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Deliverable 4.2

Report on multivariate analysis on MIP and well-being and SDGs indicators

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Summary

As we have documented in the delirevable 1.1 and 1.2 well-being and SDGs framework are currently available for almost European countries providing a strong support for the so-called *beyond-GDP* approach. Along with the research on the well-being and SDGs frameowrk, another strand of literature explores how the traditional system on national account (SNA), that is the pillar for the GDP measurement, could be extend to account for some of the main themes related to well-being and sustainability.
The aim of this deliverable is to follow this approach inside the boundaries of the macroeconomic model for Italian economy (MeMo-It) that is traditionally used for forecasting . In details we extend MeMo-It introducing both aconsumption for enerfy by firms and households and inequality measures in the consumption function.
According to the results presented we support the idea that step forward on well-being and sustainalibity could be realized inside the actual boundaries of the System of National Accounts.
The deliverable is based on the work presented in Bacchini, Golinelli, and Jona-Lasinio (Bacchini et al.), Galizzi (2020)

1. Introduction

In March 1809, leaving the US presidency, Thomas Jefferson wrote that *the care of human life and happiness, and not their destruction, is the first and only legitimate object of good government.* Echo of this intuition are scattered across history and, in recent years, it has been translated into a suitable set of indicators useful for setting and monitoring the policy agenda. As we have documented in the delirevable 1.1 and 1.2 well-being and SDGs framework are currently available for almost European countries providing a strong support for the so-called *beyond-GDP* approach (see for example OECD (2017), Istat (2019), Istat (2020)).

Having a set of indicators poses new challange in the direction of an integrated measurement system able to capture the driven forces on the evoluzion of well-being and sustanability. One strand of research has faced this issues either by proposing composite indicators, following the path illustrated by Human Development Index (HDI, UNDP (2016), Alaimo et al. (2020), Bacchini et al. (2020)) or exploring the relationship amid policy and indicators (Miola and Schiltz (2019)).

Along with the research on the well-being and SDGs frameowrk, another strand of literature (see for example Jorgenson and Schreyer (2017), Van De Ven (2019)) explores how the traditional system on national account (SNA), that is the pillar for the GDP measurement, could be extend to account for some of the main themes related to well-being and sustainability.

The aim of this deliverable is to follow this approach inside the boundaries of the macroeconomic model for Italian economy that is traditionally used for forecasting (MeMo-It, Bacchini and al. (2013), Bacchini et al. (2018), Bacchini et al. (2020)). In details we extend MeMo-It introducing both aconsumption for enerfy by firms and households and inequality measures in the consumption function.

There is a large variety of energy and environment modeling approaches (see Pollit et al (2010) for a review). A widely used modeling paradigm distinguishes between top-down and bottom-up models according to the approach adopted to represent the interactions between the energy system and the economy (Bohringer, C. and T. Rutheford (2006)).

Most of the bottom-up models are based on the general equilibrium framework through which they try to capture endogenously macroeconomic impacts (change in GDP, consumption, investments, prices, unemployment etc.) of specific energy policy instruments (i.e. carbon tax). Top-down models are best suited for predictive purposes, since their past behavior can be easily extrapolated into the future. On the other hand, top-down models fail to capture the extent of technological developments since they model technology changes as the result of a price substitution along a given production isoquant. There are also several hybrid models aiming at combining the technological explicitness of bottom-up models with the economic robustness of top-down models (see Hudson and Jorgenson, (1974) and Bergman (1990)).

Extending the measure on households seems more in line with the SNA. For example considering heterogeneity when modelling aggregate consumption is important because heterogenous consumers have different behaviours and the impact on aggregate consumption is likely to be different with respect to assuming one representative agent. In particular, we think that income inequality indexes are a suitable proxy to capture heterogenous consumption behaviours as the Marginal Propensity to Consume (MPC) is a decreasing function of income. The specific income inequality indexes that will be used in this analysis are aggregate measures calculated from the EU-SILC survey; this allows to incorporate micro information in the macro-economic model, thus improving the latter without necessarily turning to micro models. We assume that income inequality is negatively related to the aggregate consumption insofar as an income shock that increases the level of inequality implies that the decline of consumption of the poorest is larger than the increase in consumption of the richest. Even if consumption smoothing can hinder the income-consumption transmission mechanisms, the evaluation of the Italian scenario from 1995 to 2017 reveals that income inequality rose substantially during the economic crisis, when credit constraints were strict and consumption smoothing less feasible. For this reason, the increase in income inequality could have worsen the depression of aggregate consumption during the crisis and could be responsible to the subsequent slow recovery. The empirical analysis confirms our hypothesis showing that income inequality captured by the p90p10 index is statistically significant and negatively related to the aggregate consumption.

Moreover, we find that a positive income shock increases aggregate consumption in the current year, but if the increase in income is not equally distributed, its impact is completely off-set by the negative effect of the increase in inequality that becomes effective in the successive year. Running the Nested Cross-Validation for time series we also demonstrate that the new formulation of the consumption equation has a better forecasting performance with respect to the older one. Finally, as the introduction of heterogeneity promises to better assess the impact of redistributive policies, we evaluate the effect of the Italian *Reddito di Cittadinanza (RdC)* to the aggregate consumption and GDP. We find that the RdC in 2020 will increase GDP of 0.4 pp and aggregate consumption of 1.1 pp with respect to the base scenario. The results of the simulation are substantially higher with respect to those obtained using the old equation as the new one allows for the decrease in income inequality generated by the policy.

According to the results presented we support the idea that step forward on well-being and sustainalibity could be realized inside the actual boundaries of the System of National Accounts.

2. The model MeMo-It: extension for energy and inequality

2.1. Main characteristics

During her visit to the London Business School of Economics in 2008, Queen Elizabeth asked why the Global Financial Crisis (GFC) was not foreseen; the answer, coming from the British Academy Forum , focused on the inability of many bright people to understand the risk of the system as a whole (Besley and Hennessy (2009)). Macro-econometric models in place at central banks or government institutions were not able to forecast the GFC and worse, it was impossible to be foreseen using such structural models that don't consider the link between the financial and the real side of the economy and donâ€™t incorporate micro-level information to study the heterogenous agents' reaction to macroeconomic shocks. DSGE (Dynamic Stochastic General Equilibrium) models failed to predict the large variation in the GDP occurring during the GFC because they said nothing about the probability that a crisis would arise endogenously (Haldane and Turrell (2018)). The fact that an economic crisis can arise endogenously, is linked to the believe that the credit boom, responsible of the recent GFC, has been driven by a rise in inequality, economic growth, low interest rates and facilitated by financial innovations. The failure of the macro-economic models in place at that time, has lead a number of macroeconomists to work on the *Rebuilding Macroeconomic Theory Project*, aiming to identify how the benchmark NK-DSGE (New Keynesian Dynamic Stochastic General Equilibrium) model might be improved (Vines and Wills (2018)). Four key changes have been underlined:

- Introduce financial frictions
- Limit the operation of rational expectations
- Include heterogenous agents;
- Devise appropriate micro-foundation.

Today many macro-economic models have abandoned the pure structural DSGE framework becoming more data-driven and reducing the number of non-tested theoretical restrictions; this is the case of both the recent MeMo-It model created by Istat in 2011

MeMo-It belongs to a suite of economic forecasting models developed by Istat, where it plays a fundamental role in the modeling framework ensuring the overall consistency in the system. The model is composed by 53 stochastic equations and 78 identities, and represents a New Keynesian economic system including households, firms, public administration, and a foreign sector. It is an annual model that uses two sets of external (exogenous) information over the forecasting period. The first set refers to the main variables that characterize the development of the international scenario, such as trade growth, exchange rates, ECB interest rates, and the oil price. The second set instead includes annual estimates of key GDP components obtained from short-term models based on monthly and quarterly data available at the time of forecast. The main characteristic of MeMo-It is that it is strongly grounded in empirical information (data-based model) in order to assess the data-admissibility of the theoretical assumptions, and does not assume explicit micro-foundations of weak-form. Further, it has been thought as a simple and easy tool to be introduced to the users and it is timely updated with the most recent release of National Accounts. This allows to deliver updated forecasts always coherent with the last vintage of NA figures.

