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Reported MPC and Unobserved Heterogeneity

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Reported MPC and Unobserved Heterogeneity

Tullio Jappelli[*] and Luigi Pistaferri[**]

Abstract
We use panel data on reported marginal propensity to consume (MPC) in the 2010 and 2016 Italy's Survey of Household Income and Wealth. We uncover a strong negative relationship between cash-on-hand and MPC. This relation is attenuated by using regression methods that control for unobserved heterogeneity. The estimates are used to show that the effectiveness of revenue-neutral fiscal policies is much weaker relative to a case in which both observed and unobserved heterogeneity are not taken into account, particularly for policies that target the bottom part of the distribution of household resources.

Keywords: Transitory Income Shocks; Marginal Propensity to Consume; Panel Data.

JEL Classification: D12, D14, E21

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Introduction

An important parameter for evaluating the effectiveness of fiscal policy and for distinguishing between competing models of consumption is the marginal propensity to consume (MPC). Most literature measures the MPC using structural models or quasi-experiments (see Jappelli and Pistaferri, 2017, chapter 9, for a survey). A new wave of papers rely instead on a more direct measurement. The main advantage of this approach is that it does not require to take a stand on specific income processes or consumption models.

In particular, Shapiro and Slemrod (1995; 2003) pioneered the idea of eliciting the MPC from transitory income shocks using survey questions. Their approach is to ask respondents about *actual* income changes experienced due to specific tax stimulus programs. A complementary approach is to use survey questions asking respondents to report their MPC in response to *hypothetical* income changes, as in Jappelli and Pistaferri (2014). One key difference between these two papers is that while Shapiro and Slemrod (1995) rely on qualitative responses, in Jappelli and Pistaferri (2014) people report quantitative information about the MPC. Recent contributions further distinguish between reported MPC in response to positive and negative transitory income shocks and between shocks of different magnitude (Christelis et al., 2018; Fuster et al., 2017; Bunn et al., 2017).

The common finding of these papers is that there is wide heterogeneity in reported MPC, in contrast with the uniformity predicted by macroeconomic models based on representative agents. Moreover, papers using quantitative MPC questions find a negative relationship between reported MPC and measures of household resources, implying that the rich have smaller MPC than the poor. The evidence using qualitative MPC questions is, however, less clear-cut. The most natural way to interpret the negative relation between MPC and household resources is to consider models with precautionary saving and liquidity constraints, which generate a concave consumption function, as opposed to the standard PIH which predicts a linear consumption function, see Deaton (1991) and Carroll (1996). Another finding from the literature consistent with concavity is that the MPC from negative shocks is larger than the MPC from positive shocks, because liquidity constrained households can partially overcome the constraint if the income change is large enough.

One major issue with this evidence and approach is that they are based on cross-sectional data, where respondents are asked only once about actual or hypothetical income changes. In principle, both MPC heterogeneity and the negative association between MPC and household resources might be consistent with models with linear consumption function and preference heterogeneity. To see this point, suppose that the consumption function of each individual is linear, but that there is unobserved heterogeneity in "taste for saving" (due to, say, different discount rates or different propensities to leave bequests).[1] This would imply that people with high taste for savings have a flatter consumption function (a lower, but constant MPC) than people with low taste for savings (a higher, but still constant MPC). At the same time, people with high taste for savings have accumulated more wealth in the past and therefore have higher cash-on-hand (defined as current income plus wealth) than people with low taste for saving, other things being equal. This combination of preference and resource heterogeneity generates a negative relation between MPC and cash-on-hand even when the consumption function of each individual is linear.

To identify the shape of the consumption function while controlling for unobserved heterogeneity, one needs panel data on reported MPC and cash-on-hand. In this paper, we achieve this goal by relying on the panel structure of the Italian Survey of Household Income and Wealth (SHIW). In the 2010 SHIW individuals report how much they would consume of a hypothetical, unanticipated, and transitory income change equivalent to a one-month increase in disposable income. Crucially, a group of households interviewed in 2010 are also re-interviewed in 2016, thus offering longitudinal data on MPC, cash-on-hand, and other demographic variables.

The paper proceeds as follows. In Section 2 we summarize the literature that uses direct survey questions to measure the MPC. In Section 3 we describe our panel data and compare the MPC distribution in 2010 and 2016. In Section 4 we first discuss the estimate of the relationship between MPC and cash-on-hand with cross-sectional data, for comparison with what is typically done in the literature. We find that the MPC declines quite significantly with cash-on-hand. For example, moving from the 10^{th} to the 90^{th} percentile of the cash-on-hand distribution is associated with a reduction of the MPC by about 16 percentage points. Next, we use the panel structure of the SHIW to estimate the sensitivity of MPC with respect to cash-on-hand controlling for unobserved heterogeneity. We find that OLS exaggerates the negative relationship between the two variables by around 20%, supporting the idea that unobserved factors correlated with cash-on-hand account for part of the

[1] For instance, models with income risk and quadratic or exponential utility (allowing negative consumption) imply a linear relation between consumption and cash-on-hand.

relationship. To follow up on the same example, going from the 10th to the 90th percentile of the cash-on-hand distribution would reduce the MPC by about 13 percentage points. This main finding is robust to various sensitivity checks regarding the specific functional form of the relation between MPC and cash-on-hand, sample selection, additional covariates and quality of the interviews. Section 5 uses the estimates of the relationship between MPC and cash-on-hand to calculate the impact of a revenue neutral redistributive fiscal policy on aggregate consumption, showing how unobserved heterogeneity can attenuate the impact of fiscal shocks. Section 6 summarizes the evidence and concludes.

