Master Project

Swiss Bank Savings vs Piggy Bank Savings: The Effect of Offshore Wealth on Estimates of Inequality and the Marginal Propensity to Consume

Nicolas Charlton, Georgi Demirev, Daniel Ruiz Palomo, Christoph Semken, Joël Terschuur

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Abstract

Survey data containing wealth estimates at the household level is often used in conjunction with heterogeneous agent models to study the impact wealth inequality can have on an economy, including through the marginal propensity to consume (MPC). Unfortunately, these data often suffer from under-representation and differential non-response from wealthy households near the top of the distribution, leading to biased wealth distribution estimates. Using offshore wealth data from Alstadsæter et al. (2018), we propose a novel method for mitigating these issues and apply our methodology to the ECB's Household Finance and Consumption Survey (HFCS). We re-calibrate a consumption-savings model proposed by Carroll et al. (2014c) using wealth distributions estimated with and without offshore. We find that correcting for offshore wealth leads to important changes in the predicted average MPC and distribution of MPCs for several countries.

Keywords: MPC, wealth inequality, HFCS, offshore wealth, Krusell-Smith, heterogeneity

JEL Codes: D12, D31, E21, H26

Code: `https://github.com/demirev/offshore_mpc`

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1 Introduction

Extending partial and general equilibrium models to allow for heterogeneity in wealth and income can help shed light on many aspects of inequality.[1] First, they can be used to better understand the mechanisms and channels through which inequality evolves. Second, quantitative models have the potential to inform and shape policy decisions. For example, we might need to know how distorting a tax on capital or income might be,[2] or we might want to consider how much of a boost to aggregate consumption a one time stimulus shock might have.

However, these models are only as good as the quality of data with which they can be calibrated. Household surveys, often used for this kind of calibration work, can suffer from sampling and non-differential response biases. A related issue is that of hidden wealth. It is estimated that somewhere around 10% of the world's GDP is kept away in offshore accounts, far from the prying eyes of tax authorities (Zucman 2013). Unfortunately, obtaining accurate and representative wealth and income measures of the top percentiles at the micro level is hard and will continue to increase in difficulty in an ever globalized world (Alstadsæter et al. 2018). While techniques have been developed to help mitigate some of these measurement issues, problems persist (Caju 2013; Vermeulen 2017). We argue that correcting for offshore wealth can help mitigate some of these problems.

To our knowledge, there does not yet exist a paper which studies inequality using heterogeneous agent models while also considering the bias offshore wealth might have on calibration targets. Therefore, our paper's contribution to the inequality literature is twofold. First, we propose a method of modifying household survey wealth data to account for this hidden (or offshore) wealth. In particular, we apply our methodology to the Household Finance and Consumption Survey and briefly discuss some of the more important changes observed. Second, using this modified dataset, we revisit the work of Carroll et al. (2014c) (hereafter CST) and provide a robustness check on their quantitative results.

To complete the first task, we take advantage of the work recently done by Alstadsæter et al. (2018). In their paper, they estimate country-specific proportions and levels of offshore wealth held by each wealth decile. Overall, they find that 98.4% of all offshore wealth is held by the top 10% of the wealth distribution. Using their data, we are able to fit a Pareto distribution to offshore wealth estimates and add it to the wealth distribution estimated from the Eurosystem Household Finance and Consumption Survey (hereafter, HFCS). As expected, we find that the Gini coefficients implied by the adjusted HFCS increase substantially for every country analyzed.

Using this offshore-adjusted HFCS, we then proceed to calibrate the model introduced by Carroll et al. (2015). This model is characterized by prudence which implies a certain level of precautionary saving from the model's agents, heterogeneous time preferences,[3] and idiosyncratic income shocks. It is the interplay of these three forces which gives rise to an unequal wealth distribution. By calibrating the model to both non-adjusted and offshore-adjusted HFCS wealth data, we can check the robustness of CST's results to changing levels of inequality. In particular, as CST do, we focus our attention to analyzing agents' marginal propensity to consume. Overall, we find that the model is still able to generate a similar wealth distribution to the one found in the data for a reasonable range of time preference parameter estimates. However, we also observe that the model fails to fit properly those distributions which are more extremely skewed, implying that the model might only be a good policy analysis tool for countries where wealth inequality is not too extreme.

[1] See Bewley (1977)
[2] See Kaplan and Violante (2014) for a treatment on the subject
[3] An intuitive explanation for what a heterogeneous discount factor actually measures can be found in Carroll et al. (2017)

The rest of this paper is organized as follows. In the next section, we review previous work on the topic. In section 3 we discuss the HFCS dataset. In section 4, we present the methodology for offshore-wealth adjustment. The macroeconomic model used to estimate the marginal propensity to consume is laid out in section 5. We show our calibration results and discuss the results. Section 6 concludes.

2 Literature Review

Over the years, many models have emerged in an attempt to better understand the impact of wealth inequality on various macroeconomic indicators. Early work by Bewley (1977) laid the foundation for micro-founded studies in this field. Typical models with a Bewley (1977) framework have incomplete-markets and agents who save to self-insure against idiosyncratic shocks to income. Precautionary savings drive wealth concentrations in these models, but the implied wealth distributions often fail to match empirical estimates (Nardi 2015). Recent extensions such as Krusell and Smith Jr. (2006) (hereafter KS), and Hendricks (2007) include forces such as heterogeneity in preferences, and transmission of bequests and human capital across generations in attempts to yield a more realistic wealth distribution.[4] More recent work by Carroll (2011), Carroll et al. (2015), and Carroll et al. (2017) has helped improve these models considerably. These papers explore a model that allows for a modest amount of heterogeneity in consumers' preferences. An important contribution of this work is the joint analysis between preference heterogeneity and the marginal propensity to consumer out of transitory income shocks (hereafter MPC).

The MPC is an important macroeconomic measure which, depending on its size, can have serious fiscal policy implications (Jappelli and Pistaferri 2014). If the MPC is small, then one time fiscal shocks should only have small or negligible effects on aggregate consumption.[5] If the MPC is significantly larger than zero, then fiscal policy could in fact help spur aggregate consumption. While a typical representative agent model has an MPC near 0.04 (Mehra 2001), many empirical studies have found that it might in fact be far greater. Jappelli and Pistaferri (2014) find an average marginal propensity to consume of .48 using survey responses in the 2010 Italian Survey of Household Income and Wealth; while Johnson et al. (2006) find a "long-run" MPC around 60 percent on non-durables following the 2001 US fiscal stimulus package. These studies use survey responses to measure the MPC out of unanticipated income shocks. Another method of estimating the MPC has been the quasi-experimental approach.[6] A third approach, found in CST and Carroll et al. (2017), is of calibrating a theoretical model using empirical data, then reporting the MPC implied by that model's consumption function.

According to the permanent income hypothesis, MPCs (out of transitory income shocks) should be close to zero (Friedman 1957). An important mechanism which can go a long way in explaining the higher MPC found in various studies, is the presence of liquidity constraints (Campbell and Mankiw 1989). However, there are other factors at play. By combining a Krusell-Smith-framework with a Friedman/Buffer Stock income process (FBS), along with exogenous and mild heterogeneity in the time preference discount factor, Carroll et al. are able to match the empirical wealth distribution of the US (CSTW 2017) (using the U.S. Survey of Consumer Finance), as well as that of 15 European countries (CST 2014) (using the Household Finance and Consumption Survey, or HFCS) quite well. Using this model, they study the Marginal Propensity to Consume for each of these countries and find that the MPC can be as high as

[4] Nardi (2015) reports that they find mixed results. KS are able to match the variance of the wealth distribution much better than previous work, but fail to capture the "extreme degree of concentration of wealth" found at the end of the distribution.

[5] If the MPC is zero, then households will elect to spend the annuitized value of this shock.

[6] See for example Browning and Crossley (2001) who study the effect of legislated changes in unemployment insurance on consumption in Canada, or even Bodkin (1959) who studied the effect that an unexpected receipt of dividend payments had on WWII veterans (Jappelli and Pistaferri 2014)

an order of magnitude larger than implied by traditional representative agent models.[7] The right-skewed wealth distribution is a crucial component in generating a high MPC. Because each agent's consumption function is non-linear and concave, those agents with relatively low wealth will consume a relatively large portion of a transitory income shock, while those with relatively high wealth will instead save more.

Clearly, inequality is a driving force in these models' high MPC estimations. However, how robust are they to measurement errors, selection bias, and differential non-response bias in the underlying survey used for its calibration? Chakraborty and Waltl (2017), and Eckerstorfer et al. (2016) discuss some of these estimation issues as they relate to the HFCS. In general, to adjust for under-sampling or under-reporting of household wealth, five different sources of data are used: wealth tax returns, estate tax returns, investment income methods, household surveys, and journalistic rich list (Roine and Waldenström 2015). Eckerstorfer et al. (2016) propose a methodology to fit a Pareto distribution to the top tail in order to account for the "missing rich". A similar methodology is followed in Chakraborty and Waltl (2017), where they show that inequality is even more extreme than originally reported.Another reason for the "missing wealthy" is explored in Alstadsæter et al. (2018) and Alstadsæter et al. (2017a). The authors contend that much of the wealth held offshore belongs to the top 0.01%. This wealth often goes unreported and, as such, should bias survey and tax data in most European countries.

