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What drives heterogeneity in the marginal propensity to consume? Temporary shocks vs persistent characteristics

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ABSTRACT

Many empirical studies show that cash on hand is the most important source of variation in explaining heterogeneity in the marginal propensity to consume (MPC). To explain this, one class of models focuses on the role of heterogeneity in persistent characteristics across individuals while the other class focuses on the role of circumstances within individuals. This paper provides the first empirical measure of the relative importance of circumstances and characteristics in explaining the variance of the MPC. It then maps this empirical measure into a buffer stock model with discount factor heterogeneity to assess how well it explains the data.

1. Introduction

The marginal propensity to consume (MPC) out of income changes is of interest to both policymakers and academics. Studies analyzing the MPC have played a prominent role in government reports documenting and forecasting the macroeconomic effects of fiscal stimulus (Congressional Budget Office, 2009; Council of Economic Advisers, 2010). Moreover, academics study the MPC out of various forms of changes in income to evaluate theoretical models of consumption (see Jappelli and Pistaferri, 2010 for an excellent survey).

A key empirical result is that individuals with low financial resources (cash on hand) tend to have a higher MPC (See for example Jappelli and Pistaferri, 2014; Parker, 2017; Parker et al., 2013). The literature offers two broad classes of theoretical models that can generate this result.[2] One view is that temporary income shocks combined with precautionary savings or borrowing constraints play the main role. Some examples include the textbook buffer stock model with ex-ante

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[2] See Parker (2017) for a more detailed discussion.

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identical individuals (Carroll, 1997; Deaton, 1991; Zeldes, 1989) and the wealthy hand-to-mouth model of Kaplan and Violante (2014). Another view is that persistent characteristics such as preferences or behavioral traits play the main role. This may arise from simple impatience such as in Campbell and Mankiw (1989) and Krusell and Smith (1998). It may also arise from more complex mechanisms such as limited attention, problems of self-control, or propensity to plan as in Reis (2006), Angeletos et al. (2001), or Ameriks et al. (2003). Simply put, the two views in the literature boil down to temporary circumstances versus persistent characteristics and hence I use the terms “circumstances view” and “characteristics view” to distinguish the two.

While most economists would agree that both circumstances and characteristics play important roles, many studies tend to focus on one of the mechanisms to explain MPC heterogeneity. The disagreement over the relative importance of circumstances versus characteristics stems from the fact that most studies analyzing the correlation between the MPC and cash on hand use cross-sectional datasets that confound the various theoretical mechanisms. For example, a cross-sectional snapshot of cash on hand may be determined either by recent temporary shocks to income or persistent characteristics such as time preference. Since circumstances vary over time while characteristics are constant, observing both within-person cash on hand and MPC over time is vital to identification. Most data sets, however, only allow researchers to estimate the cross-sectional relationship between the MPC and cash on hand. For example, the Consumer Expenditure Survey (CE) has detailed enough data to identify the consumption response to income changes, but lacks a long enough panel structure to estimate multiple MPCs within an individual. Conversely, the Panel Study of Income Dynamics (PSID) has a long panel element, but lacks enough detail to isolate the source of income changes. Without a combination of a long panel and detailed consumption, income, and liquid balance data, it is difficult to disentangle circumstances from characteristics. Perhaps the study that comes closest to disentangling circumstances from characteristics is Sahm et al. (2012). They directly ask individuals how two separate policy-induced income changes affected their spending behavior. Their results show that changes in within-individual financial conditions can explain differences in spending behavior. Unfortunately, they do not have precise liquidity measures.

The goal of this study then is to better understand the relative importance of circumstances and characteristics in explaining MPC heterogeneity. The first contribution is to empirically decompose the fraction of MPC variance explained by within- and across-individual differences in cash on hand. The key data innovation is developing a novel panel dataset that includes joint spending, income, and liquid saving behavior from a personal finance app over several years. Using the detailed app data, I identify the receipt of several federal tax refunds within the same individual. I then estimate the monthly spending response using the high-frequency spending observations. Finally, I use the high-frequency liquid balance data to capture within- and across-individual variation in cash on hand. I find that within- and across-individual differences in cash on hand play roughly equal roles in explaining MPC variance.

The second contribution is to interpret the empirical results I find through the lens of a buffer stock saver model with discount factor heterogeneity. This relatively parsimonious model is able to capture the role of both circumstances and characteristics and map them intuitively into the data. The role of circumstances is reflected in the model by temporary shocks to income which induce within-individual differences in cash on hand. The role of characteristics is reflected in the model by heterogeneity in the discount factor which induces across-individual differences in cash on hand. Holding the variance of temporary shocks constant, a higher dispersion in the discount factor will lead to a more prominent role of across-individual variation in explaining MPC variance. Using this logic, the mean and dispersion of the discount factor is estimated from the data using the method of simulated moments. The estimates are roughly in line with the literature and show that this procedure produces sensible results.

The third contribution is to show that the buffer stock model with discount factor heterogeneity explains the data quite well. I present new evidence that the empirical distribution of the MPC within- and across- individuals matches the patterns implied by the model. Furthermore, I show that the distribution of cash on hand observed across individuals is also very similar to that generated from the model.

This paper is related to three strands of literature. The first strand is composed of theoretical models of consumption behavior best summarized by Parker (2017). As mentioned above, some papers choose to emphasize the role of circumstances while others choose to emphasize the role of characteristics. This paper includes a model that emphasizes both components and lets the data speak to the relative importance of each component. Within that literature, it is most closely related to Carroll et al. (2017) and Kaplan and Violante (2014) in the sense that they also discuss MPC heterogeneity. Carroll et al. (2017) also use a buffer stock model with discount factor heterogeneity but calibrate their model to match the wealth distribution instead of the realtive importance of characteristics versus circumstances like this paper does. Kaplan and Violante (2014) focus more on the life-cycle decision of choosing between assets with varying levels of liquidity and do not include transitory idiosyncratic income shocks. This paper includes transitory idiosyncratic shocks and in doing so focuses more on the decisions to use liquidity to buffer against these higher frequency shocks. When viewing the results of this paper through the (Kaplan and Violante, 2014) framework, we can think of persistent characteristics as capturing heterogeneity across wealthy and poor hand to mouth types while temporary circumstances captures the idiosyncratic shocks that they face. Given that both the liquidity decision and the response to transitory shocks are likely important factors in explaining MPC heterogeneity, I view the two studies as complimentary.

This paper is also related to the empirical literature that estimates the MPC out of changes in income. Some examples include Parker et al. (2013), Jappelli and Pistaferri (2014), Parker (2017), Kueng (2018), and Baugh et al. (2018). It is also related to a growing literature studying individual consumption behavior using administrative data from personal finance apps such as Gelman et al. (2014), Gelman et al. (2018), Baker (2018), Olafsson and Pagel (2018), Baugh et al. (2018), Gelman (2019), and Gelman et al. (2019). The model and data used in this paper is similar to Gelman (2019) and Gelman et al. (2019). The main difference is that Gelman (2019) aims to understand what causes excess sensitivity of spending to the receipt of regular income. Gelman et al. (2019) focuses on the joint saving and tax withholding decision to better understand over-withholding behavior and how that relates to a high MPC out of tax refunds.

The rest of the paper is organized as follows. Section 2 lays out the theoretical framework I use to generate predictions about consumption and saving behavior under the two views which I will take to the data. Section 3 discusses the dataset and provides some descriptive statistics. Section 4 presents the empirical results. Section 5 estimates the parameters of the model via the method of simulated moments and Section 6 concludes.

2. Theoretical framework

This section describes the theoretical framework used to analyze individual decisions. It introduces a buffer stock model with discount factor heterogeneity and formally defines the circumstances versus the characteristics view of MPC heterogeneity. It then generates predictions about MPC heterogeneity which are taken to the data in later sections.

2.1. Model description

Individuals behave according to the standard “buffer-stock” saver model in the spirit of Zeldes (1989), Deaton (1991), and Carroll (1997). The main difference with previous studies is the introduction of preference heterogeneity via the discount factor signified by the i subscript on β.

Optimization problem Individual i solves the following utility maximization problem

$$\max_{\{C_{ij}\}_{j=t}^{\infty}} \mathbb{E}_t\left[\sum_{j=t}^{\infty} \beta_i^{j-t} \frac{{C_{ij}}^{1-\theta}}{1-\theta}\right] \tag{1}$$

subject to

$$A_{it+1} = (1+r)(A_{it} + Y_{it} - C_{it}) \tag{2}$$

$$A_{it+1} \geq b \tag{3}$$

$$Y_{it} = \bar{Y}_i \varepsilon_{it} \tag{4}$$

$$\varepsilon_{it} \overset{iid}{\sim} N(1, \sigma_Y^2) \tag{5}$$

where β_i, r, C_{it}, A_{it} and Y_{it} represent the time discount factor, the interest rate, consumption, liquid assets, and income respectively.

Normalization Carroll (2004) shows that this problem can be rewritten by normalizing all variables by the level of permanent income. Following his notation, I define lowercase variables as uppercase variables divided through by the level of permanent income. Therefore $c_{it} = C_{it}/\bar{Y}_i$, $a_{it} = A_{it}/\bar{Y}_i$ and so on. This normalization is very useful because the same solution to the model can be used to jointly characterize the behavior of all individuals who share the same β_i and Y_{it} process while allowing the actual level of $\bar{Y}_i$ to differ.

Model Horizon An infinite horizon version of the model is chosen to abstract away from life-cycle features. Carroll (2004) shows that the infinite horizon framework can be thought of as the limiting behavior of an individual when they are far away from their end of life. This assumption is reasonable for the population analyzed in this paper and will be discussed further in the data section. When buffer stock motives are strong enough, agents are more concerned with smoothing short term shocks rather than saving for retirement.

Income process Income follows an iid process. Because the time series of the data only span four years, permanent shocks are not well identified. To match the model, the subsequent empirical analysis will condition on individuals who have a fairly stable income process and therefore have not experienced any large permanent shocks in the data. Furthermore, the iid assumption reflects the fact that the sample is selected on individuals who receive regular paychecks. This sample restriction is made to fit the model which doesn’t have permanent shocks or periods of unemployment. To confirm that the income process of the sample is not very persistent, Section 3.3.3 estimates an AR1 process in income and finds that the estimate of the first lag term is 0.096. This low value justifies specifiying the income process as iid and greatly reduces the complexity of the model by removing the previous period’s income shock as a state variable.

Solution The consumption problem specified above does not admit a closed form solution and is therefore solved computationally. I reformulate the individual’s problem in terms of a functional equation and define cash on hand $x_{it} = a_{it} + y_{it}$ to simplify the state space. This variable represents the amount of resources available to the individual in the beginning of the period.

The individual then solves the optimization problem

$$V(x_{it}) = \max_{a_{it+1}} \{u(c_{it}) + \beta_i \mathbb{E}[V(x_{it+1})]\} \tag{6}$$

subject to

$$x_{it+1} = (1+r)(x_{it} - c_{it}) + y_{it+1} \tag{7}$$

and the previous constraints (3)–(5).

Substituting in for c_{it} and x_{it+1} results in an equation in terms of x_{it}, a_{it+1}, and y_{it+1}

$$V(x_{it}) = \max_{a_{it+1}} \left\{ u\left(x_{it} - \frac{a_{it+1}}{1+r}\right) + \beta_i \mathbb{E}[V(a_{it+1} + y_{it+1})] \right\} \tag{8}$$

The individual maximizes utility by choosing next period saving (a_{it+1}) conditional on cash on hand (x_{it}). The model is solved using the method of endogenous gridpoints suggested in Carroll (2006). This solution method results in the value function $V(x_{it})$ and the consumption function $c_{it}(x_{it})$.