2. The direct survey approach

The direct survey approach to evaluate the impact of fiscal shocks on consumption consists of asking direct questions on how consumers have reacted to actual income changes, or asking them to report how they would respond to hypothetical income changes. Shapiro and Slemrod (1995) pioneered asking direct questions in the Michigan *Survey of Consumers.* These questions elicited, in a qualitative format ("mostly spend", "mostly save"), the consumer response to the Bush administration's 1992 change in tax withholding. Subsequent work used similar type of questions focusing on spending in response to the various tax rebates and tax credit interventions taking place in the US in the past two decades (Shapiro and Slemrod, 2003 and 2009; Sahm et al. 2010, 2012). These studies find that consumers differ in reported MPC along many margins; however, the relationship between MPC and measures of household resources is typically non-monotonic and many households appear to use rule-of-thumb behavior to respond to fiscal policy.

Another way to elicit the MPC is to confront consumers with hypothetical scenarios in which income changes unexpectedly. Jappelli and Pistaferri (2014) use Italian survey data from the 2010 SHIW where consumers were asked to report, quantitatively, the fraction of an income shock (a hypothetical tax rebate) that they would consume or save. They find considerable heterogeneity in the reported MPC and a strong negative relation between MPC and cash-on-hand.

Three recent papers rely on direct survey questions to study asymmetric responses, i.e., whether the consumption response to a hypothetical income shock varies with the size and direction of the shock itself. Christelis et al. (2018) rely on a representative sample of Dutch households from the CentER Internet panel. Respondents are asked to report how much their consumption would change in response to unexpected, transitory income shocks of different sign (positive and negative). The Dutch questionnaire also distinguishes between relatively small income changes (a one-month increase or drop in income), and relatively larger ones (a three-month increase or drop in income). These data indicate that consumers react more to negative income changes than to positive changes, and that the MPC from positive income shock tends to be larger when the shock is relatively small.

Bunn et al. (2017) use a set of questions in the Bank of England/NMG Consulting Survey and find that British households tend to change their consumption by significantly more in reaction to temporary and unanticipated falls in income than to increases in income of the same size. They also find that low liquid wealth relative to income is associated with higher MPC in response to negative shocks than positive shocks. Fuster et al. (2018) use data from the NY Fed's Survey of Consumer Expectations. In this survey, respondents report how they would adjust their spending over the next quarter in response to receiving or losing dollar amounts ranging from \$500 to \$5,000. As Bunn et (2017) and Christelis et al (2018), they find that the MPC from negative income shocks is greater than the MPC from positive shocks, and that the MPC is lower for high income and high wealth households.

One way to validate the informational content of MPC based on hypothetical questions is to see if planned consumption decisions are confirmed by actual consumption choices. Graziani et al. (2016) compare ex ante and ex post reported use of the extra income accruing from the 2011 US payroll tax cuts, and find that workers intend to spend less than they actually do. In contrast, Parker and Souleles (2017) investigate the same issue, comparing reported responses to hypothetical tax rebates with actual spending responses from past tax rebates and stimulus payments, and conclude that the two approaches yield similar estimates of the MPC.

3. The data

The SHIW is a biannual, representative sample of the Italian resident population. The surveys cover 7,951 households in 2010 and 7,416 households in 2016 and provide detailed information on demographic variables, income, consumption, wealth (broken down into real assets and various components of financial assets and debt). The survey has also a rotating panel component: each year close to 50% of the sample is composed of households interviewed in the previous wave, while 50% represents new interviews.

For the present study, in particular, 2,138 households interviewed in 2010 were also interviewed in 2016.[2] To make sure that the question on hypothetical income change is answered by the same person, our panel sample further selects households with a stable demographic structure (the same household head and no change in marital status across the two waves). We end up with an estimation panel sample of 1,727 households.

To estimate the relation between MPC and cash-on-hand, we rely on the following question posed to respondents in the 2010 and 2016 SHIW:

"Imagine you unexpectedly receive a reimbursement equal to the amount your household earns in a month. How much of it would you save and how much would you spend? Please give the percentage you would save and the percentage you would spend."

While the term "reimbursement" may have different interpretations, we assume that people interpret the survey question as referring to a nontaxable transfer, such as a government bonus. In Jappelli and Pistaferri (2014) we use the 2010 wave and discuss pros and cons of the survey question. The main advantage is that it provides quantitative estimate of the MPC at the individual level, thus anchoring responses in an objective way rather than having to rely on a qualitative and subjective scale of the "mostly spend/mostly save" type of questions. Several caveats are also in order: (i) the question does not distinguish between consumption and spending; (ii) the survey was fielded during a deep recession and responses may be different during normal times or expansions; (iii) it may be hard for some people to answer these type of questions and actual MPC may differ from the reported ones, and (iv) the survey question offers no period of reference for the planned spending (i.e., 12 months, etc.).

