Precautionary Saving in Europe

A panel data study on the effect of labour uncertainty on European household saving

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Abstract

The main aim of this paper is to find out whether European households show precautionary saving behaviour due to labour uncertainty. Motivated by the increased labour uncertainty during the Great Recession (2007-2009) and its aftermath, Carroll, Slacelek & Sommer (2012), as well as Mody, Ohnsorge & Sandri (2012) already showed the existence of precautionary saving following from labour uncertainty at a macro-economic level for respectively the US and OECD countries. My main results, which stem from applying various regression specifications, estimators and time samples, show that precautionary saving following from labour uncertainty was present between 1980 and 2009. However, I find evidence that the importance of precautionary saving due to labour uncertainty has diminished after 2009. Hence, I claim that the precautionary saving behaviour of European households following from labour uncertainty might not be as influential as indicated by Mody et al. (2012). With the help of a second dataset including a longer time period, I show that whether I measure precautionary saving or not depends on the variables, type of estimator and specific time sample I use. This casts doubts on general claims about aggregate precautionary household saving that have been made in previous studies.

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1. Introduction

In recent years, Europe has suffered from a severe economic crisis. Starting in 2007, the economic crisis resulted in (amongst others) the collapse of housing markets, lower consumption, declining growth expectations and higher unemployment (Hurd & Rohwedder, 2010). Probably the most striking effect of the crisis on most European countries has been the increase in unemployment (ND, 2012). As a result, uncertainty about future income and the future state of the economy rose strongly amongst most European citizens (DNB, 2014).

The increased labour uncertainty during the Great Recession (2007-2009) and its aftermath motivated Carroll, Slacalek & Sommer (2012), as well as Mody, Ohnsorge & Sandri (2012) to study the effect of labour uncertainty on household saving. They empirically investigated whether the theory of precautionary saving is in line with the economic reality of the recent decades. The theory of precautionary saving predicts that an increase in uncertainty about future consumption causes saving to rise. In order to better protect themselves against possible future income losses, households increase their saving. According to this theory, the more uncertain households are, the higher the additional saving they make (Romer, 2011). Both studies show the existence of precautionary saving at a macro-economic level. Whereas Carroll et al. (2012) focus their study on the US only, Mody et al. (2012) take 27 OECD countries into account in their research. The results of the latter study show that more than two fifth of the actual increase in household saving in OECD countries between 2007 and 2009 is directly related to the increase in the unemployment rate and GDP volatility.

The main aim of this paper is to find out whether labour uncertainty has a similar effect on the saving rates of European countries. To the best of my knowledge, a macro-economic empirical study on precautionary saving that includes only European countries has not been conducted before. Besides that, I verify whether the corresponding results change when adding data for the years 2010-2013. The reason for adding data for these years is that the total impact of the financial crisis in terms of unemployment was not completely known for in the year 2009 (last year taken into account by Mody et al. (2012)), neither it was in 2012 (year in which Mody et al. (2012) published their research). As an example, the unemployment rate of Spain reached a record height level of 27.2 percent in the first quarter of 2013 (Joy, Smith-Spark & Rebaza, 2013), after it started to fall again (Khan, 2015). Although the total impact of the crisis is still not fully known, more reliable conclusions can be drawn from an analysis that also includes data on part of the aftermath of the ‘Great Recession’.

Since this study focuses on precautionary saving in European countries, it allows for a comparison between Northern and Southern European countries. It is known that especially Southern European countries have been suffering from extremely high unemployment during the years of the crisis (Hewitt, 2013). In that sense, one could argue that the economic crisis was, overall, more visible in Southern European countries in comparison with Northern European countries. Hence, in this study I test whether, as a possible result of the crisis, the coefficient representing the effect of labour uncertainty on saving is higher for Southern European countries than for their Northern counterparts.

Apart from the contributions that were mentioned above, this paper extends the work of Mody et al. (2012) by performing various robustness checks in which multiple alternative estimators as well as a different dataset are applied. The reason for applying alternative estimators is that Mody et al. (2012) neglect potential heterogeneity in saving behaviour and hardly pay attention to the potential problems of endogeneity. On the other hand, the reason for applying a second dataset next to a dataset that is highly similar to the dataset of Mody et al. (2012), is that this second dataset covers a longer time span for all included countries. This second, more extensive database stems from Adema & Pozzi (2015), who use slightly different variables to proxy for some of the determinants of saving than that were being used by Mody et al. (2012).

The datasets that are applied in this study are unbalanced. The countries included in the first dataset are the EU-12 (as of January first, 2002), as well as Denmark, Sweden and the United Kingdom. For this dataset, observations start in 1980 and end in 2013. However, the availability of data differs per country and variable. In fact, observations for most countries only begin from 1995 onwards or start even later. On the other hand, the second database considers a substantially longer time period (1969-2012). It includes the same countries as the first dataset except for Greece, Luxembourg and Portugal. Also for this dataset it holds that the availability of data differs per country and variable. Especially some observations for the early years are missing. This second dataset is only applied in several robustness checks. Most of the data used in this study stems from OECD and IMF sources.

In order to estimate the effect of labour uncertainty on the saving rate, I use the unemployment rate as a proxy for labour uncertainty. I specify three different regression specifications. In all three regression specifications, the saving rate is regressed on the unemployment rate, the household's wealth and the availability of domestic private-sector credit. Empirically, I apply the OLS, OLS fixed effects (robust) and the two-step GMM (robust) estimators to all three regression specifications. I measure the effect of the unemployment rate on the saving rate for both a 1980-2009 and a 1980-2013 sample. After that, I check the robustness of the main results that follow from these regressions by performing various robustness checks. The first robustness check excludes the years of the economic crisis and its aftermath (2007-2013). In the second robustness check additional control variables, such as GDP volatility, stock market volatility, the government structural balance, the old age dependency ratio and the world GDP are added to the regressions. The third robustness check draws a comparison between the precautionary saving effect that is found for Northern and respectively Southern European countries. In the fourth robustness check, data on earlier years are added. In the final two robustness checks (5&6), I apply respectively the Mean Group (MG) estimator and the Common Correlated Effect Mean Group (CCEMG) estimator. The former controls for potential heterogeneity in parameters, whereas the latter allows for cross-sectional dependence. Robustness checks 4-6 employ the second, more extensive (in terms of included years) database.

The main results of this study indicate that the importance of precautionary saving following from labour uncertainty has diminished after 2009. Based on these main results, I claim that precautionary saving following from labour uncertainty might not be as influential as indicated by Mody et al. (2012). Additional results show that overall my main results are robust to the inclusion of additional control variables. However, they are not robust to the use of a different dataset covering a longer time period, nor to a combination of the use of this more extensive dataset with the application of the MG estimator respectively the CCMG estimator. Next to that, the outcomes of this study show that whether I measure precautionary saving or not depends on the variables, type of estimator and specific time sample I use. This casts doubts on general claims about aggregate precautionary household saving that have been made in previous studies.

The structure of the paper is as follows. Chapter *2* describes some important steps in the development of the theory on saving and shows a contemporary saving model that is empirically useful in guiding an analysis of aggregate precautionary household saving in a cross country panel setting. Chapter *3* discusses the relevant literature on saving and is divided into three subsections: 1) the general determinants of aggregate saving; 2) the empirical importance of precautionary saving at the individual and household level and 3) the empirical importance of precautionary saving at the aggregate level. Chapter *4* describes the data and corresponding data sources that have been applied in this study. In addition, it discusses the methodology that has been adopted to measure precautionary saving. The latter includes an explanation of the different regression specifications that are applied throughout this study. Chapter *5* presents the main results, the outcomes of the robustness checks, as well as a short reflection on all obtained outcomes. Finally, Chapter *6* concludes with a short summary of the results, a discussion on the implications of the results, as well as a discussion on the potential limitations of this paper and some recommendations for further research.

2. Theory

In this chapter, I firstly describe some important steps in the development of the theory on saving. After that, I will show a contemporary saving model that is empirically useful in guiding an analysis of aggregate precautionary household saving in a cross country panel setting.

2.1 Permanent income hypothesis

Most often Friedman's (1957) introduction of the permanent income hypothesis is considered as the starting point of modern consumption and saving theories. The basic idea of this hypothesis is that individuals smooth out consumption (*C*) over time by spending an equal part of their lifetime income each year (see equation 1). The average of the lifetime income is called permanent income and consists of endowment A_0 and (future) income Y_t.

$$C_t = \frac{1}{T}\left(A_0 + \textstyle\sum_{t=1}^{T} Y_t\right) \tag{1}$$

$$Y_t^T = Y_t - \frac{1}{T}\left(A_0 + \textstyle\sum_{t=1}^{T} Y_t\right) \tag{2}$$

In other words, according to this theory consumption (*C*) is not based on current income, but on lifetime income. Hence, the level of consumption will only change if changes in permanent income take place. The difference between current income (Y_t) and permanent income is called transitory income (Y_t^T) (see equation 2). Since income can either be saved or consumed, saving (*S*) will equal the transitory income (Y_t^T) (see equations 3 and 4 below). When in a certain year the transitory income (Y_t^T) is positive, saving (*S*) is expected to be positive as well. On the other hand, saving (*S*) is expected to be negative when the current income (Y_t) in a certain year is lower than the permanent income. A negative saving (*S*) means that individuals partly consume out of saving that has been obtained in earlier years or out of a credit loan. All this implies that according to the permanent income hypothesis, people use saving (*S*) as a tool to smooth out consumption.

$$S_t = Y_t - C_t \tag{3}$$

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

As an example, one can think of a worker who saves for his retirement. Due to the saving he makes throughout his career, he ensures that his consumption after his retirement can be similar to the consumption prior to his retirement.

2.2 Further contributions to the theory on saving

Although some observations (partly) confirmed the permanent income hypothesis, other observations did not. An example of the former is that the level of consumption (*C*) respectively saving (*S*) seems to be less affected by a temporarily cut in taxes than by a permanent tax cut (Romer, 2011). An example of the latter is that the level of consumption (*C*) respectively saving (*S*) seems to be excessively sensitive to changes in income (Campbell & Mankiw, 1990 & 1991). As a result, a thorough revision of the theory on saving took place.

A first major addition to the theory on saving was made by Leland (1968). By introducing uncertainty in a simple two-period intertemporal consumption and saving model, he claimed to be the first to take what was later called 'precautionary saving' into account. The basic intuition behind precautionary saving is that risk-averse individuals save more when uncertainty about future consumption increases (Romer, 2011). Similarly, Sandmo (1970) also created a theoretical model that showed higher saving (*S*) for people with more uncertainty. He particularly focused on the substitution and income effects that play a role when uncertainty is included in consumption and saving models. He exemplified the income effect by stating that higher uncertainty increases the volatility of future consumption, leading to an accumulation of precautionary saving. Meanwhile, he illustrated that the substitution effect lowers the accumulation of precautionary saving as consumers facing an uncertain future choose to consume earlier. The saving models of Leland (1968) and Sandmo (1970) both faced the problem of being unable to measure the magnitude of precautionary saving.

A next important contribution to the theory on saving was made by Kimball (1990). He linked precautionary saving with the Arrow-Pratt theory of risk aversion. Whereas before Certainty Equivalence (CEQ) utility functions were standard to use, from that moment onwards Constant Relative Risk Aversion (CRRA) utility functions have been used as the workhorse for consumption and saving models. The difference between CEQ and CRRA utility functions is that the former assumes linear marginal utility, whereas the latter allows for the situation of convex marginal utility (see Figure *1* and *2* below for examples). The latter is more intuitive, as one would expect the marginal utility a consumer experiences from rising consumption to fall slowly instead of to become negative.

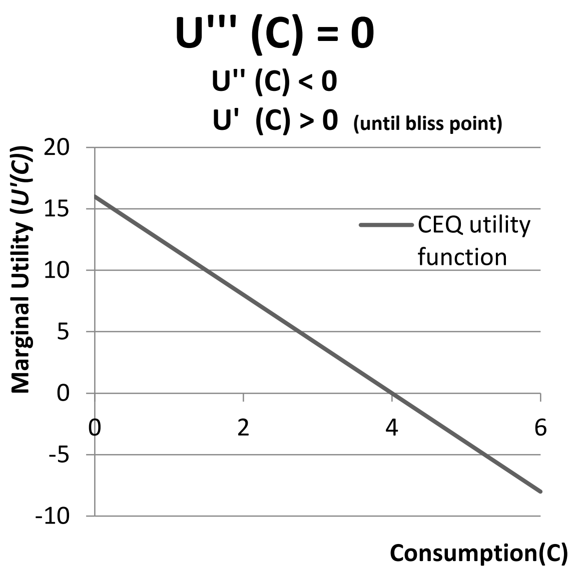

Figure 1 – CEQ utility function

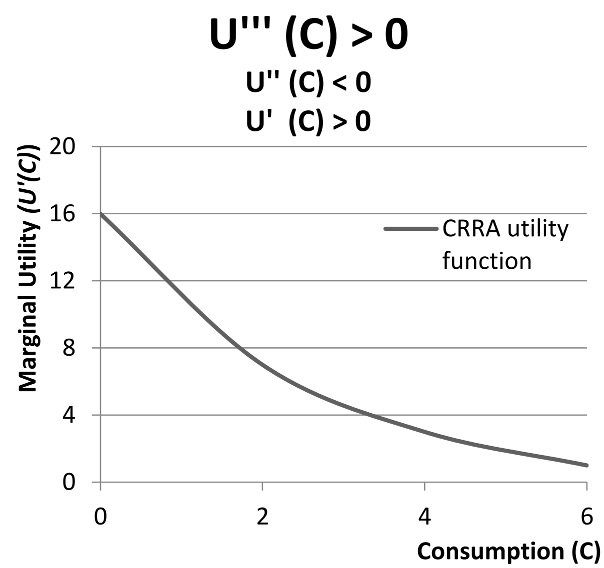

Figure 2 – CRRA utility function

The advantage of using a CRRA utility function with convex marginal utility over a CEQ utility function with linear marginal utility, is that the former allows for a certain relationship between the path of consumption and the path of income over the life cycle. In other words, changes in consumption and saving can be predicted by changes in income. Kimball (1990) illustrates that the combination of convex marginal utility with uncertainty about the future enables the measurement of the size of precautionary saving. On the contrary, measuring the magnitude of the precautionary saving was difficult when using CEQ utility functions due to their prediction that the path of consumption over the life cycle is independent of the path of income. In other words, changes in consumption (and hence changes in saving) were unpredictable. Caballero (1990) further underlines the usefulness of CRRA utility functions in the context of precautionary saving.

Another addition to the saving theory concerning precautionary saving stems from Jappelli & Pagano (1994). They introduced a three period consumption and saving model that takes the effects of liquidity constraints into account. With the help of this model they showed that not only current liquidity constraints, but also possible future constraints may lead to precautionary behaviour.

A further extension to the theory on saving follows from Carroll and Samwick (1997a). They created a buffer stock version of the standard consumption and saving model that explains why consumers aim to hold a certain amount of wealth. With the help of this model, they showed that individuals save a proportion of their wealth to buffer for future uncertainty. This is what is called buffer stock saving.

A final important contribution to the theory on saving can be attributed to Guariglia & Rossi (2002) and Carroll, Otsuka & Slacalek (2011). They designed theoretical saving models that deal with habit formation. Saving models including habit formation allow past changes in consumption to affect current consumption and saving.

All of the above described theoretical developments have contributed to our knowledge about saving and its corresponding incentives. Hence, it should be no surprise that contemporary theoretical saving models not only account for precautionary incentives, but also for buffer stock behaviour and sometimes even also for habit formation.

2.3 Contemporary saving model

To the best of my knowledge, two theoretical frameworks exist that are empirically useful in guiding the analysis of aggregate precautionary household saving in a cross country panel setting. These are the theoretical models applied by Carroll et al. (2012) and Mody et al. (2012). Since the latter model is fully based on the first, I will show the precautionary saving mechanisms that are predicted by theory by giving a concise overview of the model introduced by Carroll et al. (2012). For the sake of readability, I will stick to the essentials.

The model of Carroll et al. (2012), which is an extension of a framework of Carroll and Toche (2009), can be characterized as a buffer stock saving model and takes precautionary behaviour into account as well. The model can be used to calculate the effects of shocks in wealth, labour uncertainty and credit constraints on saving. The corresponding assumptions are as following:

1. A consumer maximizes the discounted sum of utility from an intertemporally separable CRRA utility function $U(C) = \frac{C^{1-\rho}}{(1-\rho)}$ subject to the following dynamic budget constraint:

$$W_{t+1} = (W_t - C_t)R + \tau_{t+1}\omega_{t+1}\varphi_{t+1} \tag{5}$$

with: ρ as the relative risk aversion, W_{t+1} as the next period wealth, W_t as the current period wealth, C_t as the current period consumption, R as the interest factor ($1 + r$), r as the interest rate, τ_{t+1} as the next period labour productivity, ω_{t+1} as the next period wage and φ_{t+1} as the next period employment status indicated by a zero or one.