2.2. Implementing energy consumption

Moving to the subset of macroconomic-energy models at the country level they can also be grouped according to the framework adopted to represent the economic system into Neo-Keynesian and Computable General Equilibrium models (CGEM). Neo-Keynesian models provide a more truthful representation of the actual functioning of the economy accounting explicitly for the sluggish adjustments of prices and quantities. This allows to model permanent or transitory under-optimum equilibrium (i.e. the presence of involuntary unemployment) increasing the degree of accurateness of the model. On the other hand, Neo-Keynesian models do not allow an high degree of disaggregation that is not easily combined with the explicit representation of the mechanisms of adjustments. CGEM are instead suitable for an high level of detail, usually distinguishing between type of consumers, countries and goods, in a tractable framework. CGEM are widely used to analyze the economic impact of energy and environmental policies since they often account for a large number of sectors (GREEN, 11 sectors; GEMINI-E3, 18 sectors; IMACLIM-S 10 sectors)[1]. However, CGEM are supply models founded on the very restrictive assumption of perfect price flexibility that insures full and optimal use of resources and guaranties the equilibrium, but does not allow for real-life disequilibria[2].

The diagram in Figure 1 outlines the first development of MeMo-It to incorporate the demand and supply of energy inputs. At this stage, MeMo-It is structured into five main blocks supply side, labor market, demand side, prices, and Government. Further, as can be seen in the Figure, there are three (rhombuses) main sources of external information for the age- and gender-structure of the population, the ECB policy interest rate (in the financial sector) and global variables, such as world demand, exchange rates, oil price and other import prices. The arrows identify the main transmission channels across blocks.

As mentioned above, MeMo-It is substantially based on the New-Keynesian approach where the supply side of the economy plays a central role. Accordingly, the underlying key assumption is that in the short-run the economic activity is mainly driven by the demand side, while in the long run the economic system converges to potential output given by the supply side. Prices react to the output gap and, in this way, they accounts for the disequilibrium of supply and demand. The dotted arrows in the lower portion of Figure 1 represent the interactions arising from such disequilibrium (between the supply and demand rectangles) with the output gap (in the oval circle) which, in turn, affects the prices rectangle. In turn, price changes feedback into demand variables rectangle and into wages in the labor sector rectangle. Real wages and employment affect income distribution and households consumption (in the demand rectangle). Consumption and incomes in the demand rectangle are the tax bases which, combined with (exogenous) rates, define different forms of taxation in the Government rectangle. Direct taxation and public transfers generate income redistribution that affects the demand, while

1 See Burniaux et al., (1992), Bernard and Vielle, (2008) and Ghersi and Thubin, (2009) respectively
2 See Bhattachryya (1996) for an overview of CGE models.

indirect tax and social security contributions influence prices and labor cost. Finally, investments and output in the demand rectangle interact with the supply side through the accumulation of capital stock (lower arrow), and employment in the labor market rectangle (upper arrow).

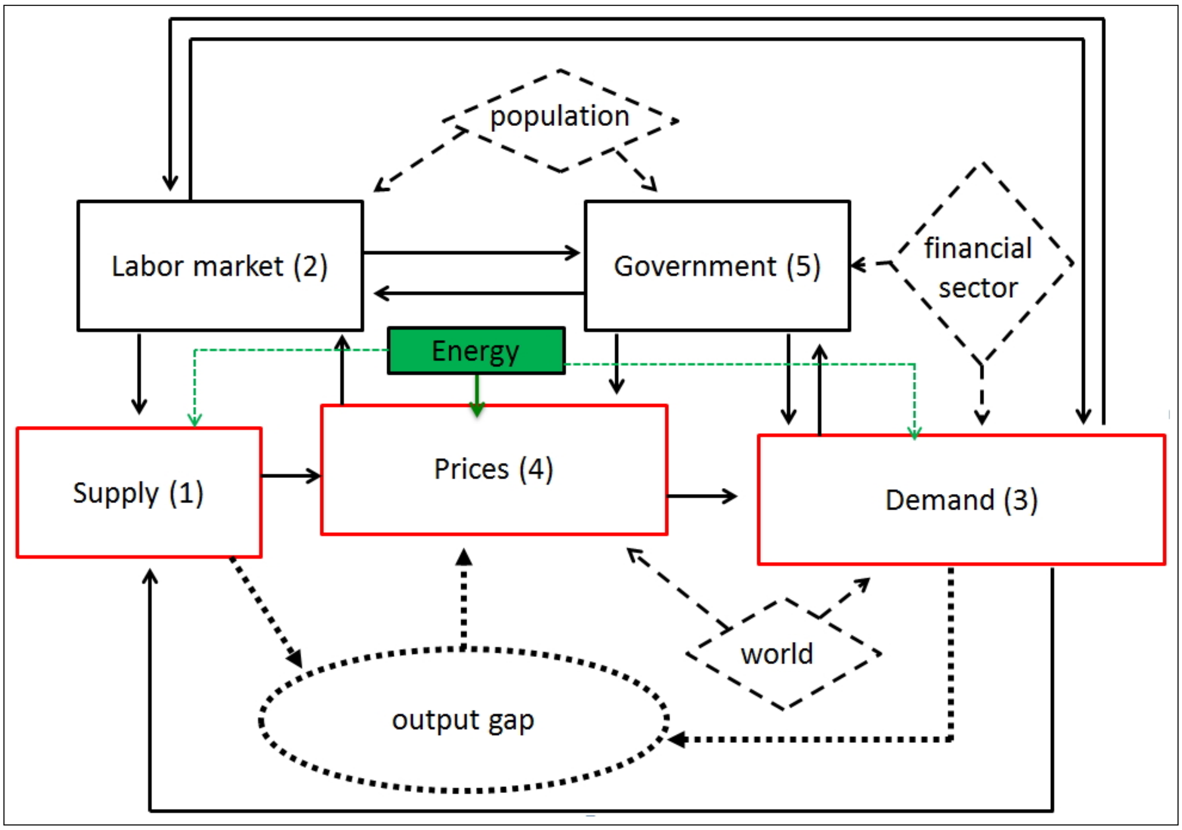

Figure 2.1: Developing 2E-MeMo - 1st step

The economy-energy-environment model (2E-MeMo-It) has been developed in the same spirit of MeMo-It focusing on data coherency and timeliness with the SEEA. As shown in Figure 1, the energy block interacts with the demand and the supply side of the economy via firms demand of energy inputs and household demands of final energy products, and affecting the price system (green arrows).

In this section we illustrate the structure of the energy block that is composed by two different energy product demand functions and two price equations. We model the firm's demand of energy inputs, the household's consumption of energy products and their relative price functions through behavioral equations able to explain both short and long run dynamics. The demand of energy inputs is specified as follows:

$$F_t^{ED} = F(Y_t, P_t^E, DD_t) \tag{2.1}$$

where Y is GDP, P are the prices of intermediate energy inputs and DD is the domestic demand. All variables are at time t. Then P_t^E is assumed to be a function of domestic and international prices of energy products as well as of specific fiscal variables. The estimating equation is:

$$P_t^{EI} = F(P_t^{OIL}, P_t^{GAS}, P_t^{EL}, P_t^{OTH}, P_t^{IMP}, T_t) \quad (2.2)$$

where superscripts refer to individual energy assets: OIL (Brent price in dollar per barrel, from OEF model), GAS and EL are Gas and Electricity prices, while OTH refers to other energy products, IMP are the prices of Imported energy inputs and T are government taxes.

Household's demand of energy products is assumed to be influenced by fuel, electricity and gas prices, and by disposable income (YD) and can be written as:

$$H_t^{ED} = F(P_t^{GAS}, P_t^{EL}, P_t^{FUEL}, YD_t) \quad (2.3)$$

and the corresponding price is:

$$P_t^{EF} = F(P_t^{GAS}, P_t^{EL}, P_t^{FUEL}, P_t^{OIL}, T_t, EXP_t) \quad (2.4)$$

where T is VAT on consumprion and Govt. direct purchases and EXP refers to total exports. we assume that energy prices are the main transmission channels between the energy block and the economic system. Energy prices affect firms investment decisions and the demand for labour. In particular, intermediate and final energy prices are assumed to interact with the economic system as defined in MeMo-It through firm's investment in machinery and equipment, firm's demand for labor, and household consumption of energy products. The above structure allows to evaluate the effects of energy policies on business and household sectors through their impact on the demand of production inputs as well as on the final demand for energy products.

2.3. Implementing inequality into consumption

2.3.1. Data

Income inequality indexes have been calculated using EU-SILC data about equivalized disposable income from 2004 to 2017.

Equivalised disposable income is formed adding up all monetary incomes received by each household member including income from work, investments, social benefits and any other form of income minus taxes and other deductions, divided by the number of equivalent households calculated according to the OECD equivalence scale. That scale considers the differences in household size and composition, in particular the number of equivalent households is calculated in which the first member of the family aged 14 years or more counts as a person, other members aged 14 or more count as a 0.5 person and members aged 13 years old or less count as a 0.3 person.

