QUADERNI DEL DIPARTIMENTO DI SCIENZE DELL' ECONOMIA

UNIVERSITÀ DEL SALENTO

Herding Behaviour on Consumption Habit Formation: an Application to Italian Panel Data

Giada Andrea Prete

Numero E/18
Agosto 2020

DIPARTIMENTO DI SCIENZE DELL'ECONOMIA
FACOLTÀ DI ECONOMIA
UNIVERSITÀ DEL SALENTO - LECCE
ISSN 2284-0818

Quaderni del Dipartimento di Scienze dell'Economia

I Quaderni intendono favorire la circolazione di studi in versione preliminare, al fine di accelerarne la diffusione e per sollecitare suggerimenti e critiche.

Vengono considerati per la pubblicazione sui Quaderni del Dipartimento solo lavori non ancora pubblicati in versione definitiva su libri o su rivista. Possono proporre lavori per la pubblicazione membri del Dipartimento (anche in collaborazione con studiosi esterni) o studiosi che abbiano presentato il lavoro in oggetto nell'ambito di conferenze o seminari svolti nell'ambito delle attività dipartimentali.

I quaderni si articolano in quattro sezioni: Aziendale, Economica, Giuridica, Matematico Statistica.
I quaderni vengono regolarmente inviati a Istituti, Dipartimenti e Biblioteche a carattere economico e sono inclusi nella serie Research Papers in Economics (REPEC).

L'accesso ai Quaderni è approvato dal Coordinatore scientifico della sezione.

Editore:

Dipartimento di Scienze dell'Economia
Indirizzo mail: direzione.dipeconomia@unisalento.it
Ecotekne - via Monteroni
73100 Lecce

Codice ISSN: 2284-0818

Herding Behaviour on Consumption Habit Formation: an Application to Italian Panel Data

Giada Andrea Prete*

Abstract

This paper applies a nonlinear panel data model of cross-sectional dependence to the study of habit formation in consumption choices. In modeling consumers' behaviour, we derive a Euler equation, following the previous specification given in Korniotis (2010) and considering the two sides of habit formation: internal and external. Accordingly, in the proposed model, current consumption changes are influenced by lagged changes of personal households consumption (internal) and by lagged consumption growth of neighbors (external). The latter is estimated with a spatial component based on the threshold mechanism proposed by Kapetanios *et al.* (2014), which allows to model the economic herding behaviour of nearby agents and to simultaneously address the problem of cross-sectional dependence in panel data. The empirical application on Italian panel data from the Survey of Household Income and Wealth (SHIW) provides some useful insights in both the economic and econometric modeling of households behaviour.

Keywords: Consumption; Cross-sectional dependence; Habit formation; Herding behaviour; Italian panel data.

JEL Classification: D12; C33; E21.

1. Introduction

The evolution of consumption patterns is a crucial point in economic research. A first crucial issue is how to choose the data. From an empirical point of view aggregate consumption data moves towards different results with respect to micro-data. In particular, an high level of aggregation yields biased estimates because the interdependence of consumers' preferences is not explicitly accounted for. On the other hand, although

*University of Salento, Department of Economic Sciences, e-mail: giadaandrea.prete@unisalento.it

the use of micro-data would be desirable, the availability of such detailed information on consumption goods is limited.

A second key step in the study of consumption decisions concerns the basic assumptions of the model. It is a common practice of many economists to model consumption behaviour through the Life Cycle Permanent Income Hypothesis, due to the seminal studies by Friedman (1957) and Modigliani (1954, 1963, 1986). According to this assumption, each individual decides how much to consume and to save in each period considering her wealth over time, given a planning horizon which could be finite (life cycle) or infinitive (permanent). As explained by Alessie and Kapteyn (1991), the consumer has to face a two stage process: in stage one, the individual defines the amount of expenditure in each life-time period "by equating the (discounted) marginal utility of wealth in all periods", and in the second stage, she decides how to allocate her endowment to different goods within each period. Therefore, she maximizes an intertemporally separable utility function under an appropriate budget constraint. In this particular framework, habit formation plays an important role in explaining the emerging phenomenon of "excess smoothness" of consumption.

The concept of habit formation relies on the idea that past decisions influence the utility of current consumption so that the insufficient reaction of consumption to current income shocks (Deaton, 1992) is justified. Habits could be introduced in the life cycle consumption function in two different ways as myopic or rational (Muellbauer, 1988). In the myopic case, the individual doesn't recognize the impact of present consumption for future decisions. The naive reaction of the consumer is translated into an intertemporal utility function which is still additively separable just like the life cycle hypothesis.

Otherwise, in case of rational habits, the individual is both forward and backward looking, and she is aware of her consumption history and of the temporal interdependence of her choices: this implies a redefinition of the utility function, by assuming time non-separable preferences.

Most empirical implementations test the presence of habit formation with the Euler equation models applied on national panel data. This method focuses on a specific first order condition implied by the optimization problem faced by a generic consumer, allowing the estimation of preference parameters (Alessie and Teppa, 2010). Specifically, as shown in Muellbauer (1988), the first order condition is different according to the distinction between myopic and rational habits. In the case of rationality about habits, consumers take into account the effect of current consumption on future marginal rate of substitution, while in the myopic case they make a mistake. They don't update the expected value of consumption in each period with the current consumption level, but they systematically take into account as reference point the same level of initial current consumption.

The application of the Euler equation approach on panel data allows the exploitation of the two dimensions, the cross-section and time-series ones. The two components allow to account contemporary for the individuals' heterogeneity between cross-section units and the dynamic behaviour of consumers' expenditure. As suggested by Baltagi and Song (2006), the major examples of available panel data are: the Panel Study of Income Dynamics (PSID) from US, the Belgian Socio-economic panel, the German Socio-Economic panel, the French household panel, the British Household Panel Survey, the Dutch Socio-Economic Panel, the Luxembourg Panel Socio-Economique and the European Community Household Panel.

For instance, Lusardi (1996) and Dynan (2000), for their studies on habit formation, used U.S. data on household expenditure coming from two different surveys: the Panel Study on Income Dynamics (PSID) and the Consumer Expenditure Survey data (CEX). The first source contains annual information about income, employment and demographic features of individual households from 1968, but limited consumption data such as food expenditure. The CEX has data on food, nondurable, semi-durable, and durable expenditure, but limited and underreported measures of income. Lusardi (1996) examined consumption data from the CEX and income data from the PSID and since the information came from two samples, the author used a generalization of the instrumental variables estimator, the so-called "two-sample instrumental variables estimator". Symmetrically, Dynan (2000) considered PSID information about food expenditure and other variables that are related to household consumption (rent payments, number of automobiles owned) and, using the CEX, he combined these variables into proxies for growth in non-durables and services consumption.

