Macroeconomic disasters and forward-looking consumers: historical evidence and evidence from the Covid-19 pandemic*

Lorenzo Pozzi†[1] and Barbara Sadaba[2]

[1] *Erasmus University Rotterdam & Tinbergen Institute*

[2] *Bank of Canada*

April 2021

Abstract

Macroeconomic disasters (wars, pandemics, depressions) are characterized by drastic shifts and increased volatility of the aggregate consumption to income ratio. By standard intertemporal budget constraint logic, this ratio is linked to expectations of future income and consumption growth rates. We investigate whether these expectations suffice to explain the shifts in the consumption-income ratio that occur during disaster periods or whether, on the other hand, consumers become more forward-looking and therefore give more weight to these expectations during disaster times. Our theoretical framework implies that the predictive ability of the current consumption-income ratio for future income and consumption growth rates is higher during disaster episodes. We check this both for past disasters and the current Covid-19 pandemic through the estimation of panel data regressions for industrial economies using historical annual data ($1870 - 2015$) and recent quarterly data ($1995Q1 - 2020Q4$). Our estimations confirm that macroeconomic disasters, contrary to ordinary recessions, make consumers more forward-looking.

JEL Classification: E21, C23

Keywords: consumption, saving, macroeconomic disasters, Covid-19, panel data

*For constructive comments, we thank Yao Cheng, Ana Figueiredo, Agnieszka Markiewicz, Sander Renes, Bauke Visser and other participants of the Economics Department seminar at Erasmus School of Economics.

†Department of Economics, P.O. Box 1738, 3000 DR Rotterdam, the Netherlands. Email: pozzi@ese.eur.nl. Website: http://people.few.eur.nl/pozzi.

1 Introduction

The Covid-19 pandemic and the lockdown measures implemented to contain it in countries around the world have triggered significant changes in the consumption and saving behavior of households. Unprecedented upward shifts have been reported in the propensities to save of US and European households during 2020. These shifts have been attributed both to forced (or, involuntary) saving caused by the lockdowns and to precautionary saving motives stemming from increased uncertainty about future income and employment prospects (see e.g., Dossche and Zlatanos, 2020; Vandenbroucke, 2021). As macroeconomic disaster episodes - i.e., pandemics such as Covid-19 but also historical wars and depressions - are characterized by drastic declines in GDP, private consumption or both (see Barro and Ursúa, 2008), it is not surprising that the changes in consumption and income that occur during these periods potentially imply large movements in the propensity to consume and to save out of income.

This paper therefore focuses on the propensity to consume out of income - as captured by the consumption to income ratio - during macroeconomic disaster episodes.[1] We consider both historical disaster episodes (such as wars, depressions and past pandemics) and the current Covid-19 pandemic by looking at historical annual data (1870-2015) and recent quarterly data (1995Q1-2020Q4) for industrial economies. We start from the observation that macro disaster periods, defined by Barro and Ursúa (2008) as peak-to-trough cumulative declines in GDP and/or private consumption of at least 10%, are characterized by multiple, often drastic shifts and increased volatility of the consumption-income ratio. As standard intertemporal budget constraint (IBC) logic implies that this ratio is linked to expectations about future income and consumption growth rates, this paper investigates whether these expectations about the future suffice to explain the shifts in the consumption-income ratio that occur during disaster periods or whether, on the other hand, consumers become more forward-looking and therefore give more weight to these expectations during disaster times. Theoretically, we build on the framework of Campbell and Mankiw (1989) and Lettau and Ludvigson (2005) in which a representative consumer satisfies the IBC by allowing for disaster-dependent discount factors. Assuming that disaster episodes constitute periods during which consumers, on average, earn and consume a smaller fraction of their lifetime wealth, these periods effectively extend the horizon of their budget constraint, making them more forward looking. Hence, during disaster episodes discount factors are higher and more weight is given to expectations about future income and consumption growth rates. Because the consumption-income ratio is linked to these (potentially volatile) expectations, it may shift more drastically and become more volatile during

[1] We focus on the consumption-income ratio instead of the saving rate to which it is inversely related as, in the theory outlined in Section 3 below, we derive expressions for the log consumption-income ratio. Denoting by $c - y$ the log consumption-income ratio, the log saving-income ratio can then be calculated as $\ln[1 - \exp(c - y)]$.

disasters. Empirically, since the theory suggests that the current log consumption-income ratio contains information about future income and consumption growth rates, this period's log consumption-income ratio should have predictive power for next period's income and consumption growth rates. Moreover, given our disaster-dependent discount factors, this predictive ability should be higher during disaster periods. Hence, we evaluate the predictive power of the log consumption-income ratio both during normal times and during disaster episodes through the estimation of panel predictive regressions for industrial economies. We first look at past disaster periods (such as World Wars I and II and the Great Depression) using our historical annual dataset and then look at the current Covid-19 pandemic using our recent quarterly dataset. We make full use of the panel structure of the data. First, we estimate country-specific predictive impact estimates which implicitly allows for cross-country differences in the underlying discount factors. These estimates are then combined using the mean group (MG) estimator to obtain estimates for the average effects. This avoids obtaining biased and inconsistent parameter estimates when falsely assuming that the regression slope parameters are identical across countries (see Pesaran and Smith, 1995). Second, we allow for cross-sectional dependence in the data as it is possible that unobserved common factors such as common business or financial cycles affect the dependent variable and the regressors in the estimated equations. This can also lead to biased and inconsistent parameter estimates. To take this cross-sectional dependence into account, we use the common correlated effects (CCE) methodology suggested by Pesaran (2006) where the unobserved common factors are controlled for by including cross-sectional averages of the dependent variable and all explanatory variables as additional regressors in the model. We use the mean group (CCEMG) variant to allow for parameter heterogeneity.

Our findings using historical data confirm that the predictive ability of the log consumption-income ratio for future income and consumption growth rates is significantly higher during macroeconomic disasters. Interpreted through the lens of the model, our results suggest that consumers are more forward-looking during disaster times and, consequently, then give more weight to expectations about future income and consumption growth rates in their consumption decisions. As such, expectations about future income and consumption growth rates, in and of themselves, do not appear to be sufficient to explain the large shifts and high volatility observed in the consumption-income ratios during these crisis periods. An increase in the weight given to future expectations is also required to explain the data. Our results survive several robustness checks. Furthermore, the increased predictive ability of the consumption-income ratio is not limited to one particular disaster type but is found for every major crisis type that we consider in our historical dataset (i.e., World Wars I and II, the Great Depression and the Spanish flu pandemic of the late 1910s and early 1920s). When looking at conventional recessions instead of disaster episodes, however, we fail to find a significantly higher predictive impact of the consumption-income ratio. The results obtained when using our recent quarterly dataset for the period $1995Q1-2020Q4$ are fully in line with the results obtained for historical disaster episodes, i.e., the predictive power of the log consumption-income ratio on next period's income and consumption growth rates is significantly higher during the Covid-19 pandemic. While these results hold across different robustness checks, they again do not hold for ordinary recessions that have occurred over the sample period.

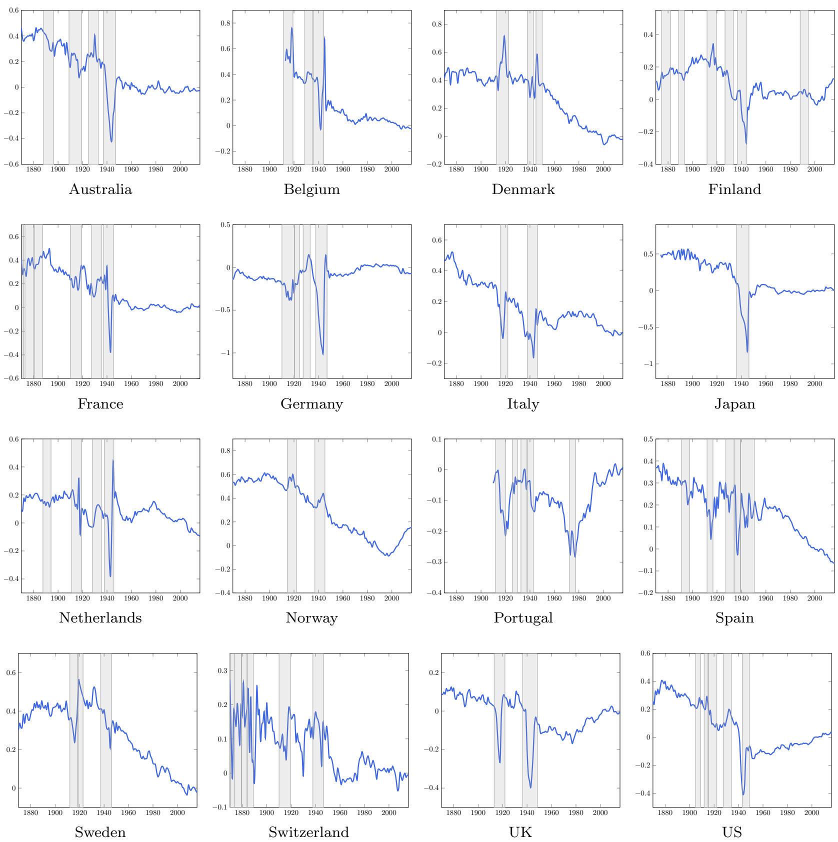
While there is a large literature that focusses on the asset-pricing implications of macroeconomic disasters (see e.g., Rietz, 1988; Barro, 2006, 2009; Barro and Ursúa, 2012; Nakamura et al., 2013; Gillman et al., 2015; Farhi and Gabaix, 2016), our paper fits in and adds to a growing literature that looks at the behavior of consumption and saving during crises - mostly, conventional recessions - and at the channels through which these crises affect the propensity to consume and save. Mody et al. (2012) report large increases in the saving rates of advanced economies during the Great Recession and attribute these increases to changes in variables that capture precautionary saving, i.e., unemployment risk and GDP volatility. Alan et al. (2012) find that increased uncertainty - rather than credit tightening - explains the rise in the saving rate of UK households during recessions. Using data covering multiple recessions in OECD countries, Adema and Pozzi (2015) present evidence that household saving ratios increase during recessions, i.e., behave countercyclically, which they attribute to higher unemployment risk, lower household wealth and tighter credit constraints. Carroll et al. (2019) report that the saving rate across the business cycle in the US is largely driven by the degree of labor income uncertainty and credit availability. Taking a different tack closer to our work, Aizenman and Noy (2015) explore the role of history-dependence in the dynamics of saving and use historical data for industrial economies to show that past crisis experiences subsequently have a strong positive impact on household saving. Recently, the existing literature looks beyond conventional recessions to explore the effects of the current Covid-19 pandemic on saving. Jordà et al. (2020) use European data going back to the 14th century and argue that pandemics, current and historical, may induce shifts to greater precautionary saving. Coibion et al. (2020) use US survey data to investigate how local lockdown measures implemented in reaction to Covid-19 have affected consumer spending and the macroeconomic expectations of households.

The outline of the paper is as follows. Section 2 graphically looks at the behavior of the consumption to income ratio during macroeconomic disaster episodes. Section 3 presents our theoretical framework. The empirical specification and the estimation method are outlined in Section 4. The results for historical macro disasters are presented in Section 5, while the results related to the Covid-19 pandemic are reported in Section 6. Section 7 concludes.

2 Macroeconomic disasters and the consumption-income ratio

Figure 1 presents historical annual time series over the period 1870 − 2015 for the log consumption to GDP ratio for sixteen industrial economies for which these data are available. The figure also shows the macroeconomic disaster episodes as identified by Barro and Ursúa (2008) of which the most prominent are (in chronological order) World War I, the Spanish flu pandemic of the late 1910s/early 1920s, the Great Depression and World War II. Details on the sources and the construction of these data are provided in Section 5.1 and Appendix B. From the figure, we note that the volatility of the log consumption-income ratio is considerably higher during disaster episodes with multiple, often drastic, shifts occurring during these periods. Many times, these shifts in the consumption-income ratio take the form of large initial drops, followed by sharp increases (e.g., France during World War II). In other instances, however, disaster episodes are characterized by temporary upward jumps (e.g., Denmark during World War I).

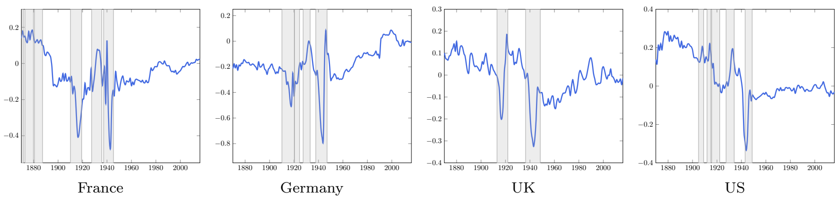
Figure 1: The log consumption-income ratio during historical disaster episodes



Notes: The blue line denotes the log consumption to GDP ratio. Shaded areas correspond to disaster episodes as identified by Barro and Ursúa (2008). We note that since consumption and GDP (in per capita real terms) are expressed as indices with baseyear 2005 = 100, the log of the ratio between both equals zero in 2005. We refer to Section 5.1 for more details on the data used in this figure.

It is instructive to investigate whether the ratio of consumption to after-tax income is also characterized by large shifts during disaster episodes. Historical data on after-tax income are not widely available however. In Figure 2, we present the consumption to disposable (after-tax) national income ratio over the period $1870 - 2015$ which can be constructed for only four out of the sixteen countries considered in Figure 1. From the figure, we note that this ratio is also typically characterized by large shifts and higher volatility during the disaster periods identified by Barro and Ursúa (2008).

Figure 2: The log consumption to disposable income ratio and macroeconomic disaster episodes

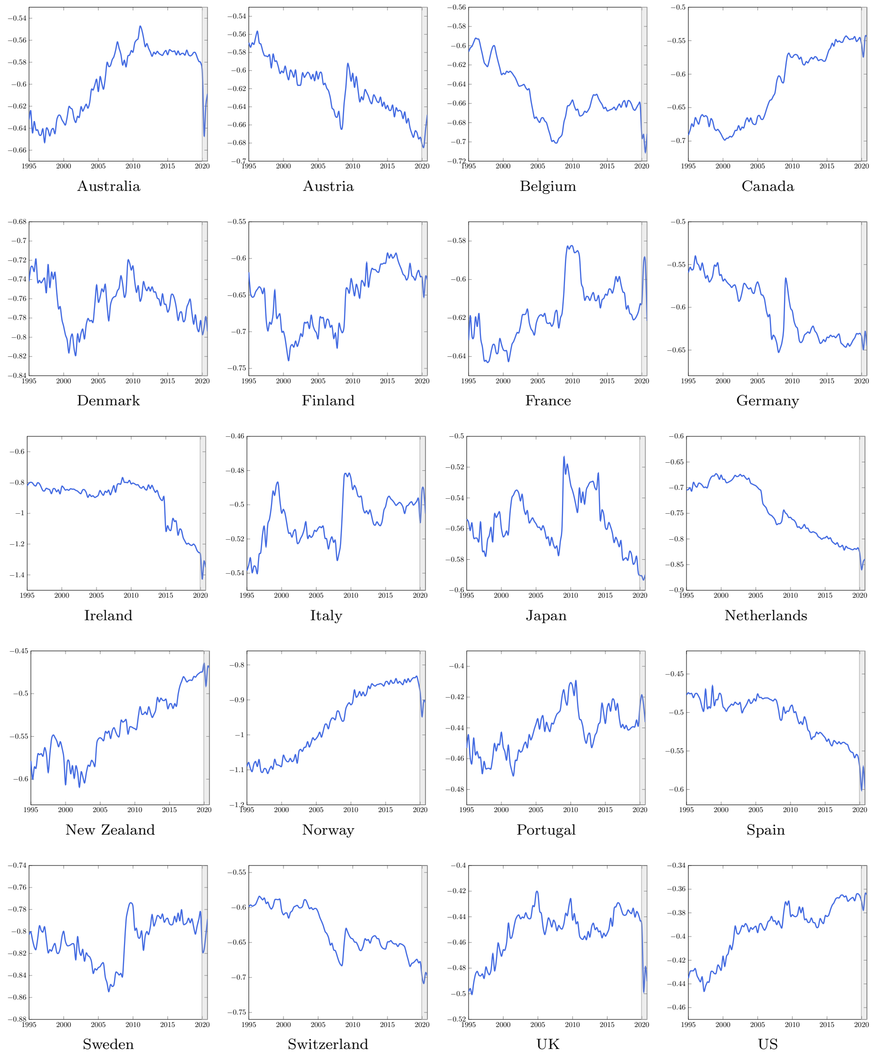


Notes: The blue line denotes the log consumption to disposable national income ratio. Shaded areas correspond to disaster episodes as identified by Barro and Ursúa (2008). We note that since consumption and disposable national income (in per capita real terms) are expressed as indices with baseyear $2005 = 100$, the log of the ratio between both equals zero in 2005. We refer to Section 5.1 and Section 5.4.4 for details on the data used in this figure.