Subsequently, the sum of the household disposable income is divided by the number of equivalent adults; the resulting variable is the equivalised disposable income that is attributed equivalently to each member of the household

After the determination of equivalised disposable income, inequality indexes have been calculated on this variable using the 'inedeq' procedure in STATA that produces a range of inequality measures commonly used by economists.
The set of income inequality indexes includes: The Gini coefficient, $P90p10$ index, $P10p50$ index. The final set of income inequality indexes is thus composed by three yearly time series that go from 2004 to 2017.
The final set of income inequality indexes is thus composed by seven yearly time series that go from 2004 to 2017.
Unfortunately, these time series are too short (only 14 observations for each index) to be inserted in the Memo-It aggregate consumption function for which yearly data are available from 1969 to 2018.
To overcome this problem, we apply a back-casting technique in order to end up with a larger sample of income inequality indexes and estimate the consumption function over a larger time span.
Due to the few observations at our disposal, it is difficult to identify an historical pattern for each index and use it to back-cast the series.
For this reason, we have searched for other variables that are related to the EU-SILC income inequality indexes and which data are available for a longer time in order to rebuild the EU-SILC indexes based on the relationship between the former and these new variables.
Data from 1995 of average individual post-tax national income for a given percentile group are available in the World Inequality Database (WID), a powerful source of data that aims to provide useful information of inequality trends on several fronts.
WID develops a technique based on the notion of Distributional National Accounts (DINA) to calculate the distribution of national income based on different information, i.e. national accounts, households survey data, tax data and release data about income for percentiles groups (World Inequality Database , 2019).

2.3.2. Insert income inequality indexes in the Memo-It consumption function

Memo-it private consumption is modelled according to the following dynamic linear equation:

$$\begin{aligned}\Delta \log CHO_t = \alpha_0 + \alpha_1 \Delta \log \frac{YDHN_t}{PCH_t} + \alpha_2 \Delta \log \frac{YDHN_{t-1}}{PCH_{t-1}} \\ + \alpha_3 \log \frac{CHO_{t-1} * PCH_{t-1}}{YDHN_{t-1}} + \alpha_4 \log \frac{1 + INTR_{t-1}}{100} \\ + \alpha_5 \log \frac{HWFA_{t-1}}{YDHN_{t-1}}\end{aligned} \tag{2.5}$$

Where CHO is the real private consumption, $YDHN$ is the disposable income net of interests at current prices, $HWFA$ is the financial wealth at current prices, PCH is the consumption deflator and $INTR$ is the short-term nominal interest rate.
All the variables are taken in the first difference both because they are integrated of order 1 as confirmed running the Augmented Dikey-Fueller tests on single variables (Table3.8) and because the function is modelled in growth rates.
The cointegration test confirms that the only long-run relationship is between the real private consumption CHO and the real disposable income $YDHN/PCH$ (Table **??**) 3.10).
Single stochastic equations in Memo-It are estimated using the 2SLS approach to solve the endogeneity

problem. Even if in the case of the consumption function all the variables are exogenous, the 2SLS approach is maintained to improve the precision of the estimation of the variance-covariance matrix. Table 3.1 provides the estimation of the consumption equation with the full sample of data available from 1969 to 2018.

As expected, real current disposable income C(41) and the real disposable income of the previous year C(42) have a positive and statistically significant impact on the aggregate consumption.
The short-term interest rate C(44) is negative, confirming that if the interest rate increases households prefer saving their money than consume. The coefficient of financial wealth C(45) is also positive even its impact is smaller than the coefficients of the disposable income variables C(41) and C(42) and the p-value is higher.
As income inequality indexes have been rebuilt up to 1995, table 3.11 provides the consumption function estimation with the same reduced sample of data.

The results with the reduced sample of data show that the sign of the coefficients are the same as before, even if the short-term interest rate C(44) is no more statistically significant. Despite that, we decide to maintain this formulation of the consumption function and to try to fix this problem after the introduction of the income inequality indexes. At this point, we try to introduce each income inequality index in the equation in order to choose which one perform better and interpret its impact on the aggregate consumption.

All the indexes show evidence of stationary, however they are inserted in the equation using the first difference both because the consumption function is defined in growth rates and because their performance is better when they are inserted using the first difference.
For each index we follow these steps:

1. Insert the index in the equation;

2. Look at the model residuals plot and try to add some dummy variables if it is necessary;

3. Following Muellbauer (2016), we try to separate debt from financial wealth adding to the consumption equation a new variable (called PASSIVITAPERC) that indicates the total householdsâ€™ debt in percentage over disposable income. This variable can reveal information about the relationship between householdsâ€™ debt and consumption and can also be interacted with the inequality index. We expect to find a positive coefficient of the interaction term as debt helps to smooth consumption reducing the negative impact of income inequality on aggregate consumption, alternatively is possible to find a negative coefficient of the interaction term if the increase of inequality together with the reduction of debt have worsened the impact of income inequality on aggregate consumption. According to the analysis of the Italian scenario, the second possibility is more plausible.

Both the Gini index and p10p50 index are not statistically significant (table 3.12 and **??**), even after adding dummies or trying to interact the indexes with the householdsâ€™ debt.
The only index that is statistically significant is p90p10 when a dummy is added in 2011.
However, also in this case both the householdsâ€™ debt and the interaction between debt and p90p10 are not statistically significant (Table 3.14and 3.15). After several trials, we end up with the following new aggregate consumption function:

$$\begin{aligned}\Delta \log CHO_t = \alpha_0 + \alpha_1 \Delta \log \frac{YDHN_t}{PCH_t} + \alpha_2 \Delta \log \frac{YDHN_{t-1}}{PCH_{t-1}} \\ + \alpha_3 \log \frac{CHO_{t-1} * PCH_{t-1}}{YDHN_{t-1}} + \alpha_4 \log \frac{1 + INTR_{t-1}}{100} \\ + \alpha_5 \log \frac{HWFA_{t-1}}{YDHN_{t-1}} + \alpha_6 \Delta \frac{p90_{t-1}}{p10_{t-1}} + \alpha D2011\end{aligned} \tag{2.6}$$

$p90/p10$ income inequality index and $D2011$ is the dummy for 2011. The new consumption function estimation is presented in table **??** while in figure **??** there is the graph of residuals.

The coefficients of the real current disposable income C(41) and the real disposable income of the previous year C(42) remains positive and statistically significant even if the impact of the current component increases, while the impact of the lagged component decreases.
The impact of the long run component remains negative with a similar magnitude and the interest rate is no more statistically significant.
The most interesting result is that the coefficient of the p90p10 index is negative and statistically significant confirming that inequality negatively impact on the aggregate consumption.
This confirms the existence of a link between heterogeneity at micro level and macro aggregates that need to be considered in formulating macro-econometric models, in fact our proxy of heterogeneity is statistically significant and also improves the goodness of fit of the consumption equation, in fact the Adjusted R-squared passes from 0.861 in the traditional equation to 0.893 in the new consumption function.
Looking at the coefficient of the new equation is possible to directly evaluate the impact of the increase in income inequality on aggregate consumption.
In fact, an increase of the p90p10 growth rate equal to its standard deviation (0.082), generates a decrease of the aggregate consumption growth rate of 0.0037% in the subsequent period.
It is interesting to compare the impact of p90p10 with the impact of the disposable income on consumption.
In particular if the real disposable income growth rate increases of one standard deviation (0.0078), the growth rate of the aggregate consumption increases of 0.0035% in the current year, while in the next year it generates an increase of the aggregate consumption growth rate equal to 0.0030%.
Taken together these results reveal that if the income increase is not equally distributed and also p90p10 experienced an increase equal to its standard deviation, in the current year consumption increases, but in the next year the negative impact of the income inequality index completely off-sets the positive effect of income.
This means that both the increment in household disposable income and its distribution are relevant in order to obtain long-lasting effects on consumption. The role of income inequality is explained by the fact that rich people, that benefit more from income increase, have a lower MPC and consume

a minimal part of the additional income whereas poor people that worsen their conditions relative to the richest one, reduce their consumption. To evaluate if the forecasting performance of the new consumption function has improved with respect to the old formulation, we run the nested Cross-Validation (CV) for time series data, an out-of-sample forecasting technique that allows to obtain robust measures of the model prediction error.

In particular, we implement the Forward-Chaining technique that consists in creating many splits in the sample and average the errors over all the splits.

We start with a train sample of data from 1995 to 2011, estimate the model, forecast the following year and then compute the distance between the real value of $\Delta \log CHO$ and the predicted value.

Once we predict 2012, we use the following year as test and we consider all the previous years in the train sample; for example, we use data from 1995 to 2012 to predict 2013, then we calculate the prediction error and we continue using this procedure until the end of the series.

We end up with a vector of errors in correspondence of each split (from 2012 to 2017), and we use it to calculate the following model accuracy measures MAE MAPE and RMSE.