Using the same data source, Lusardi (1996) estimated Euler equations on consumption and found evidence that consumption is excessively sensitive to predictable income changes, consistently with the presence of habit formation. Dynan (2000) examined a life-cycle consumption model with habit formation, estimating the first order condition with annual observations on food data. However, she found, no evidence of habits, even when proxies for non-durables and services consumption (created by combining PSID variables with weights estimated from the CEX) were taken into account. This finding is consistent with the fact that this model doesn't control for time invariant unobserved heterogeneity. According to this missing consideration, without taking into account fixed effects on panel data, it is plausible to find evidence of intertemporally separable preferences. Using individual food consumption data from the PSID, Naik and Moore (1996) found support for habit formation model by controlling for unobserved heterogeneity.

Guariglia and Rossi (2002) tested habit formation on data from the British Household Panel Survey

(BHPS) for the period 1992-1997 by using a generalization of Weil's (1993) model. According to their results, they found a strong negative effect of lagged consumption changes on current changes, rejecting the assumption of habit formation and accepting the presence of durability in consumption as suggested by Deaton (1992). Similar results have been obtained by Rossi (2005) on Italian panel data, provided by the Bank of Italy.

Similarly, in 2005, Carrasco *et al.*, following the model of Meghir and Weber (1996), tested the presence of habit formation in consumption decisions on a Spanish panel dataset with up to eight consecutive quarters observations, introducing fixed effects in order to prove that preferences are intertemporally non-separable. Using the same data source, Browning and Collado (2007) gave an important contribution to the study of preferences. They started from the perspective that "consumption" at a macro level is a composite of many goods and each good exhibits a certain degree of habit. They derived a formula to consider the degree of habit formation for consumption of six composite commodities and the relative Engel curves, accounting for heterogeneity in demand behaviour.

In addition to the aforementioned contributions about habit formation, another part of the economic literature provides a broader application of habits.

The distinction between myopic and rational habits represents a subset of the wide concept of habit formation. The statement that consumer's consumption habits are influenced, independently from their awareness, by past consumption identifies the type of internal habit formation. Although another form of habit formation, defined as external, relates to the fact that individuals are influenced by the consumption decisions of other consumers.

The external habit formation has been tested by Abel (1990) considering the "catching up with the Joneses" utility functions that depend on the consumer's level of consumption relative to the lagged cross-section average level of consumption, and then widely extended in the consumption-based asset-pricing literature (*e.g.* Gali, 1994 and Wachter, 2006).

The issue of external habits has been debated in different fields of social sciences. Psychologists and economists gave evidence to social interactions because the relative position of individuals according to their well-being could give important insights about consumption patterns.

The concept of external habit formation includes a wide range of definitions. Within economists, the main contribution deals with the presence of "peer effects" or "neighbourhood effects".

The latter case concerns, at a macro level, the strictly geographic notion of distance between units (*i.e.*

countries), while the peer effects represent the rise of particular groups of individuals who have common sociodemographic characteristics and concurrently share common behaviour in consumption.

Early studies about the relevance of consumption externalities are the works of Duesenberry (1949) and Leibenstein (1950) while two more recent contributions are due to Ravina (2007) and Maurer and Meier (2008). Ravina (2007) found evidence of the presence of both internal and external habit formation by estimating a log-linearized Euler equation for a representative sample of U.S. credit-card holders, while Maurer and Maier (2008) derived an extension of the standard life-cycle model that allows for consumption externalities and applied it on US data, finding strong predictable co-movement of household consumption within peer groups.

Closely related to our work is the time-recursive specification proposed by Korniotis (2010) who tried to incorporate in one model the two sides of habit formation. In particular, he estimated Euler equations with data for the 48 continental U.S. states involving in the regression as internal-habit measure, a time-lagged dependent variable and, as external-habit measure, a spatially lagged dependent variable given by consumption growth rates of other states spatially located in the same national economy. Differently from our approach, he considered completely exogenous spatial weights defined in a suitably manner rather than considering an endogenous selection mechanism for distance. The results of his estimates gave strong evidence of external-habit formation but weak evidence for internal habits.

Furthermore, Verhelst and Van den Poel (2014) empirically assessed habit formation in consumption by testing for both internal and external habit formation using micro data from the daily transactions of an anonymous European retailer. As in Korniotis (2010), they used a time lag in order to evaluate the inertia or persistence of consumption, whereas preference interdependence across households was captured by a spatial lag. This term is estimated by taking the weighted average of the neighbouring observations according to geographical distance.

The fact that individuals' consumption behaviour could be affected by external factors, namely by the environment that surrounds them, may give rise to a herding behaviour, in the sense that consumers are subject to the same environment and have similar information sets when they form expectations.

Therefore, the interaction between agents might be captured by the use of a spatially lagged dependent variable or, alternatively, by clustering. The idea behind clusters is to pool the subjects into different groups so that the units within a same group are homogenous in terms of the effect of independent variables (Lu and Huang,2011).

In Korniotis (2010), according to the standard spatial literature, the catching-up component of habits is built by considering an exogenous procedure. The spatial lag is given by a weighted average of past consumption decisions of other cross-section units, chosen according to a well-known and observed quantity measured through a weighted matrix. Therefore, the distance-weighted spatial matrix gives a measure of the neighbourhood of cross-sectional units, which is fundamental in the choice of the relevant units in herding.

Kapetanios *et al.* (2014, hereafter KMS) suggest a way to model the herding behaviour in the econometric specification. They propose a general economic modeling framework, that allows cross-sectional dependence to arise endogenously. The class of model is characterized by the use of a specific aggregate of past values of variables related to agents that are 'close' in some sense to a given unit. The specification of these particular aggregates represents a nonlinear form of modeling structural interactions between units. In other words, it takes as starting point a threshold mechanism which mimics the "similarity" between agents, and dynamically captures the past views of other agents close to them in order to form their own views.

Ultimately, the latter case represents a different method to build the weights considered in Korniotis (2010), using an endogenous mechanism.

Beyond the important feature that allows herding to arise, we should take into account a deeper result of this approach. It accommodates for a certain flexibility in the choice of the threshold parameter which discriminates the units in the clusters. The selection of the threshold parameter is crucial in order to account for a different degree of cross-sectional dependence (CSD). Specifically, as shown in KMS (2014), the choice of a large value of r should lead to the aggregation of units in few clusters, hence to a small degree of cross-sectional dependence; otherwise, if r is small, the number of clusters increases, leading to a higher degree of CSD.

