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Precautionary Savings in Times of Crisis

Author

Sophie Catherine Achleitner

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Student ID: 546051
Supervisor: Dr. Lorenzo Pozzi
Second assessor: Dr. Agnieszka Markiewicz

Abstract

The underlying thesis aims to analyze precautionary savings and its determinants in periods of crisis as well as to shed light on potential differences between three types of crisis, namely major recessions, wars or pandemics. By employing a long, fixed panel dataset with observations ranging from 1870 to 2016, I regress the private saving ratio for a panel of nine countries on three precautionary saving determinants, i.e. wealth, uncertainty and credit availability and on a dummy variable for crises. The estimated model confirms the precautionary savings theory: wealth, uncertainty and credit availability are able to capture any crisis effect and there appears to be no additional crisis effect for the respective dummy variable. When looking at different crisis types (recessions, wars and pandemics), there is reason to believe that the effects of recessions and wars on savings cancel each other out, which means that an overall crisis effect cannot be detected in the underlying dataset. The fact that the precautionary determinants remain surprisingly robust throughout most specifications supports this claim. Moreover, I apply several robustness checks to the model, such as adding additional control variables, presenting an alternative for wealth in order to estimate the model on a larger sample, testing alternative crisis dummies, which stem from investigations by Nakamura et al. (2013) and Barro and Ursúa (2008) and finally, I apply a dynamic set-up to the main model. The proposed model passes most robustness checks, except for the dynamic specification, under which my model collapses. This casts doubt on the model set-up and the overall robustness of the proposed model and further suggests that future research should give dynamic effects more attention as they might play a major and so far, unconsidered role in determining precautionary savings.

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1 Introduction

Disasters such as World War I & II or the Great Recession have led to severe economic and financial crises. The recent outbreak of the Corona virus resulting in the Covid-19 pandemic has reminded us of yet another type of disaster that can maneuver mankind into a major crisis. Generally speaking, periods of crisis are marked by labor and income uncertainty, economic downturn in the form of falling GDP and productivity, liquidity constraints, collapsing stock markets and most importantly: uncertainty about the future - and in the case of pandemics or wars, (economic) disasters can claim lives. A common feature of periods of crisis is the certainty to observe behavioral responses. One particular behavioral response in the presence of high uncertainty and crises is that people engage in *precautionary saving* in order to buffer up against potential future income fluctuations or negative shocks (Carroll and Samwick, 1997). Typically, life-cycle models and more precisely, the buffer stock model of saving introduced by Deaton (1991) and Carroll and Samwick (1997) predicts that rising uncertainty leads to the accumulation of wealth in the form of positive precautionary savings via diminished consumption. Thus, wealth and uncertainty in the form of income risk are considered the main 'precautionary determinants' in most empirical test of the precautionary savings theory. Increased uncertainty about future income is considered a dominant characteristic in a crisis, which leads households to buffer up their savings. Wealth holdings are assumed to decrease in a crisis which in turn drives up the precautionary motive to build up those wealth holdings again. Additionally, the severity of credit constraints is believed to play a vital role in the precautionary saving model as more binding constraints aggravate the precautionary motive to buffer up wealth holdings (Jappelli and Pagano, 1994). All three precautionary determinants, i.e. uncertainty, wealth and more binding credit constraints (expressed through less credit availability) are thus assumed to drive up the private saving ratio in a crisis (Carroll et al., 2012).

The empirical literature of precautionary saving during times of crisis primarily focuses on times when aggregate consumption fell more than GDP, such as during the Great Depression. Romer (1990) as well as Flacco and Parker (1992) find that income and labor uncertainty during the Great Depression led households to postpone consumption decisions until further information about possible outcomes of economic activity became more certain. Challe and Ragot (2016) investigate three major post-war recessions that have hit the US economy and find that precautionary saving is an important determinant of variation of consumption in times of crisis and that the precautionary motive to buffer up wealth holdings is particularly strong during the investigated recessions. One important piece of empirical work is contributed by Mody et al. (2012) who investigate precautionary saving during the Great Recession (2007-2009). According to their analysis, precautionary saving determinants (such as unemployment and GDP as well as stock market volatility) greatly matter during the Great Recession for determining changes in the household saving rate.

Abstracting from the focus on one particular recession or crisis episode, I aim to build a broader picture on precautionary saving behavior induced by different forms of crises, be that a major recession, a war or a pandemic. In other words, this thesis aims to investigate the behavior of private saving ratios and precautionary motives in times of crisis, where crisis can be a recession, a war or a pandemic. By focusing on past (economic) crises between 1870 and 2016, I aim to shed light on potential differences in the intensity of the precautionary determinants in the presence of different crisis types. To the best of my knowledge, no empirical investigation of precautionary savings throughout various periods of crisis and most importantly, different forms of crisis has been conducted on the macro-scale and for such a long time series.

The underlying dataset is a long, fixed panel dataset with many years (large t), few countries (small n) and of an unbalanced nature. My dataset mainly builds on the data efforts by Jordà, Schularick and Taylor, who provide a macro history database covering 17 advanced economies since 1870 on an annual basis and documenting 45 real and nominal variables. The 17 advanced economies included in the database are: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom (UK) and the United States of America (USA). This database was used to construct the dependent variable of this analysis, i.e. the private saving-to-GDP ratio. Data on private wealth-to-income ratios was obtained from a macro historical dataset on income and wealth created by Piketty and Zucman (2014) for nine out of the 17 countries (i.e. Australia, Canada, France, Germany, Italy, Japan, Spain, the UK and the USA). What most empirical investigations of precautionary savings have in common is the importance of the use of an uncertainty measure. Due to the lack of available unemployment rates, which are commonly used to proxy for income uncertainty, I estimate two uncertainty measures by applying ARCH(p,q)-GARCH(1,1) models, which ultimately yield the two uncertainty measures employed in this analysis, namely GDP volatility and stock market volatility. Credit availability is represented by the approximated growth rate of supplied credit to households. Lastly, I employ a self-constructed crisis dummy, which can be divided up into its three forms of crisis: recessions, wars and pandemics.

As for the empirical method to test the precautionary savings model during crises and different forms of crisis, I employ the panel regression method of a fixed effects model (FE) where I regress the private saving ratio for a panel of nine countries for the time period 1870 until 2016 on the three precautionary determinants (wealth, uncertainty, credit availability) and on a dummy for crises. Notably, the wealth variable as well as the uncertainty measures should capture the main precautionary part of savings in the model. Later on, the crisis dummy is split into its three forms, namely recessions, wars and pandemics and interactions terms are added to the analysis.

The main model seems to confirm the precautionary savings theory: wealth, uncertainty and credit availability are able to capture any crisis effect and there appears to be no additional crisis effect for the combined crisis dummy. However, a different picture emerges when looking at different crisis types. There is reason to believe that because recessions and war effects are of opposing signs - where recession shows a negative impact on the saving ratio and wars a positive one - the respective effects cancel each other out when combined, which means that an overall crisis effect cannot be detected in the underlying dataset. The fact that the model determinants remain surprisingly robust throughout most specifications supports this claim. Adding interaction terms of the respective crisis types and the precautionary determinants yields the following conclusion: for the full crisis dummy as well as the war dummy, the main result holds, i.e. the hypothesis that crises in general and specifically wars increase savings more than non-crisis or non-war periods can be rejected. In other words, this strengthens the proposed model and the hypothesis that the model can fully account for any crisis effects that act through the precautionary variables on savings.

Just like any other empirical investigation, this thesis is subject to some limitations. An obvious caveat is the fact that this is a macro study. Naturally, studies conducted on the micro level can better capture individual consumption and saving decisions. Moreover, one of the main challenges remaining is how to best measure or approximate uncertainty in order to assess its impact on consumption and savings decisions. Due to the lack of unemployment data, I was forced to construct alternative uncertainty measures, i.e. GDP and stock market volatility, which might not reflect uncertainty fluctuations that drive up the precautionary savings motive as well as being able to measure unemployment rates directly. Moreover, I apply several robustness checks to the model, such as adding additional control variables, presenting an alternative for wealth in order to estimate the model on a larger sample, testing alternative crisis dummies from investigations by Nakamura et al. (2013) and Barro and Ursúa (2008) and finally, I apply a dynamic set-up to the main model. The proposed model passes most robustness checks, except for the dynamic specification, which constitutes a major drawback of the underlying analysis, but at the same time an opportunity for future research. Given my model is not robust to the dynamic set-up, time effects seem to play a major role, which has not been properly investigated or considered in previous studies.

This thesis is structured as follows. Section 2 introduces the reader to the economic theory of the ‘Permanent Income Theory’ as well as the ‘Precautionary Savings Theory’. The literature review in section 3 provides the reader with a broad overview of the empirical investigations of precautionary savings and elaborates on proposed dependent and independent variables as well as uncertainty measures. It further highlights the previously conducted research on precautionary savings in times of crises. Section 4 outlines how the underlying dataset was constructed and specifies the creation of variables within the dataset. In section 5, I proceed to lay out the methodological approach, introduce the main identification strategy and touch upon some diagnostic tests. Section 6 presents the main results along with several robustness checks to the model and discusses some limitations of the analysis. Finally, section 7 concludes.

2 Economic Theory

2.1 Permanent Income Theory

The theory on precautionary saving dates back to John Maynard Keynes (Keynes, 1936), although more in-depth research on the topic has only started to spark economists’ interest in the early 1960s.

One of the most fundamental groundwork was laid by Milton Friedman (1957), who provided a microeconomic foundation for the macroeconomic consumption function that was initially suggested by Keynes (1936). This foundation has become to be known as the Permanent Income Hypothesis (PIH), where individuals decide on their consumption and savings within an intertemporal framework and aim to maximize their utility obtained from lifetime consumption.

The utility maximization problem is solved via an Euler equation[1], showing that individuals engage in consumption smoothing. The PIH explains how individuals spread consumption over their lifetime, where consumption in a certain period is determined by current income as well as by expected future income, called the ‘permanent income’. Changes in permanent income (instead of changes in transitory income) drive an individual’s consumption pattern in the sense that individuals smooth their consumption by spreading out transitory income changes over time. This means that as individuals consume a share of their permanent income in every period of their lifetime, the marginal propensity to consume (MPC) equals the average propensity to consume (APC)[2]. This stands in contrast to what Keynes had postulated, namely that the MPC is smaller than one, meaning that in Keynesian theory, the MPC is less than the APC because in the short-run, consumption does not change with income, but in the long-run, as income increases, consumption also rises (Keynes, 1936).

Briefly said, consumption smoothing within the PIH framework stipulates that transitory changes in income will only have a minor effect on consumption and long-term changes in income are the ones that affect consumption the most, i.e. the permanent income determines the individual’s consumption in any specific period (Friedman, 1957).

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[1]A consumption Euler equation describes the intertemporal optimal consumption choice of individuals between the current consumption and future consumption.

[2]The propensity to consume is the proportion of disposable income that individuals spend on consumption, hence the average propensity to consume (APC) refers to the ratio of consumption to the income level and the marginal propensity to consume (MPC) is the proportion of extra income that individuals consume. The MPC explains the share of changing income that is consumed.

Formally, the essence of the PIH can be depicted as follows:

$$C_t = \frac{1}{T}(A_0 + \sum_{t=1}^{T} Y_t) \qquad (1)$$

where consumption (C_t) equals the individuals' permanent income $\frac{1}{T}(A_0 + \sum_{t=1}^{T} Y_t)$, consisting of initial endowment (A_0) and future income (Y_t) that is spent in equal parts over time. The difference between current income and permanent income is called transitory income (Y_t^T) and can be written as:

$$Y_t^T = Y_t - \frac{1}{T}(A_0 + \sum_{t=1}^{T} Y_t) \qquad (2)$$

There is a noteworthy implication that can be derived from the PIH, namely that the income pattern is decisive for saving. Saving is driven by the difference between current and permanent income, which is called transitory income in this framework. As income can be either consumed or saved, one can write saving (S_t) as the difference between income and consumption. Rewriting equation (2) of transitory income and plugging it into equation (3) for saving, it follows that saving equals transitory income in equation (4).

$$S_t = Y_t - C_t \qquad (3)$$

$$S_t = \left(Y_t - \frac{1}{T}\sum_{t=1}^{T} Y_t\right) - \frac{1}{T}A_0 \qquad (4)$$

In accordance with the Life Cycle Hypothesis (LCH) developed by Modigliani and Brumberg (1954), consumption will only change when permanent income changes and people use saving to smooth their consumption over time. When current income is high compared to average income, people will save (i.e. transitory income is high). When current income is low compared to average income, people will dissave, i.e. reduce their wealth or borrow (Modigliani and Brumberg, 1954).

In 1978, Hall formulated the stochastic version of the permanent income hypothesis. By adding rational expectations to the intertemporal optimization problem, rational consumers maximize expected utility and aim to keep the expected marginal utility of consumption constant. However, Hall's model is based on the assumption of a quadratic utility function (meaning that the third derivative of the utility function equates zero, u'''(·) = 0), which results in the so-called 'Certainty Equivalence' case (CEQ), where individuals make the same consumption decisions both under certainty and uncertainty about future income. In other words, in Hall's version of the PIH, uncertainty about future income (i.e. variance) has no effect on consumption.

2.2 Precautionary Savings Theory

How does the principle of precautionary saving fit into these proposed theories? The answer is uncertainty. Leland (1968) is considered the first one to formally introduce uncertainty in a two-period intertemporal consumption model in which he investigates the level of saving as future income becomes more uncertain. He argues that solely considering risk aversion is not sufficient to explain positive precautionary saving, but rather additional assumptions on risk properties of utility functions need to be introduced. Leland (1968) stresses that a quadratic utility function is able to reflect risk avoidance, but that does not guarantee a positive demand for precautionary saving. Only with a positive third derivative of the utility function (u'''(·) > 0) and uncertainty about future income, an increase in uncertainty raises the (convex) marginal utility for a given expected consumption value. This reduces current consumption and prompts more growth of future consumption and thus, the extra savings are precautionary. Compared to quadratic utility in the case of Certainty Equivalence (CEQ), where the third derivative is zero, convex marginal utility creates more consumption growth than quadratic utility can, which is the exact reason why savings increase with income uncertainty (Leland, 1968).

Building on the two-period intertemporal consumption model that Leland (1968) introduced, several authors have contributed additional insights and extensions to the theoretical precautionary savings literature[3].

Sandmo (1970), too, shows that increased uncertainty about future income has a negative effect on consumption. As risk aversion drives individuals to self-insure themselves on intertemporal capital markets, their wealth accumulation in the form of precautionary savings increases. Sandmo (1970) notes that with pure capital risk, one cannot accurately predict an individual's response to an increase in uncertainty, as intertemporal income and substitution effects[4] will be of opposing signs. While an increase in expected future income (permanent income) drives up precautionary saving via an intertemporal income effect, the negative substitution effect depresses precautionary saving due to an increase in volatility of future income (i.e. future consumption). Nevertheless, Sandmo (1970) concludes that (for the case of pure income risk), decreasing absolute risk aversion is a sufficient condition for precautionary savings. Likewise, Drèze and Modigliani (1972) distinguish between income and substitution effects on current consumption due to an increase in uncertainty. However, they stress that with an exponential utility function, the substitution effect is zero because absolute risk aversion is not dependent on the wealth level. Solely with decreasing absolute risk aversion, as postulated by Sandmo (1970), the substitution effect is negative (Drèze and Modigliani, 1972). While Drèze and Modigliani (1972) provide proof that decreasing absolute risk aversion produces a precautionary saving motive that is stronger than risk aversion, Kimball (1990) provides a name for it: prudence.

Kimball (1990) provides a measure of the strength of the precautionary saving motive, namely 'prudence'. Analogous to the Arrow-Pratt (1965, 1964) measures of risk aversion, *absolute* and *relative risk aversion*, which are denoted as $-v''(x)/v'(x)$ *(ARA)* and $-xv''(x)/v'(x)$ *(RRA)*, Kimball (1990) introduces an equally powerful measure of prudence, which indicates how intense the precautionary saving motive is. While prudence describes the propensity to prepare to face uncertainty, risk aversion measures how much individuals dislike uncertainty. Kimball (1990) concludes that with utility being additively separable and $u(\cdot)$ being the utility of future consumption, then absolute prudence is measuring the strength of the precautionary saving motive and can be written as $-u'''/u''$, just as absolute risk aversion, $-u''/u'$, measures the strength of risk aversion. Further, he outlines that income uncertainty will increase the marginal propensity to consume at any given consumption level, provided that absolute prudence is decreasing and the effects of endogenous choice of the level of risky investment are ignored. Conversely, if absolute prudence is increasing, then income uncertainty lowers the marginal propensity to consume at any given consumption level. Lastly, Kimball (1990) provides a noteworthy re-interpretation of the substitution effect described by Drèze and Modigliani (1972): the precautionary saving motive is stronger than risk aversion in the case of decreasing absolute risk aversion, whereas it is weaker than risk aversion in the case of increasing absolute risk aversion. On a last, but important note, Kimball's work (1990) was also the starting point for *Constant Relative Risk Aversion (CRRA)* utility's popularity.

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[3]The theoretical contributions discussed focus on extending the two-period model introduced by Leland (1968). Others, such as Miller (1974, 1976) and Sibley (1975) have concentrated on continuing their analyses of precautionary savings in a multiperiod framework.

[4]The income effect is the change in consumption due to the new expected utility level resulting from a change in uncertainty. The substitution effect is the change in consumption due to the change in the desired optimal wealth at the time of receiving uncertain income (Caballero, 1990).

Building a consumption model on a quadratic utility function (where the third derivative is zero), one might get stuck in the aforementioned Certainty Equivalence case. As Leland (1968) had stressed, quadratic utility is able to reflect risk avoidance, but that does not guarantee a positive demand for precautionary savings, as optimal savings would not be impacted by uncertainty. Nevertheless, some credit has been given to quadratic utility. For instance, Caballero (1990) justifies the use of certainty equivalence (and quadratic utility) with the fact that it is highly challenging to obtain closed-form solutions in a multiperiod optimization problem and non-quadratic utility. Besides quadratic utility, the literature most commonly has made use of *Constant Absolute Risk Aversion (CARA)*, denoted as $U(C) = -\theta^{-1} exp\,(-\theta C)$ and *Constant Relative Risk Aversion (CRRA)*, denoted as $U(C) = (1-\rho)^{-1} C^{1-\rho}$.

Considering CARA preferences, one can incorporate income risk into the model solution (Caballero, 1990; among others) but the unpleasant implication arises that consumers react similarly to income uncertainty, regardless of whether they are rich or poor (Miles, 1997). Kimball (1990) notes that under CARA preferences, risk adjustments are linear and independent from wealth, which means that the model solutions do not account for the difference in 'rich-poor planning' realistically because intuitively, precaution is less needed if an individual is rich. In short, CARA preferences are unsuited to capture the precautionary saving motive accurately.

Noting the various deficiencies of quadratic utility and CARA preferences, several authors have made use of a more realistic solution to capture precautionary saving behavior: CRRA preferences (Skinner, 1988; Kimball, 1990; Carroll, 1994; among others). Under CRRA preferences, precautionary saving varies inversely with the initial wealth, which implies that risk adjustments vary with consumer wealth. Due to the fact that a specific consumption and saving solution under CRRA preferences is analytically not reachable, an approximation yields the optimal solution. Despite this analytical obstacle, CRRA preferences are seen as most realistic to reflect saving behavior (particularly in empirics) as they are able to respect 'rich-poor' differences in precautionary saving behavior (Blundell and Stoker, 1999). Caballero (1990) adds that lower consumption levels (in line with lower wealth levels) yield, *ceteris paribus*, a larger coefficient of absolute risk aversion. Carroll and Samwick (1998) argue that CRRA preferences are favorable as it safeguards that consumers in the model will save with precaution.

More recent additions to the theory of precautionary saving were made by Jappelli and Pagano (1994) who analyze a three-period consumption and saving model where liquidity constraints are imposed on households. They show that binding constraints raise the saving rate and that additive and uninsurable income shocks may induce precautionary saving and thereby strengthen the effect of growth on saving. Further, building on the work of Zeldes (1989) and Deaton (1991), Carroll and Samwick (1997) introduced the 'buffer stock saving' concept, which stipulates that consumers hold wealth in order to create a 'buffer' against future income fluctuations. Essentially, building up a buffer-stock of savings follows from the standard dynamic optimization framework given that consumers exhibit two crucial characteristics: *impatience* and *prudence*. The former consumer characteristic, i.e. impatience, implies that consumers would like to finance current consumption by borrowing against future income, given that income is certain, while the latter consumer characteristic, i.e. prudence, simply imposes a precautionary saving motive on consumers. Ultimately, consumers build up a buffer-stock of savings as impatience and prudence work in opposing directions. Impatient consumers wish to reduce their assets, i.e. dissave, whereas prudence makes them more prone to saving. According to Carroll (1992), these two opposing forces yield a so-called 'target wealth stock', which implies a simple logic of consumer behavior: prudence dominates impatience whenever consumer wealth is below target, meaning that consumers will save. On the other hand, impatience dominates prudence whenever wealth is above target, meaning that consumers will dissave (Carroll and Samwick, 1997). With this in mind, we will later on see that the empirical analysis in this thesis is essentially an empirical test of the buffer stock saving model with wealth-to-income ratios and uncertainty, reflecting negative income shocks. A last noteworthy contribution to the theory was made by Guariglia and Rossi (2002) who include habit formation in the consumption and saving model, thereby showing that including previous consumption is crucial for capturing habit formation.

