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Income distribution and wealth effects

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Preface

This document is a revised version of Jørgen Landsem's master thesis at NHH − Norwegian School of Economics, which was written during a student internship at Statistics Norway. The thesis is closely related to a research project on the Norwegian macro consumption function headed by senior researcher Eilev S. Jansen at the Research Department. The contribution of the paper is described in the abstract.

Statistics Norway, September 7, 2016.

Kjetil Telle

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I would first like to thank my advisor at NHH, Professor Jan Tore Klovland, for helpful advice and insightful comments on my work throughout the semester. At Statistics Norway, Eilev S. Jansen introduced me to the current literature on the consumption function, and has given invaluable help with methodology and data. Finally, I also want to thank members of the group for macroeconomics in the Research Department of Statistics Norway for providing a stimulating work environment during the spring of 2016.

Jørgen Landsem

Abstract

Since the financial crisis, Norwegian private consumption has fallen as a share of household disposable income. This weak development in consumption was not predicted by the contemporaneous consumption models and led to a “structural breakdown” of these models.

This thesis will attempt to build a new model for aggregate consumption that is better able to explain the developments since the financial crisis. This is done by using cointegration analysis to estimate a long run relationship and then include this in an error correction model for private consumption. With a basis in the current consumption function in Statistic Norway’s KVARTS model, the paper demonstrates the breakdown of the incumbent consumption function and conducts two separate analyses into possible explanations for the breakdown.

A first finding is that the income distribution, measured by a Gini coefficient or the wage share, does not seem to affect household consumption on the aggregate level. In another exercise the wealth variable present in the current model is split into different components. In the long run, including net housing wealth and net financial wealth separately seems to improve the model. Financial wealth is a larger determinant of household consumption in the long run than housing wealth. In the short run, the degree of liquidity affects the effect of financial wealth on consumption, while controlling for short run dynamics of debt does not improve the model.

Sammendrag

Siden finanskrisen har privat konsum falt som andel av husholdningenes disponible inntekter. Den svake utviklingen i konsumet kunne ikke forklares av eksisterende konsummodeller og ledet til det vi kan kalle et «strukturelt sammenbrudd» for disse modellene

I denne analysen forsøker vi å bygge en ny modell for aggregert konsum som er bedre i stand til å forklare utviklingen etter finanskrisen. Dette gjøres ved å benytte kointegrasjonsanalyse for å tallfeste en langsiktig sammenheng og deretter inkludere den i en feiljusteringsmodell for privat konsum. Med utgangspunkt i makrokonsumfunksjonen i Statistisk sentralbyrås kvartalsmodell KVARTS viser vi først at denne funksjonen bryter sammen og undersøker deretter to mulige forklaringer til hvorfor dette skjer.

Et første funn er at inntektsfordelingen, enten den er målt ved en Gini-koeffisient eller lønnsandelen i total faktorinntekt, ikke synes å påvirke makrokonsumet. I et annet framstøt splitter vi formuesvariabelen som inngår i makrokonsumfunksjonen i KVARTS i ulike komponenter. På lang sikt gir et skille mellom netto boligformue og netto finansformue, i alle fall tilsynelatende, en forbedring av modellen. Finansformuen har større innvirkning på konsumet enn boligformuen. På kort sikt har graden av likviditet for den finansielle formuen betydning for konsum-utviklingen, mens det å kontrollere for kortsiktige effekter av husholdningenes gjeld ikke forbedrer modellen.

Contents

1 Introduction

Since the financial crisis in 2008-2009, the development in household consumption in Norway has been feeble. The contemporary consumption-models failed in predicting this development and are not able to explain why Norwegian households now consume a smaller fraction of their disposable income. Ever since the 1970s, there has been a stable relationship between consumption, income and wealth that was able to predict household consumption relatively well up until the financial crisis. This kind of model was first estimated by Brodin and Nymoen (1992), but subsequent research has also confirmed this relationship.

Household consumption is one of the most important measures in macroeconomics. In Norway and most developed countries it represents more than half of GDP. It is crucial for policymakers to understand the drivers behind aggregate consumption, both for the government, the central bank and others. This thesis attempts to build a conditional consumption function that performs better through the financial crisis and in subsequent years. I will base my model on the existing consumption function from Jansen (2013) that is a part of Statistics Norway's KVARTS model.[1] There are several possible explanations for the weak development in consumption; increased uncertainty, pension reform, changing demographic, etc., but no one has yet presented an empirical model that is able to deal with the problem.

When building my consumption model, I have to determine which variables to include. Disposable income and wealth has already been mentioned as well-known determinants for consumption. Another factor that has been found and discussed both in economic theory and in empirical research is that between the real interest rate and consumption, which I will discuss in detail in the following chapter. Also, the age-composition of the population is expected to have an effect on consumption since different age groups have different incentives to save and consume.

But since these variables have not been adequate in explaining the latest developments in consumption in Norway, I will attempt to improve the current model by doing two different analyses. The first is to include income distribution as a variable. This is done on the basis that the marginal propensity to consume is lower for those with high income, if this holds then we would expect that changes to the income distribution would affect aggregate consumption. I use two different measures of income inequality, an adjusted version of the Gini coefficient and the wage share.

[1] KVARTS is a macroeconomic model for the Norwegian economy used in policy analysis and predictions about the future developments of the economy.

My second analysis is to split the wealth variable into several components. I will look at the effects of different wealth components on consumption. These components are housing wealth, financial wealth and debt. Financial wealth is also split into three categories according to liquidity. This enables me to investigate if the degree of liquidity affects the wealth's effect on consumption. I will also include debt as a separate variable, thus opening up for the possibility that debt can have asymmetric effects on consumption. Finally, I propose a new consumption function, and show that the new model performs better than the old one.