Considering N economic agents observed in T periods of time, we can formalize the following simple specification of the nonlinear model set up described in KMS (2014):

$$x_{i,t} = \frac{\pi}{m_{i,t}} \sum_{j=1}^{N} \ell(|x_{i,t-1} - x_{j,t-1}| \leq r) x_{j,t-1} + v_{i,t} \qquad t = 2,...T,\ i = 1,...,N.$$

and:

$$m_{i,t} = \sum_{j=1}^{N} \ell(|x_{i,t-1} - x_{j,t-1}| \leq r)$$

where $x_{i,t}$ is the variable of interest in the model, such as the consumption growth rate at time t, for agent

i which is influenced in some nonlinear fashion by the cross-sectional average of a selection of neighbouring $x_{j,t-1}$identified through a specific value assigned to the threshold parameter r. Depending on the assigned value of r, determined by the means of a grid search algorithm, the KMS class of models covers the two extreme cases of CSD, defined respectively as weak and strong CSD. In particular, for values of the threshold parameter close to zero, we have a weak CSD, while for high values (towards infinitive) of the parameter, strong CSD arises.

In distinguishing the two cases of CSD, it is important to define them. Following Bailey *et al.* (2016), the weak CSD relates the purely spatial dimension, while the strong CSD suggests the presence of common shocks that affects all the cross-section units and that could be modeled using an exogenously given number of unobserved factors.[1]

Recently, Mastromarco *et al.* (2016) applied the threshold approach of KMS in modeling technical efficiency in stochastic frontier models using a dataset of 26 OECD countries over 1970-2010 and obtaining an high-performing way in determining a ranking of efficient clusters of countries, by accommodating for both weak and strong cross-section dependence in the error term. More precisely, they coped with the weak CSD issue using the endogenous threshold efficiency regime selection mechanism of KMS and the strong CSD by combining in the error process an exogenously driven factor-based approach. (Mastromarco *et al.*, 2013).

Going back to habit formation, it is plausible to account for spatial dependence, evaluating a local rather than global concept of cross-sectional dependence.

In view of the above, this paper proposes a new idea of considering habit formation using panel data models. In particular, it accounts for both internal and external habit formation, evaluating the first with the presence in the Euler equation of a time-lagged dependent variable, and the second, introducing a spatial lagged term modeled through the KMS approach. In other words, we consider a nonlinear specification for panel models characterized by cross-sectional dependence. Through a threshold mechanism, it is plausible to evaluate the emerging of herding behavior in consumption choices and to mitigate the problem of CSD.

Differently from the aforementioned case of Korniotis (2010), this work applies the KMS specification, discussed in details in section 2, on micro-data, rather than macro-data, and specifically on Italian household panels data provided by Bank of Italy with the Survey on Household Income and Wealth (SHIW).[2]

[1] For further details on the concepts of weak and strong cross-sectional dependence, see Chudick *et al.* (2011), Pesaran (2006) and Bai (2009).

[2] Bank of Italy, “Indagine sui bilanci delle famiglie italiane”, archivio storico 10.0.

Therefore, section 2 presents the Euler equations specification for internal habit formation and the KMS contribution in determining the external component of habits. Section 3 focuses on the presentation of Italian micro-data and provides a discussion of the main empirical results, while section 4 offers some concluding remarks for further research.

2. The Model

2.1 The Economic Model

In the introduction, we proposed the relevant literature contributions for the issue of habit formation, while in this section, starting from the main models' specifications, we develop a new model to test the presence of habits in consumption behaviour.

To address the issue of internal habit formation, we begin with the specification of the Euler equation proposed by Dynan (2000). In particular, she considered the maximization problem faced by a generic household who wants to maximize his expected utility conditional on all information at time t:

$$E_t[\sum_{s=0}^{T} e^{-\beta_i} u(\breve{C}_{i,t+s};\, \psi_{i,t+s})]$$

where $\breve{C}_{i,t+s}$ represents consumption at time t, $e^{-\beta_i}$ is a time discount factor and $\psi_{i,t}$ captures some shifts in tastes and preferences at time t. The consumption argument is defined as follows:

$$\breve{C}_{i,t} = C_{i,t} - \alpha C_{i,t-1} \tag{1}$$

where α measures the strength of internal habit formation. A higher value of α corresponds to a decrease in the utility function given a certain level of expenditure.

In order to consider both the issues of internal and external habit formation, it is possible to add to the consumption argument a third element which accounts for external habits and yields to:

$$\breve{C}_{i,t} = C_{i,t} - \alpha C_{i,t-1} - \pi \tilde{C}_{i,t-1} \tag{2}$$

The specification of the external habit formation term $\tilde{C}_{i,t-1}$ will be specified in details in the proceeding.

Let us consider the first order condition in the case of time non-separable preferences as in Dynan (2000):

$$E_t[(1+r)e^{-\beta_i}\frac{MU_{i,t+1}}{MU_{i,t}}] = 1 \tag{3}$$

where r is the rate of return of Treasury bill and $MU_{i,t} = \partial U(\breve{C}_{i,t})/\breve{C}_{i,t}$ is the partial derivative of current utility with respect to current consumption.

The expectation generates an error $u_{i,t}$, so that:

$$(1+r)e^{-\beta_i}\frac{MU_{i,t}}{MU_{i,t-1}} = 1 + u_{i,t} \tag{4}$$

assuming an isoelastic form of the utility function:

$$U_{i,t} = \psi_{i,t}\frac{\breve{C}_{i,t}^{1-p}}{1-p} \tag{5}$$

we substitute equation (5) into equation (4):

$$(1+r)e^{-\beta_i}\frac{\psi_{i,t}}{\psi_{i,t-1}}\left(\frac{\breve{C}_{i,t}}{\breve{C}_{i,t-1}}\right)^{-p} = 1 + u_{i,t} \tag{6}$$

taking the natural logarithm of equation (6), we have:

$$\Delta \ln(C_{i,t} - \alpha C_{i,t-1} - \pi\tilde{C}_{i,t-1}) = \frac{1}{p}[\ln(1+r) - \beta_i] + \frac{1}{p}\Delta \ln\ \psi_{i,t} - \frac{1}{p}\ln(1+u_{i,t}) \tag{7}$$

following Dynan (2000) and Muellbauer (1988), we approximate $\Delta \ln(C_{i,t} - \alpha C_{i,t-1} - \pi\tilde{C}_{i,t-1})$ with $\Delta \ln C_{i,t} - \alpha\Delta \ln C_{i,t-1} - \pi\Delta \ln \tilde{C}_{i,t-1}$.

We rewrite equation (7) as:

$$\Delta \ln C_{i,t} = \gamma_0 + \alpha\Delta \ln C_{i,-1} + \pi\Delta \ln \tilde{C}_{i,t-1} + \gamma_1\Delta \ln\ \psi_{i,t} + e_{i,t} \tag{8}$$

where γ_0 is a function of the real interest rate, the time discount factor and forecast error variance, while γ_1 is a constant associated to taste shocks.