Building on the developments in the theoretical literature and following various approaches, we will see in the empirical literature review that all these contributions have coined and formed the estimation methods to provide empirical evidence on precautionary saving.

3 Literature Review

For the purpose of this thesis and for the sake of clarity, the empirical literature that is based on the theoretical contributions to the model outlined in section 2, should be divided into general empirical evidence of precautionary saving and more specific work on precautionary saving in times of crises, be that war, pandemics or recessions. Each of these strands of literature will be discussed in a separate subsection in the following literature review.

3.1 Empirical Precautionary Saving Literature

The empirical attempts to verify the existence of the precautionary saving motive and estimations to assess its magnitude are manifold. Studies have been conducted both on the macro and on the micro level (although the micro approach dominates as it best captures consumption and saving decisions at the individual level) by using either wealth, consumption or saving equations in a panel, cross-sectional or time series data framework. A series of control variables has been suggested to be included in the estimation, among them, measures of uncertainty, wealth and income, demographic and socio-economic as well as fiscal factors. The majority of empirical studies finds proof for the existence of the precautionary saving motive, but findings on the magnitude remain ambiguous. Moreover, one of the main challenges remaining is how to best measure or approximate uncertainty, in order to assess its impact on consumption and savings decisions. The following empirical literature section presents the evidence of the precautionary saving motive, its magnitude and provides an overview of the most relevant control variables in saving equations.

3.1.1 Consumption Puzzles

Before discussing more recent empirical work on the precautionary saving motive, a brief note should be dedicated to the so-called ‘empirical consumption puzzles’, arising from the consideration of the precautionary motive. In this regard, several authors have stressed that the permanent income hypothesis (PIH) fails to provide an explanation for the consumption puzzles, ‘excess sensitivity’ (Flavin, 1981), ‘excess smoothness’ (Deaton, 1987) and ‘excess growth’ of consumption (Deaton, 1987). Flavin (1981) claims that a strong over-response of consumption to current income (excess sensitivity) contradicts the PIH. Deaton (1987) notes that changes in aggregate income prompt comparably small changes in aggregate consumption and deviations of income from its trend are larger than those of consumption, hence, aggregate consumption is ‘smooth’ compared to aggregate income. Moreover, Deaton (1987) stresses that the PIH fails to explain ‘excess growth’ of consumption, i.e. the “persistent consumption growth despite negative real interest rates”. Despite numerous attempts to explain these consumption puzzles (general equilibrium considerations, myopia, liquidity constraints and others), the precautionary saving motive seems to explain the puzzles most appropriately (Hall and Mishkin, 1982; Campbell, 1987; Zeldes 1989; Caballero, 1990; Deaton, 1991; Carroll, 1994; among others).

3.1.2 The Dependent Variable

The first crucial choice to make when empirically analyzing precautionary saving is to define the dependent variable. That can either be savings (level, growth or saving rate), wealth (or wealth accumulation) or consumption (or consumption growth).

The most obvious approach is probably to analyze precautionary saving via a savings equation as explored by Jappelli and Pagano (1994), Hahm (1999), Menegatti (2010) and others, who all find evidence of positive precautionary savings. A noteworthy approach is contributed by Deidda (2013), who tests the existence of precautionary savings by directly using precautionary savings as the dependent variable for an Italian data sample from the Italian Survey of Household Income and Wealth (SHIW), which asks about precautionary wealth. Two advantages arise when using subjective measures of precautionary wealth. First, putting aside income risk, it allows to consider other sources of risk, such as financial and labor income risk. Second, it facilitates to untie the precautionary motive from previous income shocks or market imperfections which cause low amounts of precautionary wealth.

One could also measure the share of wealth that is explained by uncertainty, i.e. how the wealth-to-income ratio varies when uncertainty is introduced (Caballero, 1991; Hubbard et al., 1993; Guiso et al., 1996; Kazarosian, 1997; Lusardi, 1997, 1998; Carroll and Samwick, 1998). This strand of studies suggests that precautionary savings exist, and that they are determined by the relationship between uncertainty and an increasing wealth-to-income ratio. The stronger the wealth increase, the stronger the precautionary motive. The magnitudes of precautionary savings vary across the empirical studies: while Caballero (1991) finds that precautionary savings amount to 60 percent of total wealth, Kazarosian (1997) finds estimates between 30 and 46 percent of total wealth and Carroll and Samwick (1994) suggest that precautionary savings amount to around a third of household wealth for a US sample.

Another empirical approach attempts to measure the effect of uncertainty on consumption. With present uncertainty, individuals increase savings (decrease current consumption) which prompts a positive future growth in consumption. When including a measure for uncertainty, Zeldes (1989) and others (Carroll, 1994; Dardanoni, 1991; Miles, 1997; Banks et al., 2001; Menegatti, 2010) find positive precautionary savings. In contrast, Dynan (1993) empirically investigates the coefficient of relative prudence (introduced by Kimball, 1990) for the Consumer Expenditure Survey (CEX), but fails to obtain significant results, indicating that there is no precautionary saving motive at hand. Benito (2006) finds that an objective uncertainty measure (obtained from a probit estimation) yields a positive and significant result for precautionary saving, but he fails to provide the same evidence with a self-reported uncertainty measure.

3.1.3 The Measure of Uncertainty

It is essential to think about how to measure uncertainty. The underlying issue is that the conditional variance of consumption growth cannot directly be estimated as the conditional variance might be endogenous and thus dependent on accumulated wealth (Carroll, 1992). Therefore, the impact of uncertainty on future income growth has to be proxied (Hahm, 1999; Menegatti, 2007; Mody et al., 2012). Three most commonly used measures stand out: income variability, consumption or expenditure variability and labor market indicators, in particular the unemployment rate.

Income Variability

The variability of income measure serves as one possible proxy for uncertainty and it is based on the standard deviation or variance of income (see Zeldes, 1989; Dardanoni, 1991; Blundell and Stoker 1999; among others). A macro approach is taken by Kazarosian (1997) who engages in a panel data study for the US proxying uncertainty with the standard deviation of the residual of the estimated income-age profile of individuals, thereby obtaining individual income uncertainty. Guariglia and Rossi (2002) focus on a British dataset and compute the variance of residuals stemming from an income equation. Both Kazarosian (1997) as well as Guariglia and Rossi (2002) are able to provide proof of precautionary savings. Naturally, income uncertainty is also often proxied by GDP volatility. Both Hahm (1999) and Menegatti (2010) conduct analyses for OECD countries and find a positive relationship between GDP volatility and savings, in particular by studying the variance of GDP growth rates and the conditional variance of expected GDP growth. Both approaches confirm a positive precautionary saving motive affecting consumption decisions.

On the micro level, Caballero (1991) uses the standard deviation of the percentage change in the annuity value of wealth for the US while Miles (1997) makes use of the income variance and its standard deviation in order to measure labor income uncertainty. Both studies show the existence of a strong precautionary saving motive. While the aforementioned studies all use objective measures, which are either computed or predicted, Guiso et al. (1992) and Lusardi (1997) use subjective measures of income uncertainty. Guiso et al. (1992) investigate precautionary savings for CRRA preferences in Italy using data from the 1989 Bank of Italy Survey of Household Income and Wealth. By introducing a subjective household measure for income variability, based on a subjective estimation of prospective income growth and inflation measured in the year after the survey, the authors aim to determine the variance of future income and thereby measure precautionary savings. Unfortunately, their results only suggest a very limited role of precautionary savings with respect to overall savings (about 2 percent of all savings) for households expecting a higher income variance in the future. Similarly, Lusardi (1997) uses the Health Retirement Survey (HRS) and obtains a small precautionary saving estimate of between 1 and 3.5 percent of total savings by introducing a measure of subjective income risk via possible job loss.

Consumption or Expenditure Variability

Another proxy for uncertainty is consumption variability. Dynan (1993) favors consumption variability over other uncertainty proxies because solely income shocks alter an optimizing household's consumption decisions, representing a handy measure of risk. In particular, she uses the variance of consumption growth proxying for income uncertainty but fails to prove a precautionary motive for a US sample. Contrary to Dynan's findings, Guariglia and Kim (2003) are able to find strong evidence for precautionary savings by including financial risk. Likewise, Baiardi et al. (2013) control for financial risk for six advanced economies and find a positive and significant effect of the interaction of financial and environmental risk on consumption growth.

Unemployment

A noteworthy part of uncertainty can be explained by rising unemployment during economic downturns. Hence, this strand of literature uses unemployment rates or the probability of being unemployed as proxies for income uncertainty.

Micro-based estimations rely on the ex-ante (subjective) probability of losing one's job (Carroll et al., 2003; Lusardi, 1998; Guariglia, 2001; Benito, 2006; Ceritoglu, 2013 and Lugilde et al., 2016). For instance, Lusardi (1998) finds that individuals who expect an increasing income risk save more. Guariglia (2001) and Benito

(2006) make use of several waves of the British Household Panel Survey (BHPS) and find strong precautionary saving motives associated with the risk of unemployment. Following Guariglia (2001) and Benito (2006), Ceritoglu (2013) and Lugilde et al. (2016) construct similar measures of income risk and while Ceritoglu (2013) finds precautionary motives for a Turkish sample, Lugilde et al. (2016) fail to do so for a Spanish sample. Barceló and Villanueva (2010) investigate whether precautionary motives induce households with higher job instability postpone their consumption and they conclude that consumption growth increases for households with higher job loss risk. Lastly, Banks et al. (2001) add changes in unemployment risk and changes in income uncertainty by building up terms of conditional variance of income risk. They show that British households exhibit strong positive precautionary savings.

Macro-based work generally makes use of labor market conditions to proxy for uncertainty, i.e. unemployment rates or subjective unemployment expectations, which in most cases leads to the conclusion that savings increase with higher unemployment rates. A famous example of empirical evidence supporting this conclusion is a study of 27 advanced economies conducted by Mody et al. (2012). They introduce two measures of uncertainty, namely the aggregate unemployment rate and GDP volatility and confirm the positive correlation of the saving rate with both uncertainty proxies. Following Menegatti (2010), Bande and Riveiro (2013) investigate precautionary savings for 17 Spanish regions by using regional unemployment rates and future income volatility as uncertainty proxies. They, too, find precautionary saving motives, particularly with varying levels of uncertainty persisting over time.

3.1.4 Control Variables

The choice of control variables to include into the specification is equally important for measuring precautionary savings. Generally speaking, precautionary savings are determined by the consumer's perception of uncertainty, credit constraints and the economic environment in which the individual makes decisions.

The first control variable often included in saving models is income or lags of income (Caballero, 1991; Miles, 1997; Hahm and Steigerlwald, 1999; Guariglia, 2001; Menegatti, 2010; Menegatti, 2007; Bande and Riveiro, 2013). Moreover, different types of income, labor income or investment income are considered, as well as distinctions between transitory and permanent income (Kazarosian, 1997; Lusardi, 1997; Guariglia, 2001; Benito, 2006; Miles, 1997). In order to capture habit formation, Guariglia and Rossi (2002) include past consumption and Caballero (1991), among others, include past year wealth in their saving equations.

Household specific characteristics such as family size, age, sex, race, health, education, number of income earners or number of children are also often included in order to capture household-specific effects in micro studies (Skinner, 1988; Lusardi, 1993, 1997, 1998; Miles, 1997; Kazarosian, 1997; Carroll and Samwick, 1998; Dynan, 1993; among others). More educated households are generally assumed to save more, which is proven by empirical evidence (Lugilde et al., 2016) and the rationale for including health status is the assumption that individuals with poor health save more as they aim to counter for unexpected medical expenses.

With regard to unemployment, it may be straight forward to include the variance of unemployment at the macro level into the set of control variables, whereas assigning unemployment rates to individuals on the micro level might not be as easy. Therefore, various other variables are considered in the empirical literature to serve as a job-related variable. Union membership, hours worked, experience in years and employer size have shown to be negatively related to uncertainty (Lusardi, 1997; Miles, 1997; Benito, 2006) and including job insecurity or a dummy for unemployment in the previous year yields a positive relationship with uncertainty. A few studies have also focused on the type of employment. Leland (1968) as well as Sandmo (1970) suggest that self-employed, farmers and sales workers usually save more because their income is more variable. On the contrary, Skinner (1988) finds that occupations with higher income uncertainty exhibit lower savings, which is in line with Carroll (1994), Kazarosian (1997) and Lusardi (1997). Carroll (1994) points out that high-income individuals save more, "regardless of the effect of uncertainty", so assuming that occupations with more risk also have lower income, they save less.

Some studies focus on fluctuations in wealth due to changes in marital status or the birth of children (Love, 2010; Pericoli and Ventura, 2012). Pericoli and Ventura (2012), for example, provide evidence for an increase in precautionary saving prompted by a higher probability of family dissolution (divorce). A study that focuses on the individual's age is conducted by Chamon et al. (2013) who show that Chinese households respond more heavily to transitory income shocks when they are young because they need to build a buffer stock and thus, save more. Another strand of literature investigates precautionary savings in relation to health and unemployment insurance systems, which obviously differs substantially across countries. One interesting finding from China reveals that with decreasing existence of unemployment insurance and benefits, precautionary savings increase (Liu, 2014). This is in line with evidence from the US and Turkey (Gruber, 1997; Ceritoglu, 2013).

Finally, including individual's financial literacy, credit market constraints and household financial status into the set of controls, constitutes one last, but important branch of control variables. First, financially more literate individuals can better perceive uncertainty and understand its consequences which is why uncertainty affects their savings more. For instance, Bernheim et al. (2001) find that financial education in US high schools increase individuals' savings rates and their wealth accumulation throughout their adult life. Similarly, van Rooij et al. (2012) provide evidence for a positive relationship between financial literacy and wealth accumulation in the Netherlands. According to the authors, financially more literate individuals are more likely to plan for their retirement. Second, including variables reflecting credit market conditions and household's financial status have induced a vivid debate in the precautionary saving literature. While Guiso et al. (1992) and Deidda (2013) include variables such as regional financial developments, whether individuals own credit cards, how long they stay with one bank or whether the household receives help from relatives or friends, it generally remains uncertain how credit constraints affect precautionary saving, which is why some authors refrain from including liquidity constraint variables (Zeldes, 1989). However, the literature concludes that liquidity constraints can increase savings, for reasons that are twofold: first, as soon as liquidity constraints constitute a spending limit, individuals consume less than otherwise. Second, even without current spending restrictions (liquidity constraints), the possibility of future constraints is threatening enough to reduce current consumption, which is why individuals save. Hence, liquidity constraints might reinforce precautionary saving (Zeldes, 1989; Deaton, 1991; Deidda, 2013; Blundell et al., 2014).

3.2 Precautionary Saving throughout Crises

This thesis focuses on precautionary saving in times of crisis, be that war, pandemics, recessions or other forms of crisis. Thus, this section gives an overview of what research has been done in this regard so far.

First, the term 'crisis' must be clearly defined. After Rietz (1988), who tried to explain the equity premium puzzle[5] by investigating 'market crashes and shocks', Barro (2006) built on this idea and coined the term 'rare disaster' to describe such periods of crisis where an economic collapse or shock, which is usually substantial, affects the economy negatively. In the course of this rare disaster, one can observe a cumulative peak-to-trough

[5]The equity premium puzzle (EPP) describes the economic phenomenon of abnormally higher historical real stock returns over (risk free) government bonds and the puzzle is the abnormally high-risk aversion among investors reflected by the relative risk of stock returns.

fall in GDP and consumption (of at least 10 percent) (Barro and Ursúa, 2008). It is important to note that examples of such rare disasters or times of crisis can be manifold, including financial disasters such as the 1930s Great Depression or the Great Recession from 2007 until 2009, wars such as World War I & II, epidemics or pandemics, such as various influenza outbreaks, the Spanish Flu or the novel outbreak of the Covid-19 pandemic, and also natural disasters such as earthquakes, floods or other catastrophes. However, in principle any event influencing GDP and consumption substantially can be regarded as a rare disaster – in this context, it will be referred to as 'time of crisis'. Barro and Ursúa (2008) provide an extensive analysis of such rare macroeconomic disasters since 1870 divided into GDP disasters (152 crises) and consumption disasters (95 crises), while applying the disaster definition of a "cumulative decline over one or more adjacent years by 10% or more in real per capita GDP or real per capita consumption). According to this definition, the authors disentangle three most substantial global disasters since 1870, namely World War I & II and the 1930s Great Depression. The Great Influenza Epidemic (Spanish Flu of 1918-1920) closely follows the magnitude of the other three major disastrous shocks. Empirical work on three specific forms of crises (recession, war, pandemic) are described in more detail below.

3.2.1 Recession

The literature of precautionary saving during times of crisis primarily focuses on times when aggregate consumption fell more than GDP, such as during the Great Depression. Romer (1990), who investigated the relationship between consumption and stock market volatility during the Great Depression, as well as Flacco and Parker (1992), who engage in a more extended analysis, find that income and labor uncertainty during the Great Depression led households to postpone consumption decisions until further information about possible outcomes of economic activity became more certain. Flacco and Parker (1992) estimate income uncertainty from 1921 until 1930 using the variance of income in a linear moment model. They conclude that income uncertainty has substantially contributed to the fall in consumption throughout the Great Depression. Challe and Ragot (2016) investigate three major post-war recessions that have hit the US economy, in which consumption has fallen more than GDP (1974Q3, 1980Q1 and 2008Q2) and find that precautionary saving is an important determinant of variation of consumption in times of crisis. One important piece of empirical work is contributed by Mody et al. (2012) who investigate precautionary saving during the Great Recession (2007-2009) for a panel of advanced economies. According to their analysis, precautionary saving determinants (such as unemployment and GDP- and stock market volatility) greatly mattered during the Great Recession for determining changes in the household saving rate. Uncertainty during the Great Recession was responsible for rising saving rates and lower consumption and GDP growth, thereby indicating precautionary saving motives in times of uncertainty. Specifically, Mody et al. (2012) attribute two-fifths of the increase in household saving rates between 2007 and 2009 to precautionary saving motives. Likewise, Carroll et al. (2012) confirm that income uncertainty during the Great Recession has increased saving rates in the US.

3.2.2 War

To the best of my knowledge, there is no specific strand of literature investigating war or post-war periods with respect to precautionary savings. Slemrod (1988) investigates the 1980s period, when the risk of a potential nuclear war was at its peak and whether this perceived risk influenced saving behavior. The author finds that with a 10% increase in the share of the population believing in a potential nuclear war, private net saving rates declined by 4.1 percentage points. This suggests that the threat of a war decreases savings. Skinner (1990) follows up on this saving downturn during the 1980s and estimates the impact of precautionary saving using an Euler equation approach and speculatively concludes that the combined impact of "mismeasured saving rates and precautionary saving" might explain the low saving rates of the 1980s. Skinner (1990) argues that consumers saved less and consumed more during the 1980s due to revised expectations about future income. In the analysis conducted by Barro and Ursúa (2008), where the authors specify periods of crisis indicated by GDP and consumption falls, they also distinguish between wartime and nonwartime. The authors stress that during wartime, the government engages in increased military spending which causes a decrease in consumption (thus also investment) for a given GDP. As such, consumption would fall proportionately more than GDP during wartime. Indeed, the thirty-one wartime periods confirm that the fall in consumption was greater than the fall in GDP: for OECD countries, consumption fell by 32% while GDP only fell by 27.6%. In essence, this suggests greater precautionary saving motives during wartime periods, ceteris paribus. Aside from these studies, precautionary saving has been investigated in post-war settings (see Challe and Ragot, 2016), but to my knowledge, no specific research on precautionary saving before, during and after a war has been conducted.

3.2.3 Pandemic

The last type of 'crisis' this thesis looks at is a pandemic, which is beside its negative impact on the population size most importantly a period of uncertainty, both about the magnitude of the pandemic as well as about economic implications resulting from the pandemic. A noteworthy paper by Barro, Ursúa and Weng (2020) compares the novel Covid-19 pandemic with the Great Influenza Epidemic (1918-1920), also known as the 'Spanish Flu', that coincided with WWI. They estimate regressions with annual flu deaths combined with war deaths and find flu-induced economic downturns in GDP and consumption of 6 and 8 percent respectively. Moreover, they provide evidence that high flu death rates have a negative impact on realized stock returns and short-term government bills. A study by Dietrich et al. (2020) that surveys US households on their saving and consumption behavior in response to the Covid-19 crisis further confirms that higher uncertainty (due to labor uncertainty) matters as it increases saving rates. Jordà et al. (2020) investigate the long-run consequences of pandemics by studying asset return rates dating back to the 14th century. They focus on 15 substantial pandemics that claimed more than 100,000 lives, such as the Black Death in the 14th century on to several Cholera and Flu outbreaks throughout history. They, too, conclude that pandemics create great (labor) uncertainty which leads to an increase in precautionary savings.