3 The Data

The Eurosystem Household Finance and Consumption Survey provides information about households' finances and consumption patterns. Covering most of the Euro area, it samples households in waves, allowing for both aggregate and individual analysis (see Table 1). Participating countries for the first wave were Belgium, Germany, Greece, Spain, France, Italy, Cyprus, Luxembourg, Malta, Netherlands, Austria, Portugal, Slovenia, Slovakia and Finland.[8]

Table 1: Sample size for the HFCS Survey. Source: HFCN (2013)

Countries	AT	BE	CY	DE	ES	FI	FR	GR	IT	LU	MT	NL	PT	SI	SK
Interview households	2.380	2.364	1.237	3.565	6.197	10.989	15.006	2.971	7.951	950	843	1.301	4.404	343	2.057
Persons 16+ in net sample	4.356	5.608	3.151	7.084	13.952	21.696	28.952	6.601	17.274	2.037	2.016	2.517	9.638	850	4.421

The content of the survey is divided into two main blocks. The first part focuses on the net asset position of each household.[9] The second part focuses on individual-level qualitative questions such as employment status or future pension entitlements. The variables of interest to our analysis are Net Wealth and Liquid Assets. Net Wealth is already reported in the HFCS. According to the HFCS Net Wealth consists of "total household assets excluding public and occupational pension wealth minus total outstanding household's liabilities". As for Liquid Assets, we construct this measure following CST.[10]

Nine out of fifteen countries used various strategies to oversample wealthy households, while another six made no such adjustments. Spain and France used individual-level data on taxable wealth. In Finland and Luxembourg individual level income and in Cyprus household level electricity consumption were used as proxies for wealth. In Belgium and Germany the proxy for wealth was regional level income and in

[7]For the U.S., they find an MPC ranging from 0.2 to 0.6 depending on the measure of wealth used in their calibration. For the European countries, they find MPCs ranging from 0.1 to 0.4.

[8]The data is available upon request from the HFCN

[9]Here we find questions related to a household's real assets and details on financing, liabilities and credit constraints, private business and financial assets, inter-generational transfers and gifts and consumption/savings.

[10]Liquid assets is the sum of deposits, mutual funds, business wealth, shares, managed accounts, life insurance, and bonds.

Greece regional real estate prices. Other countries oversample municipalities in which higher income has been observed and in which non-response was expected to be higher.

Despite these attempts to properly estimate the top part of the wealth distribution, several authors have highlighted that wealthy households might still be underrepresented (HFCN 2016, Caju 2013, Tiefensee and Grabka 2016, and Eckerstorfer et al. 2016). Particularly striking are the recent results from Vermeulen (2017). In his paper he compares the level of wealth of the wealthiest households in the HFCS to those reported in the Forbes World's billionaires list and observes that "none of the households in the HFCS [...] comes even close to the wealth levels of individuals on the Forbes billionaires list". In spite of this, Vermeulen (2017) does note that the gap between the wealthiest households coming from the HFCS data and the Forbes billionaires list is narrower in those countries where a more complex oversampling strategy was followed compared to those where none was used at all. These results indicate that, even after applying techniques to minimize differential non-reporting and other such biases, the HFCS still fails in providing an accurate wealth distribution.

In an attempt to rectify this issue, we turn our attention to a recent paper by Zucman (2013) which estimates the amount of household wealth owned by each country in offshore tax havens. According to his calculations, the equivalent of 10% of the world's GDP is held in tax havens with a great amount of heterogeneity across different countries. Regarding European countries of interest to this paper, the amount of offshore wealth as a percentage of GDP varies from almost a 40% for Greece to less than 5% for Finland, as shown in Table 2.[11]

Table 2: Offshore wealth. Source: Zucman (2013) and Alstadsæter et al. (2018)

Countries	AT	BE	CY	DE	ES	FI	FR	GR	IT	LU	MT	NL	PT	SI	SK
Total offshore wealth (billions US$)	30,5	82	-	551,8	163,8	6,9	409,3	115,2	262,2	-	-	50,6	51	1,3	2,1
Total offshore wealth (% 2007 GDP)	7,9%	17,4%	-	16,0%	11,1%	2,7%	15,4%	36,2%	11,9%	-	-	6,0%	21,2%	2,8%	2,4%

Two follow-up papers by Alstadsæter, Johannesen, and Zucman (Alstadsæter et al. 2017a, Alstadsæter et al. 2018) provide estimates of the percentage of offshore wealth that is held by the different percentiles of the households when ordered by their net wealth and applies these to the wealth held in offshore tax havens (see Table 3). To arrive at their estimates, the authors use a mix of micro and macro-data from the Panama Papers leak, the HSBC Switzerland leak, the BIS, and the Swiss central bank.[12] Unsurprisingly, approximately 98.4% of the total offshore wealth is held by households that are in the top 10% of the wealth distribution. This result suggests a new possible correction to the wealth distribution obtained in the HFCS, which we discuss below.

Table 3: Distribution of Offshore Wealth. Source: Alstadsæter et al. (2017a)

Distribution of offshore wealth (% of offshore wealth)					
Bottom 90%	Bottom 95%	Bottom 99%	Bottom 99.5%	Bottom 99.9%	Bottom 99.99%
1.6%	2.6%	6.4%	9.9%	23.1%	48.4%

[11] Zucman (2013) computes wealth estimates for all of our countries of interest except for Cyprus, Lithuania, and Malta.
[12] A methodology that we will discuss further in 4.3 Limitations.

4 Inequality Estimates with and without Offshore Wealth

4.1 Inequality Estimates without Offshore Wealth

The Gini coefficient (hereafter, Gini) is the parameter we use to assess inequality in each country under examination (see Table 4). It can be computed using both Net Wealth or Liquid Assets. We find a modest amount of heterogeneity between country Ginis. The countries with the smallest Gini for net wealth are Slovakia and Slovenia while the countries with the highest Gini coefficient for net wealth are Austria and Germany. Regarding liquid assets, southern European countries such as Malta, Italy, Greece and Spain are those with a higher inequality.

The distribution of liquid assets is more unequal than the distribution of net wealth. This result, also highlighted previously by CST, may be explained by the inclusion of housing to which a relatively big amount of households have access to. In countries where there is a low home ownership-rate such as Austria and Germany have higher net wealth inequality (Eurostat 2018).

Table 4: Gini Coefficient for Net Wealth and Liquid Assets

Countries	AT	BE	CY	DE	ES	FI	FR	GR	IT	LU	MT	NL	PT	SI	SK
Gini Net Wealth	0.744	0.599	0.670	0.751	0.563	0.610	0.658	0.547	0.604	0.667	0.576	0.568	0.619	0.529	0.443
Gini Liquid Assets	0.736	0.760	0.770	0.697	0.807	0.768	0.768	0.808	0.838	0.700	0.837	0.784	0.775	0.802	0.781

4.2 Inequality Estimates with Offshore Wealth

In what follows, we propose a novel method of adjusting wealth estimates that relies on the estimates of the offshore wealth distributions made by Alstadsæter et al. (2018). Unlike the adjustments proposed by Vermeulen (2017) and Chakraborty and Waltl (2017) we intend to estimate that part of wealth that is held offshore for the top decile in each country under consideration and subsequently add it to the HFCS estimate. We hypothesize that much of this wealth goes unreported and, as such, won't be accounted for in the HFCS even for those countries that undertook oversampling strategies.[13] We refer to this new adjusted dataset as "offshore-adjusted HFCS". To the best of our knowledge, this correction has not yet been done and its implications on different economic indicators such as the Gini coefficient or the MPC have not yet been tested.

Based on the seminal work of Pareto (1896), the tail of the wealth distribution is typically estimated using a Pareto distribution.[14] In line with this work, we hypothesize that the distribution of offshore wealth held by different households also follows a Pareto-like equation of the form:

$$P = 1 - \left(\frac{w_m}{w}\right)^{\alpha} \tag{1}$$

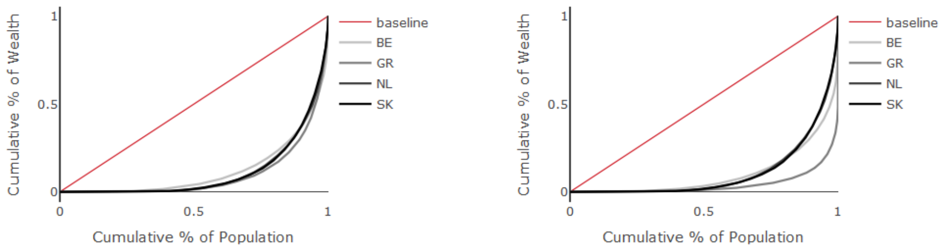
where P is the percentile of households with an offshore wealth below the w% of the total offshore wealth and w_m is the percentage of offshore wealth that can be imputed to the 90th percentile of households.