Stacking equation (8) and considering an easier notation, we have the following reduced form of the structural model:

$$c_{i,t} = \alpha c_{i,t-1} + \pi\tilde{c}_{i,t-1} + \beta' x_{i,t} + \varepsilon_{i,t} \tag{9}$$

where $c_{i,t} = \Delta \ln C_{i,t}$ is the consumption growth at time t in log terms, $c_{i,t-1} = \Delta \ln C_{i,t-1}$ is the lagged consumption growth, $\tilde{c}_{i,t-1} = \Delta \ln \tilde{C}_{i,t-1}$is the spatial lagged consumption growth and $x_{i,t} = \Delta \ln X_{i,t}$ are possible additional explanatory variables, such as income growth. The internal and external habit formation are captured, respectively, by the autoregressive parameter α associated to the lagged value of consumption $c_{i,t-1}$, and by the spatial autoregressive parameter π associated to the spatial term $\tilde{c}_{i,t-1}$.

Following Muellbauer (1988), in order to get evidence on the "excess sensitivity of income" on consumption, a crucial role is played by the presence of liquidity constraints which could be captured including as plausible regressors the real disposable income or, even better, the value of net-of-tax income, expressed in growth terms. The choice of the income growth measure relates to the literature findings on the relationship income-consumption, as suggested by Korniotis (2010). Since consumption growth is excessively sensitive to income growth (Flavin,1981), a good way of proceeding is to consider this element as an additional regressor.

Let's focus our attention on the issue of habit formation, evaluating in particular the specification of the external component of habits

The external term corresponds to the spatially lagged dependent variable, because it is given by consumption growth rates of households who are assumed to be next to each other according to a variable that expresses the economic distance between units.

Considering the model in equation (9), in Korniotis (2010), the measure of the "catching-up component" is associated to a weighted average of lagged consumption growth rate, that is $\tilde{c}_{i,t-1} = W c_{i,t-1}$, where W is a distance-weighted spatial matrix and $c_{i,t-1}$is the consumption growth rate at time $t-1$. Hence, according to this specification, equation (9) could be written as:

$$c_{i,t} = \alpha c_{i,t-1} + \pi W c_{i,t-1} + \beta' x_{i,t} + \varepsilon_{i,t} \tag{10}$$

The author suggested two different specification of W: the first measure is a 0/1 matrix and assumes that a particular state consumer is influenced only by the average consumption of nearby states, while in the second one, the weights are integer numbers, measured as the inverse of the geographic distance between the U.S. states.

At this point, it is important to mention the main difference between the work of Korniotis (2010) and this paper. As described above, he used U.S. state level data, examining habit formation in a macro perspective and so using geographical distances in order to achieve the contribution of neighbourhood as determinant of external habits.

The case described here evaluates the presence of habit formation considering as cross-sectional units households, instead of states. Therefore, in order to account for the presence of external habits, we need a different way to account for distance, based on an endogenous procedure.

KMS (2014) suggested the use of an algorithm in the construction of the “catching-up” component of habits which provides an alternative method to spatial models.

Starting from the assumption that economic agents are influenced by their peers, suggesting the emerging of an herding behavior, a key role is played by the definition of a function which endogenously determines the neighbourhood between agents according to a specific concept of economic distance. In this particular case, we assume that the difference in incomes between each household i and another one j is a good proxy for measuring economic distance.

Following KMS (2014) we can define the external-habits term $\tilde{c}_{i,t-1}$ in equation (9) as follows:

$$\tilde{c}_{i,t-1} = \frac{1}{m_{i,t}} \sum_{j=1, j\neq i}^{N} \ell(|c_{i,t-1} - c_{j,t-1}| \leq r) c_{j,t-1} \tag{11}$$

where:

$$m_{i,t} = \sum_{j=1, j\neq i}^{N} \ell(|c_{i,t-1} - c_{j,t-1}| \leq r) \tag{12}$$

In this equation, we assume that the weights are identified with the indicator function in equation (11) which captures the specific distance given by the absolute difference in consumption expenditure between the ith and jth cross-section units at time $t-1$. This absolute difference is the determinant of the indicator function ℓ: for values which lie under the threshold r, the indicator function assumes value 1 and allows to capture all the relevant $c_{j,t-1}$oriented to the plausible representation of the herding behaviour in consumption. The threshold parameter r is determined endogenously by means of a grid search algorithm, as discussed in the estimation section.

2.2 The Econometric Specification

In order to test the presence of habit formation in consumption behaviour, we will consider three different specification of the econometric model.

The first specification relates the traditional issue of internal habit formation captured by the autoregressive parameter α^* and given by:

$$c_{i,t} = \gamma + \alpha^* c_{i,t-1} + \beta^{'} x_{i,t} + \varepsilon_{i,t} \tag{13}$$

where $c_{i,t-1}$is a vector of past consumption growth rates.

The second specification considers only the "catching-up" component of habits through the parameter π^*:

$$c_{i,t} = \gamma + \pi^* \tilde{c}_{i,t-1} + \beta^{'} x_{i,t} + \varepsilon_{i,t} \tag{14}$$

where $\tilde{c}_{i,t-1}$ is the vector of weighted cross-sectional averages as described in equation (11).

The third specification represents the complete model where internal and external habits are considered separately as two different entities as in the derived economic model:

$$c_{i,t} = \gamma + \alpha c_{i,t-1} + \pi \tilde{c}_{i,t-1} + \beta^{'} x_{i,t} + \varepsilon_{i,t} \tag{15}$$

where the spatial autoregressive component is a vector of weighted averages of past consumption growth values not including the case of $i = j$, because the past values of the ith observation of the sample are already captured by the autoregressive term.

Before testing habit formation on data, it is necessary to get rid of some fixed effects related to individuals' features, time shocks or both, which are the source of global or strong cross-sectional dependence.

Following the approach suggested by Pesaran (2006) in the definition of the Pooled Common Correlated Effects (PCCE) estimator, the unobserved common factors can be consistently proxied by averages of dependent and independent variables as both N and T go to infinity and the ratio T/N tends to a value K between 0 and ∞. However, Kapetanios *et al.* (2019) recently demonstrated that the fixed effects estimator is simpler than the CCE estimator and still consistent in the presence of interactive effects, since it doesn't involve some complexity issues in selecting the correct number of unobserved factors that could affect the performance of principal component estimation.

In the following, we show how to apply the demeaning procedure to the autoregressive model written in equation (13) and given by:

$$c_{i,t} = \gamma + \alpha^* c_{i,t-1} + \beta^{'} x_{i,t} + \varepsilon_{i,t} \tag{16}$$

In particular, in order to get rid of individual fixed effects we considered cross- sectional averages of the dependent and of the independent variables, we take for each unit i the average across T time periods given by:

$$\frac{1}{T}\sum_{t=1}^{T} c_{i,t} = \gamma + \alpha^* \frac{1}{T-1}\sum_{t=1}^{T-1} c_{i,t-1} + \beta^{'} \frac{1}{T}\sum_{t=1}^{T} x_{i,t} + \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{i,t} \tag{17}$$

For time fixed effects, we consider, analogously, the average across unit i for each time period T given by:

$$\frac{1}{N}\sum_{i=1}^{N} c_{i,t} = \gamma + \alpha^* \frac{1}{N}\sum_{i=1}^{N} c_{i,t-1} + \beta^{'} \frac{1}{N}\sum_{i=1}^{N} x_{i,t} + \frac{1}{T}\sum_{i=1}^{N} \varepsilon_{i,t} \tag{18}$$

In order to get rid of fixed effects, we operate a double demeaning, that is, subtracting both (17) and (18) from equation (16).