2.2. Circumstances and characteristics view

In order to understand the mechanisms that drive MPC heterogeneity, I adopt the dichotomy laid out in Parker (2017) between two classes of models. The first class of models tend to focus on circumstances as the main driver of the MPC heterogeneity and the second class of models focuses more on characteristics as the main drive of MPC heterogeneity.

In the first class of models, temporary circumstances cause cash on hand to fluctuate. If individuals have concave consumption functions, low cash on hand leads to high MPCs and high cash on hand leads to low MPCs. Therefore, the MPC will depend on what circumstances individuals find themselves in and so I call this view the "circumstances view." Some examples include the textbook buffer stock model with ex-ante identical individuals (Carroll, 1997; Deaton, 1991; Zeldes, 1989) and the wealthy hand-to-mouth model of Kaplan and Violante (2014). In the second class of models, persistent characteristics drive the correlation between cash on hand and the MPC. This may arise from simple impatience such as in Campbell and Mankiw (1989) and Krusell and Smith (1998). It may also arise from more complex mechanisms such as limited attention, problems of self-control, or propensity to plan as in Reis (2006), Angeletos et al. (2001), or Ameriks et al. (2003). Therefore, even though individuals may find themselves in good or bad circumstances, their average behavior over time will depend on differences across persistent characteristics such as the discount factor. I call this view the "characteristics view."

Note that most economists would agree that both circumstances and characteristics play a role in explaining MPC heterogeneity. The goal of this paper is not to choose one class of models over the other. The dichotomy is merely a useful way to compare different classes of models where either circumstances or characteristics are emphasized more than the other.

In the model introduced in the previous section, temporary shocks to income capture temporary circumstances while heterogeneity in the discount factor captures persistent characteristics. In general, "characteristics" may refer to a broad range of traits such as impatience, risk aversion, present bias, or inattention. While in the model, these "characteristics" are constant across an individual's lifetime, the dataset I use is limited to a four year period. Therefore, I use characteristics that are constant across a four year period as a proxy for these immutable characteristics.[3] In that sense, the empirical results may misidentify a persistent four year temporary shock as a "characteristic." Furthermore, this four year period may also identify different phases of an individual's life-cycle.[4] Given this limitation, I interpret my estimates as an upper bound of the importance of characteristics versus circumstances.

While the literature has used many different approaches to parametrizing "characeristics," I choose to parametrize characteristics as heterogeneity in the discount factor for two reasons. The first reason is that recent studies suggest heterogeneity in the discount factor may be important for explaining the heterogeneity in the MPC. Parker (2017) shows that lack of smoothing is correlated not with temporary fluctuations but with persistent characteristics such as impatience.[5] He concludes that this behavior is consistent with models that exhibit heterogeneity in preference such as Campbell and Mankiw (1989), Krusell and Smith (1998), and Hurst (2003). Along a similar vein, Baugh et al. (2018) study the weekly response of spending to the receipt of a tax refund and find a strong immediate spending response which decays very rapidly. They argue that agents who are constrained but patient would exhibit a spike up in spending but would then smooth spending over the following weeks. Therefore they conclude that the spending response to tax refunds is consistent with some agents who exhibit myopia.

The second reason I choose to model characteristics as heterogeneity in the discount factor is that for purposes of modeling consumption behavior, the MPC is largely a function of the curvature of the consumption function. Under the modeling

[3] The results are quite stable to changing the number of months used in the analysis. While this doesn't necessarily show that the four year period is sufficient, it shows that persistent factors are stable within this four year period.

[4] While it's difficult to assess the empirical impact of misclassifying life-cycle phases as "charactersistics," Carroll et al. (2017) has explored the impact of the life-cycle on MPC dynamics. They analyze a life-cycle version of a consumption model with preference heterogeneity. Fig. 12 from their paper shows that between the ages of 30 and 50 (where most of the sample lie), the MPC varies much more by preference parameters than by age.

[5] The measure is the answer to the question "In general, are you or other household members the sort of people who would rather spend your money and enjoy it today or save more for the future?" with a binary choice of 'spend now' and 'save for the future.'

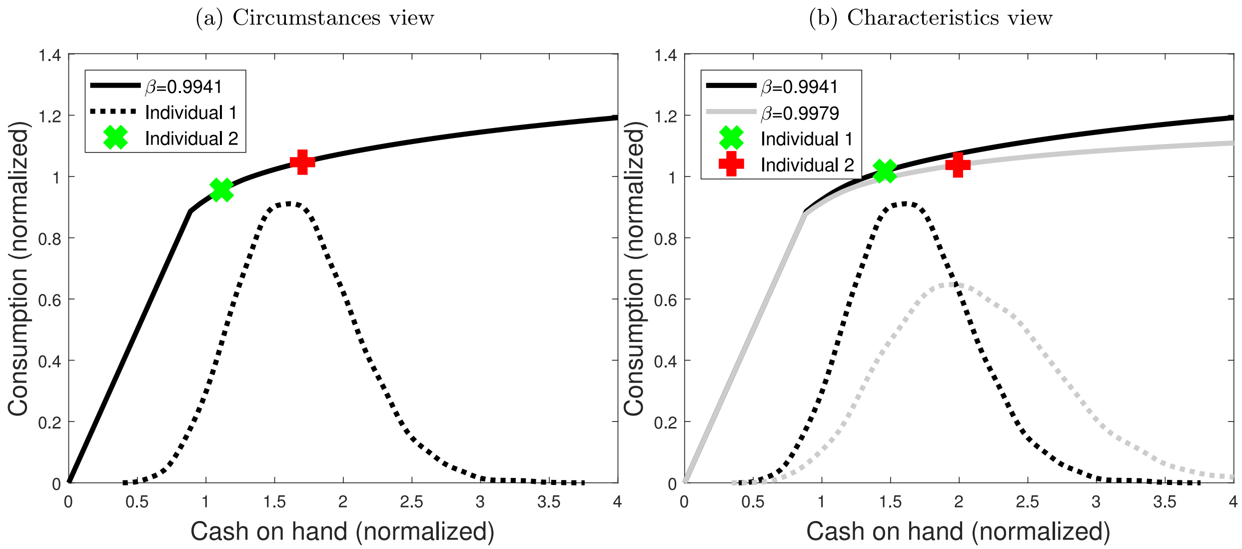

Fig. 1. Comparison of views *Notes:* Panel (a) and (b) plot the consumption function (solid line) and distribution of cash on hand (dotted line) under the circumstances view and characteristics view respectively. In panel (b) the black lines represent the more impatient individual and the grey lines represent the more patient individual.

assumptions used in this paper, changes in the discount factor alter the curvature of the consumption function is similar ways to changes in risk aversion.[6] Therefore, whether heterogeneity is introduced via the discount factor or risk aversion is not well identified from consumption behavior. The key is that introducing heterogeneity in the discount factor will capture persistent characteristics which are not correlated with high-frequency shocks to income.

Under the circumstances view, MPC heterogeneity is driven entirely by temporary shocks to income and so $\beta_i = \bar{\beta}$. Under the characteristics view, MPC heterogeneity is driven both by temporary shocks to income and heterogeneity across individuals. This is captured by defining $\beta_i \sim U\ (\bar{\beta} - \Delta, \bar{\beta} + \Delta)$ as in Carroll et al. (2017) and Krueger et al. (2016).[7]

Fig. 1 provides a simple characterization of the sources of heterogeneity under the two views via the optimal consumption function and the distribution of cash on hand. The solid line represents the consumption function while the dotted line represents the distribution of cash on hand conditional on a particular discount factor. Panel (a) shows that under the circumstances view, heterogeneity is driven entirely by differences in cash on hand. Differences between individuals are represented by different points along the consumption function. For example, the individual represented by “x” may have received a negative shock and therefore exhibits lower cash on hand than the individual represented by “+”. Because the consumption function is concave, a lower cash on hand level is associated with lower consumption and a steeper slope (higher MPC). It is differences in circumstances that generates the correlation between the MPC and cash on hand.

Alternatively, panel (b) depicts heterogeneity under the characteristics view. The main difference is that individuals with different discount factors have different consumption functions and different distributions of cash on hand. For example, the individual represented by “+” has a higher discount factor relative to the individual represented by “x.” The more patient individual has a flatter consumption function and a distribution of cash on hand that is shifted to the right. In the characteristics view, the discount factor jointly determines average MPC and average cash on hand. Impatient individuals will tend to have higher MPCs and lower cash on hand and vice versa. Contrary to the circumstances view, persistent characteristics now play a role in generating the correlation between the MPC and cash on hand.

2.3. Target buffer stock behavior

A key mechanism to help distinguish between the two views is so called “target buffer stock” behavior. Under such behavior, individuals target a cash on hand to income ratio over time that is determined by their preferences and income uncertainty. While cash on hand will fluctuate due to temporary shocks to labor income, individuals will endogenously change their consumption behavior to achieve their target cash on hand. This implies that any snapshot of cash on hand at a point in time will reflect both recent temporary shocks and persistent characteristics. Because individuals react to

[6] For example, holding all other parameters fixed, the parameter values ($\beta = 0.990, \theta = 1$) result in an almost identical consumption function as the parameter values ($\beta = 0.979, \theta = 2$). This leads to almost identical distributions of cash on hand as well as the MPC. This is not a general result and applies only to the modeling environment specified in this paper.

[7] In most buffer stock models, there is no solution when $\beta_i R \geq 1$. Therefore, for realizations where $\beta_i \geq 1/R$, I replace it with $\beta_i = 1/R - 0.0001$.

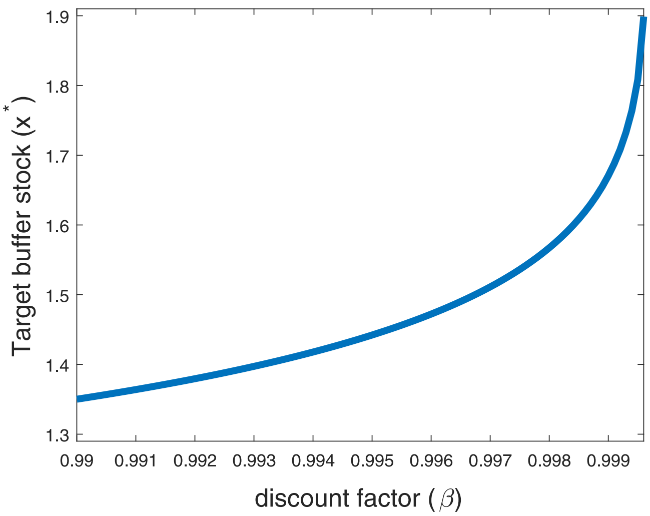

Fig. 2. Target buffer stock and the discount factor *Notes:* β refers to the monthly discount factor.

