Business Cycle Fluctuations and Excess Sensitivity of Private Consumption

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We investigate whether business cycle fluctuations affect the degree of excess sensitivity of private consumption growth to disposable income growth. Using multivariate state space methods and quarterly US data for the period 1965–2000, we find that excess sensitivity is significantly higher during recessions.

INTRODUCTION

Under very strict assumptions, the permanent income hypothesis implies that aggregate private consumption follows a random walk (Hall 1978); maximizing forward-looking consumers lend and borrow freely on perfect capital markets to smooth consumption over time. In reality, however, private consumption growth is found to be excessively sensitive to current disposable income growth. This observed excess sensitivity (ES) can be explained theoretically by dropping Hall’s assumptions. The most common interpretation of the observed ES is the prevalence of liquidity constraints (Campbell and Mankiw 1991; Bacchetta and Gerlach 1997). More recent evidence by Ludvigson (1999) and Sarantis and Stewart (2003) reinforces this conclusion. Some theoretical models predict a correlation between consumption growth and income growth when consumers are liquidity-constrained (Deaton 1991; Ludvigson 1999). The second most often mentioned explanation is precautionary savings (Zeldes 1989; Caballero 1990; Carroll 1992, 1994; Ludvigson and Michaelides, 2001). In particular, ‘buffer stock’ models of saving (Carroll 1992) predict that consumers attribute a large weight to current income in their consumption decisions. While there is no consensus in the literature on the reasons for the observed ES, the assumption that the ES parameter is constant has been abandoned in recent studies in favour of time-varying specifications (Campbell and Mankiw 1991; McKiernan 1996; Bacchetta and Gerlach 1997; Pozzi et al. 2004). In particular, the impact of long-run driving factors of ES such as financial liberalization and the development of credit markets has been documented extensively in previous studies (Campbell and Mankiw 1990, 1991; Bacchetta and Gerlach 1997).

In this paper we investigate the impact of business cycle fluctuations on the degree of excess sensitivity of private consumption growth to disposable income growth by using quarterly US data over the period 1965–2000. The contribution of the paper is both empirical and methodological.

Empirically, the paper focuses on short-run factors that could affect the degree of excess sensitivity, instead of long-run factors. While the potential impact of the business cycle on the excess sensitivity parameter has been sporadically hinted at (see e.g. Campbell and Mankiw 1991), no focused investigation of this issue has yet been conducted. This is somewhat surprising since, from a theoretical perspective, both the liquidity constraints and the precautionary savings interpretation of ES can rationalize a role for the business cycle. With respect to liquidity constraints, there is a literature that

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suggests that liquidity constraints are more severe in recessions than in booms (see e.g.
Stiglitz and Weiss 1981; Bernanke and Gertler 1989). The deterioration of households’
balance sheets in a recession decreases internal financing possibilities (i.e. through income
or accumulated wealth), thereby raising the demand for external finance. Higher
monitoring and contract enforcement costs and information asymmetries may increase
the risk for banks’ of giving loans in recessions and diminish the supply of credit. These
factors may lead to a higher ‘external finance premium’, i.e. the difference between
the cost of external and internal finance. As noted by Jappelli and Pagano (1989), a high
‘external finance premium’ may be the source of liquidity constraints and excess
sensitivity. With respect to precaution, Carroll (1992) emphasizes that spells of unemploy-
ment may be the most important source of income uncertainty. If, as predicted
by ‘buffer stock’ models of consumption, uncertainty and precaution induce a correlation
between consumption and current income growth, then spells of unemployment
occurring during recessions may reinforce this correlation.

Methodologically, we use state space methods to estimate simultaneously a
consumption growth equation and a multivariate stochastic process for the ES
parameter. This approach differs from the methods applied until now, where, if a
multivariate process for the ES parameter is considered, either a two-step approach is
used (McKiernan 1996) or the process for the ES parameter is, rather restrictively,
assumed to be a deterministic function of the variables considered (see e.g. Evans and
Karras 1998; Sarantis and Stewart 2003; Pozzi et al. 2004).