Figure 1 plots the histogram of the cross-sectional distribution of reported MPC in the two waves using all sample observations (7,951 households in 2010 and 7,416 in 2016). The

[2] The survey was also conducted in 2012 and 2014, but MPC questions are comparable only in the 2010 and 2016 waves. Data are collected through personal interviews. Questions concerning the whole household are addressed to the household head or the person most knowledgeable about the family's finances. Questions on individual incomes are answered by the individual household member. The unit of observation is the family, defined as including all persons residing in the same dwelling who are related by blood, marriage, or adoption. Individuals described as "partners or other common-law relationships" are also treated as family members.

figure shows that the two distributions are remarkably similar, supporting the reliability and information content of the data. The sample averages of the individual MPC is 48% in 2010 and 47% in 2016. Both distribution exhibit heaping at 0%, 50% and 100%. In particular, in 2010, heaping at these three values is 22%, 24% and 16%, respectively; in 2016, the values are slightly larger, at 24%, 27% and 17%.

Table 1 provides descriptive statistics on the cross-sectional and panel samples we use in the regression analysis below, separately for 2010 and 2016. To conform with the survey question (which refer to a one-month income change), we define cash-on-hand as the sum of monthly income and the stock of financial assets (transaction accounts, mutual funds, stocks, outstanding claims, and corporate and government bonds), net of consumer debt. This definition of cash-on-hand is in line with Kaplan and Violante (2014), who argue that consumption in the short-run is more strongly related to the liquid portion of total wealth since real estate can be liquidated only by incurring in high transaction costs.

Monetary variables are expressed in 2016 euro using the CPI. Table 1 shows that the cross-sectional sample does not differ appreciably from the longitudinal sample in basic demographic characteristics such as age, gender, etc. Households in the panel sample have slightly more schooling and are more likely to live in the North, which likely drive the difference in economic resources (cash-on-hand, income, and financial assets). Respondents also report whether they have been turned down for credit or were discouraged from applying for credit in the past 12 months. We use this information to construct an indicator of liquidity constraints. In the 2010 wave, which was conducted in the middle of a deep recession, 5% report to be liquidity constrained as opposed to 2% in 2016.

Figure 2 starts delving in the relationship between MPC and cash-on-hand, again separately for the 2010 and 2016 waves. We allocate households to percentiles of the cash-on-hand distribution and plot the average MPC for each percentile together with a univariate regression line. The MPC declines quite significantly with cash-on-hand in each cross-section. In 2010, a move from the 10th to the 90th percentile of the cash-on-hand distribution is associated with a reduction of the MPC of about 25 percentage points. In 2016, the same move is associated with a 18 percentage points decline in the MPC. In the next section, we use a regression framework to estimate the sensitivity of the MPC to cash-on-hand using both the pooled cross-sections, as well as the panel sample.

4. Regression evidence

To interpret the regression estimates, let's consider the following regression for the MPC:

$$MPC_{it} = \alpha + \beta X_{it} + f_i + \nu_{it} \tag{1}$$

where X_{it} is cash-on-hand (or cash-on-hand percentile) of individual i in period t, f_i is unobserved heterogeneity potentially correlated with cash-on-hand, and ν_{it} is an i.i.d. error term capturing classical measurement error in reported MPC. For simplicity, we omit exogenous and observable variables from equation (1), such as age, education, etc. However, we fully control for such characteristics in the regression analysis.

The relationship (1) nests several consumption models. In the PIH with quadratic utility and homogeneous preferences, the MPC is constant and hence $\beta = 0$. In models with precautionary savings and/or liquidity constraints, the consumption function is concave and therefore the MPC is higher at low levels of economic resources, implying $\beta < 0$. A further reason for observing a negative relation is a non-homothetic bequest motive, for instance treating intergenerational transfers as a luxury goods in models where utility depends on terminal wealth. In support of the concavity of the consumption function, most papers (using cross-sectional data and OLS estimation) find $\hat{\beta}_{OLS} < 0$. In column (1) of Table 2 we confirm these findings pooling data from 2010 and 2016, as $\hat{\beta}_{OLS} = -0.266$. This coefficient estimate implies that a move from the 10th to the 90th percentile of the cash-on-hand distribution is associated with a 21 percentage points decline in the average MPC.

However, in the presence of unobserved heterogeneity potentially correlated with cash-on-hand, the OLS estimate of $\beta$is biased and inconsistent. From regression (1), the bias can be inferred by computing the probability limit of $\hat{\beta}_{OLS}$:

$$plim\, \hat{\beta}_{OLS} = \beta + \frac{cov(X_{it}, f_i)}{var(X_{it})}$$

The expression above shows that the bias generated by unobserved heterogeneity (if it exists) depends on the sign and magnitude of the covariance term $cov(X_{it}, f_i)$. Suppose that f_i

represents unobserved differences in rates of time preference, implying that people with high values of f_i have high tastes for current consumption. Since people with high rates of time preference have a tendency to report high MPC and may be more likely to have low cash-on-hand, it follows that $cov(X_{it}, f_i) < 0$. Therefore, $\hat{\beta}_{OLS}$ will be greater (in absolute value) than the true β and the OLS estimate will exaggerate the impact of cash-on-hand on the MPC. A policy-maker who wants to forecast the impact of an expansionary fiscal policy targeting low income households using $\hat{\beta}_{OLS}$, will predict larger effects than typically produced once the policy is in place.