The results from Alstadsæter et al. (2018) provides us with five points (see Table 3) that can be used to fit a linear regression, after rearranging equation (2) and taking logs, to find an estimate for α. Following this procedure we find a point estimate for $\alpha = 2.7672$. Once this has been done, equation (1) can be

[13]For example, "90%-95% of the wealth owned by Danish and Norwegian households at HSBC Switzerland was not declared", as reported by Alstadsæter et al. (2018)"

[14]For a survey of the related literature, see Roine and Waldenström (2015) who conclude that a Pareto distribution provides a good fit for the tail of the wealth distribution, a finding which remains robust across countries and time

Figure 1: Lorenz curves for liquid assets with and without offshore wealth



(a) Without offshore assets (b) With offshore assets

inverted to find the cumulative percentage of offshore wealth that can be imputed to every percentile of the wealth distribution above the bottom 90% of the distribution:[15]

$$w = \frac{w_n}{(1-P)^{\frac{1}{\alpha}}} \tag{2}$$

Finally, for the remaining 1.6% of offshore wealth we suggest simply to evenly divide amongst the bottom 90th percentile (see Table 3).

Alstadsæter et al. (2017b) focus on the following financial assets: bank deposits, portfolios of bonds, equities, mutual fund shares and derivatives managed by foreign financial institutions. They explicitly leave aside more illiquid assets such as gold, diamonds, foreign real estate or works of arts since there is no systematic information about these assets. Therefore, in our adjustment for offshore wealth we only correct the liquid asset distributions and not the net wealth (which inevitably contains illiquid wealth such as that described above).

Once the adjustment has been done we can look at the new Gini coefficients to see how much offshore wealth changes the distribution of liquid assets. The results are summarized in Table 5. In most of the countries, adding offshore wealth increases the Gini coefficient by approximately 0.03 points. The greatest increase in Gini occurs in Greece, with an increase of more than 0.1 points while the country where the Gini coefficient increases the least is the Netherlands with a difference of 0.002 points. Not surprisingly, countries with large amounts of offshore wealth are also the countries for which the Gini coefficient increases the most after adjustment. The Lorenz curves for the distribution with and without offshore wealth, used to calculate the Ginis is shown for four countries in Figure 1.

Table 5: Gini Coefficient for Liquid Assets with and without Offshore Wealth

Countries	AT	BE	CY	DE	ES	FI	FR	GR	IT	LU	MT	NL	PT	SI	SK
Gini Liquid Assets	0.736	0.760	0.770	0.697	0.807	0.768	0.768	0.808	0.838	0.700	0.837	0.784	0.775	0.802	0.781
Gini Liquid Assets with Offshore	0.768	0.798	-	0.722	0.836	0.790	0.789	0.916	0.847	-	-	0.786	0.790	0.810	0.787

4.3 Limitations

We are confident that our approach of adding offshore wealth to the HFCS provides a lower bound for actual wealth since these households are both under-represented and they generally do not report their

[15] Note that the proposed equation is only meaningful for percentiles of households such that w is smaller than 1. This means that for percentiles very close to 1 we would be imputing more than 100% of offshore wealth to some. In order to overcome this handicap we normalized the cumulative percentage of offshore that every household gets by the maximum percentage of offshore wealth assigned to the wealthiest household.

offshore wealth (see fn. 13). For discussing the quality of the data, we differentiate between sources. On the one hand, we believe the HFCS data to be of high quality, other than the missing wealth. Tiefensee and Grabka (2016) independently confirm the high quality of the sampling methods used and their implementation. Similarly, Zucman's estimate for global offshore wealth is at the lower range of other estimates, including a written testimony by the OECD (Owens 2007). The data were directly submitted to the BIS by banks in tax havens and bank secrecy is not an issue because the figures are country-level aggregates.

On the other hand, the method used to estimate the shares of offshore wealth held by different percentiles of the wealth distribution requires some scrutiny. First, Alstadsæter et al. (2017a) use tax amnesty and leaked data only from Scandinavian countries. They note that "the distribution of hidden assets by wealth group is remarkably similar in all the available resources." This does not rule out different distributions for countries where no data was available. Yet, we are relatively confident that at least the fact that the bottom 90% hold only a few percent of offshore wealth holds for other countries. Second, following Alstadsæter et al. (2018), we use the share estimates for bank deposits to allocate other financial assets (portfolios of equities, bonds and mutual funds). The authors claim a strong correlation. Again, while we cannot verify this assumption, we are confident that at least the share held by the bottom 90% (close to zero) is roughly correct for all offshore assets. Finally, because the use of shell corporations has drastically increased since the mid-2000's, the authors limit their top offshore wealth estimates to the period 2006-2007. This way, errors in estimation that are sure to arise from the inability to account for wealth held by anonymous shell corporations are limited.[16]

Lastly, our Pareto fit of the data will not be able to replicate the distribution observed in tax amnesties (of which we only have estimates for some percentiles). Overall then, our exact distributional estimates and Ginis should be taken with a grain of salt. However, in the following estimation of MPCs we restricted ourselves to the use of deciles for the calibration. Thus, the wealth distributions used for the calibrations will be accurate if, as we have argued, the split of offshore wealth between the bottom 90% and top 10% of the wealth distribution is accurate.

5 Marginal Propensity to Consume

5.1 Model

5.1.1 Income process

Carroll et al. (2014a) integrate an income process *à la* Friedman (1957) into the Krusell and Smith model framework.[17] By imposing finite lifetimes in line with Blanchard (1985), and by allowing for a modest amount of heterogeneity in the discount factor β, they are able to match the empirical HFCS wealth distribution more accurately than Krusell and Smith (1998). This paper follows the same approach.

The aggregate production function is:

$$Z_t \mathbf{K}_t^{\alpha} (\ell \mathbf{L}_t)^{1-\alpha}$$

[16] An observant reader will have noticed a discrepancy in the years between our two datasets. The HFCS data we use was collected after 2010; the top wealth estimates are for 2006-2007. While it is possible that the Great Recession might have led to important changes in the distribution of offshore wealth in between that time, for the purpose of our estimates we assume that the distribution remained constant. We appropriately adjust for inflation.

[17] This section provides a theoretical overview of the model governing our economy. For a more technical and computational treatment, the reader is referred to Appendices B and C.

As usual Z_t denotes aggregate productivity, $\mathbf{K}_t$ stands for capital, $\mathbf{L}_t$ is employment and ℓ is hours worked per worker. The wage of the agents is equal to the marginal product of labor:

$$W_t = (1-\alpha)Z_t(\mathbf{K}_t/\mathbf{L}_t)^\alpha$$

The income process is not determined solely by the wage. Agents also face permanent and transitory shocks. Therefore the income of each agent (without capital returns) can be represented as:

$$\mathbf{y}_t = p_t \xi_t W_t$$

ξ_t is the transitory shock to income while p_t denotes the permanent component. The latter obeys the following process:

$$p_t = p_{t-1}\psi_t$$

where ψ_t is mean one, i.i.d. distributed. ξ_t is distributed in the following manner:[18]

$$\xi_t = \begin{cases} \mu & \text{with probability} \quad u \\ (1-\tau_t)l\theta_t & \text{with probability} \quad 1-u \end{cases}$$

where u stands for the probability of being unemployed, which we will keep constant. With probability u the agent will be unemployed and will receive unemployment insurance $\mu > 0$, and with probability $1-u$ the agent will get the wage, net of a tax that finances the unemployment benefit, multiplied by the hours worked and by a white noise shock θ_t. Calibration values for different parameters of the income process are taken from existing literature and can be seen in Table 8 in the appendix.

5.1.2 Consumer problem

The consumer problem is the following:

$$\begin{aligned} v(m_t) &= \max_{c_t} \; u(c_t) + \beta \not{D} E_t\left[\psi_{t+1}^{1-\rho} v(m_{t+1})\right] \\ \text{s.t} \quad a_t &= m_t - c_t \\ a_t &\geq 0 \\ k_{t+1} &= \frac{a_t}{\not{D}\psi_{t+1}} \\ m_{t+1} &= \Big((1-\delta) + r_{t+1}\Big)k_{t+1} + \xi_{t+1} \end{aligned}$$

Non-bolded variables have been normalized for the level of permanent income $\mathbf{p}_t = p_t W_t$. The utility function used is CRRA with coefficient of relative risk aversion ρ. Agents maximise current and future discounted expected utility. The state variable m_t, denotes the market resources each agent has at the beginning of each period. The assets at the end of the period a_t are simply the difference between the market resources and what has been consumed in that period. $\not{D}$ is equal to $1-D$ where D is the probability of death. When an agent dies her assets are distributed uniformly across the remaining agents. Finally, market resources in the next period are determined by the resources carried over from the previous period, capital and non-capital income. In this paper we assume there are no aggregate shocks $Z_t = Z = 1$ and a constant population $L_t = L$. Solving for optimal consumption we get the following

[18] These assumptions come from a special issue of Journal of Economic Dynamics and Control dedicated to different solutions to the Krusell and Smith model (Den Haan et al. 2010). Carroll et al. (2014a) follow this specification too.