With respect to the current Covid-19 pandemic, Figure 3 then presents recent quarterly time series over the period $1995Q1 - 2020Q4$ for the log consumption-income ratio for twenty industrial economies. Again, for many countries, we notice drastic - often downward - shifts in the consumption-income ratio during the Covid-19 part of the sample (i.e., the period $2020Q1 - 2020Q4$). Finally, in Figure 4, we present the consumption to disposable income ratio over the same period which, at the quarterly frequency, can be constructed for only seven out of the twenty countries considered in the previous figure. Unsurprisingly, the (downward) shifts during the Covid-19 part of the sample are more pronounced when we look at the consumption to disposable income ratio as household disposable incomes have decreased less than pre-tax incomes during the Covid-19 pandemic due to the implementation in many countries of a variety of tax and transfer measures (see e.g., Blanchard, 2020).

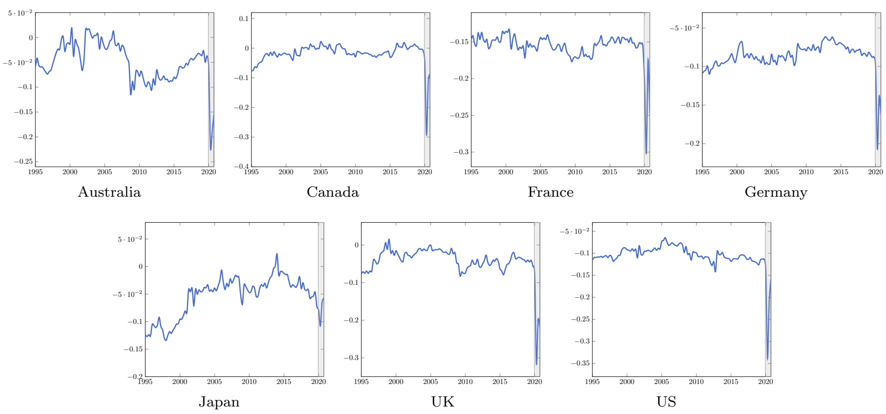
As noted in Section 1 above, the literature has documented that increases in saving ratios - which are inversely related to consumption to income ratios - during crisis periods may be triggered by increases in labor market uncertainty and precautionary motives (see e.g., Mody et al., 2012; Adema and Pozzi, 2015; Carroll et al., 2019). Conversely, decreases in saving ratios during crises could be attributed to life cycle consumption smoothing motives in reaction to decreases in income (see e.g., Attanasio et al., 2000). The increases observed in the saving rates during the Covid-19 pandemic have been attributed to forced savings stemming from the lockdowns imposed in most countries during 2020 and, to a lesser extent, to precautionary saving motives resulting from increased uncertainty about future income and employment prospects (see e.g., Dossche and Zlatanos, 2020).

Figure 3: The log consumption-income ratio during the Covid-19 pandemic



Notes: The blue line denotes the log consumption to GDP ratio. The shaded area on the far right corresponds to the Covid-19 pandemic period (2020$Q1 - Q4$). We refer to Section 6.1 for details on the data used in this figure.

Figure 4: The log consumption to disposable income ratio during the Covid-19 pandemic



Notes: The blue line denotes the log consumption to disposable income ratio. The shaded area on the far right corresponds to the Covid-19 pandemic period (2020$Q1 - Q4$). We refer to Section 6.1 for details on the data used in this figure.

In this paper, rather than focusing on the direction of the shifts, we investigate their magnitude. To explain the occurrence of these large shifts - in whatever direction - during disasters, we note that standard intertemporal budget constraint logic suggests that the current log consumption-income ratio is linked to expectations about future income and consumption growth rates. This then begs the question of whether the increases in volatility and the drastic shifts observed in the consumption-income ratio during these periods of turmoil can be explained solely by changes in these expectations, or whether the expectations about the future matter more - i.e., receive more weight - when disasters strike. In other words, we wonder whether consumers become more forward-looking during disasters. This is empirically investigated in what follows, whereby we use a theoretical framework that is presented in the next section.

3 Theory

Our framework is based on the representative agent setting considered by Campbell and Mankiw (1989) and Lettau and Ludvigson (2005) where, if the agent's intertemporal budget constraint (IBC) is satisfied, the current log consumption-income ratio is related to expectations about future income growth rates, future consumption growth rates and future returns on total wealth (where total wealth pertains to the sum of asset and human wealth). We build on this setting by allowing for disaster-dependent discount factors. In particular, by allowing for a reduction during macroeconomic disaster episodes of the average consumption and income to total wealth ratios of the consumer, the horizon of the consumer's intertemporal budget constraint is extended, i.e., it will take more periods to earn and to consume total wealth. Hence, during disaster states, discount factors are higher and more weight is given to expectations about future income growth rates, future consumption growth rates and future returns. Because the log consumption-income ratio is linked to these expectations, this potentially implies more drastic fluctuations or shifts in this ratio during disaster episodes.

If the agent's budget constraint holds intertemporally, we show in Appendix A that we can approximate the log aggregate consumption to income ratio $c_t - y_t$ in period t by,

$$c_t - y_t = E_t \sum_{j=1}^{\infty} \left[\left(\prod_{k=1}^{j} \kappa_{t+k-1} \right) (\Delta y_{t+j} - r_{t+j}) - \left(\prod_{k=1}^{j} \rho_{t+k-1} \right) (\Delta c_{t+j} - r_{t+j}) \right] \tag{1}$$

where E_t is the expectations operator conditional on period t information, r_t is the log of the gross real rate of return on total wealth, c_t is the log of real consumption, y_t is the log of real income, and where κ_t and ρ_t are time-varying discount factors (with $0 < \kappa_t < 1$ and $0 < \rho_t < 1$, $\forall t$). The intuition behind eq.(1) is straightforward. If the budget constraint holds intertemporally, high expected (discounted) future income growth rates or low expected (discounted) future consumption growth rates coincide with a high current consumption-income ratio while low expected (discounted) future income growth rates or high expected (discounted) future consumption growth rates coincide with a low current consumption-income ratio. The link between expected (discounted) future returns on wealth and the current consumption-income ratio is ambiguous as it depends on the relative magnitude of current and future values of the discount factors κ_t and ρ_t.

The discount factors κ_t and ρ_t capture the horizon of the consumer and are assumed to differ between normal periods and disaster periods, i.e., we have,

$$\kappa_t = \kappa_0(1 - d_t) + \kappa_1 d_t \tag{2}$$

$$\rho_t = \rho_0(1 - d_t) + \rho_1 d_t \tag{3}$$

where d_t is a (stochastic) binary variable that equals zero during normal periods and one during disaster periods, where the parameters κ_0 and ρ_0 denote the discount factors during normal times (with $0 < \kappa_0 < 1$ and $0 < \rho_0 < 1$), and where κ_1 and ρ_1 denote the discount factors during disaster episodes (with $0 < \kappa_1 < 1$ and $0 < \rho_1 < 1$). In particular, we can show that $\kappa = 1 - \frac{Y}{W}$ and $\rho = 1 - \frac{C}{W}$ where Y, C and W are the average (or steady state) values of income, consumption and total wealth (where the latter equals the sum of asset and human wealth). We refer to Appendix A for details. If during macroeconomic disaster episodes, which are typically characterized by large falls in income and consumption, the average income and consumption to wealth ratios are reduced compared to normal times, we have $\frac{Y_0}{W_0} > \frac{Y_1}{W_1}$ and $\frac{C_0}{W_0} > \frac{C_1}{W_1}$ where, as before, the subscript '0' refers to normal times and the subscript '1' refers to disaster episodes.[2] Since the discount factors depend negatively on the average consumption and income to wealth ratios of the consumer, this implies $\kappa_0 < \kappa_1$ and $\rho_0 < \rho_1$, i.e., if disasters occur, the consumer has a longer horizon and more weight is given to future income growth rates and future consumption growth rates. The impact of disasters on the weight given to expected future returns is ambiguous.

The intertemporal budget constraint given by eq.(1) can conveniently be rewritten as,

$$c_t - y_t = \sum_{j=1}^{\infty} \left[E_t \left(\prod_{k=1}^{j} \kappa_{t+k-1} \right) \Delta y_{t+j} - E_t \left(\prod_{k=1}^{j} \rho_{t+k-1} \right) \Delta c_{t+j} + E_t \left(\prod_{k=1}^{j} \rho_{t+k-1} - \prod_{k=1}^{j} \kappa_{t+k-1} \right) r_{t+j} \right] \tag{4}$$

where it is evident that the log consumption-income ratio in period t is linked to period t expectations of (discounted) future income growth rates, of (discounted) future consumption growth rates and of (discounted) future rates of return. As the discount factors are different for Δy_{t+j}, Δc_{t+j} and r_{t+j}, each

[2] While in this paper we indirectly test whether these unobserved ratios fall during disaster periods, a reduction in these ratios can be put forward a priori based on the validity of the intertemporal budget constraint. As total wealth can be written as a (weighted) average of income earned over the lifetime and can also be written as a (weighted) average of consumption expenditures over the lifespan, a temporary reduction with $x\%$ of income (respectively, consumption) during a disaster state is expected to reduce total wealth with only a fraction of $x\%$. Hence, the ratio of income (respectively, consumption) to wealth is expected to decrease.

of these variables has its own distinct link with the consumption-income ratio.

It is important to mention that eq.(4) does not imply a causality. It is possible for changes in the log consumption-income ratio to be driven by expectations about future consumption and income growth rates. For instance, precautionary saving motives that are prominent in buffer stock models imply higher expected consumption growth rates (see e.g., Carroll, 1992; Parker and Preston, 2005) which, through eq.(4), decrease the current log consumption-income ratio. Alternatively, according to 'saving for a rainy day' motives which are present in permanent income models (see e.g., Campbell, 1987), lower expected income growth rates decrease the current log consumption-income ratio. It is also possible, however, that changes in the log consumption-income ratio have an impact on expectations about future consumption and income growth rates. For instance, if for some reason (e.g., during lockdowns) consumers are forced to save, the ensuing change in the consumption-income ratio implies, through eq.(4), an adjustment in expectations about future consumption and income growth rates.

We note that the link between expected future returns and the log consumption-income ratio is not substantial if the discount factors κ_t and ρ_t are of similar magnitude. This happens if the average (steady state) values of the income to wealth and the consumption to wealth ratios are of equal magnitude. In this case, we have $\kappa_0 \approx \rho_0$ and $\kappa_1 \approx \rho_1$, so that $\kappa_t \approx \rho_t$ ($\forall t$). By substituting this into eq.(4), we obtain a simplified intertemporal budget constraint as a special case of the general one given by eq.(1) or eq.(4), i.e., we have,

$$c_t - y_t = \sum_{j=1}^{\infty} \left[E_t \left(\prod_{k=1}^{j} \rho_{t+k-1} \right) (\Delta y_{t+j} - \Delta c_{t+j}) \right] \tag{5}$$

where the current log consumption-income ratio is linked to expectations about (discounted) future income-consumption growth differentials $\Delta y_{t+j} - \Delta c_{t+j}$. The discount factor ρ_t is given by eq.(3) where, as before, the future matters more when disasters occur, i.e., we have $\rho_0 < \rho_1$.

The framework presented above is quite general as it only requires the validity of the IBC and the existence of state-dependent average consumption and income to wealth ratios. Its empirical implementation does not require additional theoretical structure, i.e., we do not have to specify preferences and technology.[3] Considering the limited availability of the data that would be required to test a variety of theoretical structures over the historical period that we consider, we believe that the generality of our framework is an advantage of our approach rather than a limitation. In the next section, we discuss how we take both the general budget constraint of eq.(4) and the simplified one of eq.(5) to the data.

[3]Indeed, the validity of the IBC and the implied predictive power of the log consumption-income ratio are in accordance with most models of consumer behavior. One notable exception, however, is the situation where all consumers are rule-of-thumb consumers who consume their entire income in each period. In this case, we have both $C = Y$ and $\Delta c_t = \Delta y_t$ ($\forall t$) so that the RHS of eq.(5) equals zero, i.e., $c - y$ has no predictive ability for future variables on theoretical grounds.

4 Empirical specification and estimation method

We first present and discuss the baseline and extended empirical specifications. Then, we provide details on the estimation methodology.