Our results suggest that ES is positively affected by the change in the unemploy-
ment rate; i.e. it is significantly higher during recessions. This result can be reconciled with both
the liquidity constraints and the precautionary savings interpretation of ES. We do not
find a significant impact on ES of low frequency controls, however, as we find a negative
but insignificant impact of both a dummy that allows for a different average ES
parameter in the post-1982 period and a linear time trend.

The paper is structured as follows. In Section I we present the theoretical framework.
In Section II we present the empirical specification and discuss the estimation
methodology. Section III presents the estimation results, while Section IV concludes.

I. THEORETICAL FRAMEWORK

Suppose a representative consumer maximizes expected utility by choosing a consump-
tion path over an infinite lifetime. If the instantaneous utility function of this consumer is
of the constant relative risk aversion type, if the consumer lends and borrows against the
same constant interest rate, and if the growth rate of private consumption is normally
distributed, then we can write the first-order condition for this consumer as

$$
\Delta c_t = \alpha_t + \epsilon_t,
$$

where $\Delta c_t$ is the growth rate of real per capita consumption, $\alpha_t$ encompasses the
difference between the interest rate and the rate of time preference and the conditional
variance of consumption growth, and $\epsilon_t$ is an innovation that is uncorrelated with lagged
variables. (For the derivation, see Appendix A.)

A large literature has demonstrated that private consumption growth is typically
excessively sensitive to the growth rate in disposable income (Campbell and Mankiw
1990, 1991). Thus reality may be better approximated by

$$
\Delta c_t = \alpha_t + \beta_1 \Delta y_t + \epsilon_t,
$$

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where $\Delta y_t$ is the growth rate of real per capita disposable income, and $\beta_t$ is the excess sensitivity parameter ($0 \leq \beta_t \leq 1$). The most common interpretation for $\beta_t > 0$ is that the representative agent solution does not hold because of liquidity constraints (see Campbell and Mankiw 1991; Bacchetta and Gerlach 1997). The second most often mentioned explanation is precautionary savings (Zeldes 1989; Caballero 1990; Carroll 1992, 1994; Ludvigson and Michaelides 2001). Liquidity constraints and precaution are the two explanations that we emphasize in the paper. Note that, while the early literature on excess sensitivity assumes a constant excess sensitivity parameter, we follow the approach undertaken in more recent studies, which is to consider a time-varying degree of excess sensitivity (see Campbell and Mankiw 1991; McKiernan 1996; Bacchetta and Gerlach 1997; Pozzi et al. 2004). In particular, besides allowing only for low frequency movements in $\beta_t$, as in Campbell and Mankiw (1991) and Bacchetta and Gerlach (1997), (they attribute low frequency time-variation in $\beta_t$, to the development of credit markets and financial liberalization), we also investigate the impact of business cycle fluctuations on $\beta_t$. We discuss our empirical specification for $\beta_t$ in the next section.

II. EMPIRICAL SPECIFICATION AND ESTIMATION METHODOLOGY

Empirical specification

We consider the following empirical specification:

\begin{align}
\Delta c_t &= \alpha_t + \beta_t \Delta y_t + \varepsilon_t + \theta \varepsilon_{t-1}, \\
\alpha_t &= \alpha_{t-1} + \varepsilon^z_t, \\
\beta_t &= \beta_0 + \beta_1 l f_t + \beta_2 b c_t + \varepsilon^\beta_t.
\end{align}