Euler equation:

$$\frac{\partial u(c_t)}{\partial c_t} = \beta\,\mathbb{E}_t\left[\psi_{t+1}^{-\rho}[(1-\delta)+r]\frac{\partial u(c_{t+1})}{\partial c_{t+1}}\right]$$

5.1.3 Stationarity of wealth distribution

Including a probability of death ensures that the agents have finite lives — as in Blanchard (1985). This assumption is necessary in order to obtain a stationary wealth distribution, as otherwise permanent shocks to income could imply that some lucky agents would be able to grow their market resources indefinitely. This would lead to ever-growing tails in the wealth distribution. Also, in order to have a constant population, those agents who die need to be replaced by new ones. Carroll et al. (2014a) assume that agents are born with a level of permanent income equal to the mean permanent income of the whole population. Assigning an initial level of permanent income of 1 to all agents ensures that $\mathbb{E}(p_t) = 1$ for all t (since $\mathbb{E}(\psi_t) = 1$). It can also be shown that σ_p^2 is also constant as long as $\not{D}\,\mathbb{E}\,\psi^2 < 1$.[19]

In addition, the parameters also need to fulfill the "Growth Impatience Condition" (GIC) proposed by Carroll (2011) in order to ensure for a steady state distribution of wealth to exist. Carroll et al. (2014a) generalize the GIC in order to accommodate the possibility of death. The parameters we took from the literature (shown in Table 8) meet this condition.

5.1.4 Marginal propensity to consume

In order to measure the MPC implied by our model and underlying empirical wealth distributions, we compute a mean response to transitory income shocks across agent types and wealth levels:

$$\overline{\text{MPC}} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t} MPC_{i,t}$$

with

$$MPC_{i,t} = 1 - \left(1 - \frac{\partial c_{it}(m_{it})}{\partial \xi_{it+1}}\right)^4 = 1 - \left(1 - \frac{\partial c_{it}(m_{it})}{\partial m_{it}}\right)^4$$

where $i = \{1, ..., T\}$ with T the total number of types and N_t is the total number of agents of type t.[20] Individual MPC is calculated by converting the quarterly response of consumption to annual terms. The second equality of the second line follows from the fact that $\frac{\partial c_{it}(m_{it})}{\partial \xi_{it+1}} = \frac{\partial c_{it}(m_{it})}{\partial m_{it}}\frac{\partial m_{it}}{\partial \xi_{it+1}}$ and that $\frac{\partial m_{it}}{\partial \xi_{it+1}} = 1$.

By normalizing by permanent income we are left with only the transitory component of the income process as a shock to each agent. Therefore, we can obtain a pure measure of the MPC out of transitory income shocks. Because of the concavity of the consumption policy function and the large concentration of agents near the left of the wealth distribution, we expect MPCs in each country to be greater than that predicted by the PIH.

[19] A proof can be found in Appendix A of Carroll et al. (2014a).

[20] For computational tractability, we choose $T = 7$ and $N_t = 3000\ \forall\ t$

5.2 Results

We calibrated our model using relative wealth shares of different deciles for both the HFCS and offshore-adjusted HFCS. Our results are presented in Table 6. The last column of this table reports the value of the loss function.[21] Spain, Finland, Austria, and Portugal are countries that we consider to have a very good fit, with a loss below 10 percentage points for both the distribution with and without offshore wealth. Countries with a reasonably good fitness are Belgium, Germany, France, and the Netherlands. The countries with the worst fitness are Italy without offshore wealth (a loss of 20 percentage points) and Greece with offshore wealth (a loss of 40 percentage points). The latter will be analyzed in more detail further below.

The estimated policy function that an agent in our economy should follow has three different regions depending on how constrained she might be (see Figure 2). Starting from the origin, as wealth increases, so does consumption. This relationship is one-to-one until agents accumulate enough wealth. At this point, marginal utility from consumption will have fallen enough to allow for a precautionary savings motive to flatten the policy function in a non-linear fashion. As wealth continues to rise, the policy function becomes (nearly) linear again. The interpretation of this result is that, as agents in the economy become richer, they tend to spend a lower fraction of their normalized permanent income.

Since we calibrate our model using seven different types of agents, we are faced with seven different policy functions (see Figure 2). All seven policy functions are very similar, differing only in the rate at which they flatten and the level of wealth at which they begin to do so. Notice that the policy function for those agents whose β is smaller will imply a greater level of current consumption for a given level of wealth compared to those agents whose β is greater. Intuitively, lower β agents are more impatient, therefore wish to consume more as they derive more utility from the present relative to their peers, *ceteris paribus*. Furthermore, agents with a larger β will also see their policy function begin to flatten sooner than those with a low β. This is to be expected as these agents derive less utility from present consumption relative to their more impatient counterparts.

Table 7 shows the different values for the discount factors estimated in our calibrations. The first thing one might notice is that, when offshore wealth is added to the wealth distribution, the range of β increases for all countries.[22] In a nutshell, the way inequality in the wealth distribution is generated in this model is due to a mix of luck (an agent receives a relatively unlikely sequence of good draws from the income processes) and preferences (those agents with a higher β tend to save more and to accumulate more wealth). Since adding offshore wealth increases inequality, β must become more dispersed in order to be able to generate a similar distribution of wealth.

Regarding the values for β without correcting for offshore wealth, the values that we found (around 0.94 and 0.96 for most of the countries) are in line with those found using similar models in the literature. Carroll et al. (2014b) report values of β around 0.96 when they fit the distribution of liquid assets without aggregate shocks in the economy. Note that these are quarterly, not annual, discount rates.

Table 7 also summarizes the results for the MPC for each country examined. In the baseline case (i.e. the case when only liquid assets are considered), the average MPC is around 0.55 for most countries. The smallest MPC is found in Germany (0.40) while the greatest is obtained in Italy (0.66).[23] When offshore wealth is added to the distribution of liquid assets, the MPC increases for all countries to values around 0.60.

[21] As defined in Appendix C

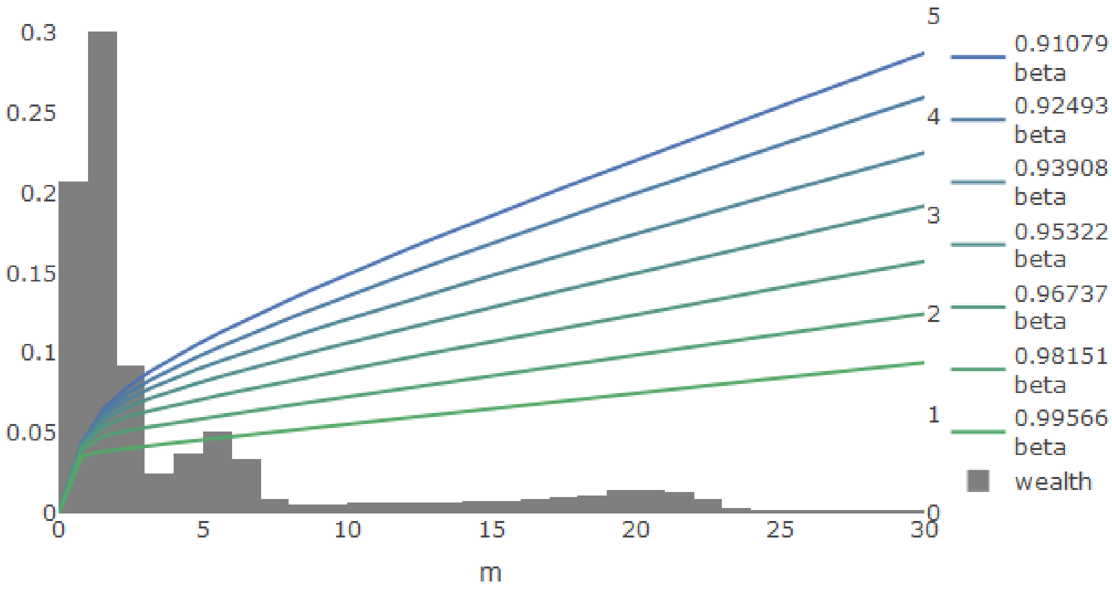
[22] Greece is the sole exception to this rule

[23] This result might be sensitive to the calibration fitness. Italy without offshore wealth has the second worse fitness.