2. Employed consumers face a constant probability μ of becoming unemployed. Once unemployed, a consumer cannot become employed anymore, i.e., a rise in unemployment risk μ is irreversible.
3. Unemployed consumers receive an unemployment benefit, which guarantees a positive level of income for unemployed households.
4. Labour productivity grows by the factor $\frac{1}{1-\mu}$.
5. Discounting takes place via the intertemporal discount factor β
6. The consumption function has a concave shape, implying that people with lower wealth have a higher marginal propensity to consume out of their wealth.

Under these assumptions, a formula for the steady state target wealth ($\breve{w}$) is derived. $\breve{w}$ is the target wealth that is optimal for the consumer and depends on the unemployment risk μ, the interest rate r, the growth rate of wages $\Delta\omega$, the relative risk aversion ρ and the discount factor β. The higher the value of $\breve{w}$, the more a household is inclined to accumulate wealth as a buffer for the future. In other words, a higher value of $\breve{w}$ coincides with higher precautionary saving.

The formula for the steady state target wealth ($\breve{w}$) and its underlying calculations go beyond the scope of this study, but can be found in Carroll (2009). In this paper it is shown that the optimal target wealth ($\breve{w}$) positively depends on the unemployment risk (μ), the interest rate (r), the relative risk aversion (ρ) and the intertemporal discount factor (β), whereas it is negatively affected by a growth in the aggregate wages ($\Delta\omega$).

So: $$\breve{w} = f(\mu(+), r(+)^{2}, \Delta\omega(-), \rho(+), \beta(+)) \quad (6)$$

Since saving is required for wealth accumulation, the steady state target wealth ($\breve{w}$) formula helps in theoretically predicting the effects of shocks in wealth, labour uncertainty and credit constraints on the saving rate.

2.3.1 A decrease in wealth

As illustrated in Figure *3*, a negative wealth shock brings about an immediate rise in the saving rate. The extra saving is required to return the wealth buffer to its optimal target ($\breve{w}$). Since saving rebuilds wealth, over time the saving rate falls back towards the level it had before the shock in wealth occurred. In other words, throughout the time, the saving rate gradually drops back to the rate at which it initially insured the optimal target wealth ($\breve{w}$).

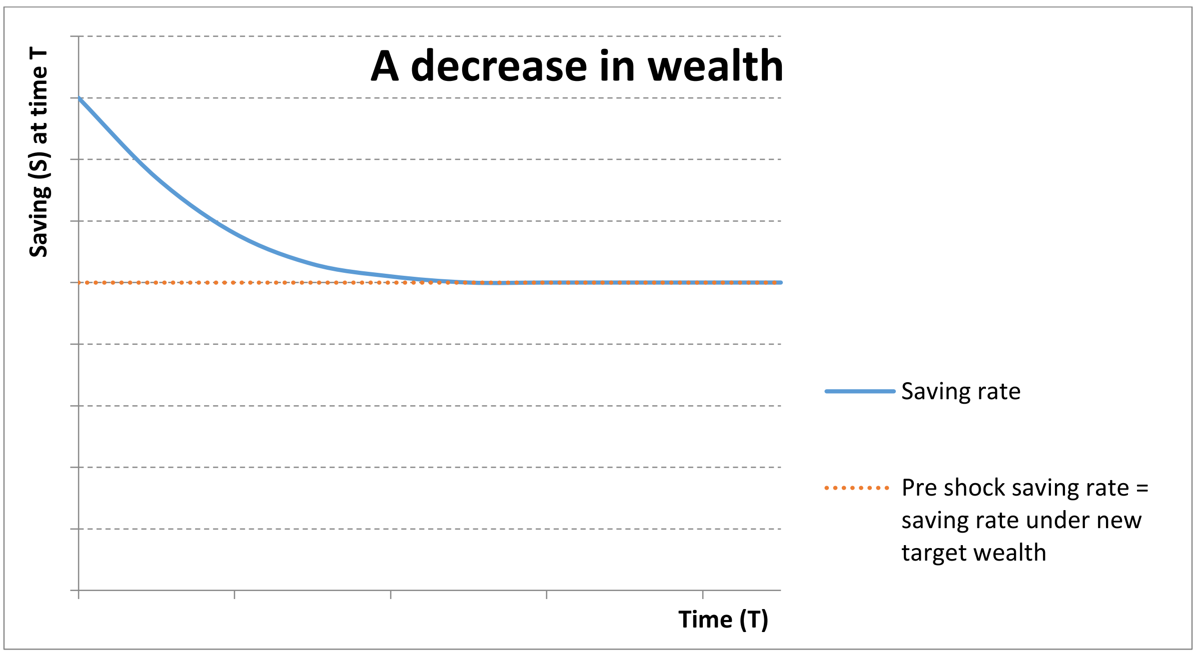

Figure 3 – A decrease in wealth

[2] This implies that the substitution effect is shown to be larger than the income effect.

2.3.2 An increase in liquidity constraints

As a result of the assumption that unemployed consumers receive an unemployment benefit (see assumption *3*), the model ensures that households that become unemployed still have a positive income. This is important in the context of liquidity constraints, because this assumption allows households with low wealth to borrow[3].

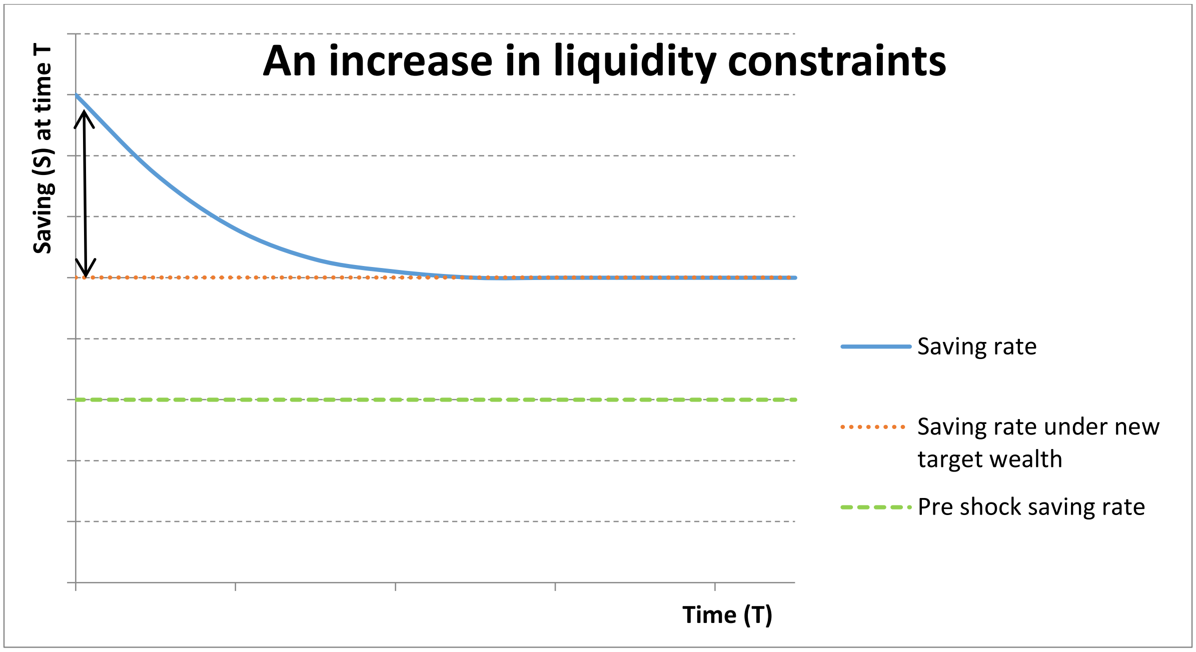

Figure 4 – An increase in liquidity constraints

A tightening of borrowing constraints leads to an immediate increase in the saving rate (see Figure *4*). The reason for the increase in saving is that households immediately start the process of accumulating a higher target wealth ($\breve{w}$). A higher wealth buffer is required due to the fact that it has become more difficult to borrow money. However, due to the additional saving, wealth increases. Hence, the saving rate decreases gradually until it satisfies the new, higher than initial, target wealth ($\breve{w}$).

It is evident that the opposite effects show up in the case of a loosening of liquidity constraints. Hence, in the situation of decreasing borrowing constraints lower saving is expected.

[3] However, low-wealth households will limit the amount of money they borrow, as it is optimal for them to ensure a positive level of consumption for the future, even in the case they become unemployed.

2.3.3 An increase in labour uncertainty

With a permanent[4] rise in labour uncertainty an immediate increase in the saving rate comes along (see Figure *5*). The reason for the increment in saving is that households immediately start the process of accumulating a higher target wealth ($\breve{w}$). The higher saving rate gradually leads to more wealth, which allows for a decrease in the saving rate over time. However, due to the permanently higher labour uncertainty, households require a higher wealth buffer. Hence, the optimal target wealth ($\breve{w}$) (and thus the optimal saving rate) will be higher than in the initial situation. Stated differently, households save more as a precaution to the increase in labour uncertainty.

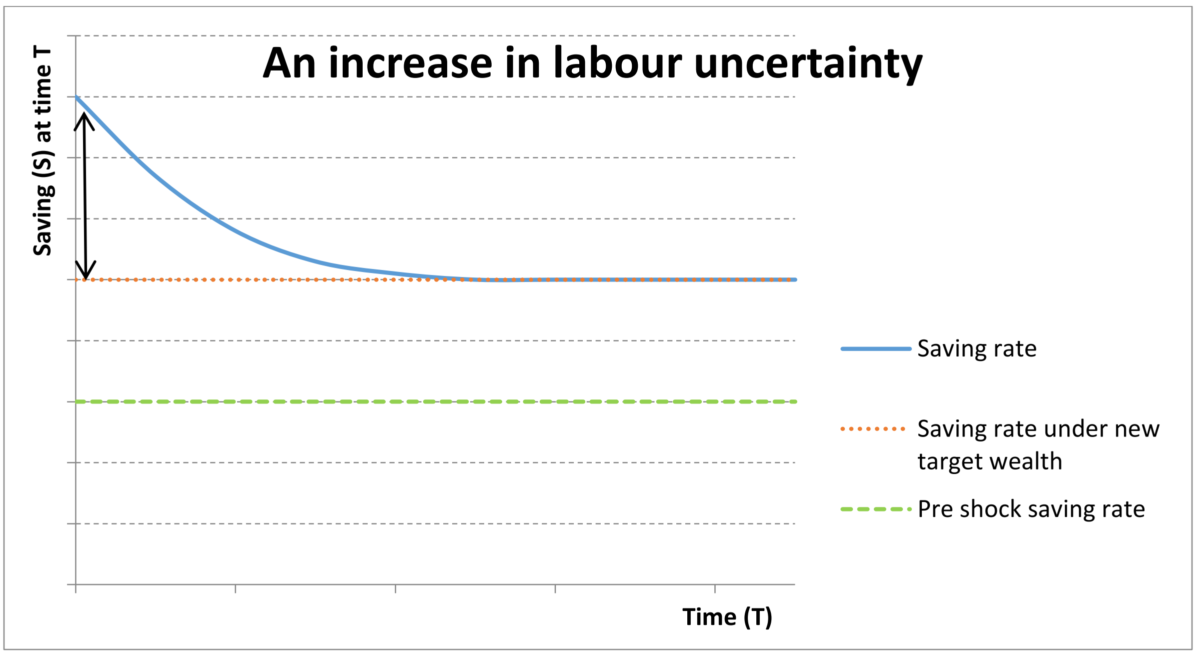

Figure 5 – An increase in labour uncertainty

As shown in Figure *4* and *5*, the effects of an increase in liquidity constraints are exactly similar to the effects of an increase in labour uncertainty. For both shocks it holds that the saving rate initially overshoots its ultimate permanent adjustment. This overshooting is marked by the black double arrow and reflects that not only a higher steady state saving rate is required when the

[4] Note that an increase in labour uncertainty is always considered permanent in this model. This follows from assumption *2*.

target wealth ($\breve{w}$) rises. Additionally, an immediately supplementary boost to saving is necessary to move from the initial inadequate level of wealth up to the new (higher) target.

2.4 Hypothesis

What we learn from this framework is that a decrease in credit availability increases the target wealth ($\breve{w}$), resulting in a higher saving rate. In addition, we learn that the precautionary saving motive gains importance when wealth drops. However, the most relevant insight of this model concerning the aim of this research is that an increase in labour uncertainty is followed by a higher saving rate due to precautionary behaviour.

To finalize, by using appropriate proxies for household wealth, credit availability and labour uncertainty in an empirical model, I expect to find a positive and significant effect of labour uncertainty on saving.

Formally:

Null hypothesis: There is no effect of labour uncertainty on the saving rates of European countries

Alternative hypothesis: There is a positive effect of labour uncertainty on the saving rates of European countries

3. Literature

The main aim of the empirical saving literature throughout the last decades was to find the determinants of saving. During this continuous search, more and more attention has been paid to the effects of precaution on saving. This implies that the empirical literature followed the theoretical developments described in Chapter *2*. The influential studies relevant for this research can roughly be divided into three categories: 1) empirical papers on the general determinants of saving; 2) empirical papers on precautionary saving at the individual and household level and 3) empirical papers on precautionary saving at the aggregate level. Each of these categories will be discussed below.

3.1 General determinants of aggregate saving

A first interesting group of studies looked at the general determinants of saving, without specifically focusing on precautionary saving. Browning and Lusardi (1996) sum up nine motives why individuals save. Amongst others, they name the precautionary, the life-cycle and the intertemporal substitution motives. The precautionary motive includes building up a reserve against unexpected expenditures, whereas the life-cycle motive is about the anticipation of a change in the relationship between income and needs. The intertemporal substitution motive, on the other hand, concerns making profit from interest and appreciation.

As the saving motives are diverse, it intuitively makes sense that various variables play a role in determining saving. Table *1* (see next page) gives an overview of the results obtained by studies that aimed at measuring the general determinants of saving. Schmidt-Hebbel et al. (1992) conducted a panel data analysis on 10 developing countries for the years 1970-1985. They claimed to be the first to apply aggregate household saving data instead of aggregate private saving data. The difference between these two is that aggregate private saving also includes corporate saving. Edwards (1996), on the contrary, used aggregate private saving as the dependent variable. In a panel study including a group of Latin American, Asian, African and industrialized countries he found that between 1970 and 1992 private saving was determined differently than government saving.

Table 1

Variable **Study***	1)	2)	3)	4)	5)	6)
Real GDP per capita level	+	+		+	+	
Real GDP per capita growth	+	+	+	+	+	+
Real interest rate	0	0	0	+	-	+
Inflation rate	0	0	+	0	+	0
Dependency ratio (<16y & >65y)	0	-		-		
Old-dependency ratio (>65y)			-		-	0
Young-dependency ratio (<16y)					-	0
Urbanization		-			-	-
Government saving		-		-	-	
Foreign saving	-	-		-		
Private credit flow		+	-		-	

The +, – and 0 signs indicate a positive significant, negative significant and no significant effect respectively. *Studies: 1) Schmidt-Hebbel, Webb & Corsetti (1992); 2) Edwards (1996); 3) Callen & Thimann (1997); 4) Masson, Bayoumi & Samiei (1998); 5) Loayza, Schmidt-Hebbel & Serven (2000); 6) Horioka & Wan (2007).

Next to a standard panel study on 21 OECD countries for the years 1975-1995, Callen & Thimann (1997) applied a cross-section model particularly focusing on tax and social welfare systems. They found a negative effect of both direct taxes and government transfers to households on household saving. Moreover, they discovered that although household saving is a primary driver of private saving, it only explains 75% of private saving, meaning that 25% of the private saving stems from corporate saving. For that reason, they decided to use household saving as their dependent variable.

Masson et al. (1998) claimed to be the first to measure the determinants of aggregate private saving for the large amount of countries that they included in their combined industrial- and developing country panel analysis (61 countries) on the years 1971-1993. Loayza et al. (2000) went even further by including data on 150 countries, spanning the years 1965-1994. This study stood out by applying a variety of different estimators and samples to verify the results. A more recent study to the general determinants of saving is conducted by Horioka & Wan (2007), who focused on household saving in Chinese provinces. They included data on the years 1995-2004.

When looking at the main results of all these studies (see Table *1*), it is clear that they indicate that real GDP level and real GDP growth positively affect aggregate saving. The intuition behind this is that households in richer countries overall earn more money that can be allocated to saving. Since saving implies future consumption (Romer, 2011) and households prefer a gradually increasing expenditure (the so called improvement motive for saving, Browning & Lusardi, 1996), the positive effect of real GDP level and real GDP growth on saving is in line with expectations and likely to be maintained throughout time.

The different studies found mixed results for the effect of the real interest rate on saving. The reason for this can be that both substitution and income effects play a role. On the one hand, an increase in the real interest rate gives households an incentive to increase saving since they can make profit from this higher interest rate (i.e., the intertemporal substitution motive). However, at the same time this higher expected income diminishes the incentive to save (the income effect). The sign of the effect of the real interest rate on saving seems to depend on the dominance of either the substitution or the income effect.