Therefore, the original model becomes:

$$\mathbf{c_{i,t}} = \alpha \mathbf{c_{i,t-1}} + \beta^{'} \mathbf{x_{i,t}} + \varepsilon_{\mathbf{i,t}}$$

corresponding to the simple autoregressive model with demeaned data.

By focusing on the complete model, we considered the issue of cross-section dependence in modeling the spatial lagged dependent variable, in order to allow the genesis of the typical herding behavior in consumption expenditure. This component is modeled by using the endogenous threshold regime selection mechanism advanced by KMS (2014).

Let $\mathbf{c_{i,t}}$ be the observation on the ith cross-section unit at time t for $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots, T$ and consider the full panel data model:

$$\mathbf{c_{i,t}} = \alpha \mathbf{c_{i,t-1}} + \pi \tilde{c}_{i,t-1} + \beta^{'} \mathbf{x_{i,t}} + \varepsilon_{\mathbf{i,t}} \tag{19}$$

where $\mathbf{c_{i,t-1}}$ is a time-lagged dependent variable which captures internal habits, $\mathbf{x_{i,t}}$ is a $k \times 1$ vector of observed individual-specific regressors, $\tilde{c}_{i,t-1}$is a spatial component which captures the external component of habit formation, considering a particular arrangement of the lagged consumption growth rate, following the approach of KMS (2014):

$$\tilde{c}_{i,t-1} = \frac{1}{m_{i,t}} \sum_{j=1, j\neq i}^{N} \ell(|c_{i,t-1} - c_{j,t-1}| \leq r) c_{j,t-1} \tag{20}$$

where:

$$m_{i,t} = \sum_{j=1, j\neq i}^{N} \ell(|c_{i,t-1} - c_{j,t-1}| \leq r) \tag{21}$$

In this specification, we are clearly considering an endogenous mechanism for the weights, since they are specified using threshold values derived from our data according to a grid search algorithm.

Equation (20) formalizes the idea that people are affected more by those with whom they share common behaviours in consumption.

This herding issue is explained by considering a concept of neighbourhood in lagged consumption values.

In particular, we assume as indicator function ℓ which is set to $\ell_t = 1$ at each time t if the absolute difference in consumption growth between the ith and jth cross-section units at time $t-1$ lies under a given threshold r. So that the relevant $c_{j,t-1}$are those for which the condition described above is true.

The model in equation (19) and the relative spatial component in equation (20) are estimated through OLS, as suggested in KMS. The authors derived that specification as an alternative to the time-space recursive model considered in Korniotis (2010), as described above in equation (10). The main difference between the two is given by the construction of the spatial term: Korniotis considers a spatial weighted matrix exogenously determined in an *ad hoc* manner, whereas KMS use an endogenous selection mechanism for distances.

In order to estimate the nonlinear component, $\tilde{c}_{i,t-1}$, we consider the following basic model:[3]

$$c_{i,t} = \pi \tilde{c}_{i,t-1} + \varepsilon_{i,t} \tag{22}$$

in which, the vector $\tilde{c}_{i,t-1}$ is defined as:

$$\tilde{c}_{i,t-1} = \frac{1}{m_{i,t}} \sum_{j=1, j\neq i}^{N} \ell(|c_{i,t-1} - c_{j,t-1}| \leq r) c_{j,t-1}$$

[3] As explained in KMS (2014), "the nonlinearity means that the appropriate aggregate model should not be specified only in terms of aggregated variables; the disaggregate or individual units should be considered simultaneously too". In this case, the nonlinearity is associated to the use of cross-sectional averages for the construction of the unit specific aggregate.

with $m_{i,t} = \sum_{j=1, j\neq i}^{N} \ell(|c_{i,t-1} - c_{j,t-1}| \leq r)$, cross-sectional average of $c_{j,t-1}$ units which share a common consumption profile, according to a specific threshold r.

In particular, we build a grid of values of r and we iteratively estimate different $\tilde{c}_{i,t-1}$ for each value of r. Once we have computed $\tilde{c}_{i,t-1}$, we estimate several least squares regressions as many as the number of values of the threshold parameter in the grid to obtain estimates of r and the autoregressive parameter π, by minimizing the sum of squared residuals given in the following expression (KMS, 2014):

$$V(r,\pi) = \min_{r,\pi} \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{v}_{it}^{2}(r,\pi)$$

$$= \min_{r,\pi}(c_{i,t} - \pi\frac{1}{m_{it}}\sum_{j=1}^{N}\ell(|c_{i,t-1} - c_{j,t-1}| \leq r)c_{j,t-1})^{2} \tag{23}$$

The minimization process allows to obtain the vector of $\tilde{c}_{i,t-1}$, subsequently included in the full model in order to test the presence of external habit formation.

Thus, we make the following assumptions on the complete model in equation (19):

i) the individual specific errors $\varepsilon_{i,t}$ are distributed independently for all i, j, t and s, $\varepsilon_{i,t} \sim i.i.d.(0, \sigma_{\varepsilon_i}^2)$ and $E(\varepsilon_{i,t}^4) < \infty$;

ii) $|\pi| < 1$;

iii) N and T are sufficiently large;

iv) $E(\mathbf{x}_{\mathbf{i,t}}^{'}\varepsilon_{j,s}) = 0$ for all i, j, s, t.

Assumption *i*) excludes any form of cross-sectional or time correlations in the error term and ensures finite fourth moments of the errors distribution. Assumption *ii*) and *iii*) relate the specific case of the spatial lagged variable modeled as in KMS, in particular assumption *ii*) relates the asymptotic stationarity of equation (19) while *iii*) ensures the consistency of the least squares estimator as N and T increase. Assumption *iv*) implies the exogeneity of any regressors with respect to the idiosyncratic errors $\varepsilon_{i,t}$.

2.3 The Test for Weak Cross-Sectional Dependence

In order to test if the residuals of the estimated models are weakly cross-sectional dependent, we used a test developed by Pesaran (2015). In particular, we have to consider the pair-wise correlations of the (i, j) units, $\hat{\rho}_{ij}$ by:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} \varepsilon_{\mathbf{i,j}} \varepsilon_{\mathbf{j,t}}}{(\sum_{t=1}^{T} \varepsilon_{\mathbf{i,t}}^2)^{1/2} \sum_{t=1}^{T} \varepsilon_{\mathbf{j,t}}^2)^{1/2}}$$

where the residuals of the estimated model are given by:

$$\varepsilon_{\mathbf{i,t}} = \mathbf{c}_{\mathbf{i,t}} - \alpha \mathbf{c}_{\mathbf{i,t-1}} - \pi \tilde{c}_{i,t-1} - \beta' \mathbf{x}_{\mathbf{i,t}}$$

In particular, the test is based on the LM statistic introduced by Breush and Pagan (1980) in the seemingly unrelated regression equation (SURE) framework, where $CD_{lm} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2$.