Table 6: Calibration results

Countries	Adjusmtent	Distribution	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Loss
AT	Without Offshore	Target	59.56%	76.05%	85.37%	91.42%	95.15%	97.54%	98.97%	99.74%	99.98%	
		Calibrated	58.55%	77.75%	86.67%	91.89%	94.63%	96.40%	97.67%	98.69%	99.52%	
		Difference in % points	1.006	-1.699	-1.298	-0.470	0.526	1.141	1.296	1.047	0.458	9.004
	With Offshore	Target	64.02%	78.65%	86.92%	92.29%	95.61%	97.74%	99.03%	99.73%	99.96%	
		Calibrated	64.06%	80.84%	88.47%	92.62%	94.89%	96.46%	97.69%	98.69%	99.52%	
		Difference in % points	-0.043	-2.195	-1.551	-0.329	0.724	1.279	1.337	1.035	0.436	9.012
BE	Without Offshore	Target	62.39%	77.65%	86.66%	92.36%	95.89%	98.04%	99.30%	99.85%	99.99%	
		Calibrated	57.39%	77.68%	86.68%	91.79%	94.53%	96.33%	97.64%	98.68%	99.52%	
		Difference in % points	4.999	-0.030	-0.025	0.570	1.367	1.705	1.659	1.173	0.470	12.063
	With Offshore	Target	67.84%	80.83%	88.50%	93.37%	96.39%	98.24%	99.34%	99.83%	99.97%	
		Calibrated	67.58%	82.45%	89.46%	93.06%	95.13%	96.62%	97.78%	98.74%	99.54%	
		Difference in % points	0.261	-1.620	-0.959	0.311	1.258	1.623	1.552	1.085	0.429	9.198
DE	Without Offshore	Target	52.21%	70.64%	82.09%	89.75%	94.69%	97.65%	99.16%	99.82%	99.99%	
		Calibrated	50.87%	72.14%	82.67%	89.16%	92.89%	95.39%	97.15%	98.48%	99.47%	
		Difference in % points	1.332	-1.493	-0.576	0.593	1.798	2.260	2.007	1.337	0.524	11.969
	With Offshore	Target	57.59%	73.86%	83.97%	90.75%	95.14%	97.78%	99.15%	99.76%	99.95%	
		Calibrated	56.05%	76.17%	85.42%	90.88%	94.07%	96.10%	97.55%	98.67%	99.53%	
		Difference in % points	1.538	-2.315	-1.450	-0.129	1.065	1.674	1.594	1.088	0.426	11.334
ES	Without Offshore	Target	69.71%	83.59%	90.73%	94.85%	97.31%	98.71%	99.49%	99.87%	99.99%	
		Calibrated	68.72%	84.53%	91.53%	94.57%	96.29%	97.48%	98.40%	99.13%	99.69%	
		Difference in % points	0.984	-0.942	-0.799	0.280	1.022	1.231	1.090	0.747	0.309	7.500
	With Offshore	Target	75.81%	86.79%	92.45%	95.73%	97.71%	98.85%	99.49%	99.83%	99.96%	
		Calibrated	75.27%	87.81%	93.43%	95.54%	96.88%	97.86%	98.63%	99.25%	99.73%	
		Difference in % points	0.541	-1.016	-0.977	0.194	0.827	0.985	0.860	0.578	0.228	6.325
FI	Without Offshore	Target	64.25%	79.44%	87.54%	92.54%	95.74%	97.79%	99.04%	99.70%	99.95%	
		Calibrated	64.89%	81.68%	89.13%	93.11%	95.22%	96.67%	97.81%	98.75%	99.54%	
		Difference in % points	-0.642	-2.238	-1.594	-0.571	0.520	1.116	1.230	0.951	0.414	9.335
	With Offshore	Target	67.41%	81.22%	88.59%	93.15%	96.06%	97.94%	99.09%	99.70%	99.95%	
		Calibrated	66.98%	82.26%	89.17%	92.77%	94.89%	96.42%	97.64%	98.64%	99.49%	
		Difference in % points	0.435	-1.034	-0.577	0.378	1.171	1.518	1.448	1.056	0.452	8.139
FR	Without Offshore	Target	63.93%	79.19%	87.67%	92.89%	96.14%	98.06%	99.15%	99.72%	99.95%	
		Calibrated	67.70%	81.81%	88.41%	91.97%	94.26%	95.97%	97.35%	98.51%	99.45%	
		Difference in % points	-3.773	-2.625	-0.745	0.922	1.879	2.095	1.802	1.211	0.498	15.709
	With Offshore	Target	67.75%	81.26%	88.79%	93.44%	96.36%	98.10%	99.11%	99.66%	99.91%	
		Calibrated	70.83%	84.06%	90.20%	93.26%	95.21%	96.65%	97.81%	98.76%	99.54%	
		Difference in % points	-3.085	-2.798	-1.412	0.180	1.148	1.456	1.307	0.898	0.369	12.771
GR	Without Offshore	Target	68.28%	84.12%	92.02%	96.27%	98.53%	99.62%	99.98%	100.00%	100.00%	
		Calibrated	71.41%	85.80%	92.10%	94.86%	96.40%	97.48%	98.34%	99.05%	99.65%	
		Difference in % points	-3.130	-1.679	-0.078	1.414	2.130	2.135	1.641	0.953	0.353	13.607
	With Offshore	Target	84.88%	91.98%	95.54%	97.53%	98.65%	99.26%	99.56%	99.71%	99.86%	
		Calibrated	80.64%	85.87%	89.09%	91.54%	93.54%	95.27%	96.81%	98.15%	99.32%	
		Difference in % points	4.241	6.111	6.450	5.988	5.110	3.997	2.751	1.563	0.538	43.768
IT	Without Offshore	Target	70.49%	87.96%	95.32%	98.78%	99.98%	100.00%	100.00%	100.00%	100.00%	
		Calibrated	76.08%	87.59%	92.91%	95.11%	96.57%	97.68%	98.54%	99.22%	99.73%	
		Difference in % points	-5.589	0.366	2.418	3.671	3.404	2.324	1.458	0.780	0.274	20.418
	With Offshore	Target	75.36%	89.53%	95.55%	98.43%	99.49%	99.61%	99.71%	99.80%	99.90%	
		Calibrated	77.11%	88.64%	93.70%	95.67%	96.97%	97.94%	98.71%	99.31%	99.75%	
		Difference in % points	-1.750	0.894	1.851	2.755	2.526	1.667	1.000	0.497	0.148	13.215
NL	Without Offshore	Target	62.80%	80.74%	90.62%	95.90%	98.63%	99.78%	100.00%	100.00%	100.00%	
		Calibrated	63.03%	80.85%	88.84%	93.24%	95.48%	96.94%	98.02%	98.88%	99.59%	
		Difference in % points	-0.223	-0.109	1.782	2.651	3.148	2.832	1.982	1.120	0.406	14.328
	With Offshore	Target	63.83%	81.12%	90.66%	95.78%	98.45%	99.60%	99.86%	99.91%	99.95%	
		Calibrated	64.84%	81.37%	89.01%	93.01%	95.18%	96.67%	97.82%	98.76%	99.54%	
		Difference in % points	-1.013	-0.251	1.650	2.771	3.273	2.930	2.044	1.151	0.411	15.582
PT	Without Offshore	Target	63.27%	81.84%	90.05%	94.48%	97.17%	98.62%	99.40%	99.80%	99.97%	
		Calibrated	65.23%	82.18%	89.56%	93.30%	95.36%	96.78%	97.88%	98.79%	99.56%	
		Difference in % points	-1.953	-0.343	0.491	1.180	1.814	1.846	1.514	1.003	0.417	10.645
	With Offshore	Target	69.47%	84.61%	91.35%	95.03%	97.30%	98.56%	99.27%	99.67%	99.90%	
		Calibrated	71.23%	85.87%	92.33%	95.09%	96.58%	97.61%	98.43%	99.10%	99.67%	
		Difference in % points	-1.758	-1.256	-0.977	-0.059	0.714	0.947	0.842	0.571	0.226	7.438
SI	Without Offshore	Target	64.83%	84.49%	93.25%	97.77%	99.56%	99.97%	100.00%	100.00%	100.00%	
		Calibrated	69.47%	84.74%	91.63%	94.67%	96.29%	97.41%	98.30%	99.03%	99.64%	
		Difference in % points	-4.646	-0.252	1.623	3.103	3.271	2.566	1.705	0.971	0.357	18.591
	With Offshore	Target	66.77%	85.21%	93.43%	97.69%	99.39%	99.82%	99.88%	99.92%	99.96%	
		Calibrated	71.20%	85.76%	92.29%	95.05%	96.53%	97.57%	98.40%	99.09%	99.67%	
		Difference in % points	-4.431	-0.551	1.142	2.638	2.858	2.247	1.482	0.834	0.296	16.576
SK	Without Offshore	Target	62.34%	81.54%	90.82%	95.67%	98.26%	99.60%	100.00%	100.00%	100.00%	
		Calibrated	65.25%	81.82%	89.23%	93.16%	95.29%	96.74%	97.87%	98.79%	99.55%	
		Difference in % points	-2.913	-0.278	1.596	2.515	2.971	2.865	2.130	1.214	0.448	17.013
	With Offshore	Target	65.93%	83.21%	91.55%	95.93%	98.28%	99.52%	99.90%	99.94%	99.97%	
		Calibrated	64.85%	82.11%	89.66%	93.42%	95.46%	96.86%	97.95%	98.84%	99.57%	
		Difference in % points	1.078	1.101	1.896	2.515	2.825	2.656	1.951	1.100	0.395	15.589

Figure 2: Policy functions for different β



Note: Consumption policies are shown for our calibration of the Finnish economy without offshore wealth. The right scale measures consumption, normalized by permanent income and the left scale shows the density of cash on hand, m, also normalized by permanent income.

