

Irina Khvostova

National Research University,
Higher School of Economics,
Russia

✉ ikhvostova@hse.ru

Alexander Larin

National Research University,
Higher School of Economics,
Russia

✉ alarin@hse.ru

Anna Novak

National Research University,
Higher School of Economics,
Russia

✉ aenovak@hse.ru

Acknowledgement: This study was carried out within The National Research University Higher School of Economics' Academic Fund Program in 2013-2014, research grant no. 12-01-0147. We thank the participants of the 18th International Conference on Macroeconomics Analysis and International Finance (2014, Greece) and two anonymous referees for valuable comments.

The Euler Equation with Habits and Measurement Errors: Estimates on Russian Micro Data

Summary: This paper presents estimates of the consumption Euler equation for Russia. The estimation is based on micro-level panel data and accounts for the heterogeneity of agents' preferences and measurement errors. The presence of multiplicative habits is checked using the Lagrange multiplier (LM) test in a generalized method of moments (GMM) framework. We obtain estimates of the elasticity of intertemporal substitution and of the subjective discount factor, which are consistent with the theoretical model and can be used for the calibration and the Bayesian estimation of dynamic stochastic general equilibrium (DSGE) models for the Russian economy. We also show that the effects of habit formation are not significant. The hypotheses of multiplicative habits (external, internal, and both external and internal) are not supported by the data.

Key words: Household consumption, Euler equation, Habit formation, Elasticity of intertemporal substitution, RLMS-HSE.

JEL: C23, E21.

Since the seminal paper of Robert E. Hall (1978), the Euler equation has become an important part of various micro- and macroeconomic models and is now widely used to describe the consumption behavior of households. In this paper, we use the Euler equation to estimate preference parameters, such as the elasticity of intertemporal substitution (EIS) and the subjective discount factor, and to investigate the habit formation of Russian households.

The motivation for this paper is the lack of precise estimates of the preference parameters for Russia, which could be used to calibrate dynamic stochastic general equilibrium models. Our estimates are based on the household micro data from the Russian Longitudinal Monitoring Survey of the Higher School of Economics (RLMS-HSE)¹ from 2000 to 2013. We show that the EIS for Russia is much higher than the estimates obtained for the U.S., and the hypothesis of the EIS being equal to 1 (or 0.5) is not supported by the data. The hypothesis of multiplicative habit formation is also not supported by the data.

The rest of the paper is organized as follows: a review of the literature is presented in Section 1; in Section 2, we present the theoretical model; we describe our

¹ **Russian Longitudinal Monitoring Survey of the Higher School of Economics.** 2014. Data Downloads. <https://www.hse.ru/en/rlms/downloads> (accessed August 01, 2014).

empirical methodology in Section 3, and our dataset and estimation results in Section 4; in Section 5, we provide a conclusion.

1. Literature Review

The Euler equation for consumption comes from the first-order condition for the optimal choice of a single, fully rational, and forward-looking representative consumer. It represents one of the key blocks of DSGE models - currently one of the most popular tools of macroeconomic analysis (Maurice Obstfeld and Kenneth Rogoff 1998; Frank Smets and Rafael Wouters 2007). A large number of empirical studies use the utility function with constant relative risk aversion preferences to identify the subjective discount factor, as well as the EIS. Despite the fact that it is common to assume that household preferences are homogeneous and separable across time, there are alternative approaches that relax these assumptions. The assumption of homogeneous preferences can be relaxed by introducing so-called taste shifters (an agent's specific and time-varying characteristics), while the assumption of time-separability is often relaxed by introducing consumption habits.

A debatable issue widely discussed in the literature regards the circumstances under which the Euler equation yields unbiased and consistent estimates of the structural parameters. Most authors agree that due to agent heterogeneity, estimation using aggregated data can lead to biased estimates of the parameters (Orazio P. Attanasio and Guglielmo Weber 1993). As a rule, to resolve this problem, authors use household-level panel data, taking into account some specific characteristics of households. Although data on household consumption suffer from appreciable measurement errors, various solutions to this problem are applicable: one may consider cohorts or clusters of households (Olesya V. Grishchenko and Marco Rossi 2012) or may use a linearized version of the Euler equation (Attanasio and Hamish Low 2004).

When estimating the Euler equation on U.S. micro data, researchers usually use data from the Panel Study on Income Dynamics (PSID) (David E. Runkle 1991; Sule Alan and Martin Browning 2010) or from the Consumer Expenditure (CEX) Survey by the Bureau of Labor Statistics (Attanasio and Weber 1995; Annette Vissing-Jørgensen 2002; Alan, Attanasio, and Browning 2009; Alan 2012). The studies show significant positive values of the EIS between 0 and 1. Runkle's (1991) estimate of the EIS is close to 0.45; Attanasio and Weber (1995) show that the EIS is about 0.67; Vissing-Jørgensen (2002) presents estimates that are between 0.3 and 1, depending on the interest rate; Alan and Browning (2010) present estimates of the relative risk aversion (RRA) coefficient of between 1.803 and 2.1, depending on educational level, which correspond to the EIS, lying between 0.48 and 0.55.