Given that the degree of cross-sectional dependence amongst the errors, ϕ, is defined by the contraction rate of $\bar{\rho}_N$, that is the rate at which the average pairwise error correlation coefficient tends to zero, the test of weak CSD on its sample estimate, given by:

$$\hat{\bar{\rho}}_N = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}$$

can be written as:

$$CD = \left[\frac{TN(N-1)}{2} \right]^{1/2} \hat{\bar{\rho}}_N$$

Pesaran (2015) demonstrates that, as N and $T \to \infty$, such that $T = O(N^{\varepsilon})$, for $0 < \varepsilon \leq 1$, $CD \to_d N(0,1)$ under the null hypothesis, the exponent of cross-sectional dependence $\phi < (2-\varepsilon)/4$.

3. Empirical Results

3.1 Data Description

We estimated the above model in equations (19- 21) using data from the Bank of Italy's Survey on Household Income and Wealth (SHIW). This source consists in a two stages survey conducted since the 60's with a frequency of two years. The primary units refer to municipalities, which are stratified by region and population size. The second stage of selection consists in a simple random sampling of the households to be interviewed. Until 1987, the survey was a collection of independent cross-sections, but since 1989, in order to foster the analysis of phenomena over time, a layout has been introduced which guarantees the presence in the sample of a percentage of units interviewed in past years (panel families). The main information concerns the measurement of income and wealth, with some indicators of consumption, related to the basic distinction between durable and nondurable goods.

In order to test the presence of habit formation for Italian families, we considered a sample of 360 households chosen within the families interviewed in all the waves in the period from 1989 until 2014. As key variables for the analysis, we considered a proxy of consumption expenditure, identified with consumption of nondurables and the net disposable income. In particular, consumption of nondurables includes all type of expenditures on food and non-food except for purchases of valuable objects, cars, life and pension insurance premiums, while income is measured as aggregate of employee income, self-employment income, capital income and retirement income.

Specifically, the examined variables have been expressed in real terms: consumption of nondurable goods has been deflated by using the consumption deflator (base year 2010) provided in the historical archive of the SHIW, derived from ISTAT estimates, while the net disposable income has been deflated by using the GDP deflator from Eurostat.

After that, we have computed the growth rates of consumption and income by using the logarithmic transformation of the two variables and taking their first differences.

3.2 Results on Habit Formation following KMS (2014)

In order to test the presence of habit formation on Italian families, we consider three different specification of the original model:

1) the first is the case where we test only the presence of internal habits, through the autoregressive term of consumption growth;

2) the second relates the presence of external habit formation behaviour in the autoregressive spatial term;

3) the third represents the decomposition of the two sides of habit into internal habits, captured by the autoregressive parameter, and the external habits term, captured by the spatial autoregressive component.

The three specifications are estimated on demeaned data in order to account for fixed effects related to individuals' features and time shocks. In addition, we introduced two dummies to capture the impact of the economic crisis (*crisis*) and the introduction of the new currency (*euro*) in the observed period. The model has been estimated with standard errors which are robust to suspected heteroskedasticity and within panel autocorrelation.

We report in table 1 the results of the complete specification for a range of estimations. In all the regressions, the lagged term of consumption growth is significant and has a negative effect on current consumption growth. A negative α indicates that not only current consumption decisions but also past choices generate utility, in a durable sense. This attitude has been described by Deaton (1992) who pointed out the magnitude and the sign of the autoregressive parameter of consumption growth. In particular, he argued that a positive α suggests the presence of habit formation in consumption, and the larger its magnitude "the less the pleasure of a given amount of consumption" derived for the individual. Conversely, when the autoregressive parameter is negative, households decisions are durable, in the sense that past decisions hold some utility and influence future choices. Therefore, we are not in the presence of habits but durability in consumption. Similar results can be found in Dynan (2000) for PSID data, Guariglia and Rossi (2002) for British data and Rossi (2005) for Italian data.

The coefficient associated to the income growth term is always positive and statistically significant. This finding is in line with the existing literature. In particular, Flavin (1981) rejected the permanent income hypothesis (PIH) of smoothness in consumption and found that income growth has a relevant influence on current consumption growth. According to him, the failure of the PIH and the empirical evidence of the excess sensitivity of consumption growth to income changes is due to the presence of imperfect capital markets and liquidity constraints.

The estimates also corroborates the absence of external habits, since the parameter π associated to the spatial autoregressive component is statistically insignificant.

From the perspective of the presence of CSD, the time effects play an important role in order to handle strong cross-sectional dependence. However, the contribution of the spatial autoregressive term is remarkable, following KMS (2014) and controlling different degrees of CSD, according to the value of the threshold parameter. Even if from an economic point of view, the spatial component gives no evidence of herding behaviours in consumption, its introduction in the model mitigates the CSD problem, jointly with the presence of temporal dummies.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
$c_{i,t-1}$	-0.201***	-0.202***	-0.202***	-0.202***	-0.209***	-0.190***	-0.204***	-0.168***	-0.201***	-0.224***	-0.201***	-0.225***
$\tilde{c}_{i,t-1}$	-0.012	0.015	0.063	0.042	0.015	0.061	0.017	0.068	0.047	0.050	0.088	0.093
$x_{i,t}$	0.616***	0.615***	0.615***	0.615***	0.615***	0.615***	0.567***	0.580***	0.568***	0.561***	0.567***	0.561***
$euro$		0.011		0.009	0.011		0.010		0.010	0.009	0.011	0.010
$crisis$			0.023	0.010		0.024		0.021	0.006	0.008	-0.004	-0.003
$euro \times c_{i,t-1}$					0.012					0.051		0.051
$crisis \times c_{i,t-1}$						-0.063*				-0.039		-0.039
$euro \times \tilde{c}_{i,t-1}$											-0.088	-0.093
$crisis \times \tilde{c}_{i,t-1}$											-0.000	-0.000
$euro \times x_{i,t}$							0.080*		0.025	0.035	0.025	0.035
$crisis \times x_{i,t}$								0.173***	0.161**	0.154**	0.161**	0.154**
CD - test	-1.95	-1.62	-1.53	-1.57	-1.61	-1.57	-1.55	-1.47	-1.48	-1.45	-1.59	-1.58
p-value	0.051	0.105	0.126	0.117	0.107	0.118	0.121	0.142	0.139	0.146	0.111	0.115

Table 1: OLS estimates with autoregressive and spatial autoregressive component
legend: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

3.3 Results on Habit Formation following Korniotis (2010)

In order to test the conclusions of the previous section, we considered the construction of a traditional spatial weighted matrix, as proposed in the work of Korniotis (2010).