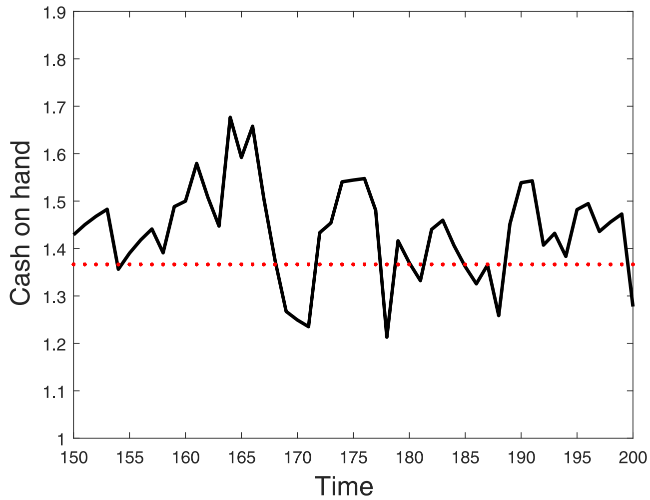

Fig. 3. Cash on hand time series *Notes:* The horizontal line represents the stable target buffer stock level.

temporary shocks by moving back towards their preferred buffer stock, taking a time average of cash on hand should isolate the level of cash on hand attributable to preferences.[8]

Another important characteristic of a target buffer stock x^* is that holding all else constant, it is an increasing function of the discount factor. While holding a buffer stock is helpful for protecting against income shocks, maintaining a high buffer stock comes at the expense of present consumption. Therefore, the more impatient individuals are, the more they will prefer to consume today instead of holding a large buffer stock. Fig. 2 graphically demonstrates the positive relationship between x^* and β. This relationship will allow x^* to be interpreted as a proxy for the discount factor.

Lastly, Fig. 3 shows the time series behavior of simulated cash on hand within an individual. The horizontal dashed line represents the target buffer stock level. As expected, temporary shocks cause cash on hand to deviate from the target value x^*. However, because the target buffer stock level is a stable equilibrium, individual consumption x_t will tend towards x^* over time. I utilize this behavior to decompose cash on hand into a circumstances and characteristics component as $x_t = (x_t - x^*) + x^*$. The next section will explore how these dynamics will aid in identifying the differential relationship of cash on hand and the MPC under the two views.

[8] See Online appendix for more details.

Table 1
Parameter values.

Parameter	Value	Notes	Description
$u(x)$	$\frac{x^{1-\theta}}{1-\theta}$	CRRA utility	utility function
θ	1	standard	coefficient of relative risk aversion
$\overline{\beta}$	0.9941		average discount factor
Δ	0.0190	0 for circumstance model	discount factor dispersion
σ_Y	0.20	estimated from dataset	S.D. of temporary shocks
$refund_{it}$	0.60	estimated from dataset	average normalized refund
r	0.01 / 12	monthly r on checking/saving	interest rate
b	0	no borrowing condition	borrowing limit

Notes: The parameters correspond to a monthly frequency.

2.4. Model simulation

Before analyzing the actual data, it's helpful to understand how consumption behavior differs under the circumstances and characteristics view. To this end, this section simulates the consumption response to income under the two views. In order to create a tight link with the data, I attempt to model the empirical environment that I observe within the dataset as closely as possible.

The dataset used in the empirical section includes transaction-level consumption, income, and cash on hand measures from a personal finance app. I take advantage of the transaction-level granularity of the data to identify receipts of multiple tax refunds within individuals. These tax refund are then used in turn to calculate the MPC out of a change in income.

The simulation environment is chosen to match this empirical environment very closely. Therefore, I simulate the consumption reaction of 200 individuals[9] to the receipt of a tax refund every 12 months over a period of 4 years. For each tax refund received, I calculate the MPC and cash on hand of each individual. I then explore how the relationship between the MPC and cash on hand differ under the two different views.

The main result is that the relationship between the MPC and cash on hand only differs when the panel structure of the data is used. Intuitively, cross-sectional snapshots will confound the role of circumstances and characteristics in driving MPC heterogeneity.

2.4.1. Calibration

The parameter values used to calibrate the model are listed in Table 1 below and represent monthly time periods. The utility function is specified as constant relative risk aversion (CRRA) with $\theta = 1$. The parameters $\overline{\beta}$ and Δ are set to the parameters estimated in the later part of the paper. The parameter σ_Y is estimated using the income process observed in the dataset. $refund_{it}$ represents the average tax refund to income ratio observed in the data set. The interest rate is set to the monthly rate on checking/savings accounts and the borrowing limit is set to zero.

2.4.2. Variable definitions

The main variables used in the analysis are the MPC and cash on hand. This section provides definitions for these concepts.

Definition 1. The MPC at time t for individual i is defined as

$$MPC_{it} = \frac{\Delta C_{it}}{\Delta Y_{it}} = \frac{\sum_{j=t}^{t+2} c_{ij} - \sum_{j=t-1}^{t-3} c_{ij}}{refund_{it}} \tag{9}$$

Because each period in the model is one month, this value represents the quarterly change in consumption as a fraction of the tax refund. For periods in which a tax refund is not received, the MPC is undefined.

Definition 2. Pre-refund cash on hand at time t for individual i is defined as

$$coh_{it}^{PR} = \frac{\sum_{j=t-1}^{t-3} x_{ij}}{3} \tag{10}$$

This measure captures the average level of cash on hand three months prior to receiving the tax refund. It is meant to mimic the measures of liquidity captured in survey data commonly used in studies estimating the consumption response to income changes.

Definition 3. Average cash on hand for individual i

$$\overline{coh}_i = \frac{\sum_{j=t}^{T} x_{ij}}{T} \tag{11}$$

[9] I choose 200 because this allows the reader to more easily see what each observation corresponds to in the figures. The simulation results are similar regardless of the number of individuals chosen.

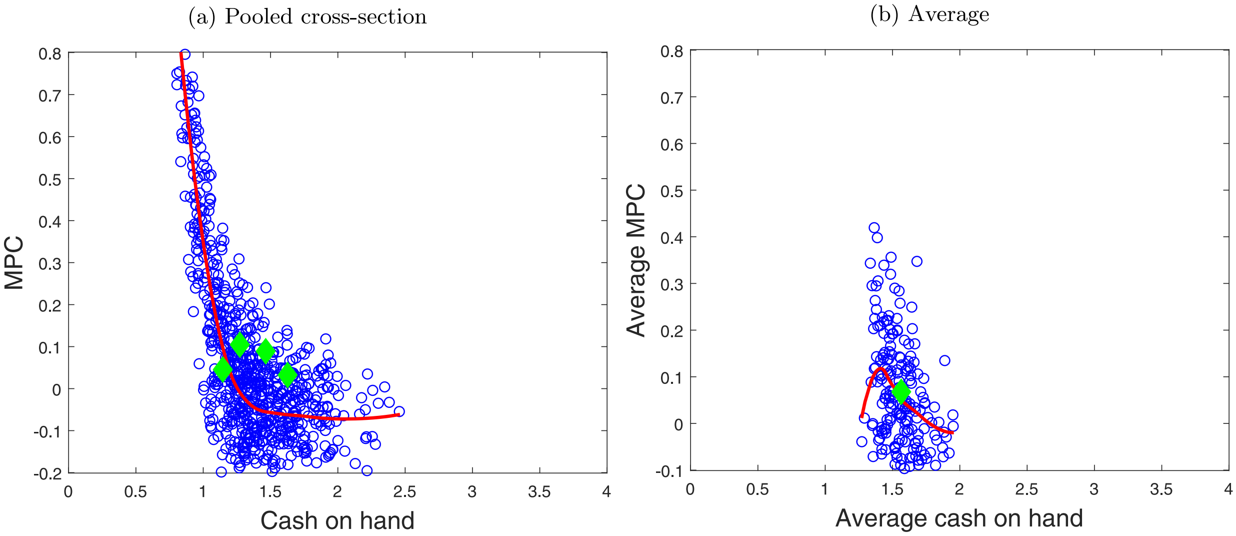

Fig. 4. Relationship between MPC and cash on hand under the circumstances view *Notes:* Panel (a) plots the relationship between pre-refund cash on hand and the MPC for individual *i* at time *t* using simulated data. Panel (b) plots the relationship between average cash on hand and the avearge MPC for individual *i*. In both plots, the solid red line represents a local-linear smoothed curve and the green diamond represents all observations for a randomly chosen individual. The first 120 periods of the simulations are discarded to allow individuals to reach steady state. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

This measure is meant to capture the target level of buffer stock for individual *i* described in the previous section and is used as a proxy for the discount factor. This measure is not usually captured in survey data such as the Consumer Expenditure Survey because the panel dimension is relatively short.

2.4.3. The relationship between MPC and cash on hand

After simulating the data, I calculate MPC_{it}, coh_{it}^{PR}, and $\overline{coh_i}$ for each individual. Fig. 4 shows the relationships between these variables under the assumptions of the circumstances view where $\beta_i = \bar{\beta}$.

Panel (a) presents a scatter plot of the MPC and pre-refund cash on hand overlaid with a local linear smoothed line. In this panel, each point represents an observation for individual *i* and time *t*. For example, the green diamonds represent all observations for a particular individual. Because each individual receives four refunds, there are four points. There is a clear negative relationship between MPC_{it} and coh_{it}^{PR}. This pattern is consistent with the concavity of the consumption function suggested by Carroll and Kimball (1996). Since the MPC is the slope of the consumption function, a concave consumption function will result in a high MPC when cash on hand is low and vice versa. Jappelli and Pistaferri (2014) also report a similar relationship when they explicitly ask individuals what their MPC would be out of a hypothetical income shock.

Panel (a) is analogous to plotting the relationship of the MPC and cash on hand in a pooled cross-section. As discussed earlier, a snapshot of cash on hand in time will reflect both circumstances as well as characteristics. In order to isolate the characteristics component of cash on hand, panel (b) presents a scatter plot of the average MPC and average cash on hand. Note that now each observation represents one individual. This is reflected in the fact that the four green diamonds in panel (a) are collapsed into one green diamond in panel (b). Once I collapse the data by average across time within an individual, the strong negative relationship between the MPC and cash on hand is no longer present. Under the circumstances view, the lack of heterogeneity in the discount factor leads to all individuals having the same target buffer stock level. Therefore, there should not be any systematic relationship between average cash on hand and any other individual level variable. The temporary shocks are beyond the control of the individual and so pre-refund cash on hand levels will influence the response to tax refunds. After the shocks have occurred, however, individuals will alter their behavior to return to their desired buffer stock level. Over a long enough horizon, this preference-driven behavior is the main determinant of the level of cash on hand. Under our parametrization, four years is a long enough time horizon for average cash on hand to reflect the theoretical target buffer stock level.

