma^2_{i,t-1} = \begin{Bmatrix} \frac{\theta^2}{\psi^2}\mathrm{Var}_{t-1}[\Delta lnc_t] + (\theta-1)^2\mathrm{Var}_{t-1}[r_{m,t}] + \mathrm{Var}_{t-1}[r_{i,t}] - \\ \frac{2\theta(\theta-1)}{\psi}\mathrm{Cov}_{t-1}[\Delta lnc_t, r_{m,t}] - \frac{2\theta}{\psi}\mathrm{Cov}_{t-1}[\Delta lnc_t, r_{i,t}] + 2(\theta-1)\mathrm{Cov}_{t-1}[r_{m,t}, r_{i,t}] \end{Bmatrix} \quad (10)$$

Therefore, the approach pursued in this paper to estimate the preference parameters is based on equation (8) along with a multivariate approach to estimate the components of $\sigma^2_{i,t-1}$, as in equation (10). The inclusion of such term has two motivations. Firstly, we are able to take the precautionary savings motive more seriously. Secondly, as mentioned before, if the variance is mistakenly assumed to be constant over-time, then equation (1) omits a relevant variable, which endangers the EIS estimation.

These motivations are valid even when CRRA utility is used. In this case, the asset return coefficient is the EIS – see equation (1) or (5) - and this quantity measures the consumer's willingness to substitute consumption over time. Thus, if asset return changes and the consumption growth rate remains the same, it means that consumer does not substitute consumption over time. However, if uncertainty is not constant, this conclusion may be premature. Suppose that assets returns are going down and, at the same time, uncertainty is increasing. Thus, one factor can compensate for the other and, consumption growth rate remains stable, even with returns falling. Therefore, the researcher will conclude that the consumer does not want to substitute consumer over time. This analysis suggests that a negative correlation between the omitted time-varying risk and the asset return leads to a downward bias in the EIS estimates. Indeed, using simulated data, Guvenen (2006) noticed that consumption conditional variance is significantly (negatively) correlated with interest rates and, after including such variance in the testing equation the EIS estimates nearly doubled.

Our general case is not different. Treating equation (8) as the data generating process, and applying the TSLS estimator to equation (1), it is possible to show that

$$plim[\hat{\psi}] = \frac{\psi(\theta-1)}{\theta}\frac{cov(\hat{r}_{i,t},\hat{r}_{m,t})}{var(\hat{r}_{i,t})} + \frac{\psi}{\theta} + \frac{\psi}{2}\frac{cov(\hat{r}_{i,t},\hat{\sigma}^2_{i,t-1})}{var(\hat{r}_{i,t})} \tag{11}$$

where $\hat{r}_{i,t}$, $\hat{r}_{m,t}$, $\hat{\sigma}^2_{i,t-1}$ are the projection of such variable into the space of the instruments. As usual, the omission of relevant variables leads the TSLS estimator to be inconsistent, unless the omitted variable is asymptotically uncorrelated with the instruments employed. Under CRRA ($\theta = 1$), a negative bias comes from a negative correlation between asset return and the variance term, as pointed out by Guvenen (2006). Under Epstein and Zin's preferences, the correlation between the single return and the omitted optimal return is also relevant.

Finally, after estimating equation (8), to test if precautionary savings affect the consumption growth rate, we test whether the coefficient of $\sigma^2_{i,t-1}$, $\psi/2\theta$, is null. Besides this statistical test, we would like to measure the contribution of the precautionary motive to the consumption growth rate. To accomplish this task, we take the time average of equation (8), leading to

$$\frac{1}{T}\sum_{t=1}^{T}\Delta lnc_t = \psi ln\beta + \frac{\psi(\theta-1)}{\theta}\frac{1}{T}\sum_{t=1}^{T} r_{m,t} + \frac{\psi}{\theta}\frac{1}{T}\sum_{t=1}^{T} r_{i,t} + \frac{\psi}{2\theta}\frac{1}{T}\sum_{t=1}^{T}\sigma^2_{i,t-1} \tag{12}$$

where we assume that $\sum_{t=1}^{T}\varepsilon_{i,t}/T$ converges to zero. Given that $\varepsilon_{i,t}$ is a zero-mean error, we are just applying the law of large numbers. If all terms on the right-hand side of equation (12) were positive, the direct contribution of the precautionary motive for consumption growth rate could be measured by

$$PMC = 100\frac{\frac{\psi}{2\theta}\bar{\sigma}^2_i}{\overline{\Delta lnc}} \tag{13}$$

where $\bar{\sigma}^2_i = \sum_{t=1}^{T}\sigma^2_{i,t-1}/T$ and $\overline{\Delta lnc} = \sum_{t=1}^{T}\Delta lnc_t/T$. However, a negative term on the right-hand side of equation (12) means that the PMC is an upper bound for the precautionary motive direct impact on consumption growth rate. Even in this case, we consider that it is worth calculating such quantity.

2.3 Related Literature

The precautionary motive for saving has been tested by many empirical studies using different techniques and data sets. In relation to the former, some authors estimated consumer Euler equations, whereas others verified if either consumption or savings responds to time-varying uncertainty. With respect to data sets, empirical studies have employed aggregated time-series and household level data, with advantages and disadvantages. As discussed by Caballero (1990), aggregate data are easily attainable; however, they do not provide a good proxy for the risk faced by families, unless idiosyncratic risk is fully insurable. On the other hand, disaggregate data usually involve short time-series observations, which prevent us from having a clear understanding of the degree of shock persistence.

Beginning with works based on U.S. aggregate time series data, Jorion and Giovannini (1993) estimated an explicit model of time varying first and second moments for nondurable and service consumption and assets return, using a structural-form Euler equation based on Epstein and Zin's preferences. The structural parameters estimates were not significant, and by testing $\theta = 1$, the CRRA utility was not rejected. Wilson (1998) estimated a trivariate ARCH for nondurable and durable consumption and income, but only the income conditional variance was included in the structural-form Euler equation. A CARA utility was adopted and the results suggest that precautionary savings is relevant.

Yi and Choi (2006) measured uncertainty using an ARCH model for consumption growth, and estimated reduced-form Euler equations using the GMM approach. Their findings, also related to U.S. aggregate data, suggested that the precautionary savings hypothesis is rejected when the CRRA utility is adopted, but the results partially changed when the Epstein and Zin approach was applied.[5] Nonetheless, in most cases the specifications based on Epstein and Zin preferences did not yield significant coefficients. As the authors estimated reduced-form Euler equations, no inference of structural parameters was carried out. Lastly, it is worth mentioning that Yi and Choi (2006) estimated $\sigma_{i,t-1}^2$ using an ARCH model for $\Delta ln(c_t)$. Despite the fact that ARCH models are intended to estimate conditional volatility, it is important to take into account that $\sigma_{i,t-1}^2$ is the conditional variance of $(\theta - 1)r_{m,t} + r_{i,t} - (\theta/\psi)\Delta lnc_t$, which implies that a multivariate approach is necessary to adequately assess this issue.