4.1 Empirical specification

We evaluate the budget constraints given by eqs.(4) and (5) by investigating an immediate implication of these constraints, namely that the log consumption-income ratio in the current period has predictive power for a number of variables in the next period and that this predictive ability is different during disaster episodes. In particular, according to the budget constraint eq.(5), the current log consumption-income ratio has predictive power for next period's income-consumption growth differential and this predictive power is higher during disaster episodes. According to the general budget constraint eq.(4), the current log consumption-income ratio has predictive power for the income growth rate, the consumption growth rate and the rate of return on wealth in the next period. For the income growth rate and the consumption growth rate, this predictive power is higher during disaster episodes. To check these implications of the theory, we estimate the following baseline specification,

$$x_{i,t+1} = \alpha_i d_{it} + \beta_i (c_{it} - y_{it}) + \gamma_i (c_{it} - y_{it}) d_{it} + \epsilon_{i,t+1} \tag{6}$$

where $x_{i,t+1}$ is the predicted variable in period $t+1$ in country i (with $i = 1, ..., N$) which equals either $\Delta y_{i,t+1} - \Delta c_{i,t+1}$, $\Delta y_{i,t+1}$, $\Delta c_{i,t+1}$ or $r_{i,t+1}$, where $c_{it} - y_{it}$ is the log consumption-income ratio, where d_{it} is a dummy variable that is equal to zero in normal times and equal to one during disaster episodes, and where $\epsilon_{i,t+1}$ is the error term. We allow for heterogeneity across countries in all slope coefficients. In particular, the predictive impact of the log consumption-income ratio and its interaction with the disaster dummy is allowed to vary across countries which, according to the theory discussed in Section 3 above, reflects potential cross-country differences in the magnitude of the discount factors and in the way they are affected by disasters. From eq.(4) and eq.(5), we note that the current log consumption-income ratio $c_{it} - y_{it}$ has a positive impact on next period's income-consumption growth differential $\Delta y_{i,t+1} - \Delta c_{i,t+1}$ and on next period's income growth $\Delta y_{i,t+1}$ and that this predictive ability is higher - i.e., more positive - during macroeconomic disaster episodes. Hence, in these cases, we expect $\beta_i > 0$ and $\gamma_i > 0$. On the other hand, we note from eq.(4) that the current log consumption-income ratio $c_{it} - y_{it}$ has a negative impact on next period's consumption growth rate $\Delta c_{i,t+1}$ and that this predictive ability is higher - i.e., more negative - during macroeconomic disaster episodes. Hence, in this case, we expect $\beta_i < 0$ and $\gamma_i < 0$. From eq.(4), we also note that the predictive ability of the current log consumption-income ratio $c_{it} - y_{it}$ on next period's returns $r_{i,t+1}$ and the impact of disasters on this ability is ambiguous. As such, we do not put forward expected signs for β_i and γ_i in this case. We also add the disaster dummy separately to eq.(6) to control for a potential predictive impact of disasters on the dependent variable that is unrelated to the predictive impact of the consumption-income ratio. Finally, the error term $\epsilon_{i,t+1}$ of eq.(6) is given by,

$$\epsilon_{i,t+1} = \mu_i + \lambda_i f_{t+1} + \varepsilon_{i,t+1} \tag{7}$$

where μ_i is a country fixed effect and where f_t is a vector of unobserved common factors with corresponding vector of loadings λ_i. The common factors can affect all countries in the sample, albeit with a potentially different impact, i.e., there can be so-called heterogeneous cross-sectional dependence. Examples of common factors are international business or financial cycles or changes in trade or financial integration that occur simultaneously in most or all countries of the sample and that may affect both the dependent variable and the regressors in the regression equation. The idiosyncratic error term $\varepsilon_{i,t+1}$ is a prediction error that should, in principle, be unpredictable based on period t information. It is possible that it is autocorrelated nonetheless, however, where the autocorrelation is of the moving average (MA) type. For example, it could follow an MA(1) process due to measurement error or time aggregation in the data.[4] Finally, the error term $\varepsilon_{i,t+1}$ can be conditionally heteroskedastic across countries and over time. Indeed, the literature documents changes in volatilities of macroeconomic variables like GDP growth (see e.g., Hamilton, 2008; Nakamura et al., 2017) and financial variables like equity returns (see e.g., Tsay, 2005, and references therein). These changes are particularly likely when considering a long historical period that includes many fundamentally different episodes (e.g., the Great Depression, Bretton Woods). The estimation methods and tests considered in this paper and detailed in the next section can deal with all the mentioned complications.

Apart from the baseline specification of eq.(6), we also estimate an extended predictive regression equation,

$$x_{i,t+1} = \alpha_i d_{it} + \beta_i (c_{it} - y_{it}) + \gamma_i (c_{it} - y_{it}) d_{it} + w_{i,t+1}\delta_i + \epsilon_{i,t+1} \tag{8}$$

which is identical to eq.(6) except for the addition of a vector of control variables $w_{i,t+1}$ with corresponding vector of parameters δ_i. The vector $w_{i,t+1}$ includes variables that enter the budget constraint other than the variable under scrutiny in $x_{i,t+1}$. This is relevant when testing the predictability implications of eq.(4). Consider the case where we investigate the predictive ability of $c_{it} - y_{it}$ for $x_{i,t+1} = \Delta c_{i,t+1}$. Then $w_{i,t+1}$ includes the variables $\Delta y_{i,t+1}$ and $r_{i,t+1}$. Hence, we make sure that, when detecting a relationship between $c_{it} - y_{it}$ and $\Delta c_{i,t+1}$, it is not driven solely by, for example, the covariance between $\Delta c_{i,t+1}$ and

[4] See e.g., Sommer (2007) for measurement error in aggregate consumption data and its implications.

$\Delta y_{i,t+1}$ in which case $c_{it} - y_{it}$ would only affect $\Delta c_{i,t+1}$ because it has predictive power for $\Delta y_{i,t+1}$. The same reasoning applies to the other cases, i.e., when $x_{i,t+1} = \Delta y_{i,t+1}$ and when $x_{i,t+1} = r_{i,t+1}$.

4.2 Estimation method

The specifications discussed in the previous section can be written more concisely as,

$$x_{i,t+1} = z_{i,t+1}\psi_i + \epsilon_{i,t+1} \tag{9}$$

where $z_{i,t+1}$ contains the regressors and ψ_i the corresponding parameters. Without error cross-sectional dependence, the error term is given by $\epsilon_{i,t+1} = \mu_i + \varepsilon_{i,t+1}$ and we can estimate eq.(9) country-by-country using ordinary least squares (OLS) provided that $E(z_{i,t+1}\varepsilon_{i,t+1}) = 0$. With error cross-sectional dependence, the error term is $\epsilon_{i,t+1} = \mu_i + \lambda_i f_{t+1} + \varepsilon_{i,t+1}$ and we have to deal with the unobserved common factors f_{t+1} since ignoring cross-sectional dependence implies inefficient estimation and may, additionally, imply biased and inconsistent OLS estimates if the unobserved common factors are correlated with the regressors. Pesaran (2006) shows that the cross-sectional averages of the dependent variable $x_{i,t+1}$ and all included regressors $z_{i,t+1}$ in eq.(9), i.e., $\bar{x}_{t+1}$ and $\bar{z}_{t+1}$, are suitable proxies for the unobserved common factors. For large enough N, these cross-sectional averages can be considered exogenous, i.e., $E(\bar{x}_{t+1}\varepsilon_{i,t+1})$ and $E(\bar{z}_{t+1}\varepsilon_{i,t+1})$. After replacing f_{t+1} by these cross-sectional averages, we can estimate eq.(9) country-by-country using OLS provided that $E(z_{i,t+1}\varepsilon_{i,t+1}) = 0$. This is the common correlated effects (CCE) estimator.

In our setting, there are two instances where the condition $E(z_{i,t+1}\varepsilon_{i,t+1}) = 0$ may be violated, necessitating the use of an instrumental variables (IV) estimator at the country level that corrects for endogeneity. First, if there is autocorrelation in the error term $\varepsilon_{i,t+1}$, it can be correlated with one or more regressors. As discussed at the end of this section, we test for autocorrelation in all our estimated specifications. Second, in our extended specification eq.(8), we include contemporaneous variables $w_{i,t+1}$ that can be correlated with the error term $\varepsilon_{i,t+1}$. When endogeneity is a concern, we report results based on IV estimation. The IV estimator uses an appropriate number of lagged values of the dependent variable and the included regressors as instruments.

We rewrite eq.(9) as,

$$x_{i,t+1} = Z_{i,t+1}\Psi_i + \varepsilon_{i,t+1} \tag{10}$$

where, if we ignore the unobserved common factors, we have $Z_{i,t+1} = \begin{bmatrix} z_{i,t+1} & 1 \end{bmatrix}$ and $\Psi_i = \begin{bmatrix} \psi_i & \mu_i \end{bmatrix}'$ and, if we proxy the unobserved common factors using cross-sectional averages, we have $Z_{i,t+1} = \begin{bmatrix} z_{i,t+1} & 1 & \bar{x}_{t+1} & \bar{z}_{t+1} \end{bmatrix}$ and $\Psi_i = \begin{bmatrix} \psi_i & \mu_i & \lambda_i^x & \lambda_i^z \end{bmatrix}'$ with $\bar{x}_{t+1}$ and $\bar{z}_{t+1}$ the cross-sectional averages of $x_{i,t+1}$ and $z_{i,t+1}$ and λ_i^x and λ_i^z the country-specific regression coefficients on these cross-sectional averages.

For a heterogeneous (dynamic) panel with a sufficiently large T and N, Pesaran and Smith (1995) suggest to obtain estimates for the average effects $\overline{\Psi} = N^{-1}\sum_{i=1}^{N}\Psi_i$ by averaging over country-specific coefficient estimates, i.e., $\widehat{\overline{\Psi}} = N^{-1}\sum_{i=1}^{N}\widehat{\Psi}_i$. The average over the N country-specific OLS estimates obtained when neglecting error cross-sectional dependence, is referred to as the mean group (MG) estimator. The average over the N country-specific CCE estimates obtained when taking error cross-sectional dependence into account, is referred to as the common correlated effects mean group (CCEMG) estimator (see Pesaran, 2006). In the instances where we use IV instead of OLS at the country level, we report the averages over the N country-specific IV estimates. The latter can be obtained both from regressions that exclude or include cross-sectional averages as proxies for the unobserved common factors (see e.g., Everaert and Pozzi, 2014). Following Pesaran et al. (1996), the asymptotic covariance matrix Σ for these mean group estimators is consistently estimated nonparametrically by,

$$\widehat{\Sigma} = \frac{1}{N-1}\sum_{i=1}^{N}\left(\widehat{\Psi}_i - \widehat{\overline{\Psi}}\right)\left(\widehat{\Psi}_i - \widehat{\overline{\Psi}}\right)' \tag{11}$$

Besides the coefficient estimates and the corresponding standard errors, we also report the results of two diagnostic tests. First, for the MG estimations, we calculate the Pesaran (2004) cross-sectional dependence statistic, which tests the null hypothesis of cross-sectional independence in the error term. This statistic indicates whether an estimator that controls for cross-sectional dependence, i.e., the CCEMG estimator, should be implemented instead of the MG estimator. Second, as we have noted above, it is important also to test for autocorrelation in the error term $\varepsilon_{i,t+1}$. Hence, we calculate the Cumby and Huizinga (1992) autocorrelation statistic which tests the null hypothesis that the error term follows a moving average process of known order $q \geq 0$ against the alternative that the autocorrelations of the error term are nonzero at lags greater than q. We calculate this statistic per country and then average it across countries.[5] This test is particularly suitable as, besides allowing to test for MA errors, it provides an autocorrelation test that is valid also if the errors are conditionally heteroskedastic. Moreover, it can also be applied when using estimators other than OLS, such as IV (see Cumby and Huizinga, 1992, for details).

[5]Note that the Cumby and Huizinga (1992) test statistic follows a χ^2 distribution. Assuming that the country-specific test statistics are independent, the average Cumby and Huizinga (1992) test still follows a χ^2 distribution with the same number of degrees of freedom as its country-specific counterparts.

5 Results from historical data

In this section, we investigate the impact of disaster episodes on the predictive ability of the log consumption-income ratio using historical data. We first elaborate on the data used. Then, we discuss the baseline results. Next, we present results of estimating predictive regression equations that contain control variables. A number of robustness checks follow, after which we investigate the results obtained when focusing specifically on the major disaster episodes that occurred over the sample period. Finally, we check whether our findings are unique to historical disaster episodes or whether they also hold during ordinary recessions.

5.1 Data

We use historical long-term macro data over the period $1870 - 2015$. These are available at the annual frequency. Data availability determines the countries included in the dataset and the periods considered per country.[6] Our sample consists of sixteen economies, i.e., $N = 16$. These are Australia, Belgium, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US. For c_{it}, we use the log of per capita real consumption, while for y_{it} we use the log of per capita real GDP. Per capita real personal consumer expenditures and per capita real GDP are taken from the Jordà-Schularick-Taylor macro-history Database (Jordà et al., 2016).[7] For r_{it}, we use the real rate of return on equity. Historical data for the nominal rate of return on equity is reported by Jordà et al. (2019).[8] We deflate nominal returns using the inflation rate calculated from the Consumer Price Index (CPI) which is also obtained from the Jordà-Schularick-Taylor macro-history Database.[9]

The disaster dummies d_{it} take on the value of one during disaster episodes and are constructed from the macroeconomic disaster episodes identified by Barro and Ursúa (2008). The authors define a disaster as a peak-to-through cumulative decline in real per capita GDP and/or real per capita personal consumer expenditure of at least 10%. We construct a general dummy that contains all identified disaster episodes over the sample period. Additionally, we also consider specific disaster episodes. In particular, we construct dummies for each of the four principal world economic crises identified by Barro and Ursúa

[6]For some countries and variables, a number of data points are missing at the beginning of the sample period which renders the panel unbalanced.

[7]The website is http://www.macrohistory.net/data. The series have codes 'rconpc' and 'rgdppc'. We note that the series that we use are both expressed as indices with baseyear 2005 = 100 (see also Figure 1 above).

[8]The data can be found at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GGDQGJ where the nominal equity returns have code 'eq-tr'. Details on the data sources are discussed in the online Appendix of Jordà et al. (2019)'s paper.

[9]The website is http://www.macrohistory.net/data. The data used has code 'cpi'.

(2008), i.e., World War I (WW1), the Spanish flu pandemic of the late 1910s/early 1920s (PAN), the Great Depression (GRD) and World War II (WW2). More details on the construction of the disaster dummies are provided in Appendix B.

5.2 Baseline results

We present the results of estimating eq.(6) for the sixteen economies in our sample over the period $1870 - 2015$ using the MG and CCEMG panel estimators discussed in Section 4.2 above. In Section 4.1, we argued that according to the budget constraint eq.(5), the log consumption-income ratio $c - y$ has predictive ability for the income-consumption growth differential $\Delta y - \Delta c$ (with positive impact), while according to the budget constraint eq.(4), the log consumption-income ratio $c - y$ has predictive ability for the income growth rate Δy (with positive impact), the consumption growth rate Δc (with negative impact) and the rate of return on wealth r (with ambiguous impact). As such, we estimate eq.(6) with each of these variables as the dependent variable.

The MG and CCEMG panel estimates for the coefficients on the regressors d, $c - y$ and $(c - y)d$ are presented in Table 1.[10] The country-specific coefficient estimates that are used in the calculation of the MG and CCEMG coefficient estimates for the regressors $c - y$ and $(c - y)d$ are presented in Appendix C. A look at Cumby and Huizinga (1992)'s test for autocorrelation shows that for none of the conducted regressions the null hypothesis of no autocorrelation is rejected. Then, a look at Pesaran (2004)'s cross-sectional dependence test reveals that, for the MG estimates, the null hypothesis of no cross-sectional dependence in the error term of the regression equation is strongly rejected. Hence, we focus on the CCEMG estimator which, as discussed in Section 4.2, deals with cross-sectional dependence by augmenting the regression with cross-sectional averages of dependent variable and regressors. The CCEMG estimates are reported in the final four columns of the table. We observe the following. First, while it can be expected that the disaster dummy d negatively affects income growth, consumption growth and returns *in the same period*, the reported results show that it also negatively affects next period's income growth. It has no predictive impact for consumption growth nor for returns, however. It further has predictive impact for the income-consumption growth differential that stems from its predictive ability for income growth. Second, in accordance with the budget constraint eq.(5), the log consumption-income ratio $c-y$ has a positive impact on next period's income-consumption growth differential. The results for

[10]The coefficients on the regressors $c-y$ and $(c-y)d$ are semi-elasticities. For example, for the coefficient of Δy on $c-y$, we have $\frac{\partial \Delta y}{\partial (c-y)} = \frac{\partial \Delta y}{\partial \ln(\frac{C}{Y})}$, i.e., the coefficient equals the change in Δy divided by the percentage change in $\frac{C}{Y}$. A coefficient equal to 0.1 then implies that if $\frac{C}{Y}$ increases with 1% (e.g., from 100% to 101%), then Δy increases with 0.1 percentage points (e.g., from 1% to 1.1%). A coefficient equal to 1 then implies that if $\frac{C}{Y}$ increases with 1% (e.g., from 100% to 101%), then Δy increases with 1 percentage point (e.g., from 0.5% to 1.5%).