The following chapter presents standard economic theory on consumption in macroeconomics, and comment on the implications of these theories with regards to the empirical consumption function. Chapter 3 presents the most relevant empirical work on the consumption function; here I separate the presentation of the international and Norwegian research. For Norway the most relevant empirical research has been conducted after the credit liberalization in the 1980s. Chapter 4 presents the econometrical methods that I use in the thesis. Here, I first present some of the most important features of time series analysis, before explaining the concept of stationarity and cointegration. Finally, in this chapter I explain the relationship between cointegration and the error correction model (ECM). Chapter 5 briefly presents the data and the stationarity properties of the series. Then, in chapter 6 I reestimate the old consumption function from Jansen (2013) and show how this breaks down around 2009, which is the motivation for this thesis. Chapter 7 investigates whether the income distribution might have an effect on aggregate consumption. My second model, where I split the wealth variable to see if the individual wealth components have different effects on consumption, is documented in chapter 8. Finally, chapter 9 concludes.

> "Consumption — to repeat the obvious — is the sole end and object of all economic activity." Keynes (1936)

2 Theory

Household consumption is one of the most studied macroeconomic variables. It has been an important part of macroeconomic research for decades and several theoretical models have been developed to explain it. This chapter will lay the theoretical foundation for this thesis and go through the most central contributions. First I explain Keynes' consumption model, then I move over to intertemporal models, beginning with a simple two-period model. Then I present two well-known intertemporal models; Modigliani et al.'s life cycle hypothesis (LCH) model and Milton Friedman's permanent income hypothesis (PIH) model. The final section shows how some specific assumptions to LCH/PIH implies that consumption should behave as a random walk.

Before I continue, it is necessary to point out the distinction between consumption in the theoretical models and the empirical consumption variable. The first is a theoretical, non-observable value, which is the use of services from goods and services in a given period, while the latter is a measure of the expenditure on goods and services bought in a given period. The difference between the two arises when expenditure and consumption happens in different time periods, which is typical for durable goods that can be consumed over a long time. It is important to be aware of such differences when testing the theoretical models empirically.

2.1 Keynes' consumption model

A discussion of the consumption function is not complete without including Keynes. In "The General Theory of Employment, Interest and Money " from 1936 John Maynard Keynes made a thorough analysis of household consumption. He divided the factors that affect consumption into two groups, objective and subjective factors.

The most important objective factor was income, but Keynes also recognized other factors as relevant. He discusses the importance of the rate of time discounting, approximated by the interest rate. The effect of the interest rate, Keynes argues, is uncertain. He especially discusses the interest rate effect on the valuation of wealth and therefore on consumption. He also recognizes the importance of the interest rate in the decision between consumption today or in the future. Another factor that he addresses is the effect of fiscal policy; it affects consumption through disposable income, but also as an instrument for more equal distribution and therefore affecting aggregate consumption. Keynes recognized that the marginal propensity to consume differs between the different parts of the income distribution. Finally, he also discusses saving as a form of investment, and that households can increase savings if they are met with good investment opportunities. This would lead to consumption being sensitive to changes in investment returns.

Of the subjective factors, Keynes mentions both psychological and sociological factors and acknowledged the importance of these, but it is standard to assume that these factors are fixed in the short term. Keynes mentions both precautionary saving, people saving more when facing uncertainty, and bequeath, people saving for the next generation, as examples of subjective factors.

The most popular way to represent Keynes' theory is to assume that consumption is a linear function of disposable income.

$$C_t = a + b * YD_t \tag{2.1}$$

where C_t is consumption in time t , YD_t is disposable income at time t, a is the autonomous consumption, which is consumption independent of income, assumed to be larger than zero, and b is the marginal propensity to consume (MPC), which is between zero and one. Implicit in this model is that households are liquidity constrained, and therefore cannot borrow to consume more than current income allows.

As we can see from figure 1, the linear relationship between income and consumption held up quite well until around 1985. Around this time we had a liberalization of the credit markets in Norway, as has been documented by Krogh (2010), this led to a consumption boom even if income did not see the same increase. Many other industrialized countries experienced a similar development. It was therefore obvious that other variables were necessary in an empirical model of household consumption.