Some studies investigated the precautionary savings induced by income risk, assuming that the interest rate is constant and income is generated by ARIMA processes. For instance, Senhadji (2000) found a closed form solution of the consumption function for exponential and recursive utility functions, showing that precautionary savings depend on preference parameters and income innovation variance. This variance was obtained by estimating different ARIMA processes for the U.S. aggregate income. Finally, using a grid for structural parameters, the author found evidence that substantial precautionary savings (up to 5.3% of income) might exist, even when smooth aggregate income data are used.

Lyhagen (2001) and Hahm and Steigerwald (1999) combined consumption aggregate data with risk measures from survey data. Lyhagen (2001) estimated a time-varying risk using a Swedish survey that asked households about their year-ahead expectations regarding the general economic situation. The conclusion was that consumption would increase by 4.9% if no uncertainty were present. Hahm and Steigerwald (1999) used a survey of professional forecasters from the U.S., and their findings suggested that time-varying income uncertainty can affect both consumption and savings. However, the adjustment does not seem to occur

[5] To be precise, only the specifications based on the CRRA utility were frequently rejected by the Hansen J test.

instantaneously. In particular, uncertainty plays a substantial role in explaining the adjustment of consumption over a longer horizon.

Finally, there is also literature based on microdata that tested the precautionary hypothesis. Using the PSID, Kuehlwein (1991) found an unexpected negative correlation between consumption growth and a measure of risk. Using the Consumer Expenditure Survey (CES), Skinner (1988) found that salespeople and self-employed workers, those usually thought to have the most risky earnings, save less than other groups. A possible explanation for this result is the self-selection of the least risk averse agents into the most risky occupation. Dynan (1993) used CES data to estimate an approximation of the consumer Euler equation, obtaining a non-significant coefficient of relative prudence.[6] Moreover, the author did not find evidence that the self-selection of households into risk professions can explain the results.

While these results cast doubt on precautionary motive relevance, some authors reached the opposite conclusion. Using the PSID, Carrol and Samwick (1997, 1998) found evidence that households' wealth is higher for consumers who face greater income risk. Indeed, Carroll and Samwick (1998) findings suggested that between 32% and 50% of wealth in their sample is attributable to the additional risk that some consumers face compared to the lowest risk group. Using data from the National Longitudinal Survey, Kazarosian (1997) findings suggest that a doubling of uncertainty increases the ratio of wealth to permanent income by 29%. Finally, as opposed to previous analyses, Kim (2013) found strong evidence of precautionary motive presence using CES data set. This new result was attributed to the different approach used to treat measurement errors.

3. Econometric Methodology

[6] To measure the sensitivity of choices to risk, Kimball (1990) introduced the coefficient of relative prudence, which is given by: $-cu'''(c)/u''(c)$, where $u'''(c)$ and $u''(c)$ are, respectively, the third and second derivative of the utility function.

This section details the data set used and the econometric methodology adopted in order to estimate the time-varying variance as well as the consumer's Euler equation.

3.1. Data Description

The data set used in this paper come from Dacy and Hasanov (2011), which consist of consumption and asset-return quarterly observations from the first quarter of 1952 until the last quarter of 2000 for the U.S. economy.

Consumption is measured by real nondurable consumption per capita and real nondurable plus service consumption per capita. Figure 1 presents the evolution of both consumption growth rates. The series are very similar with correlation of around 0.84. Table 1 presents the descriptive statistics. Considering the mean and median, nondurables have the lowest growth rate, a quarterly rate of around 0.38%, which implies an annual rate of 1.54%. For nondurables plus services, the quarterly average growth rate is 0.55%, leading to growth rate about 2.20% per year. The standard deviation of nondurables growth rate is 0.72, as opposed to 0.47 for nondurables plus services. The visual inspection of Figure 1 already points out that the series related to nondurables plus services is smoother than nondurables alone.

Figure 1 here

Table 1 here

Dacy and Hasanov (2011) built an aggregate SMF return comprised of a share-weighted average of the quarterly returns of the assets held by the typical consumer. The weights were extracted from the household holding information published in the Flow of Funds Accounts (FFA) released by the U.S. Board of Governors of the Federal Reserve System (2003) and they refer to assets such as money (M2), T-bills, treasury notes, treasury bonds, municipal bonds, corporate bonds, Stocks (S&P 500), and housing. For each asset, Dacy and Hasanov (2011) calculated both real return and after-tax real return. From now on, we only employ after-tax real returns.

Figure 2 presents the evolution of the Stocks, T-bill and SMF returns for the American data. The SMF is not as smooth as T-bill, but it is not as volatile as the Stocks return either. Furthermore, the SMF and Stocks seem to be positively correlated. Indeed, their correlation is around 0.92. Despite being highly correlated, the standard deviation of Stock is about three times the standard deviation of SMF (Table 1). The diversification of the SMF comes at a cost, a lower average return. On year basis, the average after-tax real return for SMF and Stock are, respectively, 5.08% and 7.37%.

Figure 2 here

3.2. Consumption risk measure

To develop our research, we estimate the time-varying variance using multivariate GARCH models, in order to incorporate the precautionary motive into the testing equations.

Since the seminal paper of Engle (1982), the univariate ARCH model has been extensively used to estimate volatility. While Engle, Granger, and Kraft (1984) developed the first multivariate ARCH, Bollerslev, Engle, and Wooldridge (1988) proposed the first GARCH model for the conditional covariance matrices labelled VEC model. The subsequent literature developed a series of parsimonious models, which are the models used in our research, since our sample size is lower than those usually used in finance articles. Indeed, macroeconomic applications tend to have low sample size, due to the low frequency of aggregate series.

The standard multivariate GARCH framework can be defined as follows. Consider a stochastic vector process $\{\mathrm{y}_t\}$ with dimension $\mathrm{N} \times 1$, such that $E[\mathrm{y}_t] = 0$. Suppose that y_t is conditionally heteroskedastic, such as

$$\mathrm{y}_t = H_t^{1/2} \vartheta_t \tag{14}$$

where the $\mathrm{N} \times \mathrm{N}$ matrix $H_t = [h_{ijt}]$ is the conditional covariance matrix of y_t, and ϑ_t is an i.i.d. vector error process, with $E[\vartheta_t \vartheta_t'] = I$. In the VEC model, each conditional variance and covariance is a function of all lagged conditional variances and covariances, as well as lagged squared returns and cross-products of returns. The model is such that:

$$vech(\mathrm{H}_t) = c + \sum_{j=1}^{q} A_j vech(y_{t-j} y_{t-j}') + \sum_{j=1}^{p} B_j vech(H_{t-j}) \tag{15}$$

where $vech(\cdot)$ stacks the columns of the lower triangular part of its argument square matrix, c is an $\mathrm{N}(N+1)/2 \times 1$ parameter vector, and A_j and B_j are $\mathrm{N}(N+1)/2 \times \mathrm{N}(N+1)/2$ parameter matrices. In this model, the estimation of the parameters is computationally demanding and, indeed, the number of parameters is large unless N is small (Silvennoinen and Terasvirta, 2009). In our case, $\mathrm{N} = 3$ and, even when $\mathrm{p} = \mathrm{q} = 1$, the number of parameters is 78, which is prohibitive with our sample size around 200.