4 Data

This section describes the datasets used and the rationale for including the variables, along with a description of their construction. The main dataset this thesis makes use of is the *Jordà-Schularick-Taylor Macrohistory Database* (*JST database* hereafter) which is an extensive collection of annual, historical macro data for 17 advanced economies since 1870 until 2016 and in total, it comprises 45 real and nominal variables. The 17 advanced economies included in the database are: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom (UK) and the United States of America (USA). Returns and inflation variables were obtained from another database created by Jordà et al. (2019) for their paper "The Rate of Return on Everything, 1870-2015", hereafter called *RORE database*. The *RORE database* complements the countries and the time period to the *JST database* perfectly, which is why those two databases were merged into one dataset, i.e. *JST-RORE* hereafter. Lastly, wealth data was obtained from a macro historical dataset on income and wealth created by Piketty and Zucman (2014), hereafter *PZ database*, which comprises wealth variables for nine OECD countries and time series dating back for some of the countries until 1870. Additional wealth data for Sweden was obtained from the Swedish National Wealth Database (SNWD), hereafter *SNWD database*. The available time periods for each country depending on the database are summarized in *Table A* and the technical definitions of the variables and the construction thereof are listed and described below, as well as in *Table B* (*Appendix A*).

GDP, Consumption and Saving

First and foremost, every savings story and particularly this one needs GDP data (Caballero ,1991; Miles, 1997; among others). The *JST-RORE* database provides the variable *rgdppc2005*, i.e. a real GDP per capita index with the base year 2005. As real consumption per capita, *rconpc*, is also given as an index, however with the base year 2006, real GDP per capita was computed to have the same base year as real consumption per capita, namely 2006, for better comparability. The new variable is called *rgdppc*. Following this transformation of variables into the same base year, the growth rates of real GDP per capita and real consumption per capita were computed, where the growth rate is defined as the year-on-year percentage change in a variable, i.e. the approximated growth rate of the variable computed by using the difference in the natural logarithms. The two growth variables are called *realygrowth* and *realcgrowth*. As real consumption per capita (*rconpc*) is private consumption in the dataset, one can easily compute the log consumption-to-income ratio (*lnCYratio*), which is desperately needed to construct our saving ratio for the analysis. Since the natural logarithm of a quotient is the difference between the logarithms of the numerator and the denominator, the log consumption-to-income ratio was obtained by:

$$\ln(\frac{C}{Y}) = \ln(C) - \ln\,(Y) \qquad (5)$$

and the consumption-to-income ratio (*CYratio*) is obtained by eliminating the logarithm:

$$CYratio = e^{\ln\,(\frac{C}{Y})} \qquad (6)$$

Finally, the private saving-to-GDP ratio (*SYratio*), which will be used as the main dependent variable in the regression analysis, is constructed by subtracting the consumption-to-income ratio from 1, which yields the saving-to-income ratio.

$$SYratio = 1 - e^{\ln\,(\frac{C}{Y})} \qquad (7)$$

Private Wealth

Next, the private wealth-to-national income ratio (*WYratio*) was obtained from a macro-historical dataset (*PZ database*) on income and wealth created by Piketty and Zucman (2014). The wealth-income ratio is available for nine OECD countries, namely Australia, Canada, France, Germany, Italy, Japan, Spain, the UK and the USA and dates back for some of the countries until 1870. Additional data for Sweden was obtained from the Swedish National Wealth Database (*SNWD database*), which is an extensive database for wealth indicators dating back to 1810. Conveniently, the database also provides the same wealth-income ratio, i.e. the private wealth to national income ratio, as documented by the data efforts by Piketty and Zucman (2014). Hence, wealth-income ratios are available for ten OECD countries, and for five countries (France, Germany, Sweden, the UK, the USA) the ratios date back until 1870. The private wealth-to-income ratio is expected to have a negative impact on the saving ratio.

Uncertainty Measures

One major caveat is the lack of an unemployment variable, which has proven to be a nice proxy for uncertainty in previous research. However, I therefore include two different uncertainty measures, namely the volatility of real GDP per capita growth (*gdpvolatility*) as well as the volatility of stock returns (*SMvolatility*) in order to best proxy for uncertainty in absence of the unemployment rate. First, Bloom (2014) noted, that stock market data and the volatility of stock returns can serve as a nice measure of uncertainty. Accordingly, the *RORE* *database* provides one particular variable that appears to serve as suitable proxy. The classical approach to proxy for aggregate business returns is to use equity returns. In the *RORE database*, historical total equity returns are constructed by using various sources, such as economic and financial history journals, yearbook information from statisticians and central banks, newspaper articles, stock exchange listings and corporate reports. The equity returns for each country and time period were constructed as follows:

$$r_t = \left(\frac{p_t + d_t}{p_{t-1}}\right) - 1 \qquad (8)$$

The rate of return to total equity are annualized return rates and expressed in percent per year. It should be noted that hyperinflation years (in Germany, 1922) are excluded from the time series in order to prohibit the hyperinflation years to bias and mis-measure the underlying return trends. In order to use the equity returns as a volatility measure, the same estimation technique was used as for the estimation of GDP volatility (explained in the following), namely estimating ARMA(p,q)-GARCH(1,1) models, which yield stock market volatility measures for each country, named *SMvolatility*. The plotted stock market volatility measures for each country are displayed in *Appendix B*. Second, GDP growth rates show features of time-varying volatility. It has become common practice in the empirical literature to use the aforementioned Autoregressive Conditional Heteroskedastic (hereafter ARCH) models, developed by Engle (1982) as well as the extension to Generalized ARCH (hereafter GARCH) models introduced by Bollerslev (1986), in order to model volatility of time series of economic or financial nature. Following this logic, volatility series of real GDP per capita growth per country are constructed to be used as a measure of general uncertainty. The variable is called *gdpvolatility* and the other uncertainty measure, i.e. stock market volatility (*SMvolatility*) was created by the same logic.

The important feature of the volatility of GDP growth is that it behaves countercyclically, i.e. it rises in times of crisis. Bloom (2014) notes that non-financial measures of macro uncertainty, such as the volatility of GDP growth, which is usually based on GARCH models, exhibit roughly 35 percent more conditional volatility during recessions. Likewise, stock-market volatility, which also commonly serves as a measure of uncertainty is about 58 percent higher in recessions. The uncertainty measures, i.e. the volatility of real GDP per capita growth rates for each country were constructed by applying an ARMA(p,q)-GARCH(1,1) model estimated on the growth rate of real GDP per capita growth, where ARMA stands for 'autoregressive moving average'. An AR(p) process refers to an autoregressive process of order p and can be described as a p^{th} order difference equation in which the current value of a variable depends on the past realizations of itself and a random component. An MA(q) process stands for a moving average process of order q and is thus a linear combination of realizations from a white noise process. When a process is stationary, an ARMA(p,q)-GARCH(1,1) model is applied, where ARMA fits the conditional mean and GARCH fits the conditional variance. The rationale for applying an ARMA(p,q)-GARCH(1,1) model in this context is straight forward: a GARCH(p,q) model allows an ARMA process embedded in the conditional variance and "explicitly recognizes the difference between the unconditional and the conditional variance allowing the latter to change over time as a function of past errors" (Bollerslev, 1986) and in contrast to an ARCH(q) process developed by Engle (1982), where the conditional variance is specified as a linear function of past variances, the GARCH(p,q) process allows for lagged conditional variances to enter the specification. This is why researchers have increasingly applied GARCH models to obtain the volatility of real GDP growth and why the underlying GDP volatility measure was constructed by using this approach. The plotted volatility measures (for GDP and stock market volatility respectively) for each country are enclosed in *Appendix B*.

Credit Availability

As we know from the literature (Jappelli and Pagano, 1994; among others), credit constraints in the form of less available credit can be an important determinant of savings. If credit is readily available, this would theoretically reduce the need to build up precautionary savings, which means the theory would predict a negative impact on the saving ratio with increased access to credit (Adema and Pozzi, 2015). Put differently, saving increases when credit constraints become more binding (Loayza et al., 2000). The *JST-RORE database* contains data on 'total loans to households', which are used as proxy for credit availability. Importantly, the variable includes mortgage loans to households. The year-on-year percentage change in total loans to households, i.e. the approximated growth rate of total loans to households (*creditgrowth*) was computed by using the difference in the natural logarithms. The variable '*credit availability'* is expected to have a negative sign, i.e. as the amount of credit given to households increases (credit constraint becomes less binding), the saving ratio decreases.

Inflation

As previous literature (Deaton, 1977; Fischer, 1993; among others) has shown, the inflation rate can serve as a proxy for price uncertainty, and further for macroeconomic instability which enters the equation with a negative impact on the saving rate via precautionary saving effects. The *JST-RORE database* contains the annual inflation rate for every country time series, which is applied as a control variable in a robustness check. The sole thing that was changed about the inflation variable was, again, the exclusion of hyperinflation years to counteract a potential bias.

Income

The growth rate of real per capita GDP is assumed to be an important determinant of saving both in the theory of the permanent income hypothesis as well as under the life-cycle hypothesis and it most likely exhibits a positive impact on the saving ratio. The underlying economic reason is that as individuals become richer or their income grows at a faster pace, the private saving rate rises (Loayza et al., 2000). The respective variable for the growth rate of real GDP per capita is called *realygrowth*.

Housing Prices

A novel addition to previous research is the inclusion of housing prices as a control variable. A quite recent and heterodox strand of literature has outlined the importance of rising housing prices to be supplied as collateral, which has a noteworthy impact on consumption decisions, because households who have risky mortgage loans tend to refinance in order to free up disposable income (e.g. Barba and Pivetti, 2009; Cynamon and Fazzari, 2008; Campbell and Cocco, 2007). In this sense, housing prices are expected to have a negative impact on the saving ratio, as it is expected from the life cycle model that house owners would react with saving more if housing prices were to fall unexpectedly. In order to see how this variable might fit into the model, I include the evolution of the growth rate of housing prices. The growth rate of housing prices was computed as follows. First the house price index with base year 1990 was converted to base year 2006 (the same base year as real GDP per capita). Next, the year-on-year percentage change in house prices (*hgrowth*), i.e. the approximated growth rate of house prices was computed by using the difference in the natural logarithms.

Disaster Dummies

On a last note, I created various dummy variables for crisis episodes. First, I created my own crisis dummy variables for each specified type of major disaster, namely recession, war or pandemic. In order to differentiate between these types of crisis in my analysis, three dummy variables have been created, namely *recession, war* and *pandemic* (the combined crisis dummy, which entails all three kinds of crisis, is named *crisis*). Information on the specific time periods of crisis events considered can be obtained from *Table D* in *Appendix A*. Second, the dummy variable '*disaster'* was constructed by using information on disaster episodes from Nakamura et al. (2013) who analyze an empirical model of consumption disasters for a panel of countries and a time span of over more than 100 years. A disaster episode in this paper is defined as "a set of consecutive years for a particular country such that (i) the probability of a disaster in each of the years is larger than 10 percent, and (ii) the sum of the probability of disaster for each year over the whole set of years is larger than one". The disaster episodes by Nakamura et al. (2013) are displayed in *Table E* in *Appendix A.* Third, two dummy variables, namely *'Cdisaster'* and *'GDPdisaster'* stem from Barro and Ursúa's data efforts (2008), who are able to distinguish between economic crises by using a peak-to-trough method, where cumulative declines in consumption or GDP of at least 10 percent disentangle a crisis period. The two dummy variables indicating either a consumption or a GDP crisis will later on be used as a robustness check. The disaster episodes by Barro and Ursúa (2008) are displayed in *Table F* in *Appendix A*.

5 Methodology

This section describes the econometric approach taken in this thesis, where I first outline the underlying issue with OLS and argue why the panel regression method of a fixed effects model (FE) is most appropriate to employ in this case. I then move on to present the various regression specifications that are run in this analysis and lastly, touch upon some diagnostic issues.

5.1 Issues with OLS

Suppose we were to estimate the following model with OLS:

$$S_{it} = \beta_0 + \beta_1 crisis_t + \varepsilon_{it} \qquad (9)$$

where S_{it} is the saving-income ratio for country i at time t (measured in years), β_0 is the intercept and β_1 represents the estimated effect of the *crisis* variable on the saving-to-income ratio. Lastly, ε_{it} is an error term.

Given there is no country effect η_i, equation (9) estimated by OLS yields efficient and consistent parameter estimates, provided the five OLS assumptions hold[6]. If, however, the country effect η_i is non-zero, then heterogeneity might impact assumptions 2 and 3, i.e. errors might be heteroskedastic and/or autocorrelated. This leads the OLS estimator to be no longer BLUE (best linear unbiased estimator) and panel data models can help to resolve the issue (Wooldridge, 2010). Since there is strong reason to believe that OLS yields non-BLUE estimates, I employ panel estimation methods.

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[6]OLS assumptions: First, linearity must be given, meaning that the dependent variable (*SYratio*) is expressed as a linear function of a set of independent variables and the error term (ε_{it}). Second, the exogeneity assumptions postulates that the expected value of the error term is zero and that the errors are uncorrelated with any of the explanatory variables. Third, error terms must have the same variance, i.e. they ought to be homoscedastic and not related to another (non-autocorrelation). Fourth, the observations on the regressors are fixed in repeated samples and without measurement errors. Fifth, there is no multicollinearity, i.e. there is no exact linear relationship among regressors (Wooldridge, 2010).

5.2 Panel Fixed Effects

Due to the resulting issues with OLS outlined above, I proceed with panel data methods, more precisely, with a fixed effect model (FE hereafter). The underlying dataset is a long, fixed panel dataset with many years (large *t*), few countries (small *n*) and of an unbalanced nature. In general, panel data enables us to investigate both group (here: country) and time effects, which are either fixed or random. A FE model evaluates if intercepts vary across country or time period, while a random effect model (RE) investigates differences in error variance components across country or time period. The here employed one-way model considers only one set of dummy variables, e.g. country A, country B, etc. (Wooldridge, 2010). The main difference between FE and RE models is the importance of dummy variables. The parameter estimate of a dummy variable is integrated in the intercept in a FE model, whereas it is an error component in a RE model. Following this logic, a fixed country effect model evaluates country differences in intercepts, while assuming the same slopes and constant variance across countries. As a country-specific effect is time-invariant and assumed to be integrated in the intercept, the country-specific effect, η_i can be correlated with other explanatory variables and the second OLS assumption is no longer violated. The FE model is estimated by a least square dummy variable (LSDV) regression, which is essentially an OLS regression with a set of dummies and within effect estimation features. Fixed effects are tested by the F test and if the null hypothesis (H0) is rejected, the FE regression should be favored (Torres-Reyna, 2007). The underlying analysis itself provides a strong rationale for employing a FE model. FE models are highly useful when we are only interested in investigating the impact of time-varying variables within a country, which is clearly the case here. With a FE model, there comes the assumption that something within the country might bias the dependent or independent variables, which is why it needs to be controlled for and FE gets this job done.

5.3 Main Identification Strategy

In all specifications, the saving ratio (*SYratio*) serves as the dependent variable. The most important independent variables are wealth, uncertainty and credit availability. Wealth is proxied by the private wealth-to-national income ratio (*WYratio*) for a sample of nine countries, and later on in the robustness check section, I estimate a sample where I include the investment-to-GDP ratio (*IYratio*) instead of wealth, which is available for the full set of countries. Uncertainty is represented through two uncertainty measures, namely the volatility of real GDP per capita growth (gdpvolatility) estimated by a GARCH(1,1) model, as well as the volatility of stock returns (*SMvolatility*). Lastly, credit availability is expressed by the approximated growth rate of total loans to households (*creditgrowth*). Notably, the wealth variable (*WYratio*) as well as the uncertainty measures (*gdpvolatility* and *SMvolatility*) should capture the main precautionary part of savings in the model.

Before specifying any regression equations, a brief look back on the theory is in order to discuss the relationship between (precautionary) savings, wealth, uncertainty, credit availability and crises. Economic theory, i.e. the buffer stock model of saving (Carroll and Samwick, 1997) dictates that saving is bent by whatever happens to wealth and to uncertainty, and more indirectly to credit constraints or availability. Essentially, what matters for saving in theory - regardless of whether the economy is in a crisis or not – are the precautionary model determinants. When in crisis, wealth would fall, uncertainty would rise, credit constraints become more binding if credit is less readily available and the ‘crisis’ affects savings through these variables which induces higher saving rates.

To be precise, credit availability is not really a ‘direct’ precautionary determinant, but rather affects the saving ratio directly and only acts through the wealth variable as a precautionary saving determinant, or model determinant. In other words, if credit constraints tighten up, meaning that there is less credit available, the target wealth increases, which leads to a higher savings ratio. Thus, the credit variable is treated as a so-to-say 'indirect' precautionary variable in this analysis, as merely looking at wealth and uncertainty would ignore the fact that the availability of credit matters substantially for the target buffer stock level of wealth, and thus for (precautionary) saving. For example, as credit is readily available, individuals can borrow more easily and by doing so, insure themselves against negative income shocks. As a result, precautionary savings decreases as the precautionary saving motive is mitigated through the increased amount of credit available (also noted by Mody et al., 2012). What still matters most for measuring precautionary savings in my model is observing a positive coefficient of uncertainty, i.e. higher uncertainty increases the saving ratio *because* of precautionary behavior.

If the theory is correct, then adding the precautionary model to a regression where the saving ratio is only regressed on the crisis dummy proves that the model can account for the impact of crisis on savings. Optimally, we would observe an impact of crisis on savings and once wealth, uncertainty and credit availability (and later on other control variables) are added, there is no more additional crisis effect. If the crisis dummy has additional explanatory power for the model, i.e. if a crisis year has an additional effect on savings other than through the precautionary determinants, I expect the crisis dummy to show some significant impact despite the presence of the precautionary determinants in the model.

To check the theory, I begin with estimating the following baseline regression of a FE model, equation (10):

$$S_{it} = \beta_0 + \beta_1 crisis_t + \eta_i + \varepsilon_{it} \qquad (10)$$

where S_{it} is the saving-to-income ratio for country *i* at time *t* (measured in years), β_0 is the intercept, β_1 represents the estimated effect of the *crisis* variable on the saving-to-income ratio and η_i constitutes the unobserved country fixed effects. Thus, η_i estimates the common change in the saving-to-income ratio in country *i*, relative to the baseline country (Australia), while controlling for shocks that are common to all countries (year fixed effect). Lastly, ε_{it} is the error term.

In order to check if saving is indeed driven by the precautionary parameters, I estimate the following equation:

$$S_{it} = \beta_0 + \beta_1 wealth_{it} + \beta_2 uncertainty'_{it} + \beta_3 credit\ availability_{it} + \eta_i + \varepsilon_{it} \qquad (11)$$

where $wealth_{it}$ constitutes the wealth-income ratio for country *i* at the beginning of *t*, and $uncertainty'_{it}$ is modelled by a vector of the two different uncertainty measures, i.e. GDP volatility (*gdpvolatility*) and stock market volatility (*SMvolatility*) respectively. Due to reasons discussed in section 4, credit availability imposed on household can be an important driving factor of precautionary savings. The underlying availability of credit strongly influences a household's target buffer stock of wealth and thus, the (precautionary) savings. From the theory, we would expect to see that wealth, uncertainty and credit availability reflect precautionary motives and allow us to measure precautionary savings, where the wealth-income ratio is expected to enter with a negative sign, uncertainty measures with a positive sign and credit availability with a negative sign.

When adding wealth, uncertainty and credit availability to the model with the crisis dummy, i.e. combining the precautionary model with the control for a crisis, I include the theoretical mechanism that saving is affected through wealth, uncertainty and credit availability in a crisis, so if the theory is correct, these precautionary determinants can fully account for crisis effects in the saving ratio and we would observe an insignificant crisis dummy in equation (12). Put in other words, if we expect crisis to have an additional effect that does not run through the mentioned model determinants, we would expect to see a significant crisis dummy.

$$S_{it} = \beta_0 + \beta_1 wealth_{it} + \beta_2 uncertainty'_{it} + \beta_3 credit\ availability_{it} + \beta_4 crisis_t + \eta_i + \varepsilon_{it} \qquad (12)$$

Now, in order to evaluate if slope effects are different for the crisis dummy, interaction terms are added to the FE model in equation (13), i.e. all control variables are multiplied by the dummy variable in order to disentangle the combined effects of wealth, uncertainty and credit availability in crises on savings. The different slopes allow the effect of wealth, uncertainty and credit availability to differ for crisis years and non-crisis years. Thus, this specification permits for two different population regression functions relating the saving ratio and the precautionary determinants, depending on the value of the crisis dummy. Hence, the parameter estimates for the interaction terms capture the difference in the effect of the precautionary determinants for crisis years and non-crisis years (Stock and Watson, 2015). The crisis dummy then still controls for the presence of a crisis (either recession, war or pandemic) and the interaction terms between crisis and the other independent variables denote wealth, uncertainty and credit availability in the presence of a crisis.

$$S_{it} = \beta_0 + \beta_1 wealth_{it} + \beta_2 uncertainty'_{it} + \beta_3 credit\ availability_{it} + \beta_4 wealth_{it} * crisis_t + \beta_5 uncertainty'_{it} * crisis_t + \beta_6 credit\ availability_{it} * crisis_t + \beta_7 crisis_t + \eta_i + \varepsilon_{it} \qquad (13)$$

Lastly, in order to see whether different forms of crisis have different impacts on the saving ratio, the same exercise is repeated with the different crisis dummies to disentangle the effects of the respective crisis types, i.e. recession, war and pandemic on the saving ratio.