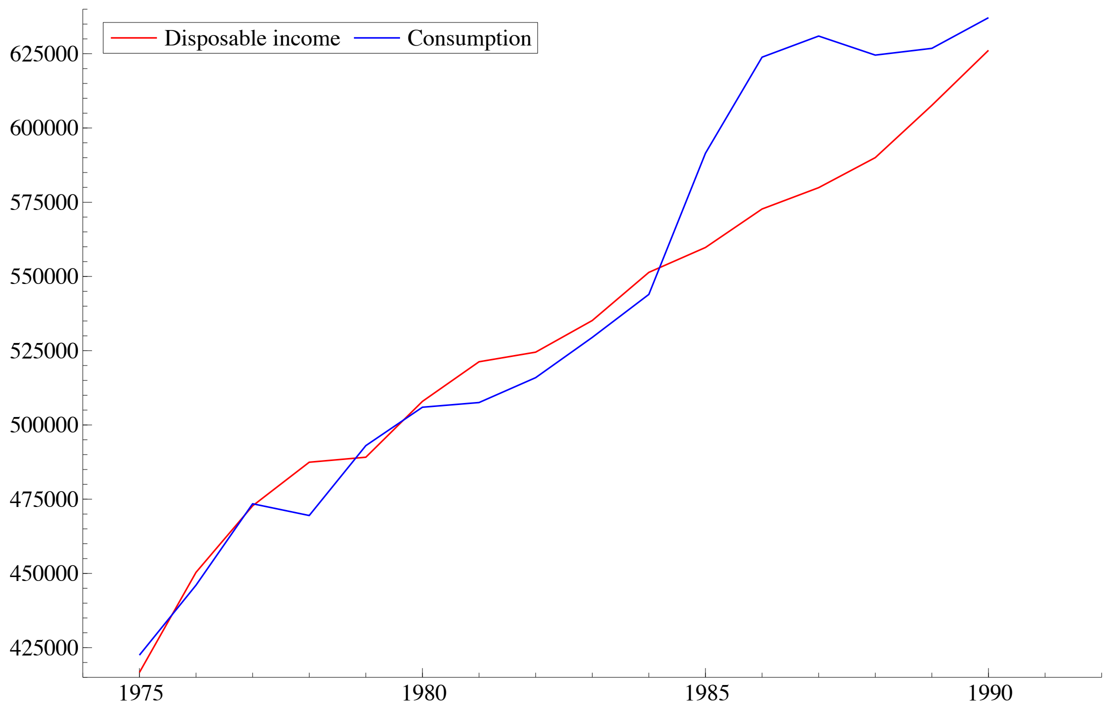

Figure 1: Private consumption and household disposable income 1975-1990. Norwegian yearly data in billion kroner, fixed 2007-prices.

It is worth to mention that this linear relationship was never proposed by Keynes and does not capture his full analysis. In fact, more resent research on consumption is more in line with Keynes' analysis than equation 2.1, for example with regards to wealth effects, the interest rate and income inequality.

Keynes' theories of consumption were very popular up until the 1950s and 1960s, but several economists refuted the assumption that consumers does not take future income into account when deciding how much to consume. Also, empirical evidence showed that the savings rate was stable even if income was rising, contrary to what a proportional relationship between income and consumption would imply. This led to new theoretical models being developed, especially theories based on microfoundations as will be presented in the following sections.[2]

2.2 Intertemporal models

Intertemporal models take into account that consumers maximize utility over their whole lifetime and therefore that their consumption not only depends on current

[2]The term microfoundations refers to the microeconomic analysis of the behavior of individual agents, usually assuming them to behave rationally.

income, but also current wealth and expected future income. This leads to the assumption that individuals will "smooth" consumption over their lifetime. They will borrow when income is low, and save when income is high. For this to be possible, individuals depend on a well functioning credit market, which is an important assumption in these models. The two most famous intertemporal models for consumption is Franco Modigliani's and his coauthors' life cycle hypothesis (LCH) and Milton Friedman's permanent income hypothesis (PIH).

Compared to Keynes' simple consumption model, LCH and PIH are richer, in that they can take several complications into account, like interest rate fluctuations, altruism, consumers' time-preferences and uncertainty of future income and of life-length. But before I present LCH and PIH, I will present a simple two-period model for consumption. This makes it easier to show the different interest rate effects that appear when households must decide between consumption today or in the future. In my presentation of the two-period model I follow Sandmo (1968), while for LCH and PIH, I follow the notation in Doppelhofer (2009).

2.2.1 The two-period model and interest rate effects

First, I introduce the simple case where individuals only have to decide between consumption over two periods. This simplification is useful to get an intuition of intertemporal consumption choices, and to explain the different interest rate effects on consumption. We assume that income is exogenous in both periods and that the individual can borrow or lend money to the same interest rate. The budget restriction can be written as

$$c_2 = (y_1 - c_1)(1 + r) + y_2 \tag{2.2}$$

Where c_t and y_t is consumption and income respectively, in time t, and r is the interest rate. Saving in period one is the difference between y_1 and c_1, this can be both positive and negative. If the saving is positive, there will be more left for consumption in the second period.

Further, we assume that the individual have preferences over the consumption-profile which can be represented by a continuous, ordinal utility function which has a positive first derivative.

$$U = U(c_1, c_2) \tag{2.3}$$

Then the first order condition to the optimization problem is

$$U_1 - (1+r)U_2 = 0 \tag{2.4}$$

Where $U_i = \frac{\delta U}{\delta c_i}$ and since $U_1/U_2 = -(dc_2/dc_1)$, for constant U, we can write

$$-\frac{dc_2}{dc_1} = (1+r) \tag{2.5}$$

Which states that the marginal rate of substitution between consumption in period 1 and 2 (the marginal rate of time preference) is equal to the interest rate.

I now turn to the interest rate effects. The comparative statics will show that the interest rate effect on consumption in the first period can be separated into an income and substitution effect. I will express this by using the Slutsky equation, and show it graphically in figure 2 and 3.

By implicit derivation of equation 2.4 with regards to y gives us

$$\frac{dc_1}{dy_1} = (1+r)\frac{(1+r)U_{22} - U_{12}}{D} \tag{2.6}$$

where

$$D = U_{11} - 2(1+r)U_{12} + (1+r)^2 U_{22} < 0 \tag{2.7}$$

which is the second order condition for maximum of the optimization problem.

To determine the sign of the derivative in 2.6 we assume that consumption in both periods is a normal good, and therefore that $0 < \frac{\delta c_1}{\delta y_1} < 1$.[3]

Next, we derivate equation 2.4 with respect to the interest rate, r. We then get

$$\frac{\delta c_1}{\delta r} = (y_1 - c_1)\frac{(1+r)U_{22} - U_{12}}{D} + \frac{U_2}{D} \tag{2.8}$$

Substituting from equation 2.6 yields

$$\frac{\delta c_1}{\delta r} = \frac{1}{(1+r)}(y_1 - c_1)\frac{\delta c_1}{\delta y_1} + \frac{U_2}{D} \tag{2.9}$$

[3]Formally, this is given by $(1+r)U_{22} - U_{12} < 0$ and that $U_{11} - (1+r)U_{12} < 0$, or that the indifference curves are convex.

where the first term on the right-hand side is the income effect, and the last term is the substitution effect.