Also mixed results were obtained for the effect of the inflation rate on saving. This effect can be linked to the precautionary saving motive that Browning & Lusardi (1996) mention. In fact, a positive effect of the inflation rate on saving would imply that households, as a precautionary measure, start saving more in response to an increase in inflation. As shown in Table *1,* only two studies show a positive sign, whereas the others do not show a significant effect of the inflation rate on saving.

To continue, the different studies that took the dependency ratios into account found either a negative effect on saving or no significant effect at all. A negative sign means that households overall save less in countries with many young and old people. The intuition behind this is that people mainly save during their working-age period. The corresponding general determinants of saving (dependency ratio, old dependency ratio, young dependency ratio) can be related to the life-cycle motive for saving (Browning & Lusardi, 1996). That is because the relationship between income and needs is different depending on the composition of households.

There seems to be consensus among the different studies about a negative effect of urbanization, government saving and foreign saving on aggregate saving. The negative sign of urbanization might result from the idea that social welfare is better organised in urbanized areas if compared to rural areas. In order to compensate for this, household living in rural areas save more. As a result, it could be the case that households in countries with a high urbanization rate overall save less than households in a country with a low urbanization rate. The negative signs of government saving and foreign saving might follow from respectively Ricardian principles and open financial markets. According to the Ricardian principles, all government expenditures in a certain country need to be paid by the households living in that country. Hence, if a government increases its saving, implying that they cut their expenditures, households are less inclined to save and expected to lower their saving instead (Romer, 2011). The intuition behind the negative sign that was obtained for foreign saving is that open financial markets make it possible to borrow money abroad. Hence, if foreign saving increases, a larger amount of money can be borrowed from abroad, resulting in lower household saving in the home country.

To finish, the studies including the private credit flow leave ambiguity about the effect of this determinant on saving. As explained in Section *2.3.2*, it is expected that an increase in the availability of private credit decreases household saving.

3.2 Empirical importance of precautionary saving at the individual and household level

Next to empirical studies on the general determinants of saving, a subdivision of saving studies started to focus specifically on precautionary saving. Inspired by the theoretical papers that predicted that precaution matters for saving, empirical studies were being conducted in order to verify this initially only theoretical result.

Skinner (1988) was one of the first that tried to quantify the importance of precautionary saving. Based on survey data, he proxied uncertainty by the income risk of different occupations people were in. His model including occupations with different income uncertainties provided little support for the importance of precautionary saving. More specifically, in a cross-section analysis, he found that persons involved in more risky jobs, such as sales persons and selfemployed, save less than persons who work in less risky jobs, such as teachers and craftsmen. This is in contrast with theoretical predications on precautionary saving.

A possible reason for this is that self-selection plays a role (Skinner, 1988). I.e., more risk-averse persons choose a more risk-averse job. This suggestion is confirmed by Schündeln & Schündeln (2005), who used the German unification to show that risk averse people tend to take a low risk job, implying that self-selection leads to an underestimation of precautionary saving. Another suggestion that Skinner (1988) brought forward is that uncertainty diminishing programs, such as unemployment insurance, reduce saving. Hubbard et al. (1995) also point at the importance of looking at the interaction between uncertainty and social welfare programs. Engen & Gruber (2001) studied this interaction and found indeed a negative effect of social welfare programs on saving.

Guiso et al. (1992) also tested for the presence of precautionary saving and faced a similar problem as Skinner (1988) in empirically proving it. Although their empirical findings are in line with most theoretical expectations about saving in general, hardly any precautionary saving is measured for their Italian sample. As they believed that individual risk instead of aggregate risk is likely to be the main driver of precautionary saving, Guiso et al. (1992) proxied uncertainty by a self-reported measure of uncertainty of future earnings. This in contrast to Skinner (1988), whose measure of uncertainty was objectively calculated from a combination of the interest rate and a self-invented earnings risk. On the contrary, Carroll & Samwick (1997b) used the variability in income as a proxy for uncertainty. Their results indicate that a larger variability in income results in higher wealth due to precautionary saving. A year later, Carroll & Samwick (1998) confirmed this result. In this follow-up research they additionally divided households in different uncertainty groups to be able to simulate a situation in which all households had the same uncertainty as the lowest uncertainty group. They show that between 32 and 50 percent of wealth stems from the additional uncertainty that some groups of households have compared to the lowest uncertainty group. However, in their second study Carroll & Samwick (1998) also mention that it is hard to measure uncertainty correctly.

Carroll, Dynan & Krane (2003) continued on this by stating that income variability is not a good proxy for uncertainty. They illustrated this statement by explaining that a professor who occasionally teaches an evening course might have higher variability in his income than a construction worker, whereas the latter is expected to be laid off sooner than the former. Hence, Carroll et al. (2003) proxied uncertainty by job loss risk, which they statistically predicted by using objective data from both the Current Population Survey and the Survey of Consumer Finances. As a result, Carroll et al. (2003) somewhat surprisingly found that precautionary saving is at present for middle and high income households only. A couple of years earlier, Lusardi (1998) had already proxied uncertainty by job loss risk. However, she had used subjective data to predict this risk. In the corresponding study, Lusardi (1998) found evidence in favour of the existence of precautionary saving for individuals that were close to retirement. Although it was not the main aim of their research, Fafchamps & Pender (1997), Gourinchas & Parker (2001) and Cagetti (2003) empirically confirmed the existence of precautionary saving at the household level. Whereas Cagetti (2003) concluded that especially young households have a motive for precautionary saving, Famchamps & Pender (1997), as well as Gourinchas & Parker (2001) found that individual households in general have a motive for precautionary saving.

All in all, mixed results are obtained when trying to empirically measure the importance of precautionary saving at the individual and household level. Although theory predicts a large and important role for precaution in saving, in reality it seems hard to correctly measure this impact at a micro-level. As mentioned by Carroll & Samwick (1998), this is likely due to the fact that good proxies for individual (household) uncertainty are hard to find.

3.3 Empirical importance of precautionary saving at the aggregate level

The final group of studies of interest combines the findings of studies that tried to disentangle the general determinants of aggregate saving with the insights of studies that focused on uncertainty and the corresponding precautionary saving this brings about at a micro-level. Their aim is to investigate the empirical importance of precautionary saving at the aggregate level. Loayza et al. (2000) already mentioned uncertainty in an aggregate setting, but suggested inflation as an empirical proxy for it. The use of this proxy was criticized by Carroll et al. (2012), who argued that inflation insufficiently measures the uncertainty that people face. For that reason, they proxied uncertainty by unemployment risk, which they estimated based on individual expectations and forecast regressions. According to their results, U.S. personal saving between 1960 and 2011 can be well predicted by a buffer stock type of model including labour income uncertainty and credit constraints as determinants of saving next to the standard determinants.

Their study highlighted that labour uncertainty and borrowing constraints play a significant and substantial role as a determinant of aggregate saving.

Mody et al. (2012) conducted a similar study on a panel of 27 advanced economies for the years 1980-2009. They proxied uncertainty by the unemployment rate and GDP volatility. Their results were perfectly in line with the results that Carroll et al. (2012) obtained for the U.S. While controlling for the standard determinants of saving, such a credit constraints, demographics, the government's fiscal balance, the wealth/income ratio and some additional factors, such as stock-market volatility, global growth and financial stress, Mody et al. (2012) showed that two-fifth of the changes in the saving rate is due to the precaution following from unemployment and GDP volatility. Adema & Pozzi (2015) confirmed that labour uncertainty, together with household wealth and credit constraints, is a significant and important determinant of the aggregate household saving rate. In addition, they employed their panel dataset on 16 OECD countries over the period 1969-2012 to show that the household saving ratio is countercyclical.

Hence, in contrast with the mixed experiences one had with measuring precautionary saving at the micro-level, the larger availability of macro-economic risk factors seem to allow for the measurement of precautionary saving at a macro-level.

4. Data & Methodology

In this chapter, I firstly describe the two datasets that I apply. After that, I will discuss the methodology that I adopt to disentangle the effect of labour uncertainty on the saving rate.

4.1 Functional form model

Following Mody et al. (2012), I write the saving rate as a function of its plausible determinants:

$$\text{Saving rate } (S) = f(\text{UR}, \text{W}, \text{C}, \text{R}, \text{GB}, \text{DI}^{a}, \text{GDPV}^{a}, \text{SMV}^{a}, \text{ODR}^{a}, \text{YDR}^{a}, \text{GDPW}^{a}, \text{COGO}^{a}, \text{TED}^{a})$$

The function saving rate (S) is determined by the following set of variables:

- UR = unemployment rate (as a proxy for labour uncertainty)
- W = household wealth
- C = credit availability
- R = real short term interest rate
- GB = government structural balance
- DI = disposable income growth
- GDPV = GDP volatility (as a proxy for general uncertainty)
- SMV = stock market volatility
- ODR = old age dependency ratio
- YDR = young age dependency ratio
- GDPW = world GDP
- COGO= copper/gold price ratio
- TED = difference between the three-month interbank rate and US T-bill rate

The control variables marked with ^{a} are only included in dataset A

4.2 Datasets

As mentioned before, two different panel datasets will be applied in this study. The advantage of using two datasets is that I can perform many robustness checks. The first dataset (dataset A) that I apply is highly similar to the dataset that Mody et al. (2012) applied in their study. In comparison with their dataset, dataset A is different in the fact that it includes only European countries, as well as that it includes additional years of observations. Besides, for several control variables other data sources were consulted to collect the data. Another main difference is that dataset A includes individual country-based stock market volatility, whereas the dataset of Mody et al. (2012) only accounts for general stock market volatility without differentiating between countries. The advantage of looking at individual country-based stock market volatility is that differences in stock market volatility among countries are not neglected in the corresponding estimations. Dataset A contains data on the years 1980-2013. However, it should be stressed that observations for this whole time span are only available for France, whereas for all other countries the observations start in 1995 or later[5]. The 15 included European countries are: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, The Netherlands, Portugal, Spain, Denmark, Sweden and the United Kingdom.

The second dataset (dataset B) that I use is a part of the dataset that Adema & Pozzi (2015) applied in their 2014 study on business cycle fluctuations and household saving[6]. Dataset B considers a substantially longer time period (1969-2012)[7] and includes the same countries as dataset A except for Greece, Luxembourg and Portugal. In comparison with dataset A, some of the variables included in dataset B stem from different sources. Besides that, dataset B differs from dataset A since it includes less control variables. This is indicated in the functional form model.

Both dataset A and B should be considered unbalanced since observations for especially the early years are missing. Due to the poor quality and availability of quarterly data, I choose to use annualized data only. This is in line with Mody et al. (2012) and Adema & Pozzi (2015). All variables are rescaled in order to represent values between 0 and 1 instead of values between 0 and 100.

4.2.1 Description of variables Dataset A[8]

First of all, dataset A includes data on the net household saving rate (*S*), the real household net disposable income growth (*DI*) and the household's financial net worth. The latter variable is divided by the gross household adjusted disposable income to proxy for household wealth (*W*). Data on these variables stem from the OECD National Accounts (different volumes). It should

[5] An overview of the years included per country in dataset A can be found in Table *5* (Appendix).
[6] I am very grateful to Yvonne Adema and Lorenzo Pozzi for providing me with their dataset.
[7] An overview of the years included per country in dataset B can be found in Table *5* (Appendix).
[8] See Table *6* (Appendix) for an overview of the variables included in dataset A, together with their definitions and sources.

be noted that the proxy that I apply for household wealth (*W*) is imperfect due to the fact that it excludes housing wealth. Also obtained from the OECD is data on the short-term interest rate (*R*) (Economic Outlook database, volume 96). Further included is data on the unemployment rate (*UR*) and the government structural balance (*GB*), both originating from IMF's World Economic Outlook Database. I use the data on the unemployment rate (*UR*) to proxy for labour uncertainty. Also included is data on the domestic credit to the private sector, as well as data on the young- and old age dependency ratios (*YDR* & *ODR*), which are obtained from the World Bank's Development Indicators. The former data does not proxy the availability of credit (*C*) perfectly since it depends on credit demand as well.

In line with Mody et al. (2012), I added world GDP growth (*GDPW*), the copper-to-gold-price (*COGO*) and the TED-spread (*TED*) to the dataset as world market indicators. This allows me to capture common variation across countries. An alternative, more general, way of controlling for these common trends would be to add time fixed effects. However, I included these three specific market indicators in order to examine whether they show a similar effect as found by Mody et al. (2012). The copper price is known to reflect future growth prospects. However, in order to abstract from commodity price cycles, copper is deflated by gold to be more representative for future growth prospects (Mody et al., 2012). On the other hand, the TED-spread (*TED*), measured as the difference between the three-month Libor rate and the three-month US Treasury bill rate, reflects financial conditions (Mody et al., 2012). The three world market indicators respectively stem from the IMF's World Economic Outlook Database, the World Bank's Global Economic Monitor (GEM) Commodities and the FRED.

The remaining two control variables of dataset A: GDP volatility (*GDPV*) and stock market volatility (*SMV*), need to be discussed in more detail since they are based on own calculations. In order to calculate GDP volatility, I firstly used OECD and IMF data on yearly GDP and population to calculate the year-on-year growth of real GDP per capita. After that, I applied a Garch (1,1) model to derive the volatility of the year-on-year growth of real GDP per capita. A Garch (1,1) model is very helpful in this setting, as it calculates the current period GDP variance based on information from the past, i.e., the lagged(1) GDP variance and the lagged(1) squared residual (Hill, Griffiths & Lim, 2012). The former is called the Garch term, whereas the latter is called the Arch term. Ultimately, I took the square root of the variance to obtain the standard deviation, which corresponds to the volatility of GDP (*GDPV*).

In order to calculate stock market volatility (*SMV*), I firstly used DataStream to extract the daily price indices of the most influential stock market exchange for each individual country involved[9]. With these daily price indices, I calculated the daily price changes in each stock market index. Next, to calculate the daily stock market volatility, I took the standard deviation of the daily price changes in the different stock market indices over the period of one year. To finalize, I multiplied the daily stock market volatility with the square root of the number of trading days to obtain the annualized stock market volatility (*SMV)*.

4.2.2 Description of variables Dataset B[10]

Firstly, dataset B contains data on nominal household saving, nominal household disposable income, GDP and the unemployment rate (*UR*). Nominal household saving is divided by nominal household disposable income to obtain the household saving rate (*S*). Also included in dataset B are data on the nominal long-term interest rate on government bonds, the inflation rate and nominal government saving. The inflation rate is subtracted from the nominal long-term interest rate on government bonds in order to calculate the real interest rate (*R*). Nominal government saving is divided by nominal GDP to obtain the government saving rate, which represents the government structural balance (*GB*). So far, all data in dataset B originates from the OECD ECO Outlook team, as well as from the OECD Economic Outlook Database (volume 94).

Apart from that, data on nominal net household wealth and nominal gross household liabilities stem for NiGEM. Nominal net household wealth is divided by nominal disposable income to calculate the household wealth ratio (*W*). Likewise, nominal gross household liabilities are divided by nominal disposable income to obtain the household liabilities ratio. The latter ratio serves as a proxy for the credit that is available to the domestic private-sector (*C*).

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[9] See Table *8* (Appendix) for an overview of the most influential stock market exchange per country.
[10] See Table *7* (Appendix) for an overview of the variables included in dataset B, together with their sources.

4.3 Methodology

In this section, I explain the route that I will take to answer my research question. Below, I will discuss the main model that I apply, as well as six robustness checks that I will perform to verify the main results. The main model takes on three different specifications: the main regression specification, the adjusted regression specification and the first-differenced regression specification. These different specifications of the main model are initially applied to 1980-2009 and 1980-2013 samples, which are extracted from dataset A. The results following from the corresponding estimations will be regarded as the main results of this research.

I will discuss the methodology related to the main regression specification in detail first. After that, the methodology concerning the adjusted and first-differenced regression specifications will be explained, as far as this does not overlap the already explained methodology that is adopted to the main regression specification. In addition, the content of the robustness checks, as well as accompanying methodological aspects, will be described. Dataset A is used for all estimations performed in robustness checks 1-3 and 4 (partly). On the other hand, dataset B is employed for the estimations performed in robustness checks 4 (partly), 5 and 6. The robustness checks will be discussed one by one.