5.4 Diagnostic Tests

Before running the various regression specifications, a few diagnostic tests are in order to assure consistent and unbiased estimates (Torres-Reyna, 2007).

Testing for Time Fixed Effects

Technically, time effects could be added to the country effects in order to get a time and country fixed effects model. By including time fixed effects, we can control for variables that are constant across country but vary over time. Time effects should especially be controlled for if there is reason to believe that unexpected variation or special events might affect the dependent variable (Torres-Reyna, 2007). A STATA test (testparm i.year) checks if the dummies for all years included are equal to zero (H0) and if they are (H0 holds), no time fixed effects are necessary to be included in the model. The test reveals a strong need for time fixed effects inclusion as we can confidently reject the null hypothesis (H0). Despite the result of the STATA test for time fixed effects, I choose not to include time fixed effects for the following reason: the employed crisis dummy does not exhibit any variation across countries, which is why there is strong reason to believe that the crisis dummy is close to collinear with year fixed effects, i.e. the time dummies. Thus, by additionally including the year fixed effects, I would expect my crisis dummy not to be able to capture enough variation in the outcome that happens over time which is why I restrain from using time fixed effects.

Testing for Cross-Sectional Dependence

Especially with macro panels that have long time periods (over 30 years), cross-sectional dependence might cause a bias in the estimates (Baltagi et al., 2012). Cross-sectional dependence is tested for using the Breusch-Pagan LM test of independence (1980) with the null hypothesis (H0) that residuals across countries are uncorrelated. Another option is to use the Pasaran CD test, with the null hypothesis (H0) that residuals are uncorrelated across countries. Both tests reveal significant p-values, which indicates cross-sectional dependence. As suggested by Hoechle (2007), this issue can be resolved by using Driscoll and Kraay (1998) standard errors. Hence, the regressions are run with using Driscoll and Kraay standard errors, which are robust to cross-sectional dependence.

Testing for Heteroskedasticity

Heteroskedasticity occurs when the variance of the error terms is non-constant, which violates the Gauss-Markov assumptions of OLS, even though it will not bias the coefficients (but the standard errors). A STATA test for heteroskedasticity (xttest3) is conducted by using the modified Wald test for groupwise (country-wise) heteroskedasticity in fixed effects regression models (Greene, 2000). The null hypothesis (H0) of the presence of homoskedasticity (constant variance) can be confidently rejected, indicating country-wise heteroskedasticity. The simplest solution to heteroskedasticity-robust error terms is to use the STATA command 'robust', which yields heteroskedasticity-robust standard errors. The aforementioned Driscoll and Kraay (1998) standard errors also do this job, which provides another rationale for employing Driscoll-Kraay standard errors.

Testing for Serial Correlation

Another issue that might arise with a long macro panel (over 30 years) is serial correlation - or autocorrelation - in the residuals, which does not pose a problem in micro panels with few time series. Serial correlation might prompt a higher R-squared as well as smaller standard errors of the coefficients, compared to their actual size. By using the LM test for serial correlation with the null hypothesis (H0) of no serial correlation, we cannot reject the null hypothesis for all variables, meaning that there is some serial correlation in the residuals. Again, this will be accounted for by using Driscoll-Kraay standard errors clustered by country, which allow for serial correlation of the error terms (Born and Breitung, 2016).

A brief note on the mentioned Driscoll and Kraay (1998) standard errors is in order. The error structure of the Driscoll-Kraay (DK) standard errors is perfectly suited to account for the three mentioned issues, i.e. heteroskedasticity, autocorrelation and cross-sectional dependence. DK standard errors can account for cross-sectional or 'spatial' as well as temporal dependence, especially when there is a long time series (large *t*). The number of panels is not restricted, but it is highly recommended to favor DK standard errors for balanced or unbalanced panels with smaller number of groups (small *n*) and longer time dimensions (large *t*), which suits the underlying panel dataset and complements the list of reasons for using DK standard errors in this analysis nicely.

6 Results

This section presents the main results obtained from the regression specifications outlined in section 5 and elaborates on various robustness checks of the model.

6.1 Main Results

Table 1 presents the baseline regressions where I first 'naïvely' check if the dummy variable crisis has an impact on the dependent variable, i.e. the private saving-to-income ratio (*SYratio*). Column (1) shows that there appears to be no significant effect of the crisis dummy on the saving ratio. It should however be noted that this constitutes a so-called "naïve regression" as solely the crisis dummy has explanatory power in determining the saving ratio. For that reason, the results of the first column should not be interpreted compared to specification (3), where the model determinants are combined with the crisis dummy.

In specification (2), I test the precautionary saving determinants, i.e. wealth, uncertainty and credit availability for their impact on the saving ratio. As expected from a precautionary savings model, almost all parameters show strongly significant coefficients (except for GDP volatility) and the signs are of the expected direction. The wealth-income ratio shows a negative and significant coefficient, which indicates that the "need to re-build precautionary wealth" drove up the saving ratio in the underlying sample. One of the proxies for uncertainty, i.e. stock market volatility shows a positive and statistically significant coefficient on the 99% significance level, which is expected from the precautionary saving motive. This is evidence that an increase in uncertainty (measured by stock market volatility) prompts individuals to increase their savings in order to buffer stock against negative income shocks in the future. Credit availability also seems to matter greatly in determining the saving ratio and decreases saving as the more credit becomes available or in other words, as the credit constraint becomes less binding.

In specification (3), the baseline model, I combine the precautionary model with the crisis dummy in order to see whether controlling for a crisis alters the model coefficients, i.e. whether there is an additional effect of crisis on the saving ratio which is not accounted for by the model determinants. As is evident from column (3), adding the crisis dummy to the precautionary model determinants does not change the model parameters greatly. In fact, controlling for a crisis does not seem to impact the explanatory power of the model determinants at all. When comparing columns (2) and (3), it becomes clear that the precautionary determinants, i.e. wealth, uncertainty and credit availability remain almost identical in sign, magnitude and significance as well as size of their standard errors.

For now, I can only conclude that the model remains surprisingly robust to controlling for crises via the dummy and the crisis dummy itself remains insignificant, thereby suggesting that there does not seem to be an additional effect of the crisis dummy on savings and that the precautionary determinants most likely account for any crisis effect themselves.

Table 1: Baseline Regressions - Crisis

DEPENDENT VARIABLE: *SYratio*	(1) only crisis	(2) only precautionary saving determinants	**(3) Baseline Model**
crisis	-0.0190		-0.0114
	(0.0170)		(0.0147)
WYratio		-0.0395***	-0.0391***
		(0.0107)	(0.0107)
gdpvolatility		-0.459	-0.486
		(0.309)	(0.318)
SMvolatility		0.219***	0.218***
		(0.0640)	(0.0630)
credit availability		-0.105***	-0.104***
		(0.0162)	(0.0160)
Constant	-0.0490***	0.0751	0.0811
	(0.0143)	(0.0486)	(0.0500)
Observations	582	582	582
Number of Country	9	9	9
R-squared	0.006	0.318	0.320

Driscoll-Kraay (DK) standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

In *Table 2*, I present the results of the same baseline regressions, but I distinguish between the different crisis types, i.e. recessions, wars and pandemics. Interestingly, when disentangling the previously used crisis dummy into its three types of crises, a different picture emerges. First, both the recession- as well as the war dummy show significant (however only on a 90% significance level) coefficients, but of opposing signs. The pandemic dummy remains insignificant. Again, these naïve regressions do not draw a clear picture of the true effect of crisis years on the saving ratio as they are the only explanatory variables in the first three columns. Second, when combining the precautionary determinants with the different crisis dummies, the model again remains surprisingly robust to controlling for the recessions, wars and pandemics. The model parameters only marginally change in magnitude and can all maintain their significance and signs. It seems that the precautionary determinants cannot account for the impact of recessions and wars, given that those dummy variables remain highly significant in columns (5) and (6), and given that the pandemic dummy already did not show any significant impact on the saving ratio in the naïve regression of column (3), the model coefficients in column (7) remain almost exactly the same as compared to specification (4). This means that adding or not adding the crisis dummies to the precautionary model does not make a difference for the impact of the model determinants on savings. When taking a closer look at the different crisis types and their signs and significance levels and comparing them to the previous *Table 1* result, where the crisis dummy remained insignificant, one could argue that the apparent significant impacts of recessions and wars, which are of opposing signs, cancel each other out, yielding the insignificant and slightly negative crisis dummy in *Table 1.* Put differently, it could be the case that the negative recession effect and the positive war effect on savings cancel each other out and when combined with the insignificant pandemic dummy into the full crisis dummy, none of the crisis types has a strong enough impact to produce a significant crisis dummy. Lastly, in specification (8), I use all three crisis types jointly in the same regression, instead of including them one by one into the regression. The recession coefficient turns insignificant in this combined specification, but the magnitude remains roughly the same. War periods still significantly increase savings and pandemics remain insignificant, just as before. Again, the other model determinants do not change much in sign, significance and magnitude, which once again strengthens the proposed model along with the hypothesis that the model can account for any form of crisis effects that act through the precautionary variables on savings.

How do these findings compare to the literature? For recessions, my findings very much contradict the findings of previous empirical investigations (e.g. Mody et al., 2012; Carroll et al., 2012). Against all expectations, my recession coefficient is mostly negative, which would indicate that recessions actually decrease rather than increase saving ratios. There are two possible explanations for this finding: First, and most likely, my data is unable to capture any crisis effects and the mentioned 'cancelling-out' effect of negative recession impacts and positive war effects in the underlying data yields non-reliable findings for any seemingly significant crisis effect. Thus, the significant coefficients for recessions might simply be an artefact of the underlying dataset. Second, there is one theoretical rationale that could explain a negative effect of recessions on saving ratios, namely the so-called 'Samaritan's Dilemma' (Berlemann et al., 2015). During disasters and thus also throughout recession episodes, governments and other state institutions provide financial compensation and aid, which motivates 'crisis-affected' individuals to reduce their precautionary savings (Lusardi, 1998). Then, moral hazard effects might swoop in and if financial compensation is granted, individuals reduce their precautionary savings because of the provided support, which constitutes the essence of the Samaritan's Dilemma (Buchanan, 1975; Coate, 1995), also named the 'Charity Hazard' (Raschky and Weck-Hannemann, 2007). It might also be the case that individuals are somehow 'forced' to reduce their savings during recessions as they experience negative income shocks. However, empirical evidence for this phenomenon is scarce and it might as well apply for wars and pandemics (if not even more so than for recessions). Thus, this theoretically convenient explanation does not have much relevance in the practical application of this analysis.

Table 2: Baseline Regressions - Types of Crisis

DEPENDENT VARIABLE: *SYratio*	(1) only recession	(2) only war	(3) only pandemic	(4) only precautionary saving determinants	**(5) Baseline Model recession**	**(6) Baseline Model war**	**(7) Baseline Model pandemic**	**(8) Baseline Model (3 crisis types)**
recession	-0.0349*				-0.0286*			-0.0247
	(0.0182)				(0.0160)			(0.0154)
war		0.0815*				0.102**		0.0942**
		(0.0470)				(0.0447)		(0.0450)
pandemic			-0.0169				-0.00401	-0.00136
			(0.0253)				(0.0221)	(0.0212)
WYratio				-0.0395***	-0.0363***	-0.0387***	-0.0395***	-0.0360***
				(0.0107)	(0.0107)	(0.0105)	(0.0108)	(0.0106)
gdpvolatility				-0.459	-0.593*	-0.556*	-0.444	-0.659**
				(0.309)	(0.332)	(0.324)	(0.297)	(0.312)
SMvolatility				0.219***	0.233***	0.235***	0.217***	0.246***
				(0.0640)	(0.0629)	(0.0652)	(0.0654)	(0.0655)
credit availability				-0.105***	-0.104***	-0.105***	-0.105***	-0.105***
				(0.0162)	(0.0159)	(0.0162)	(0.0163)	(0.0159)
Constant	-0.0436***	-0.0623***	-0.0574***	0.0751	0.0765	0.0680	0.0754	0.0698
	(0.0125)	(0.0117)	(0.0112)	(0.0486)	(0.0499)	(0.0487)	(0.0500)	(0.0507)
Observations	582	582	582	582	582	582	582	582
Number of Country	9	9	9	9	9	9	9	9
R-squared	0.022	0.015	0.003	0.318	0.332	0.341	0.318	0.351

Driscoll-Kraay (DK) standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

As for war periods, my findings seem to be in line with the very limited literature on precautionary savings throughout war episodes (e.g. Challe and Ragot, 2016; Barro and Ursúa, 2008). Wars exhibit positive and sometimes highly significant coefficients in my analysis, which confirms the expectations: war periods fuel greater precautionary saving motives.

Lastly, pandemics remain mostly insignificant throughout my whole analysis. Novel research by e.g. Dietrich et al. (2020) or Jordà et al. (2020) suggests great pandemic-induced increases in uncertainty, which ultimately leads to a rise in precautionary savings. My analysis cannot confirm these findings. However, it should be noted that one of the biggest pandemics in my dataset, i.e. the Great Influenza Epidemic, coincided with World War I. Thus, some of the pandemic effects are likely soaked up by the war effects.

Next, I consider interaction terms in the model, i.e. I interact all control variables with the crisis dummy as well as with the three crisis types in order to see if the interaction between the various control variables with the crisis dummies yield different results as compared to only controlling for the presence of a crisis or a specific type of crisis. It can be useful to include an interaction term to the model if one wants to test the hypothesis that the relationship between the precautionary determinants (wealth, uncertainty, credit availability) differs between crisis years and non-crisis years. Then, if a significant interaction term appears, the effect of e.g. wealth on savings is different for crisis versus non-crisis years. By including interactions of the model determinants with the crisis dummy, I specifically control for those determinants in years of crisis, i.e. for the mechanism that wealth, uncertainty and credit availability in crisis episodes affect savings. The results are presented in *Table 3*.

Table 3: Interaction Terms

DEPENDENT VARIABLE: *SYratio*	(1) crisis	(2) recession	(3) war	(4) pandemic
crisis/type of crisis	-0.0681	-0.132*	0.137	-0.163***
	(0.0669)	(0.0780)	(0.300)	(0.0597)
WYratio	-0.0429***	-0.0420***	-0.0385***	-0.0425***
	(0.0111)	(0.0104)	(0.0109)	(0.0103)
gdpvolatility	-0.597*	-0.581**	-0.449	-0.682**
	(0.342)	(0.274)	(0.329)	(0.338)
SMvolatility	0.191***	0.175***	0.236***	0.181***
	(0.0699)	(0.0629)	(0.0672)	(0.0583)
credit availability	-0.102***	-0.108***	-0.105***	-0.110***
	(0.0155)	(0.0167)	(0.0158)	(0.0187)
*WYratio*crisis/type of crisis*	0.00734	0.0143	0.0277	0.00313
	(0.0106)	(0.0104)	(0.0725)	(0.0113)
gdpvolatility crisis/type of crisis	0.332	0.0800	-1.851	0.710
	(0.622)	(0.818)	(1.431)	(0.610)
SMvolatility crisis/type of crisis*	0.0766	0.180	-0.572	0.558***
	(0.143)	(0.161)	(0.491)	(0.131)
credit availability crisis/type of crisis*	-0.00342	0.00998	0.0130	0.00847
	(0.0164)	(0.0177)	(0.0363)	(0.0178)
Constant	0.105**	0.111***	0.0635	0.105**
	(0.0453)	(0.0405)	(0.0518)	(0.0410)
Observations	582	582	582	582
Number of Country	9	9	9	9
R-squared	0.324	0.341	0.348	0.351

DK standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

The first thing that becomes evident is that regardless of the crisis type, almost all interaction terms remain insignificant (except for stock market volatility in pandemics). The wealth-income ratio, stock market volatility and credit availability all exhibit the expected signs and are statistically significant. GDP volatility seems to be of negative significance in three of the four specifications, which is most likely a statistical artefact of the volatility measure (also note the higher standard errors for this variable). Again, the coefficients of the precautionary determinants barely change in magnitude, sign or significance and seem to remain robust to adding both interaction terms as well as the respective crisis dummy variables. One main difference to the results in *Table 2*, where the model was estimated without any interaction terms, is the significance of the dummy variables. While the full crisis dummy remains slightly negative and statistically insignificant and the recession dummy again shows a slight negative and significant impact, the war and the pandemic dummy are both subject to some changes. The war dummy loses its significance but remains positive, while the pandemic dummy now shows a strongly significant and negative coefficient. In general, this would suggest that being in a recession and in a pandemic has an additional effect on the saving ratio, which cannot be accounted for by neither the precautionary determinants nor by the interaction terms. Naturally, adding interaction terms changes the interpretation of the other coefficients as well. In the absence of the interaction terms, the β_1 wealth coefficient in column (1) would represent the sole effect of wealth on savings. Adding the interaction term means that the effect of wealth on savings is different for different values of the crisis dummy. Thus, the effect of wealth is then represented by $\beta_1 + \beta_4 * crisis$. Only when $crisis = 0$, then β_1 can be interpreted as the unique effect of wealth on savings. The effect of crisis is then $\beta_7 + \beta_4 * wealth$, which is different at any value of wealth.

The interpretation of the included variables is demonstrated with the example of wealth; however, all other variables can be interpreted accordingly. The wealth coefficient is negative and statistically significant, which means that the hypothesis that decreased wealth leads to more savings holds, all else equal. The crisis coefficient is negative, but statistically insignificant, which indicates that we can´t rule out the possibility that the coefficient on crisis is really zero. Thus, we could reject any hypothesis that says that crisis episodes increase savings more than non-crisis episodes. Lastly, the interaction coefficient is positive, but insignificant. This tells us that we cannot accept the hypothesis that wealth has a stronger negative effect on savings in crisis years compared to non-crisis years.

As mentioned, distinguishing between crisis types does slightly change the interpretation of the crisis dummies. In column (2) for example, where I focus on recessions, the recession dummy is slightly significant and negative, which would indicate that we actually cannot reject the hypothesis that recessions *decrease* savings more than years without recessions. The same interpretation follows from column (4), where we look at pandemics. For the full crisis dummy as well as the war dummy, the main result holds: we can reject the hypothesis that crises in general and specifically wars increase or decrease savings more than non-crisis or non-war periods. The interpretations of the precautionary determinants also remain the same: wealth and credit availability exhibit the expected negative impacts on the saving ratio while uncertainty has a positive effect on savings, all else equal. This only strengthens the proposed model and the hypothesis that the model can fully account for any crisis effects that act through the precautionary variables on savings.

6.2 Robustness Checks

In this section, I employ various robustness checks, such as presenting additional controls, alternative variables and dummy variables as well as running a dynamic fixed effect regression. The respective results of the robustness checks are presented in *Appendix A*.

6.2.1 Adding Additional Controls – Augmented Model

In this robustness check, a vector X'_{it} of control variables is being employed in the analysis in order to check how the model reacts to the additions of control variables and to see if the signs of the additional controls are in accordance to the expected signs. The results of the augmented models are presented in *Table 4*.

In the odd-numbered columns (1), (3), (5) and (7), the respective baseline models for crisis and the three crisis types are presented specifically for the same sample of observations to facilitate comparability. The even-numbered columns (2), (4), (6), (8) and additionally column (9) depict the baseline models augmented by three additional control variables, i.e. inflation, GDP per capita growth and housing prices. When comparing column (1) and (2), i.e. comparing the more restricted model with the augmented model, a few things become evident.