Other models were built on the idea of modeling the conditional variances and correlations instead of working with the conditional covariance matrix (Silvennoinen and Terasvirta, 2009). For instance, Bollerslev (1990) worked with a parsimonious model called Constant Conditional Correlation (CCC). As suggested, the conditional correlation matrix is time-invariant and, the conditional covariance matrix is such as:

$$H_t = D_t P D_t \tag{16}$$

where $D_t = diag(h_{1t}^{1/2}, \dots, h_{Nt}^{1/2})$ and $P = [\rho_{ij}]$ is positive definite with $\rho_{ij} = 1$, for $i = 1, \dots, N$. For $\mathrm{N} = 3$ and $\mathrm{p} = \mathrm{q} = 1$, the CCC model has only 12 parameters.

The CCC model was generalized by making the conditional correlation matrix time-varying, such as $H_t = D_t P_t D_t$. For instance, Engle (2002) introduced a Dynamic Conditional Correlation (DCC) where:

$$P_t = (I \odot Q_t)^{-1/2} Q_t (I \odot Q_t)^{-1/2} \tag{17}$$

$$Q_t = (1 - a - b)S + a\varepsilon_{t-1}\varepsilon_{t-1}' + bQ_{t-1} \tag{18}$$

where a is a positive scalar and b is a non-negative scalar such that $a + b < 1$, S is the unconditional correlation matrix of the standardized errors ε_t, and Q_0 is a positive definite matrix. Compared with the CCC model, the DCC model requires the estimation of only two additional parameters, a and b. However, the estimation procedure is no longer simple as the correlation matrix has to be inverted for each t during every iteration. Despite that, we apply both methods.

3.3. Estimation and Testing Procedures

The equation of interest can be estimated using the GMM approach, as it has an additive zero-mean forecast error. Equations (8) and (10) lead to the following population moment:

$$h_t(\beta,\psi,\theta) = \left\{ \begin{array}{c} \frac{\Delta lnc_t}{\psi} - ln\beta - \frac{(\theta-1)}{\theta} r_{m,t} - \frac{1}{\theta} r_{i,t} - \frac{1}{2\theta}\left[\frac{\theta^2}{\psi^2} V_{t-1}^{c} + (\theta-1)^2 V_{t-1}^{r_m} + V_{t-1}^{r_i}\right] \\ -\frac{1}{2\theta}\left[-\frac{2\theta(\theta-1)}{\psi} C_{t-1}^{c,r_m} - \frac{2\theta}{\psi} C_{t-1}^{c,r_i} + 2(\theta-1) C_{t-1}^{r_m,r_i}\right] \end{array} \right\} \quad (19)$$

where $V_{t-1}^{x} = Var_{t-1}(x_t)$ and $C_{t-1}^{x,z} = Cov_{t-1}(x_t, z_t)$. Equation (19) will be estimated for nondurables consumption and nondurables consumption plus services. In addition, we use two measures for $r_{m,t}$: Stock and SMF returns, resulting in four specifications. Hence, following Dacy and Hasanov's (2011) advice, we substitute the Stock return by the SMF asset return, which was built to mimic a typical consumer portfolio. Finally, we confront the CRRA and the Epstein and Zin (1989) preferences, by testing $\theta = 1$.

The error associated with the Euler equations is uncorrelated with any information available to agents during the planning period, such as $E_{t-\tau}[h_t(\beta,\psi,\theta) \times Z_{t-\tau}] = 0$, where $Z_{t-\tau}$ are lagged variables ($\tau > 0$) used as instruments. Tauchen (1986), Mao (1990) and Fuhrer et al. (1995) found that GMM performs better with instrument sets formed by a very few lags of variables in the equation being estimated. However, due to aggregation problems in quarterly data, the use of lags of variables no closer than the second lag has been recommended by Hall

(1988).[7] That is why we opted for instrument list composed of consumption growth rate, SMF, T-bill lagged twice, i.e. $\tau = 2$. The term $\sigma^2_{i,t-1}$ is a variance conditional on information available in period $t - 1$, being possibly endogenous. For this reason, we also employ its first lag as instrument, which belongs to the information set from period $t - 2$.[8]

Finally, the moment condition used is given by: $E[h_t(\beta, \psi, \theta) \times Z_{t-2}] = 0$. The parameters are globally identified only when this moment condition holds just for $\varphi = \varphi_0$, where $\varphi = (\beta, \psi, \theta)$. If the correlations between the model $h_t(\beta, \psi, \theta)$ and the instruments Z_{t-2} are low even for false values of φ, then the instruments are weak, and φ is weakly identified. As a consequence, the criterion function becomes nearly flat, being insensitive to modest changes in the parameters. As a result, the two-step GMM and iterated GMM point estimators can be quite different, and their confidence sets can also be quite different (Stock et al., 2002).

Hansen et al. (1996) found evidence that, under weak identification, the CUE-GMM is less biased, and its confidence intervals have better coverage rates than the two-step GMM. However, simulations indicate that, in spite of being less biased, the CUE-GMM estimator has heavy tails and can produce extreme estimates under weak identification (Hansen et al., 1996; Stock and Wright, 2000). Therefore, in order to estimate equation (19) we employ the CUE-GMM, but also the two-step and iterated GMM methods. After those estimations, we make use of Hansen's J-statistics to test the validity of each specification. As the power of this overidentification test decreases inasmuch asthe number of moment conditions increases, we only use as instruments the second lag of variables that appear in the test equation, instead of many lags. Thus, we avoid an excessive number of moment conditions.

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[7] Such aggregation problem can lead the error term to exhibit a first-order moving average process with serial correlation 0.25 (Working, 1960).

[8] For simplicity, hereafter we will only mention that instruments are the variables that appear in testing equation lagged twice.

4. Results

To begin with, we present the variance and covariance terms estimated by the multivariate GARCH models. After that, we report the GMM estimations related to equation (19), using stock return. Finally, the SMF asset return is employed and, we are able to verify if the results are robust.

4.1. EIS Estimates

First of all, we employ the CCC and DCC models for nondurables consumption growth rate, Stocks and T-bill, assuming $p = q = 1$. The estimated conditional variances and covariance are presented in Figure 3. Both methods yield similar results, especially for the variances. For the covariances, the DCC estimates a higher volatility, especially in the mid-1970s. Figure 4 presents the results for nondurables plus services consumption growth, Stocks and T-bill. The results are similar to those in Figure 3, except for the consumption variance, especially because the CCC model yields more pronounced volatilities. For both consumption measures, after DDC estimations, we test jointly if $a = 0$ and $b = 0$ (see equation 18), because such restrictions imply that DCC collapses to CCC model. The null hypothesis was not rejected only for nondurable consumption; however, for the sake of completeness we present the results for both GARCH models.

Figure 3 here

Figure 4 here

Using the multivariate GARCH results, we employ the GMM to estimate equation (19), where the Stock return measures the consumer optimal portfolio return, and the single-asset return is represented by the T-bill return. As mentioned previously, the instrument list is composed of the second lag of variables that appear in the testing equation.