With panel data, one can eliminate the bias by differencing the relationship (1), and hence estimate:[3]

$$\Delta MPC_{it} = \beta \Delta X_{it} + \Delta v_{it} \qquad (2)$$

The top panels of Figure 3 report the histograms of the dependent and independent variables of equation (2), the change in the MPC (the left panel) and the change in the percentile of cash-on-hand (the right panel). There is much less heaping in the distribution of changes in MPC than in the level of MPC in the cross-sectional distribution of Figure 1. There is also considerable mobility in the cash-on-hand distribution, which is useful for identification purposes. In the bottom panel of Figure 3 we plot the change in MPC against the change in the percentile of cash-on-hand together with a regression line, a way of describing graphically the relation in equation (2). The estimated coefficient (reproduced in column (2) of Table 2) is -0.16, implying that a move from the 10th to the 90th percentile of the cash-on-hand distribution is associated with a 13 percentage points reduction in the MPC, significantly less than the 21 percentage points decline we found when using OLS. This suggests that unobserved heterogeneity may potentially account for a substantial portion of the correlation between MPC and cash-on-hand estimated with cross-sectional data.

Some of the bias may be due to failure to control for observable characteristics correlated with cash-on-hand. In the remaining columns of Table 2 we provide estimates of β

[3] Christelis et al. (2018) control for unobserved heterogeneity by considering within-person differences in MPC. This is because the same person responds to questions eliciting the MPC with respect to income changes of different sign and magnitude. Their approach can only identify *differences* in the sensitivity of MPC with respect to cash-on-hand across different scenarios (of income changes of different sign and size). However, the policy-relevant parameter (the *actual* sensitivity of MPC with respect to cash-on-hand) is not identified, and can only be estimated using genuine panel data, as we do in this paper.

obtained after introducing in the regression a rich set of demographic and socio-economic characteristics of survey participants. In particular, besides the percentile of cash-on-hand, we include age dummies, gender, marital status, years of schooling, residence in the South and large city, family size, a dummy for unemployment and an indicator for credit constraints. Columns (3) and (4) report OLS estimates on the pooled cross-sectional sample (15,366 observations) and on the longitudinal sample (3,452 observations), respectively. The last column of Table 2 reports fixed effect estimates. Given that we have only two years of data, fixed effect estimates coincide with OLS first difference estimates.

Column (3) indicates that the estimate of $\beta = -0.197$ is quite precisely measured. Comparison of columns (1) and (3) suggests that a considerable share of the association between MPC and cash-on-hand can be attributed to the omission of observables. The estimated coefficients indicate that the MPC is lower for married couples, higher for households with higher education, is 11 percentage points higher for households living in the South and 9 percentages point higher in large cities, and that it increases with family size. It is also significantly higher (6.4 percentage points) if the head is unemployed. As for age, we find that the MPC is negatively associated with it. The standard life-cycle model predicts that the young should report a lower MPC since they have a longer horizon; however, there might be cohort effects working in the opposite direction, for instance, because younger generations might have lower discount factors. In general, the effect of age on the MPC is hard to interpret since it is not feasible to separate age and cohort effects in cross-sectional data. Finally, the coefficient of the credit constraint dummy is not statistically different from zero.

Column (4) replicates the specification of column (3) on the panel sample. The estimate of $\beta = -0.182$, which is again precisely estimated and not statistically different from the estimate in column (3). The pattern of the other coefficients is similar to the full sample estimates, but as expected standard errors tend to be larger given the reduced number of observations.

In column (5) we report fixed effect estimates. The main coefficient of interest is $\beta = -0.158$. The first remarkable result is that the relation between MPC and cash-on-hand is negative and significant even controlling for unobserved heterogeneity. The second important result is that unobserved heterogeneity reduces the sensitivity of MPC with respect to cash-on-hand by about 20% (1-(0.158/0.197)). The third result is that the gap between cross-sectional and panel estimates of β is consistent with $cov(X_{it}, f_i) < 0$, namely that people with high taste for current composition (as reflected in higher MPC) also tend to have relatively lower cash-on-hand.

In Table 3 we use two different measures of cash-on-hand to check the robustness of our baseline estimates. In columns (1)-(3) we replace the percentile of cash-on-hand with the log of cash-on-hand itself. The sensitivity of MPC with respect to log cash-on-hand is -0.037 in the pooled OLS estimates, essentially unchanged in the panel sample, and -0.030 (again a 20% decline in absolute value) with the fixed effect estimator. In columns (4)-(6) we break down cash-on-hand into quintiles to check for possible non-linear effects of cash-on-hand on MPC. The pattern of the coefficients suggests a monotonically declining relation, ranging from 0 (the excluded first quintile) to -0.157 (the top 20% group). There is mild evidence of non-linearity, as the effect of cash-on-hand on MPC is stronger at low than at high levels of cash-on-hand. Moreover, the estimates are all significantly different from zero. The OLS estimates in the panel sample essentially mirror those in the whole sample. Finally, the fixed effect estimates confirm a monotonic relationship, but weaker from both a statistical and quantitative point of view, with the estimates ranging from 0 (for the excluded first quintile) to -0.123 (the top quintile).