Despite the problems raised by agents' heterogeneity, most of the empirical work on habit formation has been done on aggregated data. The studies based on macro data for the U.S. and European economies usually show the existence of habits in consumption. In the DSGE framework, Smets and Wouters (2003) obtain an external habit stock of 0.55 of past consumption. Using aggregated monthly data for the U.S., Lawrence J. Christiano, Martin Eichenbaum, and Charles Evans (2005) present an estimate of habit persistence equal to 0.65. This value is close to the point estimate reported in the paper of Michele Boldrin, Christiano, and Jonas D. M. Fisher (2001).

The studies based on micro data show contradictory results: some papers confirm habit formation (Raquel Carrasco, José M. Labeaga, and J. David López-Salido

2005; Browning and Dolores M. Collado 2007; Wayne-Roy Gayle and Natalia Khorunzhina 2014), while others do not (Costas Meghir and Weber 1996; Karen E. Dynan 2000). There may be at least two possible explanations for the contradictory results. The first explanation is the difference in the definition of nondurable consumption. Authors whose research is based on PSID have to use food consumption, whereas authors who use CEX are free to construct a good measure of nondurable consumption, which, besides food, may include expenditures on services, fuel, personal care, and so on. However, an important problem with CEX is that it does not present information on household income and this may also have a significant impact on the estimation results. The second explanation is that each household in the survey is observed for only a short period of time so that it is hard to uncover the long-term paths of consumption.

To solve this problem, Carrasco, Labeaga, and López-Salido (2005) and Browning and Collado (2007) use Spanish panel data, containing information on nondurables for up to eight quarters for each household. The authors find strong habits for nondurables, services, food, alcohol, and tobacco, and no habits related to clothing. In this paper, we use RLMS-HSE data, for which, as in the Spanish data set, the consumption of nondurables is observed for each household over a long period of time.

Considering models for the Russian economy, authors do not estimate preference parameters and usually base their calibration on the results of standard real business cycle (RBC) models for the U.S. economy (Kirill Sosunov and Oleg Zamulin 2007; Andrey V. Polbin 2013; Roman Semko 2013). However, first estimates of EIS for the Russian economy, based on the micro data, are significantly higher compared to the estimates for the U.S. economy (Alexander Larin, Anna Novak, and Irina Khvostova 2013). However, as shown in the complete review by Tomas Havranek et al. (2013), the EIS estimates obtained for different countries vary significantly: from negative values for Argentina and France, to high positive values for Austria and New Zealand. Thus, parameter estimates obtained for one country may not be valid for another, which is why estimates obtained using Russian data are in demand.

To estimate the parameters, we use nonlinear generalized method of moments, which accounts for measurement errors without imposing parametric restrictions on their distribution. The estimator was first proposed by Alan, Attanasio, and Browning (2009) for the Euler equation with time-separable preferences. Later, it was extended by Gayle and Khorunzhina (2014) for the Euler equation with habit formation. This method takes account of the fact that preferences may depend on household-specific characteristics and the parameters of the model. We adapt this approach to the RLMS-HSE data, which is characterized by varying lengths of periods between interviews - a feature that allows us to obtain consistent estimates not only for the EIS, but also for the subjective discount factor. There are two key differences in this approach from Gayle and Khorunzhina's (2014) model. First, we present a model that accounts for the varying number of months between two interviews with a household, which is a feature of the RLMS-HSE data set, and show that in this case the subjective discount factor can be identified and estimated. Second, we do not estimate the model with internal habit formation as there is a problem with identification and some strong assumptions about parameters are necessary to solve this problem. Instead of this, to check for internal and external multiplicative habits, we suggest using the Lagrange

multiplier test, which helps to avoid estimation of the full model with habit formation.

2. The Model

2.1 Preferences

We assume that the preferences of household i in period t may be described by the following utility function:

$$U_{it} = \sum_{\tau=t}^{\infty} \beta^{\tau-t} \frac{\tilde{c}_{i\tau}^{1-\gamma}}{(1-\gamma)} \phi_{i\tau}, \quad (1)$$

where $\tilde{c}_{i\tau}$ denotes consumption services, $\phi_{i\tau}$ denotes household-specific taste shifters, $0 < \beta < 1$ is the subjective discount factor, and $\gamma > 0$ is the utility curvature parameter.

We mainly focus our attention on estimating β and γ as they are the key parameters that determine consumer behavior in DSGE models. In the absence of internal habit formation, parameter γ equals both the RRA and the reciprocal of the EIS. In its turn, the EIS reflects the strength of the link between interest rates and consumption growth so that γ defines the co-movement of these two variables. For the model with internal habit formation, the interpretation of γ is more complicated as both the RRA and EIS depend now on household-specific characteristics and other parameters of the model (see, for example, Gayle and Khorunzhina 2014).