Table 2 displays the results for equation (19) by making use of nondurable consumption goods. We notice that the Hansen J-test did not reject any specification, at 5% level. As for the parameters, we first notice that $\hat{\beta}$ is always slightly above one. This is an undesirable result, but not surprising, as discussed in detail below. The EIS estimates are significant, at 10% level, in any specification. The CUE-GMM estimates of the EIS are around 0.45, for both CCC and DCC volatilities. The two-step and iterated GMM lead to larger values, especially when the DCC volatilities are used. The θ estimates are positive and significant, at 1% level, in all cases. The two-step and iterated GMM estimates are slightly above 0.9, while the CUE-GMM leads to estimates slightly below 0.9. The RRA coefficient implied by ψ and θ is also presented in Table 2, as well as its standard error estimated by means of the Delta method. In all cases, the RRA estimate is significant, at 5% level, varying from 0.702 to 2.161. The CUE-GMM yields the larger values, around 2.

Table 2 here

When the EIS estimate is higher (lower) than one, the RRA coefficient is lower (higher) than one (Table 2). These results are qualitatively compatible with the CRRA utility. However, when the CRRA utility is evaluated by testing $\theta = 1$, the null hypothesis is rejected, at 5% level, in all cases. It means that there is strong evidence against the assumption that EIS is the inverse of the RRA coefficient.

When looking at the relevance of precautionary motive, we firstly calculated the implied coefficient of the variance term in equation (8), i.e. $\psi/2\theta$, and its standard error using the Delta method. This coefficient was precisely estimated and it was significant at 10% level in all cases. For instance, in the CUE-GMM with DCC, when volatility increases by one, the consumption growth rate increases by 0.269 percentage point on average. By making use of the two-step and iterated GMM we found larger coefficients, indicating that uncertainty has a sizable effect on consumption growth rate. However, while the average growth rate of nondurables consumption is 0.38% per quarter, the average value of the variance term ($\sigma^2_{i,t-1}$) is only 0.025% for the CUE-GMM with DCC. As a result, the PMC measure, as defined in equation (13), is below 2%. It means that less than 2% of the consumption growth rate can be attributed directly to precautionary motive. Summarizing, consumers react to risk, but the risk term is not expressive. Hence, so far, on statistical grounds, the GMM provides significant coefficients of the volatility term, but the contribution of precautionary motive to consumption growth rate is limited due to low risk level.

Table 3 displays the results for equation (19) when nondurables plus service is employed, along with Stocks and T-bill. Once again, the Hansen-J test did not reject any specification, at 5% level. Only when the two-step GMM is used along with the DCC volatility, the moment condition is rejected at 10% level. Beginning with the subjective discount factor, its estimates are slightly above one, as before. The EIS estimates are significant, at 10% level, except for CUE-GMM. When significant, the EIS tends to be above one. The θ estimates are positive and significant, at 1% level, in all cases. While the two-step and iterated GMM estimates are slightly above 0.9, and close to each other, the CUE-GMM estimates are slightly above 0.8. The implied RRA coefficient is significant, at 5% level, except for CUE-GMM. Focusing only on the significant estimates, while the EIS tends to be above one, the RRA coefficient tends to be below one. However, the result of the hypothesis testing, for $\theta = 1$, remains the same. In all specifications, the unitary null hypothesis is rejected, at 1% level, which leads to the rejection of the CRRA utility function.

Table 3 here

As for the precautionary motive, the coefficient of the variance term, $\psi/2\theta$, was relevant, at 10% level, in 4 out of 6 specifications, being statistically different from zero only when the EIS is also significant. When significant, this coefficient varies from 0.511 to 0.971, indicating a sizable response to risk. However, as previously found, the PMC measure is very low. Consumers respond to risk, but given that the risk is not large, a limited percentage of consumption growth rate can be attributed directly to the precautionary savings motive. The largest PMC measure was obtained for the CUE-GMM estimator (around 3%). However, the coefficient $\psi/2\theta$ is not statistically different from zero in these cases.

So far, the variance coefficient was significant in most cases, but the PMC measure indicates that the uncertainty contribution to consumption growth is very limited. Most importantly, both EIS and RRA coefficient estimates were significant, at 10% level, in 10 out of 12 cases (see Tables 2 and 3), and these estimates are economically meaningful: while the EIS ranges from 0.4 to 1.8, the RRA varies from 0.6 to 2.2. On the other hand, as for the subjective discount factor, the point estimates are above one. When the variance term is treated as constant, the intercept of equation (1) depends on β and σ_i^2, i.e., $\alpha_{1,i} = \psi(ln\beta + 0.5\sigma_i^2)$, and, in most cases, $\hat{\beta}$ is not recovered.[9] When the variance changes over time, the intercept is only $\psi ln\beta$, and it should be negative. However, in 11 out of 12 specifications used, Yi and Choi (2006) estimated a positive intercept.[10]

When the Euler equation is not linearized, the subjective discount factor is identified, and estimates above one were found in different frameworks. See, for instance, Ferson and Harvey (1992) and Lettau and Ludvigson (2009) for CRRA utility; Ferson and Constantinides (1991), Weber (2002) and Lettau and Ludvigson (2009) for habit formation preferences; Eichenbaum et al (1988) for jointly consumption and leisure decisions; Eichenbaum and Hansen (1990) and Okubo (2011) for jointly nondurables and durables consumption decisions. Finally, Epaulard and Pommeret (2001) found β estimates above one, for French data, using CRRA, recursive and habit formation preferences.[11]

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[9] An exception is Hansen and Singleton (1983) who employed a Maximum Likelihood estimator, identifying β and σ_i^2. And, β estimates above one were obtained.

[10] These results are displayed in tables 3-6 in Yi and Choi (2006).

[11] Investigating the cause of these results goes beyond our objectives, and we are just pointing out that it is recurrent.

4.2. Robustness analysis

The literature usually makes use of stock and T-bill returns to estimated equation (1). However, when the Epstein and Zin (1989) approach is adopted, one asset must be used to measure consumer portfolio performance. For instance, Yi and Choi (2006) chose the Dow Jones Composite Index as the return on total wealth, while Jorion and Giovannini (1993) employed the value-weighted NYSE market index. However, consumers also have government bonds, corporate bonds, residential and commercial real estate - among other assets – in their portfolios. Hence, following Dacy and Hasanov's (2011) advice, we employ the SMF to measure the return on total wealth. As before, firstly we employed the CCC and DCC models to estimate the volatilities of interest, but for the sake of space we move directly to estimation of equation (19).[12]

Table 4 displays the results for equation (19) using nondurable consumption goods.[13] To begin with, notice that $\hat{\beta}$ is slightly above one. The EIS estimates are significant, at 10% level, in 5 out of 6 specifications. The estimates from CUE-GMM are lower than those of two-step and iterated GMM. The θ estimates are positive and significant, at 1% level, in all cases, being around 0.7. The RRA estimate is always significant, at 5% level, varying from 0.768 to 1.926. As before, when the CRRA utility is evaluated by testing $\theta = 1$, the null hypothesis is rejected, at 5% level, in all cases. Furthermore, the Hansen J-test did not reject any specification, at 5% level.

Table 4 here

[12] Complete results are available upon request.