4.3.1 Main model – main regression specification

The main regression specification that will be applied in this study is the following:

$$\text{(OLS)} \qquad S_{i,t} = \alpha_0 + \beta_1 UR_{i,t} + \beta_2 W_{i,t-1} + \beta_3 C_{i,t} + \varepsilon_{i,t} \tag{7}$$

where *i* represents the country and *t* represent the year

In order to be able to compare the outcomes of this study to the outcomes of Mody et al. (2012) as well as possible, this main regression specification is similar to the regression specification applied by Mody et al. (2012). However, for the sake of conciseness, the main regression specification focuses on the three most important determinants of saving only. Following from the theoretical model discussed in Chapter *2*, these are the unemployment rate (*UR*), household wealth (*W*) and the availability of credit (*C*). In robustness check 4, the additional control variables (*R*, *GB*, *DI*, *GDPV*, *SMV*, *ODR*, *YDR*, *GDPW*, *COGO* and *TED*) applied by Mody et al. (2012) will be added to the main model, allowing for a more extensive comparison between the outcomes of the underlying study and the study of Mody et al. (2012).

4.3.1.1 OLS

The coefficient of main interest is β_1. I will start with a simple Ordinary Least Squares (OLS) estimation. The OLS estimator selects the β's in such a way that $\varepsilon_{i,t}$, the unexplained part of the model (the error term), is minimized. When using the OLS estimator, β_1 correctly identifies the causal effect of the unemployment rate (*UR*) on the saving rate (*S*) if I assume that $E(\epsilon_{i,t}|X) = 0$, where X represents the independent variables UR_t, W_{t-1} and C_t. Additionally, it should hold that $Var(\epsilon_{i,t}|X) = \sigma^2$ as well as that $Cov(\varepsilon_t, \varepsilon_{t-1}) = 0$. In words, these assumptions imply that: 1) X is unrelated to the other factors determining the saving rate (the error term); 2) the precision of the obtained estimates is similar for all countries included, i.e., homoscedastic error terms; 3) the error term of one year does not give any information on the error term of another year, i.e., absence of autocorrelation. If all these assumption are met, the estimates obtained by the OLS estimator are what is called unbiased and efficient (Hill, Griffiths & Lim, 2012). Since there are reasons to believe that the assumptions underlying simple OLS do not hold, I will make use of other estimation techniques too.

4.3.1.2 Fixed effects

First of all, it is likely that the error term in the regression of equation 7 contains unobservable country-specific and time-invariant variables that are related to X. As an example of such an unobservable variable, one could think of cultural differences in attitude towards saving, which might for example be related to the wealth that households (*W*) obtain in the different countries. In that case, $E(\epsilon_{i,t}|X) \neq 0$, implying that the true effect of the unemployment rate (*UR*) on the saving rate (*S*) is not identified (Verbeek, 2012). In order to control for this, I add fixed effects to the regression:

$$\text{(OLS – fixed effects)} \qquad S_{i,t} = \alpha_i + \beta_1 UR_{i,t} + \beta_2 W_{i,t-1} + \beta_3 C_{i,t} + \varphi_{i,t} \qquad (8)$$

Fixed effects control for unobserved factors that do not vary for the individual countries across the years. This is done by making the constant α country dependent (Verbeek, 2012). In the example of the cultural differences, this implies that the constant α_i controls not only for cultural differences, but also for all other country fixed effects. This only occurs when these cultural differences remain equal throughout all included years for all included countries. By making the constant α country specific, β_1 becomes unbiased again. $\varphi_{i,t}$ is the remainder of the original error term ($\varepsilon_{i,t}$), i.e., the unexplained part of the model that cannot be taken away by the fixed effects (Verbeek, 2012).

4.3.1.3 Unit root and autocorrelation

To verify whether the regression of equation 8 provides correct estimates, I need to test for a unit root and autocorrelation. The problem with a unit root is that a variable cannot be measured in a statistically logical way (Hill, Griffiths & Lim, 2012). In the underlying regression this would be the case when for example the saving rate (S) is not mean reverting, meaning that it follows a random walk. A solution to the random walk problem is to first-difference the variables of the model (Hill, Griffiths & Lim, 2012). As an example, this would imply estimating the effect of the change in the unemployment rate (ΔU) from one period to the next on the change in the saving rate (ΔS) from one period to the next.

In order to test whether the dependent variable (S) or the independent variables (X) follow a random walk, I apply the Augmented Dickey Fuller (ADF) test by Fisher. This test is especially designed for panel data and combines information from unit root tests on all individual countries. The main advantage of this test is that it allows for the combined use of multiple ADF tests, as well as for different time lengths per country. The major disadvantage of this test is, however, that a rejection of the null hypothesis for a variable does not automatically imply that this variable is stationary for all countries. The only conclusion that can be drawn after rejecting the null hypothesis of the ADF test by Fisher is that the particular variable is stationary for at least one country (Verbeek, 2012).

The reason for using this not completely informative test is that the econometric literature has not come up with better alternatives so far (Verbeek, 2012). Stated differently, the alternatives that were introduced all brought along their own problems[11]. Before conducting the ADF test by Fisher, I need to make a plot of the variables to determine what type of ADF test to perform (Verbeek, 2012). I can choose among three alternatives:

- No constant and no trend (the variable fluctuates around zero)
- A constant, but no trend (the variable fluctuates around a number different from zero)
- Both a constant and a trend (the variable fluctuates around a linear trend)

[11] Alternatives that were introduced are, amongst others, the Levin–Lin–Chu test and the Im–Pesaran–Shin test.

ADF test (Fisher) for unit root	
H0:	**the dependent variable (*S*), independent variable (*X*) of all individual countries have a unit root**
Ha:	**the dependent variable (*S*), independent variable (*X*) of at least one individual country is stationary**

The problem with autocorrelation, on the other hand, is that two or more consecutive error terms are correlated (Hill, Griffiths & Lim, 2012). This occurs when-the error terms of period t are correlated with the error terms of one or more previous periods $Cov(\varepsilon_t, \varepsilon_{t-1}) \neq 0$. Even when autocorrelation is present, the fixed effects regression still provides unbiased estimates as long as $E(\epsilon_{i,t}|X) = 0$. The consequence of autocorrelation is, however, that the estimates are inefficient (Verbeek, 2012). Hence, if I conclude that the errors are autocorrelated, the corresponding model requires an adjustment. One solution is to use Driscoll-Kraay robust standard errors (Drukker, 2003). To test whether autocorrelation is at present I use the Wooldridge test. This test is especially designed to measure autocorrelation in unbalanced panel datasets. Hence, the Wooldridge test fits the unbalanced datasets that I apply in this study (Drukker, 2003).

Wooldridge test for autocorrelation	
H0:	**no first-order autocorrelation**
Ha:	**first-order autocorrelation**

I will not test for homoscedasticity of the error terms $\varepsilon_{i,t}$, but both the use of Driscoll-Kraay standard errors, which I discussed above, as well as the estimation method described in Section *4.3.1.5* is consistent with heteroskedastic error terms.

After making the required modifications following from the ADF and Wooldridge tests, the fixed effects regression provides unbiased and efficient estimates if, as mentioned before, I assume that $E(\epsilon_{i,t}|X) = 0$. However, endogeneity problems might cause this assumption to fail.

4.3.1.4 Endogeneity

First of all, omitted variables can play a role. As saving is related to many aspects of the larger macro-economic environment, it is possible that a relatively important determinant of saving is not included in the regression of equation 8. When such an omitted determinant of the saving rate is related to another determinant of the saving rate (X), $E\left(\epsilon_{i,t}|X\right)=0$ does not hold (Verbeek, 2012). This means that β_1 cannot correctly identify the causal effect of the unemployment rate (UR) on the saving rate (S). To minimize this problem, I will run several regressions including additional control variables as a robustness check, which I further explain below under robustness check 2. However, one can never be certain that all control variables of interest are included, meaning that the possibility that the model suffers from an omitted variable bias cannot be excluded.

Secondly, reverse causality might be at present. This is the case when the saving rate (S) also has a causal effect on one of its determinants (X) (Verbeek, 2012). Take for example household wealth (W). In the current model I assume that the causality runs from wealth (W) to the saving rate (S), i.e., wealth (W) affects saving (S). At the same time, one could argue that saving (S) affects wealth (W), i.e., the higher a household's saving (S), the higher its wealth (W). Also in the case of reverse causality the assumption $E\left(\epsilon_{i,t}|X\right)=0$ is not satisfied, leading to unbiased estimates (Verbeek, 2012). To correct for the specific reverse causality following from the above example, W_{t-1} instead of W_t is used. This solves the reverse causality bias, as one would not expect current saving (S_t) to affect last periods wealth (W_{t-1}). However, solely applying lagged independent variables does not support precise measurement of the household saving rate (S_t). Hence, non-lagged independent variables (UR_t & C_t) remain. Although it is hard to think of examples, any reverse causality following from these variables cannot be ruled out.

Thirdly, measurement errors might influence the estimates that are obtained. A measurement error in the dependent variable is usually not very problematic, as it only leads to biased estimates when the error in measurement is related to one of the explanatory variables (Verbeek, 2012). In the case of saving, it is hard to think of a situation in which a measurement error in the saving rate (S) is related to one of the explanatory variables (X). Alternatively, a measurement error in one or more of the independent variables (X) gives more complications. In that case the assumption $E\left(\epsilon_{i,t}|X\right)=0$ is not met, resulting in estimates that are biased towards zero (Verbeek, 2012). Although all data originates from high quality and generally reliable sources, such as the OECD and the IMF, one can never exclude the possibility that one of the independent variables (X) is observed with error.

4.3.1.5 GMM

An often applied method in empirical work to solve for the bias that comes along with endogenous variables is General Methods of Moments (GMM). GMM is related to two-stage-least squared (2SLS), as both methods apply instruments to filter out the exogenous effect of an endogenous independent variable on the dependent variable (Arellano, 2003). Two types of the GMM estimator exist, namely the one-step GMM estimator and the two-step GMM estimator. The former assumes that the error term ($\varepsilon_{i,t}$) is homoscedastic and exhibits no autocorrelation, whereas the latter allows the error term to be heteroskedastic and autocorrelated (Verbeek, 2012). As it is conceivable that either the precision of the obtained estimates is different for all countries included (i.e., $\varepsilon_{i,t}$ is heteroskedastic), or that the error term of one year gives information on the error term of another year (i.e., $\varepsilon_{i,t}$ exhibits autocorrelation), I apply the more efficient two-step GMM estimator in this study. Because Newey & Smith (2004) found that the standard errors are biased when using the two-step GMM estimator, I additionally apply the two-step GMM estimator with Windmeijer standard errors to correct for this bias (Windmeijer, 2005).

Since reliable external instruments are lacking, I apply internal instruments. Instruments should be considered valid when they are correlated with the endogenous variables (relevant) and uncorrelated with the error term of the original model (exogenous). If valid instruments are applied, the GMM estimator provides consistent estimators (Arellano, 2003). Different from 2SLS, GMM does not suffer from the disadvantage of reduced sample sizes, since all missing values are replaced by the value zero (Verbeek, 2012). In order to account for fixed effects, GMM first differences the variables of equation 7:

$$\text{(OLS - First-differenced)} \qquad \Delta S_{i,t} = \beta_1 \Delta UR_{i,t} + \beta_2 \Delta W_{i,t-1} + \beta_3 \Delta C_{i,t} + \Delta\varphi_{i,t} \qquad (9)$$

with $\Delta X_{i,t} = X_{i,t} - X_{i,t-1}$

Again, what remains of the original error term ($\varepsilon_{i,t}$) is the unexplained part of the model ($\varphi_{i,t}$) that cannot be taken away by first differencing (Verbeek, 2012). I will use up to three (1-3) lagged values of the first-differenced independent variables as internal instruments. Limiting the number of instruments is recommended by Verbeek (2012) and in line with Adema & Pozzi (2015).

To illustrate this, I will instrument ΔUR_t with Z, where Z is a set of instruments including ΔUR_{t-1}, ΔUR_{t-2} and ΔUR_{t-3}. The aim of doing this is to filter out the exogenous effect of the change in the unemployment rate (ΔUR_t) on the change in the saving rate (ΔS_t). The set of instruments Z is valid if ΔUR_{t-1}, ΔUR_{t-2} and ΔUR_{t-3} are all individually significantly correlated with ΔUR_t, i.e., the instruments are relevant ($E(\Delta UR_t|Z) \neq 0$). Additionally required is that these instruments are not related to $\varphi_{i,t}$, i.e., the instruments are exogenous ($E\left(\varphi_{i,t}\middle|Z\right) = 0$). If these requirements are met, it is safe to assume that β_1 correctly identifies the causal effect of the change in the unemployment rate (ΔUR_t) on the change in the saving rate (ΔS_t). However, if one or more of the instruments included in Z are either hardly related to ΔUR_t, or affect $\Delta S_{i,t}$ also through other ways than through $\Delta UR_{i,t}$, these particular instruments are weak. Weak instruments lead to biased estimates (Arellano, 2003).

The same technique as described in this illustration will be applied for each time period (*t*), as well as to the other possible endogenous independent variables ($\Delta W_{i,t-1}$ and $\Delta C_{i,t}$).

4.3.1.6 2SLS-based Cragg-Donald, Sargan and Arrellano & Bond test

Whether an instrument is relevant in a GMM panel data setting cannot be examined directly in Stata, as this statistical programme does not allow for the use of the Cragg-Donald test in a GMM setting. However, the Cragg-Donald test can be performed in a 2SLS setting. Since GMM and 2SLS are closely related (as discussed in Section *4.3.1.5*), the result of the 2SLS-based Cragg-Donald test gives a good indication of the strength of the instruments that I use in this study (Cragg & Donald, 1993). The corresponding test result will be compared to the Stock-Yogo critical values, which have been specifically designed for testing identification strength. More specifically, I will compare the Cragg-Donald test statistic with the Stock-Yogo critical value that limits the bias of the 2SLS estimator relative to the OLS estimator to a maximum of 30% (Stock & Yogo, 2004).

2SLS-based Cragg-Donald test	
H0:	**instruments are weak**
Ha:	**instruments are relevant**

Next to that, the exogeneity of the instruments can be tested by means of a Sargan test of overidentifying restrictions. An assumption underlying this test is that at least one of the applied instruments is exogenous. The conclusion of rejecting the null hypothesis is that at least one of the instruments is endogenous. The Sargan test does not clarify which of the instruments lacks exogeneity in that case (Verbeek, 2012).

Sargan test of overidentifying restrictions	
H0:	**all instruments are exogenous**
Ha:	**at least one instrument is not exogenous**

To further verify whether the instruments are exogenous, an Arrellano & Bond test for autocorrelation will be applied. The Arrellano & Bond test checks whether the error terms show autocorrelation (Verbeek, 2012). Since all variables are first-differenced, I expect first order autocorrelation (*AR(1)*) to be present. On the other hand, finding second order autocorrelation (*AR(2)*) implies that ($E\left(\varphi_{i,t}\middle|Z\right) \neq 0$). To illustrate this for the regression in equation 9, I expect $\Delta\varphi_{i,t}$ to be related with $\Delta\varphi_{i,t-1}$ by definition, since both error terms contain $\varphi_{i,t-1}$. However, when $\Delta\varphi_{i,t}$ is related to $\Delta\varphi_{i,t-2}$, the exogeneity requirement $E\left(\varphi_{i,t}\middle|Z\right) = 0$ is unfulfilled.

Arrellano & Bond test for autocorrelation	
H0:	**no second order autocorrelation**
Ha:	**second order autocorrelation**

In sum, different estimation methods are available to disentangle the effect of the unemployment risk (*UR*) on the saving rate (*S*). Whether the effect that is measured by a certain estimator is the true effect depends on the extent to which underlying assumptions of the particular estimator are met. The auxiliary tests that I described help to determine whether a certain estimation method is reliable.

In the first place, I will make use of the main regression specification to run regressions for both a 1980-2009 sample, as well as for a 1980-2013 sample. These samples are extracted from dataset A. The aim of running these regressions is to verify the effect of including the additional years 2010-2013. In addition, it will enable me to compare the results for the 1980-2009 sample with the outcomes that were found by Mody et al. (2012).

4.3.2 Main model – adjusted regression specification

The adjusted regression specification differs in two ways from the main regression specification. Firstly, I add the lagged value of the saving rate (S_{t-1}) to the main model as an explanatory variable. Secondly, I substitute the unemployment rate (UR_t) for the lead of the unemployment rate (UR_{t+1}). Although this differs from the specification applied by Mody et al. (2012), both modifications are in line with the regression specification that Adema & Pozzi (2015) apply. The reason underlying the first modification is that the saving rate (*S*) might be sticky. The second modification is based on the finding of Carroll et al. (2012) that the current year *(t)* unemployment rate is highly correlated to the labour uncertainty that households experienced in the previous year *(t-1)*. If that is indeed the case, the lead of the unemployment rate (UR_{t+1}) should be taken to measure the effect of the current years labour uncertainty on the current years saving rate (S_t). The corresponding adjusted regression specification looks as follows (in OLS):

$$\text{(OLS – adjusted)} \qquad S_{i,t} = \alpha_0 + \beta_0 S_{i,t-1} + \beta_1 UR_{i,t+1} + \beta_2 W_{i,t-1} + \beta_3 C_{i,t} + \varepsilon_{i,t} \qquad (10)$$

In this dynamic specification possible fixed effects are, by construction, correlated with the lag dependent variable ($S_{i,t-1}$). For that reason, the estimators obtained by a fixed effects estimation and a standard GMM estimation are inconsistent. This is known as the dynamic panel bias (Nickell, 1981). To solve for this bias, I apply the Arrellano & Bond (AB) type GMM estimator instead of the standard GMM estimator. When the accompanying instruments are relevant and exogenous, the AB GMM estimator provides consistent estimates for this adjusted regression specification (Verbeek, 2012). Further methodology that is applied to the adjusted regression specification is identical to the methodology that has been explained already for the main regression specification.