Finally, in Table 4 we break down cash-on-hand percentiles separately into income and financial wealth percentiles. Column (1) shows that there is a negative gradient between both income and financial assets and cash-on-hand. Comparing columns (1) and (3), it appears that both variables, contribute to the exaggeration effect of cross-sectional OLS estimates; if one compares columns (2) and (3), the exaggeration effect is mostly due to income .

We check that our main findings are robust to sample selection focusing on a sample of household heads younger than 60. We also control for real estate wealth and debt, which may create overhang effects (Dynan, 2012). Finally, we verify that the results do not depend on the quality of the interview or for the ability to understand the survey questions, using a set of indicators provided by the survey interviewer at the end of each one-to-one personal interview. All these checks leave the pattern of results qualitatively unchanged: controlling for fixed effects attenuates the sensitivity of MPC with respect to cash-on-hand. These additional results are available upon request.

5. Fixed effects at work in a simulated fiscal experiment

One way of assessing the implications of unobserved heterogeneity for the estimation of the MPC is to simulate the macroeconomic impact of a revenue neutral fiscal reform. We consider a policy that transfers the equivalent of 1% of national income (in equal amounts) to the bottom x% of the cash-on-hand distribution. The policy is financed by taxing the top 10% of the cash-on-hand distribution (in the form of a lump-sum tax). In models with a homogenous MPC, such as the PIH with certainty equivalence and no liquidity constraints, this redistributive policy has no aggregate effects (absent labor supply and general equilibrium effects).

Consider a policy-maker who is trying to forecast the impact of the policy using estimates of the relationship between MPC and cash-on-hand. A naive policy-maker would simply multiply the average reported MPC at each cash-on-hand percentile, i.e., the estimated $E(MPC_{it}|X_{it})$ from column (1) of Table 2, by the transfer received/tax paid and aggregate the corresponding consumption change. This is the calculation reported in the first column of Table 5. Transferring resources only to the bottom 10% would boost aggregate consumption by 0.33% because the poor report higher MPC than the rich. Reducing the average size of the transfer by increasing the number of recipients would increase aggregate consumption by 0.28% (targeting the bottom quartile), 0.21% (if households below the median are targeted), and so forth.

However, cash-on-hand correlates with many variables, so that one should consider that differences in MPC by cash-on-hand party reflect such correlation. To isolate the effect of cash-on-hand on MPC controlling for *observable* characteristics, one should perform the experiment using the predicted MPC obtained from the OLS regression reported in column (3) of Table 2, i.e. $E(MPC_{it}|X_{it}, Z_{it})$, where Z_{it} are observable characteristics. This is what we do in column (2) of Table 5, showing that there is substantial attenuation of the aggregate effect of the redistributive policy. For instance, transferring 1% of national income to the bottom decile of the cash-on-hand distribution would boost aggregate consumption by only 0.23% (down from 0.33%). There is a similar pattern if the transfer is more diffuse.

Still, the conditional correlation between MPC and cash-on-hand may be affected by *unobserved* heterogeneity (such as preferences), as argued above. For the final experiment, one should rely on the predicted value of the MPC obtained from the fixed effect regression reported in column (5) of Table 2, i.e., use $E(MPC_{it}|X_{it}, Z_{it}, f_i)$. The results, reported in column (3) of Table 5, show that the aggregate consumption effect of the redistributive policy is further attenuated with respect to the case in which unobserved heterogeneity is ignored. For instance, the boost in aggregate consumption is 0.19% for the most concentrated transfer policy that targets the bottom decile. Note that comparison of columns (1) and (3) across the size of groups targeted by the policy reveals that the bias induced by neglecting heterogeneity (both observed and unobserved) is higher when the targets are the bottom decile or quartile than when the policy is more diffuse. The reason is that people at the bottom of the cash-on-hand distribution are also more likely to report high MPC (as revealed by OLS regression estimates), given their characteristics: they are more likely to be unemployed, living in large cities or in the South, or being young. At the same time, people at the bottom of the cash-on-hand distribution are also more likely to have preferences for current consumption, as revealed by the difference between cross-sectional and panel estimates.

Finally, it is worth stressing that all these calculation neglect general equilibrium effects (deriving, e.g., from changes in interest rates), and are therefore likely to provide an upper bound to the true effects of redistributive fiscal policies.

6. Summary

In this paper we analyze reported MPC from hypothetical income change questions posed to participants to the 2010 and 2016 Italy's Survey of Household Income and Wealth. We confirm findings from the existing literature, such as considerable heterogeneity in MPC as well as a negative association between it and cash-on-hand, consistent with models of consumption with precautionary savings and liquidity constraints. One limitation of the studies that use survey-based reported MPC is that they rely on cross-sectional data. However, some of the association between MPC and cash-on-hand could be spurious, and attributable to unobserved heterogeneity. A unique feature of the SHIW is that the same hypothetical MPC question is available in two waves (2010 and 2016) and that the survey itself has a sizable longitudinal component. This allows us to use standard panel data estimation methods to purge the effect of cash-on-hand on MPC by fixed unobserved heterogeneity.