We can easily see that the income effect will be negative for a borrower ($y_1 - c_1 < 0$) and positive for a lender ($y_1 - c_1 > 0$). This is natural since a higher interest rate will lead to higher interest payments for a borrower and therefore lowers disposable income in the second period. The substitution effect will always be negative, since an increase in the interest rate will make current consumption relatively more expensive compared to consumption in period 2. The total effect will therefore depend on whether the individual is an initial borrower or lender. For the borrower, both effects will be negative. For the lender the substitution effect will be negative and the income effect positive, it is therefore not possible to draw any conclusions about the total effect.

The effect of an increase in the interest rate can for both cases be illustrated graphically in a diagram with consumption in period 1 on the x-axis and consumption in period 2 on the y-axis. Figure 2 shows the consumption decisions for a lender.

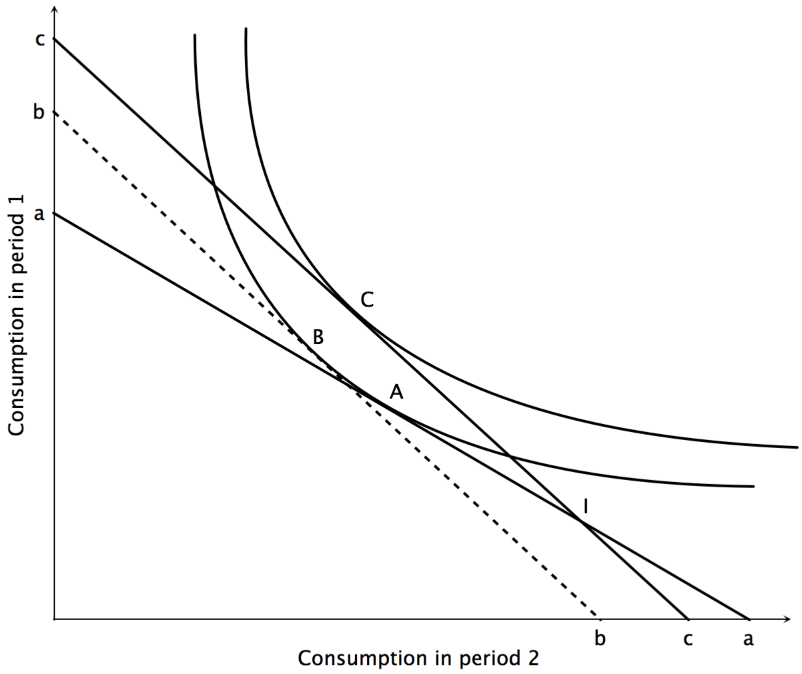

Figure 2: Effects of increased interest rate for lender

The exogenous income (y_1, y_2) is point I in the diagram. The initial budget constraint is the line aa, while the budget constraint with the new interest rate is given by the line cc. The initial, optimal consumption is given by point A, and the optimal consumption decision given the new interest rate is at point C. The change in interest rate gives a steeper budget constraint while still crossing point

I. The line bb is parallel to the line cc but is tangent to the indifference curve at the initial utility level. The change in consumption between point A and B is a pure substitution effect, while the change from B to C is the income effect. As we see from the figures, the substitution effect is negative in both cases, while the income effect has the opposite sign.

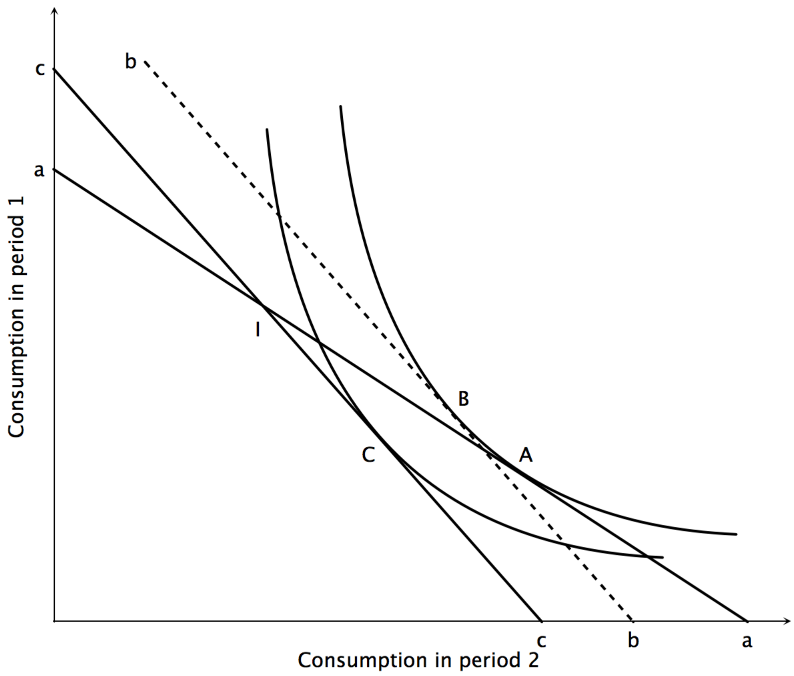

Figure 3: Effects of increased interest rate for borrower

In addition to these two effects, we can also talk about a wealth effect of the interest rate on consumption. This is really a pricing effect, which comes from the fact that wealth is often priced by discounting future cash flows. When the interest rate increases, we discount by a higher factor and the value of the wealth falls. This should, *ceteris paribus*, lead to lower current consumption.

In an empirical analysis it is difficult to disentangle these interest rate effects or to know which coefficients that pick up what effect. In my definition of disposable income I include both income from interest carrying wealth and interest payments on debt. It is therefore possible that the income effect of changes in the interest rate is included in the coefficient for disposable income. It is also possible that the wealth effect of interest rate changes is picked up by the wealth variable.