Estimations using the dynamic specification will initially be performed for a 1980-2009 sample, as well as for a 1980-2013 sample. Again, these samples are extracted from dataset A. The outcomes for these different time samples will be compared with each other, as well as with the outcomes following from the application of the main regression specification.

4.3.3 Main model – first-differenced regression specification

The first-differenced regression specification transforms the main regression specification in first differences. For an illustration of a first-differenced version of the main model (in OLS), I refer to the regression in equation 9.

The reason for applying this specification is twofold. Firstly, taking first differences ascertains that any possible random walk cannot trouble the regression outcomes. Secondly, it is in line with Adema & Pozzi (2015), whose main regression specification consisted of first-differenced variables.

Also for the first-differenced regression specification it holds that the applicable methodology has already been introduced above when discussing the main regression specification. Estimations in the first-differenced specification will first of all be performed for a 1980-2009 sample and a 1980-2013 sample. These samples, once again, are extracted from dataset A. The outcomes for these different samples will be compared with each other, as well as with the outcomes found when applying the main regression specification. It should be noted that Luxembourg drops out the 1980-2009 sample when applying the first-differenced regression specification. This is due to the short time span of observations for this particular country.

4.3.4 Robustness checks

As denoted before, I regard the results of the above mentioned regressions for the 1980-2009 and 1980-2013 samples as the main results of this study. To verify whether the effects corresponding to these main results are robust, I will perform various robustness checks.

4.3.4.1 Robustness check 1 – excluding the economic crisis and its aftermath

In this robustness check, I reduce the considered time period to 1980-2007. The reason behind this is to rule out the possibility that the main results are solely driven by the economic crisis and its aftermath. It should be noted that Greece and Luxembourg are not taken into account in the reduced sample that is applied in this robustness check. This is due to the short time span of observations for these particular countries. I will run regressions in the main, adjusted and first-differenced specification of the main model for the years 1980-2007. The outcomes of these regressions will be compared to the main results.

4.3.4.2 Robustness check 2 – adding additional control variables

A next robustness check that I perform is that I add all available control variables (*R*, *GB*, *DI*, *GDPV*, *SMV*, *ODR*, *YDR*, *GDPW*, *COGO*, *TED*) to the main model. Accounting for these additional control variables minimizes the omitted variable bias (see Section *4.3.1.4*). I will run regressions in all three main model specifications for the time periods 1980-2009 and 1980-2013. The outcomes of these regressions will be compared to the outcomes that are found without adding extra control variables.

4.3.4.3 Robustness check 3 – North/South effect

To check whether the effect of the unemployment rate (*UR*) on the saving rate (*S*) is different for Southern European countries compared to Northern European countries, I add the interaction term *South*UR* to the main model. When this interaction term turns out to have a significant effect on the saving rate (*S*), one can conclude that Southern European countries are affected differently by changes in the unemployment rate (*UR*) than their Northern counterparts. To correctly measure the effect of this interaction term, I will additionally incorporate a dummy variable *South* into the model, taking the value 1 for Southern European countries and the value 0 for Northern European countries (Hill, Griffiths & Lim, 2012).

Since fixed effects models cannot deal with dummy variables (Verbeek, 2012) no fixed effects estimations will be made in this robustness check. The additional control variables that were introduced in robustness check 2 will be added again to the regressions performed in this robustness check. I will run regressions in the main specification, the adjusted specification and the first-differenced specification for the years 1980-2009 and 1980-2013.

4.3.4.4 Robustness check 4 – additional years

As mentioned earlier, the disadvantage of dataset A is its relatively short period of observations. This is where dataset B comes in as a useful source for performing some additional robustness checks. First of all, the extra time periods that are included in dataset B can be utilized to verify whether the main results also hold over the longer time period 1969-2012. At the same time, dataset B offers the opportunity to verify whether the main results are robust to the use of slightly different variables and data sources.

I will run regressions in the main, adjusted and first-differenced regression specifications for the periods 1969-2009 and 1969-2012. The outcomes will be compared with each other, as well as with the main results. In order for this latter comparison to make sense, I will re-run the corresponding dataset A-regressions, this time considering 12 countries only. The reason behind this is that dataset B does not contain observations for Greece, Luxembourg and Portugal. As a final step, I will compare these twelve-country-based main results with the original (fifteen-country-based) main results to verify whether the inclusion of Greece, Luxembourg and Portugal drive the main results.

4.3.4.5 Robustness check 5 – Mean Group (MG) estimator

To make fully use of the large time span of dataset B, one of the final robustness checks that I conduct is applying the mean group (MG) estimator. As Mody et al. (2012) already mentioned, an implicit assumption made in the current research is that the saving rate function is similar for the countries involved, implying that the parameters determining saving are homogenous across countries. However, it might be the case that these parameters are heterogeneous instead. An example of the latter could be that the unemployment rate (*UR*) affects the Spanish saving rate differently than the Dutch saving rate. Peseran & Smith (1995) found that neglecting heterogeneous parameters results in biased estimates. Ul Haque, Pesaran & Sharma (1999) confirmed this result in the context of saving regressions.

Mean group estimation firstly measures the coefficients for each individual country separately by OLS, before ultimately estimating the average effects of all countries. This average effect is what the mean group estimates represent. The mean group estimator is unbiased and consistent, also under heterogeneous parameters (Peseran & Smith, 1995).

In order to control for potential heterogeneity in parameters, I will run MG-regressions in all three main model specifications. Additional control variables R and GB will be added to these regressions also. Both the periods 1969-2009 and 1969-2012 will be investigated. The outcomes of the regressions will be compared with each other, with the main results, as well as with the results following from robustness check 4.

4.3.4.6 Robustness check 6 – Common Correlated Effects Mean Group (CCEMG) estimator

Next to the general mean group estimator, a different type of mean group estimator exists that allows for cross-sectional dependence. Cross-sectional dependence is present when the error term of a panel data model contains omitted unobserved common shocks that influence the saving rates differently across countries (Everaert & Pozzi, 2014). Due to European integration, it is likely that such common shocks play a role for the countries included in this study. If one or more of these common European shocks affect the saving rate (S) differently across countries, biased and inconsistent estimates are obtained (Everaert & Pozzi, 2014). To solve for this bias, I will add the cross-sectional average of the saving rate ($\bar{S}$), as well as of the explanatory variables ($\bar{X}$) as additional coefficients. The common correlated effects mean group estimation (CCEMG) is the corresponding type of the mean group estimator. The CCEMG estimator provides unbiased and consistent estimates, also in the situation of cross-sectional dependence and heterogeneity in parameters (Everaert & Pozzi, 2014).

To control for potential cross-sectional dependence in combination with heterogeneous parameters, I will run CCEMG- regressions in the main specification, the adjusted specification and the first-differenced specification. Additional control variables R and GB will be added to these regressions too. Both the periods 1969-2009 and 1969-2012 will be taken into account. The outcomes of these regressions will be compared with each other, as well as with the results following from robustness checks 4 and 5.

5. Results

As described in Chapter *4*, I have performed many regressions and accompanying tests to disentangle the effect of the unemployment rate (*UR*) on the saving rate (*S*). In this chapter, the corresponding results will be presented. Firstly, the outcomes of applying the main model regression specifications to the 1980-2009 and 1980-2013 samples will be discussed. After presenting these main results, the outcomes of the robustness checks will be considered sequentially.

5.1 Main results

Table *2* (see next page) shows the results obtained from the main regression specification. When applying OLS to the 1980-2009 sample, the unemployment rate (*UR*) shows a significant positive effect (0,49) on the saving rate (*S*) (see Column *1*). The interpretation of this effect is as following: an increase in the unemployment rate of 1 percentage point leads to an increase in the saving rate of 0,49 percentage point. When fixed effects are added, a similar significant positive effect is found (see Column *2*). This result is equivalent to the result found by Mody et al. (2012). The ADF test by Fisher, including a constant but no trend, rejects the null hypothesis that the saving rates (*S*), the unemployment rates (*UR*) and the household wealth (*W*) of all countries follow a unit root (see Appendix, Table *9*). However, the ADF test by Fisher including a constant and a trend, does not reject the null hypothesis that the credit availability (*C*) of all countries follow a unit root (see Appendix, Table *9*). This indicates that the problem of a unit root could be assumed absent for the dependent variable *S*, as well as for the independent variables *UR* and *W*. At the same time, it seems that the independent variable *C* follows a random walk. This indicates that the estimates obtained from the main regression specification might be biased. I will show results that correct for this bias when I present the results of the first-differenced regression specification. Since Mody et al. (2012) did not seem to test for any random walk at all and applied the independent variable credit availability (*C*) only in levels, I remain the credit availability (*C*) in levels when presenting the results of the main and adjusted regression specification regressions. This contributes to a good comparison between the results of Mody et al. (2012) and the results of the current study.

The Wooldridge test for autocorrelation, on the other hand, shows that autocorrelation is present. For that reason, the fixed effects estimation is also performed with Driscoll-Kraay standard errors. The unemployment rate (*UR*) still has a similar significant positive effect on the saving rate (*S*) in the fixed effects estimation with Driscoll-Kraay standard errors (see Column *3*). Also applying the GMM two-step estimator with normal standard errors shows a significant and positive effect of the unemployment rate (*UR*) on the saving rate (*S*) (see Column *4*). The latter effect is similar in size and significance to the effects that have been found by the OLS and fixed effects estimations. However, this effect becomes insignificant when including the Windmeijer standard errors in the two-step GMM estimation (see Column *5*).

Table 2 – main regression specification results

S_t	(1) OLS	(2) Fixed effects	(3) Fixed effects DK-robust	(4) GMM two-step	(5) GMM two-step WC-robust	(6) OLS	(7) Fixed effects	(8) Fixed effects DK-robust	(9) GMM two-step	(10) GMM two-step WC-robust
UR_t	0,49*** (0,15)	0,52*** (0,13)	0,52** (0,21)	0,46*** (0,08)	0,46 (0,82)	-0,07 (0,09)	0,07 (0,07)	0,07 (0,12)	0,19*** (0,06)	0,19 (0,28)
W_{t-1}	0,03*** (0,01)	0,01* (0,01)	0,01 (0,01)	-0,01*** (0,00)	-0,01 (0,09)	0,03*** (0,01)	0,01* (0,01)	0,01 (0,01)	-0,02*** (0,00)	-0,02 (0,13)
C_t	-0,01 (0,01)	0,00 (0,01)	0,00 (0,01)	-0,00 (0,01)	-0,00 (0,07)	-0,02** (0,01)	-0,00 (0,01)	-0,00 (0,01)	0,01 (0,02)	0,01 (0,07)
Constant	-0,01 (0,02)	-0,00 (0,02)	-0,00 (0,03)	0,05*** (0,01)	0,05 (0,17)	0,04** (0,02)	0,03* (0,02)	0,03 (0,02)	0,05** (0,03)	0,05 (0,27)
Observations	168	168	168	168	168	226	226	226	226	226
(Within) R^2	0,20	0,09	0,09			0,15	0,02	0,02		
Instruments				110	110				146	146
Countries	15	15	15	15	15	15	15	15	15	15
Dataset	A	A	A	A	A	A	A	A	A	A
Wooldridge		37,08*** [0,00]					35,10*** [0,00]			
2SLS Cragg-Donald				1,01	1,01				1,08	1,08
AB-test				AR(1): [0,13] AR(2): [0,29]	AR(1): [0,68] AR(2): [0,62]				AR(1): [0,54] AR(2): [0,38]	AR(1): [0,82] AR(2): [0,51]
Sargan				13,12 [1,00]	13,12 [1,00]				10,04 [1,00]	10,04 [1,00]
First year included	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980
Last year included	**2009**	**2009**	**2009**	**2009**	**2009**	**2013**	**2013**	**2013**	**2013**	**2013**

Standard errors are in parentheses, *p*-values are in square brackets. *, **, *** indicate significance at the 10%, 5% and 1% respectively.

The 2SLS-based Cragg-Donald test does not reject the null hypothesis that the instruments applied in the two-step GMM estimation are weak. This implies that the corresponding instruments are irrelevant and that the estimates obtained by GMM are biased. Next to that, the Sargan test of overidentifying restrictions does clearly not reject its null hypothesis that all instruments applied in the two-step GMM estimation are exogenous. However, since a p-value of 1,00 is highly suspicious, the conclusion that the instruments are exogenous should be drawn with caution. This is particularly the case since applying lagged values (2-4) instead of (1-3) of the independent variables as internal instruments also results in a p-value of 1,00 when performing a Sargan test accordingly. The Arrellano & Bond autocorrelation (AB) test supports the result that the instruments are exogenous, since it does not reject the null hypothesis of no second order autocorrelation.

When looking at the results for the 1980-2013 sample, no significant effect of the unemployment rate (*UR*) on the saving rate (*S*) is found in the OLS estimation (see Column *6*). Also the fixed effects estimation, both with normal and Driscoll-Kraay standard errors, shows no significant effect of the unemployment rate (*UR*) on the saving rate (*S*) (see Columns *7* & *8*). Contrastingly, the two-step GMM estimation with normal standard errors shows a significant and positive effect of the unemployment rate (*UR*) on the saving rate (*S*) (see Column *9*). This effect (0,19) is clearly smaller than the effect found for the 1980-2009 sample. Again, the unemployment rate (*UR*) does not significantly affect the saving rate (*S*) when adding Windmeijer standard errors to the two-step GMM model (see Column *10*). The 2SLS-based Cragg-Donald test does not reject its null hypothesis of weak instruments. In line with the outcomes for the 1980-2009 sample, this results seems to indicate that the two-step GMM estimates are unreliable. Again, the Sargan test does not reject its null hypothesis of exogenous instruments with a suspicious *P*-value of 1,00, whereas the AB-test shows no second order autocorrelation (*AR(2)*). This would imply that the instruments applied in the two-step GMM estimations are exogenous.

When comparing the results for the 1980-2009 sample with the corresponding results for the 1980-2013 sample, it seems that the importance of the unemployment rate (*UR*) as a determinant of the saving rate (*S*) has diminished in the years after 2009.

Table *2* additionally demonstrates that mixed results are obtained for the other two determinants of the saving rate, the household's wealth (*W*) and the credit availability (*C*). Whereas credit availability (*C*) reports insignificant results mostly, household wealth (*W*) shows, depending on the type of estimator, both positive and negative coefficients. As mentioned in Section *4.2.1*, this might be due to the fact that the domestic credit to the private sector and the household's financial net worth (as a proportion of the gross household adjusted disposable income) are bad proxies for the real credit that is available to households (*C*), respectively the true household wealth (*W*). Different from the results found in this study, Mody et al. (2012) showed a significant negative effect of the household's wealth (*W*) and the credit availability (*C*) on the saving rate (*S*). However, it should be noted that the negative effect that was found for the credit availability (*C*) was very small.

Table 3 – adjusted regression specification results

S_t	(1) OLS	(2) Fixed effects	(3) Fixed effects DK-robust	(4) GMM two- step	(5) GMM two-step WC-robust	(6) OLS	(7) Fixed effects	(8) Fixed effects DK-robust	(9) GMM two-step	(10) GMM two-step WC-robust
S_{t-1}	0,94*** (0,03)	0,73*** (0,06)	0,73*** (0,05)	0,63*** (0,15)	0,63 (0,78)	0,95*** (0,03)	0,74*** (0,05)	0,74*** (0,07)	0,34*** (0,09)	0,34 (0,70)
UR_{t+1}	0,19*** (0,05)	0,43*** (0,09)	0,43*** (0,09)	0,53*** (0,17)	0,53 (1,31)	-0,01 (0,03)	0,05 (0,05)	0,05 (0,08)	0,14 (0,09)	0,14 (0,98)
W_{t-1}	0,00 (0,00)	0,02*** (0,01)	0,02* (0,01)	0,02*** (0,01)	0,02 (0,09)	0,00 (0,00)	0,01 (0,01)	0,01 (0,01)	-0,01 (0,01)	-0,01 (0,07)
C_t	0,01*** (0,00)	0,01* (0,00)	0,01 (0,01)	0,01* (0,01)	0,01 (0,06)	0,01** (0,00)	0,01 (0,00)	0,01 (0,01)	0,00 (0,01)	0,00 (0,05)
Constant	-0,03*** (0,01)	-0,05*** (0,02)	-0,05*** (0,01)	-0,06*** (0,01)	-0,06 (0,27)	-0,01 (0,01)	-0,01 (0,01)	-0,01 (0,02)	0,04** (0,02)	0,04 (0,13)
Observations	168	168	168	149	149	213	213	213	194	194
(Within) R^2	0,89	0,54	0,54			0,88	0,54	0,54		
Instruments				88	88				109	109
Countries	15	15	15	15	15	15	15	15	15	15
Dataset	A	A	A	A	A	A	A	A	A	A
Wooldridge		14,21*** [0,00]					31,59*** [0,00]			
2SLS Cragg-Donald				0,23	0,23				1,07	1,07
AB-test				AR(1): [0,15] AR(2): [0,51]	AR(1): [0,56] AR(2): [0,61]				AR(1): [0,14] AR(2): [0,29]	AR(1): [0,74] AR(2): [0,35]
Sargan				11,53 [1,00]	11,53 [1,00]				11,29 [1,00]	11,29 [1,00]
First year included	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980
Last year included	**2009**	**2009**	**2009**	**2009**	**2009**	**2013**	**2013**	**2013**	**2013**	**2013**

Standard errors are in parentheses, *p*-values are in square brackets. *, **, *** indicate significance at the 10%, 5% and 1% respectively.