Fig. 5 repeats the exercise in Fig. 4 under the assumptions of the characteristics view where $\beta_i \sim U\ (\overline{\beta} - \Delta, \overline{\beta} + \Delta)$. The results in panel (a) look similar across the two views. Once again, a strong negative relationship exists between MPC_{it} and coh_{it}^{PR}; however, it's not clear whether this is driven by the concavity of the consumption function or the differences in the discount factor across individuals. This formalizes the idea that observing the relationship between the MPC and cash on hand in the cross-section cannot separately identify the role of circumstances and characteristics. Once again, the problem stems from the fact that any snapshot of cash on hand is influenced both by recent changes to temporary circumstances as well as persistent characteristics. Plotting panel (b) under the characteristics view reveals that the relationship between $\overline{MPC_i}$ and $\overline{coh_i}$ exhibits a strong negative relationship. This result is driven by the fact that discount factors are allowed to

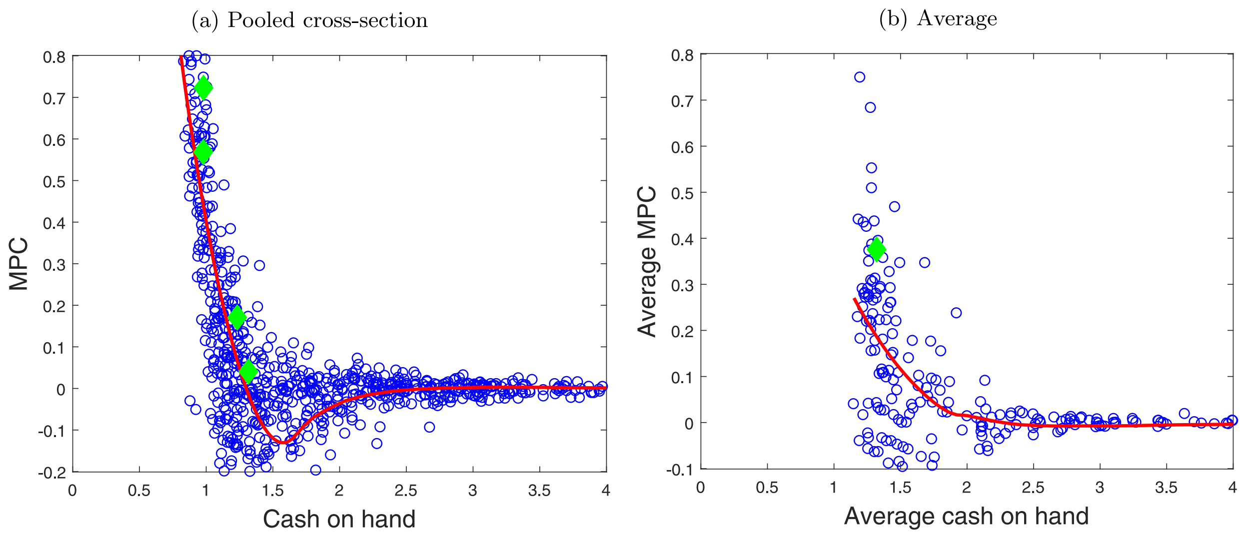

Fig. 5. Relationship between MPC and cash on hand under the characteristics view *Notes:* Panel (a) plots the relationship between pre-refund cash on hand and the MPC for individual i at time t using simulated data. Panel (b) plots the relationship between average cash on hand and the avearge MPC for individual i. In both plots, the solid red line represents a local-linear smoothed curve and the green diamond represents all observations for a randomly chosen individual. The first 120 periods of the simulations are discarded to allow individuals to reach steady state. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

vary across individuals. On average, impatient individuals with low discount factors will tend to hold low cash on hand and have high MPCs and vice versa. Even after averaging out the temporary shocks, these persistent characteristics drive the negative correlation between the average MPC and average cash on hand.

In summary, estimating the cross-sectional relationship between the MPC and pre-refund cash on hand will lead to similar results under both views. A negative correlation is observed regardless of which view actually holds in the data. The views can only be distinguished by isolating the persistent characteristics component by calculating the average MPC and average cash on hand within individuals. The circumstances view implies a very weak relationship between the average MPC and average cash on hand while the characteristics view implies a strong negative relationship.

2.4.4. Variance decomposition

The previous section helps to visualize how the relationship between the MPC and cash on hand differs under different assumptions about the relative importance of cirumstances and characteristics. In this section, I introduce a more quantitative measure that decomposes the relative role of circumstances and characteristics in explaining the MPC variance.

The theory makes it clear that MPC_{it} is a function of cash on hand. Furthermore, the section on buffer stock behavior showed that cash on hand can be decomposed into a circumstances and characteristics component. This decomposition can be used to determine the relative importance of each component using the following equation

$$MPC_{it} = \alpha + \underbrace{\gamma_1 \times \overline{coh}_i}_{\text{characteristics}} + \underbrace{\gamma_2 \times (coh_{it}^{PR} - \overline{coh}_i^{PR})}_{\text{circumstances}} + \varepsilon_{it} \tag{12}$$

where $\mathbb{E}[\varepsilon_{it}] = 0$. While the discount factor is not explicitly observed, the buffer stock model implies that average cash on hand is a function of the discount factor. Therefore $\overline{coh}_i$ is used to capture the characteristics component of cash on hand. The circumstances component of cash on hand is captured by using pre-refund cash on hand (coh_{it}^{PR}). Because the level of coh_{it}^{PR} is still related to the discount factor, it is demeaned by its average ($\overline{coh}_i^{PR}$) in order to extract the temporary component that is orthogonal to the individual level average.

Under this specification, the variance is easily decomposed because all the terms are uncorrelated with each other (see Online appendix for more details). The following equation applies the variance operator to both sides.

$$var(MPC_{it}) = var(\alpha) + var(\gamma_1 \times \overline{coh}_i) + var(\gamma_2 \times (coh_{it}^{PR} - \overline{coh}_i^{PR})) + var(\varepsilon_{it}) \tag{13}$$

Defining $var(\gamma_1 \times \overline{coh}_i) = \sigma_{char}^2$ and $var(\gamma_2 \times (coh_{it}^{PR} - \overline{coh}_i^{PR})) = \sigma_{circ}^2$, these terms capture the variance contribution of the characteristics and circumstances component of cash on hand respectively. Another way to think about this equation is that the characteristics component captures across-individual variation and the circumstances component captures within-individual variation.

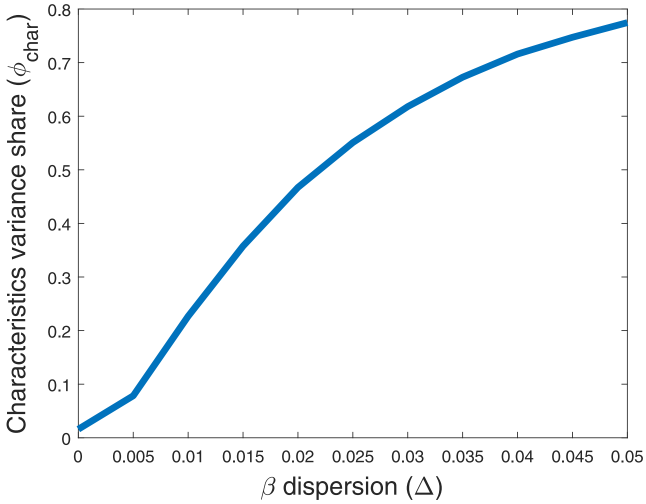

Fig. 6. Relationship between the dispersion of β and ϕ_{char} *Notes:* This figure plots the relationship between the dispersion in the discount factor Δ against the characteristics component variance share (ϕ_{char}). It uses a $\bar{\beta}$ of 0.9941.

Defining $\phi_{char} = \frac{\sigma^2_{char}}{\sigma^2_{char}+\sigma^2_{circ}}$, this value represents the fraction of $var(MPC_{it})$ explained by cash on hand that is attributable to characteristics. Since ϕ_{char} is bound between 0 and 1, it can be used to determine the relative importance of characteristics in explaining MPC variance.

The characteristics share of variance (ϕ_{char}) can also be connected back to the model. Recall that under the circumstances view $\beta_i = \overline{\beta}$, while under the characteristics view $\beta_i \sim U\ (\overline{\beta} - \Delta, \overline{\beta} + \Delta)$. Higher values of the dispersion in the discount factor (Δ) lead to greater heterogeneity in average cash on hand levels. Holding the variance of temporary shocks constant, this should lead to a greater contribution of the characteristics component of cash on hand in explaining the MPC. Fig. 6 shows this relationship by calculating ϕ_{char} under different values of Δ while holding all other parameters constant. As expected, ϕ_{char} is an increasing function of Δ.

In summary, calculating ϕ_{char} in the data will identify the relative importance of characteristics in explaining MPC heterogeneity. Furthermore, ϕ_{char} will later be used to estimate the amount of heterogeneity in the discount factor (Δ) using the method of simulated moments.

3. Data

This section describes the data source, sample filters, variable definitions and descriptive statistics.

3.1. Data source

This paper utilizes a novel dataset derived from de-identified transactions and account data, aggregated and normalized at the individual level. The data are captured in the course of business by a personal finance app.[10],[11] More specifically, the app offers financial aggregation and bill-paying services. Users can link almost any financial account to the app, including bank accounts, credit card accounts, utility bills, and more. Each day, the app logs into the web portals for these accounts and obtains central elements of the user's financial data including balances, transaction records and descriptions, the price of credit and the fraction of available credit used. Prior to analysis, the data are stripped of personally identifying information such as name, address, or account number. The data have scrambled identifiers to allow observations to be linked across time and accounts.

I draw on the entire de-identified population of active users and data derived from their records from December 2012 until November 2016. For a subset of the data, I have made use of demographic information provided to the app by a third party. The Online appendix compares the age, education, gender, and geographic distributions in the sample that matched with an email address to the distributions in the U.S. Census American Community Survey (ACS), representative of the U.S. population in 2012. The Online appendix also compares the income distribution in the app to total family income in the ACS. Users who use the app are on average higher income than individuals surveys in the ACS.

[10] These data have previously been used to study the high-frequency responses of households to changes in income such as regular paychecks (Gelman et al., 2014), gas prices (Gelman et al., 2016), and the government shutdown (Gelman et al., 2018). They have also been used to understand what causes excess sensitivity to regular income (Gelman, 2019) as well as over-withholding of taxes (Gelman et al., 2019).

[11] Similar account data has been used in Baugh et al. (2018), Baker (2018), Kuchler (2015), Ganong and Noel (2019), and Kueng (2018).

In summary, the app is not perfectly representative of the US population, but it is heterogeneous, including large numbers of users of different ages, education, income, and geographic location.

3.2. Sample filters

The sample is filtered on various characteristics to ensure that the analysis sample matches the model specified in the earlier sections.

First, the model assumes the researcher observes a comprehensive view of spending, income, and liquid assets. Therefore, I require data from individuals who add all (or most) of their accounts,[12] generate a long time series of observations, and have positive income in each month. This reduces the sample size because there is a large amount of churn from users who try out the app but later decide not to continue using it. Moreover, there are some users that only track one or two credit cards without adding all their other accounts.

Second, the model is meant to abstract away from life-cycle motives and large permanent shocks to income so that reactions stem from either temporary circumstances or persistent characteristics. Therefore, I condition on individuals who receive regular paychecks.[13] While this filter helps to better identify temporary circumstances, it may also drop individuals who rely on non-regular sources of income such as from the sharing economy. For those individuals, temporary circumstances are likely to play an important role in explaining fluctuations in the MPC.

Lastly, since the MPC is estimated from the consumption reaction to tax refunds, I condition on individuals who received more than one tax refund in the sample.

In summary, I select users based on length of panel, number of accounts, connectedness of accounts, regular paycheck status, no missing income data, and whether they received more than one tax refund.[14]

3.3. Variable definitions

Most survey data sets such as the Consumer Expenditure Survey (CE), Panel Study of Income Dynamics (PSID), and Survey of Consumer Finances (SCF) are created with the explicit goal of facilitating academic research. The data set used in this study is naturally occurring and was not explicitly designed for use in academic studies. Constructing variables in this data set to match our models is not necessarily a trivial exercise. In order to study the relationship between the MPC out of tax refunds and cash on hand, the main variables I utilize are consumption, income, tax refunds, and liquid assets.

3.3.1. Consumption

The empirical analysis will focus on non-durable consumption because durable goods are not explicitly modeled. In particular, I attempt to match the composition of the widely used “strictly non-durable” definition from Lusardi (1996).