[13] Initially, the instrument list was composed of the second lag of variables that appear in the testing equation. However, for nondurables consumption, 2 out of 6 specifications present convergence problems: the iterated GMM with DCC and the CUE-GMM with DCC. In both cases convergence was achieved after the exclusion of the lagged variance of the T-bill and of the covariance between T-bill and SMF from the instrument list.

Finally, the implied coefficient of the variance term in equation (8), i.e. $\psi/2\theta$, is significant, at 10% level, in 4 out of 6 specifications. For instance, the CUE-GMM along with DCC volatilities led to a significant estimate, about 0.448. However, the average value of $\sigma^2_{i,t-1}$ is only 0.013%, while the average growth rate of nondurable consumption is 0.38% per quarter. Also, the PMC measure remains very low.

Table 5 displays the results for equation (19) when nondurables plus service is employed, along with SMF and T-bill. The β estimates are slightly above one for any specification. The EIS is significant, at 10% level, in 4 out of 6 specifications. When significant, it ranges from 0.727 to 1.501. As before, θ estimates are positive and significant, at 1% level, in all cases, being around 0.8. Finally, the RRA coefficient is significant, at 10% level, in almost all specifications, varying from 0.695 to 1.288. In all specifications, the CRRA utility ($\theta = 1$) is rejected, at 1% level. Moreover, the Hansen J-test did not reject any specification, even at 10% level.

Table 5 here

As for the precautionary motive, the coefficient of the variance term, $\psi/2\theta$, was relevant, at 10% level, in half of the specifications, being statistically different from zero only when the EIS was also significant. The significant coefficients vary from 0.473 to 0.913. However, the PMC measure is, in general, very small. The CUE-GMM estimator, along with the DCC volatility, yields a PMC measure around 6.46%. However, the coefficient $\psi/2\theta$ is not statistically different from zero in this case.

Dacy and Hasanov (2011) and Gomes and Paz (2013) also estimated equation (1) using the SMF return for the same sample period. In both cases, the significant EIS estimates fall in the range between 0.10 and 0.40. Differently from those studies, we use two assets returns at the same time in equation (14) and, most importantly than that, we add a time-varying risk covariate. And, by the reasons explained in Section 2, our large EIS estimates are not viewed as an unexpected result. Indeed, based on estimated parameters, we built $\sigma^2_{i,t-1}$ (equation (10)) and, after that, we calculated the limit probability of EIS (equation (11)). In fact, this procedure was done for each of our 24 specifications. Except by one case, this limit probability was less than $\hat{\psi}$, which is in line with a downward bias in previous studies. Restricting $\theta = 1$, as done by Dacy and Hasanov (2011) and Gomes and Paz (2013), $plim[\hat{\psi}] < \psi$ when $cov(\hat{r}_{i,t}, \hat{\sigma}^2_{i,t-1}) < 1$, which always happened.[14]

Table 6 summarizes the main results, considering the 24 specifications based on Stocks and SMF returns. In 19 cases, the EIS estimate was significant, at 10% level, ranging from 0.378 to 1.775. When Stocks are substituted by the SMF, the lower and upper bound of the significant EIS estimates decrease. However, in most specifications the point estimates are far above the ones obtained by Hall (1988) and Yogo (2004), for instance. Focusing on CUE-GMM results, when significant, the EIS ranges from 0.378 to 0.727, which is yet above the estimates found in the literature.

Table 6 here

As for the RRA coefficient, it was precisely estimated in 21 out of 24 specifications, ranging from 0.601 to 2.161 (see Table 6). Focusing on CUE-GMM results, a narrow interval is obtained: 1.288 to 2.161. In any case, the parameter estimates are plausible. Finally, the coefficient of the variance term was significant, at 10%, in 17 cases, being more frequently significant when Stock returns are employed. Perhaps this is the main difference between specifications based on Stocks and SMF.

5. Conclusions

[14] These calculations should be viewed with caution. Differently from a Monte Carlo study, we did not create the data generating process (DGP), we assumed that equation (8) represents the DGP. As a consequence, we were only able to calculate $\sigma^2_{i,t-1}$, $cov(\hat{r}_{i,t}, \widehat{\sigma}^2_{i,t-1})$, and $plim[\hat{\psi}]$ using the estimated parameters. But, even a conservative conclusion is that we cannot discard a downward bias in previous EIS estimates.

This paper estimated the EIS, using aggregate time series data for the U.S. economy. By making use of Epstein and Zin's (1989) recursive preferences, an approximation of consumer Euler equation implies that consumption growth rates depend on asset returns and a time-varying variance, which captures the precautionary motive. The GMM was used to estimate this testing equation. The importance of taking into account the time-varying variance term goes beyond any interest in precautionary savings, since the omission of a relevant term might lead to inconsistent estimates of the structural parameters.

As for the econometric methodology, we made use of the two-step and iterated GMM, and the CUE-GMM as well, in order to estimate the Euler equation. The results indicated that no specification is rejected by the Hansen J test, at 5% level, no matter how the testing equation or the time-varying variance are estimated. Most specifications led to significant estimates of the EIS and the RRA coefficient. When significant, the EIS estimates range from 0.4 to 1.8, while the RRA coefficient varies from 0.6 to 2.2. When the former tends to be above (below) 1, the latter tends to be below (above) 1. However, in all specifications we rejected the CRRA utility.

Finally, the impact of precautionary savings on consumption growth seems to be limited. Although consumers react to risk, its low magnitude causes low effect on consumption allocation. In spite of that, our approach provides significant estimates of both EIS and RRA coefficients. It is worth mentioning that estimates based on aggregate data are extremely useful to researchers in their calibration exercises and to policymakers interested in the aggregate economy. By adding the time-varying variance, we avoid a potential cause of inconsistent estimates and, indeed, unlike most part of the literature, we obtained larger estimates of the EIS.

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Appendix: Euler equation and log-normality assumption

Assume that $X_{i,t}$ is a log-normal random variable. Then,

$$\mathrm{E}_{t-1}\left[X_{i,t}\right] = exp\left(\mathrm{E}_{t-1}\left[x_{i,t}\right] + 0.5\mathrm{Var}_{t-1}\left[x_{i,t}\right]\right) \quad \text{(A.1)}$$

where $x_{i,t} \equiv lnX_{i,t}$. If $\mathrm{E}_{t-1}\left[X_{i,t}\right] = 1$, then the property (A.1) implies that

$$\mathrm{E}_{t-1}\left[x_{i,t}\right] + 0.5\mathrm{Var}_{t-1}\left[x_{i,t}\right] = 0 \quad \text{(A.2)}$$