Taste shifters $\phi_{i\tau}$ introduce agent heterogeneity into the model and allow preferences to depend on household-specific characteristics, such as income and working time. We define them as:

$$\phi_{i\tau} = \exp(\mu_i + x_{i\tau}' \delta), \quad (2)$$

where $x_{i\tau}$ denotes a vector of household-specific characteristics, δ is a vector of coefficients, and μ_i is a constant term that relates to household-specific time-invariant individual effects.

In the absence of habits, consumption services $\tilde{c}_{i\tau}$ equals current consumption $c_{i\tau}$. In this case, preferences are time-separable, so that current period utility depends only on current consumption.

Habit formation implies that current consumption is not significant by itself, but is compared to the benchmark consumption level. In this paper, we consider multiplicative habits, meaning that utility depends on the ratio of consumption to the habit stock (Bennett McCallum and Edward Nelson 1999; Jeffrey Fuhrer 2000; Jeffrey D. Amato and Thomas Laubach 2004), so that consumption services is given by:

$$\tilde{c}_{i\tau} = \frac{c_{i\tau}}{c_{i\tau-1}^\alpha \bar{c}_{\tau-1}^\omega}. \quad (3)$$

Here, $\bar{c}_{\tau-1}$ denotes the past average consumption of a reference group, which we define as the average consumption of all other households in the economy, $0 \leq \alpha < 1$ measures the strength of internal habits, and $0 \leq \omega < 1$ measures the strength

of external habits (here also $\alpha + \omega < 1$). We do not test for additive habits because we use micro data that are characterized by a high variation in consumption. The high variation in consumption makes estimation problematic as for high values of α and/or ω , consumption services may be negative so that the utility cannot be computed. We do not test for deep habits and leave this issue for further research.

2.2 Measurement Errors

As mentioned above, to take agent heterogeneity into account, the Euler equation is usually estimated using micro data. The main problem of micro data on household consumption is that measurement errors may lead to inconsistent estimates of the parameters. For instance, Runkle (1991) finds that 76% of consumption growth variation in the PSID is due to measurement errors.

A number of techniques have been proposed to address this problem. Instead of analyzing particular households, some authors consider cohorts (Attanasio and Weber 1995; Kris Jacobs and Kevin Q. Wang 2004) or clusters of households (Grishchenko and Rossi 2012), which they construct using individual characteristics, such as income, education, age, savings rate, and so on. This technique assumes that measurement errors are averaged out from the *per capita* consumption of a cohort or cluster. Even using data aggregated by cohorts or clusters, it is still possible to account for agent heterogeneity by allowing preferences of households from different cohorts or clusters to be different.

Other authors prefer to estimate a linearized version of the Euler equation, which is less sensitive to the influence of measurement errors (Attanasio and Low 2004). It is assumed that measurement errors move to the error term of regression such that the instrumental variable estimator can be used to obtain consistent estimates. One can apply log-linearizing as well as Taylor approximation around a steady state, which allows for a higher-order approximation of the equation. However, this technique has several disadvantages. For instance, it does not allow us to identify a subjective discount factor and fails to address the problem of measurement errors in the case of internal habit formation (Alan, Attanasio, and Browning 2009).

In this paper, we use the idea that under certain assumptions, measurement errors may lead to inconsistent estimates only of the subjective discount factor, while estimates of the EIS remain consistent (see, for example, Han Hong and Elie Tamer 2003). Moreover, we show that if the time between two observations may vary across households, it is also possible to obtain consistent estimates of the subjective discount factor (see Subsection 3.1).

We assume that observed consumption is given by:

$$c_{it}^o = c_{it} v_i \eta_{it}, \quad (4)$$

where v_i and η_{it} are random variables within the domain $(0, +\infty)$ that represent household-specific time-invariant and time-varying components of measurement error, respectively.

As shown by Gayle and Khorunzhina (2014), under the assumptions made above and in the absence of habit formation, the Euler equation for the observed consumption is:

$$\mathbb{E} \left(\kappa \beta \exp(\Delta x_{it+1}' \delta) \left(\frac{c_{it+1}^o}{c_{it}^o} \right)^{-\gamma} R_{it+1} - 1 \middle| \mathbf{F}_{it} \right) = 0, \quad (5)$$

where R_{it+1} is the real gross return for the period from t to $t+1$, $\Delta x_{it+1} = x_{it+1} - x_{it}$ is the future change in household-specific characteristics, \mathbf{F}_{it} is the information set of the i -th household in period t , and κ is a constant that depends on the parameters of the distribution of η_{it} and the parameters of the model. It is necessary to note that this form still allows for correlation between household characteristics and measurement errors (at least, the time-invariant part) and does not impose parametric restrictions on the distribution of measurement errors (in terms of Gayle and Khorunzhina 2014, this is in nonparametric form).