Considering the low number of observations in the train sample our goal is not to measure the error of the new and the old equation, but to evaluate if adding the inequality index to the aggregate consumption function improves the model prediction performance.

We perform the time series Cross-Validation and we calculate the three measures for both the old consumption function and the new one. Results are displayed in Table 3.1.

All the three out of sample accuracy measures are lower for the new consumption function indicating than the forecasting performance of the new equation is better than the previous one.

The only problem that still remained in the new aggregate consumption function is the insignificance of the short-term interest rate coefficient. We try to solve this problem looking for other methods to introduce the interest rate in the consumption function.

In particular, we use an alternative formulation of the MeMo-It consumption function in which we substitute the short-term interest rate $INTR$ with EPU uncertainty index for Italy [3] ($BLOOM\_IT$), that captures the political uncertainty and the short-run interest rate calculated on the Italian government bonds ($INTRBTP$) that captures the uncertainty on the markets. Results show that the interest rate is negative and statistically significant, but the EPU index is not statistically significant (Table **??**). As our strategy does not appear to be sufficiently satisfactory and, considering that Istat is working on a new definition of the short-run interest rate, we decide to defer the problem of the interest rate to further developments.

[3] The Economic Policy Uncertainty Index (EPU) for Italy, is an index based on newspapers articles regarding policy uncertainty. For Italy the analyzed newspapers are *Corriere della Sera* and *LaStampa*. For more details see: (Economic Policy Uncertainty, 2016)

3. Results and further steps

3.1. Main result for energy

As shown above, the energy block is composed by four equations: firm's demand of intermediate energy inputs, household demand of energy products and two corresponding price equations [1]. In a first stage, we have tested for the presence of common components of firm's and household's energy demand, energy prices and an indicator of internal total demand. Figure 1 shows the results of the augmented Dickey-Fuller test for the demand of energy intermediates as well as for the demand of each intermendiate energy product.

The results suggest that the series are integrated of order 1 so we also test whether a long-run relationship among them exists. We investigate the cointegration between the common components using standard time series tests such as the Johansen reduced rank approach (Johansen,1995). Figure 2 shows that intermediate energy demand and domestic demand are weakly correlated with the corresponding energy prices thus suggesting the existence of a long run relationship.

Apparently, household demand of energy products is not integrated of order 1 (Figure 3) while the opposite is true if we test the demand of each individual energy asset. To get a sense of the dynamic behaviour of firm's and households demand of energy products and their main components, Figures 4 and 5 show their rates of change over the sample period. Equations 1 to 4 have then been estimated by means of two stage least squares. Estimation results are shown in figure 6 and 7.

3.2. Simulating the impact of Italian *Reddito di Cittadinanza* using the new consumption function

One of the main advantages of the introduction of heterogeneity in MeMo-It is the improvement of the model's policy evaluation function. The introduction of income inequality in the aggregate consumption equation may allow to better evaluate the macro-economic consequences of redistributive policies.

In fact, the old formulation of the consumption function is able to evaluate the effects of economic policies that increase households' income, without saying nothing on the effects of the distribution of that additional income. The income inequality measure can capture heterogenous agents' behaviours considering that if the policy is addressed to poor people with higher MPC, the effects on aggregate consumption and other macro-variables may be amplified.

To prove it we try to use the new consumption function to predict the impact of a new and debated redistributive policy, the Italian *Reddito di Cittadinanza (RdC).*

The Rdc is a passive labour market policy introduced in the Italian law in 2019 (D.L. 4/2019) that aims to reduce poverty, inequality, social exclusion guaranteeing labour rights and promoting activism in the labour market.

The RdC is a public transfer based on patrimonial and income requirements, that is provided to Italian families that have lived in Italy for at least 10 years.

[1] At this stage,we model energy consumption without distinguishing among different energy assets but referring to an energy aggregate including gas, oil, and electricity.

The amount of the transfer is based on the age of the family components and the ownership of the dwelling house and it is composed of two elements: an income integration and a contribution to pay rental costs.
The RdC can be required by all the families whose income or patrimonial parameters are under a fixed threshold and, after appropriate checks, the transfer is paid for a maximum period of 18 months and can be renewed after a month from the end of the period.
RdC is a labour market policy that supports unemployed or inactive people able to work to find a job, in fact RdC beneficiaries have to subscribe a labour pact in which they declare to be willing to accept possible vacancies. People that cannot work are also helped by municipalities and they sign a pact in which they declare to be available to participate to social inclusion programmes.
The economic transfer established by the RdC is suspended if an active person doesnâ€™t subscribe the pact or refuses three job offers in line to its experience and aptitudes, or if a person unable to work refuses to subscribe the social inclusion pact or to participate to public initiatives (Ministero dell'Economia e delle Finanze, 2019).
The functioning of the Italian *Reddito di Cittadinanza* is therefore akin to that of a redistributive policy that aims to reduce the gap between rich and poor by providing social transfers and labour assistance to people at the bottom of the income distribution.
The final effect is the increase of the aggregate household income generated by RdC transfers combine with the expected reduction of income inequality.
The impact generated by the RdC can be assessed by looking at the MeMo-It public spending multiplier, that is used to evaluate the transmission mechanisms of specific economic policies on GDP and other macro-economic variables.
The MeMo-It public spending multiplier is able to assess the transmission of a redistributive policy; by assuming an exogenous shock and comparing the simulated effects with respect to the base scenario (i.e. without RdC), it is possible to understand the net effects generated by the policy.
Istat (2018) assesses the impact that an increase in public spending due to a family transfer equal to that estimated in 2019 for the RdC, would have generated looking at the results produced by the public spending multiplier in the MeMo-It model with the old formulation of the consumption function.
The model simulation was conducted under two different scenarios:

- Scenario 1: Assuming a positive income shock equal to the increase in public transfers generated by the RdC, that was estimated equal to 9 billions of euros.

- Scenario 2: Assuming that the total RdC public transfer is consumed, and thus generating a direct positive shock on the private consumption equal to 9 billions of euros

The first scenario can underestimate the effects of RdC, because the part of the additional income that is consumed depends on the average MPC estimated in the consumption function, even if the RdC is a redistributive policy addressed to poor people that have a greater MPC than the average.
On the contrary, in the second scenario the MPC of the RdC beneficiaries is assumed to be equal to one, a strong assumption that can overestimate the impact of the policy.
Under the first scenario the introduction of the RdC generates an increase of 0.2 percentage points (pp) of the Italian GDP in 2019 with respect to the base scenario, while under the second scenario,

the GDP increases of 0.3 pp (Istat, 2018).
Before the introduction of the measure of heterogeneity in the aggregate consumption function, it was possible to evaluate the impact of the redistributive policies only shocking household disposable income or directly shocking the private consumption and both alternatives donâ€™t allow to evaluate the positive impact of inequality reduction generated by redistributive policies. The new formulation of the aggregate consumption function proposed in this thesis, makes possible to evaluate the impact of the Italian RdC on GDP and other macro-variables considering a positive income shock accompanied by a decrease in the inequality measure.
This makes the policy evaluation more realistic, because we considered that the transfer not only increases household income, but it is also addressed to the lower segment of the society. This solution is aimed to solve both the underestimation of the policy impact that emerges considering only the income shock and the overestimation problem considering a direct shock to the aggregate consumption. The shock on income is transmitted to consumption assuming that beneficiaries spend a fraction of the transfer received according to the average MPC, but the simultaneous shock on inequality allows to consider that the transfer is addressed to the poorest and stimulates aggregate consumption more than considering only the change in income.
For these reasons, we evaluate the impact of Italian *Reddito di Cittadinanza* in 2019 and 2020, using the new consumption function and the new information released by MEF (Ministero dell'Economia e delle Finanze) on the amount of the transfers and the impact on inequality. In particular, MEF (2019) reports that the maximum expected outlay of the RdC is 7.1 billions in 2019 and 8.055 billions in 2020.
Moreover, MEF (2019) states that this policy has generated a reduction of income inequality measured through the p80p20 index of 0.3 points (from 5.9 to 5.6) in 2019.
Summarizing, the advantages of the new simulation with respect to that realized in 2018 by Istat are:

- The possibility to define the impact of *Reddito di Cittadinanza* by assuming both an increase in household income and a reduction of inequality thanks to the new income inequality variable inserted in MeMo-It;

- The use of the new information released by MEF to better reproduce the magnitude of the shock to household income and the change in the inequality index;

- The possibility to assess the effect of the RdC in 2019 and 2020;

Two different scenarios are simulated:

- Scenario 1: Assuming an increase in the householdsâ€™ disposable income of 7.1 billions in 2019 and 8.055 billions in 2020.