On average, Norwegian households have held more debt than interest carrying wealth; therefore the aggregate income effect is expected to be negative. Since the other effects also should be negative, we expect that the coefficient for the interest rate in our analysis is negative.

2.2.2 Life cycle hypothesis (LCH)

The LCH first appeared in Modigliani and Brumberg (1954). Modigliani with co-authors developed the LCH in the 1950s to describe consumption and saving behavior of individuals over their lifetime. They argued that consumers were maximizing their utility over their lifespan subject to a budget constraint, and therefore smoothed consumption over their lifespan. The optimization problem can be written as:

$$\begin{array}{rcl} Max\,U & = & \sum_{t=0}^{T} \frac{1}{(1+\rho)^t} u(c_t),\ u' > 0,\ u'' < 0 \\ s.t. & & y_1 + \frac{y_2}{1+r} + ... + \frac{y_T}{(1+r)^{T-1}} + b_0(1+r) = \\ & & c_1 + \frac{c_2}{1+r} + ... + \frac{c_T}{(1+r)^{T-1}} + \frac{b_T}{(1+r)^{T-1}} \end{array} \tag{2.10}$$

Where $u(c_t)$ is the utility of consuming c_t in time t, y_t is income in time t, b_o is the initial wealth (e.g. from bequests) and b_T are bequests to the next generation, r is the interest rate and ρ is the time preference of consumption. If $\rho > 0$ then one values consumption today more than later consumption. In the LCH one assumes that individuals have finite horizons and that they leave behind no assets, this means that b_T is set to zero. We also assume that the utility function is homothetic w.r.t. consumption in the different periods, meaning that the composition of lifetime consumption will not be sensitive to the size of the lifetime income, in other words that wealthy individuals smooth their consumption as much as less wealthy individuals.

The first-order conditions of this problem are $u'(c_t) = \frac{1+r}{1+\rho} u'(c_{t+1})$, for all t. Thus, $r = \rho$ implies that consumption will be the same in all periods. If $r > \rho$, then $c_1 < c_2 < ... < c_T$, i.e. consumption will grow over time, and vice versa for $r < \rho$.

The results from the LCH can be aggregated to make predictions for aggregate consumption. According to the LCH, individuals would borrow before entering the labor market, accumulate savings while working, and then dissave after retirement. It also implies that consumption will respond little to temporary changes in income, but that unexpected, permanent changes to income would lead to an proportional change in consumption.

Another implication is that the marginal propensity to consume (MPC) out of current income depends on age. This means that the age-composition of the population will have an effect on aggregate consumption. A country with high population growth will have a higher aggregate savings rate because of the relative larger share of workers. Also, an economy with economic growth will have dissavers living on assets accumulated out of lower incomes than current workers are earning. On the face of it, this should result in a higher aggregate saving rate. However, higher expected real per capita income growth will, if borrowing is possible for the young, result in higher consumption for them which could offset (for very high growth rates) the higher saving rate of the working population. In practice however, there are credit constraints that limit consumption for the young.

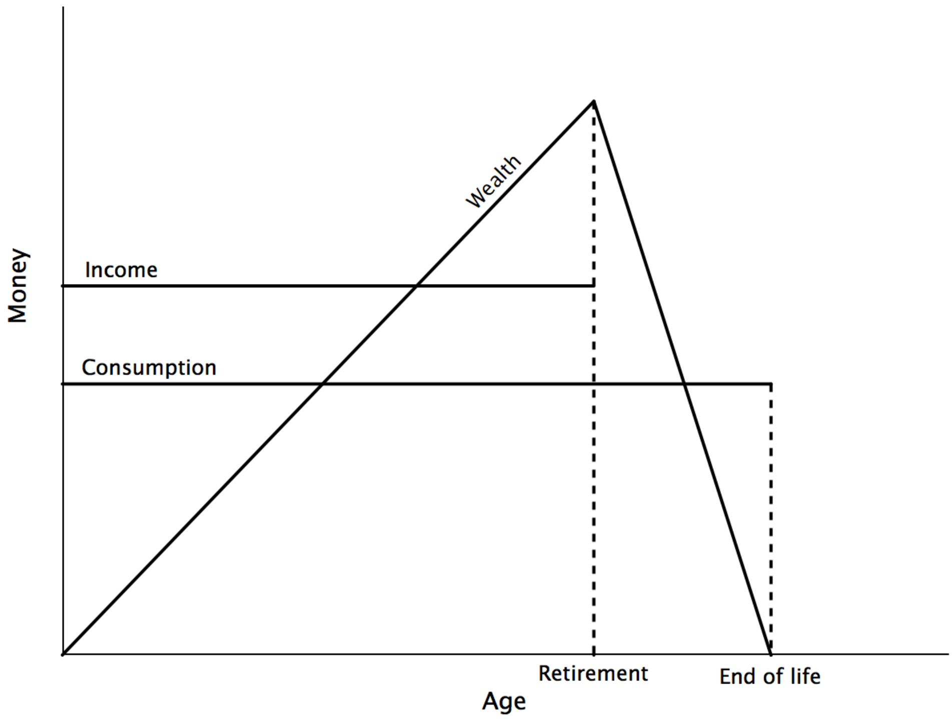

Figure 4: Illustration of Modigliani et al.'s life cycle hypothesis model.

Empirically, several of the assumptions behind LCH do not hold quite so well. First, young individuals consume too little compared to their expected lifetime income and have a large propensity to consume. This might be due to myopia, or credit constraints that are mostly due to the lack of collateral. Also, consumption seems to vary over the working life, which is not what we would expect from consumption smoothing. Reasons for this could be precautionary saving and demographic changes in families; households consume more when they have children. Finally, data also tells us that individuals consume too little after retirement. This could also be explained by precautionary saving because people do not know how long they will live, another factor could be presence of bequests ($b_T > 0$) (Doppelhofer, 2009).