3. Empirical Methodology

To obtain estimates, we use two-step optimal GMM. In the second step of estimation and to compute standard errors, we use estimates of the moment covariance matrix, which accounts for the correlation between observations of the same period. In particular, this correlation may arise due to macroeconomic shocks.

3.1 Accounting for Varying Lengths of Periods

In this paper, we use data of annual frequency - households are interviewed once a year concerning their last month's consumption, income, working hours, and so on. However, the month of the interview may change from one wave of the survey to another. Therefore, the number of months between two interviews may vary from wave to wave and between households. To account for the different number of months between interviews, we need to specify our notations. Let subscript t denote the wave of the interview and $h(i, t)$ denote the number of months between interviews of the i -th household in waves t and $t + 1$. Then, the Euler equation for this notation is almost the same:

$$\mathbb{E} \left(\kappa \beta^{h(i, t)/12} \exp(\Delta x_{it+1}' \delta) \left(\frac{c_{it+1}^o}{c_{it}^o} \right)^{-\gamma} R_{it+1} - 1 \middle| \mathbf{F}_{it} \right) = 0, \quad (6)$$

except for the fact that β - the discount factor for annual data - is powered by the appropriate length of the period between two interviews. Note that R_{it+1} here is the real gross return for the period between two interviews, and hence may have different terms for different observations.

An interesting result is that if the length of the periods did not change, we could not separate the estimate of β from that of κ , but due to the varying lengths of periods between interviews, we can identify both the subjective discount factor β and the constant κ .

3.2 LM Test for Habit Formation

To test the hypotheses concerning habit formation, we use the LM test. The reason for using this test is the problems with identification that arise when we try to estimate the Euler equation with habits and measurement errors (Gayle and Khorunzhina 2014). One may note that the GMM estimator for this model has a trivial solution when sample counterparts to moment conditions (and thus the objective function for the maximization problem of GMM) are equal to zero and do not depend on data. This is why the identification of parameters becomes problematic. To solve this problem, Gayle and Khorunzhina (2014) suggest fixing one of the coefficients, which shows the impact of taste shifters. In our opinion, this is too restrictive an ad hoc assumption. For this reason, we suggest using the LM test, which does not require estimating the model with habit formation. This test is valid as the parameters of the unrestricted model are locally identified regardless of the trivial solution (we verify this by checking that the Jacobian of moment conditions has full rank). We test the null hypothesis of no habit formation against three alternative hypotheses: external habits, internal habits, and both external and internal habits.

4. Data and Estimation Results

4.1 Sample Structure

The samples used in the paper are drawn from waves 9-21 of the RLMS-HSE representative sample, which correspond to the period from September 2000 to February 2013. The RLMS-HSE is an unbalanced panel based on a survey conducted by the National Research University Higher School of Economics and ZAO “Demoscope”, together with the Carolina Population Center at the University of North Carolina at Chapel Hill and the Institute of Sociology RAS.

In comparison with other commonly used databases (the PSID and CEX Survey for the U.S.), the RLMS-HSE includes information not only about food consumption, but also questions concerning the complete measure of consumption expenditures for each household over a long period of time, so that it is possible to conduct meaningful longitudinal analysis (Mirko Savić 2007). To add to this, the advantage of the RLMS-HSE is that it presents information on both nondurable consumption and household income, whereas most of the estimates for the U.S. are obtained using data sets that do not present household income or present information only on food consumption but not nondurable consumption.

We use household files to construct variables such as the consumption of nondurable goods and services, household income, place of residence (urban/rural), number of household members, their sex and age, and the weights for the basket of nondurable goods and services to calculate inflation. To obtain the working hours of household members, we use the (individual) files of the survey for household members.

Each household is interviewed once in each wave in the period from September to March. However, the month of the interview for the same household may vary from wave to wave. We account for this by rewriting the Euler equation in the form (6).

The initial representative sample of waves 9-21 of the survey contains data on approximately 12,375 households. From the initial sample, we drop those households that live in rural areas, and we drop household-wave observations if there is no non-retired adult member in the household. Following Attanasio and Weber (1995), to exclude obvious reporting and coding errors, we drop household-wave observations if consumption growth is such that one of the following criteria holds: (a) $c_{it+1}^o / c_{it}^o < 0.2$ or $c_{it+1}^o / c_{it}^o > 5$; (b) $c_{it}^o / c_{it-1}^o < 0.5$ and $c_{it+1}^o / c_{it}^o > 2$; (c) $c_{it}^o / c_{it-1}^o > 2$ and $c_{it+1}^o / c_{it}^o < 0.5$. We use a similar filter for income growth.

To obtain estimates, we need each household to be interviewed in at least four consecutive waves – two waves to construct growth rates, plus two waves to construct a set of instruments. Moreover, to test for internal habit formation, we need one additional wave to construct one additional lead of the variables. Thus, households with no observations in *four* consecutive waves are excluded from *the long sample*, and households with no observations in *five* consecutive waves are excluded from *the short sample*.