To continue, the results following from applying the adjusted regression specification are presented in Table *3*. All estimations with the 1980-2009 sample, except for the two-step GMM estimation with Windmeijer standard errors, show a positive and significant effect (0,19 → 0,53) of the unemployment rate (*UR*) on the saving rate (*S*) (see Columns *1-5*). This is highly different for the 1980-2013 sample, where the unemployment rate (*UR*) does not appear significant in any estimation at all (see Columns *6-10*). For both samples, the 2SLS-based Cragg-Donald test does not reject its null hypothesis of weak instruments, meaning that the instruments that are applied in the two-step GMM estimations are irrelevant. At the same time, the Sargan test does not reject exogeneity of the instruments, again with a suspicious *P*-value of 1,00. Moreover, second order autocorrelation is not found to be present, which indicates that the instruments are exogenous. Hence, also when applying the adjusted regression specification it is unsafe to draw strong conclusions based on the GMM estimations. This is due to weak instruments.

The results using the adjusted regression specification do not differ substantially from the results obtained with the main regression specification. In line with the outcomes from applying the main regression specification, it seems that the importance of the unemployment rate as a determinant of the saving rate has decreased in the years 2010-2013.

Table 4 – first-differenced regression specification results

ΔS_t	(1) OLS	(2) Fixed effects	(3) Fixed effects DK-robust	(4) GMM two-step	(5) GMM two-step WC-robust	(6) OLS	(7) Fixed effects	(8) Fixed effects DK-robust	(9) GMM two-step	(10) GMM two-step WC-robust
ΔUR_t	0,58*** (0,14)	0,57*** (0,14)	0,57* (0,29)	0,69*** (0,07)	0,69 (0,88)	0,14 (0,11)	0,35*** (0,12)	0,35** (0,17)	0,53* (0,31)	0,53 (0,97)
ΔW_{t-1}	-0,01* (0,01)	-0,02* (0,01)	-0,02** (0,01)	-0,01* (0,01)	-0,01 (0,01)	-0,03*** (0,01)	-0,03*** (0,01)	-0,03** (0,01)	-0,04*** (0,01)	-0,04 (0,03)
ΔC_t	0,01 (0,01)	0,01 (0,01)	0,01** (0,00)	0,02 (0,02)	0,02 (0,08)	0,01 (0,01)	0,01 (0,01)	0,01* (0,01)	0,02*** (0,01)	0,02 (0,07)
Constant	0,00 (0,00)	0,00 (0,00)	0,00 (0,00)	-0,00 (0,00)	-0,00 (0,00)	-0,00 (0,00)	-0,00 (0,00)	-0,00 (0,00)	-0,00* (0,00)	-0,00 (0,01)
Observations	151	151	151	151	151	209	209	209	209	209
(Within) R^2	0,20	0,20	0,20			0,10	0,16	0,16		
Instruments				103	103				139	139
Countries	14	14	14	14	14	15	15	15	15	15
Dataset	A	A	A	A	A	A	A	A	A	A
Wooldridge		8,22** [0,01]					0,72 [0,41]			
2SLS Cragg-Donald				3,34	3,34				3,47	3,47
AB-test				AR(1)**: [0,05] AR(2): [0,40]	AR(1)*: [0,09] AR(2): [0,43]				AR(1)***: [0,01] AR(2): [0,51]	AR(1)**: [0,02] AR(2): [0,54]
Sargan				10,47 [1,00]	10,47 [1,00]				11,26 [1,00]	11,26 [1,00]
First year included	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980
Last year included	**2009**	**2009**	**2009**	**2009**	**2009**	**2013**	**2013**	**2013**	**2013**	**2013**

Standard errors are in parentheses, *p*-values are in square brackets. *, **, *** indicate significance at the 10%, 5% and 1% respectively.

Next, the outcomes of applying the first-differenced regression specification are shown in Table *4*. The first-differenced estimations for the 1980-2009 sample, except for the two-step GMM estimation with Windmeijer standard errors, show a significant and positive effect (0,57 → 0,74) of the change in the unemployment rate (*UR*) on the change in the saving rate (*S*) (see Columns *1*-*5*). For the 1980-2013 sample, the OLS and two-step GMM with adjusted standard errors estimations report an insignificant effect of the change in the unemployment rate (*UR*) on the change in the saving rate (*S*) (see Columns *6* & *10*). On the other hand, a significant positive effect of the change in the unemployment rate (*UR*) on the change in the saving rate (*S*) is found for the fixed effects estimation (0,35), both with normal and Driscoll-Kraay standard errors, as well as for the two-step GMM estimation with normal standard errors (0,53) (see Columns *7*-*9*). It should be noted that these significant coefficients representing the effect of the change in the unemployment rate (*UR*) on the change in the saving rate (*S*) are lower in value than their counterparts in the 1980-2009 sample. This again seems to imply that after 2009, the unemployment rate (*UR*) has become less important in determining the saving rate (*S*).

When looking at the auxiliary tests, it is interesting to note that the Wooldridge test is not rejected for the 1980-2013 sample. This implies that autocorrelation can be assumed absent in de corresponding estimation. However, the results for the fixed effects estimation with Driscoll-Kraay standard errors are presented in Table *4* for the sake of completeness. To continue, all four AB-tests presented in Table *4* do not reject the null hypothesis of no second order autocorrelation (*AR(2)*). In addition, the results of the Sargan test show that it cannot be rejected that all instruments are exogenous. However, the corresponding p-values are again suspicious, meaning that the GMM estimates might not be fully reliable. Since the results of the 2SLS-based Cragg-Donald test point at the presence of irrelevant instruments, it is indeed the case that the GMM estimates that are obtained by applying the first-differenced regression specification are unreliable.

Applying the first-differenced regression specification instead of the main regression specification slightly changes the results. The most obvious alterations lie in the results for the 1980-2013 sample. Whereas the estimations using the main regression specification mainly find insignificant effects of the unemployment rate (*UR*) on the saving rate (*S*), some estimations in the first-differenced regression specification show a significant effect instead.

Overall, the above outcomes (Tables *2*, *3* & *4*) show a significant positive effect of the unemployment rate (*UR*) on the saving rate (*S*) for the 1980-2009 sample, whereas for the 1980-2013 sample this effect is lower or even insignificant. Hence, these main results seem to indicate that the importance of the unemployment rate (*UR*) as a determinant of the saving rate (*S*) has reduced after 2009.

5.2 Robustness checks

Since all GMM estimations that have been performed so far are suspected from providing biased estimates due to a weak instrument problem, the results of the robustness checks discussed below are mostly based on fixed effects estimations.

5.2.1 Robustness check 1 - excluding the economic crisis and its aftermath

Table *10* (Appendix) shows the results of the fixed effects estimations for the 1980-2007 sample. By applying the main regression specification, no significant effect of the unemployment rate (*UR*) on the saving rate (*S*) is found (see Columns *1* & *2*). Similarly, when using the adjusted regression specification, the fixed effects regression with normal standard errors shows no significant relationship between the unemployment rate (*UR*) and the saving rate (*S*) (see Column *3*). In contrast, a small positive significant effect of the unemployment rate (*UR*) on the saving rate (*S*) is obtained when including Driscoll-Kraay errors (see Column *4*). On the other hand, when making use of the first-differenced regression specification, one finds a significant negative effect for the fixed effects estimation, both with and without Driscoll-Kraay standard errors (see Columns *5* & *6*). Hence, the effect of unemployment rate (*UR*) on the saving rate (*S*) for the sample 1980-2007 is somewhat ambiguous. This is different from the main results, which might suggest that the results obtained for the sample 1980-2009 are driven by the economic crisis (2007-2009).

5.2.2 Robustness check 2 – adding additional control variables

The outcomes of the fixed effects estimations including additional control variables are presented in Table *11* (Appendix). To facilitate the comparison of the underlying results with the results of the fixed effects estimations without additional control variables (i.e., with the more restricted fixed effects estimations), Columns *2* & *7* of respectively Table *2-4* are added to Table *11* (see the even Columns). Starting with the results for the 1980-2009 sample, the first Column considers the estimation in the main regression specification. The result of this estimation shows a positive significant effect (0,41) of the unemployment rate (*UR*) on the saving rate (*S*) that is comparable to the outcome obtained in the more restricted fixed effects regression (see Column *2*). Also when using the adjusted regression specification, a positive and significant effect (0,21) of the unemployment rate (*UR*) on the saving rate (*S*) is found (see Column *3*). The size of the corresponding coefficient, however, is approximately half the size of the coefficient that was obtained in the more restricted fixed effects estimation (see Column *4*). When applying the first-differenced regression specification, a positive and significant effect (0,50) of the change in the unemployment rate (*UR*) on the change in the saving rate (*S*) is found (see Column *5*). This effect is approximately similar to the effect that was found in the more restricted fixed effects regression (see Column *6*).

When applying the main regression specification to the 1980-2013 sample, the fixed effects estimation with additional control variables shows a positive significant effect (0,19) of the unemployment rate (*UR*) on the saving rate (*S*) (see Column *7*). This is in contrast with the result in the more restricted fixed effects estimation (see Column *8*). On the other hand, no significant effect is found when including additional control variables in the adjusted regression specification (see Column *9*). Contrastingly, a significant positive effect of the change in the unemployment rate (*UR*) on the change in the saving rate (*S*) is found when applying the first-differenced regression specification with additional control variables (see Column *11*). This effect (0,49) is somewhat higher than in the corresponding restricted fixed effects regression (see Column *12*).

Overall, in terms of sign and significance, the effect of the unemployment rate (*UR*) on the saving rate (*S*) measured with the more restricted fixed effects estimations seems to be robust to the inclusion of additional control variables. Control variables that show a positive significant effect on the saving rate (*S*) are the household wealth (*W*) (see Columns *1*, *3*, *7* & *9*) and the real short term interest rate (*R*) (see Columns *5* & *11*). The small positive effect of the household wealth (*W*) on the saving rate (*S*) is not in line with theoretical expectations and Mody et al. (2012), whereas it is indeed predicted by Mody et al. (2012), as well as by other literature, that the real short term interest rate (*R*) affects the saving rate (*S*) positively. On the other hand, the following control variables show a negative significant effect on the saving rate (*S*): the government structural balance (*GB*) (see Columns *3*, *5*, *7*, *9* & *11*), the world GDP (*GDPW*) (see

Columns *3, 5*, *7*, *9* & *11*), the TED-spread (*TED*) (see Column *3*), the old age dependency ratio (*ODR*) (see Column *7*) and the stock market volatility (*SMV*) (see Column *11*). The frequently obtained negative coefficients for the government structural balance (*GB*) and the world GDP (*GDPW*) are in line with the general literature and Mody et al. (2012).[12] The TED-spread (*TED*), old age dependency ratio (*ODR*) and stock market volatility (*SMV*) only turned out significant once. A negative coefficient for the old dependency ratio (*ODR*) is in accordance with the result found by Mody et al. (2012), whereas the negative effect of the TED-spread (*TED*) is not. Mody et al. (2012) found an ambiguous effect of the stock market volatility (*SMV*) on the saving rate (*S*). Hence, no judgement can be made upon the negative outcome that is found for the stock market volatility (*SMV*). Finally, the control variables that show no significant effect on the saving rate (*S*) in any of the estimations are: the disposable income (*DI*), the GDP volatility (*GDPV*), the young age dependency ratio (*YDR*) and the copper/gold price ratio (*COGO*). The insignificance of the latter variables is not in line with the expectations following from Mody et al. (2012), as they found a significant negative, significant positive, significant positive and significant negative estimate for respectively *DI*, *GDPV*, *YDR* and *COGO*. Apart from that, it should be noted that the statistical programme Stata omits the common trend variables (*GDPW*, *COGO* and *TED*) from the corresponding regressions when time fixed effects are added. This implies that these world market indicators are captured by the time fixed effects, which is in line with the expectations described in Section *4.2.1*.

5.2.3 Robustness check 3 - North/South effect

Since fixed effects models cannot be performed for this robustness check, the results presented in Table *12* (Appendix) all follow from OLS estimations. Applying the main regression specification to the 1980-2009 sample does not show significant effects of either the dummy variable *South* or the interaction term *South*UR* on the saving rate (*S*) (see Column *1*). When adding all control variables, the interaction term *South*UR* becomes marginally significant with a negative value (see Column *2*). This would imply that the effect of the unemployment rate (*UR*) on the saving rate (*S*) is lower for Southern European countries compared to Northern European countries. Using the adjusted regression specification instead, leads to a small negative significant effect of the dummy variable *South* on the saving rate (*S*) (see Column *3*). However,

[12] Note that the negative coefficient representing the effect of the world GDP (*GDPW*) on the saving rate (*S*) is not significant at conventional levels in Mody et al. (2012).

the dummy variable *South* becomes insignificant when adding additional control variables (see Column *4*). The interaction term *South*UR* does not appear significant in the estimations that are performed with the adjusted regression specification (see Columns *3* & *4*). On the other hand, when using the first-differenced regression specification, the interaction term *South*UR* is significant and positive (0,70) (see Column *5*), also in the estimation with additional control variables (0,50) (see Column *6*). This would imply that the effect of the unemployment risk (*UR*) on the saving rate (*S*) is higher for Southern European countries than for Northern European countries. The dummy variable *South* is not significant in the corresponding estimations (see Columns *5* & *6*).

To continue with the outcomes for the 1980-2013 sample, the estimations performed with the main regression specification show a significant negative effect (-0,42 & -0,63) of the interaction term *South*UR* on the saving rate (*S*). At the same time, no significant effect is found for the dummy variable *South* (see Columns *7* & *8*). The former indicates that the effect of the unemployment rate (*UR*) on the saving rate (*S*) is lower for Southern European countries compared to Northern European countries. Applying the adjusted regression specification does not provide significant outcomes for neither the dummy variable *South* nor the interaction term *South*UR* (see Columns *9* & *10*). Columns *11* & *12* of Table *12* consider estimations in the first-differenced regression specification. The corresponding outcomes show no significant effect for the interaction term *South*UR*, whereas a small negative significant effect is found for the dummy variable *South*. The latter would imply that Southern European save, on average, less.

In short, the outcomes for both the dummy variable *South* and the interaction term *South*UR* depend on the type of regression specification. Hence, mixed results are obtained about the differences in precautionary saving behaviour between Northern and Southern European countries.

5.2.4 Robustness check 4 – additional years

Table *13* (Appendix) shows the fixed effects estimates for the enlarged time periods 1969-2009 (see Columns *1*, *3* & *5*) and 1969-2012 (see Columns *7*, *9* & *11*). The even Columns show the corresponding results for the 1980-2009 and 1980-2013 samples.

The estimations using the main and adjusted regression specification, show an insignificant effect of the unemployment rate (*UR*) on the saving rate (*S*) for the 1969-2009 sample (see Columns *1* & *3*). This is in contrast with the results for the 1980-2009 sample, which show a positive significant effect of the unemployment rate (*UR*) on the saving rate (*S*) (see Columns *2* & *4*). Alternatively, using the first-differenced specification for the 1969-2009 sample results in a significant positive effect (0,29) of the change in the unemployment rate (*UR*) on the change in the saving rate (*S*) (see Column *5*). This effect is approximately half of the effect that is found for the 1980-2009 sample (see Column *6*).

Outcomes of the estimations on the 1969-2012 sample are similar. The estimations applying the main and adjusted regression specifications do not find a significant effect of the unemployment rate (*UR*) on the saving rate (*S*) (see Columns *7* & *9*), whereas the estimation applying the first-differenced regression specification finds the effect of interest to be significantly positive (0,22) (see Column *11*). Meanwhile, the results for the 1980-2013 sample indicate that the saving rate (*S*) is significantly positively affected by the unemployment rate (*UR*) (see Columns *8*, *10* & *12*).