The raw data consists of individual transactions with characteristics such as amount, transaction type (debit or credit), and transaction description. While the type of spending (non-durable, durable) is not directly observed, I use a machine learning (ML) algorithm (see Online appendix for more details) to aid in categorization. The goal of the ML algorithm is to provide a mapping from transaction descriptions to spending categories. For example, any transaction with the keyword “McDonalds” should map into “Fast Food”. A subset of these categories are then combined to create the consumption variable.

The finest level of categorization is derived from merchant category codes (MCCs) which are directly observable in two of the account providers in the data. MCCs are four digit codes used by credit card companies to classify spending and are also recognized by the U.S. Internal Revenue Service for tax reporting purposes. The ML algorithm works by using a subset of the data where the truth is known in order to create a mapping from transaction description to MCCs.

After training the ML algorithm on the data where the truth is known, the algorithm is then applied to the rest of the data set. I then define consumption as spending on restaurants, groceries, gasoline, entertainment, and services.

3.3.2. Tax refunds

In order to disentangle temporary circumstances from persistent characteristics, it’s important to observe several MPCs across time within an individual. While many studies have analyzed the MPC out of tax rebates, one disadvantage of tax rebates is that they occur at a fairly low frequency. Since most people receive federal tax refunds in multiple years, this study utilizes the MPC out of tax refunds over time within individuals.

Federal tax refunds are identified by searching for identifying keywords in the transaction description (all tax refunds include the keywords “TAX”, “TREAS”, and “REF”). I exclude individuals that receive multiple tax refunds within the same year. Fig. 7 shows the time series of the count of tax refunds observed in the data from December 2012 to November 2016. The figure shows that most tax refunds are received in February, March, April, and May.

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[12] See section Online appendix for more details.

[13] See section Online appendix for more details.

[14] The Online appendix shows how each of these filters affects the sample size.

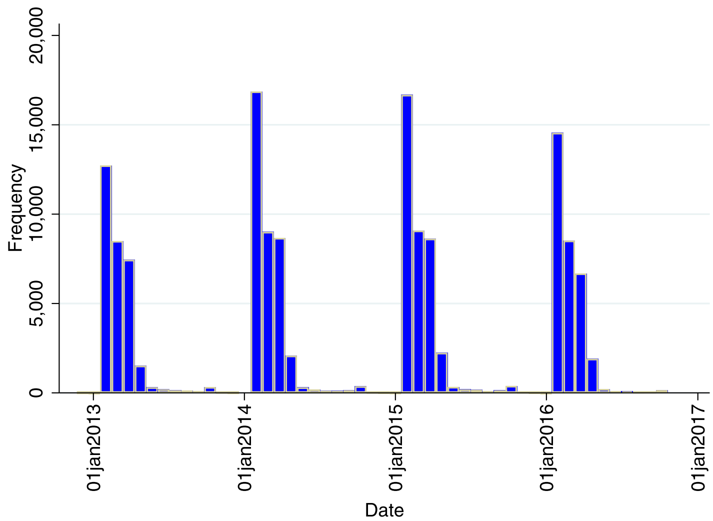

Fig. 7. Federal tax refund time series *Notes:* This figure shows the number of tax refunds received per month.

Table 2
Income parameter estimation.

VARIABLES	(1) y_t
y_{t-1}	0.096***
	(0.000)
Constant	0.799***
	(0.002)
Observations	1,873,585
R-squared	0.148

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$ *Notes:* The upper and lower 5% of observations are trimmed.

Table 3
Summary statistics.

	mean	p25	p50	p75
Spending ($)	6046	2772	4483	7299
Income ($)	6243	3365	5012	7579
Liquid balance ($)	8483	883	2398	7301
Tax refund ($)	3116	1119	2279	4383

Notes: N=46,200. Variables are winsorized at the 1% level.

3.3.3. Income

Income is important in determining the variance of temporary shocks as well as an input into cash on hand. Total income is defined as the sum of all inflows from checking and saving accounts minus incoming transfers.

In order to calibrate the income process in the model, I first estimate the parameters using Eq. (14). To fit the model, I subtract out any tax refunds and normalize by average income. I further filter the data to help control for outliers. First, I remove the highest non-paycheck non-refund transaction over $1,000 each month. Second, I drop months where the number of paychecks differs from the median number of paychecks.[15]

Eq. (14) specifies an AR(1) model in non-tax refund normalized income and controls for seasonality using monthly fixed effects.

$$y_{it} = \rho y_{it-1} + month_t + \varepsilon_{it} \tag{14}$$

Table 2 shows the results of estimating Eq. (14). The value of 0.096 indicates that there is a small amount of persistence in the income process. This is much lower than standard estimates because the sample conditions on individuals who receive a regular paycheck.

I also estimate the variance of temporary shocks as $var(\varepsilon_{it}) = 0.039$. This is the value that is used throughout the analysis to calibrate the model.

3.3.4. Cash on hand and liquid assets

As discussed in Section 2 (theoretical framework), cash on hand plays a crucial role in identifying changes in circumstances as well as providing a proxy for characteristics. Cash on hand is defined as $X_{it} = A_{it-1} + Y_{it}$ where A_{it-1} represents liquid balances for individual i in the previous period and Y_{it} represents income received in the current period.

Liquid balances (A) are defined as the sum of checking and saving account balances observed in the app. These balances are captured daily as the app takes a snapshot of the balance from each provider.

3.3.5. Normalization

To match the theoretical framework, the main variables in the empirical analysis are normalized by individual average income. The normalization is denoted with lower case variables and so $c_{it} = C_{it}/\bar{Y}_i, x_{it} = X_{it}/\bar{Y}_i$ and so on. The observed level of average income serves as a proxy for unobserved permanent income.

3.4. Summary statistics

This section provides summary statistics of the main variables used in the analysis. The mean and median values for spending and income are roughly in line with the data used in Baker (2018) from a different personal finance app.

4. Empirical results

This section discusses the empirical results used to estimate the relative importance of circumstances and characteristics in explaining MPC heterogeneity. It finds that both circumstances and characteristics play a roughly equal role in explaining MPC heterogeneity. It also shows that the buffer stock model with discount factor heterogeneity fits the data quite well. The empirical distribution of the MPC across- and within- individuals as well as the distribution of cash on hand across individuals are both consistent with model simulations.

4.1. Tax refund impulse response function

As a preliminary step, I estimate the consumption impulse response function to receiving a tax refund. This analysis helps to confirm that the variables are constructed properly and behave according to economic theory. More specifically, I estimate the distributed lag of receiving a tax refund using the following specification.

$$c^q_{it} = \alpha^q + \sum_{j=-6}^{6} MPC^q_j \times ref^q_{it-j} + \delta^q_t + \varepsilon^q_{it}, \text{ where } q \in \{1, ., 5\} \tag{15}$$

The q superscript represent quintiles of average cash on hand ($\overline{coh_i}$), c_{it} represents normalized consumption, ref_{it-j} represents the normalized tax refund, δ_{it} represents month fixed effects, and ε_{it} is the error term. Fig. 8 below plots the MPC_j for each cash on hand quintile. The estimates show that there is little anticipatory response of consumption to receiving a tax refund and much of the response occurred within the first three months. The magnitude of the response is roughly in line with Souleles (1999) which examines the consumption response to income tax refunds in the CE. Souleles (1999) does not calculate the MPC across cash on hand quintiles so I compare those results with the average response across all individuals in this paper. The average response is very similar to the third quintile in Fig. 8 (see Online appendix). A more recent paper by Baugh et al. (2018) studies the weekly response of spending to the arrival of tax refunds using similar account data. They also find that individual spending reacts strongly when the refund is received followed by a quick decay.

Splitting the sample up into quintiles of average cash on hand reveals the heterogeneous response in the data. Individuals in the lowest quintile of cash on hand tend to react much more strongly to the receipt of a tax refund relative to those in the highest quintile of cash on hand. This relationship is broadly consistent with most of the literature examining the consumption response to income changes (for example, many of the studies discussed in Jappelli and Pistaferri (2010)).

In summary, the estimated response of consumption to receiving a tax refund is similar in dynamics and magnitude to previous studies. This fact helps to confirm that both consumption, tax refunds, and cash on hand are identified properly in the data set.

[15] More specifically, a month is dropped if the number of paychecks is more than one above the median number of paychecks or less than one below the median number of paychecks.

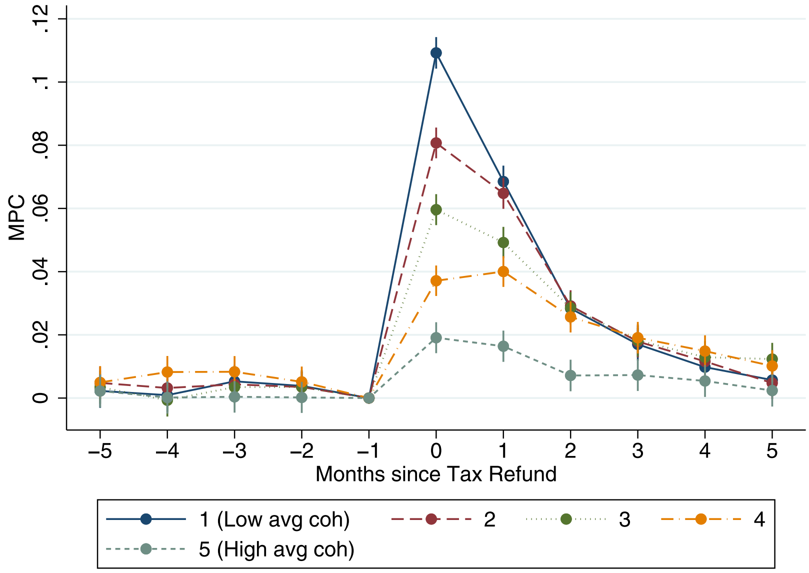

Fig. 8. Tax refund impulse response function *Notes:* 1,407,121 observations from 46,200 individuals. The vertical bars on each coefficient represent 95% confidence intervals using heteroskedasticity robust errors clustered at the individual level.

4.2. The relationship between the MPC and cash on hand

This section analyzes the relationship between the MPC and cash on hand using two different levels of aggregation. The first level of aggregation is at the individual-refund level and the second level of aggregation is at the quantile level.

4.2.1. Individual-refund level analysis

I estimate the quarterly MPC out of tax refunds for individual i at time t is using the following specification.

$$c_{it} = \alpha_{ir} + MPC_{ir} \times ref_{it} + \delta_t + \varepsilon_{it} \tag{16}$$

where i represents individual, t represents month, r represents refund year, α_{ir} represents a dummy variable for each individual-refund year[16], ref_{it} represents the refund amount, δ_t represents time fixed effects, and ε_{it} is the error term.

The estimated MPC measures from this specification are then plotted against different concepts of cash on hand in Fig. 9.

Panel (a) plots the results of a smoothed local linear kernel regression of the relationship between the individual-refund level MPC (MPC_{it}) and pre-refund cash on hand (coh_{it}^{PR}). The MPC is falling rapidly as cash on hand increases until it starts to level out around a value of 1.6. This empirical relationship is consistent with the simulation results presented earlier in Figs. 4 and 5. While previous studies have shown that a negative correlation exists between the MPC and cash on hand, this is the first paper to estimate the relationship using smooth kernel regressions with such a high level of precision. This high level of flexibility and precision provides novel evidence that the relationship between the MPC and cash on hand is consistent with a concave consumption function as argued by Carroll and Kimball (1996).