For the short sample, the final number of different households is 1363, while for the long sample it is 1800. As most of the households are not observed in all the waves, the total number of observations is less than the number of the households multiplied by the number of waves. For the short sample, the total number of observations is 5109, while for the long sample it is 7042.

4.2 Nondurable Goods and Services

When investigating the Euler equation on panel data, authors traditionally define consumption as expenditures on nondurable goods and services per household member. There are several definitions of nondurable goods in the literature (Jacobs and Wang 2004; Grishchenko and Rossi 2012).

In this paper, we follow a standard approach to define consumption. The theoretical framework of the permanent income hypothesis implies analyzing durable and nondurable consumption excluding investments in durables and adding services (Robert E. Hall 1978). However, there are no available data on the stock of durables to separate investments from consumption. Moreover in the basic model, consumption is time-separable, so that a household receives utility from current consumption only in the current period and no utility from that consumption thereafter. As the theoretical foundations of the utility function apply to individual categories of consumption, we follow Hall (1978) and drop durables altogether, considering the consumption of nondurable goods and services.

In this paper, we compute consumption as the sum of expenditures on items such as food, alcoholic beverages, tobacco products, utilities, clothing, public transport, fuel, personal care items, and communication services.

4.3 Key Variables

We compute observed consumption c_{it}^o as the real consumption of nondurable goods and services, defined above. As asset returns, we use real bank interest rates: up to one-year average interest rates on individual credits R_{it+1}^C and deposits R_{it+1}^D .

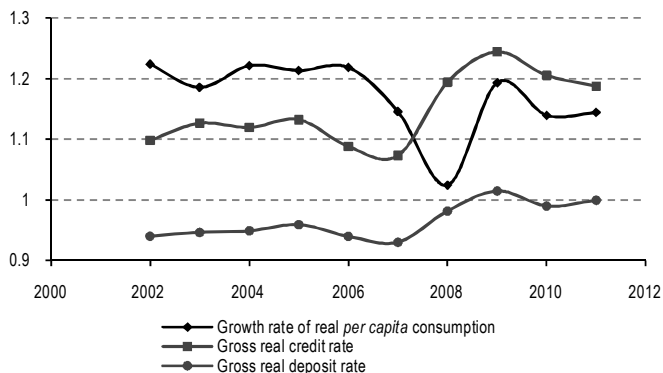
As the Euler equation must hold for both these rates, we use both of them to construct moment conditions for the GMM estimation. We do not use stock market returns because Russian households prefer to use bank credits and deposits to transfer money between periods, so that the share of stockholders in the sample we use is less than 1%.

As taste shifters, we use the logarithm of real household income y_{it} and working time share l_{it} so that:

$$\phi_{it} = \exp(\mu_i + \delta_y y_{it} + \delta_l l_{it}). \tag{7}$$

We assume that observed income may suffer from measurement errors like observed consumption. In this case, Equation (6) does not change, except for the fact that κ depends now on the distribution of measurement errors of both consumption and income. We define working time share as the average number of working hours for adult members in the last month divided by 720 (the approximate number of hours in a month).

The dynamics of consumption growth and interest rates are shown in Figure 1. Table 1 presents descriptive statistics for the variables. Here, the number of observations is the number of observations for all households and for all periods. The average number of households per wave is computed as the number of observations divided by the number of waves.



Note: The average growth rate of real per capita consumption is the mean value of $\overline{c_{it+1}^o/c_{it}^o}$, where t is the current date.

Source: Authors' calculations.

Figure 1 Dynamics of Average Real Consumption Growth, the Gross Credit Rate and the Gross Deposit Rate

Table 1 Descriptive Statistics for the Variables

Description	Notation	Short sample	Long sample
Growth rate of real per capita consumption	c_{it+1}^o/c_{it}^o	1.162 (0.565)	1.167 (0.581)
Change in logarithm of real per capita income	$\Delta \ln(y_{it+1}^o)$	0.099 (0.408)	0.095 (0.406)

Change in working time	Δl_{it+1}	0.004 (0.155)	0.002 (0.158)
Gross real credit rate	R_{t+1}^C	1.148 (0.058)	1.153 (0.057)
Gross real deposit rate	R_{t+1}^D	0.964 (0.027)	0.968 (0.028)
Number of waves	T	9	10
Average number of households per wave	N	568	704
Number of observations	$N \times T$	5109	7042
Sample period		2000:2013	2000:2013
Sample period without lags and leads		2002:2011	2002:2012

Notes: The table presents mean values of variables. Standard deviations are in parentheses.

Source: Authors' calculations.

4.4 Instruments

Instrumental variables, which form the information set F_{it} of the i -th household, should satisfy two conditions. First, they must be available to the household at the moment of making a decision about current consumption c_{it} . Second, they must contain useful information for making the decision, meaning information about current and future dynamics of such variables as consumption, income, working hours, and returns.