Δy and Δc as dependent variables then show that $c - y$ has predictive power for *both* the income growth rate and the consumption growth rate where the signs are in accordance with the budget constraint logic of eq.(4), i.e., a high consumption-income ratio today is followed by future increases in income growth and future decreases in consumption growth. We do not find a significant impact of $c - y$ on returns, however. Third, in line with the theory, we find strongly significant coefficient estimates for the regressor $(c - y)d$ in the equations for the variables Δy, Δc and $\Delta y - \Delta c$. For the dependent variable r, the significance is only marginal and, as we discuss in the next section, it is not withheld once we add control variables to our baseline regression specification. Hence, the predictive ability of $c - y$ for $\Delta y - \Delta c$, Δy and Δc is significantly higher during disaster episodes, i.e., from the CCEMG point estimates reported in the table we find that this ability is about twice as large during disaster periods. Interpreted through the lens of the theory of Section 3, this suggests that during disaster episodes, consumers are more forward looking and give more weight to expectations about future income and consumption growth rates in their consumption decisions. As such, expectations about future income and consumption growth rates, in and of themselves, are not sufficient to explain the large shifts and high volatility observed in the consumption-income ratios (or, conversely, the saving ratios) during disaster periods. An increase in the weight given to future expectations is also required to explain the data.

Table 1: Baseline results

	MG				CCEMG			
	Dependent variable $x_{i,t+1}$				Dependent variable $x_{i,t+1}$			
	$(\Delta y_{i,t+1} - \Delta c_{i,t+1})$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$	$(\Delta y_{i,t+1} - \Delta c_{i,t+1})$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$
d_{it}	-0.028	-0.042^{***}	-0.014	-0.049	-0.053^{***}	-0.066^{***}	-0.004	-0.058
	(0.022)	(0.015)	(0.016)	(0.043)	(0.021)	(0.018)	(0.017)	(0.041)
$(c_{it} - y_{it})$	0.049^{***}	0.013	-0.035^{*}	-0.064^{*}	0.216^{***}	0.074^{**}	-0.151^{***}	-0.107
	(0.014)	(0.026)	(0.020)	(0.033)	(0.055)	(0.037)	(0.029)	(0.067)
$(c_{it} - y_{it})d_{it}$	0.246^{***}	0.109^{*}	-0.137^{*}	0.208	0.289^{***}	0.146^{**}	-0.135^{**}	0.325^{*}
	(0.060)	(0.059)	(0.082)	(0.178)	(0.064)	(0.066)	(0.063)	(0.195)
Cumby-Huizinga AC	2.261	2.425	3.843	4.000	3.591	2.458	2.466	3.710
	[0.322]	[0.297]	[0.146]	[0.135]	[0.166]	[0.292]	[0.291]	[0.156]
Pesaran CD	12.944	25.246	22.385	45.666				
	[0.000]	[0.000]	[0.000]	[0.000]				

Notes: Reported are the results of the estimation of eq.(6). Estimation is based on panel data for 16 countries over the period 1870 − 2015. Standard errors are in parentheses, p-values are in square brackets. *,**,*** indicate significance at the 10%, 5% and 1% level respectively. The Cumby-Huizinga test shows the average of the individual countries' Cumby and Huizinga (1992) autocorrelation test, testing the null hypothesis of no autocorrelation against the alternative that the autocorrelations of the error term are nonzero at lags greater than zero (with maximum lag equal to 2). The Pesaran CD statistic tests the null hypothesis of cross-sectional independence (see Pesaran, 2004).

Since our baseline results provide confirmation that the predictive ability of the consumption-income ratio for future income and consumption growth rates is significantly higher during disaster episodes, a natural question one might then ask is whether we can draw the same conclusion when looking at ordinary recessions. In Section 5.6 below, we provide evidence that indicates that conventional recessions do not have a similar impact on consumption and saving. In what follows, we first investigate the robustness of our results by adding control variables to the baseline specification and by considering a number of alternatives for the variables used in the baseline regressions.

5.3 Adding controls

We now estimate the extended specification eq.(8) where predictable variables from the budget constraint eq.(4), other than the variable under scrutiny x, are included as controls in the vector w. For example, when $x = \Delta c$, we have $w = \begin{bmatrix} \Delta y & r \end{bmatrix}$. As such, we make sure that when we uncover a predictive relationship between $c - y$ and x, it does not merely stem from to the combination of $c - y$ having predictive power for w and the presence of nonzero covariances between x and w.

The results are reported in Table 2. We note that our panel estimates are based on IV estimates at the country level. We estimate eq.(8) using IV in this case because of the potential contemporaneous correlation between the error term and the control variables w. As instruments, we use lagged values of the dependent variable and the regressors.[11] We further report the Sargan-Hansen overidentifying restrictions statistic that tests the null hypothesis that the instruments used are valid. From the table, we note that, as before, the results of Pesaran (2004)'s cross-sectional dependence test suggest that we focus on the CCEMG estimates which are reported in the last three columns of the table. The autocorrelation tests and tests for overidentifying restrictions indicate that the regression equations and instrument sets are well-specified. The results for the dependent variables Δy and Δc are generally in accordance with the baseline CCEMG results reported for Δy and Δc in Table 1, i.e., the log consumption-income ratio has significant predictive ability for income and consumption growth and this ability is significantly higher during disaster episodes. The magnitude of the estimates on the regressors $c - y$ and $(c - y)d$ differs to some extent between both tables, but this is not surprising as some of the added controls - i.e., Δc in the equation for Δy and Δy in the equation for Δc - are highly significant. Finally, we note that in the predictive regression equation for returns on wealth r, none of the regressors are significant, i.e., there is no robust significant predictive ability of $c - y$ and $(c - y)d$ for returns.

[11] More specifically, the MG (IV) estimation of eq.(8) uses an instrument set that consists of a constant, the predetermined regressors d_{it}, $(c_{it} - y_{it})$ and $(c_{it} - y_{it})d_{it}$ and lags 1 and 2 of the variables $\Delta y_{i,t+1}$, $\Delta c_{i,t+1}$ and $r_{i,t+1}$ (i.e., periods t and $t-1$). The instrument set used for CCEMG (IV) estimation additionally includes the cross-sectional averages of the dependent variable and of all regressors to the instrument set.

Table 2: Results when including control variables

	MG (IV)			CCEMG (IV)		
	Dependent variable $x_{i,t+1}$			Dependent variable $x_{i,t+1}$		
	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$
d_{it}	-0.042***	0.025	0.078	-0.058***	0.009	-0.053
	(0.017)	(0.030)	(0.094)	(0.019)	(0.034)	(0.058)
$(c_{it} - y_{it})$	0.043	-0.051***	0.137	0.162***	-0.107**	-0.089
	(0.034)	(0.016)	(0.154)	(0.038)	(0.049)	(0.165)
$(c_{it} - y_{it})d_{it}$	0.253***	-0.173***	0.061	0.194***	-0.172***	0.003
	(0.069)	(0.066)	(0.275)	(0.062)	(0.063)	(0.165)
$\Delta y_{i,t+1}$		0.641***	0.096		0.558***	0.186
		(0.160)	(0.764)		(0.173)	(0.760)
$\Delta c_{i,t+1}$	0.514*		1.661	0.512***		-0.671
	(0.289)		(1.214)	(0.166)		(0.954)
$r_{i,t+1}$	0.046	-0.049		-0.022	-0.069	
	(0.029)	(0.031)		(0.035)	(0.047)	
Cumby-Huizinga AC	2.034	2.124	2.957	2.681	1.825	2.814
	[0.361]	[0.345]	[0.228]	[0.261]	[0.401]	[0.245]
Sargan-Hansen OR	8.561	5.551	5.160	7.714	6.768	7.022
	[0.073]	[0.235]	[0.271]	[0.103]	[0.149]	[0.135]
Pesaran CD	8.456	6.029	35.669			
	[0.000]	[0.000]	[0.000]			

Notes: Reported are the results of the estimation of eq.(8) where the vector of controls is $w_{i,t+1} = \begin{bmatrix} \Delta c_{i,t+1} & r_{i,t+1} \end{bmatrix}$ when $x_{i,t+1} = \Delta y_{i,t+1}$, $w_{i,t+1} = \begin{bmatrix} \Delta y_{i,t+1} & r_{i,t+1} \end{bmatrix}$ when $x_{i,t+1} = \Delta c_{i,t+1}$ and $w_{i,t+1} = \begin{bmatrix} \Delta y_{i,t+1} & \Delta c_{i,t+1} \end{bmatrix}$ when $x_{i,t+1} = r_{i,t+1}$. Estimation is based on panel data for 16 countries over the period $1870 - 2015$. Standard errors are in parentheses, p-values are in square brackets. $^{*},^{**},^{***}$ indicate significance at the 10%, 5% and 1% level respectively. The Cumby-Huizinga test shows the average of the individual countries' Cumby and Huizinga (1992) autocorrelation test, testing the null hypothesis of no autocorrelation against the alternative that the autocorrelations of the error term are nonzero at lags greater than zero (with maximum lag equal to 2). The Pesaran CD statistic tests the null hypothesis of cross-sectional independence (see Pesaran, 2004). The Sargan-Hansen OR test reported is the average of the country-specific Sargan-Hansen overidentifying restrictions statistics that test the joint validity of the instruments used (see Sargan, 1958; Hansen, 1982). MG (IV) estimation uses an instrument set that consists of a constant, the predetermined regressors d_{it}, $(c_{it} - y_{it})$ and $(c_{it} - y_{it})d_{it}$ and lags 1 and 2 of the variables $\Delta y_{i,t+1}$, $\Delta c_{i,t+1}$ and $r_{i,t+1}$ (i.e., periods t and $t-1$). The instrument set used for CCEMG (IV) estimation additionally includes the cross-sectional averages of the dependent variable and all regressors to the instrument set.

5.4 Robustness checks

The results reported in the previous section imply that the log consumption-income ratio has significant predictive power for income growth and consumption growth but no significant predictive ability for returns on wealth. Theoretically, this implies that we can focus on the simplified intertemporal budget constraint eq.(5) presented in Section 3. In this section and the next, we therefore only consider the predictive impact of $c - y$ for the income-consumption growth differential $\Delta y - \Delta c$. This section presents a number of robustness checks for the baseline results reported in Section 5.2. First, we investigate the impact of adding lags of the dependent variable to the equation. Next, we check whether our results are robust to the detrending of the persistent log consumption-income ratio. Then, we consider an alternative disaster dummy. Finally, we check whether the results also hold when, for the variable y, we use after-tax income instead of GDP.

5.4.1 Lagged dependent variable

Controlling for the lagged dependent variable is useful to make sure that, when detecting a relationship between $c_{it} - y_{it}$ and the dependent variable $x_{i,t+1}$, this relationship is not driven solely by the possible covariance between $c_{it} - y_{it}$ and x_{it}, i.e., x_{it} has predictive power for $x_{i,t+1}$ and $c_{it} - y_{it}$ only affects $x_{i,t+1}$ because it is correlated with x_{it}. To deal with this, we estimate an extended version of eq.(6) where one lag of the dependent variable is added as a control variable. We add only one lag because, when conducting estimations with more lags, we find that the coefficient estimates on additional lags are not significant. The results are reported in the columns 'Lag dep. var.' of Table 3. The lagged dependent variable has a significant impact in the regression for $\Delta y - \Delta c$ when applying the MG estimator. However, as with the baseline results, we find that, using Pesaran (2004)'s cross-sectional dependence test, there are strong indications of cross-sectional dependence in the error term. As such, we focus on the CCEMG estimates reported in the table for which we find that the coefficient on the lagged dependent variable is not significant. Therefore, we are not surprised to find that the results are very similar to the baseline results reported in Table 1, i.e., the log consumption-income ratio has positive predictive power for $\Delta y - \Delta c$ and this predictive ability is magnified during disaster episodes.

5.4.2 Detrended log consumption-income ratio

Figure 1 suggests that the log consumption-income ratio, while expected to be stationary on theoretical grounds, is quite persistent and has unit root-like characteristics in many countries. To be on the safe side, we therefore check whether our predictability results also hold when we take out this potential non-stationarity. To this end, we estimate eq.(6) using a detrended version of the log consumption-income ratio. We detrend $c-y$ by calculating the deviation of $c-y$ from its stochastic trend $\overline{c-y}$. The latter is approximated by a ten-year moving average as $\overline{c-y} = \frac{1}{10}\sum_{j=0}^{9}(c_{-j} - y_{-j})$.[12] The results of estimating eq.(6) for dependent variable $x = \Delta y - \Delta c$ using this detrended measure instead of the actual $c-y$ variable are presented in Table 3 under the columns 'Detrended $c-y$'. For both the MG and CCEMG estimators, the estimates of, in particular, the coefficient on the interaction variable $(c-y)d$ are quite similar in magnitude and significance to those reported in Table 1, i.e., the baseline results with dependent variable $\Delta y - \Delta c$.

5.4.3 Alternative disaster dummy

Our results so far are based on disaster dummies constructed from consumption and GDP disaster episodes identified by Barro and Ursúa (2008). More recently, Nakamura et al. (2013) estimate a model of consumption disasters that generates endogenous estimates of the timing and length of disasters. We use the start and end dates of their identified disaster episodes (see Table 2 in Nakamura et al., 2013) to construct an alternative disaster dummy. We then check wether our predictability results also hold when estimating eq.(6) with this alternative dummy variable for d. The results with $\Delta y - \Delta c$ as the dependent variable are presented in Table 3 under the columns 'Alt.disaster'. Upon comparing these results to the baseline results reported in Table 1 with dependent variable $\Delta y - \Delta c$, we find similar results with respect to the predictive power of the log consumption-income ratio for income and consumption growth during both normal times and disaster periods.

5.4.4 Disposable income

The baseline results are based on estimations that use real GDP as a proxy for income. Theoretically, using an after-tax measure of income is more appropriate but historical data on disposable income are not widely available. Piketty and Zucman (2014) provide historical data on national income after taxes which are available for only four countries out of the sixteen considered when using GDP data.[13] These

[12] This detrending approach takes out the low frequency movements (i.e., long swings) in the data as well as high frequency noise as opposed to a first-differencing approach which takes out low and medium frequency movements (see e.g., Sarno and Schmeling, 2014). We note that our baseline results are also confirmed if we proxy the stochastic trend using a moving average calculated over 5 or 20 years.

[13] The website is http://piketty.pse.ens.fr/fr/capitalisback. The data used are in the country excel files, Table 1, columns 9 and 14. From the reported per capita real national income series and the reported series for the ratio of national income after taxes to national income, a series is constructed for per capita real disposable national income (=national income minus taxes plus transfers). Note that, in line with our consumption data (see Section 5.1), we express this series as an index with baseyear 2005 = 100 (see also Figure 2 above). The data used are available uninterruptedly from 1870 onward. One exception is the UK where the ratio of after-tax national income to national income is only available from 1948 onward. Here, we extrapolate the 1948 value of this ratio to the period 1870 − 1947. Note further that we update the calculated historical per capita real disposable income series from 2011 to 2015 using data from OECD Economic Outlook.

countries are France, Germany, the UK and the US. In Table 3, under the columns 'Disp. income', we therefore report the results of estimating eq.(6) with the variable y calculated as the log of real per capita national disposable (after-tax) income. We note that with the number of cross-sections equal to only $N = 4$, consistency of the CCE estimates is not guaranteed as the cross-sectional averages of the dependent variable and the regressors that proxy the unobserved common factors in the regression can be considered exogenous only if N is large enough. Hence, in this case, we focus also on the OLS estimates as summarized by the MG results reported in the table. Both MG and CCEMG results confirm our baseline results when using real per capita disposable income for y instead of real per capita GDP. We find that the log consumption-income ratio $c - y$ has significant predictive ability for the income-consumption growth differential $\Delta y - \Delta c$ and we find that this predictive impact is significantly higher during disaster episodes.