The above outcomes show that the main results are, in general, not robust to the use of a different dataset with an enlarged time period. This follows from the fact that the positive effect of the unemployment rate (*UR*) only appears significant when applying the first-differenced regression specification (see Columns *5* & *11*).

Besides, when comparing the outcomes from applying the first-differenced specifications to respectively the 1969-2009 and the 1969-2012 sample, one sees that the unemployment rate (*UR*) shows a larger effect in the first sample. This might indicate that after 2009, the unemployment rate (*UR*) has become less important in determining the saving rate (*S*). Next to that, the twelve-country-based main results show a similar effect of the unemployment rate (*UR*) on the saving rate (*S*) as the original (fifteen-country-based) main results. This points out that the main results are not driven by the observations for Greece, Luxembourg and Portugal.

5.2.5 Robustness check 5 – Mean Group (MG) estimator

The results of applying the MG estimator to the 1969-2009 sample are shown in Table *14* (Appendix). As follows from Columns *1, 3* & *5*, none of the specifications lead to a significant effect of the unemployment rate (*UR*) on the saving rate (*S*). However, adding the additional control variables (*GB* & *R*) results in different outcomes. This is shown in Columns *2*, *4* & *6*, where the MG estimates are all significantly negative (-0,63 → -0,20).

Additionally shown in Table *14* are the outcomes for the 1969-2012 sample. Also for this time period, none of the specifications show a significant effect of the unemployment rate (*UR*) on the saving rate (*S*) (see Columns *7*, *9* & *11*). Again, this changes when the additional control variables (*GB* & *R*) are added. Columns *8*, *10* & *12* show that in that case, all specifications find a significant negative effect (-0,56 → -0,16) of the unemployment rate (*UR*) on the saving rate (*S*).

The results obtained in this robustness check are similar for both time samples (1969-2009 and 1969-2012) and not in line with the main results. Hence, the main results are not robust to the application of the MG estimator. It should additionally be noted that the MG-regression-based results found in this robustness check differ from the corresponding results in robustness check 4, which were found by using the OLS-fixed effects estimator.

5.2.6 Robustness check 6 - Common Correlated Effects Mean Group (CCEMG) estimator

The CCEMG estimates representing the effect of the unemployment rate (*UR*) on the saving rate (*S*) are presented in Table *15* (Appendix). Columns *1*, *3* & *5* show that for the 1969-2009 sample, none of these estimates is significant. Contrastingly, when extending the model with the additional control variables, a significant negative estimate (-0,25) is found. This is only the case when applying the first-differenced regression specification (see Column *6*). The estimates following from the main and adjusted regression specifications show no significant effect of the unemployment rate (*UR*) on the saving rate (*S*) in the extended model (see Columns *2* & *4*).

Identical outcomes are found for the 1969-2012 sample. The more restricted model shows no significant effect of the unemployment rate (*UR*) on the saving rate (*S*). This holds for all regression specifications (see Columns *7*, *9* & *11*). The model including the additional control variables provides a significant negative estimate when applying the main (-0,28) and first-differenced (-0,26) regression specification (see Columns *8* & *12*). No significant effect of the unemployment rate (*UR*) on the saving rate (*S*) is found when applying the adjusted regression specification to the extended model (see Column *10*).

The results obtained with the CCEMG estimator are approximately similar for both the 1969-2009 and the 1969-2012 sample. Moreover, they are similar to the results that followed from applying the MG estimator (robustness check 5). This means that the results found in the current robustness check are not in line with the main results and the results found in robustness check 4. Hence, the main results are not robust to the application of the CCEMG estimator.

6. Conclusions

The main aim of this study was to find out whether labour uncertainty has a positive effect on saving in European countries. I used the unemployment rate as a proxy for labour uncertainty. After applying various regression specifications, estimators and time samples, my main results show a significant positive effect of the unemployment rate on the saving rate for the 1980-2009 sample, whereas for the 1980-2013 sample this effect is lower or even insignificant. This suggests that the importance of the unemployment rate as a determinant of saving has reduced after 2009. In other words, the importance of precautionary saving following from labour uncertainty diminished after 2009. The latter outcome might indicate that households got used to labour uncertainty during the aftermath of the ‘Great Recession’. The main results overall have shown to be robust to the inclusion of additional control variables.

Additional results show that the effect of unemployment on saving is ambiguous for the time sample 1980-2007. This indicates that the positive effect of the unemployment rate on saving that was found for the 1980-2009 sample might be particularly driven by the ‘Great Recession’ (2007-2009). In this paper, I found mixed results concerning the differences in precautionary saving behaviour between Northern and Southern European countries. I further showed that the main results are, overall, not robust to the use of a second dataset covering a longer time period. In addition, I showed that the main results are not robust to a combination of the use of this more extensive dataset with the application of the MG estimator respectively the CCMG estimator.

The above mentioned results imply that whether I measure precautionary saving or not depends on the variables, type of estimator and specific time sample I use. This casts doubts on general claims about aggregate precautionary household saving that have been made by previous studies. When I apply the exact same time period (1980-2009) as Mody et al. (2012), the main outcomes of this study are in line with their results. Extending (1980-2013) or shortening (1980-2007) this time span leads to different results. This seems to imply that the outcomes of Mody et al. (2012) are driven by the ‘Great Recession’, at least to the extent to which they consider European countries. The latter suggests that precautionary saving following from labour uncertainty might not be as influential as indicated by Mody et al. (2012).

Limitations & directions for further research

Due to several limitations of this study, the results that have been found should be considered with caution. A first limitation relates to the data that has been used. For two (Greece and Luxembourg) out of the fifteen countries that were included, only a very limited amount of observations was available. Additionally, many observations for the early years were missing for all other countries except for France. This implies that the main results most probably do not equally represent the true situation for all included countries and years. A second drawback is that the results of applying the fixed effects estimator to the enlarged time sample (sample that starts in 1969) differ from the results of applying the MG and CCMG estimators to this longer time period. This makes it hard to draw a comprehensive conclusion regarding the existence of precautionary saving over a longer time period. A third limitation of this paper is that it did not solve the potential problems of endogeneity, since the GMM estimations that have been performed are suspected from providing biased estimates due to a weak instrument problem. A final limitation of this study is that the results rely on the assumption that the unemployment rate is a good proxy for labour uncertainty. However, it might for example be the case that the unemployment rate is lagging the true labour uncertainty that households experience. Although one of the regression specifications that I have applied takes this scenario into account, the corresponding correction (taking one lead of the unemployment rate) might still be insufficient. If the unemployment rate is not a good proxy for labour uncertainty, the results of this study would be less representative.

If, in the future, more data on European household saving becomes available, it would be interesting to further examine possible differences in precautionary saving behaviour between Northern and Southern European countries. With the use of limited data only, this study found mixed results concerning these differences in precautionary saving behaviour. Hence, future researchers that have more European household saving data at their disposal might find a more unambiguous result instead. A further examination of these potential differences in precautionary saving behaviour might be helpful for policymakers of the European Central Bank when deciding on policy measures that aim at stimulating the consumption of European households. More in general, a next study on aggregate precautionary household saving may focus specifically on the effect of possible heterogeneity in saving behaviour between countries.

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Appendix

Table 5 – years included in datasets

Country	Included years dataset A	Included years dataset B
Austria	1995-2013	1970-2012
Belgium	1995-2013	1970-2012
Finland	1995-2012	1968-2012
France	1980-2013	1970-2012
Germany	1995-2013	1968-2012
Greece	2006-2013	-
Ireland	1999-2013	1977-2012
Italy	1995-2013	1970-2012
Luxembourg	2006-2012	-
Netherlands	1995-2013	1970-2012
Portugal	1995-2013	-
Spain	1999-2013	1968-2012
Denmark	1995-2013	1968-2012
Sweden	1995-2013	1968-2012
United Kingdom	1999-2013	1968-2012

Table 6 - dataset A: variables, definitions & sources

Variable	Explanation	Source
Household net saving rate	Percentage of households net disposable income	OECD National Accounts (different volumes)
Unemployment rate	Percentage of total labour force	IMF World Economic Outlook Database
Real household net disposable income growth	Annual growth rates, deflated by final consumption of household	OECD National Accounts (different volumes)
Real short-term interest rate	Annual rate	OECD Economic Outlook database (volume 96)
GDP volatility	Own calculations with data on annual GDP and population	OECD Economic Outlook database (volume 97); IMF International Financial Statistics (IFS)
Stock market volatility	Own calculations with data on daily price index of the most influential stock market exchange per country	DataStream
Household financial net worth	Per capita, at current PPPs, millions US dollars	OECD National Accounts
Gross household adjusted disposable income	Per capita, at current PPPs, millions US dollars	OECD National Accounts (different volumes)
General government structural balance	Percentage of potential GDP	IMF World Economic Outlook Database
Old age dependency ratio	Percentage of working-age population	World Bank World Development Indicators
Young age dependency ratio	Percentage of working-age population	World Bank World Development Indicators
Domestic credit to private sector	Percentage of GDP	World Bank World Development Indicators
World real GDP growth	Constant prices, percent change	IMF World Economic Outlook Database
Copper-to-gold price	Copper, $/mt, real 2010$; Gold, $/toz, real 2010$	World Bank Global Economic Monitor (GEM) Commodities
TED spread	Annual average	Federal Reserve Economic Data (FRED)

Table 7 - dataset B: variables & sources

Variable	Source
Nominal household saving	OECD Economic Outlook database (different volumes)
Nominal household disposable income	OECD Economic Outlook database (different volumes)
Unemployment rate	OECD Economic Outlook (volume 96)
Nominal net household wealth	NiGEM
Nominal gross household liabilities	NiGEM
Nominal long-term interest rate on government bonds	OECD Economic Outlook database (different volumes)
Price index of private consumption	OECD Economic Outlook database (different volumes)
Nominal government saving	OECD Economic Outlook database (different volumes)
Nominal GDP	OECD Economic Outlook (volume 96)

Table 8 - most influential stock market exchange per country

Country	Index (short name)	Index (long name)
Austria	ATX	Austrian Traded Index
Belgium	BEL20	Brussels Stock Exchange
Finland	OMXH25 (formerly: HEX25)	Helsinki Stock Exchange
France	CAC	Cotation Assistée en Continu
Germany	DAX	Deutscher Aktienindex
Greece	ATHEX	Athens Stock Exchange
Ireland	ISEQ	Irish Stock Exchange
Italy	FTSE MIB (formerly: S&P/MIB)	Milano Italia Borsa
Luxembourg	LuxX	Luxembourg Stock exchange
Netherlands	AEX	Amsterdam Exchange index
Portugal	PSI-20	Portuguese Stock Index
Spain	IBEX-35	Índice Bursátil Español
Denmark	OMXC20 (formerly: KFX)	Copenhagen Stock Exchange
Sweden	OMXS30	Stockholm Stock Exchange
United Kingdom	FTSE100	Financial Times Stock Exchange 100 Index

Table 9 – Unit root test

ADF test (Fisher) for unit root (*S*) with constant; without trend	
1980-2009	94,19***
1980-2013	95,11***

ADF test (Fisher) for unit root (*UR*) with constant; without trend	
1980-2009	96,02***
1980-2013	74,96***

ADF test (Fisher) for unit root (*W*) with constant; without trend	
1980-2009	78,38***
1980-2013	98,95***

ADF test (Fisher) for unit root (*C*) with constant; with trend	
1980-2009	8,16
1980-2013	10,86

*, **, *** indicate significance at the 10%, 5% and 1% respectively. The test statistics follow from an inverse chi-squared distribution.

Table 10 – results of robustness check 1: excluding the economic crisis and its aftermath

S	(1) Fixed effects	(2) Fixed effects DK-robust	(3) Fixed effects	(4) Fixed effects DK-robust	(5) Fixed effects	(6) Fixed effects DK-robust
S_{t-1}			0,73*** (0,06)	0,73*** (0,05)		
UR	0,18 (0,15)	0,18 (0,14)	0,12 (0,12)	0,12** (0,05)	-0,34* (0,20)	-0.34*** (0,09)
W	0,01* (0,01)	0,01 (0,01)	0,03*** (0,01)	0,03*** (0,01)	-0,02* (0,01)	-0,02 (0,01)
C	-0.02** (0,01)	-0,02 (0,01)	-0,00 (0,00)	-0,00 (0,01)	0,01 (0,01)	0,01* (0,00)
Constant	0.04* (0,02)	0,04 (0,02)	-0,03* (0,02)	-0,03** (0,01)	-0,00** (0,00)	-0,00 (0,00)
Observations	139	139	139	139	123	123
Within R^2	0,07	0.07	0,56	0,56	0,05	0,05
Countries	14	14	14	14	13	13
Dataset	A	A	A	A	A	A
Wooldridge	29,39*** [0,00]		20,78*** [0,00]		4,32* [0,06]	
First year included	1980	1980	1980	1980	1980	1980
Last year included	2007	2007	2007	2007	2007	2007
Regression specification	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First- differenced**

Standard errors are in parentheses, *p*-values are in square brackets. *, **, *** indicate significance at the 10%, 5% and 1% respectively. Note that: 1) *S* represents S_t in the main and adjusted regression specifications and ΔS_t in the first-differenced regression specification; 2) *UR* represents UR_t in the main regression specification, UR_{t+1} in the adjusted regression specification and ΔUR_t in the first-differenced regression specification; 3) *W* represents W_{t-1} in the main and adjusted regression specifications and ΔW_{t-1} in the first-differenced regression specification and 4) *C* represents C_t in the main and adjusted regression specifications and ΔC_t in the first-differenced regression specification.

Table 11 – results of robustness check 2: additional control variables

S	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects	(4) Fixed effects	(5) Fixed effects	(6) Fixed effects	(7) Fixed effects	(8) Fixed effects	(9) Fixed effects	(10) Fixed effects	(11) Fixed effects	(12) Fixed effects
S_{t-1}			0,72*** (0,06)	0,73*** (0,06)					0,73*** (0,05)	0,74*** (0,05)		
UR	0,41*** (0,13)	0,52*** (0,13)	0,21** (0,09)	0,43*** (0,09)	0,50*** (0,18)	0,57*** (0,14)	0,19** (0,08)	0,07 (0,07)	0,08 (0,06)	0,05 (0,05)	0,49*** (0,14)	0,35*** (0,12)
W	0,04*** (0,01)	0,01* (0,01)	0,04*** (0,01)	0,02*** (0,01)	0,01 (0,01)	-0,02* (0,01)	0,05*** (0,01)	0,01* (0,01)	0,02*** (0,01)	0,01 (0,01)	-0,00 (0,01)	-0,03*** (0,01)
C	0,01 (0,01)	0,00 (0,01)	0,01 (0,01)	0,01* (0,00)	0,01 (0,01)	0,01 (0,01)	0,00 (0,01)	-0,00 (0,01)	0,01 (0,01)	0,01 (0,00)	0,01 (0,01)	0,01 (0,01)
R	-0,04 (0,22)		-0,01 (0,16)		0,63*** (0,23)		0,23 (0,23)		0,21 (0,15)		0,56*** (0,19)	
GB	-0,09 (0,12)		-0,30*** (0,09)		-0,28** (0,11)		-0,29*** (0,10)		-0,17*** (0,06)		-0,33*** (0,08)	
DI	-0,14 (0,09)		-0,01 (0,07)		-0,04 (0,08)		-0,04 (0,09)		0,02 (0,06)		-0,03 (0,07)	
GDPV	-0,12 (0,52)		-0,04 (0,37)		0,53 (0,43)		0,25 (0,19)		0,17 (0,13)		0,11 (0,13)	
SMV	0,01 (0,03)		0,00 (0,02)		-0,02 (0,02)		-0,04 (0,03)		-0,03 (0,02)		-0,04* (0,02)	
ODR	-0,27 (0,17)		-0,15 (0,12)		0,80 (0,85)		-0,27* (0,15)		-0,14 (0,10)		0,23 (0,58)	
YDR	-0,30 (0,26)		-0,15 (0,19)		-0,56 (1,04)		-0,12 (0,26)		-0,15 (0,17)		-0,85 (0,77)	
GDPW	-0,21 (0,19)		-0,37*** (0,14)		-0,68*** (0,22)		-0,48*** (0,15)		-0,65*** (0,10)		-0,77*** (0,18)	
COGO	-0,26 (0,17)		-0,03 (0,12)		-0,07 (0,18)		-0,17 (0,15)		0,07 (0,10)		0,01 (0,16)	
TED	-0,01 (0,01)		-0,01* (0,00)		-0,00 (0,01)		-0,01 (0,01)		-0,01 (0,00)		0,00 (0,00)	
Constant	0,13 (0,09)	-0,00 (0,02)	0,02 (0,07)	-0,05*** (0,02)	0,02 (0,01)	0,00 (0,00)	0,09 (0,09)	0,03* (0,02)	0,05 (0,06)	-0,01 (0,01)	0,03*** (0,01)	-0,00 (0,00)
Observations	163	168	163	168	147	151	207	226	207	213	191	209
Within R²	0,31	0,09	0,65	0,54	0,39	0,20	0,24	0,02	0,66	0,54	0,38	0,16
Countries	15	15	15	15	14	14	15	15	15	15	15	15
Dataset	A	A	A	A	A	A	A	A	A	A	A	A
First year included	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980
Last year included	2009	2009	2009	2009	2009	2009	2013	2013	2013	2013	2013	2013
Regression specification	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**

Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% respectively. Note that: 1) *S* represents S_t in the main and adjusted regression specifications and ΔS_t in the first-differenced regression specification; 2) *UR* represents UR_t in the main regression specification, UR_{t+1} in the adjusted regression specification and ΔUR_t in the first-differenced regression specification; 3) *W* represents W_{t-1} in the main and adjusted regression specifications and ΔW_{t-1} in the first-differenced regression specification and 4) *C* represents C_t in the main and adjusted regression specifications and ΔC_t in the first-differenced regression specification. The same systematic also applies to all other variables in the first column.