In addition, one of the assumptions we use to obtain the Euler Equation (6) is that measurement errors should not correlate with instrumental variables. It is easy to show that measurement error η_{it} of consumption, for example, is correlated with observed consumption growth c_{it}^o/c_{it-1}^o . It is implied by the fact that observed current consumption c_{it}^o depends on this measurement error. Therefore, we cannot include current growth rates of consumption and income in the list of instruments. Bearing these assumptions in mind, we use the following set of instruments:

- reciprocal of the past consumption growth rate: $(c_{it-1}^o/c_{it-2}^o)^{-1}$;
- exponent of the change in past income: $\exp(\Delta \ln(y_{it-1}^o))$;
- reciprocal of the exponent of current and past change in working time: $\exp(-\Delta l_{it}), \exp(-\Delta l_{it-1})$;
- lagged credit rates: R_{it}^C, R_{it-1}^C ;
- lagged deposit rates: R_{it}^D, R_{it-1}^D ;
- growth rates of average consumption: $\bar{c}_t/\bar{c}_{t-1}, \bar{c}_{t-1}/\bar{c}_{t-2}$;
- dummy variables for the crisis period: $d_{2007}, d_{2008}, d_{2009}$;
- constant term.

From a theoretical point of view, there is no difference between using the past consumption growth rate or its reciprocal as an instrument. However, in practice, the reciprocal $(c_{it-1}^o/c_{it-2}^o)^{-1}$ gives better identification of the parameters as consumption

growth c_{it+1}^o/c_{it}^o enters the Euler Equation (6) as a negative power. For the same reason, we use the reciprocal of the exponent of change in working time.

We add growth rates for average consumption as these instruments may help households to make the decision about consumption in the case of external habit formation. Therefore, these instruments may be crucial when testing for external habits. Here we assume that measurement errors in average consumption are averaged out and thus we may use the current growth rate \bar{c}_i/\bar{c}_{i-1} as an instrument.

We use dummy variables d_{2007} , d_{2008} , d_{2009} as instruments to account for the effects of the financial crisis of 2008-2009. These dummy variables take the value 1 if the year of the interview is equal to 2007, 2008, or 2009, respectively, and they take the value 0 otherwise. We do not split the sample into two periods and do not exclude the crisis period as the number of observations per household would be extremely small. However, as pointed out by Attanasio and Low (2004), have a small number of periods in the panel may lead to an essential bias in the preference parameter estimates. If we do not include these dummy variables, our main results do not change, but the estimate of the EIS becomes higher (this can easily be explained by the extreme increase in interest rates and the fall in consumption in 2009, which is shown in Figure 1).

4.5 Estimation Results

As long sample estimates are more precise because they use more observations, we interpret only these estimates here. We use the short sample purely to test for habits. The key result is that our estimate of the utility curvature parameter γ is significantly greater than zero. This result supports the consumption-smoothing hypothesis, and suggests a positive relationship between expected consumption growth and the interest rate in Russia. This value of γ corresponds to an EIS of 4.167 with a 95% asymptotic confidence interval (2.499, 5.834). This estimate of the EIS is much higher than most estimates obtained for the U.S. economy. Moreover, the EIS confidence interval rejects the hypothesis of the logarithmic utility function (the EIS equal to 1), which is usually used to calibrate DSGE models for the Russian economy.

From our point of view, such a high estimate for the EIS is mainly due to our choice of return rates. Attanasio and Vissing-Jørgensen (2003) show that the EIS for bond holders is significantly higher than that for shareholders. A simple explanation for this phenomenon is that a 1% change in bond returns brings more information and is more important than a 1% change in share returns as bond returns are less volatile. Thus, we may expect the response of consumption growth to a 1% change in bond returns to be more significant and hence we may expect the EIS to be higher. In our paper, we use credit and deposit rates, which are less volatile than both share returns and bond returns, so that the high estimate we obtain for the EIS seems reasonable.

However, this result is not as uncommon as it may seem. For example, positive estimates of the EIS significantly higher than 1 have been obtained for the U.S. (see, among others, Attanasio and Vissing-Jørgensen 2003; Henrik Hasseltoft 2012), Japan (Masakatsu Okubo 2011), Korea (Atsuo Ueda 2000), Greece (Chien-Chung Nieh and Tsung-Wu Ho 2006).

Table 2 GMM Model Estimates

Parameter	Short sample	Long sample
β	0.808*** (0.056)	0.905*** (0.055)
γ	0.149*** (0.042)	0.240*** (0.049)
δ_y	0.511*** (0.039)	0.589*** (0.043)
δ_l	0.203*** (0.026)	0.222*** (0.029)
κ	1.093*** (0.075)	0.962*** (0.058)
Hansen J-test for overidentification	14.201 [0.921]	15.809 [0.863]
LM test (H_1 : external habits)	0.111 [0.739]	0.205 [0.651]
LM test (H_1 : internal habits)	4.074 [0.254]	-
LM test (H_1 : internal and external habits)	4.176 [0.383]	-
Number of waves	9	10
Average number of households per wave	568	704

Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses; p -values for tests are in square brackets.