2.2.3 Permanent income hypothesis (PIH)

Milton Friedman's PIH is similar to the LCH, but with an infinite time horizon. This is similar to saying that individuals value the consumption of later generations as well as their own consumption. We simplify by assuming that each generation live for one period and that they care about the utility of the next generation:

$$\begin{aligned} t = 1: &\quad U_1 = u(c_1) + \beta U_2 \\ t = 2: &\quad U_2 = u(c_2) + \beta U_3 \\ \ldots \end{aligned}$$

where U_t stands for the total utility for the generation born in period t, while u represents the utility of own consumption. Since the total utility of the generation born in $t = 1$ also depends on the utility of the generation born in $t = 2$, which depends on the utility of generation born in $t = 3$, we can write the total utility of the first generation as:

$$u(c_1) + \beta u(c_2) + \beta^2 u(c_3) + ... = \sum_{t=1}^{\infty} \beta^{t-1} u(c_t) \tag{2.11}$$

Since individuals value the consumption of later generations, they will act as if they had an infinite horizon for their consumption choices, with β as the discount factor for future consumption.[4] Comparing this to the LCH, the difference is that $\beta = \frac{1}{1+\rho}$, and that the time horizon is infinite for the PIH.

Again, we assume the individual maximizes utility subject to a budget constraint, which in this case is:

$$\sum_{t=1}^{\infty} \frac{y_t}{(1+r)^{t-1}} + b_0(1+r) = \sum_{t=1}^{\infty} \frac{c_t}{(1+r)^{t-1}} + \lim_{T\to\infty} \frac{b_T}{(1+r)^{T-1}} \tag{2.12}$$

On the left hand side we have the present value of total income, plus initial assets over the infinite horizon. This must be equal to the present value of all consumption, plus the present value of wealth as time goes towards infinity.

Where we for the LCH-model assumed that b_T was zero, we now impose the condition that $\lim_{T\to\infty} \frac{b_T}{(1+r)^{T-1}} \geq 0$ which means that the present value of assets must

[4] Some have argued that it is immoral to discount the consumption of future generations, and that therefore the only morally right number of β is one.

be non-negative and that potential debt must not grow faster than the interest rate.[5] The consequences of this restriction is that consumers cannot finance infinite consumption by borrowing ever increasing amounts. We can also argue that it will not be optimal for consumers to accumulate savings at a faster rate than the interest rate, we would then have that the present value of savings would be unbounded. Therefore, the optimal consumption path must satisfy the so-called transversality condition

$$\lim_{T\to\infty} \frac{b_T}{(1+r)^{T-1}} = 0 \tag{2.13}$$

We can then simplify the budget constraint to

$$\sum_{t=1}^{\infty} \frac{y_t}{(1+r)^{t-1}} + b_0(1+r) = \sum_{t=1}^{\infty} \frac{c_t}{(1+r)^{t-1}} \tag{2.14}$$

Solving this optimization problem of maximizing utility from equation 2.11 subject to the budget constraint in equation 2.14, gives us the Euler equation[6]

$$u'(c_t) = (1+r)\beta u'(c_{t+1}) \tag{2.15}$$

Since, β is the discount factor for future consumption, the result is equal to that of the LCH (only now we talk about discount between generations instead of "own" consumption). If we consider the special case of $\beta = \frac{1}{1+r}$, then we get that

$$u'(c_t) = u'(c_{t+1}) \tag{2.16}$$

which implies that consumption should be constant over time, $c_t = c_{t+1} = \bar{c}$. If we substitute this in the budget constraint and solve, we get

$$\sum_{t=1}^{\infty} \frac{\bar{c}}{(1+r)^{t-1}} = \sum_{t=1}^{\infty} \frac{y_t}{(1+r)^{t-1}} + b_0(1+r) \tag{2.17}$$

which states that in each period, individuals will consume the annuity value of the total wealth, Milton Friedman (1957) called this annuity the permanent income, y^P.[7]

[5] This is also called the non-ponzi scheme condition.

[6] An Euler equation is a difference or differential equation that is an intertemporal first-order condition for a dynamic choice problem.

[7] In deriving equation 2.18 we use $\sum_{t=1}^{\infty} 1/(1+r)^{t-1} = (1+r)/r$.

$$c_t = y_t^P \equiv \frac{r}{1+r}\left(\sum_{s=0}^{\infty}\frac{y_{t+s}}{(1+r)^s} + b_{t-1}(1+r)\right) \tag{2.18}$$

This shows us that consumption should respond proportionally to permanent increases in income, but almost not at all to temporary changes. In this way, the PIH can explain why we over shorter periods can observe changes in the marginal propensity to consume (MPC) out of current income, while over longer time periods MPC is relatively stable.

2.3 Consumption as a random walk

As shown above, the assumptions we make have implications for what predictions we can draw from the theories. One popular set of assumptions, made by Hall (1978), gives us the (perhaps surprising) result that current consumption is independent from current income, and that consumption follows a random walk.

If we begin by introducing uncertainty over future income, this means that individuals maximize the utility function

$$\max_{c_1,c_2,\dots} E_1\left\{\sum_{t=1}^{\infty}\beta^{t-1}u(c_t)\right\} \tag{2.19}$$

here E_1 indicates the expectations conditional on all the information known at time $t = 1$. The budget constraint is still given from equation 2.14. In the budget constraint it is the present value of realized consumption that must be equal to the realized total wealth. Solving this stochastic version of the PIH, we get that the marginal utility of consumption in period should equal the expected discounted marginal utility in period 2

$$u'(c_1) = (1+r)\beta E_1\left[u'(c_2)\right] \tag{2.20}$$

Now Hall (1978) makes two simplifying assumptions. The first is that we assume a quadratic utility function

$$u(c) = c - ac^2/2 \tag{2.21}$$

where a is bigger than zero. Then the marginal utility will be $u'(c) = 1 - ac$, which is linear in consumption. This has the effect that the individual exhibits certainty equivalence in his consumption decision, which means that any individual will act as if future consumption is at its conditional mean value and ignore its variation.