As we did for the increase in β range, we turn once again to Figure 2 to provide intuition for these results. By including offshore wealth, we increase inequality in each country. Higher inequality leads to a greater range of β. This larger range forces most of the policy functions to become steeper in the unconstrained parts of the wealth distribution which, in turn, makes the MPC increase.

The values for the MPC that we found for the baseline situation seem to be above those found in the literature. In particular, Carroll et al. (2014b) find values around 0.35 for the case of no aggregate shocks while ours are closer to 0.55. This result could be explained by differences in the way MPC is computed between CST and ourselves. Unfortunately, CST do not clearly explain how they arrive at their estimates.

For a cross-country comparison, Figure 3 plots the Gini of each country against the average MPCs reported above. The figure shows a very strong positive relationship between the two variables, both with and without offshore wealth. Importantly, adjusting for offshore wealth shifts both the Gini and MPC monotonically upwards in an economically significant manner. This result implies that underestimating the wealth held by the decile in a country leads to a consistently large downward bias.

In addition to the analysis conducted by CST and Carroll et al. (2017) we also report on the distribution of MPCs. Figure 4 shows a kernel estimate for the MPC distribution (i.e. the amount of people that have a particular MPC) for each country without (left-hand side) and with (right-hand side) offshore wealth adjustments. The most remarkable feature of this graph is how the different percentiles shift when offshore wealth is added to the liquid asset distribution. One can notice that for most of the countries the 75th percentile barely changes while the median and the 25th percentile tend to shift upwards (indicating a higher MPC at each quartile). This result is in line with our previous discussion: more offshore wealth increases inequality, which in turn increases the range of β, which leads to steeper policy functions associated with higher MPCs.

Table 7: Distribution of MPCs and β

	Distribution and parameters	AT	BE	DE	ES	FI	GR	IT	NL	PT	SI	SK	FR
MPC Without Offshore	Top 10%	0.11	0.12	0.11	0.11	0.12	0.11	0.12	0.11	0.12	0.11	0.12	0.15
	Top 20%	0.12	0.13	0.12	0.13	0.13	0.13	0.14	0.13	0.13	0.14	0.14	0.17
	Top 40%	0.15	0.16	0.14	0.18	0.17	0.19	0.25	0.16	0.17	0.19	0.17	0.22
	Top 60%	0.22	0.23	0.19	0.33	0.28	0.35	0.43	0.26	0.29	0.35	0.29	0.34
	Top 80%	0.35	0.36	0.28	0.49	0.43	0.51	0.57	0.41	0.43	0.50	0.43	0.47
	Bottom 50%	0.76	0.77	0.64	0.93	0.86	0.95	0.97	0.85	0.86	0.94	0.86	0.87
	Bottom 20%	0.96	0.97	0.89	1.00	0.99	1.00	1.00	0.99	0.99	1.00	0.99	0.99
	Avg. MPC	0.47	0.48	0.40	0.59	0.54	0.60	0.66	0.52	0.54	0.60	0.54	0.57
	β_{mid}	0.962	0.960	0.969	0.948	0.953	0.945	0.933	0.956	0.952	0.945	0.952	0.947
	∇	0.038	0.039	0.031	0.052	0.042	0.055	0.064	0.044	0.045	0.055	0.045	0.038
MPC With Offshore	Top 10%	0.12	0.13	0.11	0.11	0.13	0.28	0.11	0.12	0.11	0.11	0.12	0.14
	Top 20%	0.14	0.15	0.12	0.14	0.15	0.37	0.14	0.14	0.13	0.13	0.13	0.16
	Top 40%	0.18	0.20	0.15	0.23	0.20	0.55	0.25	0.17	0.18	0.18	0.17	0.22
	Top 60%	0.28	0.32	0.22	0.41	0.32	0.68	0.45	0.28	0.35	0.35	0.29	0.35
	Top 80%	0.42	0.65	0.52	0.75	0.65	0.84	0.78	0.62	0.71	0.71	0.63	0.68
	Bottom 50%	0.84	0.89	0.74	0.97	0.87	0.99	0.98	0.85	0.95	0.95	0.87	0.91
	Bottom 20%	0.98	0.99	0.95	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	0.99
	Avg. MPC	0.53	0.57	0.46	0.65	0.56	0.81	0.67	0.54	0.61	0.61	0.55	0.60
	β_{mid}	0.953	0.948	0.964	0.938	0.948	0.904	0.932	0.953	0.945	0.945	0.952	0.945
	∇	0.042	0.044	0.036	0.062	0.044	0.046	0.067	0.045	0.055	0.055	0.045	0.045

Note: $\beta \in (\beta_{mid} - \nabla, \beta_{mid} + \nabla)$

As a prototypical case, consider the differences between Finland and Portugal. These two countries have a similar Gini coefficient when offshore wealth is not taken into account. However, they differ notably in the amount of offshore wealth their citizens hold in offshore havens: around 3% of 2007 GDP for Finland compared to around 20% of 2007 GDP for Portugal (see Table 2). The MPC distribution barely changes for Finland while it changes considerably in the Portuguese case. Note how, in the latter case, the median moves from 0.5 to a value above 0.6 while the 75th percentile also shifts upwards to an MPC near one. This result clearly suggests that the MPC changes because there are now more agents constrained (or close to the constrained region) than before we considered offshore wealth.

The case of Greece is particularly striking, potentially uncovering a limitation of the model. According to the data reported by Alstadsæter et al. (2018), the amount of offshore wealth held by Greek citizens amounts to approximately 36% of 2007 GDP. This massive amount of offshore wealth creates a very unequal distribution that can only be explained by very low values for β (0.9). As a result, the MPC increases drastically to 0.81. Implying that nearly all agents in this economy have wealth levels near or in the borrowing constraint region. In Figure 4, we can see that the MPC for the median person when offshore wealth is not included is approximately equal to the MPC for the 75th agent when offshore wealth is included. In fact, the change in distribution is so drastic that agents with MPCs less than 0.2 completely disappear.[24]

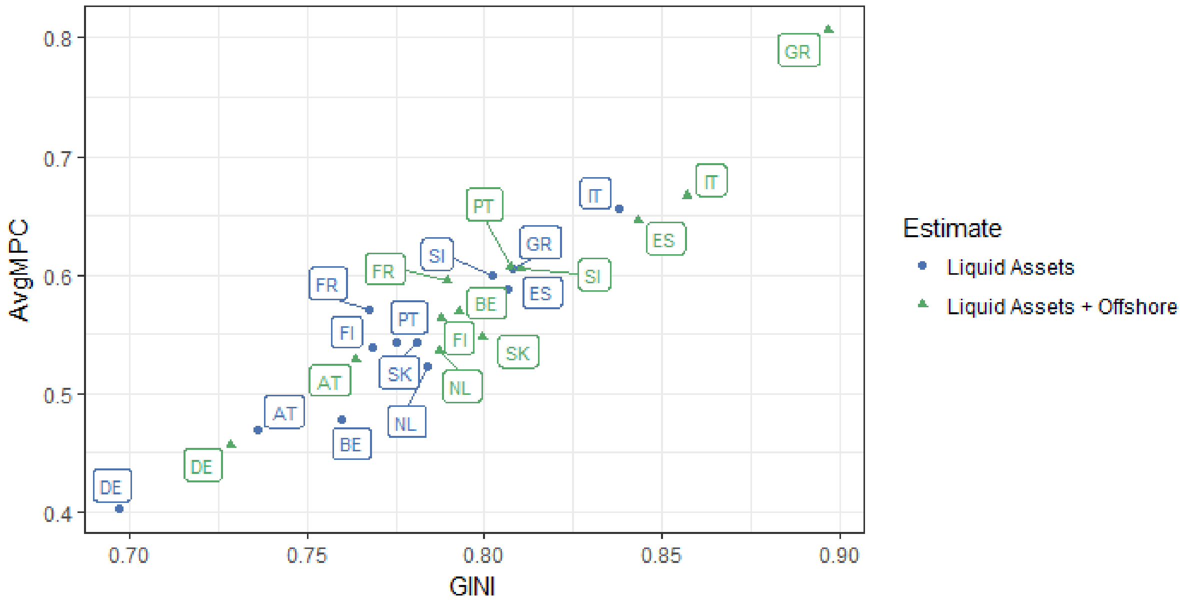
5.3 Discussion and Limitations

Our findings have several important implications. First, we showed that calibrating the CST model with relative wealth shares makes the predicted MPC (both its average and distribution) sensitive to miss-measurements of wealth in the top of the distribution. This finding might come as a surprise, since the households that have offshore wealth are not generally constrained. Yet, by calibrating using relative shares, the number of constrained households — and with it the MPC — increases in the model. This puts into question some of the quantitative results obtained by CST (2014c) and Carroll et al. (2017).