Source: Authors' calculations.

The estimate of β , which refers to the subjective discount factor for annual data, is also consistent with the theoretical model - it is positive and close to 1. Assuming exponential discounting, the estimate of the subjective discount factor for quarterly data is a 4th root of the estimate for annual data and equals 0.975. The 95% asymptotic confidence interval for the parameter is (0.852, 1.098), meaning that the hypothesis of the subjective discount factor being close to 1 is not rejected by the data.

The hypothesis of no habit formation in household consumption is not rejected by the data. Thus it is not necessary to account for external and/or internal habits when modeling consumption dynamics for Russian households. However, this result does not imply that there are no habits in the consumption of Russian households. In this paper, we use data on monthly consumption with annual frequency and thus we define habit stock as the amount of consumption in a month of the year of the interview. Hence, the result we obtain says only that households do not form habits related to the previous year's consumption, but they may still form habits, for example, based on the last month or the last quarter.

Both taste shifters - income and working hours - significantly influence household utility. According to the estimation results, an increase in household income (or a decrease in working hours) - current or expected in the future - raises household utility.

Based on the estimation results for the long sample, we present in Table 3 parameter values that may be used as priors for Bayesian estimation or for the calibration of DSGE models for Russia.

Table 3 Parameter Values for DSGE models

Parameter	Estimate	Standard error
Relative risk aversion coefficient	0.240	0.049
Elasticity of intertemporal substitution (EIS)	4.167	0.851
Subjective discount factor, annual data	0.905	0.055
Subjective discount factor, quarterly data	0.975	0.063

Notes: Standard errors for the estimates of the elasticity of intertemporal substitution and the subjective discount factor for quarterly data are computed using the Delta method.

Source: Authors' calculations.

5. Conclusion

In this paper, we present estimates of the Euler equation for Russia. The estimation is based on household data from the RLMS-HSE panel survey and accounts for preference heterogeneity and measurement errors in consumption and income. We use credit and deposit rates as asset returns. Preference heterogeneity is introduced using taste shifters - household income and working hours. To estimate the parameters of the model, we use GMM. We run an LM test to check for multiplicative habit formation.

The estimates of the elasticity of intertemporal substitution and the subjective discount factor are both consistent with the theoretical framework. The significant positive estimate for the EIS supports the hypothesis of consumption smoothing. The hypothesis of preference heterogeneity is also supported by the data - both income and working hours influence household utility and as a consequence, the marginal utility of consumption. The hypotheses of multiplicative habit formation (external, internal, and both external and internal) are not supported by the data.

References

- Alan, Sule, Orazio P. Attanasio, and Martin Browning.** 2009. "Estimating Euler Equations with Noisy Data: Two Exact GMM Estimators." *Journal of Applied Econometrics*, 24(2): 309-324.
- Alan, Sule, and Martin Browning.** 2010. "Estimating Intertemporal Allocation Parameters Using Synthetic Residual Estimation." *Review of Economic Studies*, 77(4): 1231-1261.
- Alan, Sule.** 2012. "Do Disaster Expectations Explain Household Portfolios?" *Quantitative Economics*, 3(1): 1-28.
- Amato, Jeffrey D., and Thomas Laubach.** 2004. "Implications of Habit Formation for Optimal Monetary Policy." *Journal of Monetary Economics*, 51(2): 305-325.
- Attanasio, Orazio P., and Guglielmo Weber.** 1993. "Consumption Growth, the Interest Rate and Aggregation." *Review of Economic Studies*, 60(3): 631-649.
- Attanasio, Orazio P., and Guglielmo Weber.** 1995. "Is Consumption Growth Consistent with Intertemporal Optimization? Evidence from the Consumer Expenditure Survey." *Journal of Political Economy*, 103(6): 1121-1157.
- Attanasio, Orazio P., and Annette Vissing-Jørgensen.** 2003. "Stock-Market Participation, Intertemporal Substitution, and Risk-Aversion." *American Economic Review*, 93(2): 383-391.
- Attanasio, Orazio P., and Hamish Low.** 2004. "Estimating Euler Equations." *Review of Economic Dynamics*, 7(2): 405-435.
- Boldrin, Michele, Lawrence J. Christiano, and Jonas D. M. Fisher.** 2001. "Habit Persistence, Asset Returns, and the Business Cycle." *American Economic Review*, 91(1): 149-166.
- Browning, Martin, and Dolores M. Collado.** 2007. "Habits and Heterogeneity in Demands: A Panel Data Analysis." *Journal of Applied Econometrics*, 22(3): 625-640.
- Carrasco, Raquel, José M. Labeaga, and J. David López-Salido.** 2005. "Consumption and Habits: Evidence from Panel Data." *The Economic Journal*, 115(500): 144-165.
- Christiano, Lawrence J., Martin Eichenbaum, and Charles Evans.** 2005. "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy*, 113(11): 1-45.
- Dynan, Karen E.** 2000. "Habit Formation in Consumer Preferences: Evidence from Panel Data." *American Economic Review*, 90(3): 391-406.
- Fuhrer, Jeffrey.** 2000. "Habit Formation in Consumption and Its Implications for Monetary-Policy Models." *American Economic Review*, 90(3): 367-390.
- Gayle, Wayne-Roy, and Natalia Khorunzhina.** 2014. "Micro-Level Estimation of Optimal Consumption Choice with Intertemporal Nonseparability in Preferences and Measurement Errors." <http://ssrn.com/abstract=1431093>.
- Grishchenko, Olesya V., and Marco Rossi.** 2012. "The Role of Heterogeneity in Asset Pricing: The Effect of a Clustering Approach." *Journal of Business and Economic Statistics*, 30(2): 297-311.
- Hall, Robert E.** 1978. "Stochastic Implications of the Life Cycle-Permanent Income Hypothesis: Theory and Evidence." *Journal of Political Economy*, 86(6): 971-987.
- Hasseltoft, Henrik.** 2012. "Stocks, Bonds, and Long-Run Consumption Risks." *Journal of Financial and Quantitative Analysis*, 47(2): 309-332.