From equation (3) we note that the error term in consumption growth now has an MA(1) structure, where for the $MA(1)$ parameter $\theta$ we have $-1 \leq \theta \leq 1$. The reasons that we allow for an $MA(1)$ error in consumption growth are potential time aggregation (Working 1960), problems related to the presence of durable components in our consumption measure (Mankiw 1982) and potential transitory components in the log of consumption. Following Bacchetta and Gerlach (1997), we specify $\alpha_t$ as a random walk in (4). Equation (5) is our specification for the time-varying excess sensitivity parameter $\beta_t$. We model $\beta_t$ as a straightforward linear function of a low frequency control ($lf_t$), and a variable reflecting the state of the business cycle ($bc_t$). For $lf_t$ we use both a linear time trend and a dummy variable that takes on the value 0 before 1982 (I) and 1 from 1982 (I) onward. For $bc_t$ we proxy by the change in the unemployment rate $\Delta u_t$. As can be seen in Figure 1, this variable is highly correlated with the turning points of the business cycle as calculated by the National Bureau of Economic Research (i.e. the NBER recession dummy, which takes on the value 1 in recessions). Note, finally, that the error terms $\varepsilon_t$, $\varepsilon^z_t$ and $\varepsilon^\beta$ are assumed to be independent Gaussian white noise terms (with variances $\sigma^2_{\varepsilon}, \sigma^2_{\varepsilon^z}$ and $\sigma^2_{\varepsilon^\beta}$, respectively).

Methodology

The system given by equations (3)–(5) can be written in state space form, and Kalman filter estimates of the unknown states as well as maximum likelihood estimates of the parameters in the system can be obtained provided that the endogeneity issues are
resolved first (see Hamilton 1994, chapter 13). Both $\Delta y_t$ and $bc_t$—which is proxied by $\Delta u_t$—are endogenous; i.e. they are correlated with the error terms $e_t$, $e^D_t$, and $e^B_t$. To avoid inconsistent estimation, we replace $\Delta y_t$ and $\Delta u_t$ by their fitted counterparts which are contemporaneously uncorrelated with the errors in the system. We construct the fitted disposable income growth series $\Delta y^f_t$ as the fitted values of a regression of disposable income growth on a number of instruments suggested by Campbell and Mankiw (1990), i.e. lagged disposable income growth, lagged consumption growth, lagged changes in the short-term nominal interest rate and a lagged error correction term, i.e. log consumption minus log disposable income (see also Campbell 1987). We construct the fitted change in the unemployment rate series $\Delta u^f_t$ as the fitted values of a regression of the change in the unemployment rate on lagged changes in the unemployment rate, the lagged NBER dummy, lagged values of the term spread (i.e. the difference between the short-term and the long-term interest rate), and lagged values of the corporate spread (i.e. the difference between the interest rate on BAA bonds and the interest rate on AAA bonds). The term spread and the corporate spread are reported by Estrella and Mishkin (1998) as good predictors of US recessions. Note that we use lags 2–5 for all instruments except for the error correction term (only lag 2). The reason for starting with lag 2 in the construction of $\Delta y^f_t$ and $\Delta u^f_t$ is the presence of an $MA(1)$ term in equation (3). For $\Delta y^f_t$ and $\Delta u^f_t$ to be predetermined, the instruments must be lagged at least twice. In Table 1 we report the (adjusted) $R^2$ and the $F$-test statistic (and $p$-value) of the first-stage regressions conducted for $\Delta y_t$ and $\Delta u_t$.$^6$ We note also that our results are robust to the use of alternative instrument sets (e.g. the inclusion of an

<table>
<thead>
<tr>
<th>TABLE 1</th>
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<tr>
<td><strong>Statistics for the First-Stage OLS Regression of $\Delta y_t$ and $\Delta u_t$ on Instruments</strong></td>
</tr>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>$\Delta y_t$</th>
<th>$\Delta u_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.1850</td>
<td>0.4684</td>
</tr>
<tr>
<td>$R^2_{adj}$</td>
<td>0.1077</td>
<td>0.4098</td>
</tr>
<tr>
<td>$F$</td>
<td>2.3929</td>
<td>7.9904</td>
</tr>
<tr>
<td>$F$ (p-val)</td>
<td>0.0063</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

*Note: The $F$-statistic tests the null hypothesis that all the coefficients in the first-stage regression are zero (except for the constant).*

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additional lag). Results with alternative instrument sets are not reported but are available from the authors upon request.