In particular, we looked at the following general model:

$$c_{i,t} = \alpha c_{i,t-1} + \pi W c_{i,t-1} + \beta' x_{i,t} + \varepsilon_{i,t} \tag{24}$$

where W is the matrix of weights which satisfies some important properties. The matrix W is an $N \times N$ matrix with elements w_{ij} given by:

$$w_{ij} = \frac{|c_{i,t-1} - c_{j,t-1}|}{\sum_{j=1}^{N} w_{ij}}$$

where the numerator is the absolute difference in consumption growth rates between household i and household j in each year of observation, while the denominator introduces a form of normalization.

These imply that the matrix W is a real nonnegative matrix because each $w_{ij} \geq 0$, or better the diagonal elements $w_{ii} = 0$, while the off-diagonal elements are higher than zero.

Once computed the spatial component as weighted average of consumption growth, we implemented the hybrid estimator defined in Korniotis (2010). This estimator is a mixture between the least squares dummy variable estimator (LSDV) and the instrumental variable estimator by Anderson and Hsiao (1982, AH hereafter). In particular, Korniotis introduced in the analysis of habit formation this hybrid estimator because of the biases of the simpler LSDV. The presence of fixed effects gives rise to the so called incidental parameter problem. Since the panel has N observations over T periods, if N grows at a higher rate than T, the fixed effects are computed over a short period T and this leads to biased estimates.

In order to solve this problem, Korniotis proposed to modify the LSDV estimator by instrumenting the control variables as in AH.

This hybrid estimator, as implemented in his paper, is defined as follows by considering a transformation of the AH estimator in order to accommodate for the presence of the autoregressive spatial component:

$$\hat{\varphi}_{hy} = \left[\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (\tilde{Z}_{i,t-2})' \Delta \tilde{X}_{i,t-1} \right]^{-1} \left[\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (\tilde{Z}_{i,t-2})' \Delta Y_{i,t} \right]$$

where $\tilde{Z}_{i,t-2}$ is a vector of instruments given by $[c_{i,t-2}, Wc_{i,t-2}, Z_{i,t-2}]$ for $\Delta\tilde{X}_{i,t-1} = (\Delta c_{i,t-1}, W\Delta c_{i,t-1}, \Delta x_{it})$. Hence, we consider demeaned data by first-differencing the original model in equation (24) and by taking the instruments in levels at lag 2.

Furthermore, in order to get rid of time effects we considered, as in the previous section, the dummies for the economic crisis (*crisis*) and for the introduction of the single currency (*euro*), as well as the presence of year dummies to capture some other unobserved factors.

Tables 2 and 3 show the results for different estimates. In all the specifications, if we look at the signs of the coefficients on the lagged consumption growth rate and on the income growth rate, these seem to confirm the results obtained in the previous section. In particular, past consumption changes are significant and exhibit a negative influence on current consumption changes, while income growth enters significantly and positively in consumption changes. The spatial component remains non-significant and positive in all the estimates, suggesting that there is no external-habit formation in consumption. The euro dummy has an ambiguous sign and has a weak power to explain current consumption growth. On the contrary, the dummy for the economic crisis enters significantly and positively in all the estimates.

This check highlights the relevant contribution of the proposed spatial component with respect to the well-known methodology in solving the distortions caused by CSD. The traditional spatial component based on the weighted matrix W is not able to delete the presence of cross-sectional dependence in the data: some bias may still remain. The time effects are pervasive and the classic spatial component alone is not sufficient to endorse the CSD problem. In fact, even when the temporal dummies are incorporated into the specification as in regression (15), the CD-statistic is small but there is a persistence of CSD at a level of significance of 10%.

4. Final Remarks

This work suggests the application of a new class of models to a particular aspect of habit formation in consumption on Italian panel data. Through the derivation of the Euler equation as previously done by Dynan (2000) and Korniotis (2010), we studied how current consumption growth is influenced by past consumption and current income changes. Past consumption decisions are observed from two different points of view. From an internal perspective, households take care of their own past decisions to make their future choices; while from an external point of view, they observe and incorporate the consumption acting of nearby agents, giving rise to an imitating or herding behaviour. In order to analyze this form of proximity between consumers, we derived a Euler equation in which, in addition to the time-lagged dependent variable as internal-habit measure, we introduced a spatially lagged variable, constructed in a nonlinear fashion as described by KMS (2014). It is measured as a weighted average of past consumption changes where the weights are computed as the absolute distance in consumption growth between the nearby households, identified through an endogenous threshold mechanism derived from the data.

The estimation of the Euler equation using data from the SHIW gives some important evidence. The coefficient of lagged changes in consumption is significant and negative, suggesting that past consumption changes exhibit a form of durability in their current utility. The concept of durability could be associated to the fact that the basket of nondurables is a mixture of different goods. In particular, even if food, as underlined in Dynan (2000), "is most likely completely nondurable at the annual frequency", there could be expenditures of other goods, included in the basket, that a are complementary to foodstuffs and could show a form of durability (*i.e.* alcohol, eating out, etc.).

Furthermore, income changes have a powerful impact on current consumption growth, which seems to react excessively. The fast reaction of consumption to income changes is associated to the presence of liquidity constraints, and is in contrast with the excess smothness of consumption assumed in the permanent income hypothesis.

The external component term doesn't play any role in households decisions, therefore there is no evidence of an imitating behaviour of Italian families. However, from an econometric point of view, the introduction of the spatial autoregressive component, designed by following KMS, gives a strong evidence in taking out the problem of cross-sectional dependence.

As additional check, the external-habit component has been replaced with a traditional spatial term given by the product of a spatial weighted matrix of distances and past consumption choices of cross-sectional units. This analysis confirms the results obtained previously but it is less efficient than the KMS approach in removing the presence of CSD in the panel.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
$c_{i,t-1}$	-0.129***	-0.131***	-0.132***	-0.129***	-0.144***		
$\tilde{c}_{i,t-1}$						0.040	0.037
$x_{i,t}$	0.626***	0.625***	0.621***	0.623***	0.608***	0.665***	0.664***
euro		0.043		-0.086**	-0.092***		0.055*
crisis			0.136***	0.1348***	0.145***		
temporal dummies	no	no	no	no	yes	no	no
CD - test	22.53	27.03	42.52	38.72	-1.68	16.24	19.69
p-value	0.000	0.000	0.000	0.000	0.093	0.000	0.000

Table 2: AH-IV estimates with a traditional spatial autoregressive component
legend: * p<0.05; ** p<0.01; *** p<0.001

Variable	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
$c_{i,t-1}$				-0.129***	-0.130***	-0.132***	-0.129***	-0.144***
$\tilde{c}_{i,t-1}$	0.038	0.041	0.036	0.027	0.024	0.023	0.027	0.023
$x_{i,t}$	0.661***	0.661***	0.651***	0.626***	0.625***	0.621***	0.623***	0.608***
euro		-0.060*	-0.056*		0.043		-0.087**	-0.092***
crisis	0.128***	0.128***	0.122***			0.136***	0.135***	0.145***
temporal dummies	no	no	yes	no	no	no	no	yes
CD - test	26.35	25.48	-1.79	22.75	27.28	42.78	38.97	-1.70
p-value	0.000	0.000	0.073	0.000	0.000	0.000	0.000	0.090

Table 3: AH-IV estimates with a traditional spatial autoregressive component
legend: * p<0.05; ** p<0.01; *** p<0.001

References

Abel, A. B. (1990), Asset prices under habit formation and catching up with the joneses, Technical report, National Bureau of Economic Research.