Comparison of cross-sectional and panel data estimation reveals that unobserved heterogeneity exaggerates the sensitivity of MPC to cash-on-hand by roughly 20%. In the last part of the paper we study the implications of such bias for the effectiveness of revenue neutral redistributive fiscal policies. We find that such policies have less impact on aggregate consumption once unobserved heterogeneity is control for, in particular for policies that target the bottom part of the distribution of household resources.

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Figure 1. Histogram of the distribution of reported MPC, 2010 and 2016

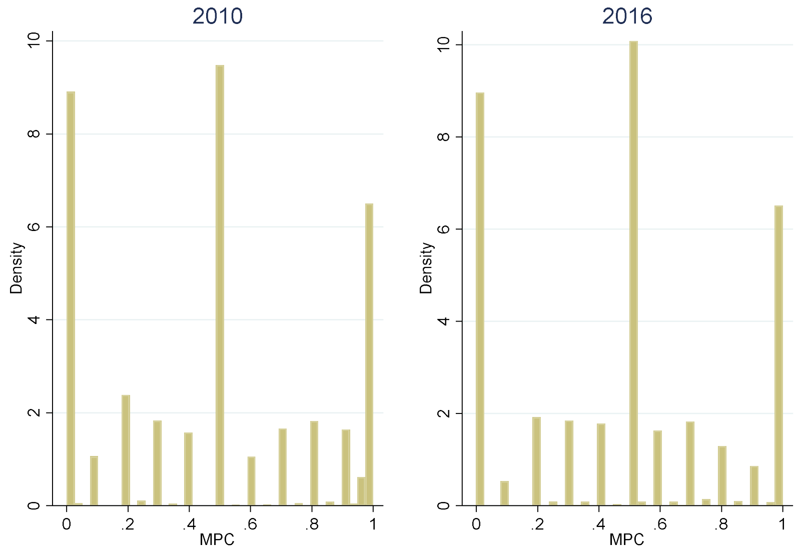

Figure 2. The relationship between MPC and cash-on-hand, 2010 and 2016

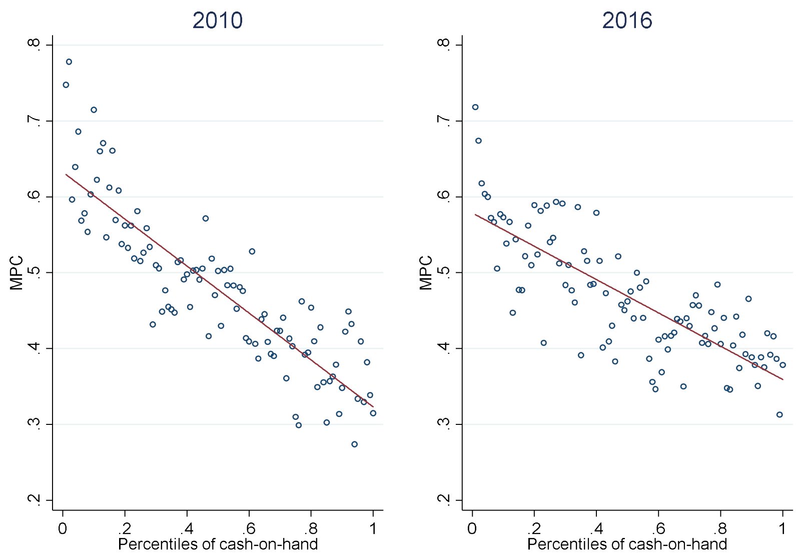

Figure 3. Panel data evidence: The distribution of the change in MPC and the relation between the change in the MPC and the change in cash-on-hand