In addition, $x_{i,t} = \mathrm{E}_{t-1}\left[x_{i,t}\right] + \vartheta_{i,t}$, as long as $\mathrm{E}_{t-1}\left[\vartheta_{i,t}\right] = 0$. And, $x_{i,t} + 0.5\mathrm{Var}_{t-1}\left[x_{i,t}\right] = \vartheta_{i,t}$. Define $X_{i,t} \equiv \left[\beta\left(\frac{\mathrm{C_t}}{\mathrm{C_{t-1}}}\right)^{-\frac{1}{\psi}}\right]^{\theta}\left[\frac{1}{R_{m,t}}\right]^{1-\theta} R_{i,t}$. Thus, equation (3) becomes

$$\theta ln\beta - \frac{\theta}{\psi}\Delta lnc_t + (\theta - 1)r_{m,t} + r_{i,t} + \frac{1}{2}\sigma^2_{\mathrm{i,t-1}} = \vartheta_{i,t} \quad \text{(A.3)}$$

where $r_{m,t} = lnR_{m,t}$, $r_{i,t} = lnR_{i,t}$, and $\sigma^2_{\mathrm{i,t-1}} = \mathrm{Var}_{t-1}\left[x_{i,t}\right]$. After manipulation, equation (A.4) leads to

$$\Delta lnc_t = \psi ln\beta + \frac{\psi(\theta-1)}{\theta}r_{m,t} + \frac{\psi}{\theta}r_{i,t} + \frac{\psi}{2\theta}\sigma^2_{\mathrm{i,t-1}} + \varepsilon_{i,t} \quad \text{(A.4)}$$

where $\varepsilon_{i,t} = -(\psi/\theta)\vartheta_{i,t}$, and $\mathrm{E}_{t-1}\left[\varepsilon_{i,t}\right] = 0$. Thus,

$$\sigma^2_{\mathrm{i,t-1}} = \mathrm{Var}_{t-1}[x_t] = \mathrm{Var}_{t-1}\left[\theta ln\beta - \frac{\theta}{\psi}\Delta lnc_t + (\theta - 1)r_{m,t} + r_{i,t}\right] \quad \text{(A.5)}$$

$$\sigma^2_{\mathrm{i,t-1}} = \left\{\begin{array}{c} \frac{\theta^2}{\psi^2}\mathrm{Var}_{t-1}[\Delta lnc_t] + (\theta-1)^2\mathrm{Var}_{t-1}\left[r_{m,t}\right] + \mathrm{Var}_{t-1}\left[r_{i,t}\right] - \\ \frac{2\theta(\theta-1)}{\psi}\mathrm{Cov}_{t-1}\left[\Delta lnc_t, r_{m,t}\right] - \frac{2\theta}{\psi}\mathrm{Cov}_{t-1}\left[\Delta lnc_t, r_{i,t}\right] + 2(\theta-1)\mathrm{Cov}_{t-1}\left[r_{m,t}, r_{i,t}\right] \end{array}\right\}$$

(A.7)

Finally, equation (A.5) implies the following the moment condition

$$h_t = \frac{\Delta lnc_t}{\psi} - ln\beta - \frac{(\theta-1)}{\theta}r_{m,t} - \frac{1}{\theta}r_{i,t} - \frac{1}{2\theta}\sigma^2_{\mathrm{i,t}} \quad \text{(A.8)}$$

The restriction $\theta = 1$ is equivalent to assume the CRRA utility. As mentioned in the introduction, under this restriction, equations (A.5) and (A.6) become, respectively,

$$\Delta lnc_t = \psi ln\beta + \psi r_{i,t} + \frac{\psi}{2}\sigma^2_{\mathrm{i,t-1}} + \varepsilon_{i,t} \quad \text{(A.9)}$$

$$\sigma^2_{\mathrm{i,t-1}} = \mathrm{Var}_{t-1}\left[r_{i,t} - \frac{1}{\psi}\Delta lnc_t\right] \quad \text{(A.10)}$$

And, $\sigma_{i,t-1}^2$ is the conditional variance of $r_{i,t} - \frac{1}{\psi}\Delta lnc_t$. Assuming homoskedasticity, the intercept of equation (A.9) becomes $\alpha_i = \psi ln\beta + 0.5\psi\sigma_i^2$.

Tables

Table 1 - Descriptive Statistics

Statistic	Consumption Growth Rate		Returns		
	ND	NDS	SMF	T-bill	Stocks
Mean	0.38%	0.55%	1.25%	0.09%	1.76%
Median	0.38%	0.57%	1.38%	0.13%	2.77%
Std. Deviation	0.72%	0.47%	2.35%	0.47%	7.37%

Note: Growth rates and returns are at quarterly basis.

Table 2 – GMM estimates of Model (19), using Nondurable, Stocks and T-bill

Method	GMM Estimates β (s.e.)	GMM Estimates ψ (s.e.)	GMM Estimates θ (s.e.)	Implied γ (s.e.)	Hypotheses Tests θ=1 (p-value)	Hypotheses Tests J-test (p-value)	Implied ψ/2θ (s.e.)	PMC measure
Two-Step GMM								
CCC	1.005***	0.835***	0.939***	1.185***	7.512***	7.548	0.445***	1.07%
	(0.001)	(0.224)	(0.022)	(0.301)	(0.006)	(0.374)	(0.120)	
DCC	1.003***	1.060***	0.942***	0.946***	6.419**	10.615	0.563***	0.99%
	(0.001)	(0.342)	(0.023)	(0.287)	(0.011)	(0.156)	(0.186)	
Iterated GMM								
CCC	1.005***	0.781***	0.933***	1.262***	5.084**	5.229	0.419***	1.14%
	(0.002)	(0.294)	(0.030)	(0.449)	(0.024)	(0.632)	(0.156)	
DCC	1.003***	1.479*	0.919***	0.702**	9.381***	10.321	0.805*	1.38%
	(0.001)	(0.755)	(0.026)	(0.315)	(0.002)	(0.171)	(0.419)	
Continuous updating GMM								
CCC	1.010***	0.433**	0.888***	2.161**	5.424**	3.746	0.244**	1.88%
	(0.004)	(0.182)	(0.048)	(0.839)	(0.020)	(0.809)	(0.098)	
DCC	1.009***	0.478***	0.890***	1.971***	5.085**	4.944	0.269***	1.79%
	(0.004)	(0.174)	(0.049)	(0.676)	(0.024)	(0.667)	(0.098)	

Note: For coefficients, in parenthesis is the standard error (s.e.). For hypotheses testing, the parenthesis contains the p-value. *,**,*** means significant at 10%, 5% and 1%, respectively. The implied RRA coefficient, γ, is given by $1-\theta(1-\psi^{-1})$. The coefficient of the variance term, $\sigma_{i,t-1}^2$, is $\psi/2\theta$ (see equation 4). The standard errors of γ and $\psi/2\theta$ are calculated using the Delta method. PMC is given by equation (8). In all specifications, the GMM weighting matrix is based on Newey-West estimator along with Bartlett kernel and Newey and West's (1994) method of bandwidth selection.