Table 3: Robustness checks

	Dependent variable $x_{i,t+1} = (\Delta y_{i,t+1} - \Delta c_{i,t+1})$							
	MG				CCEMG			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Lag dep. var.	Detrended $c - y$	Alt. disaster	Disp. income	Lag dep. var.	Detrended $c - y$	Alt. disaster	Disp. income
d_{it}	-0.023	0.029	-0.038***	0.011	-0.043*	0.012	-0.062***	0.006
	(0.023)	(0.031)	(0.015)	(0.020)	(0.023)	(0.024)	(0.021)	(0.022)
$(c_{it} - y_{it})$	0.052***	0.102**	0.025	0.071*	0.194***	0.204***	0.170***	0.126**
	(0.014)	(0.050)	(0.016)	(0.036)	(0.041)	(0.053)	(0.042)	(0.058)
$(c_{it} - y_{it})d_{it}$	0.269***	0.253***	0.280***	0.129**	0.287***	0.322***	0.362***	0.196***
	(0.060)	(0.105)	(0.037)	(0.062)	(0.072)	(0.097)	(0.086)	(0.032)
$(\Delta y_{it} - \Delta c_{it})$	0.095**				-0.009			
	(0.046)				(0.038)			
Cumby-Huizinga AC	2.243	2.733	2.271	3.969	4.372	3.724	2.682	5.253
	[0.326]	[0.255]	[0.321]	[0.137]	[0.112]	[0.155]	[0.261]	[0.072]
Pesaran CD	11.928	13.647	16.076	7.950				
	[0.000]	[0.000]	[0.000]	[0.000]				

Notes: Reported are the results of the estimation of eq.(6) with $x_{i,t+1} = (\Delta y_{i,t+1} - \Delta c_{i,t+1})$. Data used are the same as for the results reported in Table 1, except that in column (2) the detrended log consumption-income ratio is used for $c - y$, in column (3) a disaster dummy based on disasters identified by Nakamura et al. (2013) is used for d, and in column (4) log per capita real disposable income is used for y instead of log per capita real GDP. Details are provided in the text. Estimation is based on panel data for 16 countries (columns 1, 2 and 3) or 4 countries (column 4) over the period $1870 - 2015$. Standard errors are in parentheses, p-values are in square brackets. *,**,*** indicate significance at the 10%, 5% and 1% level respectively. The Cumby-Huizinga test shows the average of the individual countries' Cumby and Huizinga (1992) autocorrelation test, testing the null hypothesis of no autocorrelation against the alternative that the autocorrelations of the error term are nonzero at lags greater than zero (with maximum lag equal to 2). The Pesaran CD statistic tests the null hypothesis of cross-sectional independence (see Pesaran, 2004).

5.5 Major disaster episodes

In this section, we investigate whether all disaster episodes magnify the predictive impact of the log consumption-income ratio or whether only particular episodes do so. In other words, we wonder whether consumers become more forward looking only during certain particular crises or whether they give more weight to future expectations during each and every disaster period. To look at this issue, we investigate the separate impact of the major disaster episodes that occurred during the sample period according to Barro and Ursúa (2008), i.e., World War I (WW1), the Spanish flu pandemic of the late 1910s/early 1920s (PAN), the Great Depression (GRD) and World War II (WW2). Following the discussion of the previous sections, we focus on the predictive ability of the log consumption-income ratio $c - y$ for next year's income-consumption growth differential $\Delta y - \Delta c$. Hence, we estimate predictive regression equations of the following form,

$$(\Delta y_{i,t+1} - \Delta c_{i,t+1}) = \alpha_i d_{it}^j + \alpha_i^{-j} d_{it}^{-j} + \beta_i(c_{it} - y_{it}) + \gamma_i(c_{it} - y_{it})d_{it}^j + \gamma_i^{-j}(c_{it} - y_{it})d_{it}^{-j} + \epsilon_{i,t+1} \quad (12)$$

where the error term $\epsilon_{i,t+1}$ is, as before, given by eq.(7). We estimate the equation per major disaster episode j (with $j = WW1, PAN, GRD, WW2$) while controlling for all other disasters. To this end, we include the specific disaster dummy variable d^j that equals one during disaster period j, but also a dummy variable d^{-j} that takes on the value of one when disasters other than j occur, i.e., the dummy d^{-j} equals $d - d^j$ where d is the disaster dummy used in previous sections. Both dummies d^j and d^{-j} enter the equation interacted with the log consumption-income ratio and also, as before, separately. As not all specific disasters occur in all sixteen countries of our sample, the estimations are conducted with a different number of countries for each particular disaster episode j. We refer to Appendix B for an overview of the exact dates of the major disaster episodes in each country. In particular, estimation is based on panel data for thirteen countries when $j = WW1$, for five countries when $j = PAN$, for eight countries when $j = GRD$ and for fifteen countries when $j = WW2$.[14]

In Table 4, we report the results of estimating eq.(12) for every major disaster episode j. From looking at both the MG and CCEMG estimation results in the table, we first note that the largest disasters also have the largest impact on the predictive ability of the log consumption-income ratio, i.e., the estimates

[14] We note that since estimations occur at the country level, a country can only be included in the panel estimation if both dummies d^j and d^{-j} are defined for that country (i.e., if both dummies take on the value of one at least once over the sample period for that country). For example, even though for $j = WW2$ the dummy variable d^j is defined for all sixteen countries, we cannot include Japan in the sample as the dummy d^{-j} is not defined for Japan, i.e., the only disaster identified by Barro and Ursúa (2008) for Japan is $WW2$. Hence, for $j = WW2$, we have $N = 15$ instead of $N = 16$. If we do not include the dummy d^{-j} in the estimations, we can add Japan to the sample when $j = WW2$ and we find that the results with respect to the impact of $WW2$ on the predictive impact of $c - y$ are very similar to those reported in Table 4. These results are not reported, but are available upon request.

on the regressor $(c-y)d^j$ (with d^j containing the major disaster episode under scrutiny) are generally larger in magnitude than those on the regressor $(c-y)d^{-j}$ (with d^{-j} containing the other major disasters but also all the minor ones). Furthermore, we find that for all major disasters considered, the predictive power of the log consumption-income ratio becomes significantly higher during the occurrence of these major crises. Hence, the finding that disasters tend to make consumers more forward looking so that they then give more weight to expectations about future income and consumption growth rates is not limited to one particular disaster type but occurs during every major crisis type that we consider in our historical dataset.

Table 4: Results for major disaster episodes

	Dependent variable $x_{i,t+1} = (\Delta y_{i,t+1} - \Delta c_{i,t+1})$							
	MG				CCEMG			
	Disaster episode j				Disaster episode j			
	WW1	PAN	GRD	WW2	WW1	PAN	GRD	WW2
d_{it}^j	-0.177	-0.137***	-0.146***	-0.049	-0.137	-0.108	-0.135***	-0.129***
	(0.123)	(0.041)	(0.056)	(0.035)	(0.116)	(0.096)	(0.043)	(0.053)
d_{it}^{-j}	-0.056***	-0.029	-0.019	-0.092***	-0.108***	-0.104*	-0.087**	-0.056*
	(0.019)	(0.031)	(0.018)	(0.025)	(0.029)	(0.061)	(0.043)	(0.033)
$(c_{it} - y_{it})$	0.057***	0.010	0.062***	0.050***	0.208***	0.048***	0.239***	0.209***
	(0.016)	(0.006)	(0.024)	(0.015)	(0.056)	(0.010)	(0.070)	(0.073)
$(c_{it} - y_{it})d_{it}^j$	0.717***	0.615***	0.530***	0.487***	0.620***	0.804***	0.432***	0.642***
	(0.210)	(0.090)	(0.129)	(0.057)	(0.196)	(0.198)	(0.157)	(0.139)
$(c_{it} - y_{it})d_{it}^{-j}$	0.242***	0.268***	0.189***	0.319***	0.384***	0.432***	0.306***	0.186**
	(0.076)	(0.080)	(0.067)	(0.087)	(0.068)	(0.146)	(0.083)	(0.085)
Cumby-Huizinga AC	1.751	3.238	1.502	2.596	2.469	3.161	3.323	3.604
	[0.416]	[0.198]	[0.472]	[0.273]	[0.291]	[0.206]	[0.190]	[0.165]
Pesaran CD	9.760	2.888	11.634	12.077				
	[0.000]	[0.004]	[0.000]	[0.000]				

Notes: Reported are the results of the estimation of eq.(12). The dummy variable d^j (with $j = WW1, PAN, GRD, WW2$) equals one during the considered major disaster episode (World War I, Spanish flu pandemic, Great Depression, World War II). We refer to Appendix B for details on the exact dates of these disasters. The dummy d^{-j} takes on the value of one when disasters other than j occur (i.e., it equals $d - d^j$ where d is the general disaster dummy used in previous sections). Estimation is based on panel data for 13 countries (WW1), 5 countries (PAN), 8 countries (GRD) or 15 countries (WW2) over the period $1870 - 2015$. Standard errors are in parentheses, p-values are in square brackets. *,**,*** indicate significance at the 10%, 5% and 1% level respectively. The Cumby-Huizinga test shows the average of the individual countries' Cumby and Huizinga (1992) autocorrelation test, testing the null hypothesis of no autocorrelation against the alternative that the autocorrelations of the error term are nonzero at lags greater than zero (with maximum lag equal to 2). The Pesaran CD statistic tests the null hypothesis of cross-sectional independence (see Pesaran, 2004).

5.6 What about ordinary recessions?

To investigate whether our results hold not only for disasters, but also for ordinary recessions, we estimate our baseline regression, eq.(6), using a recession dummy instead of the disaster dummy considered in the main text. To focus on ordinary recessions, we restrict our sample to the period $1960 - 2015$ with the same $N = 16$ countries considered in the analysis of historical disasters. Over this period, almost no disasters of the type defined by Barro and Ursúa (2008) have occurred, while a large number of recessions have taken place. We calculate an annual recession dummy d^{rec} from the OECD Composite Leading Indicator (CLI) of activity which provides monthly data on recession dates - i.e., turning points - for each country in our sample.[15] The other data used in the estimations are as before, albeit taken over a smaller sample period.

Table 5: Results for ordinary recessions

	MG				CCEMG			
	Dependent variable $x_{i,t+1}$				Dependent variable $x_{i,t+1}$			
	$(\Delta y_{i,t+1} - \Delta c_{i,t+1})$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$	$(\Delta y_{i,t+1} - \Delta c_{i,t+1})$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$
d_{it}^{rec}	-0.006***	-0.015***	-0.008***	0.094***	-0.001	-0.009***	-0.008***	0.016
	(0.001)	(0.001)	(0.001)	(0.026)	(0.001)	(0.001)	(0.002)	(0.026)
$(c_{it} - y_{it})$	0.060***	0.047	-0.013	0.101	0.074***	0.004	-0.091***	-0.006
	(0.018)	(0.045)	(0.048)	(0.314)	(0.019)	(0.025)	(0.023)	(0.251)
$(c_{it} - y_{it})d_{it}^{rec}$	0.042*	0.048*	0.005	-0.283	0.021	0.026	0.001	0.107
	(0.022)	(0.027)	(0.035)	(0.529)	(0.023)	(0.024)	(0.031)	(0.299)
Cumby-Huizinga AC	2.300	7.753	9.313	2.794	2.337	4.125	4.150	2.888
	[0.316]	[0.021]	[0.010]	[0.247]	[0.311]	[0.127]	[0.125]	[0.236]
Pesaran CD	11.715	32.888	24.717	37.145				
	[0.000]	[0.000]	[0.000]	[0.000]				

Notes: Reported are the results of the estimation of eq.(6) with recession dummy d^{rec} instead of disaster dummy d. The recession dummy is constructed from the OECD Composite Leading Indicator (CLI) of activity. Estimation is based on panel data for 16 countries over the period 1960−2015. Standard errors are in parentheses, p-values are in square brackets. $^{*},^{**},^{***}$ indicate significance at the 10%, 5% and 1% level respectively. The Cumby-Huizinga test shows the average of the individual countries' Cumby and Huizinga (1992) autocorrelation test, testing the null hypothesis of no autocorrelation against the alternative that the autocorrelations of the error term are nonzero at lags greater than zero (with maximum lag equal to 2). The Pesaran CD statistic tests the null hypothesis of cross-sectional independence (see Pesaran, 2004).

The results are presented in Table 5. The results of the Pesaran cross-sectional dependence (CD) test suggest that we focus on the CCEMG results. The log consumption-income ratio $c - y$ has, as

[15] We first calculate a monthly recession dummy per country which is set to one for the months after the peak and up to and including the trough. A quarterly recession dummy for that country then equals one if the monthly dummy equals one during at least two months of the quarter under consideration. An annual recession dummy for that country then equals one if the quarterly dummy equals one during at least two quarters of the year under consideration.

is theoretically expected, positive predictive power for the income-consumption growth differential and negative predictive ability for the consumption growth rate over this period. The coefficients on the variable $(c-y)d^{rec}$ are never significantly different from zero, however, suggesting that this predictability is not amplified during recession episodes. Hence, while our previous results show that the consumption-income ratio has more predictive ability for future income and consumption growth rates during disaster episodes, we cannot draw the same conclusion when looking at ordinary recessions. This is not entirely surprising given that Figure 1 shows that the log consumption-income ratios are relatively stable over the period $1960-2015$, even during recessions. When interpreted using the theory of Section 3, the absence of high volatility of and large shifts in the consumption-income ratio observed during this period suggests that, during ordinary recessions, consumers do not give more weight to (potentially volatile) expectations about the future when deciding on the fraction of income to consume.

6 Results from the Covid-19 pandemic

This section investigates the impact of the Covid-19 pandemic, a contemporaneous macroeconomic disaster, on the predictive ability of the log consumption-income ratio. First, we discuss the quarterly dataset used to investigate this. To estimate the effect of the pandemic on next period's income and consumption growth rates, we need data for at least one additional period following the start period of the pandemic. Hence, annual data cannot be used at the moment of writing as we do not yet have data for 2021. Next, we present the baseline results and a number of robustness checks regarding the predictive ability of the log consumption-income ratio for income-consumption growth differentials during the pandemic. We also check whether ordinary recessions that occurred over the sample period have affected the predictive power of the consumption-income ratio. Finally, we investigate to what extent Covid-19 has separately affected the predictive ability of the log consumption-income ratio for income growth, consumption growth and returns on wealth.