Panel (b) plots the relationship between the average MPC ($\overline{MPC}_i$) and average cash on hand ($\overline{coh}_i$). The results imply a statistically significant negative relationship between $\overline{MPC}_i$ and $\overline{coh}_i$. To my knowledge, this is the first paper to use panel data to estimate this relationship. This is important because averaging across time within individual isolates the role of persistent characteristics in driving the relationship between the MPC and cash on hand. The earlier simulation results showed that estimating the cross-sectional relationship between the MPC and cash on hand is not sufficient to separately disentangle the role of circumstances and characteristics. This is made clear when comparing panel (a) in Figs. 4 and 5. The two components can only be disentangled by isolating the characteristics component via the relationship between the average MPC and average cash on hand represented in panel (b) of Figs. 4 and 5. The significant negative relationship between $\overline{MPC}_i$ and $\overline{coh}_i$ imply that the characteristics component plays an important role in explaining MPC heterogeneity.

One possible concern is there there exists a mechanical relationship between the MPC and cash on hand that is orthogonal to both characteristics and circumstances. For example, individuals who over-withhold income taxes from their paychecks may tend to hold lower cash on hand before the arrival of a higher tax refund. Indeed, that is one of the conclusions in Gelman et al. (2019) which focuses more on the income tax withholding decision and shows that preferences are

[16] More specifically, this variable represents a series of dummy variables for each individual that takes a value of 1 for the three month windows before after a refund is received and 0 for all other periods. This variable ensures that the MPC captures the change in consumption during the three months after receiving the refund relative to the three months prior to receiving the refund. This is the definition of the quarterly MPC.

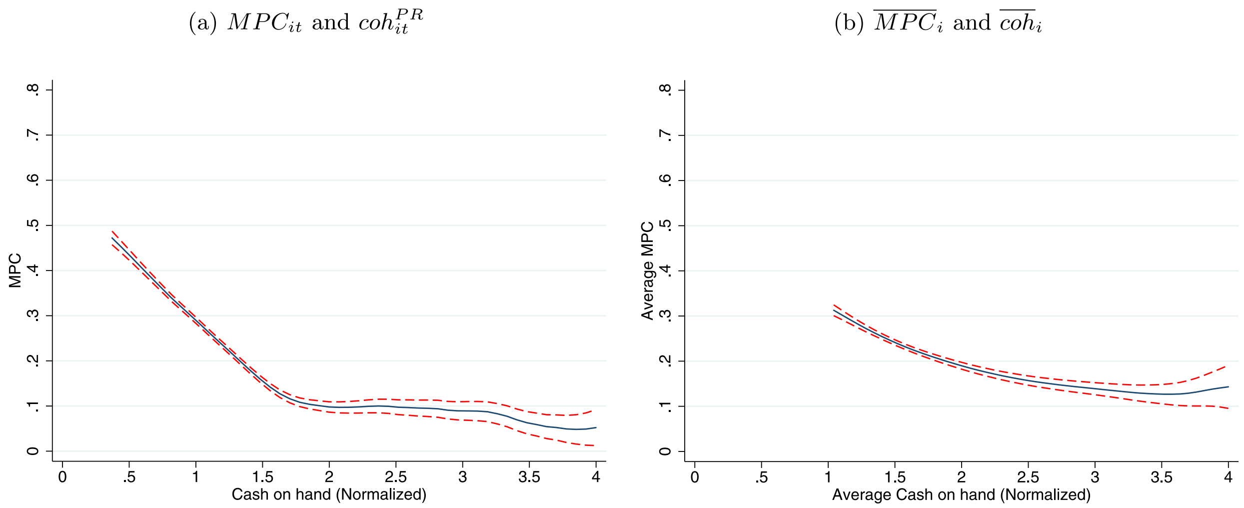

Fig. 9. MPC and pre-refund cash on hand *Notes:* 124,535 observations from 46,140 individuals in panel (a). 46,189 observations from 46,189 individuals in panel (b). The vertical bars on each coefficient represent 95% confidence intervals using heteroskedasticity robust errors clustered at the individual level. The MPC and cash on hand are winsorized at 5% and 1% respectively.

Table 4
Quintile sample statistics (raw).

	coh_{it}^{PR}			$\overline{coh}_i$		
	mean	median	N	mean	median	N
1	−1177.14	0.78	25,594	−2189.64	1.18	27,970
2	1.10	1.10	25,594	1.35	1.35	27,969
3	1.39	1.38	25,593	1.58	1.57	27,968
4	1.90	1.86	25,594	2.05	2.02	27,969
5	4.76	3.54	25,593	61.24	3.64	27,967
Total	−233.60	1.38	127,968	−424.71	1.57	139,843

Notes: The first three columns reflect quintiles of pre-refund cash on hand. The last three columns reflect quintiles of average cash on hand.

correlated with the average amount of over- or under-withholding an individual choses. Therefore, while the withholding decision is not modeled explicitly in this study, the framework is general enough to capture the correlation between average cash on hand and average MPC as part of the characteristics component.

4.2.2. Quantile level estimates

This section estimates the MPC at the quantile level. More specifically, it estimates the MPC for each group defined by the interaction of coh_{it}^{PR} and $\overline{coh}_i$ quintiles. The econometric specification is

$$c_{it} = \alpha_{jk} + MPC_{jk} \times ref_{it} + \delta_t + \varepsilon_{it} \tag{17}$$

where i represents individual, t represents month, j refers to pre-refund cash on hand quintile, and k refers to average cash on hand quintile.

More concretely, MPC_{jk} represents the MPC for individuals with pre-refund cash on hand quintile j and average cash on hand quintile k. The average cash on hand quintile is an individual-level trait and so does not vary within i. On the other hand, j is allowed to vary within individual based on the level of cash on hand that is observed before the tax refund is received. To understand these concepts better, Table 4 tabulates the mean and median levels of each quintile.

Fig. 10 plots the coefficients of MPC_{jk}. There are two relevant patterns to highlight. The first is that the MPC is falling as coh_{it}^{PR} increases. Consistent with the previous section, this suggests a role for cirumstances in explaining MPC heterogeneity. However, because coh_{it}^{PR} is influenced by both circumstances and characteristics, the next section will more clearly isolate the circumstances component. The second pattern is that conditional on coh_{it}^{PR} quintiles, the level of MPCs differs across individuals. This pattern suggests a role for characteristics in explaining MPC heterogeneity. While the gap between MPC levels across individuals is apparent in coh_{it}^{PR} quintiles 1, 2, and 3, it is less prevalent in quintiles 4 and 5. One explanation is that for the low average cash on hand individuals, higher levels of coh_{it}^{PR} are less commonly observed (see Fig. 12) and thus cause imprecise estimates.

While a difference in MPC levels conditional on cash on hand is consistent with heterogeneity in the discount factor, the ordering of the MPC levels across individuals also further helps to assess the validity of the model. To illustrate, Fig. 11 plots

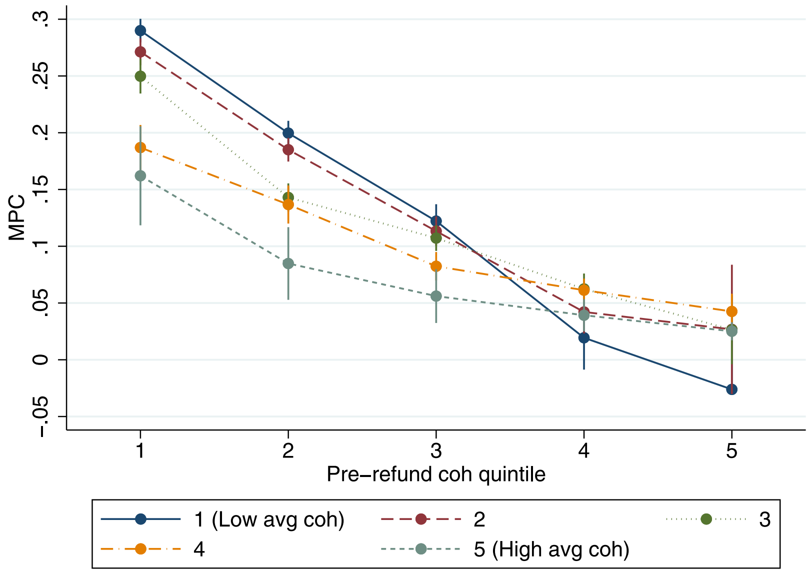

Fig. 10. MPC by quintile interactions (raw) *Notes:* This figure plots the MPC for each pre-refund and average cash on hand quintile combination.

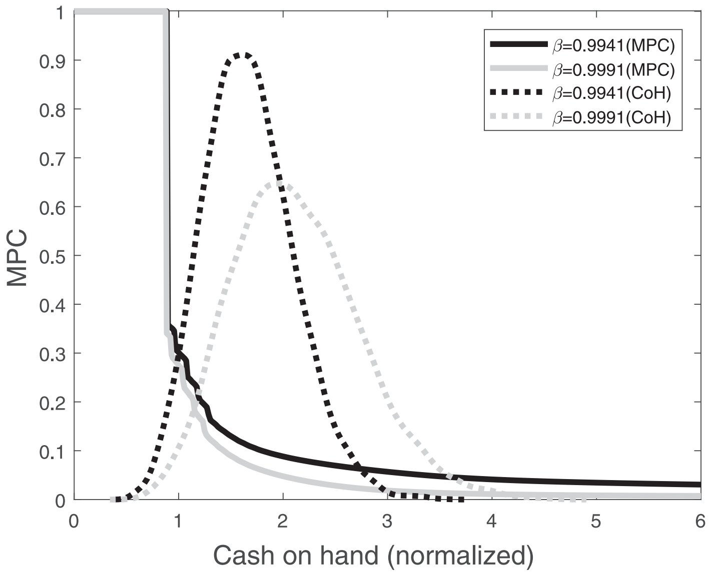

Fig. 11. The marginal propensity to consume and distribution of cash on hand *Notes:* The solid black line represents the MPC of the relatively more impatient individual and the solid grey line represents the MPC of the relatively more patient individual. The dotted lines represent the kernel density estimates of the distribution of cash on hand for each respective individual.

the MPC and distribution of cash on hand for individuals with different patience parameters. The solid black line represents the MPC of the relatively more impatient individual and the solid grey line represents the MPC of the relatively more patient individual. The dotted lines represent the kernel density estimates of the distribution of cash on hand for each individual. Aside from when the MPC is 1, the MPC is always higher for the more impatient individual conditional on the level of cash on hand. This pattern is broadly reflected in Fig. 10. While the point estimates for individuals with low average cash on hand are imprecise for higher quintiles of coh_{it}^{PR}, we can reject the hypothesis that the MPCs are equivalent across individuals for the same coh_{it}^{PR} quintiles. If there are no differences in characteristics, all individuals have the same consumption function so we would not observe any differences in the MPCs after conditioning on cash on hand.

The distribution of pre-refund cash on hand is also consistent with discount factor heterogeneity. Fig. 11 shows that in the simulated data, the cash on hand distribution of impatient individuals is more tightly centered around a lower mean. Conversely, the cash on hand distribution for patient individuals is more dispersed around a higher mean.