The second assumption is that $1 + r = 1/\beta$. This ensures that consumers want to hold marginal utility (and consumption) constant over time. This is the same assumption as we used under the discussion of LCH.

Given these two assumptions the stochastic Euler equation becomes

$$c_1 = E_1(c_2) \tag{2.22}$$

Or conversely that $c_t = c_{t-1} + \epsilon_t$, which is a standard random walk. That consumption follows a random walk derives from the fact that rational individuals use all information available at time $t = 1$ to smooth consumption so that only new, unforeseen information about income will impact the consumption level. Another implication is that changes in consumption are unpredictable. Hall (1978) argued that this was an approximation that holds if the market interest rates and the subjective discount rate are not far apart, and if consumption shocks are small relative to the level of consumption.

Hall (1978) tests this theory on postwar aggregate data from the US and he concludes that past levels of consumption and income have no predictive power for future consumption, which is in line with his predictions. However, he does find that lagged levels of the S&P stock market prices are significant in predicting aggregate consumption. Since then, researchers have not been able to find strong evidence for Hall's model, and even if it did fit the data well, it does not help in explaining the changes in consumption over time.

Even though there is much evidence that consumption can, in fact, be predictable by using lagged variables of consumption, income and wealth, and that such predictions are better than the simple random walk model, many researchers still use the Euler equation approach when modeling consumption. Especially in academia and among central banks, the most common way to model the economy is through DSGE-models that have sound theoretical foundation from microeconomics and that are fairly small models that do not require much data.[8] This is in contrast to building econometric models that can explain the data well, but with a looser

[8]Dynamic stochastic general equilibrium models are macroeconomic models that are derived from microeconomic principles, often based on rational individuals.

connection to theory. Researchers are still divided on this issue, but empirical evidence seems to support econometric models, both with regards to forecasting and being able to explain developments in consumption.

This concludes the chapter presenting economic theory about private consumption. As we have seen throughout this chapter, there are many different factors in the economy that eventually affect aggregate consumption. It is impossible to incorporate all these factors in an econometric model, but the goal is to build a model that is able to explain the main developments in consumption.

The following chapter will present the current empirical literature on the consumption function both internationally and for Norway I then continue with introducing the empirical methods used in the analysis in this thesis, before I shift focus to my own analysis beginning with presenting the data in chapter 5.

3 Literature review

In this chapter I present the most central empirical work on the consumption function. As the different theories of consumption developed over time, so has the empirical research. Up until the 1980s the common way to model aggregate consumption was by Keynes' consumption model, where current income was the main explanatory variable. But these models were unable to explain the developments following the liberalization of credit markets in many industrialized countries during the 1980s, which led to new conditional consumption models usually including some form of wealth. In Norway, consumption models including income and wealth had much success up until 2008, but since then they have been unable to explain the low level of consumption that has persisted since the financial crisis, and researchers have been unable to find satisfactory answers to why this has happened.

I begin with a brief overview of some the most important international research and then move over to the Norwegian consumption function. I focus on the empirical work on conditional consumption functions from the 1980s up until today.

3.1 International research

Given the importance of consumption in macroeconomics, it has been one of the most studied of the aggregate expenditure relationships and a central part of all macroeconomic model building. One of the first attempts of such modeling was Klein and Goldberger (1955). Following Keynes, they built a econometric model for the American economy where the consumption function was relatively simple. They included different forms of income, liquid assets and the population as explanatory variables. There were a lot of problems facing the early empirical work on the consumption function. Statistical problems of working with non-stationary time series were not really understood and data were not as readily available, especially for households' assets.

1978 was an important year for empirical research on consumption. Two papers were published that had different approaches on modeling consumption. The first was Hall (1978) who argued for modeling consumption by Euler-equations as explained in section 2.3. The second was the study by Davidson et al. (1978) (DSHY) who were one of the first to use an error correction model (ECM) to find a robust empirical relationship between income and consumption. DSHY managed to find a long run relationship between income and consumption, which also satisfied economic theory. The use of ECM gained further popularity when Engle and Granger (1987) found that cointegrated relationships can be represented by an ECM, the so-called Granger representation theorem. ECM and cointegration is explained in chapter 4.

The most popular way to model aggregate consumption up until the 1980s was according to Keynes' consumption model from section 2.1. These were simple models where income was the main explanatory variable. In the 1980s some researchers claimed that "the consumption function has faded as a topic of intense research because of the success of previous research in achieving a workable consensus" (Darby, 1987 in the New Palgrave, found in Muellbauer and Lattimore (1995)). However, researchers at the time were not aware that their models were in the process of breaking down. Up until the 1980s income and wealth had moved mostly in tandem, it was therefore difficult to empirically find a significant effect of wealth on consumption when already including income. But the liberalization of credit markets made it easier for households to borrow money using wealth as collateral which altered the relationship between income, consumption and wealth. The failure of the existing models in explaining the fall in the savings rate in the mid-1980s, both in the US and in other industrial countries, reinvigorated the empirical research on the consumption function. The solution was often to include some form of wealth in the models. This is also consistent with the broad implications of the life cycle hypothesis and the permanent income hypothesis (Muellbauer and Lattimore, 1995).