Table 4: Adding Additional Controls - Augmented Model

DEPENDENT VARIABLE: *SYratio*	(1) Baseline Model *crisis*	(2) Augmented Model *crisis*	(3) Baseline Model *recession*	(4) Augmented Model *recession*	(5) Baseline Model *war*	(6) Augmented Model *war*	(7) Baseline Model *pandemic*	(8) Augmented Model *pandemic*	(9) Augmented Model (3 crisis types)
crisis	-0.00394	-0.0112							
	(0.0139)	(0.0121)							
recession			-0.00859	-0.0233*					-0.0231*
			(0.0141)	(0.0119)					(0.0118)
war					-0.0136	-0.00177			-0.00753
					(0.0480)	(0.0515)			(0.0500)
pandemic							0.0141	0.0129	0.0117
							(0.0161)	(0.0195)	(0.0176)
WYratio	-0.0392***	-0.0655***	-0.0385***	-0.0651***	-0.0392***	-0.0651***	-0.0391***	-0.0650***	-0.0646***
	(0.0107)	(0.00628)	(0.0107)	(0.00595)	(0.0107)	(0.00631)	(0.0101)	(0.00620)	(0.00586)
gdpvolatility	-0.337	0.488	-0.365	0.449	-0.318	0.492	-0.396	0.431	0.397
	(0.385)	(0.348)	(0.393)	(0.347)	(0.406)	(0.358)	(0.391)	(0.373)	(0.364)
SMvolatility	0.263***	0.0872**	0.268***	0.0954**	0.261***	0.0864**	0.263***	0.0874**	0.0955**
	(0.0755)	(0.0385)	(0.0771)	(0.0367)	(0.0749)	(0.0419)	(0.0726)	(0.0398)	(0.0371)
credit availability	-0.145***	-0.120***	-0.145***	-0.118***	-0.146***	-0.122***	-0.147***	-0.123***	-0.119***
	(0.0229)	(0.0175)	(0.0229)	(0.0177)	(0.0233)	(0.0174)	(0.0235)	(0.0177)	(0.0181)
inflation		0.211		0.187		0.215		0.213	0.196
		(0.173)		(0.176)		(0.192)		(0.171)	(0.196)
GDP per capita growth		0.00397***		0.00379***		0.00422***		0.00436***	0.00390***
		(0.00144)		(0.00141)		(0.00152)		(0.00152)	(0.00140)
housing prices		0.00186***		0.00191***		0.00184***		0.00184***	0.00191***
		(0.000224)		(0.000218)		(0.000226)		(0.000228)	(0.000220)
Constant	0.0624	0.0903***	0.0612	0.0917***	0.0605	0.0834**	0.0606	0.0831***	0.0902***
	(0.0495)	(0.0324)	(0.0502)	(0.0310)	(0.0495)	(0.0323)	(0.0469)	(0.0315)	(0.0302)
Observations	439	439	439	439	439	439	439	439	439
Number of Country	9	9	9	9	9	9	9	9	9
R-squared	0.475	0.639	0.476	0.645	0.475	0.637	0.476	0.639	0.646

Driscoll-Kraay (DK) standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

The crisis dummy remains insignificant but becomes slightly more negative. The wealth-income ratio remains highly significant on a 99% level and the wealth effect in the augmented model is even more negative. The coefficient on GDP volatility remains insignificant in the augmented model but turns positive (note however the large standard errors). Stock market volatility exhibits a strongly positive effect on the saving ratio in the baseline model, and this effect decreases both in magnitude and significance in the augmented model – yet, it remains positive and significant on a 95% level. The credit availability coefficient only changes marginally in size and remains strongly negative. Out of the added control variables, only GDP per capita growth and housing prices seem to have a strong, but small positive effect on the saving ratio, whereas inflation does not exhibit a significant coefficient. GDP per capita growth does exhibit the expected positive sign, but housing prices display a (however small) positive effect on savings, which is not in accordance with the expectation or the findings of previous literature.

Moving on to the disentangled crisis types, the three crisis type dummies in the baseline regressions of columns (3), (5) and (7) are all insignificant. When adding the set of controls, we observe a slight change in the crisis dummies in magnitude, but solely the recession dummy actually turns slightly significant on a 90% level when adding the control variables in column (4). The stock market volatility variable, GDP per capita growth and housing prices all exhibit positive and significant effects on the saving ratio. The positive effect of stock market volatility is in line with the expectations from a precautionary savings model. Likewise, GDP per capita growth was expected to have a positive impact on savings, which is also in line with other empirical findings (e.g.

Loayza et al., 2000). A negative and significant effect is obtained from the wealth-income ratio as well as credit availability, which are both findings in line with the expectations. Non-significant results are observed from GDP volatility as well as inflation. Given that both GDP volatility and inflation are considered uncertainty measures, their non-significance could be explained by the very significant effect of stock market volatility, which could already ‘soak up’ the uncertainty effect and by including both GDP volatility as well as inflation (proxy for price uncertainty), I could be overcontrolling for uncertainty.

Overall, the effects of the precautionary determinants on the savings ratio seem to be robust (both in size and significance) to applying the augmented regression model with additional controls. This is further confirmed when looking at specification (9), where all three crisis types are included jointly in the augmented model. The coefficients of the respective crisis forms - recessions, wars and pandemics - are almost the same as compared to the specifications of the augmented model where they are included separately.

6.2.2 Alternative to Wealth

One major caveat of the underlying dataset is that the wealth-to-income ratio (*WYratio*) is only available for a panel of nine countries, whereas most other variables are available for the whole set of 17 advanced economies. Thus, I run a robustness check where I present an alternative variable for wealth which is offered by the *JST-RORE database*, namely the private investment-to-GDP ratio (*IYratio*). The rationale why the private investment-to-GDP ratio might be a good alternative to wealth is as follows: private wealth is usually assumed to be positively correlated with private investments and thus, also with consumption (Greenwald et al., 1984) meaning that we would expect a negative impact on the saving ratio (Guillemette et al., 2018). Boldly said, with higher wealth concentration, there will be more investment, which would impact the saving ratio negatively, theoretically. For this robustness check, I replace the private wealth-to-income ratio (*WYratio*) with the private investment-to-GDP ratio (*IYratio*) and re-run the regression specifications presented in section 5 for a panel of 15 countries. *Tables G.1-G.3*, which present the results are enclosed in *Appendix A*.

When testing the alternative specification with the private investment-to-income ratio instead of wealth-to-income, it first becomes evident that – against all expectations – the investment-to-income ratio seems to impact the savings ratio positively and strongly significantly so. This fact does not change throughout the process of applying different specifications. Regardless of only estimating the precautionary determinants on the saving ratio, including or not including the crisis dummy, or even disentangling the crisis dummy into its three components, the investment-to-income ratio always remains positive and strongly significant. Again, the other model determinants (which are the same as in the main analysis) remain quite robust in terms of significance, sign and also magnitude. The only exception is GDP volatility, which now has an even stronger negative impact on the saving ratio than it had before. Note however, that it is not wise to directly compare two samples of such differing sizes. It might well be the case that the results found in this robustness check are entirely driven by the additional countries included. Thus, it only gives a vague idea of how well this change of variable really plays into the model results.

When inspecting the crisis dummy and its three components though, it is nice to see a similar pattern as in all the previously specifications. The crisis dummy of the baseline model is insignificant and slightly negative, which indicates, again, that we cannot rule out the possibility that the coefficient on crisis is really zero. Thus, we could reject any hypothesis that says that crisis episodes increase savings more than non-crisis episodes. When distinguishing between the crisis types, again a highly negatively significant recession dummy paired with a highly positively significant war dummy could be cancelling each other out, yielding the slightly negative or almost zero combined crisis dummy.

Finally, when adding interaction terms, the same result emerges as before: the interaction coefficients remain mostly insignificant (except for war-type crises). This tells us that we cannot accept the hypothesis that any of the precautionary determinants has a stronger effect on savings in crisis years compared to non-crisis years. The sole exception here are war years: here, the interaction terms are strongly significant for the war interactions with the investment-to-GDP ratio and for stock market volatility. In this specification, investment seems to have a stronger negative effect on savings in war years compared to non-war years and stock market volatility affects saving in war years strongly, but negatively which would mean that less uncertainty on stock markets increases savings more in war years.

6.2.3 Dynamic Fixed Effects

As another robustness check, I estimate a dynamic panel FE regression, i.e. a dynamic saving equation with fixed effects where the private saving ratio is regressed on the lagged saving ratio (*SYratio* at time t-1), meaning that the fixed effects in this regression specification are correlated with the lag of the saving ratio by construction (Bun and Sarafidis, 2015). The reason I estimate a dynamic fixed effects regression is that the saving rate is assumed to be persistent, or sticky, so the coefficient might be inflated and yield different results than the 'normal' FE model. One caveat of dynamic panel FE regressions is that there might be a bias if the number of time dimension (years) is not big enough compared to the number of cross sections (countries). However, given that the time dimension is quite large, dynamic bias does not seem to be an issue in this case (Nickell, 1981). Likewise, if it weren't for the large time dimension of this analysis, the switch to a dynamic estimation would have most likely required a change of methodology (e.g. employing a GMM estimator). However, the large number of years in my analysis again saves me from further complications and I can use the fixed effects estimation even with a dynamic panel.

The results of the dynamic fixed effects saving regression are presented in *Table H* in *Appendix A*. First, we notice that the lagged saving ratio shows – as expected – a positive and statistically significant impact on the saving rate. The coefficient is of substantial magnitude, which points towards a high degree of persistence of the saving rate and a high level of explanatory power of the lagged saving ratio for the dependent variable. However, when turning to specifications (2) and (3), it is evident that the proposed model seems to be non-robust to the dynamic version. All driving factors of the saving ratio (wealth, uncertainty, credit availability) remain insignificant, both with and without the inclusion of the crisis dummy, which means the main model collapses in the dynamic set-up and therefore does not pass this robustness check.

6.2.4 Alternative Crisis Dummy Variables

As a last robustness check, I employ two alternative crisis dummies from different data sources, namely the '*disaster*' dummy by Nakamura et al. (2013) as well as the consumption and GDP disaster dummy variables by Barro and Ursúa (2008), *Cdisaster* and *GDPdisaster,* to see how they compare to my self-constructed crisis dummy. The respective alternative dummy variables simply replace the self-constructed and previously employed *crisis* dummy. Recall that the disaster dummy by Nakamura et al. (2013) comprises a time span of over more than 100 years and that a disaster episode is defined as "a set of consecutive years for a particular country such that (i) the probability of a disaster in each of the years is larger than 10 percent, and (ii) the sum of the probability of disaster for each year over the whole set of years is larger than one". Barro and Ursúa (2008) engage in a peak-to-trough method, where cumulative declines in Consumption or GDP of at least 10 percent disentangle a crisis period. Those crisis periods are coded as *Cdisaster* and *GDPdisaster* respectively. The results are presented in *Tables I, J* and *K* in *Appendix A*.

First, I look at the disaster dummy constructed by Nakamura et al. (2013). Direct comparability of *Table I* with *Table 1* of my analysis is given, since the sample sizes are the same. The *disaster* dummy itself is insignificant and slightly negative, just like my own *crisis* dummy in *Table 1*, column (1). To be precise, the magnitudes of the coefficients of the disaster dummy versus the crisis dummy are actually quite similar. Once the precautionary determinants, wealth, uncertainty and credit availability are added to the specification in column (2), we observe very familiar results compared to the baseline regressions. While the disaster dummy remains insignificant, the model determinants yield almost the exact same coefficients as compared to the baseline results in *Table 1*. Adding interaction terms in column (3) does not alter the coefficients much and all interaction terms, except for the one with stock market volatility, remain insignificant. The disaster dummy in the model specification with interaction terms also remains insignificant but becomes more negative. Overall, I can safely say that my model remains robust to the *disaster* dummy by Nakamura et al. (2013) and yields very similar model coefficients compared to my baseline model. Thus, the model passes this robustness check.

Next, I consider consumption disasters (*Cdisaster*) as defined by Barro and Ursúa (2008). When looking at the results depicted in *Table J*, a slightly different picture emerges. The consumption disaster dummy is still insignificant in the naïve regression, but slightly positive (however with a rather big standard error). Adding the model determinants once again confirms the robustness of the baseline regression model, as wealth, uncertainty and credit availability yield very similar results compared to *Table 1* in terms of magnitude and significance. When adding interaction terms, the consumption disaster dummy becomes negative and significant on a 90% confidence level and the interaction between wealth and the consumption disaster is strongly significant and positive. The negative and significant consumption disaster dummy indicates that we cannot reject the hypothesis that consumption disasters *decrease* savings more than years without consumption disasters. The positive and significant interaction term of wealth and consumption disasters tells us that we actually could accept the hypothesis that wealth has a stronger positive effect on savings during consumption disaster years compared to non-consumption disaster years. Overall, this robustness check yields results of the model parameters which are in line with the baseline regressions. However, adding interaction terms produces ambiguous implications for the relationship between consumption disasters and wealth.

As a last robustness check, I employ a dummy variable for GDP disasters constructed by Barro and Ursúa (2008). The results are shown in *Table K* in *Appendix A*. The GDP disaster dummy itself is insignificant and slightly negative, comparable to my own crisis dummy in *Table 1*, column (1). Again, the magnitudes of the coefficients of the GDP disaster dummy versus the crisis dummy are actually quite similar. Once wealth, uncertainty and credit availability are added to the specification in column (2), similar results compared to the baseline regressions emerge. While the GDP disaster dummy remains insignificant, yet becomes slightly less negative, the model determinants yield almost the exact same coefficients as compared to the baseline results in *Table 1*. Adding interaction terms in column (3) does not alter the coefficients much. This time, however, we observe two significant interaction terms, i.e. a positive interaction with wealth and a negative interaction with stock market volatility. The positive and significant interaction term of wealth and GDP disasters tells us that we could accept the hypothesis that wealth has a stronger positive effect on savings during GDP disaster years compared to non-GDP disaster years. Likewise, the negative interaction with stock market volatility indicates that stock market volatility or uncertainty has a stronger negative effect on savings during GDP disaster years compared to non-GDP disaster years. The disaster dummy in the model specification with interaction terms also remains insignificant but becomes more negative, which means we cannot accept the hypothesis that GDP disaster episodes increase or decrease savings more than non-GDP disaster episodes. Overall, I once again claim that my model remains robust to the GDP dummy by Barro and Ursúa (2008) and yields sufficiently similar model coefficients compared to my baseline model. Thus, employing this alternative dummy variable also passes the robustness check.

6.3 Limitations

A last, brief note on some limitations of the underlying thesis is in order. First, and most obviously, missing observations for several years and countries pose a major caveat to the power of the analysis. Out of data for 17 advanced economies, I am only able to estimate most of my regressions for nine countries on a substantially collapsed sample size due to missing data.

Second, one of the main challenges remaining is how to best measure or approximate uncertainty, in order to assess its impact on consumption and savings decisions. As the dataset does not provide the most commonly used uncertainty measure, i.e. unemployment rates, and which are also not available for such long time series in general, I was forced to construct two uncertainty measures, namely the GDP and stock market volatility. Even though carefully estimated, those variables might still not serve as 'perfect' proxies for uncertainty, because they might not be able to reflect uncertainty fluctuations that drive up the precautionary savings motive that well compared to unemployment rates.

Third, I estimate a macro model which is based on very micro-founded assumptions. While a macro model can provide some clues on the relationship between my aggregate variables (wealth, uncertainty, credit availability) and the savings ratio, it fails to capture differences across individuals, for instance wealth differences, which might affect an individual's propensity to consume or save (also noted by Carroll, 2012). Thus, studies conducted on the micro level can better capture individual consumption and saving decisions.

As regards future research, dynamic effects in analyzing precautionary savings should be given some attention. Given my model is not robust to the dynamic set-up, time effects seem to play a role, which has not been properly investigated or considered in previous studies.

7 Conclusion

The aim of this thesis was to investigate precautionary savings in different types of crisis, whether crisis years and different forms of crises have an additional impact on the saving ratio (other than through the model determinants) and whether the precautionary saving determinants, i.e. less wealth, more uncertainty and less credit availability indeed drive up the saving rate in periods of crisis. I can conclude with confidence that the precautionary saving model holds throughout most specifications and passes several robustness checks. The results confirm the precautionary savings theory: wealth, uncertainty and credit availability are able to capture any crisis effect and there appears to be no additional crisis effect for the combined crisis dummy. With regards to differentiating between different forms of crisis, there seem to be additional effects of recessions and wars at work (while pandemics do not seem to have any impact on savings), but these results need to be considered with a grain of salt. I claim that the respective effects cancel each other out when combined, which means that an overall crisis effect cannot be detected in the underlying dataset. The fact that the precautionary determinants remain surprisingly robust throughout most specifications supports this claim. Adding interaction terms of the respective crisis types and the precautionary determinants yields the following conclusion: for the full crisis dummy as well as the war dummy, the main result holds, i.e. the hypothesis that crises in general and specifically wars increase savings more than non-crisis or non-war periods can be rejected. In other words, this strengthens the proposed model and the hypothesis that the model can fully account for any crisis effects that act through the precautionary variables on savings. Nevertheless, the results need to be interpreted with caution due to the aforementioned limitations and given that my model collapses in the dynamic set-up. Therefore, future research should give dynamic effects more attention as they might play a major and so far, unconsidered role in determining precautionary savings.

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APPENDIX

A. TABLES

Table A: Data sources and time periods

Country	**Database**	**Time Period**
Australia	JST-RORE	1870-2016
	PZ	1960-2011
Belgium	JST-RORE	1870-2016
Canada	JST-RORE	1870-2016
	PZ	1970-2011
Denmark	JST-RORE	1870-2016
Finland	JST-RORE	1870-2016
France	JST-RORE	1870-2016
	PZ	1870-2010
Germany	JST-RORE	1870-2016
	PZ	1870-2011
Italy	JST-RORE	1870-2016
	PZ	1966-2011
Japan	JST-RORE	1870-2016
	PZ	1970-2010
Netherlands	JST-RORE	1870-2016
Norway	JST-RORE	1870-2016
Portugal	JST-RORE	1870-2016
Spain	JST-RORE	1870-2016
	PZ	1987-2010
Sweden	JST-RORE	1870-2016
	SNWD	1870-2016
Switzerland	JST-RORE	1870-2016
UK	JST-RORE	1870-2016
	PZ	1870-2011
USA	JST-RORE	1870-2016
	PZ	1870-2010

Table B: Variable description

Variable	Description	Data source
rgdppc	Real GDP per capita (index, 2006=100)	JST-RORE
rconpc	Real (private) consumption per capita (index, 2006=100)	JST-RORE
CYratio	consumption-income (GDP) ratio	JST-RORE
SYratio	(private) saving-income (GDP) ratio	JST-RORE
WYratio	private wealth-national income ratio	PZ & SNWD
realygrowth	growth rate of real GDP per capita	JST-RORE
realcgrowth	growth rate of real consumption per capita	JST-RORE
credit availability	growth rate of total loans to households	JST-RORE
ROE	total return on equity	RORE
SMvolatility	stock market volatility proxied by volatility of total equity returns, own calculations	RORE
inflation	yearly inflation rate per country	RORE
gdpvolatility	GDP volatility as proxy for (general) uncertainty, own calculations	JST-RORE
housing prices	growth rate of house prices	RORE
IYratio	investment-to-GDP ratio	JST-RORE
crisis	crisis dummy, own calculations	
recession	recession dummy, own calculations	
war	war dummy, own calculations	
pandemic	pandemic dummy, own calculations	
disaster	disaster dummy	Nakamura et al. (2013)
Cdisaster	consumption disaster dummy	Barro and Ursúa (2008)
GDPdisaster	GDP disaster dummy	Barro and Ursúa (2008)

Table C: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
rgdppc	2,499	36.94145	31.38634	3.219438	113.3195
rconpc	2,411	40.04322	30.86085	4.0744	115.4359
CYratio	2,411	1.148271	.2254981	.3942916	2.116768
SYratio	2,411	-.1482706	.2254981	-1.116768	.6057084
WYratio	918	4.156775	1.512032	1.54	7.92
realygrowth	2,482	1.773839	5.395514	-108.072	51.37289
realcgrowth	2,394	1.612109	5.629336	-52.80754	44.77818
creditgrowth	1,290	.0946775	.0904049	-.3564961	.7151065
ROE	2,181	.108909	.2305529	-.8841469	1.670378
SMvolatility	2,205	.2231032	.1327074	.0341257	1.364539
inflation	2,312	.0394934	.094059	-.3767606	.969541
gdpvolatility	2,499	.0469162	.0636676	.0065185	2.111418
housing prices	1,597	23.54413	38.4225	-1	176.9102
IYratio	2,279	.1862891	.0640229	.0172873	.3888761

Table D: Crisis episodes dummy variables (self-constructed)

Crisis type	Start year	End year
War		
World War I	1914	1918
World War II	1939	1945
Pandemic		
Cholera outbreak	1881	1886
Flu pandemic	1889	1890
Spanish Flu (the Great Influenza)	1918	1919
Asian Flu	1957	1958
Hong Kong Flu	1968	1972
Swine Flu	2009	2010
Recession		
Long Depression	1873	1896
Panic of 1901 (economic recession)	1901	1901
Panic of 1907 (economic recession)	1907	1907
Depression following end of WWI	1920	1921
Great Depression	1929	1939
OPEC oil price shock	1973	1973
Secondary banking crisis (UK)	1973	1975
Energy crisis	1979	1979
Japanese asset price bubble	1986	1992
Black Monday (US)	1987	1987
Saving and loan crisis	1986	1995
Finnish banking crisis	1990	1993
Swedish banking crisis	1990	1994
Asian financial crisis	1997	1997
Russian financial crisis	1998	1998
Dot-com bubble	2000	2002
9/11 attacks (US)	2001	2001
Great Recession	2007	2009
Oil price bubble (energy crisis)	2003	2009
Subprime mortgage crisis (US)	2007	2010