- Scenario 2: Assuming the same shock for income as the scenario 1, plus a reduction of the income inequality index p90p10 of 0.21, proportional to the reduction estimated by MEF for p80p20 index. It is important to remember that, as the income inequality index enters in the consumption function at time t-1, the inequality reduction generated by the *Reddito di Cittadinanza* in 2019 produces its effect only in 2020.

Table 3.20 presents the results in 2019 and 2020 for both the two different scenarios expressed as a difference between each scenario and the base scenario (without the introduction of the RdC).

3.3. Final remarks

According to the results presented we support the idea that step forward on well-being and sustainalibity could be realized inside the actual boundaries of the System of National Accounts.

In details, looking at the Italian economy we find that the available improvements in the system of environmental accounts toger

At the same time, our results support also find a strong relationship between heterogeneity at micro level and macro-aggregates that cannot be forgotten in macro-economic models. Moreover, we demonstrate that heterogeneity can be added to macro-economic models using an innovative technique that emphasises the strict link between macro variables and micro data sources without abandoning the macro analysis and overcoming the difficulties to build more complex micro-econometric models.

Tables and Figures

Null Hypothesis: LOG(IH_EN) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.348536	0.9982
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LOG(IH_EST) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.679397	0.9669
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LOG(IH_CORF) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.099417	0.9999
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LOG(IH_ELGAS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 8 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.375191	0.9999
Test critical values:	1% level	-4.339330	
	5% level	-3.587527	
	10% level	-3.229230	

*MacKinnon (1996) one-sided p-values.

Figure 3.1: ADF test for intermediate

Table 3.1: MAE, MAPE and RMSE calculated with the time series Cross-Validation for both the new and the old consumption function

	old consumption function	new consumption function
MAE	0.0049	0.0039
MAPE	0.2493	0.0459
RMSE	0.0061	0.0052

Series: LOG(IH_EN) LOG(DDO) LOG(PINT_EN)
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.488830	33.97350	29.79707	0.0156
At most 1	0.169732	11.15769	15.49471	0.2020
At most 2 *	0.132518	4.833471	3.841466	0.0279

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.464070	21.21182	15.49471	0.0061
At most 1	0.000126	0.004279	3.841466	0.9465

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Figure 3.2: Johansen test for intermediate

Null Hypothesis: LOG(FH_EN) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.881137	0.0237
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LOG(FH_CORF) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.554299	0.7905
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LOG(FH_ELGAS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.993401	0.5845
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

*MacKinnon (1996) one-sided p-values.

Figure 3.3: ADF test for final

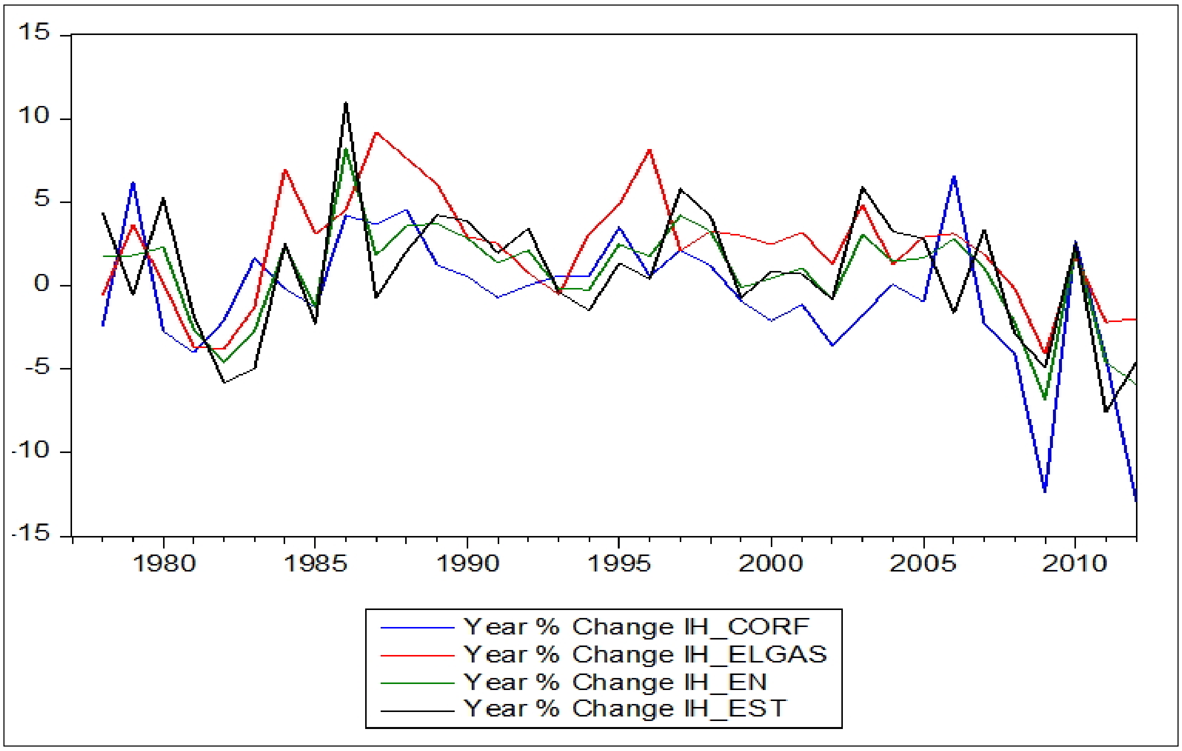

Figure 3.4: Energy intermediate inputs Y-Y growth rate

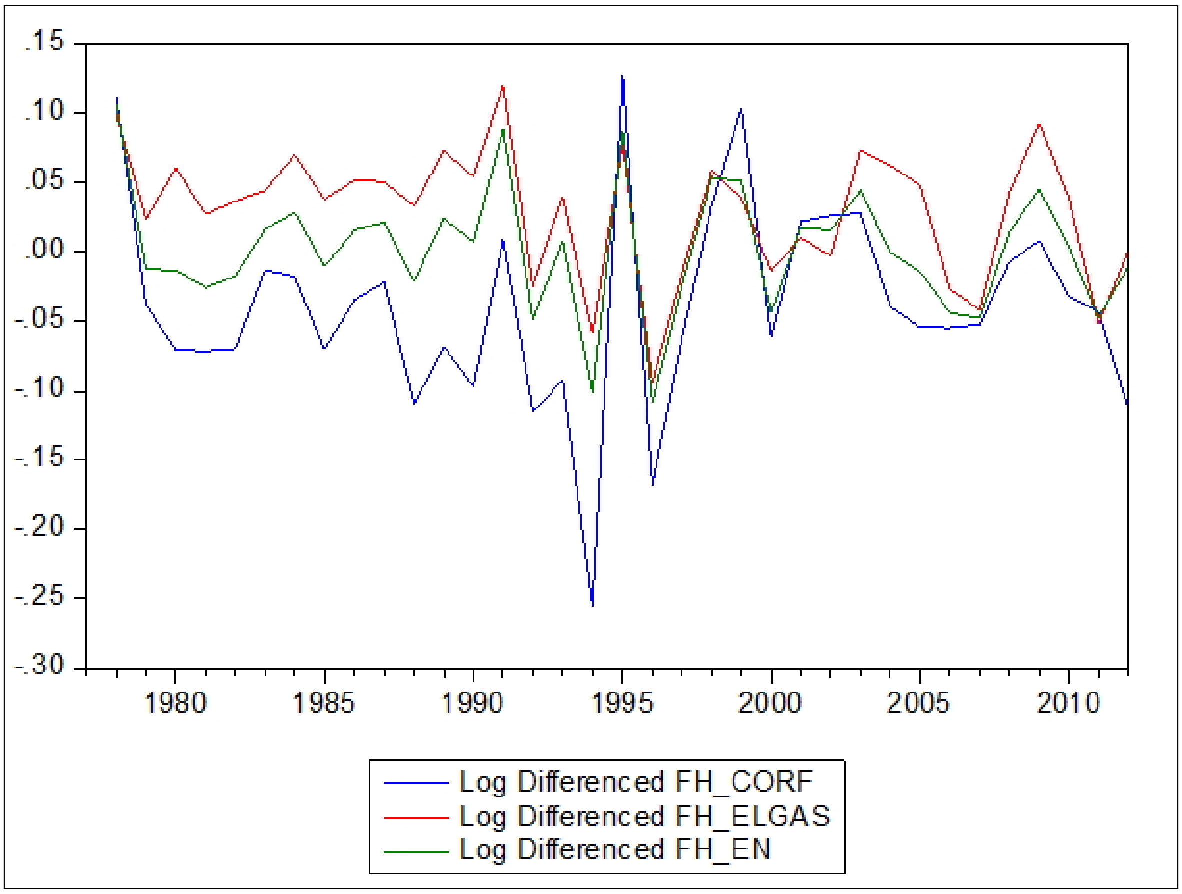

Figure 3.5: Energy final inputs Y-Y growth rate

Dependent Variable: DLOG(IH_EN)
Method: Two-Stage Least Squares
Date: 01/24/14 Time: 03:47
Sample (adjusted): 1979 2012
Included observations: 34 after adjustments
DLOG(IH_EN)=C(3)*DLOG(PINT_EN)+C(4)*DLOG(DDO)+C(5)*D1986
+C(6)*D2009+C(7)*D1993
Instrument specification: DLOG(IH_EN(-1)) DLOG(PINT_EN(-1))
DLOG(DDO(-1)) D1986 D2009 D1993
Constant added to instrument list