In Appendix B we report the state space representation of the model. Application of the Kalman filter recursions (see Hamilton 1994, chapter 13) to the system provides estimates and standard errors for the unobserved excess sensitivity parameter, i.e. the state $b_t$. With the Kalman filter, the sample log likelihood function can be constructed which is maximized numerically with respect to the unknown parameters in the system (i.e. the parameters are $\beta_0, \beta_1, \beta_2, \theta, \sigma^2_{\epsilon}, \sigma^2_{\eta}$, and $\sigma^2_{\epsilon \eta}$). We report these maximum likelihood estimates of the parameters and associated standard errors based on the Hessian. Refer to Appendix B for more details. As a specification test, we also calculate the Ljung–Box statistic for autocorrelation. This statistic tests whether the so-called one-step-ahead prediction errors of the state space system are autocorrelated (see Durbin and Koopman 2001, p. 34).

To estimate the system, we use quarterly data for the United States over the period 1965(I)–2000(IV) (i.e. we have 144 observations). The effective sample size is 139, since 5 observations are lost as a result of lagging. Data are seasonally adjusted where necessary. For $c_t$ we use the log of real per capita expenditures on nondurables and services (excluding shoes and clothing). For $y_t$ we use the log of real per capita disposable income. Both are deflated by the deflator of nondurables and services (excluding shoes and clothing) with base year 1982 = 100. Expenditures on nondurables and services, disposable income and the deflator are taken from the National Product and Income Accounts (NIPA). Population data are taken from the US Census Bureau. The unemployment rate $u_t$ is taken from the Bureau of Labor Statistics. With respect to the instruments used in the construction of $\Delta y_t$ and $\Delta u_t$, we note that for the short-run interest rate we use the nominal 3-month Treasury bill rate, for the long-run interest rate we use the 10-year government bond rate (both taken from OECD), and for the corporate spread we use the BAA corporate rate minus AAA corporate rate series as reported by the Federal Reserve Bank of St Louis.

### III. Results

In Table 2 we present the results from the estimation of the system over the period 1965(I)–2000(IV) (effective sample period 1966(II)–2000(IV)). First, in column (1) we report the results of estimating the state space model under the restriction that $z_t$ and $b_t$ are constant. We find a value for the excess sensitivity parameter over the sample period of about 0.28 (significant at the 5% level). This value is close to the values of about 0.3 found by Bacchetta and Gerlach (1997) for the United States over the period 1970–95. The question is then whether this value hides important time variation. In column (2) of Table 2 we report the results of estimating the system given in equations (3)–(5) with the fitted variables $\Delta y_t^f$ and $\Delta u_t^f$ used for $\Delta y_t$ and $bc_t$ and with the 1982 dummy used for $lf_t$. We find that there is a significant positive impact of changes in the unemployment rate on the excess sensitivity parameter. This suggests that excess sensitivity is significantly higher during recessions. As noted in Table 2, we find that the average value of $b_t$ during recessions is about 0.37 while during expansions it is about 0.22. While it has the expected sign, the estimate for the coefficient on the low frequency control is not significant. To allow for a less drastic shift in excess sensitivity, in column (3) of Table 2 we use a deterministic linear time trend for $lf_t$. Again, we find a significant positive impact of $bc_t$ on the excess sensitivity parameter. The coefficient on the low frequency control is
negative but insignificant. We note further that in the time-varying cases we find estimates for the MA(1) parameter $\gamma$ of about 0.31. This value is close to the theoretical value of this parameter under time aggregation of the variables in the consumption function and continuous decision making by consumers (see Hall 1988, or Karras 1994). Finally, we mention that our time-varying specifications are well supported by our Ljung–Box test for autocorrelation. In fact, based on this test, the time-varying cases reported in columns (2) and (3) of Table 2 are preferred over the time-invariant case reported in column (1).