Table E: Disaster episodes (Nakamura et al., 2013)

Country	**Start year**	**End year**
Australia	1914	1923
	1930	1934
	1939	1956
Belgium	1913	1920
	1939	1950
Canada	1914	1926
	1930	1933
Denmark	1914	1926
	1940	1950
Finland	1890	1893
	1914	1921
	1930	1934
	1940	1945
France	1914	1921
	1940	1945
Germany	1914	1932
	1940	1950
Italy	1940	1949
Japan	1914	1918
	1940	1952
Netherlands	1914	1919
	1940	1952
Norway	1914	1924
	1940	1944
Portugal	1914	1921
	1940	1942
Spain	1914	1919
	1930	1961
Sweden	1914	1923
	1940	1951
Switzerland	1914	1921
	1940	1950
UK	1914	1921
	1940	1946
USA	1914	1922
	1930	1935

Table F: Consumption and GDP disasters (Barro and Ursúa, 2008)

	Consumption disasters		GDP disasters	
Country	**Peak**	**Trough**	**Peak**	**Trough**
Australia	1913	1918	1889	1895
	1927	1932	1910	1918
	1938	1944	1926	1931
			1943	1946
Belgium	1913	1917	1913	1918
	1937	1942	1930	1934
			1937	1943
Canada	1873	1876	1874	1878
	1906	1908	1917	1921
	1912	1915	1928	1933
	1918	1921		
	1929	1933		
Denmark	1919	1921	1914	1918
	1939	1941	1939	1941
	1946	1948		
Finland	1890	1893	1876	1881
	1913	1918	1913	1918
	1928	1932	1938	1940
	1938	1944	1989	1993
	1989	1993		
France	1864	1871	1868	1870
	1912	1915	1874	1897
	1938	1943	1882	1886
			1912	1918
			1929	1935
			1939	1944
Germany	1912	1918	1913	1919
	1922	1923	1922	1923
	1928	1932	1928	1932
	1939	1945	1943	1946
Italy	1939	1945	1918	1920
			1939	1945
Japan	1937	1945	1940	1944
Netherlands	1889	1893	1913	1918
	1912	1918	1929	1934
	1939	1944	1939	1944
Norway	1916	1921	1916	1918
	1939	1944	1920	1921
			1939	1944
Portugal	1913	1919	1927	1928
	1934	1936	1934	1936
	1939	1942		

	1974	1976		
Spain	1892	1896	1892	1896
	1913	1915	1929	1933
	1929	1930	1935	1938
	1935	1937		
	1940	1945		
	1945	1949		
Sweden	1913	1917	1916	1918
	1920	1921	1920	1921
	1939	1945	1939	1941
Switzerland	1870	1872	1875	1879
	1876	1878	1912	1918
	1881	1883	1939	1942
	1885	1886		
	1887	1888		
	1912	1918		
	1939	1945		
UK	1915	1918	1918	1921
	1938	1943	1943	1947
USA	1917	1921	1906	1908
	1929	1933	1913	1914
			1918	1921
			1929	1933
			1944	1947

Table G.1: Alternative Wealth – Baseline Model

DEPENDENT VARIABLE: *SYratio*	(1) only crisis	(2) only precautionary saving determinants	**(3) Baseline Model**
crisis	-0.00774		-0.0128
	(0.0179)		(0.0125)
IYratio		0.817***	0.811***
		(0.221)	(0.222)
gdpvolatility		-0.864**	-0.879**
		(0.350)	(0.349)
SMvolatility		0.267***	0.270***
		(0.0528)	(0.0517)
credit availability		-0.0728***	-0.0736***
		(0.0181)	(0.0179)
Constant	-0.0686***	-0.258***	-0.250***
	(0.0127)	(0.0464)	(0.0450)
Observations	1,170	1,170	1,170
Number of Country	15	15	15
R-squared	0.001	0.280	0.282

DK standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table G.2: Alternative Wealth - Baseline Models – Types of Crisis

DEPENDENT VARIABLE: *SYratio*	(1) only recession	(2) only war	(3) only pandemic	(4) only precautionary saving determinants	**(5) Baseline Model recession**	**(6) Baseline Model war**	**(7) Baseline Model pandemic**
type of crisis	-0.0249	0.127*	-0.0300		-0.0407***	0.233***	-0.0182
	(0.0216)	(0.0743)	(0.0318)		(0.0153)	(0.0850)	(0.0217)
IYratio				0.817***	0.782***	1.026***	0.826***
				(0.221)	(0.221)	(0.119)	(0.218)
gdpvolatility				-0.864**	-0.977***	-0.859**	-0.810**
				(0.350)	(0.349)	(0.343)	(0.336)
SMvolatility				0.267***	0.290***	0.267***	0.262***
				(0.0528)	(0.0549)	(0.0495)	(0.0514)
credit availability				-0.0728***	-0.0783***	-0.0769***	-0.0725***
				(0.0181)	(0.0163)	(0.0170)	(0.0181)
Constant	-0.0624***	-0.0758***	-0.0686***	-0.258***	-0.235***	-0.306***	-0.258***
	(0.0111)	(0.0126)	(0.0121)	(0.0464)	(0.0488)	(0.0276)	(0.0464)
Observations	1,170	1,170	1,170	1,170	1,170	1,170	1,170
Number of Country	15	15	15	15	15	15	15
R-squared	0.009	0.026	0.007	0.280	0.305	0.361	0.282

Driscoll-Kraay (DK) standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table G.3: Alternative Wealth - Interaction Terms

DEPENDENT VARIABLE: *SYratio*	(1) crisis	(2) recession	(3) war	(4) pandemic
crisis/type of crisis	0.0450	-0.130*	0.873***	-0.123**
	(0.0657)	(0.0681)	(0.139)	(0.0597)
IYratio	0.966***	0.548*	1.118***	0.779***
	(0.152)	(0.304)	(0.0974)	(0.250)
gdpvolatility	-0.674*	-0.442	-0.897**	-0.847**
	(0.403)	(0.344)	(0.355)	(0.350)
SMvolatility	0.248***	0.254***	0.262***	0.244***
	(0.0467)	(0.0529)	(0.0491)	(0.0493)
credit availability	-0.0705***	-0.0770***	-0.0775***	-0.0751***
	(0.0162)	(0.0150)	(0.0162)	(0.0182)
*IYratio*crisis/type of crisis*	-0.244	0.560*	-5.341***	0.170
	(0.299)	(0.286)	(0.622)	(0.258)
gdpvolatility crisis/type of crisis	-0.421	-1.142	0.196	-0.0910
	(0.608)	(0.867)	(1.741)	(0.858)
SMvolatility crisis/type of crisis*	0.0349	0.0608	-1.435**	0.331
	(0.116)	(0.131)	(0.613)	(0.211)
*credit availability * crisis/type of crisis*	-0.00465	-0.00336	0.193***	0.00581
	(0.0151)	(0.0151)	(0.0421)	(0.0131)
Constant	-0.285***	-0.197***	-0.323***	-0.242***
	(0.0374)	(0.0639)	(0.0252)	(0.0529)
Observations	1,170	1,170	1,170	1,170
Number of Country	15	15	15	15
R-squared	0.286	0.333	0.423	0.293

DK standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table H: Dynamic Fixed Effects

DEPENDENT VARIABLE: *SYratio*	(1) only lag of *SYratio*	(2) without crisis	(3) with crisis
SYratio lag 1	0.971***	0.957***	0.956***
	(0.0154)	(0.0207)	(0.0206)
crisis			-0.00311
			(0.00293)
WYratio		-0.000350	-0.000287
		(0.00153)	(0.00150)
gdpvolatility		-0.0669	-0.0745
		(0.121)	(0.122)
SMvolatility		0.0190	0.0189
		(0.0126)	(0.0125)
credit availability		-0.00496	-0.00495
		(0.00351)	(0.00348)
Constant	-0.00166	-0.00274	-0.00103
	(0.00208)	(0.00830)	(0.00717)
Observations	582	582	582
Number of Country	9	9	9
R-squared	0.934	0.934	0.935

DK standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table I: Nakamura et al. (2013) 'disaster' dummy

DEPENDENT VARIABLE: *SYratio*	(1) only disaster	(2) adding the model	(3) interaction terms
disaster	-0.0156	-0.00985	-0.112
	(0.0742)	(0.0817)	(0.367)
WYratio		-0.0396***	-0.0396***
		(0.0105)	(0.0112)
gdpvolatility		-0.440	-0.339
		(0.302)	(0.316)
SMvolatility		0.217***	0.236***
		(0.0654)	(0.0701)
credit availability		-0.105***	-0.106***
		(0.0163)	(0.0147)
*WYratio*disaster*			0.112
			(0.0895)
*gdpvolatility*disaster*			-0.176
			(1.023)
*SMvolatility*disaster*			-2.109***
			(0.430)
*credit availability *disaster*			0.0408
			(0.0341)
Constant	-0.0590***	0.0761	0.0681
	(0.0117)	(0.0477)	(0.0526)
Observations	582	582	582
Number of Country	9	9	9
R-squared	0.0007	0.318	0.391

DK standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table J: Barro-Ursúa (2008) 'Consumption disaster'

DEPENDENT VARIABLE: *SYratio*	(1) only Cdisaster	(2) adding the model	(3) interaction terms
Cdisaster	0.0186	0.0420	-0.423**
	(0.0523)	(0.0510)	(0.194)
WYratio		-0.0393***	-0.0398***
		(0.0106)	(0.0111)
gdpvolatility		-0.467	-0.504
		(0.306)	(0.326)
SMvolatility		0.223***	0.233***
		(0.0644)	(0.0674)
credit availability		-0.105***	-0.106***
		(0.0162)	(0.0149)
*WYratio*Cdisaster*			0.140***
			(0.0387)
*gdpvolatility*Cdisaster*			3.928
			(3.119)
*SMvolatility*Cdisaster*			-1.330
			(0.899)
*credit availability *Cdisaster*			-0.0105
			(0.0368)
Constant	-0.0603***	0.0725	0.0736
	(0.0117)	(0.0484)	(0.0513)
Observations	582	582	582
Number of Country	9	9	9
R-squared	0.0008	0.322	0.364

DK standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1

Table K: Barro-Ursúa (2008) 'GDP disaster'

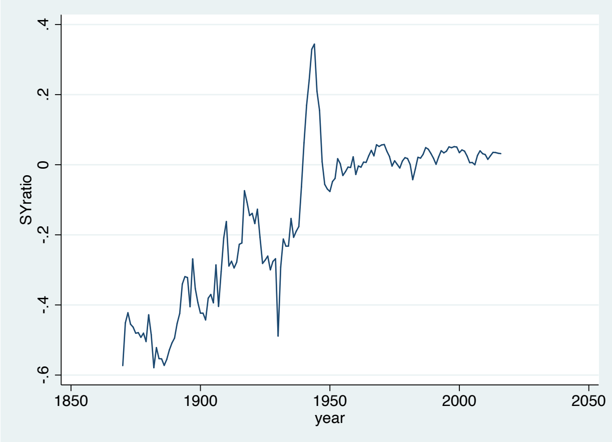
DEPENDENT VARIABLE: *SYratio*	(1) only GDP disaster	(2) adding the model	(3) interaction terms
GDPdisaster	-0.0175	-0.00887	-0.343
	(0.0629)	(0.0736)	(0.245)
WYratio		-0.0396***	-0.0395***
		(0.0106)	(0.0109)
gdpvolatility		-0.440	-0.372
		(0.312)	(0.347)
SMvolatility		0.217***	0.229***
		(0.0646)	(0.0675)
credit availability		-0.105***	-0.107***
		(0.0162)	(0.0147)
*WYratio*GDPdisaster*			0.168***
			(0.0557)
*gdpvolatility*GDPdisaster*			-0.292
			(1.136)
*SMvolatility*GDPdisaster*			-1.624**
			(0.794)
*credit availability *GDPdisaster*			0.0129
			(0.0497)
Constant	-0.0591***	0.0755	0.0708
	(0.0114)	(0.0481)	(0.0506)
Observations	582	582	582
Number of Country	9	9	9
R-squared	0.0007	0.318	0.371