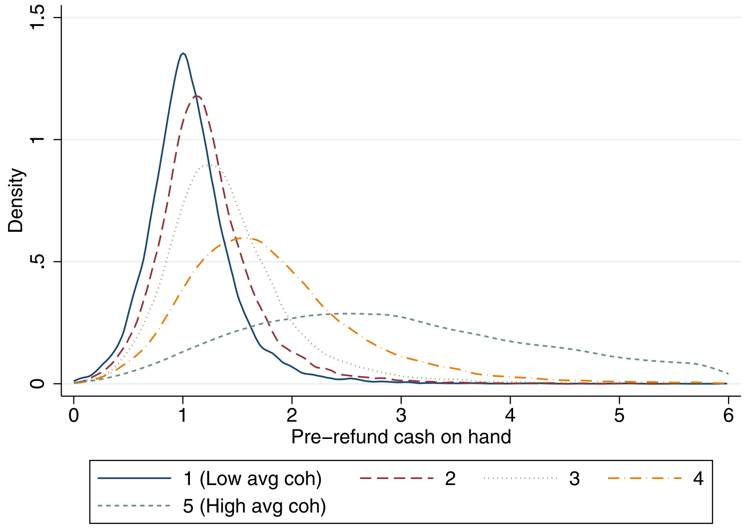

Fig. 12. Empirical coh_{it}^{PR} distribution by $\overline{coh}_i$ quintiles *Notes:* This figure plots the empirical pre-refund cash on hand distribution by average cash on hand quintiles.

To check whether this same pattern of the distribution of coh_{it}^{PR} holds in the data, Fig. 12 plots the empirical coh_{it}^{PR} distribution by $\overline{coh}_i$ quintiles. Consistent with the theory, individuals with low average cash on hand tend to have a tighter distribution of pre-refund cash on hand centered around a lower mean. Conversely, individuals with high average cash on hand tend to have a more disperse distribution of pre-refund cash on hand centered around a higher mean. This pattern explains the size of the confidence intervals for each estimate of MPC_{jk} in Fig. 10. For individuals with low average cash on hand, estimates at the lower quintiles of pre-refund cash on hand are measured with relatively high precision. However, the estimates for pre-refund cash on hand quintiles 4 and 5 are rather imprecise because it is rare that these individuals hold such high levels of pre-refund cash on hand.

To summarize, this section estimates the relationship between the MPC and cash on hand at both the individual-refund and quantile level. Both levels of aggregation confirm that both circumstances and persistent characteristics play important roles in explaining MPC heterogeneity. The next section will provide a quantitative measure of the relative importance of each component. This section also provides novel evidence showing that the distribution of the MPC and cash on hand is consistent with the buffer stock model with discount factor heterogeneity.

4.3. Variance decomposition

This section decomposes the variance of the MPC that is attributable to cash on hand into circumstances and characteristics components. The analysis first starts by adapting the quintile level analysis in the previous section to isolate the circumstances and characteristics components of cash on hand. The MPCs for the adjusted quintile interactions are estimated and plotted to visualize the decomposition. Lastly, the point estimates of the share of the variance of the MPC explained by both circumstances and characteristics components of cash on hand are calculated.

4.3.1. Graphical analysis

The graphical analysis starts by adjusting the quintiles in the previous section to capture the effect of circumstances and characteristics. The previous section estimated the MPC using the interactions of quintiles of pre-refund (coh_{it}^{PR}) and average cash on hand ($\overline{coh}_i$). Previous sections showed that $\overline{coh}_i$ captures the characteristics component of cash on hand because it acts as a proxy for the discount factor in the buffer stock theory. coh_{it}^{PR} does not, however, isolate the circumstances component of cash on hand because it is also influenced by the discount factor. To isolate the circumstances component, demeaned pre-refund cash on hand is used. More precisely, the quintiles are based on $coh_{it}^{PR} - \overline{coh}_i^{PR}$ instead of coh_{it}^{PR}. Table 5 shows the mean and median values of these quintiles. As expected, $coh_{it}^{PR} - \overline{coh^{PR}}_i$ has a mean of 0 and is approximately normally distributed.

The MPC for each quintile interaction is estimated using the following specification

$$c_{it} = \alpha_{dk} + MPC_{dk} \times ref_{it} + \delta_t + \varepsilon_{it} \tag{18}$$

where i represents individual, t represents months, d represents demeaned pre-refund cash on hand quintiles, and k represents average cash on hand quintiles.

Fig. 13 plots the coefficients of MPC_{dk}. The main difference with Fig. 10 in the previous section is that now the demeaned pre-refund cash on hand quintiles represent different actual cash on hand levels. This isolates the circumstances component

Table 5
Quintile sample statistics (demeaned).

	$coh_{it}^{PR} - \overline{coh^{PR}}_i$			$\overline{coh}_i$		
	mean	median	N	mean	median	N
1	−24.92	−0.72	25,594	−2189.64	1.18	27,970
2	−0.24	−0.23	25,594	1.35	1.35	27,969
3	−0.02	−0.02	25,593	1.58	1.57	27,968
4	0.19	0.18	25,594	2.05	2.02	27,969
5	24.99	0.72	25,593	61.24	3.64	27,967
Total	0.00	−0.02	127,968	−424.71	1.57	139,843

Notes: The first three columns reflect quintiles of demeaned pre-refund cash on hand. The last three columns reflect quintiles of average cash on hand.

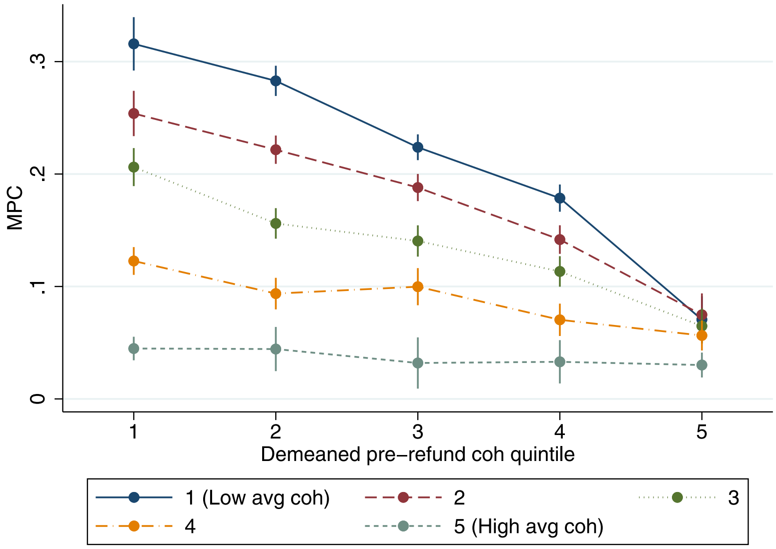

Fig. 13. MPC by quintile interactions (demeaned) *Notes:* This figure plots the MPC for each demeaned pre-refund and average cash on hand quintile combination.

of cash on hand and also leads to a more even distribution of observations across the quintiles. This is reflected in the fact that the standard errors are fairly consistent across $coh_{it}^{PR} - \overline{coh^{PR}}_i$ quintiles relative to using the raw quintiles of coh_{it}^{PR}.

This figure can be thought of as decomposing the circumstances and characteristics components of cash on hand represented by within and across individual variation. For example, consider the top blue line which represents individuals with low average cash on hand. The MPC drops from about 0.3 to about 0.08 when moving from the first to the last quintile of $coh_{it}^{PR} - \overline{coh^{PR}}_i$. Because the blue line holds average cash on hand constant, this drop from 0.3 to 0.08 represents the change in MPC when cash on hand changes within a person due to a change in circumstances. Another pattern that emerges is that the MPC drops more for low average cash on hand individuals relative to high relative cash on hand individuals. This pattern is explained by once again referring to the simulated MPC functions in Fig. 11. For impatient individuals (identified in the data via low average cash on hand), their pre-refund cash on hand distribution is tightly centered around a lower mean. The left tail of the distribution includes regions where the MPC function is very steep while the MPC function flattens out as cash on hand increases. This is consistent with the large change in MPC seen for the low average cash on hand individuals as cash on hand moves from the lowest to the highest quintile of $coh_{it}^{PR} - \overline{coh^{PR}}_i$. Conversely, patient individuals (identified in the data via high average cash on hand) have a more dispersed distribution around a larger mean. The cash on hand distribution rarely falls into areas where the MPC function is very steep. Therefore, there will be a less dramatic change in the size of the MPC as cash on hand moves from the lowest to the highest quintile of $coh_{it}^{PR} - \overline{coh^{PR}}_i$.

A change in the persistent characteristics component of cash on hand holding circumstances constant is represented by looking at how the MPC changes when holding the $coh_{it}^{PR} - \overline{coh^{PR}}_i$ quintile constant and moving across $\overline{coh}_i$ quintiles. For example, $coh_{it}^{PR} - \overline{coh^{PR}}_i$ quintile 3 represents the case where pre-refund cash on hand is close to the mean for each individual. At this quintile, the MPC ranges from about 0.22 for those with low $\overline{coh}_i$ and about 0.03 for those with high $\overline{coh}_i$. This distance represents across individual variation or variation that results from the persistent characteristics component of cash on hand which is a proxy for the discount factor.

To better understand how circumstances and characteristics influence the estimates in this section, Fig. 14 shows how Fig. 13 would look if only one source of variation was important.

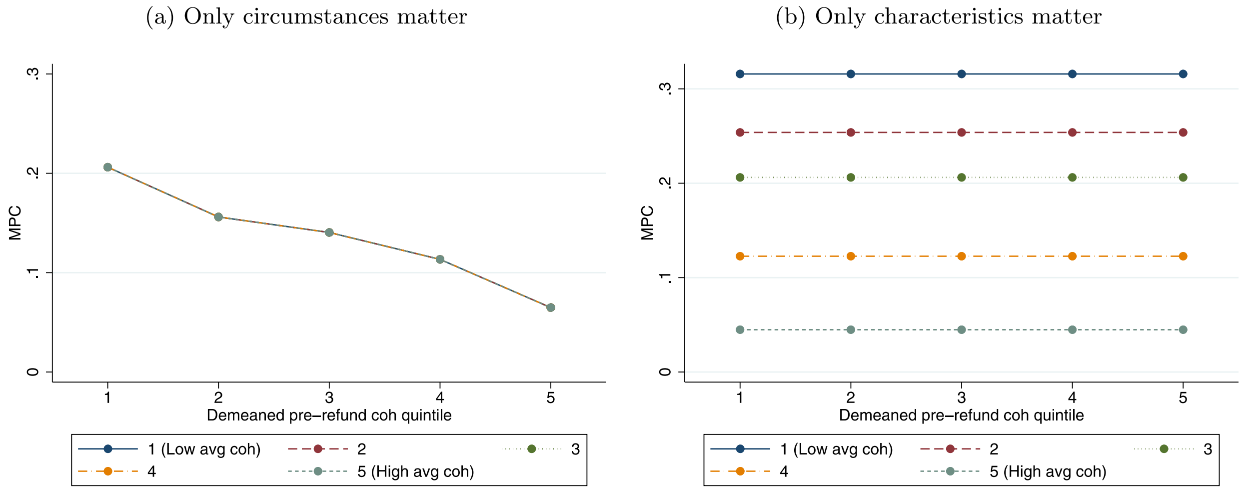

Fig. 14. Alternative scenarios *Notes:* This figure shows what the empirical MPC would look like under two alternative scenarios. Panel (a) considers the case where only circumstances matter and panel (b) considers the case where only characteristics matter.