- Havranek, Tomas, Roman Horvath, Zuzana Irsova, and Marek Rusnak.** 2013. "Cross-Country Heterogeneity in Intertemporal Substitution." William Davidson Institute Working Paper 1056.
- Hong, Han, and Elie Tamer.** 2003. "A Simple Estimator for Nonlinear Error in Variable Models." *Journal of Econometrics*, 117(1): 1-19.
- Jacobs, Kris, and Kevin Q. Wang.** 2004. "Idiosyncratic Consumption Risk and the Cross-Section of Asset Returns." *Journal of Finance*, 59(5): 2211-2252.
- Larin, Alexander, Anna Novak, and Irina Khvostova.** 2013. "Consumption Dynamics in Russia: Estimates on Microdata." *Applied Econometrics*, 32(4): 29-44.
- McCallum, Bennett, and Edward Nelson.** 1999. "Nominal Income Targeting in an Open-Economy Optimizing Model." *Journal of Monetary Economics*, 43(3): 553-578.
- Meghir, Costas, and Guglielmo Weber.** 1996. "Intertemporal Nonseparability or Borrowing Restrictions? A Disaggregate Analysis Using a US Consumption Panel." *Econometrica*, 64(5): 1151-1181.
- Nieh, Chien-Chung, and Tsung-Wu Ho.** 2006. "Does the Expansionary Government Spending Crowd Out the Private Consumption? Cointegration Analysis in Panel Data." *The Quarterly Review of Economics and Finance*, 43(1): 133-148.
- Obstfeld, Maurice, and Kenneth Rogoff.** 1998. "Risk and Exchange Rates." National Bureau of Economic Research Working Paper 6694.
- Okubo, Masakatsu.** 2011. "The Intertemporal Elasticity of Substitution: An Analysis Based on Japanese Data." *Economica*, 78(310): 367-390.
- Polbin, Andrey V.** 2013. "Development of a Dynamic Stochastic General Equilibrium Model for an Economy with High Dependence on Oil Export." *Higher School of Economics Economic Journal*, 17(2): 323-359.
- Runkle, David E.** 1991. "Liquidity Constraints and the Permanent Income Hypothesis." *Journal of Monetary Economics*, 27(1): 73-98.
- Savić, Mirko.** 2007. "Questions about Household Consumption in Surveys." *Panoeconomicus*, 54(3): 347-357.
- Semko, Roman.** 2013. "Optimal Economic Policy and Oil Prices Shocks in Russia." Economics Education and Research Consortium Working Paper 13/03E.
- Smets, Frank, and Rafael Wouters.** 2003. "An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area." *Journal of the European Economic Association*, 1(5): 1123-1175.
- Smets, Frank, and Rafael Wouters.** 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review*, 97(3): 586-606.
- Sosunov, Kirill, and Oleg Zamulin.** 2007. "Monetary Policy in an Economy Sick with Dutch Disease." Centre for Economic and Financial Research at New Economic School Working Paper 101.
- Ueda, Atsuo.** 2000. "A Growth Model of 'Miracle' in Korea." *Journal of Policy Modeling*, 22(1): 43-59.
- Vissing-Jørgensen, Annette.** 2002. "Limited Stock Market Participation and the Elasticity of Intertemporal Substitution." *Journal of Political Economy*, 110(4): 825-853.

THIS PAGE INTENTIONALLY LEFT BLANK