Graphs of the evolution of the filtered estimates for $\beta_t$, as implied by the estimations in Table 2 (column 2), are presented in Figure 2. In this figure the positive impact of recessions on $\beta_t$ is clear. Also, $\beta_t$ is slightly declining over time. This reflects the negative (though insignificant) value of the coefficient on the low frequency control $lf_t$. Finally, while in a few periods $\beta_t$ is slightly negative, these negative values are never significant.

### IV. CONCLUSIONS

We have investigated the impact of business cycle fluctuations on the degree of excess sensitivity (ES) of private consumption growth to disposable income growth by...
using quarterly US data over the period 1965–2000. Our results suggest that ES is positively affected by the change in the unemployment rate; i.e. ES is significantly higher during recessions. This result can be reconciled with both the liquidity constraints and the precautionary savings interpretation of ES. We do not find a significant impact on ES of low frequency controls, however. These results suggest that short-run factors should be given more weight in future ES studies, especially because the relevance of short-run factors is implied by the economic theories used to explain the observed ES.

APPENDIX A: DERIVATION OF EQUATION (1)

The representative consumer maximizes \( E_t \sum_{j=0}^{\infty} (1 + \rho)^{-j} u(C_j) \) with \( 0 < \rho < 1 \) subject to a standard budget constraint with constant interest rate \( r \). \( C_j \) is real per capita consumption and \( E_t \) is the expectations operator conditional on information available up to period \( t \). With an instantaneous utility function of the constant relative risk aversion type, i.e. \( u(C_j) = (1 - \gamma)^{-1} C_j^{1-\gamma} \) with \( \gamma > 0 \), the first-order condition is \( E_{t-1}[X_j] = (1 + \rho)(1 + r)^{-1} \) with \( X_j \equiv \ln(C_j) \), \( x_i \equiv \ln X_i \) and \( \Delta c_i \equiv \ln(C_i/C_{i-1}) \); then \( x_i = -\gamma \Delta c_i \). Under the assumption that \( \Delta c_i \) is normally distributed with mean \( E_{t-1}[\Delta c_i] \) and variance \( V_{t-1}[\Delta c_i] \), we know that \( x_i \) is also Gaussian with mean \( -\gamma E_{t-1}[\Delta c_i] \) and variance \( \gamma^2 V_{t-1}[\Delta c_i] \). From the lognormal property, we then have that \( E_{t-1}(\exp(x_i)) = E_{t-1}[X_i] = \exp(-\gamma E_{t-1}[\Delta c_i] + 0.5 \gamma^2 V_{t-1}[\Delta c_i]) \). After substituting the last expression into the first-order condition, taking logs and rearranging, we obtain \( \Delta c_i = \alpha_i + \epsilon_i \) where \( \alpha_i = (r - \rho)\gamma^{-1} + 0.5\gamma V_{t-1}[\Delta c_i] \) and where \( \epsilon_i = \Delta c_i - E_{t-1}[\Delta c_i] \).

APPENDIX B: STATE SPACE REPRESENTATION OF THE MODEL

We report the state space representation of equations (3)–(5) with \( \Delta y_t \) and \( b c_t \) replaced by \( \Delta y_t' \) and \( \Delta y_t' \). The state vector is \( S_t \).

\[
\begin{align*}
A1 & \quad \Delta c_t = H_t S_t, \\
A2 & \quad S_t = F S_{t-1} + D Z_t + V_t,
\end{align*}
\]