DK standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

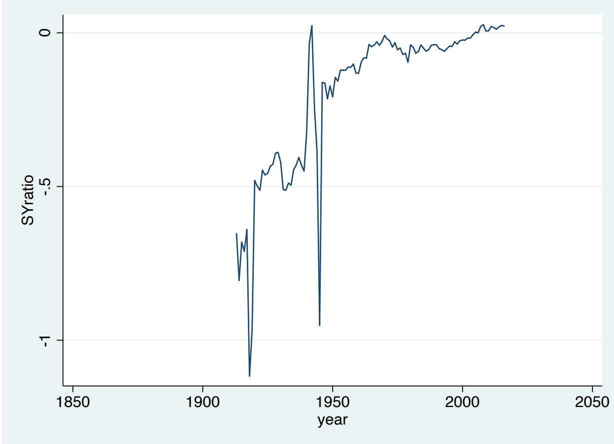
B. FIGURES

Saving ratios per country

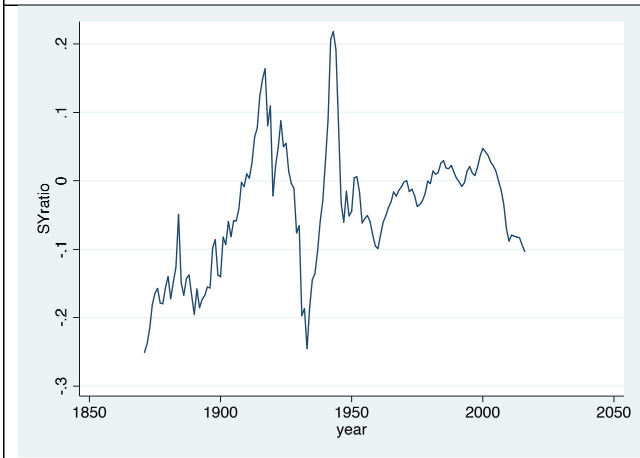
Australia



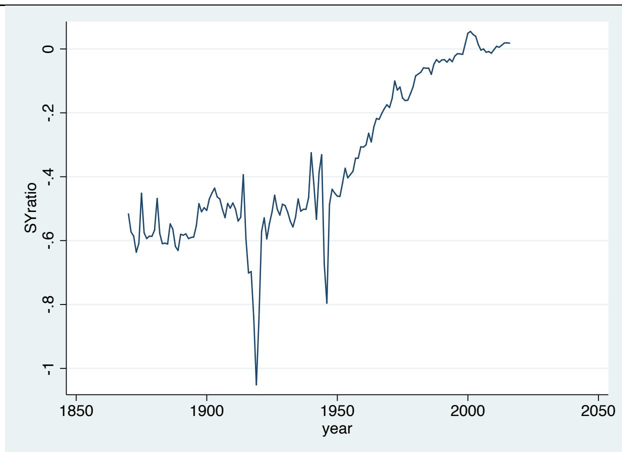
Belgium



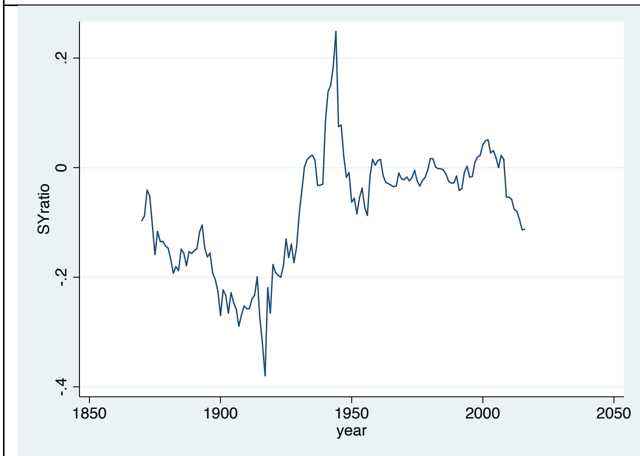
Canada



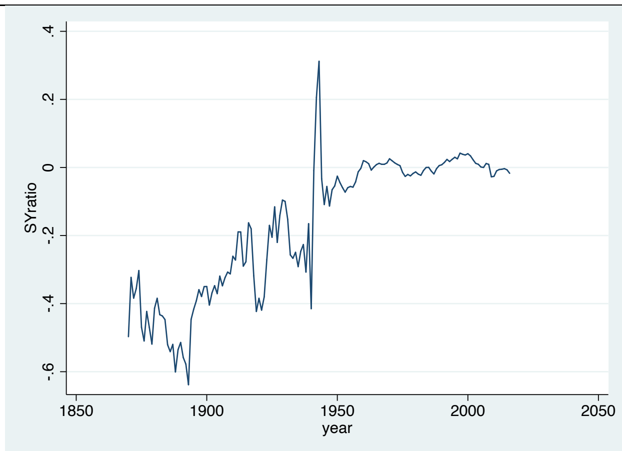
Denmark



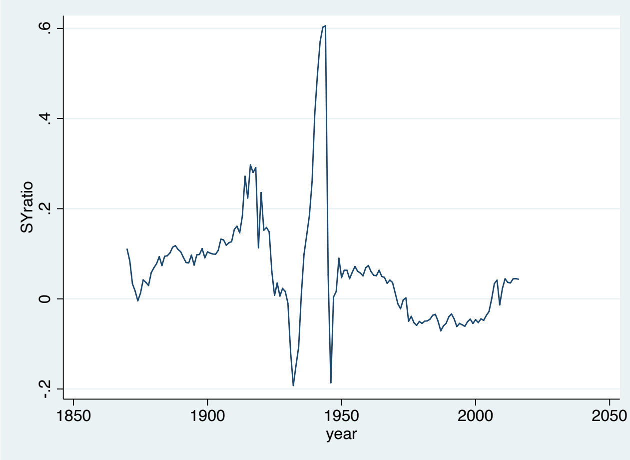
Finland



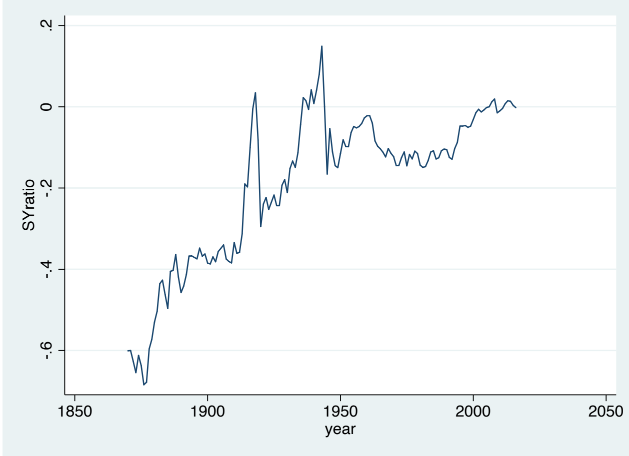
France



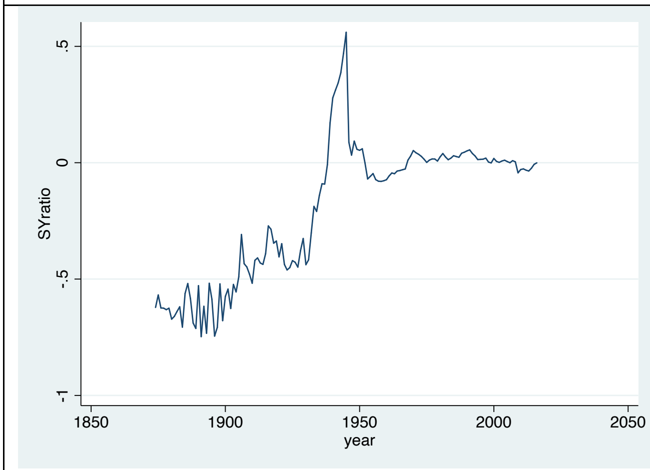
Germany



Italy

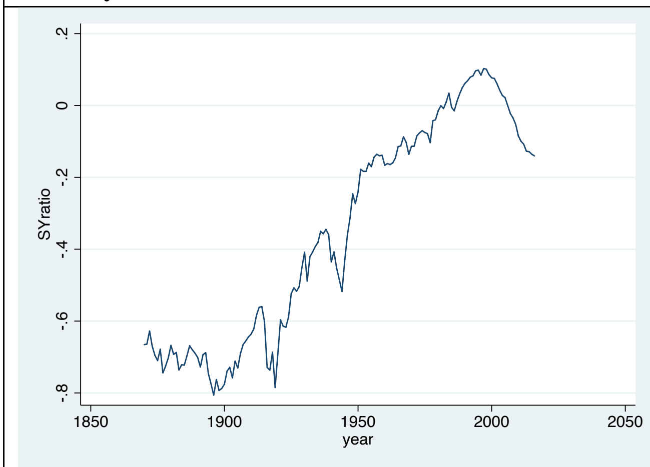


Japan

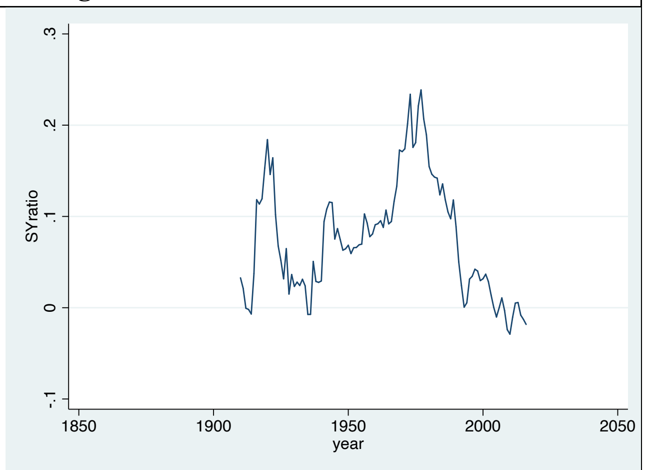


Netherlands

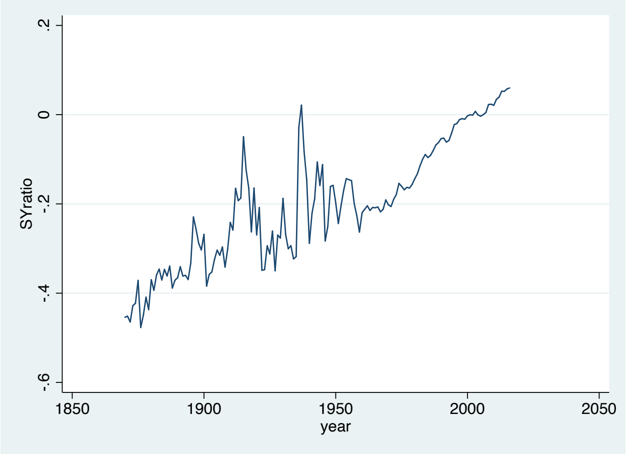
Norway



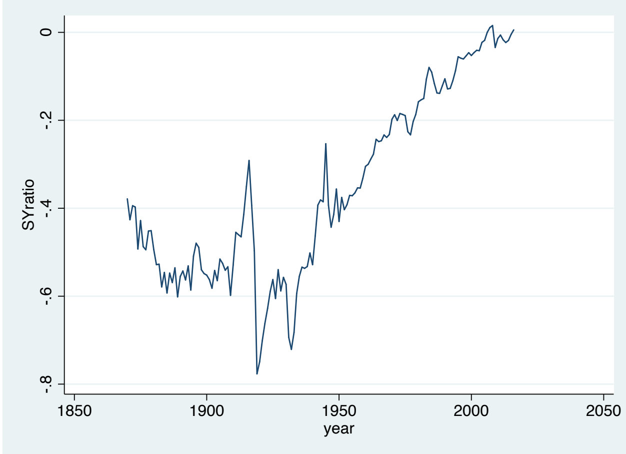
Portugal



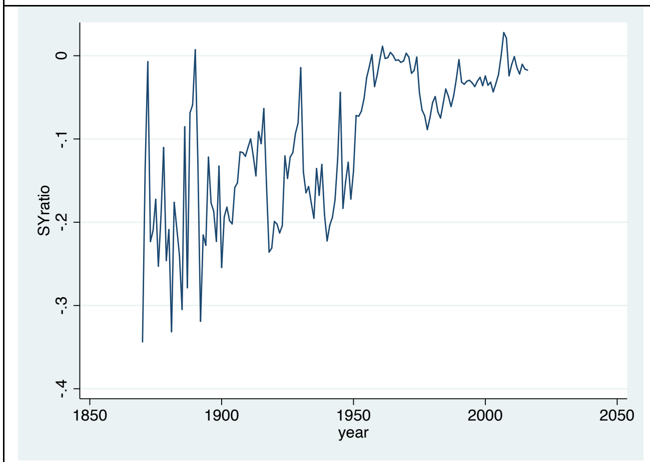
Spain



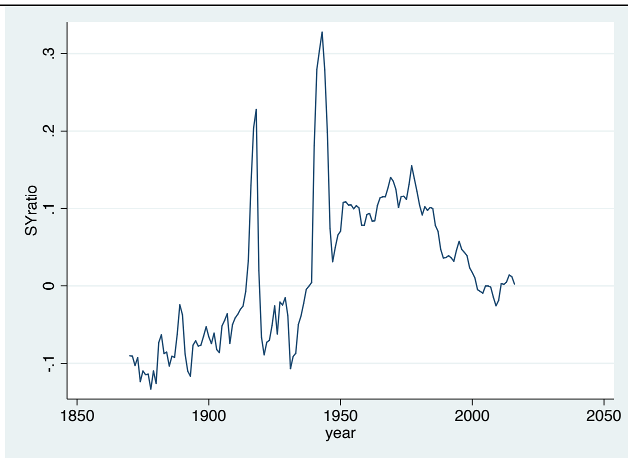
Sweden



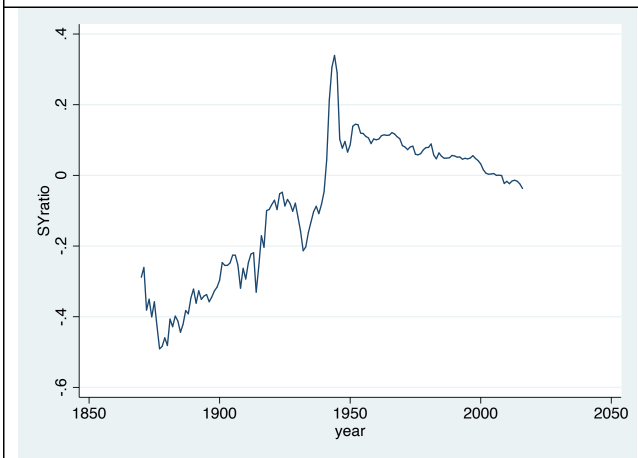
Switzerland



UK

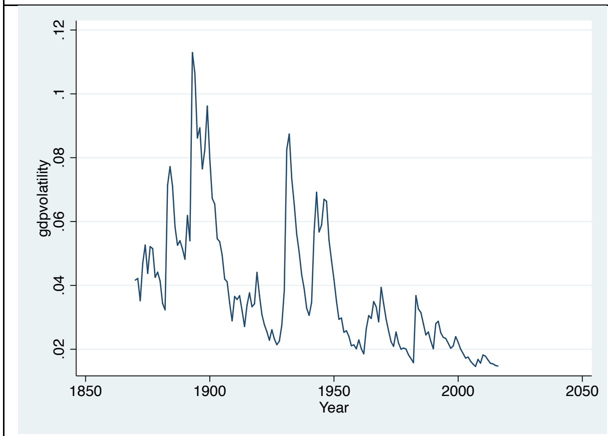


USA

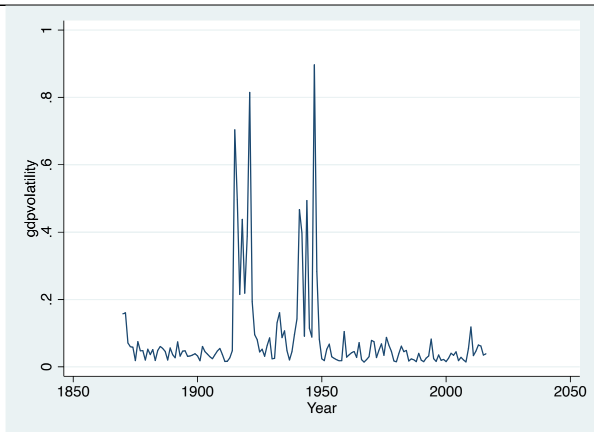


GDP volatility plots per country

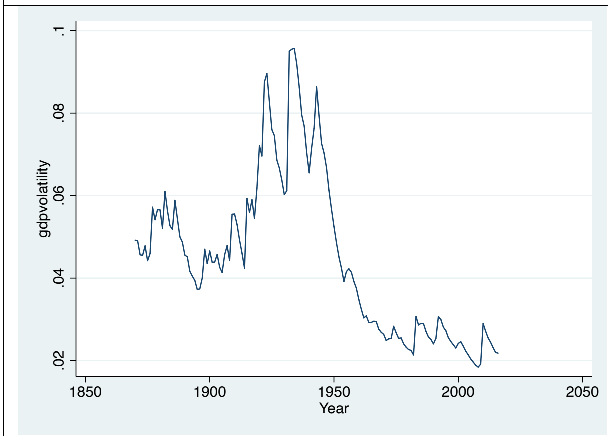
Australia



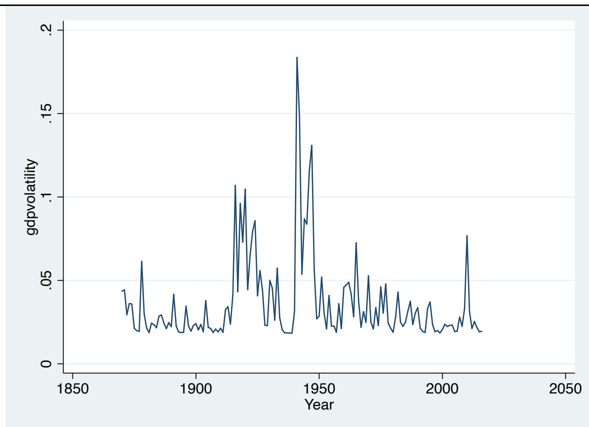
Belgium



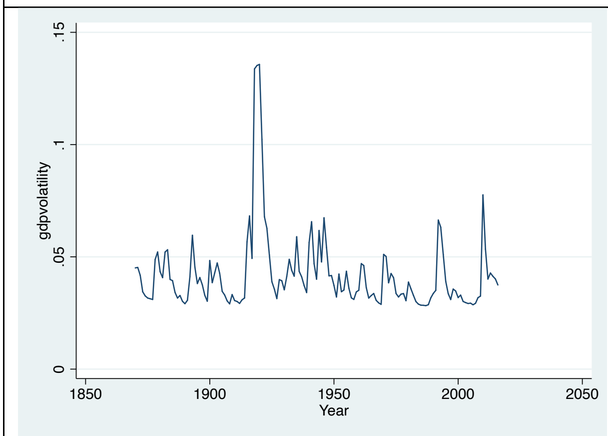
Canada



Denmark



Finland



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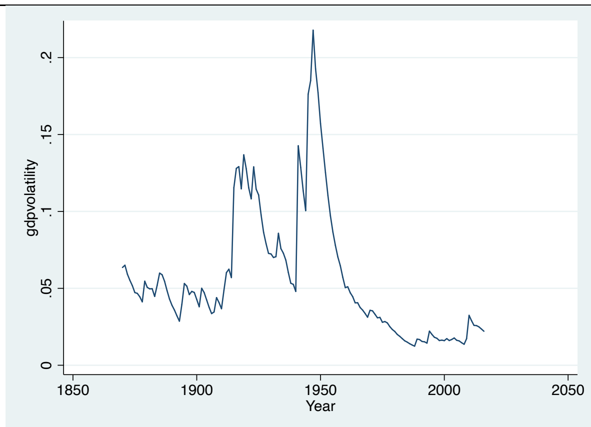

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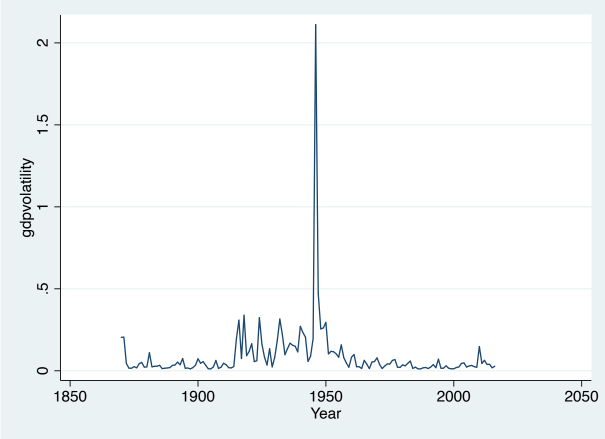
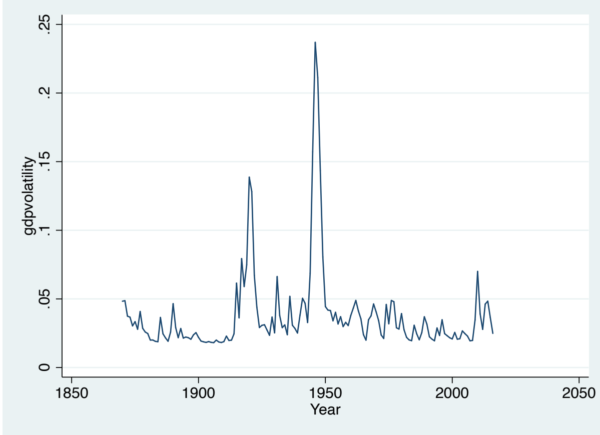


Italy



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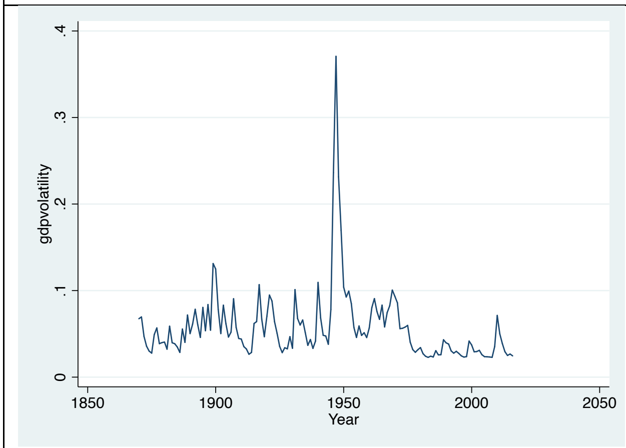

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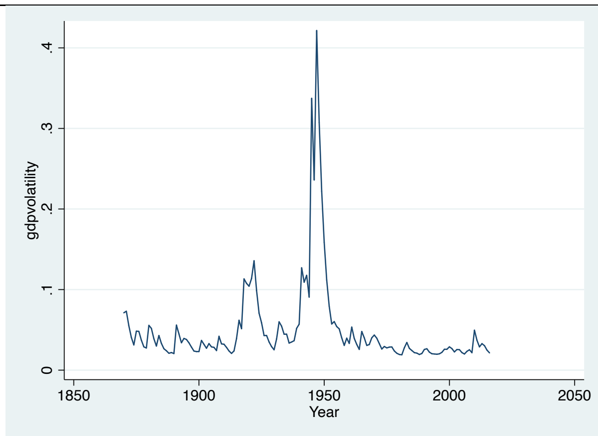

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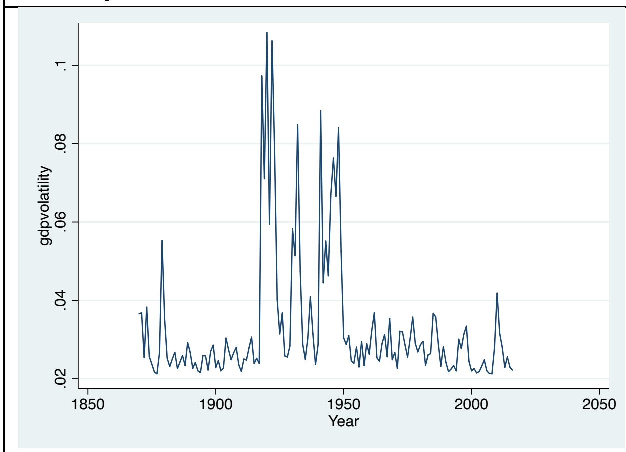

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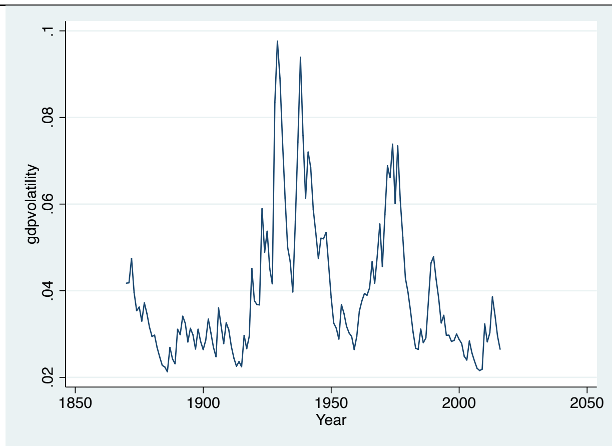

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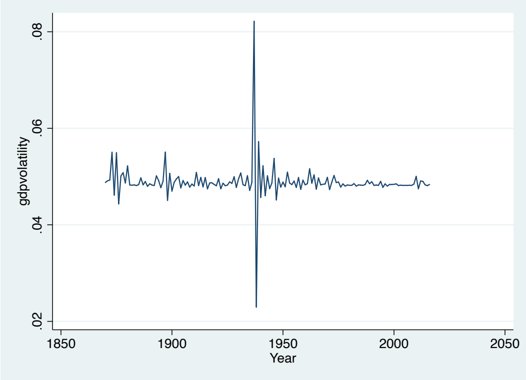

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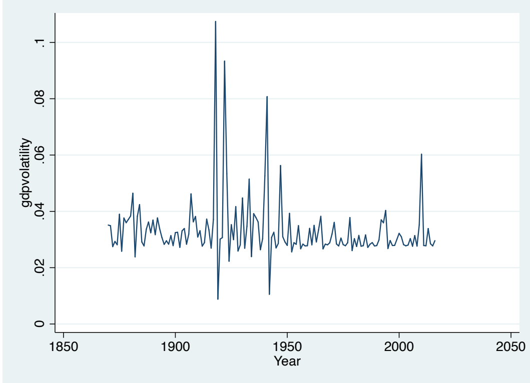

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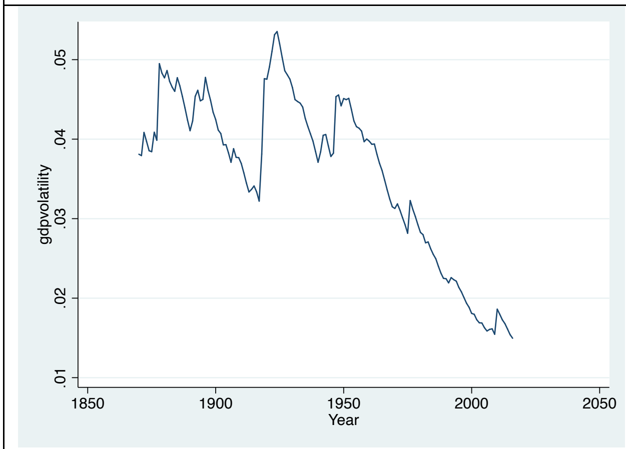

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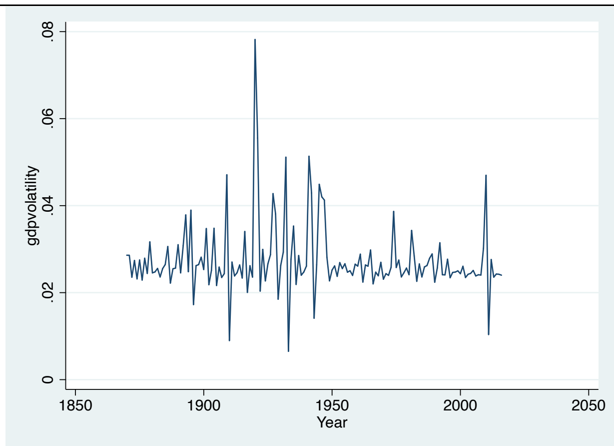