For example, panel (a) shows the scenario in which circumstances drives all the variation in the MPC. In this case, the MPC will fall as demeaned pre-refund coh increases. However, there is no variation across average cash on hand quintiles. Conversely, panel (b) shows the scenario in which characteristics drives all the variation in the MPC. In this case, the MPC does not change as demeaned pre-refund cash on hand quintiles change. All the variation is driven by across individual variation and so the result is horizontal parallel lines. The estimates plotted in Fig. 13 represent a middle ground between the extremes in Fig. 14. This graphical analysis reveals that both circumstances and characteristics play important roles in explaining MPC variance. The next section builds upon this intuition and quantitatively estimates the contribution of the circumstances and characteristics component in explaining the variance of the MPC.

4.3.2. Regression analysis

The previous section estimated the MPC for each interaction of $coh_{it}^{PR} - \overline{coh_i}^{PR}$ and $\overline{coh_i}$ quintiles. This section uses the same variables to calculate the point estimates of the share of the variance in the MPC explained by both the circumstances and characteristics components of cash on hand. I use the same framework defined earlier in Section 2.4.4 which approximates the relationship between the MPC and the different concepts of cash on hand as follows.

$$MPC_{it} = \alpha + \underbrace{\gamma_1 \times \overline{coh_i}}_{\text{characteristics}} + \underbrace{\gamma_2 \times (coh_{it}^{PR} - \overline{coh_i}^{PR})}_{\text{circumstances}} + \varepsilon_{it} \tag{19}$$

where $\mathbb{E}[\varepsilon_{it}] = 0$. Under this specification, the variance is easily decomposed because all the terms are uncorrelated with each other. The following equation applies the variance operator to both sides.

$$var(MPC_{it}) = var(\alpha) + var(\gamma_1 \times \overline{coh_i}) + var(\gamma_2 \times (coh_{it}^{PR} - \overline{coh_i}^{PR})) + var(\varepsilon_{it}) \tag{20}$$

Defining $var(\gamma_1 \times \overline{coh_i}) = \sigma_{char}^2$ and $var(\gamma_2 \times (coh_{it}^{PR} - \overline{coh_i}^{PR})) = \sigma_{circ}^2$, these terms capture the variance contribution of the persistent characteristics and circumstances component of cash on hand respectively. Defining $\phi_{char} = \frac{\sigma_{char}^2}{\sigma_{circ}^2 + \sigma_{char}^2}$, this value represents the fraction of $var(MPC_{it})$ explained by cash on hand that is attributable to characteristics.

The results from estimating specification (19) are presented in Table 6 below. The sign of the coefficients show that both $\overline{coh_i}$ and $(coh_{it}^{PR} - \overline{coh_i}^{PR})$ vary negatively with the MPC. This is consistent with economic theory, the earlier empirical analysis, and the empirical literature. Calculating the ratio $\phi_{char} = \frac{\sigma_{char}^2}{\sigma_{circ}^2 + \sigma_{char}^2} = 0.45$ shows that about half of the variance of the MPC that is explained by cash on hand is driven by the characteristics component. This is in line with the graphical results in the previous section that showed both the characteristics and circumstances component play an important role in explaining the variance of the MPC.

There are some alternative ways to calculate the characteristics variance share using the framework laid out in this section. The first alternative is to define the circumstances share differently. In this section, the circumstances component is defined as pre-refund cash on hand subtracted by its mean $(coh_{it}^{PR} - \overline{coh_i}^{PR})$. The alternative methodology is to demean pre-refund cash on hand by total average cash on hand instead of just the average of pre-refund cash on hand $(coh_{it}^{PR} - \overline{coh_i})$. The difference arises because the circumstances component only captures the state of liquidity preceding the receipt of a

Table 6
Variance decomposition.

Variables	$\hat{\gamma}$	$\hat{Var}$	$\hat{\gamma}^2 \times \hat{Var}$	$Var\hat{Share}$
$\overline{coh}_i$	-0.047*** (0.002)	1.127	0.0024	0.45*** (0.033)
$(coh_{it}^{PR} - \overline{coh}_i^{PR})$	-0.088*** (0.004)	0.376	0.0029	0.55*** (0.033)
Observations	124,535	124,535	124,535	124,535

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ For $\hat{\gamma}$, heteroskedasticity and cluster robust standard errors in parentheses. For $Var\hat{Share}$, cluster bootstrapped standard errors in parenthesis with 10,000 draws. All variables winsorized at the 5% level.

Table 7
First stage parameter values.

Parameter	Value	Source	Description
$u(x)$	$\frac{x^{1-\theta}}{1-\theta}$	CRRA utility	utility function
θ	1	standard	coefficient of relative risk aversion
σ_Y	0.20	income time series	S.D. of temporary shocks
$refund_{it}$	0.6	tax refund distribution	average normalized refund
r	0.01 / 12	external savings data	interest rate
b	0	no borrowing condition	borrowing limit

Notes: The parameters correspond to a monthly frequency.

refund that occurs once a year. Demeaning using $\overline{coh}_i^{PR}$ represents deviations from average liquidity right before the refund is received while demeaning using $\overline{coh}_i$ also includes seasonal fluctuations in liquidity over the course of the year. The Online appendix discusses the calculation of the characteristics variance share using this alternative method. Using this method leads to a characteristics variance share of 0.43.

The second alternative is to include higher order terms in specification (19). While including higher order terms helps to better capture the total variance of the MPC, it results in roughly the same characteristics variance share (0.45) as not including the terms. The Online appendix presents the analysis with the higher order terms included.

To summarize, this section used both graphical and regression analysis to decompose the variance of the MPC into a circumstances and characteristics component. The results show that both components play a roughly equal role in explaining the variance of the MPC.

5. Structural estimation

This section connects the empirical results back to the model by estimating the model parameters via the method of simulated moments. The estimation proceeds in two steps. In the first step, I estimate and calibrate the parameters that don't rely on the explicit solution of the model. In the second stage, I estimate the remaining parameters that rely on the model solution conditional on the first stage estimates.

5.1. First stage estimation and calibration

I calibrate the coefficient of risk aversion (θ), the interest rate (r), and the borrowing limit (b) by setting them to reasonable values. As mentioned earlier, the discount factor (β) and risk aversion (θ) are not easily separately identified so I choose to set $\theta = 1$ which allows me to compare β to other papers using similar methods such as Carroll et al. (2017) and Krueger et al. (2016).

The income process is governed by the standard deviation of income shocks (σ_Y). I estimate σ_Y directly from the data by using the panel nature of the income process. The estimation process was presented earlier in Section 3.3.3. The average level of tax refunds in the data is also estimated directly from the data by taking the unconditional mean of normalized tax refunds.

The values of the first stage parameters are listed below in Table 7.

5.2. Second stage estimation

In the second stage, I use the method of simulated moments to estimate the parameters that rely explicitly on the model. This estimation procedure is used because there is no simple analytic expression for the theoretical moments in the model.

More specifically, the average discount factor ($\overline{\beta}$) and the dispersion in the discount factor (Δ) are estimated by matching the fraction of $var(MPC_{it})$ explained by cash on hand that is attributable to characteristics (ϕ_{char}) and median cash on hand ($\widetilde{CoH}_i$). The parameters are exactly identified because I use two moments to estimate two parameters.

Table 8
Second stage parameter and moment estimates.

Parameter	Value	Description
$\hat{\bar{\beta}}$	0.9941	average discount factor
$\hat{\Delta}$	0.0190	discount factor dispersion
Moment		
$\hat{\phi}_{char}$	0.4500	characteristics variance share
$\widetilde{CoH}_i$	1.5700	median cash on hand

Notes: The parameters correspond to a monthly frequency.

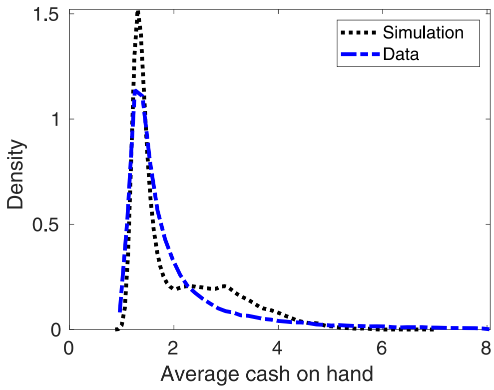

Fig. 15. Average cash on hand distribution *Notes:* This figure compares the average cash on hand distribution simulated in the model to the empirical distribution estimated from the data.

The parameter estimate $\hat{\Theta} = \{\hat{\bar{\beta}}, \hat{\Delta}\}$ is the solution to the criterion function

$$\hat{\Theta} = \arg\min_{\Theta}(m_{data} - m_{sim}(\Theta))(m_{data} - m_{sim}(\Theta))' \tag{21}$$

where $m = \{\phi_{char}, \widetilde{CoH}_i\}$, m_{data} represent moments calculated from the data, and $m_{sim}(\Theta)$ represent moments calculated from simulating the model under parameters Θ.

The parameter estimates and empirical moments are shown in Table 8.

The estimated parameters are roughly in line with Carroll et al. (2017) who calibrate their model at the quarterly level by matching either liquid financial and retirement assets.

5.3. Fit of other variables

This section assesses the fit of variables that weren't explicitly targeted in the estimation procedure.

Cash on hand distribution Fig. 15 compares the average cash on hand distribution in the model to the data. The fitted model matches the empirical disitribution fairly well. This ability to match the distribution of cash on hand partially explains why the estimates are similar to Carroll et al. (2017). Their paper estimates the dispersion of the discount factor by matching the shape of the liquid assets distribution. Therefore, introducing heterogeneity in the discount factor is important to explaining the relationship between the MPC and cash on hand as well as explaining inequality in the wealth distribution.

MPC The aggregate MPC in the model is 0.10 compared to 0.14 in the data. While this paper doesn't explicitly target the aggregate MPC, it is reassuring to know that the model is relatively close its empirical counterpart.

6. Conclusion

The literature has broadly focused on two classes of models to better understand what factors drive MPC heterogeneity. One class emphasizes persistent characteristics across individuals while the other class emphasizes temporary circumstances within individuals. Because most empirical studies of MPC heterogeneity use cross-sectional data, it is challenging to disentangle the relative importance of circumstances and characteristics. This paper overcomes this empirical challenge by using detailed panel data capturing high frequency responses of consumption to the arrival of a tax refund jointly with detailed liquidity measures. This novel dataset allows me to empirically decompose the variance of the MPC that is explained by cash on hand into a circumstances and characteristics component. I find that both circumstances and characteristics play roughly equal roles in explaining the variance of the MPC.

Using this novel measure of the relative importance of circumstances versus characteristics in explaining MPC heterogeneity, I estimate a buffer stock model with discount factor heterogeneity. The estimates are roughly in line with other studies and the estimated model performs well in explaining various aspects of the data. More specifically, the model is able to account for the distribution of MPC within- and across- individuals that is estimated from the data. For example, for individuals with large average cash on hand, the estimated MPC does not vary much across within-individual cash on hand quintiles. The model is able to explain this pattern because patient individuals hold high levels of average cash on hand and tend to inhabit the relatively flat portion of the consumption function. Conversely, the estimated MPC for individuals with low levels of average cash on hand tends to vary greatly across within-individual cash on hand quintiles. This is explained by the fact that impatient individuals inhabit the much steeper portion of the consumption function. Therefore, a relatively parsimonious buffer stock model with discount factor heterogeneity is able to match these new empirical facts well.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2020.03.006.

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