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where

\[ H_t = \begin{bmatrix} 1 \\ \Delta y_t \\ 1 \\ \theta \end{bmatrix} \]

\[ D = \begin{bmatrix} 0 & 0 & 0 \\ \beta_0 & \beta_1 & \beta_2 \\ 0 & 0 & 0 \\ e_{t-1} & e_t & 0 \end{bmatrix} \]

\[ S_t = \begin{bmatrix} \alpha_t \\ \beta_t \\ e_{t-1} & e_t & 0 \end{bmatrix} \]

\[ F = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \]

\[ Z_t = \begin{bmatrix} 1 \\ \Delta u_t \end{bmatrix} \]

where \( v_t \sim N(\mathbf{0}, \mathbf{Q}) \) with

\[ Q = E(v_tv_t') = \begin{bmatrix} \sigma_{e_0}^2 & 0 & 0 & 0 \\ 0 & \sigma_{e_0}^2 & 0 & 0 \\ 0 & 0 & \sigma_{e_0}^2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \]

Given that the variables in \( H_t \) and \( Z_t \) are either exogenous or predetermined, the Kalman filter equations (see Hamilton 1994, chapter 13) can be applied to the system. To initialize the filter we use a diffuse prior; i.e. we assume that the initial state vector \( S_0 \) is random with covariance matrix \( kI \) where \( k \to \infty \) and where \( I \) is an identity matrix. We use the Kalman filter to construct the sample log likelihood function which is then maximized numerically with respect to the unknown parameters in \( H_t \), \( D \) and \( Q \). This procedure provides the filtered states \( S_{0t} \) (for \( t = 1, \ldots, T \)), the associated mean squared error matrices \( P_{0t} \) (for \( t = 1, \ldots, T \)) used to construct confidence bounds for the states, and the maximum likelihood estimates of the parameters in \( H_t \), \( D \) and \( Q \). The asymptotic standard errors of the maximum likelihood estimates are calculated from the matrix of second derivatives of the log likelihood function (i.e. we calculate Hessian-based standard errors). We refer to Hamilton (1994, chapter 13) for details.

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NOTES

1. So far, there is only empirical evidence on liquidity constraints and the business cycle for firms, not households. Gertler and Gilchrist (1994), Vermeulen (2002) and Peersman and Smets (2005) find that small firms are more liquidity-constrained during downturns.

2. Note that the possibility of a positive external finance premium (e.g. a wedge between lending and deposit rates) is a deviation from the standard permanent income hypothesis. The latter theorem is based on the assumption that the same interest rate applies to both lenders and borrowers.

3. Other explanations are myopia (see Flavin 1985, who dismisses this explanation in favour of a liquidity constraints explanation) and imperfect information (see Pischke 1995). Contrary to the liquidity constraints and precaution hypotheses, the latter two explanations offer no rationale however of why business cycle fluctuations would have an impact on excess sensitivity, and therefore are less relevant in the present context.

4. This date is qualified by Kaminsky and Schmukler (2003) as the point in time where the domestic financial sector in the United States can be considered ‘fully liberalized’ (to be interpreted as the date on which regulations like credit allocation control were fully lifted). However, it may also capture other events that may have had an impact on excess sensitivity, e.g. the Volcker disinflation.

5. When estimating the system with the NBER recession dummy instead of the change in the unemployment rate, we encountered numerical problems and our results were meaningless.

6. Our two-step procedure implies that we have a limited information maximum likelihood (LIML) procedure. If, instead, we were to add an equation for the change in the unemployment rate and an
equation for the growth rate of disposable income to our state space system and estimate the full system in one step, we would have a full information maximum likelihood (FIML) procedure. Reasons why the former method may be preferred over the latter are given in Greene (2003, p. 509). The most important reason in our context is that the equations for the change in the unemployment rate and for the growth rate in disposable income contain a very large number of variables and therefore a very large number of parameters to estimate. A joint estimation of all parameters is numerically difficult since FIML is nonlinear. In a two-step approach, however, most of the parameters are estimated by linear OLS in a first step and the second step nonlinear maximum likelihood estimation contains only a small number of parameters.

REFERENCES