6.1 Data

For most of the estimations conducted in Section 6, we use quarterly data over the period $1995Q1-2020Q4$ for twenty economies, i.e., $N=20$. These are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US. The disaster dummy d_{it} that we use in this section, i.e., the Covid-19 dummy, is set to one over the period $2020Q1-2020Q4$ for all countries. This implies that it is identical across countries, i.e., we have $d_{it}=d_t$ $(\forall i)$. For c_{it}, we use the log of per capita real private final consumption expenditures, while for y_{it} we use the log of per capita real GDP. Real private final consumption expenditures and real GDP are taken from OECD Economic Outlook (No.108). We calculate per capita measures using quarterly population data from Datastream. In one robustness check, we use the log of per capita real disposable income instead of the log of per capita real GDP for y_{it}. Nominal disposable income of households and non-profit institutions serving households is taken from OECD Economic Outlook (No.108) and is available for seven countries, i.e., Australia, Canada, France, Germany, Japan, the UK and the US. We calculate per capita real disposable income using the deflator of private final consumption expenditures (also from OECD Economic Outlook) and population data from Datastream. When conducting estimations for returns on wealth r_{it} in Section 6.3 below, we use the real rate of return on equity. Nominal returns are calculated from country equity return indices reported by Global Financial Data. We deflate nominal returns using the inflation rate calculated from the deflator of private final consumption expenditures (from OECD Economic Outlook).

6.2 Predictability results for the variable $\Delta y - \Delta c$

6.2.1 Baseline results and robustness checks

In line with the estimations conducted in Section 5, we estimate the following regression equation,

$$(\Delta y_{i,t+1} - \Delta c_{i,t+1}) = \alpha_i d_t + \beta_i(c_{it} - y_{it}) + \gamma_i(c_{it} - y_{it})d_t + \epsilon_{i,t+1} \tag{13}$$

where d_t denotes the Covid-19 dummy. Based on the theory of Section 3, we expect a positive and significant impact of the variables $(c_{it} - y_{it})$ and $(c_{it} - y_{it})d_t$ on $(\Delta y_{i,t+1} - \Delta c_{i,t+1})$. As before, the error term is given by $\epsilon_{i,t+1} = \mu_i + \lambda_i f_{t+1} + \varepsilon_{i,t+1}$ where μ_i is the country fixed effect and where f_t is a vector of unobserved common factors with corresponding vector of loadings λ_i. With MG estimation (OLS at the country level), we do not control for unobserved common factors so that we implicitly set $\lambda_i = 0$ $(\forall i)$. With CCEMG estimation (CCE at the country level), we proxy the vector of common factors f_t by the cross-sectional averages of the dependent variable and the regressors. Details are provided in Section 4.2 above. In our current setting, the disaster dummy (i.e., the Covid-19 dummy) is common across countries. Hence, when applying the CCEMG estimator we do not include it separately in the regression - i.e., we set $\alpha_i = 0$ $(\forall i)$ - as, in this case, it is controlled for through the component $\lambda_i f_{t+1}$ of the error term $\epsilon_{i,t+1}$.

The baseline estimates are reported in the columns 'Baseline' of Table 6. From both the MG and CCEMG estimates reported in the table, we note that this period's log consumption-income ratio $c-y$ has a positive impact on next period's income-consumption differential $\Delta y - \Delta c$. Moreover, this predictive ability is significantly higher during the Covid-19 pandemic. Hence, our results for the Covid-19 pandemic confirm the results obtained for historical disaster episodes reported in Section 5. Based on the theory of Section 3, this implies that consumers are more forward looking and give significantly more weight to their expectations about the future during the pandemic. This can be interpreted as consumption and saving decisions being more affected by expectations about future consumption and income growth during the pandemic. Alternatively, given the forced nature of saving during the Covid-19 lockdowns, this can also be interpreted as consumption and saving having a larger impact on expectations about future consumption and income growth during the pandemic. The theory of Section 3, based solely on intertemporal budget constraint logic, does not impose causality in this respect.

Table 6: Baseline results and robustness checks

	Dependent variable $x_{i,t+1} = (\Delta y_{i,t+1} - \Delta c_{i,t+1})$							
	MG				CCEMG			
	(1) Baseline	(2) Lag dep. var.	(3) Detrended $c-y$	(4) Disp. income	(1) Baseline	(2) Lag dep. var.	(3) Detrended $c-y$	(4) Disp. income
d_t	0.833***	0.816***	0.038***	0.263***				
	(0.134)	(0.131)	(0.016)	(0.037)				
$(c_{it} - y_{it})$	0.045***	0.041***	0.048***	0.170***	0.052***	0.044***	0.081***	0.230***
	(0.009)	(0.009)	(0.010)	(0.025)	(0.013)	(0.011)	(0.019)	(0.048)
$(c_{it} - y_{it})d_t$	1.245***	1.227***	1.289***	1.301***	1.353***	1.509***	1.380***	2.340
	(0.153)	(0.161)	(0.176)	(0.063)	(0.269)	(0.258)	(0.283)	(2.494)
$(\Delta y_{it} - \Delta c_{it})$		-0.016				-0.122***		
		(0.043)				(0.042)		
Cumby-Huizinga AC	3.962	3.324	3.344	4.195	5.106	3.740	4.464	7.203
	[0.138]	[0.190]	[0.188]	[0.123]	[0.078]	[0.154]	[0.107]	[0.027]
Pesaran CD	14.894	14.532	15.738	11.729				
	[0.000]	[0.000]	[0.000]	[0.000]				

Notes: Reported are the results of the estimation of eq.(13). Data used are reported in Section 6.1. d_t denotes the Covid-19 dummy which equals one over the period $2020Q1 - 2020Q4$. Column (1) presents the baseline results while in column (2) the first lag of the dependent variable is added as a regressor to eq.(13). In column (3) the detrended log consumption-income ratio is used for $c - y$ and in column (4) log per capita real disposable income is used for y instead of log per capita real GDP. Details are provided in the text. Estimation is based on panel data for 20 countries (columns 1, 2 and 3) or 7 countries (column 4) over the period $1995Q1 - 2020Q4$. Standard errors are in parentheses, p-values are in square brackets. *,**,*** indicate significance at the 10%, 5% and 1% level respectively. The Cumby-Huizinga test shows the average of the individual countries' Cumby and Huizinga (1992) autocorrelation test, testing the null hypothesis of no autocorrelation against the alternative that the autocorrelations of the error term are nonzero at lags greater than zero (with maximum lag equal to 2). The Pesaran CD statistic tests the null hypothesis of cross-sectional independence (see Pesaran, 2004).

The baseline results in the table are complemented by a number of robustness checks. First, the results of including the lagged dependent variable as a regressor in eq.(13) are reported in the columns 'Lag dep. var.'. We find that the baseline estimations are confirmed while this inclusion improves the Cumby-Huizinga autocorrelation test when applying CCEMG estimation. Second, given the high persistence of the log consumption-income ratio, we check whether our results remain valid when we detrend the predictor variable $c-y$. In particular, we consider $c-y$ in deviation from its stochastic trend $\overline{c-y}$ where the latter is approximated by a twenty-quarter moving average as $\overline{c-y} = \frac{1}{20}\sum_{j=0}^{19}(c_{-j} - y_{-j})$. The results reported in the columns 'Detrended $c-y$' confirm our baseline results.[16] Finally, the results of using log per capita real disposable income instead of log per capita real GDP as a proxy for y are reported in the columns 'Disp. income'. While the findings obtained with the MG estimator confirm our baseline results, the CCEMG results reported in column 'Disp. income' are not convincing. In the latter case, we find that the coefficient on the regressor of interest $(c-y)d$, while positive, is not significant and we also find that the Cumby-Huizinga test for autocorrelation strongly rejects the null of no autocorrelation. As quarterly data for disposable income are only available for $N = 7$ countries out of the twenty considered when using GDP data, the cross-sectional averages of the dependent variable and the regressors used in the CCEMG estimation may poorly proxy the unobserved common factors in this case. Hence, the results obtained from OLS estimation and summarized by the reported MG estimates are probably more reliable here.

6.2.2 Covid-19 versus ordinary recessions

As before, we ask ourselves whether the increased predictive ability of the log consumption-income ratio during the Covid-19 pandemic is specific to this disaster episode or whether it occurs also during more ordinary recessions that have taken place over the sample period $1995Q1 - 2020Q4$. To investigate this, we estimate predictive regression equations of the following form,

$$(\Delta y_{i,t+1} - \Delta c_{i,t+1}) = \alpha_i d_t + \beta_i(c_{it} - y_{it}) + \gamma_i(c_{it} - y_{it})d_t + \alpha_i^{rec} d_{it}^{rec} + \gamma_i^{rec}(c_{it} - y_{it})d_{it}^{rec} + \epsilon_{i,t+1} \quad (14)$$

with d_t the Covid-19 dummy which is common across counties and with the country-specific recession dummy d_{it}^{rec}. We calculate a quarterly recession dummy from the OECD Composite Leading Indicator (CLI) of activity which provides monthly data on recession dates - i.e., turning points - for each country in our sample.[17] If ordinary recessions also increase the predictive power of $c_{it} - y_{it}$ for $\Delta y_{i,t+1} - \Delta c_{i,t+1}$, we should not only find a significantly positive impact of the regressor $(c_{it} - y_{it})d_t$ but also of the regressor $(c_{it} - y_{it})d_{it}^{rec}$. As detailed in the previous subsection, we do not include the Covid-19 dummy d_t separately in the regression when conducting CCE estimation as, in this case, all common variables are controlled for through the common unobserved factors included in the error term.

The MG and CCEMG estimates are presented in Table 7. We report the results from estimating eq.(14) (columns 'Baseline') and also from estimating eq.(14) with the lagged dependent variable included as an additional regressor (columns 'Lag dep. var.') as the latter results are less affected by

[16]This is also the case if we proxy the stochastic trend using a moving average calculated over 10 or 40 quarters.
[17]See footnote 15 above for details.

autocorrelation in the residuals. In line with the findings for annual data reported and discussed in Section 5.6 above, there is no evidence to suggest that ordinary recessions have an impact on the predictive ability of the consumption-income ratio, i.e., the coefficient on the regressor $(c_{it} - y_{it})d_{it}^{rec}$ is not significantly different from zero in all estimated regressions. Hence, we conclude that it is only during very severe crises that consumers become more forward-looking.

Table 7: Results for the Covid-19 pandemic and ordinary recessions

	Dependent variable $x_{i,t+1} = (\Delta y_{i,t+1} - \Delta c_{i,t+1})$			
	MG		CCEMG	
	(1) Baseline	(2) Lag dep. var.	(1) Baseline	(2) Lag dep. var.
d_t	0.828***	0.775***		
	(0.134)	(0.130)		
$(c_{it} - y_{it})$	0.046***	0.040***	0.053***	0.044***
	(0.010)	(0.010)	(0.013)	(0.013)
$(c_{it} - y_{it})d_t$	1.235***	1.160***	1.262***	1.475***
	(0.154)	(0.161)	(0.247)	(0.261)
d_{it}^{rec}	0.003	0.004	0.011	0.009
	(0.008)	(0.007)	(0.008)	(0.007)
$(c_{it} - y_{it})d_{it}^{rec}$	0.009	0.011	0.020	0.015
	(0.015)	(0.013)	(0.014)	(0.013)
$(\Delta y_{it} - \Delta c_{it})$		-0.064*		-0.177***
		(0.037)		(0.039)
Cumby-Huizinga AC	4.149	3.274	6.134	3.924
	[0.125]	[0.194]	[0.046]	[0.141]
Pesaran CD	12.403	13.017		
	[0.000]	[0.000]		

Notes: Reported are the results of the estimation of eq.(14). Data used are reported in Section 6.1. Estimation is based on panel data for 20 countries over the period $1995Q1 - 2020Q4$. d_t denotes the Covid-19 dummy which equals one over the period $2020Q1 - 2020Q4$. d_{it}^{rec} denotes the recession dummy which is constructed from the OECD Composite Leading Indicator (CLI) of activity. Standard errors are in parentheses, p-values are in square brackets. *,**,*** indicate significance at the 10%, 5% and 1% level respectively. The Cumby-Huizinga test shows the average of the individual countries' Cumby and Huizinga (1992) autocorrelation test, testing the null hypothesis of no autocorrelation against the alternative that the autocorrelations of the error term are nonzero at lags greater than zero (with maximum lag equal to 2). The Pesaran CD statistic tests the null hypothesis of cross-sectional independence (see Pesaran, 2004).

6.3 Predictability results for the variables Δy, Δc and r

The previous subsections look at the predictive ability of the log consumption-income ratio before and during the Covid-19 disaster based on the simplified budget constraint of eq.(5). Given the general budget constraint of eq.(4), this implicitly assumes that the log consumption-income ratio has no predictive power for returns on wealth. In this section, we therefore check the implications of eq.(4), i.e., whether or not the log consumption-income ratio $c-y$ has a separate predictive impact for income growth Δy, consumption growth Δc and returns on wealth r over the period $1995Q1-2020Q4$. To this end, we estimate eq.(8) where $d_{it}=d_t$ $(\forall i)$ with d_t the Covid-19 dummy used in the previous subsections. As before, we do not separately include d_t in the regression when applying CCE estimation as, in this case, all common variables are controlled for through the common unobserved factors included in the error term. Given the inclusion of the control variables $w_{i,t+1}$ which can be contemporaneously correlated with the error term, we use IV estimation at the country level as detailed in Section 4.2 above. As instruments, we use lagged values of the dependent variable and the regressors.[18]

The results are reported in Table 8. Based on the results of the Pesaran cross-sectional dependence (CD) test, which rejects the null hypothesis of cross-sectional independence when applying MG estimation, we focus mainly on the CCEMG estimation results which are reported in the final three columns of the table. As expected, we find that the current log consumption-income ratio has a significant positive impact on next quarter's income growth rate and a significant negative impact on next quarter's consumption growth rate. Moreover, this predictability is significantly higher during the Covid-19 pandemic. We do not find a significant predictive impact of $c-y$ for real equity returns however, neither before nor during the Covid-19 pandemic. These results, which are similar to those obtained with historical data in Section 5.3, justify our focus in the previous subsections on the predictive ability of $c-y$ for $\Delta y-\Delta c$, i.e., on the simplified budget constraint of eq.(5).

[18] More specifically, the MG (IV) estimation uses an instrument set that consists of a constant, the variables d_{t-1}, $(c_{i,t-1}-y_{i,t-1})$ and $(c_{i,t-1}-y_{i,t-1})d_{t-1}$ and lags 2 to 4 of the variables $\Delta y_{i,t+1}$, $\Delta c_{i,t+1}$ and $r_{i,t+1}$ (i.e., the periods $t-1$, $t-2$ and $t-3$). The instrument set used for CCEMG (IV) additionally includes the cross-sectional averages of the dependent variable and of all included regressors. Note that instruments used are lagged at least twice (i.e., starting from $t-1$) as for estimations that use instruments lagged only once (i.e.., starting from t), the Sargan-Hansen overidentifying restrictions statistics tend to reject the validity of the instruments.