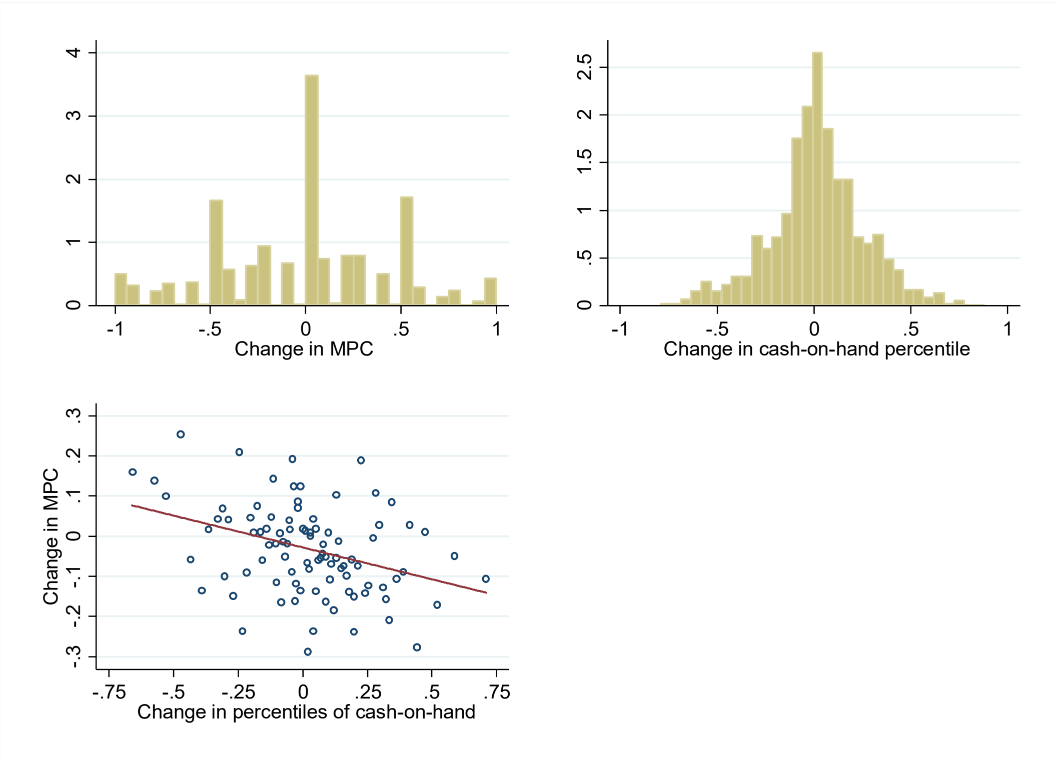

Table 1. Descriptive statistics

Sample	*2010, All*		*2010, Panel*		*2016, All*		*2016, Panel*	
Statistics	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
MPC	0.48	0.36	0.48	0.36	0.47	0.35	0.45	0.35
Age	58.37	15.76	58.35	13.77	62.17	15.67	64.35	13.77
Male	0.55	0.50	0.55	0.50	0.53	0.50	0.55	0.50
Married	0.62	0.49	0.65	0.48	0.53	0.50	0.65	0.48
Years of education	9.58	4.60	10.03	4.58	9.69	4.45	10.04	4.48
Resident in the South	0.32	0.47	0.36	0.48	0.33	0.47	0.36	0.48
Family size	2.50	1.26	2.60	1.27	2.22	1.21	2.39	1.22
Large city	0.09	0.29	0.06	0.24	0.08	0.28	0.06	0.24
Cash-on-hand (€1,000)	34.40	106.24	39.89	107.23	33.36	133. 74	39.42	103.13
Income (€1,000)	2.95	2.19	3.14	2.21	2.54	1.90	2.84	2.07
Financial assets (€1,000)	31.45	105.21	36.74	106.00	30.82	133.06	36.58	102.18
Unemployed	0.04	0.19	0.04	0.20	0.06	0.23	0.04	0.20
Liquidity constrained	0.05	0.21	0.03	0.18	0.02	0.14	0.02	0.13
N	7950		1726		7416		1726	

Note. The table reports sample statistics for 2010 and 2016 SHIW, and for the subsamples used in panel estimation.

Table 2. MPC regressions using percentiles of cash-on-hand

	All OLS	Panel sample Fixed effects	All OLS	Panel sample OLS	Panel sample Fixed effects
	(1)	(2)	(3)	(4)	(5)
Age <=30			0.052	0.026	-0.028
			(0.017)***	(0.051)	(0.097)
Age 30-45			0.036	0.017	0.004
			(0.009)***	(0.021)	(0.051)
Age 45-60			0.030	0.029	0.020
			(0.007)***	(0.015)**	(0.031)
Years of education			0.002	0.002	-0.001
			(0.001)***	(0.001)	(0.008)
Male			-0.005	-0.021	
			(0.006)	(0.013)*	
Married			-0.017	-0.017	
			(0.007)**	(0.016)	
Resident in the South			0.113	0.119	
			(0.006)***	(0.013)***	
Family size			0.014	0.022	-0.002
			(0.003)***	(0.007)***	(0.016)
City size >500,000			0.087	0.054	-0.064
			(0.010)***	(0.024)**	(0.263)
Unemployed			0.064	0.044	-0.041
			(0.014)***	(0.030)	(0.052)
Credit constrained			-0.012	0.071	0.005
			(0.015)	(0.037)*	(0.052)
Percentiles of cash-on-hand	-0.266	-0.165	-0.197	-0.182	-0.158
	(0.010)***	(0.045)***	(0.011)***	(0.024)***	(0.046)***
Constant	0.607	0.555	0.470	0.460	0.579
	(0.006)***	(0.025)***	(0.010)***	(0.021)***	(0.097)***
R^2	0.05	0.05	0.08	0.09	0.01
N	15,366	3,452	15,366	3,452	3,452

Note. Each regression includes a time dummy. We report standard errors in parenthesis. *, **, *** indicate significance level at 10%, 5%, and 1%, respectively.