Second, by showing that miss-measurements in survey data underestimates both the level of inequality

[24]One might argue that the fitness is not good enough to discuss this case seriously. However, an improvement in the fitness would only make the situation worse because even lower values for β would be found.

Figure 3: Average predicted MPC and Gini



Note: Ginis were estimated from the HFCS as explained in section 4; average MPCs were estimaed using the model described earlier in this section.

in a country and its MPC, we provide clues on if and how fiscal policy should be implemented. For example, a government might be deciding whether a tax rebate is appropriate to stimulate the economy. Our results indicate that, not only will every 1 € rebate lead to a significant increase in the aggregate consumption of an economy (since MPC is so far from zero for all countries), but by targeting this rebate to those households which are most constrained the policy can be made even more effective. Furthermore, this effect is particularly striking in countries with large offshore wealth holdings.

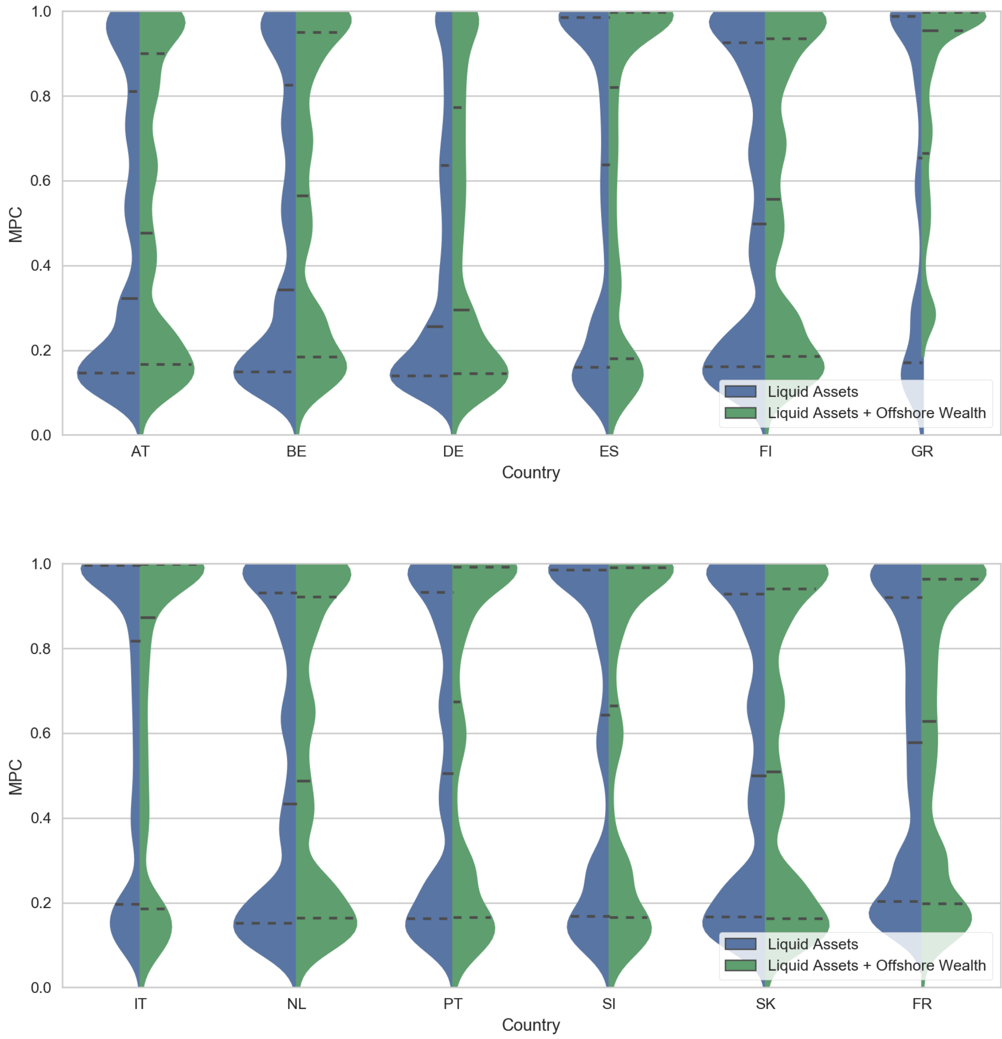
Our findings also have important limitations. One of those is that we have restricted our attention to calibrations using liquid assets. The reason for this is three-fold. First, liquid assets are theoretically more relevant to the MPC, since illiquid assets cannot readily be used for consumption.[25] Second, CST found calibrations of consumption-savings models based on liquid assets to be closer to reality. Finally, offshore wealth consists mostly of financial instruments that fall into the category of liquid assets, as explained above. However, one could still argue that, even though offshore wealth mostly consists of liquid financial instruments, it should still be considered somewhat illiquid due to possible frictions related with gaining access to these assets. In general, such assets are often linked to tax evasion and their use for "onshore" consumption may therefore be difficult.

Another issue which arises naturally from the calibration procedure is that comparisons between the MPCs might be misleading considering how poor the fitness is for some countries. To minimize the risk of this hazard affecting our results, we focused our attention on those countries that displayed both large differences in the estimated wealth distributions and a good calibration fitness. Doing this, we can be confident that the qualitative changes to the predicted distribution of MPCs induced by adding offshore wealth is not due to random error. For those countries with small corrections, however, the (already small) differences in the distribution of MPCs could be driven by random error instead of structural shifts in the distribution of agents and estimated discount factors.[26] In future work, a formal test for the

[25] See for example Kaplan and Violante (2014)

[26] For example, the sum of absolute deviations from the target deciles for Slovenia is over 18% and 16% for our best models

Figure 4: Distribution of MPCs



Note: densities were estimated using the kernel parameters proposed by Scott (1979). The dotted lines represent (from top to bottom) the 75th percentile, the median, and 25th percentile.

significance of changes to the predicted MPC distribution should be included in the analysis.

Finally, we have only implemented a simplified version, with no aggregate shocks, of the augmented Krusell-Smith economy. To test for robustness in terms of exogenous parameters, the model could be run under different specifications. Implementing the model with aggregate shocks and additional features remains an interesting avenue for future research.

6 Conclusion

Relying on the previous work made by Alstadsæter et al. (2018) we have proposed a methodology to update the wealth distribution obtained in the HFCS in order to account for offshore wealth. Our methodology consists of estimating the percentage of offshore wealth held by each percentile of households

with and without offshore, respectively. These differences are larger than the differences in the target distributions, which makes the estimate poor.

when ordered by reported wealth and then fitting a Pareto distribution of wealth to the top 10% calibrated using this offshore wealth. Our adjustment suggests an average increase of 0.03 points for the Gini coefficient of those countries we analyzed. To show how this adjustment might be useful for modeling purposes we make use of a Carroll (2011) framework to calibrate a consumption-saving model with the resulting offshore-adjusted wealth distributions.

Following CST's (2014c) proposed methodology, we calculated the marginal propensity to consume when offshore wealth was added to liquid assets. Our results suggest that the corrected distribution of liquid assets can be explained by a discount factor between 0.93 and 0.95 for most of the eurozone, with a half-range of approximately 0.05. An important prediction of the model is that increasing inequality leads to an increase in the MPC from values around 0.55 to values around 0.60. This adjustment is monotonically increasing and has important economic implications. Together, our findings imply that the under-estimation of relative wealth held by the top decile leads to a consistently large downward bias in the MPC for most countries.

The case of Greece is particularly striking and we believe it shows one possible limitation of the model. According to the data reported by Alstadsæter et al. (2018), the amount of offshore wealth held by Greek citizens amounts to approximately 36% of 2007 GDP. This massive amount of offshore wealth creates a very unequal distribution that can only be explained by very low values for β. We argued that this in turn forces the MPC to increase up to a point which would implying that nearly all agents in this economy have wealth levels near or in the borrowing constraint region. An in-depth analysis of the distribution of the MPC for this country shows that the MPC for the median person when offshore wealth is not included is approximately equal to the MPC for the 75th agent when offshore wealth is included. Furthermore, the same analysis also shows that adding offshore wealth makes agents with an original MPC between 0.2 and 0 completely disappear from the economy.

One of this paper's objectives was to provide a robustness check to CST (2014c). We showed that calibrating the CST model with relative wealth shares makes the predicted MPC (both its average and distribution) sensitive to miss-measurements of wealth in the top of the distribution. This finding might come as a surprise, since the households that have offshore wealth are not generally constrained. Yet, by calibrating using relative shares, the number of constrained households — and with it the MPC — increases in the model. This finding puts into question some of the quantitative results obtained by CST (2014c) and Carroll et al. (2017).

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Appendix A Parameters

Table 8: Parameter Values

Description	Parameter	Value
Representative agent model		
Time discount factor	β	0.99
Coefficient of relative risk aversion	ρ	1
Capital share	α	0.36
Depreciation rate	δ	0.025
Time worked per employee	ℓ	1/0.9
Steady state		
Capital-output ratio	$\boldsymbol{K}/\boldsymbol{Y}$	10.26
Effective interest rate	$r - \delta$	0.01
Wage rate	W	2.37
Heterogeneous agents models		
Unemployment insurance payment	μ	0.15
Unemployment rate	u	0.07
Probability of Death	D	0.00625
Variance of log $\theta_{t,i}$	σ_θ^2	0.010×4
Variance of log $\psi_{t,i}$	σ_ψ^2	0.010/4

Notes: The models are calibrated at the quarterly frequency. The steady state values are calculated on a quarterly basis.
This table was reproduced from Carroll et al. (2015) and shows the parameters used to calibrate our model.