Table 3 – GMM estimates of Model (19), using Nondurable plus Services, Stocks and T-bill

Method	GMM Estimates β (s.e.)	GMM Estimates ψ (s.e.)	GMM Estimates θ (s.e.)	Implied γ (s.e.)	Hypotheses Tests θ=1 (p-value)	Hypotheses Tests J-test (p-value)	Implied ψ/2θ (s.e.)	PMC measure
Two-Step GMM								
CCC	1.005***	1.199**	0.937***	0.844***	15.651***	11.703	0.640**	0.58%
	(0.002)	(0.479)	(0.016)	(0.311)	(0.000)	(0.111)	(0.259)	
DCC	1.004***	1.499**	0.932***	0.690***	19.192***	12.651*	0.805**	0.70%
	(0.002)	(0.612)	(0.016)	(0.253)	(0.000)	(0.081)	(0.332)	
Iterated GMM								
CCC	1.006***	0.964***	0.943***	1.035***	9.366***	10.857	0.511***	0.50%
	(0.002)	(0.321)	(0.019)	(0.326)	(0.002)	(0.145)	(0.172)	
DCC	1.003***	1.775*	0.914***	0.601**	16.880***	9.933	0.971*	1.04%
	(0.002)	(0.992)	(0.021)	(0.286)	(0.000)	(0.192)	(0.549)	
Continuous updating GMM								
CCC	1.008***	1.214	0.813***	0.857	23.696***	7.371	0.747	2.90%
	(0.005)	(1.148)	(0.038)	(0.633)	(0.000)	(0.391)	(0.708)	
DCC	1.005***	1.813	0.837***	0.625	27.270***	7.343	1.084	3.16%
	(0.003)	(1.731)	(0.031)	(0.440)	(0.000)	(0.394)	(1.039)	

Note: For coefficients, in parenthesis is the standard error (s.e.). For hypotheses testing, the parenthesis contains the p-value. *,**,*** means significant at 10%, 5% and 1%, respectively. The implied RRA coefficient, γ, is given by $1 - \theta(1 - \psi^{-1})$. The coefficient of the variance term, $\sigma_{i,t-1}^2$, is $\psi/2\theta$ (see equation 4). The standard errors of γ and $\psi/2\theta$ are calculated using the Delta method. PMC is given by equation (8). In all specifications, the GMM weighting matrix is based on Newey-West estimator along with Bartlett kernel Newey and West's (1994) method of bandwidth selection.

Table 4 – GMM estimates of Model (19), using Nondurable, SMF and T-bill

Method	GMM Estimates			Implied	Hypotheses Tests		Implied	PMC measure
	β	ψ	θ	γ	θ=1	J-test	ψ/2θ	
	(s.e.)	(s.e.)	(s.e.)	(s.e.)	(p-value)	(p-value)	(s.e.)	
Two-Step GMM								
CCC	1.005***	1.018**	0.826***	0.986***	5.386**	9.081	0.616**	0.91%
	(0.002)	(0.399)	(0.075)	(0.318)	(0.020)	(0.247)	(0.276)	
DCC	1.004***	1.391***	0.826***	0.768***	12.666***	11.012	0.843***	0.98%
	(0.001)	(0.466)	(0.049)	(0.193)	(0.000)	(0.138)	(0.308)	
Iterated GMM								
CCC	1.005***	1.200	0.777***	0.871**	5.933**	6.816	0.772	1.11%
	(0.002)	(0.729)	(0.091)	(0.387)	(0.015)	(0.448)	(0.520)	
DCC	1.004***	1.154***	0.828***	0.890***	4.122**	7.074	0.697**	0.94%
	(0.001)	(0.425)	(0.085)	(0.258)	(0.042)	(0.215)	(0.305)	
Continuous updating GMM								
CCC	1.018***	0.378*	0.562***	1.926**	9.784***	4.888	0.336	1.98%
	(0.008)	(0.215)	(0.140)	(0.900)	(0.002)	(0.674)	(0.216)	
DCC	1.011***	0.600**	0.670***	1.447***	7.392***	5.817	0.448*	1.54%
	(0.004)	(0.268)	(0.121)	(0.523)	(0.007)	(0.324)	(0.231)	

Note: For coefficients, in parenthesis is the standard error (s.e.). For hypotheses testing, the parenthesis contains the p-value. *,**,*** means significant at 10%, 5% and 1%, respectively. The implied RRA coefficient, γ, is given by $1 - \theta(1 - \psi^{-1})$. The coefficient of the variance term, $\sigma_{i,t-1}^2$, is $\psi/2\theta$ (see equation 4). The standard errors of γ and $\psi/2\theta$ are calculated using the Delta method. PMC is given by equation (8). In all specifications, the GMM weighting matrix is based on Newey-West estimator along with Bartlett kernel and Newey and West's (1994) method of bandwidth selection.

Table 5 – GMM estimates of Model (19), using Nondurable plus Services, SMF and T-bill

Method	GMM Estimates β (s.e.)	GMM Estimates ψ (s.e.)	GMM Estimates θ (s.e.)	Implied γ (s.e.)	Hypotheses Tests θ=1 (p-value)	Hypotheses Tests J-test (p-value)	Implied ψ/2θ (s.e.)	PMC measure
GMM Two-Step								
CCC	1.005***	1.501*	0.822***	0.726**	17.244***	10.576	0.913*	0.59%
	(0.002)	(0.845)	(0.043)	(0.306)	(0.000)	(0.158)	(0.525)	
DCC	1.006***	1.205***	0.813***	0.862***	26.111***	10.682	0.741**	0.55%
	(0.002)	(0.453)	(0.037)	(0.252)	(0.000)	(0.153)	(0.291)	
Iterated GMM								
CCC	1.007***	1.134*	0.778***	0.908**	11.368***	7.109	0.729	0.63%
	(0.003)	(0.646)	(0.066)	(0.388)	(0.001)	(0.418)	(0.447)	
DCC	1.005***	1.673	0.757***	0.695**	16.468***	8.417	1.105	0.93%
	(0.002)	(1.167)	(0.060)	(0.307)	(0.000)	(0.297)	(0.808)	
Continuous updating GMM								
CCC	1.010***	0.727**	0.768***	1.288***	8.510***	6.558	0.473**	0.55%
	(0.003)	(0.295)	(0.080)	(0.439)	(0.004)	(0.476)	(0.213)	
DCC	1.021***	1.485	0.399***	0.869	45.427***	5.493	1.859	6.50%
	(0.012)	(3.812)	(0.089)	(0.691)	(0.000)	(0.600)	(4.782)	

Note: For coefficients, in parenthesis is the standard error (s.e.). For hypotheses testing, the parenthesis contains the p-value. *,**,*** means significant at 10%, 5% and 1%, respectively. The implied RRA coefficient, γ, is given by $1 - \theta(1 - \psi^{-1})$. The coefficient of the variance term, $\sigma^2_{i,t-1}$, is $\psi/2\theta$ (see equation 4). The standard errors of γ and $\psi/2\theta$ are calculated using the Delta method. PMC is given by equation (8). In all specifications, the GMM weighting matrix is based on Newey-West estimator along with Bartlett kernel and Newey and West's (1994) method of bandwidth selection.