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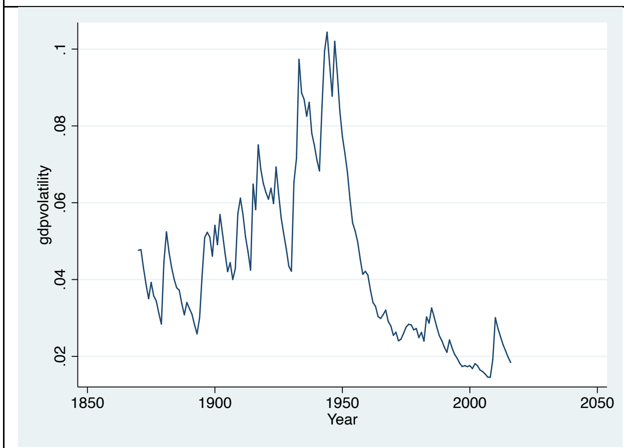
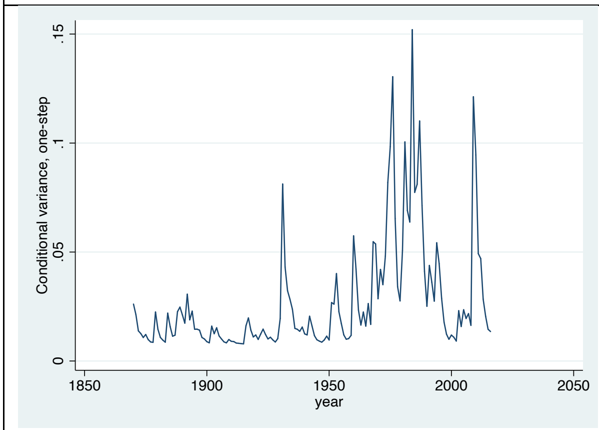
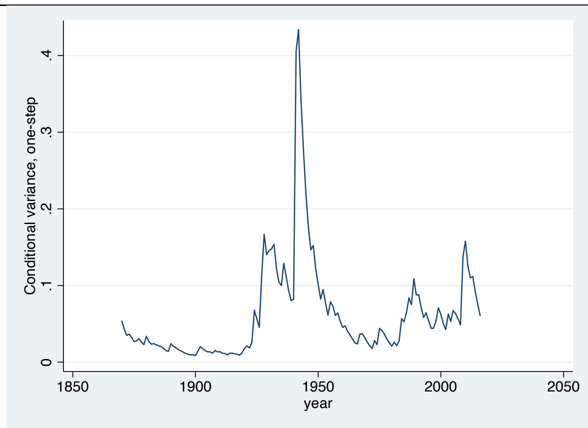


Stock market volatility plots per country

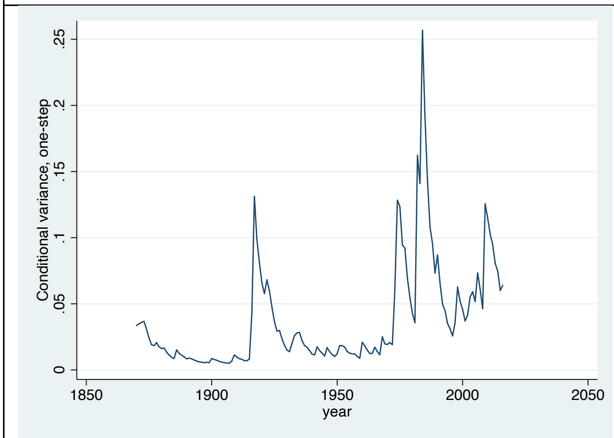
Australia



Belgium



Denmark



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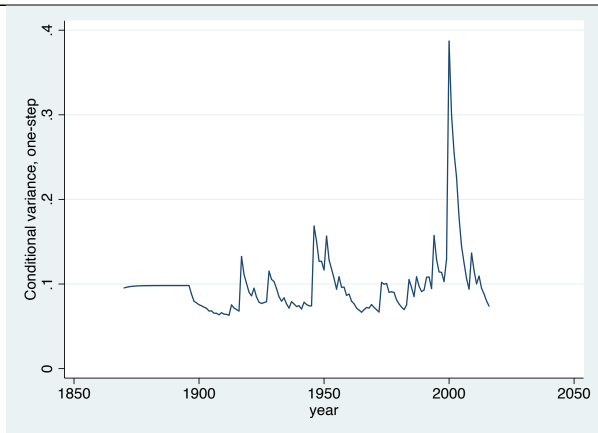

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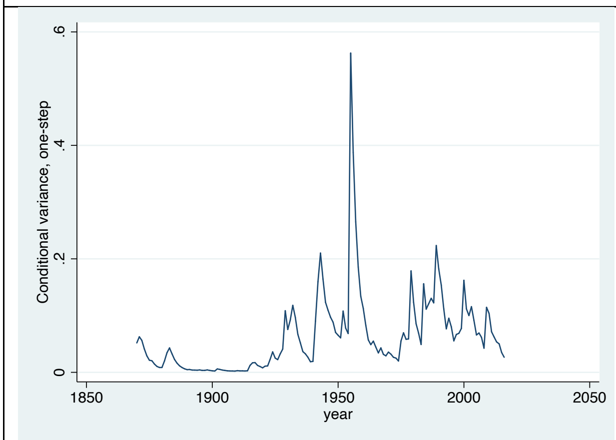

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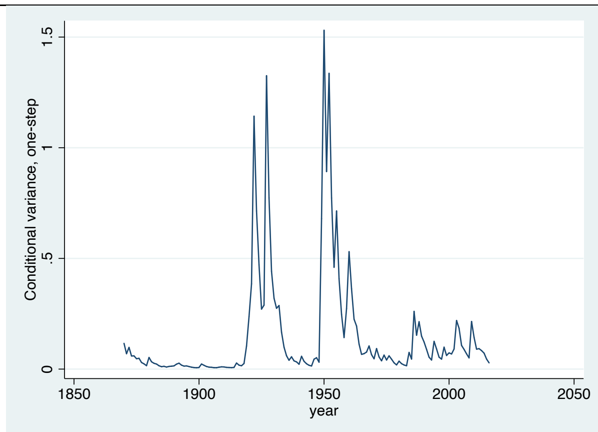

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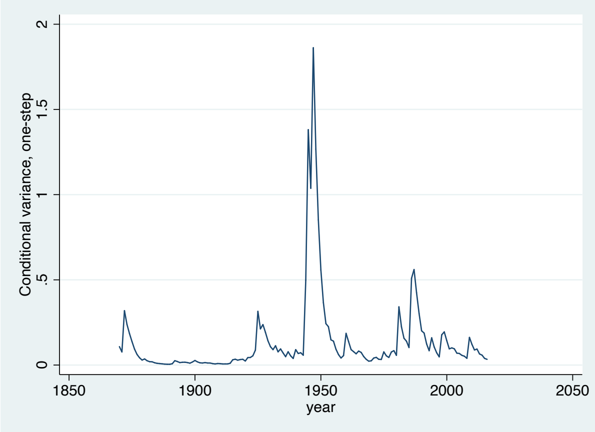

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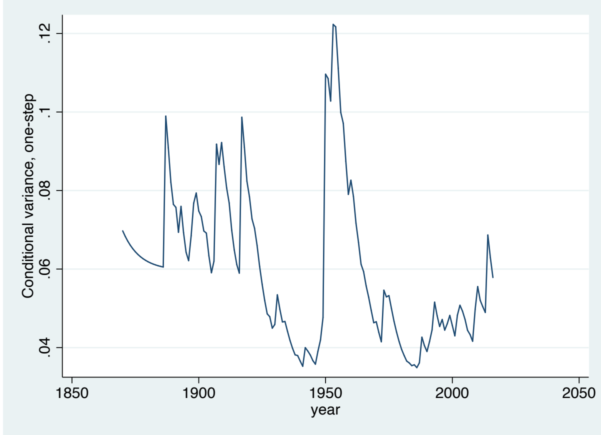

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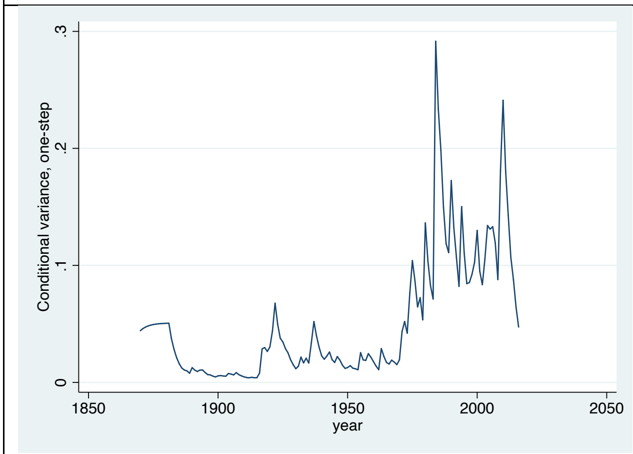

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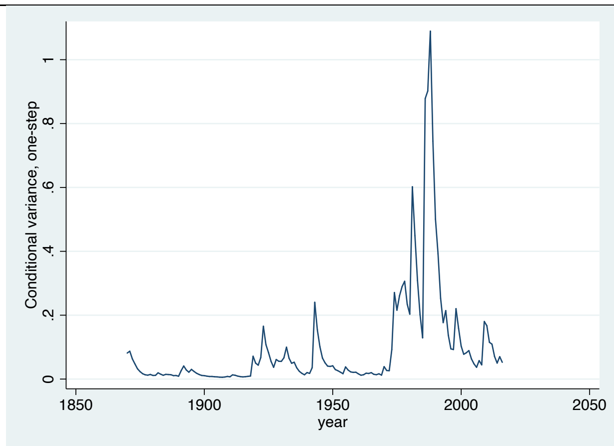

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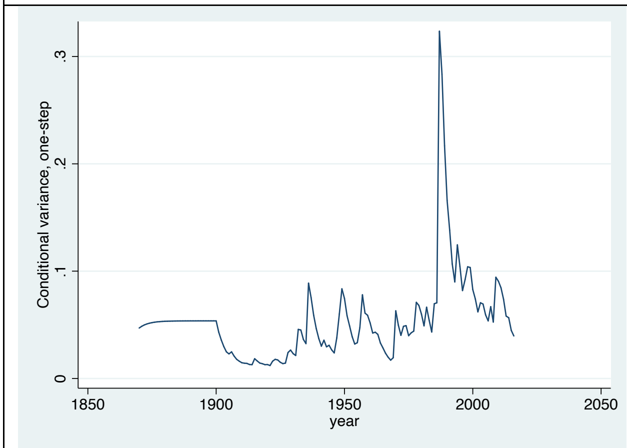

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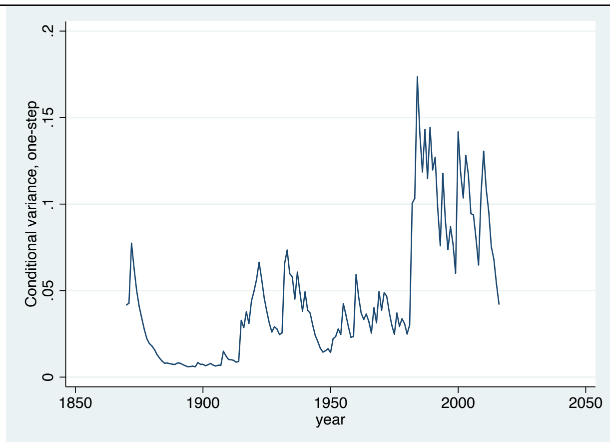

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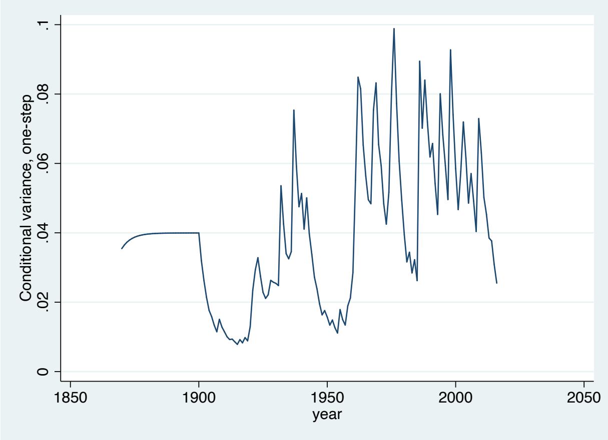

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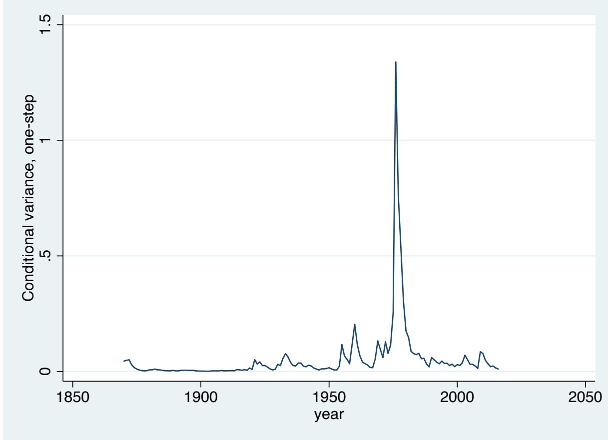
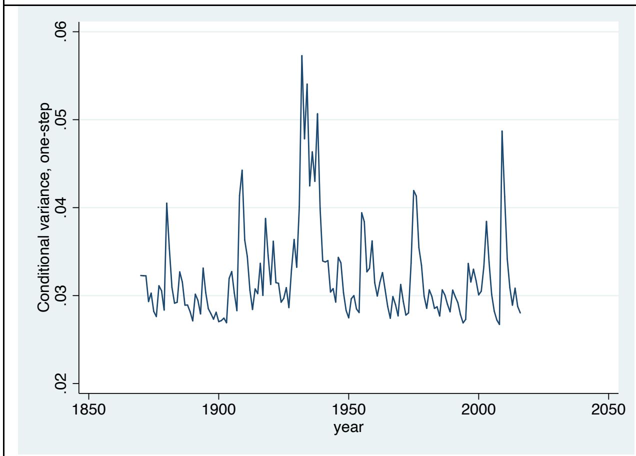
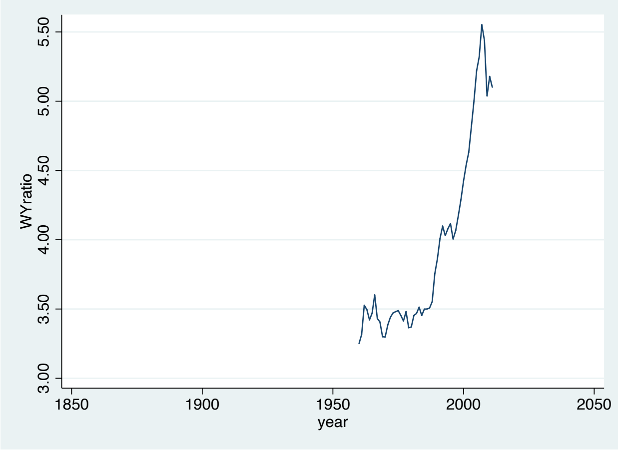


USA

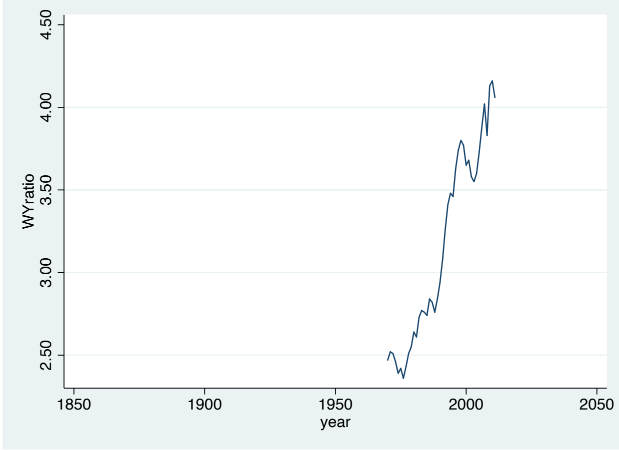


Wealth-to-Income ratios per country

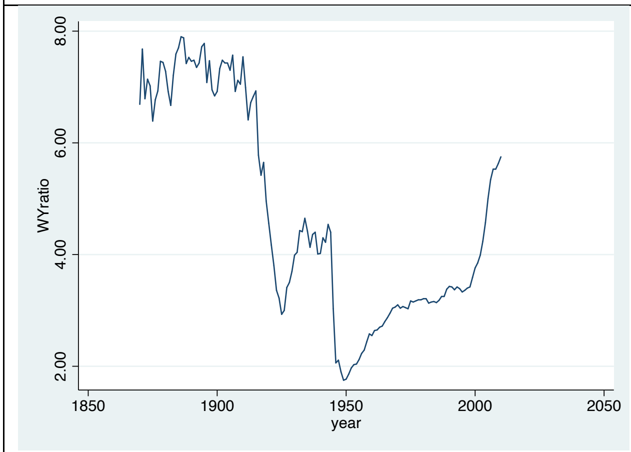
Australia



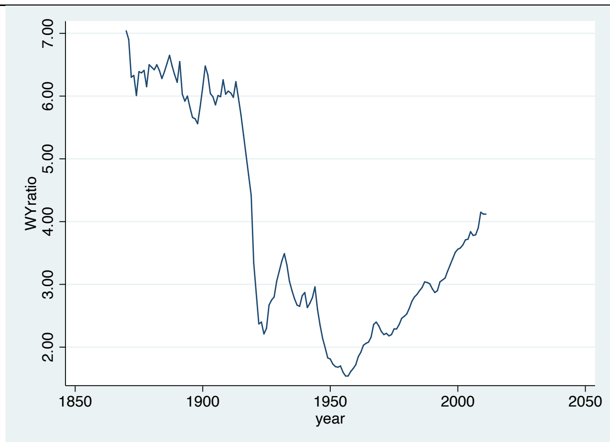
Canada



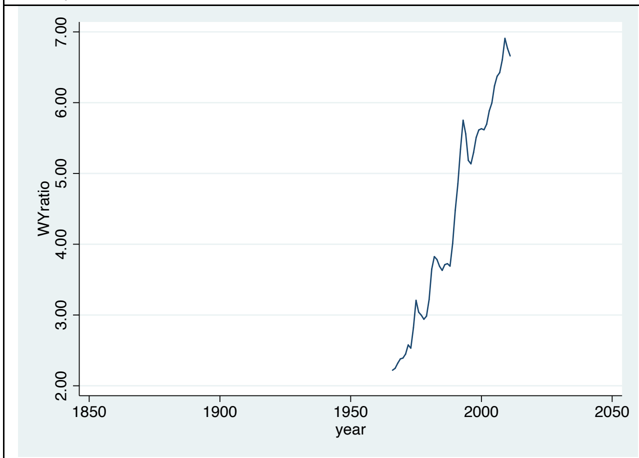
France



Germany

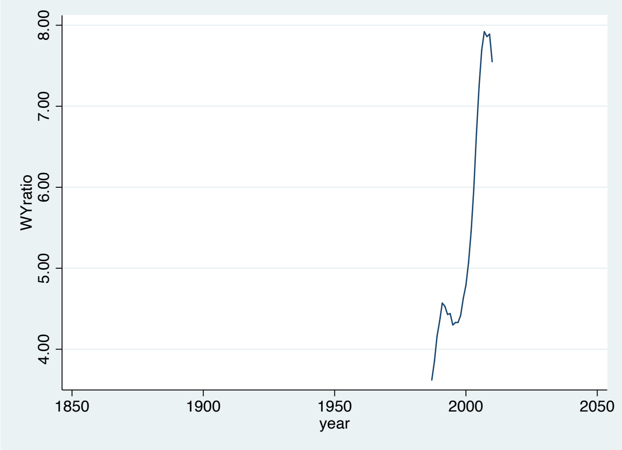


Italy

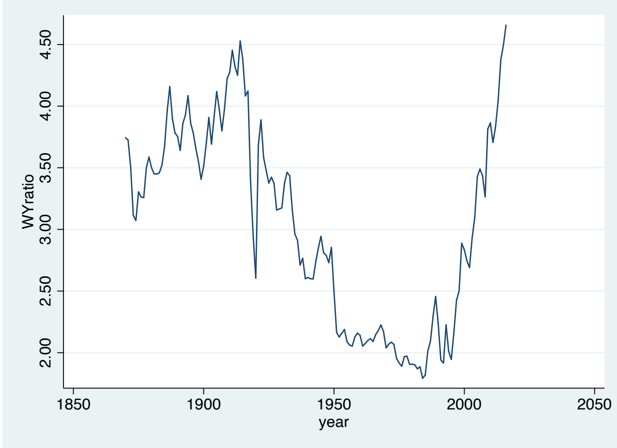


Japan

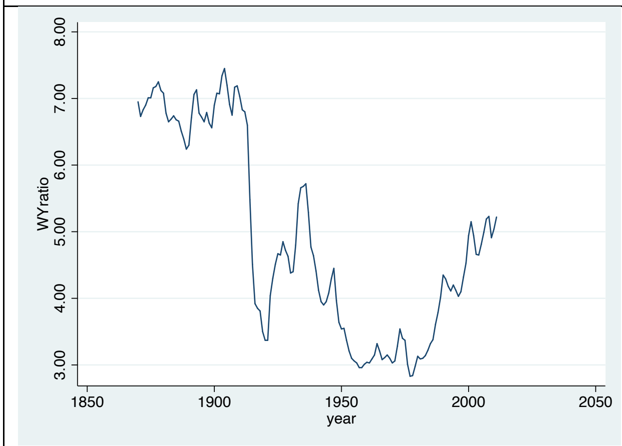
Spain



Sweden



UK



USA