Table 8: Predictive results for Δy, Δc and r

	MG (IV)			CCEMG (IV)		
	Dependent variable $x_{i,t+1}$			Dependent variable $x_{i,t+1}$		
	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$
d_t	0.482*	-1.042***	-0.813			
	(0.255)	(0.282)	(3.146)			
$(c_{it} - y_{it})$	0.027*	-0.035***	0.322***	0.022**	-0.047***	0.042
	(0.014)	(0.013)	(0.117)	(0.011)	(0.013)	(0.064)
$(c_{it} - y_{it})d_t$	0.814*	-1.518***	-1.147	0.543*	-0.723**	-0.245
	(0.450)	(0.519)	(5.778)	(0.301)	(0.325)	(2.650)
$\Delta y_{i,t+1}$		0.787***	0.938		0.795***	0.533
		(0.069)	(0.919)		(0.102)	(0.810)
$\Delta c_{i,t+1}$	0.717***		0.608	0.400***		0.749
	(0.057)		(0.853)	(0.079)		(0.492)
$r_{i,t+1}$	0.025	0.015		0.011	0.012	
	(0.016)	(0.012)		(0.011)	(0.013)	
Cumby-Huizinga AC	2.436	2.373	3.342	2.814	3.678	2.221
	[0.296]	[0.305]	[0.188]	[0.245]	[0.159]	[0.329]
Sargan-Hansen OR	7.460	7.964	5.643	7.825	11.000	8.165
	[0.382]	[0.336]	[0.582]	[0.451]	[0.202]	[0.417]
Pesaran CD	9.472	18.772	57.387			
	[0.000]	[0.000]	[0.000]			

Notes: Reported are the results of the estimation of eq.(8) where $d_{it} = d_t$ $(\forall i)$ with d_t the Covid-19 dummy and where the vector of controls is $w_{i,t+1} = \left[\begin{array}{cc} \Delta c_{i,t+1} & r_{i,t+1} \end{array} \right]$ when $x_{i,t+1} = \Delta y_{i,t+1}$, $w_{i,t+1} = \left[\begin{array}{cc} \Delta y_{i,t+1} & r_{i,t+1} \end{array} \right]$ when $x_{i,t+1} = \Delta c_{i,t+1}$ and $w_{i,t+1} = \left[\begin{array}{cc} \Delta y_{i,t+1} & \Delta c_{i,t+1} \end{array} \right]$ when $x_{i,t+1} = r_{i,t+1}$. Estimation is based on panel data for 20 countries over the period $1995Q1 - 2020Q4$. The Covid-19 dummy d_t equals one over the period $2020Q1 - 2020Q4$. Standard errors are in parentheses, p-values are in square brackets. *,**,*** indicate significance at the 10%, 5% and 1% level respectively. The Cumby-Huizinga test shows the average of the individual countries' Cumby and Huizinga (1992) autocorrelation test, testing the null hypothesis of no autocorrelation against the alternative that the autocorrelations of the error term are nonzero at lags greater than zero (with maximum lag equal to 2). The Pesaran CD statistic tests the null hypothesis of cross-sectional independence (see Pesaran, 2004). The Sargan-Hansen OR test reported is the average of the country-specific Sargan-Hansen overidentifying restrictions statistics that test the joint validity of the instruments used (see Sargan, 1958; Hansen, 1982). MG (IV) estimation uses an instrument set that consists of a constant, the variables d_{t-1}, $(c_{i,t-1} - y_{i,t-1})$ and $(c_{i,t-1} - y_{i,t-1})d_{t-1}$ and lags 2 to 4 of the variables $\Delta y_{i,t+1}$, $\Delta c_{i,t+1}$ and $r_{i,t+1}$ (i.e., the periods $t-1$, $t-2$ and $t-3$). The instrument set used for CCEMG (IV) additionally includes the cross-sectional averages of the dependent variable and of all included regressors.

7 Conclusions

This paper investigates the multiple, often drastic, shifts and increased volatility that can be observed in the aggregate consumption to income ratio during macroeconomic disaster episodes, i.e., historical wars, depressions and pandemics as well as the current Covid-19 pandemic. As standard intertemporal budget constraint logic implies that this ratio is linked to expectations about future income and consumption growth rates, we investigate whether these expectations about the future suffice to explain the shifts in the consumption-income ratio that occur during disaster periods or whether, on the other hand, consumers become more forward-looking and therefore give more weight to these expectations during disaster times. Our theoretical framework implies that the current consumption-income ratio has predictive power for future income and consumption growth rates and that this power is higher during disaster episodes. Using both a historical annual dataset ($1870 - 2015$) and a recent quarterly dataset ($1995Q1 - 2020Q4$) for industrial economies, we evaluate the predictive power of the log consumption-income ratio both during normal times and during disaster episodes through the estimation of panel predictive regressions.

Our results confirm that the predictive ability of the log consumption-income ratio for future income and consumption growth rates is significantly higher during macroeconomic disasters. Interpreted through the lens of the model, these results imply that consumers are more forward-looking during disaster times and, consequently, give more weight to their expectations about future income and consumption growth rates during these periods. Our findings are not limited to one particular disaster type but are found for every major crisis type that we consider, including the current Covid-19 pandemic. While our results hold for macroeconomic disasters, we do not find similar evidence for the conventional recessions that have occurred over the sample periods that we consider in our estimations. To conclude, we note that our findings have some potentially important policy implications, i.e., during severe crises, the announcement and implementation of policy, be it fiscal or monetary, may have a larger impact on forward-looking consumers and may therefore be more effective.

References

Adema, Y. and Pozzi, L. (2015). Business cycle fluctuations and household saving in OECD countries: a panel data analysis. *European Economic Review*, 79:214–233.

Aizenman, J. and Noy, I. (2015). Saving and the long shadow of macroeconomic shocks. *Journal of Macroeconomics*, 46:147–159.

Alan, S., Crossley, T., and Low, H. (2012). Saving on a rainy day, borrowing for a rainy day. *IFS Working Paper*, W12/11.

Attanasio, O., Picci, L., and Scorcu, A. (2000). Saving, growth and investment: a macroeconomic analysis using a panel of countries. *Review of Economics and Statistics*, 82(2):182–211.

Barro, R. and Ursúa, J. (2008). Macroeconomic crises since 1870. *Brookings Papers on Economic Activity*, 38(1):255–335.

Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. *Quarterly Journal of Economics*, 121(3):823–866.

Barro, R. J. (2009). Rare disasters, asset prices and welfare costs. *American Economic Review*, 99:243–264.

Barro, R. J. and Ursúa, J. F. (2012). Rare macroeconomic disasters. *Annual Review of Economics*, 4:83–109.

Blanchard, O. J. (2020). The Covid economic crisis. *Additional chapter for 'Macroeconomics', 8th edition.*

Campbell, J. (1987). Does saving anticipate declining labor income? An alternative test of the permanent income hypothesis. *Econometrica*, 55(6):1249–1273.

Campbell, J. and Mankiw, N. (1989). Consumption, income, and interest rates: reinterpreting the time series evidence. *NBER Macroeconomics Annual*, 4:185–216.

Carroll, C. D. (1992). The buffer-stock theory of saving: some macroeconomic evidence. *Brookings Papers on Economic Activity*, 1992(2):61–156.

Carroll, C. D., Slacalek, J., and Sommer, M. (2019). Dissecting saving dynamics: measuring wealth, precautionary, and credit effects. *NBER Working Paper 26131.*

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). The cost of the Covid-19 crisis: lockdowns, macroeconomic expectations, and consumer spending. *CESifo Working Paper series*, 8292.

Cumby, R. E. and Huizinga, J. (1992). Testing the autocorrelation structure of disturbances in ordinary least squares and instrumental variables regressions. *Econometrica*, 60(1):185–195.

Dossche, M. and Zlatanos, S. (2020). Covid-19 and the increase in household savings: precautionary or forced? *ECB Economic Bulletin*, 6/2020.

Everaert, G. and Pozzi, L. (2014). The predictability of aggregate consumption growth in OECD countries: a panel data analysis. *Journal of Applied Econometrics*, 29(3):431–453.

Farhi, E. and Gabaix, X. (2016). Rare disasters and exchange rates. *Quarterly Journal of Economics*, 131(1):1–52.

Gillman, M., Kejak, M., and Pakoš, M. (2015). Learning about rare disasters: implications for consumption and asset prices. *Review of Finance*, 19:1053–1104.

Hamilton, J. (2008). Macroeconomics and ARCH. *NBER Working Papers*, 14151.

Hansen, L. (1982). Large sample properties of generalized method of moment estimators. *Econometrica*, 50:1029–1054.

Jordà, Ò., Knoll, K., Kuvshinov, D., Schularick, M., and Taylor, A. (2019). The rate of return on everything, 1870-2015. *Quarterly Journal of Economics*, 134(3):1225–1298.

Jordà, Ò., Schularick, M., and Taylor, A. (2016). Macrofinancial history and the new business cycle facts. In Eichenbaum, M. and Parker, J., editors, *NBER Macroeconomics Annual 2016*, volume 31. University of Chicago Press, Chicago.

Jordà, Ò., Singh, S., and Taylor, A. (2020). Longer-run economic consequences of pandemics. *NBER Working Papers*, 26934.

Lettau, M. and Ludvigson, S. (2005). Expected returns and expected dividend growth. *Journal of Financial Economics*, 76(3):583–626.

Mody, A., Ohnsorge, F., and Sandri, D. (2012). Precautionary savings in the Great Recession. *IMF Economic Review*, 60(1):114–138.

Nakamura, E., Sergeyev, D., and Steinsson, J. (2017). Growth-rate and uncertainty shocks in consumption: cross-country evidence. *American Economic Journal: Macroeconomics*, 9(1):1–39.

Nakamura, E., Steinsson, J., Barro, R., and Ursúa, J. (2013). Crises and recoveries in an empirical model of consumption disasters. *American Economic Journal: Macroeconomics*, 5(3):35–74.

Parker, J. and Preston, B. (2005). Precautionary savings and consumption fluctuations. *American Economic Review*, 95(4):1119–1143.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. *IZA Discussion Paper*, no. 1240.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4):967–1012.

Pesaran, M. H. and Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1):79–113.

Pesaran, M. H., Smith, R., and Im, K.-S. (1996). Dynamic linear models for heterogeneous panels. In Matyas, L. and Sevestre, P., editors, *The Econometrics of Panel Data*, pages 145–195. Kluwer Academic Publishers, Dordrecht, second edition.

Piketty, T. and Zucman, G. (2014). Capital is back: wealth-income ratios in rich countries 1700-2010. *Quarterly Journal of Economics*, 129(3):1255–1310.

Rietz, T. A. (1988). The equity risk premium a solution. *Journal of Monetary Economics*, 22(1):117–131.

Sargan, J. (1958). The estimation of economic relationships using instrumental variables. *Econometrica*, 26:393–415.

Sarno, L. and Schmeling, M. (2014). Which fundamentals drive exchange rates? A cross-sectional perspective. *Journal of Money, Credit and Banking*, 46(2-3):267–292.

Sommer, M. (2007). Habit formation and aggregate consumption dynamics. *The B.E. Journal of Macroeconomics - Advances*, 7(1).

Tsay, R. (2005). *Analysis of Financial Time Series*. Wiley.

Vandenbroucke, G. (2021). Personal saving during the Covid-19 recession. *Federal Reserve Bank of St. Louis Economic Synopses*, No. 2, https://doi.org/10.20955/es.2021.2.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4):817–838.

Appendices

Appendix A Derivation of eq.(1)

This appendix describes the steps in the derivation of eq.(1) in the main text. Our framework extends the setting considered by Campbell and Mankiw (1989) and Lettau and Ludvigson (2005) by allowing for time-varying discount factors that are different in normal times versus disaster times. When total wealth is tradeable, the period-by-period budget constraint of a consumer can be written as,

$$W_{t+1} = R_{t+1}(W_t - C_t) \tag{A-1}$$

where W_t is real total wealth, C_t is real consumption and R_t is the gross real return on total wealth. Dividing both sides by W_t, we can write $\frac{W_{t+1}}{W_t} = R_{t+1}\left(1 - \frac{C_t}{W_t}\right)$. After taking logs, this gives

$$\Delta w_{t+1} = r_{t+1} + \ln\left(1 - \exp(c_t - w_t)\right) \tag{A-2}$$

with $w_t = \ln W_t$, $r_t = \ln R_t$ and $c_t = \ln C_t$.

We linearize the term $\ln(1 - \exp(c_t - w_t))$ by taking a first-order Taylor approximation which gives,

$$\ln\left(1 - \exp(c_t - w_t)\right) \approx -\frac{C}{W - C}(c_t - w_t) \tag{A-3}$$

where we ignore the linearization constant and where W and C are the average or steady state values of W_t and C_t.[1]

We assume that during macroeconomic disaster episodes, which are typically characterized by large falls in consumption, the average consumption to wealth ratio is lower than in normal times. As such, we have $\frac{C_0}{W_0} > \frac{C_1}{W_1}$ where the subscript '0' refers to normal times and the subscript '1' refers to disaster episodes. Upon defining d_t as a (stochastic) binary variable that equals zero during normal times and one during disaster episodes, we can then rewrite eq.(A-3) as

$$\ln\left(1 - \exp(c_t - w_t)\right) \approx -\left((1 - d_t)\frac{C_0}{W_0 - C_0} + d_t\frac{C_1}{W_1 - C_1}\right)(c_t - w_t) \tag{A-4}$$

where we note that $\frac{C_0}{W_0 - C_0} > \frac{C_1}{W_1 - C_1}$. Defining the discount factor in normal times as $\rho_0 \equiv 1 - \frac{C_0}{W_0}$ and during disaster times as $\rho_1 \equiv 1 - \frac{C_1}{W_1}$, we rewrite eq.(A-4) as,

$$\ln\left(1 - \exp(c_t - w_t)\right) \approx \left((1 - d_t)(1 - \frac{1}{\rho_0}) + d_t(1 - \frac{1}{\rho_1})\right)(c_t - w_t) \tag{A-5}$$

$$= \left(1 - \frac{1}{\rho_t}\right)(c_t - w_t) \tag{A-6}$$

where, on the second line, ρ_t is given by $\rho_t = (1 - d_t)\rho_0 + d_t\rho_1$.

[1] Note that the linearization occurs around the point $c_t - w_t = c - w$ with $c - w = \ln\left(\frac{C}{W}\right)$.

Substituting eq.(A-6) into eq.(A-2), we obtain $\Delta w_{t+1} = r_{t+1} + \left(1 - \frac{1}{\rho_t}\right)(c_t - w_t)$. Note that we can write Δw_{t+1} as $\Delta w_{t+1} = \Delta c_{t+1} + (c_t - w_t) - (c_{t+1} - w_{t+1})$. Upon combining these results and rearranging terms, we obtain,

$$c_t - w_t = \rho_t(r_{t+1} - \Delta c_{t+1}) + \rho_t(c_{t+1} - w_{t+1}) \tag{A-7}$$

Solving eq.(A-7) forward ad infinitum, imposing the transversality condition $(\prod_{k=1}^{\infty} \rho_{t+k-1})(c_{t+\infty} - w_{t+\infty}) = 0$ and taking expectations at period t then gives,

$$c_t - w_t = E_t \sum_{j=1}^{\infty} \left[\left(\prod_{k=1}^{j} \rho_{t+k-1} \right) (r_{t+j} - \Delta c_{t+j}) \right] \tag{A-8}$$

with E_t is the expectations operator conditional on period t information.