	Coefficient	Std. Error	t-Statistic	Prob.
C(3)	-0.115954	0.045562	-2.544971	0.0165
C(4)	0.961207	0.210270	4.571294	0.0001
C(5)	0.040400	0.020670	1.954478	0.0603
C(6)	-0.046909	0.020102	-2.333570	0.0268
C(7)	0.047560	0.021794	2.182198	0.0373

R-squared	0.682783	Mean dependent var	0.006464
Adjusted R-squared	0.639029	S.D. dependent var	0.031259
S.E. of regression	0.018781	Sum squared resid	0.010229
Durbin-Watson stat	1.841472	J-statistic	1.738308
Instrument rank	7	Prob(J-statistic)	0.419306

Dependent Variable: LOG(FH_EN/POP_T)
Method: Two-Stage Least Squares
Date: 01/24/14 Time: 03:47
Sample (adjusted): 1978 2012
Included observations: 35 after adjustments
LOG(FH_EN/POP_T)=C(1)+C(2)*LOG(PFIN_EN)+C(3)*D1991+C(4)
*LOG(YDHN(-1)/POP_T(-1))+C(5)*D1997
Instrument specification: C LOG(FH_EN(-1)/POP_T(-1)) LOG(PFIN_EN)
LOG(YDHN(-2)/POP_T(-2)) D1991 D1997

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.039294	0.128515	8.086945	0.0000
C(2)	-0.224111	0.047328	-4.735257	0.0000
C(3)	0.093286	0.029618	3.149634	0.0037
C(4)	0.128183	0.031944	4.012677	0.0004
C(5)	-0.088773	0.029728	-2.986191	0.0056

R-squared	0.625309	Mean dependent var	0.391622
Adjusted R-squared	0.575351	S.D. dependent var	0.044777
S.E. of regression	0.029179	Sum squared resid	0.025542
Durbin-Watson stat	2.072692	J-statistic	0.988668
Instrument rank	6	Prob(J-statistic)	0.320068

Figure 3.6: Demand equations

Dependent Variable: DLOG(PINT_EN)
Method: Two-Stage Least Squares
Date: 01/24/14 Time: 03:47
Sample (adjusted): 1982 2012
Included observations: 31 after adjustments
DLOG(PINT_EN)=C(2)*DLOG(XO)+C(3)*DLOG(OIL)+C(5)
*DLOG(PINT_ELGAS)
Instrument specification: DLOG(XO(-1)) DLOG(OIL(-1)) DLOG(PINT_ELGAS
(-1)) D1986 DLOG(PINT_CORF)
Constant added to instrument list

	Coefficient	Std. Error	t-Statistic	Prob.
C(2)	0.718806	0.246184	2.919796	0.0068
C(3)	0.104001	0.049135	2.116630	0.0433
C(5)	0.707344	0.120937	5.848848	0.0000

R-squared	0.805167	Mean dependent var	0.062645
Adjusted R-squared	0.791250	S.D. dependent var	0.088960
S.E. of regression	0.040645	Sum squared resid	0.046257
Durbin-Watson stat	1.925523	J-statistic	6.074069
Instrument rank	6	Prob(J-statistic)	0.108062

Dependent Variable: DLOG(PFIN_EN/PV)
Method: Two-Stage Least Squares
Date: 01/24/14 Time: 03:47
Sample (adjusted): 1991 2012
Included observations: 22 after adjustments
DLOG(PFIN_EN/PV)=C(3)*DLOG(OIL/PV)+C(5)*DLOG(PFIN_ELGAS/PV)
+C(4)*DLOG(TIVA)
Instrument specification: DLOG(PFIN_EN/PV) DLOG(OIL(-1)/PV(-1))
DLOG(OIL(-2)/PV(-2)) DLOG(PFIN_ELGAS(-1)/PV(-1)) LOG(TIVA(-1))
Constant added to instrument list

	Coefficient	Std. Error	t-Statistic	Prob.
C(3)	0.130426	0.035970	3.625991	0.0018
C(5)	0.725013	0.142768	5.078247	0.0001
C(4)	0.485118	0.194034	2.500168	0.0217

R-squared	0.781400	Mean dependent var	0.008398
Adjusted R-squared	0.758389	S.D. dependent var	0.056659
S.E. of regression	0.027850	Sum squared resid	0.014737
Durbin-Watson stat	1.434549	J-statistic	1.919744
Instrument rank	6	Prob(J-statistic)	0.589230

Figure 3.7: Prices equations

Variable	Dikey-Fuller	p-value	lags	conclusion
log(cho)	-1.0147	0.9270	3	non-stationary
log(ydhn/pch)	-1.6209	0.7263	3	non-stationary
log(1+intr/100)	-2.4173	0.4060	3	non-stationary
log(hwfa/ydhn)	-2.0484	0.5549	3	non-stationary
Δlog(cho)	-5.0197	<0.01	3	stationary
Δlog(ydhn/pch)	-4.2409	<0.01	3	stationary
Δlog(1+intr/100)	-4.4662	<0.01	3	stationary
Δlog(hwfa/ydhn)	-3.2466	0.0904	3	stationary

Figure 3.8: Augmented Dikey Fuller tests on single variables using 3 lags.

Dependent variable	log CHO			
Method	Ordinary Least Square			
Sample	1969-2018			
formula	log CHO ~ log(YDHN/PCH)			
	Coefficient	St.error	t-statistic	Pr(>|t)
intercept	-3.8771	0.2492	-15.5600	<2e-16 ***
log(YDHN/PCH)	1.2794	0.0183	69.7800	<2e-16 ***
significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual st. error on 48 df	0.0278			
Multiple R-squared	0.9902			
Adjusted R-squared	0.9900			
F-statistic	4870	p-value	< 2.2e-16	

Figure 3.9: Cointegration test between the real private consumption (CHO) and the real disposable income (YDHN/PCH):Regression between real consumption and real income

Variable	Dikey-Fuller	p-value	lags	conclusion
model residuals	-3.3478	0.07428	3	Stationary

Figure 3.10: Cointegration test between the real private consumption (CHO) and the real disposable income (YDHN/PCH):Augmented Dickey-Fuller test on the regression residuals

Dependent Variable: DLOG(CHO)
Method: Two-Stage Least Squares
Date: 11/21/19 Time: 15:06
Sample (adjusted): 1997 2017
Included observations: 21 after adjustments
DLOG(CHO) = C(4*10+0) +C(4*10+1)*DLOG(YDHN/PCH) +C(4*10+2)
*DLOG(YDHN(-1)/PCH(-1)) +C(4*10+3)*LOG(CHO(-1)*PCH(-1)/YDHN(
-1)) +C(4*10+4)*DLOG(1+INTR(-1)/100) +C(4*10+5)*DLOG(HWFA(-1)
/YDHN(-1)) + +C(4*10+6)*D(GINI(-1))
Instrument specification: C DLOG(YDHN/PCH) DLOG(YDHN(-1)/PCH(-1))
LOG(CHO(-1)*PCH(-1)/YDHN(-1)) DLOG(1+INTR(-1)/100)
DLOG(HWFA(-1)/YDHN(-1)) DLOG(CHO(-1)) D(GINI(-1))

	Coefficient	Std. Error	t-Statistic	Prob.
C(40)	-0.004034	0.002553	-1.579981	0.1364
C(41)	0.376836	0.113243	3.327662	0.0050
C(42)	0.438360	0.111748	3.922755	0.0015
C(43)	-0.243680	0.134264	-1.814933	0.0910
C(44)	-0.193127	0.159083	-1.213996	0.2448
C(45)	0.101859	0.027300	3.731066	0.0022
C(46)	-0.154613	0.269807	-0.573051	0.5757

R-squared	0.898192	Mean dependent var	0.007078
Adjusted R-squared	0.854559	S.D. dependent var	0.017998
S.E. of regression	0.006864	Sum squared resid	0.000660
Durbin-Watson stat	1.814909	J-statistic	4.437518
Instrument rank	8	Prob(J-statistic)	0.035157