Table 3. MPC regressions using log cash-on-hand and cash-on-hand quintiles

	All OLS	Panel sample OLS	Panel sample Fixed effects	All OLS	Panel sample OLS	Panel sample Fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)
Age <=30	0.052	0.022	0.077	0.059	0.028	0.051
	(0.017)***	(0.051)	(0.090)	(0.017)***	(0.051)	(0.089)
Age 30-45	0.035	0.015	0.067	0.040	0.019	0.054
	(0.009)***	(0.021)	(0.045)	(0.009)***	(0.021)	(0.045)
Age 45-60	0.029	0.027	0.048	0.032	0.031	0.043
	(0.007)***	(0.015)*	(0.029)*	(0.007)***	(0.015)**	(0.029)
Years of education	0.002	0.002	-0.000	0.001	0.002	-0.002
	(0.001)***	(0.001)*	(0.008)	(0.001)**	(0.001)	(0.008)
Male	-0.004	-0.020		-0.006	-0.022	
	(0.006)	(0.013)		(0.006)	(0.013)*	
Married	-0.017	-0.016		-0.017	-0.019	
	(0.007)**	(0.016)		(0.007)**	(0.016)	
Resident in the South	0.114	0.118		0.114	0.122	
	(0.006)***	(0.013)***		(0.006)***	(0.013)***	
Family size	0.015	0.022	0.008	0.014	0.022	0.006
	(0.003)***	(0.007)***	(0.015)	(0.003)***	(0.007)***	(0.015)
City size >500,000	0.088	0.061	-0.061	0.087	0.055	-0.056
	(0.010)***	(0.024)**	(0.264)	(0.010)***	(0.024)**	(0.264)
Unemployed	0.055	0.040	-0.054	0.065	0.046	-0.036
	(0.014)***	(0.031)	(0.053)	(0.014)***	(0.031)	(0.052)
Credit constrained	-0.014	0.065	0.005	-0.013	0.072	0.011
	(0.015)	(0.038)*	(0.052)	(0.015)	(0.038)*	(0.052)
Log cash-on-hand	-0.037	-0.036	-0.030			
	(0.002)***	(0.005)***	(0.009)***			
II cash-on-hand quintile				-0.056	-0.046	-0.023
				(0.009)***	(0.020)**	(0.030)
III cash-on-hand quintile				-0.100	-0.084	-0.039
				(0.009)***	(0.020)***	(0.031)
IV cash-on-hand quintile				-0.129	-0.105	-0.074
				(0.009)***	(0.021)***	(0.034)**
V cash-on-hand quintile				-0.157	-0.146	-0.123
				(0.010)***	(0.022)***	(0.038)***
Constant	0.458	0.450	0.505	0.462	0.447	0.512
	(0.009)***	(0.021)***	(0.095)***	(0.010)***	(0.022)***	(0.096)***
R^2	0.08	0.09	0.01	0.08	0.09	0.01
N	15,303	3,445	3,445	15,366	3,452	3,452

Note. Each regression includes a time dummy. We report standard errors in parenthesis. *, **, *** indicate significance level at 10%, 5%, and 1%, respectively.

Table 4. MPC regressions distinguishing between financial assets and income

	All OLS	Panel sample OLS	Panel sample Fixed effects
	(1)	(2)	(3)
Age <=30	0.048	0.006	-0.025
	(0.017)***	(0.051)	(0.097)
Age 30-45	0.031	0.006	0.005
	(0.009)***	(0.021)	(0.051)
Age 45-60	0.029	0.027	0.022
	(0.007)***	(0.015)*	(0.031)
Years of education	0.003	0.004	-0.001
	(0.001)***	(0.002)***	(0.008)
Male	-0.003	-0.018	
	(0.006)	(0.013)	
Married	-0.011	-0.005	
	(0.007)	(0.017)	
Resident in the South	0.106	0.109	
	(0.006)***	(0.013)***	
Family size	0.019	0.028	0.002
	(0.003)***	(0.007)***	(0.016)
City size >500,000	0.088	0.057	-0.054
	(0.010)***	(0.024)**	(0.263)
Unemployed	0.054	0.028	-0.047
	(0.014)***	(0.031)	(0.052)
Credit constrained	-0.016	0.061	0.002
	(0.015)	(0.037)	(0.052)
Percentiles of financial assets	-0.138	-0.112	-0.122
	(0.011)***	(0.024)***	(0.040)***
Percentiles of disposable income	-0.103	-0.143	-0.090
	(0.015)***	(0.032)***	(0.064)
Constant	0.465	0.456	0.589
	(0.009)***	(0.021)***	(0.098)***
R^2	0.09	0.09	0.01
N	15,366	3,452	3,452

Note. Each regression includes a time dummy. We report standard errors in parenthesis. *, **, *** indicate significance level at 10%, 5%, and 1%, respectively.

Table 5. The effect of a redistributive fiscal policy on aggregate consumption

Percentile of cash-on-hand receiving transfer	Unconditional MPC (1)	Conditional MPC, OLS (2)	Conditional MPC, Fixed effects (3)
≤ 10	0.33	0.23	0.19
≤ 25	0.28	0.21	0.17
≤ 50	0.21	0.18	0.15
≤ 75	0.17	0.15	0.12
≤ 90	0.14	0.13	0.10

Note. The Table reports the growth in aggregate consumption corresponding to a redistributive policy that transfers the equivalent of 1% of national income to people in the bottom 10, 25, 50, 75, 90 percent of the cash-on-hand distribution and finances it by taxing people in the top decile. Column (1) uses OLS estimate of the relationship between MPC and cash-on-hand estimated from column (1) of Table 2; column (2) uses the OLS estimate from column (3) of Table 2; and column (3) uses the panel data estimate from column (5) of Table 2.