Appendix B Numerical Solution

B.1 The KS algorithm

In this part of the Appendix we provide more details on the particular computational techniques used to solve and calibrate the model. The main challenge in terms of finding a numerical solution to the model presented in this paper stems from the heterogeneous agent setup, where agents differ both in the realisations of their idiosyncratic shocks to income, as well as in their time preference. As a result, the dynamics of the system's state are quite complex.

To work around this issue we employ the stochastic simulation method, first developed by Krusell and Smith (1998). The same approach was used in the paper by CST (2014c), to which we largely adhere. That being said, we develop our own implementation for solving the model, which of course differs in some minor design choices.

The general idea of the Krussel Smith approach is to begin by solving for an optimal policy for each agent type given some guess about the aggregate law of motion of the economy. After that an artificial economy with many agents of each type is simulated for multiple periods (until reaching a stable wealth distribution), drawing specific realizations of the income shock. The generated path of the capital stock is observed, and the guess for the law of motion updated. This process continues until the guess for the law of motion of aggregate capital is close enough to the simulated one. The algorithm box below spells out the outline:

Input parameters: A vector of discount factors for each agent type.
Initialize predicted law of motion $logk_{t+1} = \phi_0 + \phi_1 logk_t$
while *stopping criterion is false* **do**
  for *Each agent type* τ **do**
    Calculate optimal consumption policy c_τ^ϕ via policy iteration.
  end
  for *T+burnin periods* **do**
    Simulate aggregate outcomes and idiosyncratic shocks for period.
    For each simulated agent i out of I calculate $a_i = c_\tau^\phi(m_i)$
    Calculate aggregate savings as $\sum_i a_i$. Add them to the depreciated capital stock
    A portion $\not{D}$ of the agents 'dies'. New agents with wealth zero are created in their place.
    The wealth of the deceased is split evenly among the living.
  end
  Calculate $\phi = (1-\eta)\phi + \eta(\tilde{\phi})$, where $\tilde{\phi}$ is a fit on simulated capital motion.
  if *Update was small* **then**
    Set stopping criteria to true.
  end
end
Calculate final policy functions using the learned law of motion.

Algorithm 1: Stochastic Simulation (Krussel-Smith 1998)

Given that in the models presented in this paper we have not used aggregate shocks, we could have opted for a slightly simpler version in which we do not calculate a law of motion, but rather just a guess for the steady state capital. Since however we wanted our code to be more general and to allow for easy extensions, the version presented in the algorithm box was implemented. We also give more details on the policy function fitting and the simulation procedure in the next two subsections.

B.2 Policy Iteration

The policy of each agent is a mapping between their individual state (wealth - m) and the aggregate state (aggregate capital per labor unit - k) to the agents action variable (savings - a). To derive the optimal policy we use the agent's FOC (as derived in the main text). The process is the standard policy iteration routine. In order to do this we discretize our state space into a finite grid. We chose 40 m-values equally spaced on the interval $[0, 35]$, and 4 k values equal to $0.8, 1, 1.2$, and 1.5 times the steady state value of capital of the last Krusell-Smith iteration. These discretization values were chosen by experimentation[27].

To find the optimal actions on the grid, first we use the current guess of the law of motion to compute return on capital next period. Next we draw 100 possible realizations of the transitory and idiosyncratic shocks. The joint pdf of each of the shocks is approximated over these discrete realizations (using the histogram method). We use this to calculate expected future wealth over permanent income (m).

Having computed $E(m)$ we plug it in in the FOC and use a Brent solver to find the value of savings a for which the FOC is zero. Savings can be between 0 and m. If the FOC is positive (or negative) at both of these extremes, we conclude that we have a corner solution, and set savings to 0 (or m[28]).

This process is repeated for all points on the grid and iterated until the optimal action values on the grid stop changing (within some tolerance level). When searching for the root of the FOC the solver needs

[27] Obviously, with aggregate shocks the k grid would have to be much finer.
[28] This is never the case in practice

to evaluate the policy function on multiple off-grid points. To do that we fit an interpolating function using the previous iteration's values for the optimal policy. The interpolation is done using thin-plane regression splines over the state space.

This process is repeated for every agent type in our model. Since we compute a model with 7 types we end up with 7 different policy functions. For the first type and the first Krussel-Smith iteration the initial optimal actions in the policy iteration procedure are chosen arbitrarily. In order to speed up calculations, for every subsequent type we set the initial values as the final optimal values of the previous type. For subsequent Krussel-Smith iterations each agent type begins the policy iteration process with their previous optimal actions as an initial guess.

B.3 Simulation

Once we have a set of policy functions for each agent type we simulate the economy to derive the steady wealth distribution, and to update our guess of capital's law of motion.

Each simulated period proceeds as follows:

1. Aggregate capital (aggregated individual agents decision) and labor (fixed supply) are combined to produce output. Factor prices are determined.

2. Individual realizations for each agent's income shocks (both permanent and transitory) are drawn. Labor and capital income is distributed to agents. Individual capital depreciates.

3. Each individual simulated agent updates their permanent income value (pW) and normalized wealth (m), and decides how much to save. This is done using the policy function of the type to which the agent belongs. The interpolating fit is used, since most of the time agents will have values of m that are off the grid. Capital is set to the sum of savings.

4. Based on a random draw of a binary RV (one for each simulated agents), a fraction $\not{D}$ of the agents die. New agents with wealth 0 and permanent income equal to 1 take their place. The wealth of the deceased is distributed equally among the surviving agents (including the newborns).

We do this for a minimum of 1000 periods using 3000 simulated agents of each type. We check each 100 periods whether the wealth distribution is still evolving, This is done by finding $\max |d_t - d_{t-100}|$ and checking whether it is below a tolerance threshold (d_t is a vector of deciles of the simulated wealth distribution at period t). As a sanity check we also perform a Kolmogorov-Smirnoff test to see whether the distribution is really converging.

After the wealth distribution has reached a steady point (and the minimum number of periods has passed) the simulation stops and the observed law of motion of capital is returned (discarding the first 200 observations as burn-in). This history vector is used to fit a linear model of k_{t+1} on k_t. The resulting coefficients for the intercept and slope (call them $\bar{\phi}$) are used to update the law-of-motion guess as per the formula in the algorithm box above. The learning rate η was set to 0.3. If the highest difference between the old and new coefficients is less than 0.02 we say that the model has converged and we have found the solution (in terms of optimal policy functions).

Appendix C Calibration

After solving the model for a given set of parameters, we perform a calibration exercise to match the observed wealth distribution (of both liquid assets and offshore-augmented liquid assets). The only parameter changed during calibration was the time preference factor β.

In this model, it is assumed that there is a continuum of agent types, differing in their discount factor β. The agents are uniformly distributed over some interval $\mathbf{B} \in [0, 1]$. We approximate this by allowing for seven agent types with equally spaced discount factors. In essence that means that we are trying to fit the real data with two parameters - the mid-point of the distribution over $\mathbf{B}$ (which we call β^{mid}, and the length of the interval (in practice half the length, denoted Δ_β). Once we know these two parameters, the seven types' discount factors are pinned down.

Our calibration target was the sum of absolute differences between the simulated wealth deciles, and the ones observed in the data:

$$Loss = \sum_{j=1}^{10} \left| d_j^S - d_j^D \right| \tag{3}$$

Where d_j^S is the cumulative percent of wealth held by the top $j-th$ decile in the simulated data, and the variable superscript with D is the empirical counterpart. In order to minimize this loss we develop a simple genetic algorithm to calibrate the two tuning parameters. The algorithm works as follows:

Input parameters: Number of generations G. Feasible ranges of the calibration parameters
Initialize by creating a "population" of 10 random tuples of potential values of β^{mid} and Δ_β.
for *each generation* $g \leq G$ **do**
  for *Each tuple of parameters* i *in the population* **do**
    Find the steady state wealth distribution using the Krussel Smith procedure detailed above.
    Calculate $Loss_i^g$
  end
  Choose the four tuples with the lowest loss ("survivors" or "parents"). Keep them in the population for the next generation.
  Choose two random sets of size three from the "survivors". For each of the two sets create two new tuples as the centroids in the $\beta^{mid}, \Delta_\beta$ space of the sets ("children"). Add them to the population for the next generation.
  Create four additional parameters tuples by random draws ("mutants")
end

Algorithm 2: Genetic Calibration

The process above was repeated for each country in our study, for both liquid assets and offshore-enhanced liquid assets. The results of each parameter combinations were saved after they were evaluated. In the end the parameters that had the lowest loss for each country were chosen as the one to be reported in the main text.