Figure 3.11: Estimation of the aggregate consumption function from 1995 to2017 adding the Gini index

Dependent Variable: DLOG(CHO)
Method: Two-Stage Least Squares
Date: 11/21/19 Time: 15:16
Sample (adjusted): 1997 2017
Included observations: 21 after adjustments
DLOG(CHO) = C(4*10+0) +C(4*10+1)*DLOG(YDHN/PCH) +C(4*10+2)
*DLOG(YDHN(-1)/PCH(-1)) +C(4*10+3)*LOG(CHO(-1)*PCH(-1)/YDHN(
-1)) +C(4*10+4)*DLOG(1+INTR(-1)/100) +C(4*10+5)*DLOG(HWFA(-1)
/YDHN(-1)) +C(4*10+6)*D(P10P50_YD(-1))
Instrument specification: C DLOG(YDHN/PCH) DLOG(YDHN(-1)/PCH(-1))
LOG(CHO(-1)*PCH(-1)/YDHN(-1)) DLOG(1+INTR(-1)/100)
DLOG(HWFA(-1)/YDHN(-1)) DLOG(CHO(-1)) D(P10P50_YD(-1))

	Coefficient	Std. Error	t-Statistic	Prob.
C(40)	-0.004314	0.002551	-1.690940	0.1130
C(41)	0.355811	0.108104	3.291387	0.0054
C(42)	0.453284	0.112940	4.013484	0.0013
C(43)	-0.259574	0.137211	-1.891794	0.0794
C(44)	-0.181654	0.159564	-1.138442	0.2740
C(45)	0.105122	0.028040	3.748960	0.0022
C(46)	0.046986	0.224359	0.209421	0.8371

R-squared	0.896129	Mean dependent var	0.007078
Adjusted R-squared	0.851613	S.D. dependent var	0.017998
S.E. of regression	0.006933	Sum squared resid	0.000673
Durbin-Watson stat	1.749591	J-statistic	3.115785
Instrument rank	8	Prob(J-statistic)	0.077537

Figure 3.12: Estimation of the aggregate consumption function from 1995 to 2017 adding the p10p50 index

Dependent Variable: DLOG(CHO)
Method: Two-Stage Least Squares
Date: 11/21/19 Time: 16:26
Sample (adjusted): 1997 2017
Included observations: 21 after adjustments
DLOG(CHO) = C(4*10+0) +C(4*10+1)*DLOG(YDHN/PCH) +C(4*10+2)
*DLOG(YDHN(-1)/PCH(-1)) +C(4*10+3)*LOG(CHO(-1)*PCH(-1)/YDHN(
-1)) +C(4*10+4)*DLOG(1+INTR(-1)/100) +C(4*10+5)*DLOG(HWFA(-1)
/YDHN(-1)) +C(4*10+6)*D(P90P10_YD(-1))+C(4*10+7)
*D(PASSIVITA_PERC(-1)) +C(4*10+8)* D2011
Instrument specification: C DLOG(YDHN/PCH) DLOG(YDHN(-1)/PCH(-1))
LOG(CHO(-1)*PCH(-1)/YDHN(-1)) DLOG(1+INTR(-1)/100)
DLOG(HWFA(-1)/YDHN(-1)) DLOG(CHO(-1)) D(P90P10_YD(-1))
D(PASSIVITA_PERC(-1)) D2011

	Coefficient	Std. Error	t-Statistic	Prob.
C(40)	-0.004727	0.002671	-1.770115	0.1021
C(41)	0.452378	0.106518	4.246963	0.0011
C(42)	0.382544	0.105743	3.617679	0.0035
C(43)	-0.261944	0.119777	-2.186927	0.0493
C(44)	-0.168162	0.140211	-1.199356	0.2535
C(45)	0.123459	0.025409	4.858817	0.0004
C(46)	-0.045401	0.024506	-1.852637	0.0887
C(47)	-4.25E-05	0.000795	-0.053414	0.9583
C(48)	0.013861	0.007227	1.917891	0.0792

R-squared	0.930926	Mean dependent var	0.007078
Adjusted R-squared	0.884876	S.D. dependent var	0.017998
S.E. of regression	0.006107	Sum squared resid	0.000448
Durbin-Watson stat	1.519319	J-statistic	1.814215
Instrument rank	10	Prob(J-statistic)	0.178003

Figure 3.13: Estimation of the new aggregate consumption function from 1995 to 2017 adding households debt

Dependent Variable: DLOG(CHO)
Method: Two-Stage Least Squares
Date: 11/21/19 Time: 16:36
Sample (adjusted): 1997 2017
Included observations: 21 after adjustments
DLOG(CHO) = C(4*10+0) +C(4*10+1)*DLOG(YDHN/PCH) +C(4*10+2)
*DLOG(YDHN(-1)/PCH(-1)) +C(4*10+3)* LOG(CHO(-1)*PCH(-1)/YDHN(
-1)) +C(4*10+4)*DLOG(1+INTR(-1)/100) +C(4*10+5)*DLOG(HWFA(-1)
/YDHN(-1)) +C(4*10+6)*D(P90P10_YD(-1))+C(4*10+7)
*D(PASSIVITA_PERC(-1)) +C(4*10+8)* D2011 +C(4*10+9)
*D(PASSIVITA_PERC(-1))*D(P90P10_YD(-1))
Instrument specification: C DLOG(YDHN/PCH) DLOG(YDHN(-1)/PCH(-1))
LOG(CHO(-1)*PCH(-1)/YDHN(-1)) DLOG(1+INTR(-1)/100)
DLOG(HWFA(-1)/YDHN(-1)) DLOG(CHO(-1)) D(P90P10_YD(-1))
D(PASSIVITA_PERC(-1)) D2011

	Coefficient	Std. Error	t-Statistic	Prob.
C(40)	-0.033592	0.213613	-0.157259	0.8779
C(41)	0.032873	3.255847	0.010097	0.9921
C(42)	0.502742	1.368612	0.367338	0.7203
C(43)	-0.585619	2.655825	-0.220504	0.8295
C(44)	-0.115114	1.440532	-0.079910	0.9377
C(45)	0.262160	1.049107	0.249888	0.8073
C(46)	0.482650	3.885346	0.124223	0.9034
C(47)	0.004175	0.031955	0.130655	0.8984
C(48)	0.062010	0.360737	0.171897	0.8666
C(49)	-0.293724	2.156981	-0.136174	0.8941

R-squared	-5.194840	Mean dependent var	0.007078
Adjusted R-squared	-10.263345	S.D. dependent var	0.017998
S.E. of regression	0.060404	Sum squared resid	0.040134
Durbin-Watson stat	2.597763	J-statistic	1.83E-21
Instrument rank	10		

Figure 3.14: Estimation of the new aggregate consumption function from 1995 to 2017 Adding households debt and the interaction between the debt and the p90p10 index

Dependent Variable: DLOG(CHO)
Method: Two-Stage Least Squares
Date: 11/21/19 Time: 15:13
Sample (adjusted): 1971 2017
Included observations: 47 after adjustments
DLOG(CHO) = C(4*10+0) +C(4*10+1)*DLOG(YDHN/PCH) +C(4*10+2)
*DLOG(YDHN(-1)/PCH(-1)) +C(4*10+3)*LOG(CHO(-1)*PCH(-1)/YDHN(
-1)) +C(4*10+4)*DLOG(1+INTR(-1)/100) +C(4*10+5)*DLOG(HWFA(-1)
/YDHN(-1))
Instrument specification: C DLOG(YDHN/PCH) DLOG(YDHN(-1)/PCH(-1))
LOG(CHO(-1)*PCH(-1)/YDHN(-1)) DLOG(1+INTR(-1)/100)
DLOG(HWFA(-1)/YDHN(-1)) DLOG(CHO(-1))

	Coefficient	Std. Error	t-Statistic	Prob.
C(40)	-0.001722	0.003188	-0.540035	0.5921
C(41)	0.494746	0.104362	4.740681	0.0000
C(42)	0.272697	0.102082	2.671346	0.0108
C(43)	-0.090195	0.037330	-2.416150	0.0202
C(44)	-0.294771	0.109680	-2.687543	0.0104
C(45)	0.056656	0.037614	1.506239	0.1397

R-squared	0.755664	Mean dependent var	0.019256
Adjusted R-squared	0.725867	S.D. dependent var	0.025712
S.E. of regression	0.013462	Sum squared resid	0.007430
Durbin-Watson stat	2.131473	J-statistic	0.234237
Instrument rank	7	Prob(J-statistic)	0.628400

Figure 3.15: Estimation of the MeMo-It aggregate consumption function from 1969 to 2017