Table 6 – Summary of GMM Results

Consumer's portfolio return ($r_{m,t}$)	Consumption measure (C_t)	Range of significant estimates, at 10% level (number of significant estimates)		
		ψ	γ	ψ/2θ
Stocks	ND	0.433-1.479 (6)	0.702-2.161 (6)	0.244-0.805 (6)
Stocks	NDS	0.964-1.775 (4)	0.601-1.035 (4)	0.511-0.971 (4)
SMF	ND	0.378-1.391 (5)	0.768-1.926 (6)	0.448-0.843 (4)
SMF	NDS	0.727-1.501 (4)	0.695-1.288 (5)	0.473-0.913 (3)

Figures

Figure 1 - Consumption Growth Rate

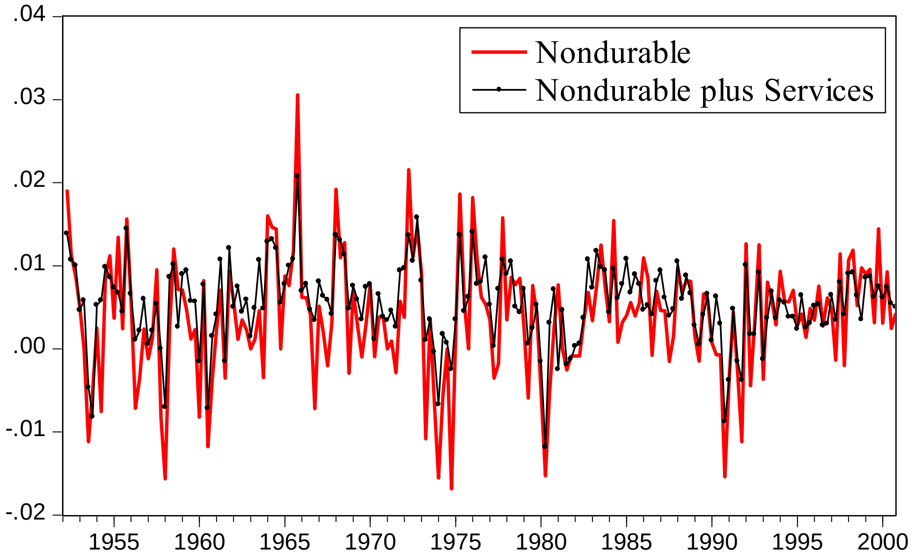

Figure 2 - Assets Returns

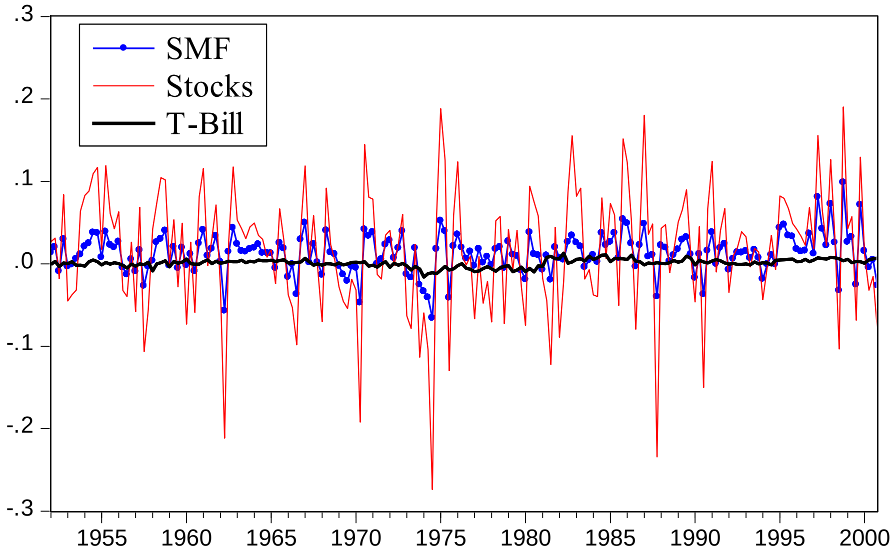

Figure 3 – CCC and DCC results: Nondurable, Stock and T-bill

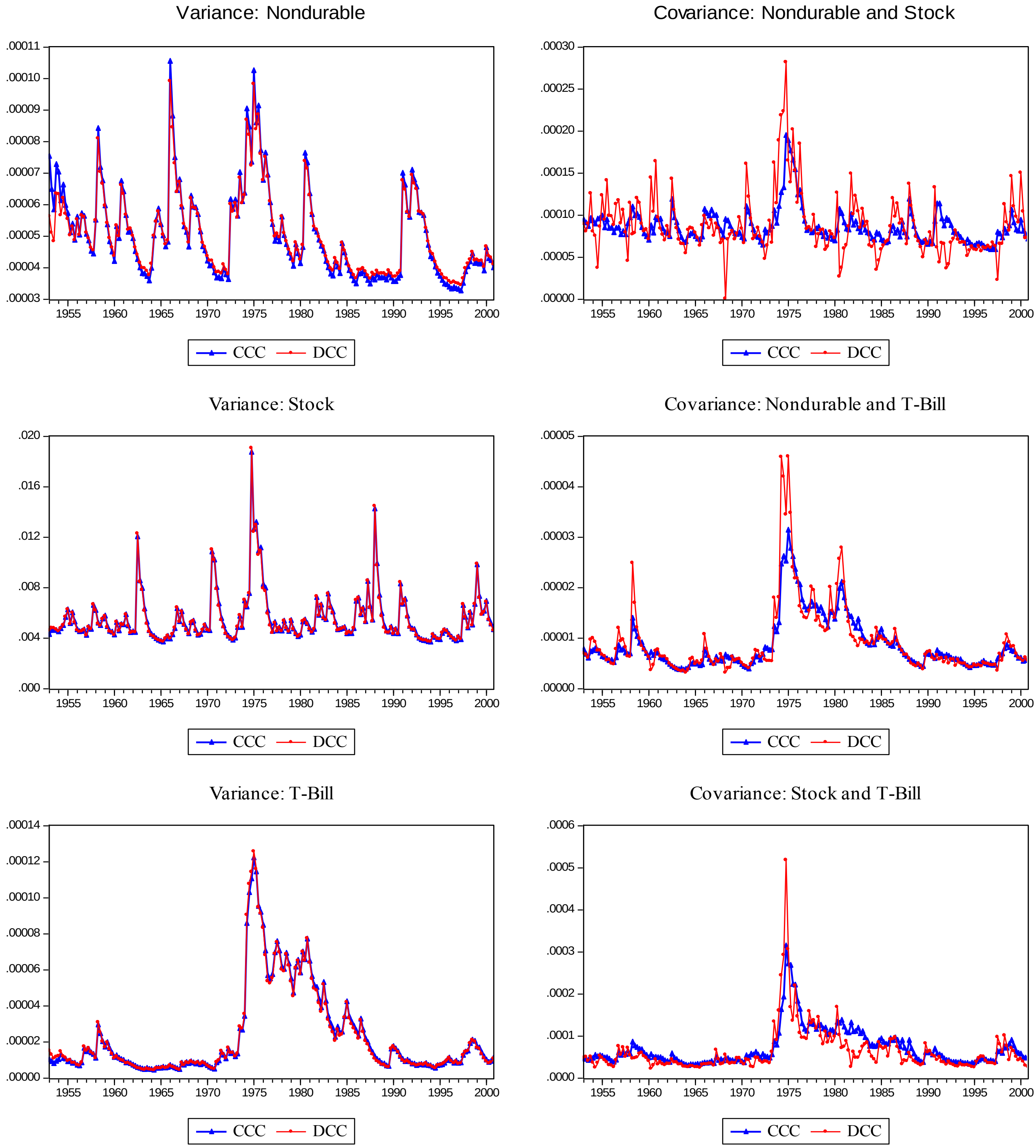

Figure 4 – CCC and DCC: Nondurable plus Services, Stock and T-bill