Since log total wealth w_t is unobserved over the time frame and for the countries considered in this paper, we cannot empirically implement eq.(A-8). Instead, we derive an income-based budget constraint by assuming total wealth W_t consists of N_t shares with ex-dividend price given by P_t and where Y_t is real income (i.e., the real dividend) obtained from total wealth. As such, we have $W_t = N_t(P_t + Y_t)$ where $P_t + Y_t$ is the cum-dividend price of a share. The gross real return on total wealth is given by $R_{t+1} = \frac{P_{t+1}+Y_{t+1}}{P_t}$. By combining these results and rearranging terms, we obtain,

$$W^*_{t+1} = R_{t+1}(W^*_t - Y_t) \tag{A-9}$$

with $W^*_t \equiv \frac{W_t}{N_t}$. Eq.(A-9) is in the same form as eq.(A-1) so the same steps (linearization, defining the discount factor, forward solving) can be applied to obtain,

$$y_t - w^*_t = E_t \sum_{j=1}^{\infty} \left[\left(\prod_{k=1}^{j} \kappa_{t+k-1} \right) (r_{t+j} - \Delta y_{t+j}) \right] \tag{A-10}$$

where $w^*_t = \ln W^*_t$ and $y_t = \ln Y_t$. The discount factor κ_t is given by $\kappa_t = (1 - d_t)\kappa_0 + d_t\kappa_1$ where $\kappa_0 \equiv 1 - \frac{Y_0}{W^*_0}$ and $\kappa_1 \equiv 1 - \frac{Y_1}{W^*_1}$ with W^*_0 and Y_0 the average values of W^*_t and Y_t in normal times and with W^*_1 and Y_1 the average values of W^*_t and Y_t during disaster episodes. We assume that during macroeconomic disaster episodes, which are typically characterized by large falls in income, we have $\frac{Y_0}{W^*_0} > \frac{Y_1}{W^*_1}$, so that $\kappa_0 < \kappa_1$. We then combine eqs.(A-8) and (A-10) where, after imposing the normalization $N_t = 1$ or $\ln N_t = 0$, we obtain eq.(1) in the main text.

Appendix B Historical disaster episodes and dummies

Table B-1 presents the disaster periods used in the construction of the disaster dummies. The periods are obtained by combining the consumption and GDP disasters reported in Tables 6 and 8 in Barro and Ursúa (2008).

Table B-1: Disaster periods used in the construction of disaster dummies

	Episodes				
	All	WW1	PAN	GRD	WW2
Australia	1889-95	1910-18		1926-32	1938-46
	1910-18				
	1926-32				
	1938-46				
Belgium	1913-18	1913-18		1930-34	1937-43
	1930-34				
	1937-43				
Denmark	1914-21	1914-18	1919-21		1939-41
	1939-41				1946-48
	1946-48				
Finland	1876-81	1913-18		1928-32	1938-44
	1913-15				
	1913-18				
	1928-32				
	1938-44				
	1989-93				
France	1870-71	1912-18		1929-35	1938-44
	1874-79				
	1882-86				
	1912-18				
	1929-35				
	1938-44				
Germany	1912-19	1912-19		1928-32	1939-46
	1922-23				
	1928-32				
	1939-46				
Italy	1918-20		1918-20		1939-45
	1939-45				
Japan	1937-45				1937-45
Netherlands	1889-93	1913-18		1929-34	1939-44
	1912-18				
	1929-34				
	1939-44				
Norway	1916-21	1916-18	1919-21		1939-44
	1939-44				
Portugal	1913-19	1913-19			1939-42
	1927-28				
	1934-36				
	1939-42				
	1974-76				
Spain	1892-96	1913-15		1929-33	1940-49
	1913-15				
	1929-33				
	1935-38				
	1940-49				
Sweden	1913-18	1913-18			1939-45
	1920-21				
	1939-45				
Switzerland	1870-72	1912-18			1939-45
	1875-79				
	1881-83				
	1885-88				
	1912-18				
	1939-45				
UK	1915-21	1915-18	1918-21		1938-47
	1938-47				
US	1906-08		1917-21	1929-33	1944-47
	1913-14				
	1917-21				
	1929-33				
	1944-47				

Notes: The periods in the table correspond to periods reported by Barro and Ursúa (2008) as either GDP disaster episodes, consumption disaster episodes or both. The grouping of episodes according to principal world economic crises in columns 'WW1' (World War I), 'PAN' (Spanish flu pandemic), 'GRD' (Great Depression) and 'WW2' (World War II) follows the grouping reported by Barro and Ursúa (2008).

The grouping of consumption and GDP disasters according to principal world economic crises (World War I, Spanish flu pandemic, Great Depression, World War II) is based on Tables 7 and 9 in Barro and

Ursúa (2008).[2,3,4]

The episodes in column 'All' are used to construct the general dummy d_t which is equal to one over the reported periods in the column. The episodes in columns 'WW1' (World War I), 'PAN' (Spanish Flu pandemic), 'GRD' (Great Depression) and 'WW2' (World War II) are used to construct the episode-specific dummies d_t^j with $j = WW1, PAN, GRD, WW2$ which are equal to one over the reported periods in the respective columns. The episode-specific dummies are used in the estimations reported in Section 5.5.

Appendix C Per country baseline estimates using historical data

The following table reports the per country OLS and CCE estimates of the coefficients β_i and γ_i obtained from estimating the baseline specification eq.(6). These estimates are used in the calculation of the MG and CCEMG estimates reported in Table 1 in the text. Also reported, between brackets, are heteroskedasticity-consistent standard errors (see White, 1980).

[2] To illustrate, the UK experienced a consumption disaster over the period $1915-18$ attributed to World War I and a GDP disaster over the period $1918-21$ attributed to the Spanish flu pandemic. Hence, the overall disaster period is $1915-21$ and the general dummy d_t for the UK takes on the value of one during this period. Additionally, the episode-specific dummies d_t^{WW1} and d_t^{PAN} take on the value of one during the periods $1915-18$, respectively $1918-21$.

[3] We slightly deviate from the grouping considered in Barro and Ursúa (2008) by allocating a number of their post-World War II disaster episodes, occurring in the immediate aftermath of World War II, to our World War II category. This is the case for Denmark (the $1946-48$ consumption disaster), Spain (the $1946-49$ consumption disaster, UK (the $1943-47$ output disaster) and US (the $1944-47$ output disaster). This minor change has a minimal impact on the estimates and no impact on the conclusions of the paper.

[4] The Spanish flu pandemic is based on the $1920s$ grouping of Barro and Ursúa (2008) where we include an episode if the first year of the GDP or consumption disaster is either 1918 or 1919. Some episodes from Barro and Ursúa (2008)'s $1920s$ grouping are therefore not included in our Spanish flu pandemic group. Examples are Germany $(1922-23)$ and Portugal (late twenties).

Table C-1: Per country estimates of β_i and γ_i in the baseline specification eq.(6)

		OLS				CCE			
		Dependent variable				Dependent variable			
Country	Regressor	$(\Delta y_{i,t+1} - \Delta c_{i,t+1})$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$	$(\Delta y_{i,t+1} - \Delta c_{i,t+1})$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$
Australia	$(c_{it} - y_{it})$	0.017	0.002	-0.015	0.117	0.372	0.064	-0.327	0.019
		(0.016)	(0.023)	(0.025)	(0.076)	(0.075)	(0.087)	(0.118)	(0.247)
	$(c_{it} - y_{it})d_{it}$	0.054	-0.054	-0.109	-0.139	0.094	-0.068	-0.202	-0.111
		(0.082)	(0.056)	(0.078)	(0.097)	(0.087)	(0.089)	(0.115)	(0.245)
Belgium	$(c_{it} - y_{it})$	0.209	0.281	0.071	-0.033	0.916	0.563	-0.336	0.361
		(0.136)	(0.107)	(0.061)	(0.169)	(0.311)	(0.177)	(0.269)	(0.399)
	$(c_{it} - y_{it})d_{it}$	-0.049	-0.091	-0.042	0.906	-0.070	-0.070	0.268	1.265
		(0.212)	(0.217)	(0.202)	(0.746)	(0.227)	(0.234)	(0.327)	(0.856)
Denmark	$(c_{it} - y_{it})$	0.005	0.024	0.019	-0.118	0.110	0.013	-0.158	-0.312
		(0.012)	(0.012)	(0.018)	(0.091)	(0.030)	(0.033)	(0.040)	(0.125)
	$(c_{it} - y_{it})d_{it}$	0.372	0.230	-0.142	-0.497	0.469	0.215	-0.304	-0.031
		(0.171)	(0.122)	(0.247)	(0.225)	(0.133)	(0.144)	(0.131)	(0.286)
Finland	$(c_{it} - y_{it})$	0.055	-0.033	-0.089	-0.301	0.134	-0.038	-0.170	-0.229
		(0.025)	(0.033)	(0.034)	(0.299)	(0.045)	(0.051)	(0.065)	(0.335)
	$(c_{it} - y_{it})d_{it}$	0.002	-0.082	-0.085	-0.212	0.006	-0.199	-0.239	-0.443
		(0.144)	(0.116)	(0.148)	(0.491)	(0.114)	(0.089)	(0.137)	(0.697)
France	$(c_{it} - y_{it})$	0.042	0.004	-0.038	-0.008	0.278	0.124	-0.068	0.443
		(0.022)	(0.025)	(0.024)	(0.099)	(0.078)	(0.117)	(0.122)	(0.286)
	$(c_{it} - y_{it})d_{it}$	0.175	0.152	-0.024	0.530	0.362	0.281	-0.221	-0.065
		(0.210)	(0.115)	(0.134)	(0.169)	(0.158)	(0.159)	(0.129)	(0.235)
Germany	$(c_{it} - y_{it})$	0.063	-0.022	-0.085	0.010	0.105	0.012	-0.149	-0.554
		(0.054)	(0.052)	(0.049)	(0.338)	(0.083)	(0.068)	(0.064)	(0.409)
	$(c_{it} - y_{it})d_{it}$	0.129	0.311	0.181	-0.094	0.072	0.103	0.208	0.902
		(0.236)	(0.266)	(0.064)	(0.360)	(0.148)	(0.181)	(0.117)	(0.474)
Italy	$(c_{it} - y_{it})$	0.012	-0.045	-0.057	-0.028	0.112	0.055	-0.062	-0.369
		(0.015)	(0.016)	(0.017)	(0.110)	(0.041)	(0.040)	(0.033)	(0.229)
	$(c_{it} - y_{it})d_{it}$	0.287	0.600	0.314	0.477	0.639	0.710	0.131	1.859
		(0.197)	(0.262)	(0.212)	(1.450)	(0.188)	(0.267)	(0.212)	(1.939)
Japan	$(c_{it} - y_{it})$	0.029	-0.043	-0.072	0.046	0.334	0.101	-0.290	-0.210
		(0.020)	(0.020)	(0.015)	(0.131)	(0.084)	(0.070)	(0.062)	(0.435)
	$(c_{it} - y_{it})d_{it}$	0.555	0.536	-0.018	0.410	0.757	0.560	-0.103	0.895
		(0.385)	(0.098)	(0.324)	(0.252)	(0.299)	(0.143)	(0.208)	(0.530)

Notes: Reported estimates are for β_i and γ_i in equation (6). Heteroskedasticity-robust White standard errors are in parentheses. The OLS estimates reported are used to calculate the MG estimates reported in Table 1 while the CCE estimates reported are used to calculate the CCEMG estimates reported in Table 1.

Table C-1 (continued)

Country	Regressor	OLS				CCE			
		Dependent variable				Dependent variable			
		$(\Delta y_{i,t+1} - \Delta c_{i,t+1})$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$	$(\Delta y_{i,t+1} - \Delta c_{i,t+1})$	$\Delta y_{i,t+1}$	$\Delta c_{i,t+1}$	$r_{i,t+1}$
Netherlands	$(c_{it} - y_{it})$	0.099	0.192	0.093	-0.328	0.201	0.169	-0.074	-0.076
		(0.086)	(0.168)	(0.088)	(0.200)	(0.110)	(0.122)	(0.095)	(0.199)
	$(c_{it} - y_{it})d_{it}$	0.463	0.124	-0.340	0.129	0.555	0.337	-0.172	-0.081
		(0.291)	(0.287)	(0.287)	(0.244)	(0.303)	(0.258)	(0.437)	(0.284)
Norway	$(c_{it} - y_{it})$	0.005	-0.015	-0.020	-0.085	0.022	-0.034	-0.072	-0.281
		(0.007)	(0.007)	(0.009)	(0.081)	(0.030)	(0.031)	(0.041)	(0.218)
	$(c_{it} - y_{it})d_{it}$	0.199	0.156	-0.042	-1.053	0.373	0.363	-0.339	-0.105
		(0.096)	(0.235)	(0.247)	(0.344)	(0.077)	(0.177)	(0.162)	(0.463)
Portugal	$(c_{it} - y_{it})$	0.083	-0.180	-0.263	-0.047	0.078	-0.120	-0.236	-0.282
		(0.045)	(0.060)	(0.043)	(0.553)	(0.045)	(0.048)	(0.043)	(0.445)
	$(c_{it} - y_{it})d_{it}$	-0.086	0.158	0.243	2.307	-0.096	0.137	0.269	1.778
		(0.087)	(0.209)	(0.167)	(0.700)	(0.092)	(0.199)	(0.166)	(0.622)
Spain	$(c_{it} - y_{it})$	0.023	-0.005	-0.028	-0.055	0.165	0.045	-0.109	-0.032
		(0.016)	(0.035)	(0.041)	(0.198)	(0.045)	(0.062)	(0.093)	(0.248)
	$(c_{it} - y_{it})d_{it}$	0.377	-0.208	-0.586	0.149	0.278	-0.155	-0.408	-0.116
		(0.147)	(0.157)	(0.285)	(0.328)	(0.133)	(0.137)	(0.252)	(0.399)
Sweden	$(c_{it} - y_{it})$	0.005	0.021	0.016	-0.179	0.067	-0.003	-0.078	-0.033
		(0.012)	(0.015)	(0.014)	(0.122)	(0.025)	(0.034)	(0.038)	(0.128)
	$(c_{it} - y_{it})d_{it}$	0.205	-0.129	-0.334	0.197	0.154	-0.055	-0.126	-0.269
		(0.133)	(0.295)	(0.323)	(0.413)	(0.162)	(0.202)	(0.182)	(0.312)
Switzerland	$(c_{it} - y_{it})$	0.107	0.085	-0.022	0.176	0.413	0.055	-0.312	0.230
		(0.053)	(0.048)	(0.058)	(0.317)	(0.116)	(0.084)	(0.096)	(0.359)
	$(c_{it} - y_{it})d_{it}$	0.851	-0.189	-1.040	0.025	0.551	-0.157	-0.631	-0.761
		(0.170)	(0.163)	(0.226)	(0.782)	(0.198)	(0.139)	(0.191)	(0.710)
UK	$(c_{it} - y_{it})$	0.033	-0.043	-0.076	-0.141	0.066	0.045	0.031	-0.246
		(0.019)	(0.023)	(0.021)	(0.232)	(0.034)	(0.039)	(0.034)	(0.322)
	$(c_{it} - y_{it})d_{it}$	0.171	0.123	-0.048	0.001	0.299	0.163	-0.235	0.239
		(0.129)	(0.072)	(0.079)	(0.410)	(0.225)	(0.189)	(0.074)	(0.656)
US	$(c_{it} - y_{it})$	-0.006	-0.010	-0.004	-0.049	0.080	0.135	-0.001	-0.140
		(0.017)	(0.021)	(0.017)	(0.079)	(0.031)	(0.042)	(0.040)	(0.167)
	$(c_{it} - y_{it})d_{it}$	0.228	0.105	-0.123	0.200	0.188	0.180	-0.059	0.252
		(0.097)	(0.077)	(0.052)	(0.344)	(0.105)	(0.108)	(0.054)	(0.337)

Notes: Reported estimates are for β_i and γ_i in equation (6). Heteroskedasticity-robust White standard errors are in parentheses. The OLS estimates reported are used to calculate the MG estimates reported in Table 1 while the CCE estimates reported are used to calculate the CCEMG estimates reported in Table 1.