Dependent Variable: DLOG(CHO)
Method: Two-Stage Least Squares
Date: 11/21/19 Time: 15:12
Sample: 1997 2017
Included observations: 21
DLOG(CHO) = C(4*10+0) +C(4*10+1)*DLOG(YDHN/PCH) +C(4*10+2)
*DLOG(YDHN(-1)/PCH(-1)) +C(4*10+3)*LOG(CHO(-1)*PCH(-1)/YDHN(
-1)) +C(4*10+4)*DLOG(1+INTR(-1)/100) +C(4*10+5)*DLOG(HWFA(-1)
/YDHN(-1))
Instrument specification: C DLOG(YDHN/PCH) DLOG(YDHN(-1)/PCH(-1))
LOG(CHO(-1)*PCH(-1)/YDHN(-1)) DLOG(1+INTR(-1)/100)
DLOG(HWFA(-1)/YDHN(-1)) DLOG(CHO(-1))

	Coefficient	Std. Error	t-Statistic	Prob.
C(40)	-0.004274	0.002462	-1.736182	0.1030
C(41)	0.349367	0.100275	3.484097	0.0033
C(42)	0.462075	0.101452	4.554640	0.0004
C(43)	-0.253822	0.130078	-1.951303	0.0700
C(44)	-0.177441	0.153162	-1.158513	0.2648
C(45)	0.103832	0.026469	3.922797	0.0014

R-squared	0.895804	Mean dependent var	0.007078
Adjusted R-squared	0.861071	S.D. dependent var	0.017998
S.E. of regression	0.006708	Sum squared resid	0.000675
Durbin-Watson stat	1.780611	J-statistic	3.307168
Instrument rank	7	Prob(J-statistic)	0.068978

Figure 3.16: Estimation of the MeMo-It aggregate consumption function from 1995 to 2017

Dependent Variable: DLOG(CHO)
Method: Two-Stage Least Squares
Date: 11/22/19 Time: 12:51
Sample (adjusted): 1997 2017
Included observations: 21 after adjustments
DLOG(CHO) = C(4*10+0) +C(4*10+1)*DLOG(YDHN/PCH) +C(4*10+2)
*DLOG(YDHN(-1)/PCH(-1)) +C(4*10+3)*LOG(CHO(-1)*PCH(-1)/YDHN(
-1)) +C(4*10+4)*DLOG(1+INTR(-1)/100) +C(4*10+5)*DLOG(HWFA(-1)
/YDHN(-1)) +C(4*10+6)*D(P90P10_YD(-1)) + C(4*10+7)*D2011
Instrument specification: C DLOG(YDHN/PCH) DLOG(YDHN(-1)/PCH(-1))
LOG(CHO(-1)*PCH(-1)/YDHN(-1)) DLOG(HWFA(-1)/YDHN(-1))
DLOG(CHO(-1)) D(P90P10_YD(-1)) DLOG(1+INTR(-1)/100) D2011

	Coefficient	Std. Error	t-Statistic	Prob.
C(40)	-0.004804	0.002167	-2.216884	0.0451
C(41)	0.450962	0.099129	4.549263	0.0005
C(42)	0.383039	0.101217	3.784324	0.0023
C(43)	-0.261730	0.115028	-2.275369	0.0405
C(44)	-0.167442	0.134101	-1.248626	0.2338
C(45)	0.123376	0.024370	5.062686	0.0002
C(46)	-0.044861	0.021453	-2.091194	0.0567
C(47)	0.013743	0.006615	2.077719	0.0581

R-squared	0.930909	Mean dependent var	0.007078
Adjusted R-squared	0.893707	S.D. dependent var	0.017998
S.E. of regression	0.005868	Sum squared resid	0.000448
Durbin-Watson stat	1.518578	J-statistic	1.705830
Instrument rank	9	Prob(J-statistic)	0.191527

Figure 3.17: Estimation of the new aggregate consumption function from 1995 to 2017

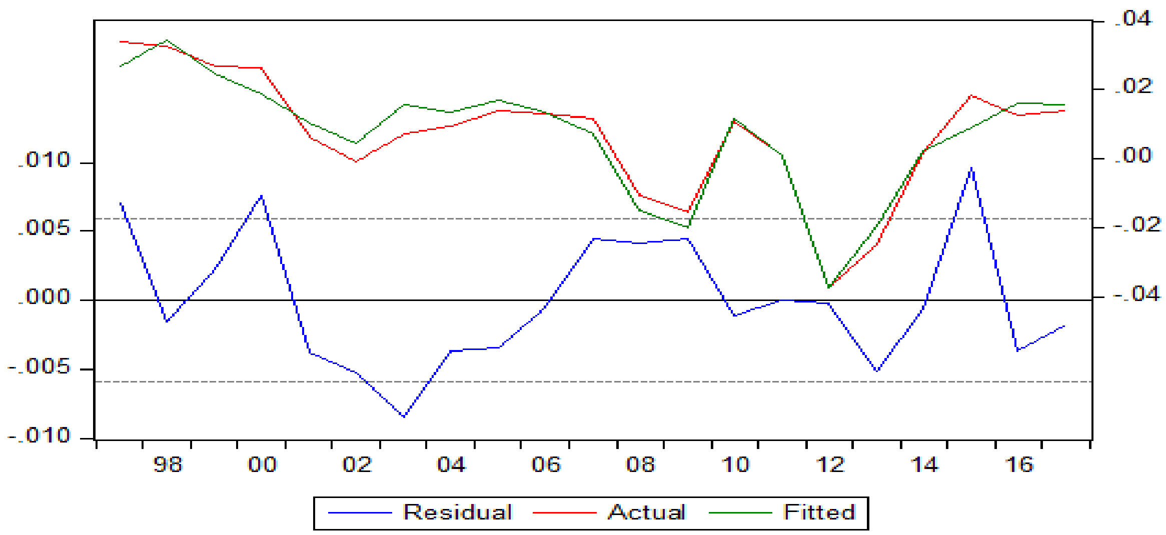

Figure 3.18: Actual values, residuals and fitted values of the new consumption function

Dependent Variable: DLOG(CHO)
Method: Two-Stage Least Squares
Date: 11/22/19 Time: 12:38
Sample (adjusted): 1997 2017
Included observations: 21 after adjustments
DLOG(CHO) = C(4*10+0) +C(4*10+1)*DLOG(YDHN/PCH) +C(4*10+2)
*DLOG(YDHN(-1)/PCH(-1)) +C(4*10+3)*LOG(CHO(-1)*PCH(-1)/YDHN(
-1)) +C(4*10+4)*DLOG(1+INTRBTP(-1)/100) +C(4*10+5)
*DLOG(HWFA(-1)/YDHN(-1)) +C(4*10+6)*D(P90P10_YD(-1)) + C(4*10
+7)*D2011 + C(4*10+8)*D(BLOOM_IT(-1))
Instrument specification: C DLOG(YDHN/PCH) DLOG(YDHN(-1)/PCH(-1))
LOG(CHO(-1)*PCH(-1)/YDHN(-1)) DLOG(HWFA(-1)/YDHN(-1))
DLOG(CHO(-1)) D(P90P10_YD(-1)) D2011 D(BLOOM_IT(-1)) DLOG(1
+INTRBTP(-1)/100)

	Coefficient	Std. Error	t-Statistic	Prob.
C(40)	-0.003972	0.002016	-1.970442	0.0723
C(41)	0.347615	0.102061	3.405966	0.0052
C(42)	0.396448	0.091946	4.311751	0.0010
C(43)	-0.191367	0.113620	-1.684269	0.1179
C(44)	-0.415687	0.185947	-2.235507	0.0452
C(45)	0.108092	0.023488	4.602051	0.0006
C(46)	-0.050679	0.019620	-2.583093	0.0240
C(47)	0.014563	0.006008	2.424114	0.0321
C(48)	-7.81E-05	5.68E-05	-1.374940	0.1943

R-squared	0.947567	Mean dependent var	0.007078
Adjusted R-squared	0.912612	S.D. dependent var	0.017998
S.E. of regression	0.005321	Sum squared resid	0.000340
Durbin-Watson stat	1.731108	J-statistic	0.619177
Instrument rank	10	Prob(J-statistic)	0.431353

Figure 3.19: Estimation of the new aggregate consumption function from 1995 to 2017 substituting the short-run interest rate with the bloom index and the long-run interest rate

		2019	2020
SCENARIO 1:	GDP	0.2	0.1
	CHO	0.2	0.3
	PCH	0	0.1
SCENARIO 2:	GDP	0.2	0.4
	CHO	0.2	1.1
	PCH	0	0.2

Figure 3.20: Effects of the Italian *Reddito di Cittadinanza* on GDP, real private consumption (CHO) and consumption deflator with respect to the base scenario in percentage points (pp)

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