Alessie, R. & Kapteyn, A. (1991), 'Habit formation, interdependent preferences and demographic effects in the almost ideal demand system', *The Economic Journal* **101**(406), 404–419.

Alessie, R. & Teppa, F. (2010), 'Saving and habit formation: evidence from dutch panel data', *Empirical Economics* **38**(2), 385–407.

Anderson, T. W. & Hsiao, C. (1982), 'Formulation and estimation of dynamic models using panel data', *Journal of Econometrics* **18**(1), 47–82.

Ando, A. & Modigliani, F. (1963), 'The" life cycle" hypothesis of saving: Aggregate implications and tests', *The American Economic Review* **53**(1), 55–84.

Bailey, N., Holly, S. & Pesaran, M. H. (2016a), 'A two-stage approach to spatio-temporal analysis with strong and weak cross-sectional dependence', *Journal of Applied Econometrics* **31**(1), 249–280.

Baltagi, B. H. & Song, S. H. (2006), 'Unbalanced panel data: A survey.', *Statistical Papers* **47**(4), 493–523.

Breusch, T. S. & Pagan, A. R. (1980), 'The lagrange multiplier test and its applications to model specification in econometrics', *The Review of Economic Studies* **47**(1), 239–253.

Browning, M. & Collado, M. D. (2007), 'Habits and heterogeneity in demands: a panel data analysis', *Journal of Applied Econometrics* **22**, 625–640.

Camilla, M., Serlenga, L. & Shin, Y. (2013), 'Globalisation and technological convergence in the eu', *Journal of Productivity Analysis* **40**(1), 15–29.

Carrasco, R., Labeaga, J. M. & Lopez-Salido, J. D. (2005), 'Consumption and habits: Evidence from panel data', *The Economic Journal* **115**, 144–165.

Deaton, A. (1992), *Understanding consumption*, Oxford University Press.

Duesenberry, J. S. et al. (1949), 'Income, saving, and the theory of consumer behavior'.

Dynan, K. E. (2000), ‘Habit formation in consumer preferences: Evidence from panel data’, *American Economic Review* **90**(3), 391–406.

Flavin, M. A. (1981), ‘The adjustment of consumption to changing expectations about future income’, *Journal of Political Economy* **89**(5), 974–1009.

Friedman, M. (1957), The permanent income hypothesis, *in* ‘A theory of the consumption function’, Princeton University Press, pp. 20–37.

Gali, J. (1994), ‘Keeping up with the joneses: Consumption externalities, portfolio choice, and asset prices’, *Journal of Money, Credit and Banking* **26**(1), 1–8.

Guariglia, A. & Rossi, M. (2002), ‘Consumption, habit formation, and precautionary saving: evidence from the british household panel survey’, *Oxford Economic Papers* **54**(1), 1–19.

Kapetanios, G., Mitchell, J. & Shin, Y. (2014), ‘A nonlinear panel data model of cross-sectional dependence’, *Journal of Econometrics* **179**(2), 134–157.

Kapetanios, G., Serlenga, L. & Shin, Y. (2019), ‘Testing for correlated factor loadings in cross sectionally dependent panels’.

Korniotis, G. M. (2010), ‘Estimating panel models with internal and external habit formation’, *Journal of Business & Economic Statistics* **28**(1), 145–158.

Leibenstein, H. (1950), ‘Bandwagon, snob, and veblen effects in the theory of consumers’ demand’, *The Quarterly Journal of Economics* **64**(2), 183–207.

Lu, C., Chang, M., Huang, E., Ching-Wen, C. et al. (2011), ‘Usability of context-aware mobile educational game’, *Knowledge Management & E-Learning* **3**(3), 448.

Lusardi, A. (1996), ‘Permanent income, current income, and consumption: Evidence from two panel data sets’, *Journal of Business & Economic Statistics* **14**(1), 81–90.

Mastromarco, C., Serlenga, L. & Shin, Y. (2016), ‘Modelling technical efficiency in cross sectionally dependent stochastic frontier panels’, *Journal of Applied Econometrics* **31**(1), 281–297.

Maurer, J. & Meier, A. (2008), ‘Smooth it like the "joneses"? estimating peer-group effects in intertemporal consumption choice’, *The Economic Journal* **118**(527), 454–476.

Meghir, C. & Weber, G. (1996), 'Intertemporal nonseparability or borrowing restrictions? a disaggregate analysis using a us consumption panel', *Econometrica: Journal of the Econometric Society* pp. 1151–1181.

Modigliani, F. (1986), 'Life cycle, individual thrift, and the wealth of nations', *Science* **234**(4777), 704–712.

Modigliani, F., Brumberg, R. et al. (1954), 'Utility analysis and the consumption function: An interpretation of cross-section data', *Post-keynesian Economics* **1**, 338–436.

Muellbauer, J. (1988), 'Habits, rationality and myopia in the life cycle consumption function', *Annales d'Economie et de Statistique* pp. 47–70.

Naik, N. Y. & Moore, M. J. (1996), 'Habit formation and intertemporal substitution in individual food consumption', *The Review of Economics and Statistics* pp. 321–328.

Pesaran, M. H. (2015), 'Testing weak cross-sectional dependence in large panels', *Econometric Reviews* **34**(6-10), 1089–1117.

Ravina, E. (2007), 'Habit formation and keeping up with the joneses: evidence from micro data', *Working paper, New York University* .

Rossi, M. (2005), 'Households'consumption under the habit formation hypothesis. evidence from italian households using the survey of household income and wealth (shiw)'.

Verhelst, B. & Van den Poel, D. (2014), 'Deep habits in consumption: a spatial panel analysis using scanner data', *Empirical Economics* **47**(3), 959–976.

Wachter, J. A. (2006), 'A consumption-based model of the term structure of interest rates', *Journal of Financial Economics* **79**(2), 365–399.

Weil, P. (1993), 'Precautionary savings and the permanent income hypothesis', *The Review of Economic Studies* **60**(2), 367–383.