Table 12 – results of robustness check 3: North/South effect

S	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) OLS	(10) OLS	(11) OLS	(12) OLS
S_{t-1}			0,93***	0,91***					0,93***	0,94***		
			(0,03)	(0,03)					(0,03)	(0,03)		
UR	0,47**	0,74***	0,15*	0,13	0,11	0,29	0,35*	0,77***	0,10	0,12	0,08	0,27
	(0,21)	(0,21)	(0,08)	(0,09)	(0,23)	(0,28)	(0,20)	(0,21)	(0,08)	(0,08)	(0,21)	(0,24)
W	0,03***	0,03***	0,00	0,00	-0,02**	0,00	0,03***	0,03***	0,00	0,00	-0,03***	0,00
	(0,01)	(0,01)	(0,00)	(0,00)	(0,01)	(0,01)	(0,01)	(0,01)	(0,00)	(0,00)	(0,01)	(0,01)
C	-0,01	-0,01	0,01***	0,01	0,01	0,01	-0,01	-0,01	0,01***	0,01	0,01	0,01
	(0,01)	(0,01)	(0,00)	(0,00)	(0,01)	(0,01)	(0,01)	(0,01)	(0,00)	(0,00)	(0,01)	(0,01)
R		-0,99***		-0,19		0,48**		-0,57*		0,00		0,45**
		(0,33)		(0,14)		(0,23)		(0,30)		(0,11)		(0,19)
GB		-0,42***		-0,08		-0,20**		-0,21*		-0,03		-0,34***
		(0,13)		(0,05)		(0,10)		(0,12)		(0,05)		(0,08)
DI		0,11		0,10		0,11		0,26*		0,12*		0,09*
		(0,17)		(0,07)		(0,07)		(0,15)		(0,06)		(0,05)
GDPV		-3,23***		-0,37		0,10		-1,14***		0,01		0,05
		(0,64)		(0,28)		(0,25)		(0,28)		(0,11)		(0,11)
SMV		0,12**		0,03		-0,01		0,07		0,01		-0,03
		(0,05)		(0,02)		(0,02)		(0,05)		(0,02)		(0,02)
ODR		-0,69***		-0,09		0,36		-0,58***		-0,05		0,16
		(0,17)		(0,07)		(0,54)		(0,15)		(0,06)		(0,44)
YDR		-0,96***		-0,04		-0,31		-0,76***		-0,04		-0,45
		(0,18)		(0,08)		(0,73)		(0,16)		(0,07)		(0,60)
GDPW		-0,42		-0,50***		-0,55**		-0,46*		-0,68***		-0,67***
		(0,35)		(0,14)		(0,21)		(0,27)		(0,11)		(0,18)
COGO		0,22		0,22*		-0,15		0,09		0,22**		-0,07
		(0,29)		(0,12)		(0,18)		(0,25)		(0,10)		(0,15)
TED		-0,01		-0,01		-0,01		-0,01		-0,00		-0,00
		(0,01)		(0,01)		(0,01)		(0,01)		(0,01)		(0,00)
South	-0,04	-0,01	-0,02*	-0,01	-0,00	-0,00	0,01	0,00	0,00	-0,00	-0,01**	-0,00*
	(0,02)	(0,02)	(0,01)	(0,01)	(0,00)	(0,00)	(0,02)	(0,02)	(0,01)	(0,01)	(0,00)	(0,00)
South*UR	0,24	-0,53*	0,13	0,09	0,70***	0,50*	-0,42*	-0,63**	-0,11	-0,09	0,17	0,32
	(0,30)	(0,30)	(0,11)	(0,12)	(0,26)	(0,28)	(0,23)	(0,25)	(0,09)	(0,09)	(0,24)	(0,25)
Constant	-0,01	0,45***	-0,02**	0,03	0,00	0,02*	0,01	0,35***	-0,02*	0,02	0,00	0,03***
	(0,03)	(0,08)	(0,01)	(0,04)	(0,00)	(0,01)	(0,02)	(0,07)	(0,01)	(0,03)	(0,00)	(0,01)
Observations	168	163	168	163	151	147	226	207	213	207	209	191
R^2	0,23	0,49	0,90	0,92	0,25	0,38	0,19	0,40	0,88	0,91	0,12	0,36
Countries	15	15	15	15	14	14	15	15	15	15	15	15
Dataset	A	A	A	A	A	A	A	A	A	A	A	A
First year included	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980
Last year included	2009	2009	2009	2009	2009	2009	2013	2013	2013	2013	2013	2013
Regression specification	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**

Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% respectively. Note that: 1) *S* represents S_t in the main and adjusted regression specifications and ΔS_t in the first-differenced regression specification; 2) *UR* represents UR_t in the main regression specification, UR_{t+1} in the adjusted regression specification and ΔUR_t in the first-differenced regression specification; 3) *W* represents W_{t-1} in the main and adjusted regression specifications and ΔW_{t-1} in the first-differenced regression specification and 4) *C* represents C_t in the main and adjusted regression specifications and ΔC_t in the first-differenced regression specification. The same systematic also applies to all other variables in the first column.

Table 13 – results of robustness check 4: additional years

S	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects	(4) Fixed effects	(5) Fixed effects	(6) Fixed effects	(7) Fixed effects	(8) Fixed effects	(9) Fixed effects	(10) Fixed effects	(11) Fixed effects	(12) Fixed effects
S_{t-1}			0,69*** (0,04)	0,69*** (0,06)					0,69*** (0,03)	0,71*** (0,05)		
UR	-0,08 (0,06)	0,68*** (0,14)	0,02 (0,04)	0,51*** (0,10)	0,28** (0,12)	0,58*** (0,15)	-0,04 (0,05)	0,35*** (0,08)	0,02 (0,04)	0,14* (0,07)	0,22* (0,12)	0,42*** (0,13)
W	0,00 (0,00)	0,02** (0,01)	0,00 (0,00)	0,02*** (0,01)	0,02*** (0,00)	-0,02* (0,01)	0,00 (0,00)	0,02** (0,01)	0,00 (0,00)	0,01** (0,01)	0,01*** (0,00)	-0,02*** (0,01)
C	-0,07*** (0,01)	0,01 (0,01)	-0,02*** (0,00)	0,01* (0,00)	-0,11*** (0,02)	0,01 (0,01)	-0,06*** (0,00)	0,00 (0,01)	-0,02*** (0,00)	0,01 (0,00)	-0,11*** (0,02)	0,01 (0,01)
Constant	0,17*** (0,01)	-0,02 (0,02)	0,04*** (0,01)	-0,06*** (0,02)	0,00 (0,00)	0,00 (0,00)	0,15*** (0,01)	0,00 (0,02)	0,04*** (0,01)	-0,02 (0,01)	0,00 (0,00)	-0,00 (0,00)
Observations	468	150	464	150	456	136	503	197	488	186	491	183
Within R^2	0,33	0,16	0,63	0,56	0,10	0,21	0,30	0,10	0,63	0,56	0,09	0,16
Countries	12	12	12	12	12	12	12	12	12	12	12	12
Dataset	B	A	B	A	B	A	B	A	B	A	B	A
First year included	1969	1980	1969	1980	1969	1980	1969	1980	1969	1980	1969	1980
Last year included	2009	2009	2009	2009	2009	2009	2012	2013	2012	2013	2012	2013
Regression specification	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**

Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% respectively. Note that: 1) *S* represents S_t in the main and adjusted regression specifications and ΔS_t in the first-differenced regression specification; 2) *UR* represents UR_t in the main regression specification, UR_{t+1} in the adjusted regression specification and ΔUR_t in the first-differenced regression specification; 3) *W* represents W_{t-1} in the main and adjusted regression specifications and ΔW_{t-1} in the first-differenced regression specification and 4) *C* represents C_t in the main and adjusted regression specifications and ΔC_t in the first-differenced regression specification.

Table 14 – results of robustness check 5: Mean Group (MG) estimator

S	(1) Mean Group	(2) Mean Group	(3) Mean Group	(4) Mean Group	(5) Mean Group	(6) Mean Group	(7) Mean Group	(8) Mean Group	(9) Mean Group	(10) Mean Group	(11) Mean Group	(12) Mean Group
S_{t-1}			0,51*** (0,07)	0,36*** (0,08)					0,51*** (0,06)	0,35*** (0,07)		
UR	-0,07 (0,17)	-0,63*** (0,22)	0,05 (0,09)	-0,20* (0,12)	0,21 (0,20)	-0,33** (0,13)	-0,03 (0,15)	-0,56*** (0,18)	0,07 (0,08)	-0,16* (0,09)	0,19 (0,19)	-0,33*** (0,12)
W	-0,01 (0,01)	0,01 (0,01)	-0,00 (0,01)	0,00 (0,01)	-0,00 (0,01)	0,01 (0,01)	-0,01 (0,01)	0,01 (0,01)	0,00 (0,01)	0,00 (0,01)	-0,00 (0,01)	0,01 (0,01)
C	-0,05*** (0,01)	-0,07*** (0,02)	-0,02*** (0,01)	-0,03** (0,01)	-0,14*** (0,03)	-0,11*** (0,02)	-0,06*** (0,02)	-0,07*** (0,02)	-0,03*** (0,01)	-0,05*** (0,01)	-0,14*** (0,03)	-0,11*** (0,03)
R		0,04 (0,18)		0,04 (0,10)		0,07 (0,10)		0,02 (0,19)		0,01 (0,10)		0,06 (0,10)
GB		-0,64*** (0,10)		-0,37*** (0,09)		-0,64*** (0,08)		-0,59*** (0,09)		-0,32*** (0,08)		-0,66*** (0,08)
Constant	0,16*** (0,02)	0,17*** (0,03)	0,06*** (0,01)	0,09*** (0,02)	0,00 (0,00)	0,00 (0,00)	0,15*** (0,02)	0,17*** (0,03)	0,06*** (0,01)	0,10*** (0,02)	0,00 (0,00)	-0,00 (0,00)
Observations	468	466	464	462	456	454	503	501	488	486	491	489
Countries	12	12	12	12	12	12	12	12	12	12	12	12
Dataset	B	B	B	B	B	B	B	B	B	B	B	B
First year included	1969	1969	1969	1969	1969	1969	1969	1969	1969	1969	1969	1969
Last year included	2009	2009	2009	2009	2009	2009	2012	2012	2012	2012	2012	2012
Regression specification	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**

Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% respectively. Note that: 1) *S* represents S_t in the main and adjusted regression specifications and ΔS_t in the first-differenced regression specification; 2) *UR* represents UR_t in the main regression specification, UR_{t+1} in the adjusted regression specification and ΔUR_t in the first-differenced regression specification; 3) *W* represents W_{t-1} in the main and adjusted regression specifications and ΔW_{t-1} in the first-differenced regression specification and 4) *C* represents C_t in the main and adjusted regression specifications and ΔC_t in the first-differenced regression specification. The same systematic also applies to all other variables in the first column.

Table 15 - results of robustness check 6: CCEMG estimator

S	(1) CCE Mean Group	(2) CCE Mean Group	(3) CCE Mean Group	(4) CCE Mean Group	(5) CCE Mean Group	(6) CCE Mean Group	(7) CCE Mean Group	(8) CCE Mean Group	(9) CCE Mean Group	(10) CCE Mean Group	(11) CCE Mean Group	(12) CCE Mean Group
S_{t-1}			0,30*** (0,05)	0,13*** (0,05)					0,31*** (0,06)	0,16*** (0,05)		
UR	-0,09 (0,17)	-0,22 (0,16)	-0,01 (0,12)	-0,08 (0,10)	-0,08 (0,10)	-0,25** (0,11)	-0,08 (0,19)	-0,28** (0,14)	0,03 (0,12)	-0,09 (0,10)	-0,06 (0,10)	-0,26** (0,11)
W	-0,02 (0,01)	-0,00 (0,01)	-0,01 (0,01)	-0,01 (0,01)	-0,01 (0,01)	-0,00 (0,01)	-0,01 (0,01)	0,00 (0,01)	-0,01 (0,01)	-0,01 (0,01)	-0,01 (0,01)	-0,00 (0,01)
C	-0,15*** (0,04)	-0,10*** (0,03)	-0,13*** (0,03)	-0,11*** (0,04)	-0,21*** (0,03)	-0,16*** (0,03)	-0,15*** (0,05)	-0,10** (0,04)	-0,13*** (0,04)	-0,11** (0,04)	-0,21*** (0,04)	-0,16*** (0,03)
R		0,47** (0,18)		0,32* (0,17)		0,12 (0,14)		0,32 (0,21)		0,21 (0,18)		0,07 (0,11)
GB		-0,61*** (0,09)		-0,57*** (0,09)		-0,56*** (0,07)		-0,60*** (0,11)		-0,55*** (0,09)		-0,54*** (0,07)
$\bar{S}$	0,79*** (0,25)	0,73** (0,30)	0,83*** (0,30)	0,73*** (0,25)	0,84*** (0,29)	0,69*** (0,24)	0,85*** (0,26)	0,79*** (0,26)	0,85*** (0,29)	0,73*** (0,22)	0,85*** (0,28)	0,70*** (0,22)
$\bar{S}_{t-1}$			-0,25 (0,19)	-0,09 (0,16)					-0,20* (0,11)	-0,08 (0,10)		
$\overline{UR}$	-0,07 (0,20)	0,06 (0,32)	-0,06 (0,17)	0,08 (0,23)	0,05 (0,21)	-0,03 (0,34)	0,01 (0,20)	0,23 (0,27)	-0,04 (0,16)	0,11 (0,24)	0,08 (0,22)	0,04 (0,35)
$\bar{W}$	0,01 (0,01)	0,01 (0,01)	0,01 (0,01)	0,02 (0,01)	0,01 (0,01)	0,00 (0,01)	0,01 (0,01)	0,01 (0,01)	0,01* (0,01)	0,02 (0,01)	0,00 (0,01)	0,00 (0,01)
$\bar{C}$	0,09*** (0,03)	0,05 (0,03)	0,10*** (0,03)	0,06* (0,03)	0,15*** (0,03)	0,08*** (0,02)	0,09*** (0,02)	0,04 (0,03)	0,10*** (0,02)	0,05 (0,03)	0,15*** (0,04)	0,10*** (0,03)
$\bar{R}$		-0,27 (0,20)		-0,15 (0,13)		-0,17 (0,20)		-0,19 (0,18)		-0,08 (0,13)		-0,12 (0,15)
$\overline{GB}$		0,37* (0,21)		0,46*** (0,15)		0,33 (0,20)		0,47** (0,23)		0,42*** (0,14)		0,30* (0,17)
Constant	0,05 (0,05)	0,02 (0,07)	0,03 (0,04)	0,01 (0,05)	0,00 (0,00)	0,00 (0,00)	0,03 (0,06)	0,03 (0,06)	0,01 (0,04)	0,02 (0,05)	0,00 (0,00)	0,00 (0,00)
Observations	468	466	464	462	456	454	503	501	488	486	491	489
Countries	12	12	12	12	12	12	12	12	12	12	12	12
Dataset	B	B	B	B	B	B	B	B	B	B	B	B
First year included	1969	1969	1969	1969	1969	1969	1969	1969	1969	1969	1969	1969
Last year included	2009	2009	2009	2009	2009	2009	2012	2012	2012	2012	2012	2012
Regression specification	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**	**Main**	**Main**	**Adjusted**	**Adjusted**	**First-differenced**	**First-differenced**

Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% respectively. Note that: 1) *S* represents S_t in the main and adjusted regression specifications and ΔS_t in the first-differenced regression specification; 2) *UR* represents UR_t in the main regression specification, UR_{t+1} in the adjusted regression specification and ΔUR_t in the first-differenced regression specification; 3) *W* represents W_{t-1} in the main and adjusted regression specifications and ΔW_{t-1} in the first-differenced regression specification and 4) *C* represents C_t in the main and adjusted regression specifications and ΔC_t in the first-differenced regression specification. The same systematic also applies to all other variables in the first column.