Since then a lot of research has found support for a long run relationship between consumption, income and wealth. It is generally accepted that the three variables are cointegrated, and that there exists only one long run relationship. Using the Granger representation theorem (Engle and Granger, 1987) one can therefore model consumption with a error correction model. However, which variable that equilibrium corrects, i.e. the variable that adjusts to reach equilibrium, is disputed. Lettau and Ludvigson (2001, 2004) find support for cointegration and that wealth is the variable that equilibrium corrects, using data from the US, while Hamburg et al. (2008) find, using German data, that income equilibrium corrects. To make the uncertainty complete, Barrell and Davis (2007) argue that consumption is the variable that equilibrium corrects. If consumption equilibrium corrects then we have empirical support for the conditional consumption function. Barrell and Davis (2007) also investigate the effect of liberalization of credit markets on consumption in seven OECD countries, and find, in five out of seven countries, that the liberalization leads to bigger wealth effects on consumption, and lower consumption out of current income.

Davis (2010) gives a survey on the studies done on wealth effects on consumption for several countries. He states that there are effects on consumption of tangible wealth as well as financial wealth. There is reason to believe that the effects of housing wealth on consumption differs more across countries than that of financial wealth given that there are large differences in housing finance systems. He also notes that the effects, both long and short run, seem to vary across countries. While it is reasonable that the short-run effects differ because of different culture, financial systems etc., some argue that the long-run effects should be the same for all countries like Labhard et al. (2005), but Davis (2010) concludes that the empirical evidence does not support this.

Davis (2010) also discusses disaggregation of the wealth variable. He notes that the different characteristics of financial wealth, notably liquidity, may impact its effect on consumption. Byrne and Davis (2003) analyzed the impact of disaggregated net financial wealth on consumption for the G7 countries. They found that illiquid financial wealth (equities, bonds, life insurance and pension assets less mortgage debt) was a more significant long run determinant of consumption than liquid financial wealth. This may be because liquid financial wealth is not held as a long term store of value, but rather as a means of transactions.

There has also been research on the effect of tangible wealth on consumption, mostly housing wealth. Higher house prices may give more room for household consumption, but it can be argued that there is a negative effect of higher house prices on consumption through the increase in opportunity cost of housing services (Buiter, 2008). We could also have that the benefits of higher house prices to incumbents is offset by costs to new entrants and higher rental prices for tenants (Aoki et al., 2004). Another factor is that housing, unlike financial wealth, may be held as an end in and of itself Case et al. (2005). These views were influential in the period 2000-2007, but after the financial crisis there has been more focus on the role of housing wealth on consumption (Davis, 2010).

3.1.1 Consumption function based on Euler equations

Since Hall (1978) there has also been much research on Euler-equations. Empirical research has shown that consumption is predictable in practice, using lagged variables of income, consumption or wealth. The Euler-equation approach has given worse results than the conditional consumption function when it comes to analyzing and predicting consumption, also the Euler equation-approach gives little insight to what drives consumption (Jansen, 2013). As Muellbauer and Lattimore

(1995) pointed out, the Euler equations leaves out long run information on the relationship between assets, income and consumption, and may also suffer worse aggregation problems than "solved out" equations incorporating lags. Still, models based on Euler equations remain popular among several researchers, which might be because of the theoretical foundation, or because such models are smaller and require less data.

3.2 The Norwegian consumption function

As in the rest of the world, the norm in Norway was for a long time to include income as the only explanatory variable in the consumption function. And as in many other countries, these models broke down after the deregulation of the credit markets and the following consumption-boom in 1985-87, they failed both in forecasting and to explain the data *ex post*. The failure of these models is documented in Eitrheim et al. (2002).

This led Brodin and Nymoen (1992) to include wealth in their model. Earlier attempts of including wealth had been made by using the tax value of houses, however these have several weaknesses. The tax value is usually very low compared to the market value and do not always follow the changes in the market value which is the relevant value for households. Due to the lack of good time series on wealth Brodin and Nymoen (1992) constructed their own wealth variable defined as

$$W_t = (L_{t-1} - CR_{t-1} + (PH/PC)_t * K_{t-1}) \tag{3.1}$$

Where L_t is household sector liquid assets, CR_t is household sector loans by banks and financial institutions, PH_t is housing prices, PC_t is private consumption expenditure deflator, and K_t is the volume of the residential housing stock. Therefore the wealth variable is net financial wealth plus wealth in housing, where wealth in housing is defined as the housing prices multiplied with the volume of the residential stock. Brodin and Nymoen (1992) conducted a cointegration analysis, and found the long run relationship

$$c = constant + 0.56y + 0.27w \tag{3.2}$$

Where total consumption (c) is in a long-run relationship with household real disposable income (y) and household real wealth (w). Here, small letters indicate that the variables are log-transformed. Brodin and Nymoen (1992) also tested for weak exogeneity, and found that income and wealth were weakly exogenous with respect to the long run coefficient (see section 4.3.2 for explanation of weak exogeneity). This means that consumption is the variable that equilibrium corrects. They also found structural breaks in the processes of the conditioning variables as well as a stable conditional model. This points to income and wealth being super-exogenous, which refutes the Lucas-critique.[9]

After the article from Brodin and Nymoen (1992), Jansen (1992) commented that the parameters from Brodin and Nymoen's model were stable also outside the original sample, and that the model forecasted well out of sample. Magnussen and Moum (1992) answered Jansen by arguing that the model was flawed, especially since it did not have a sound theoretical foundation. They argued that the deregulation of the credit market in 1985 represented a structural break which should be included in the consumption function. They rejected the assumption that the parameters could be stable before and after the deregulation because the increased access to credit should have changed consumers preferences. They also argued for including the real, after-tax interest rate as a variable that should have an effect after the deregulation, and that the lack of homogeneity in income and wealth was a weakness, as this rules out a steady-state growth where consumption, income and wealth grows proportionally over time. The most central criticism from Magnussen and Moum (1992) was however, that the wealth-variable, and especially the house prices included in Brodin and Nymoen (1992), did not reflect the actual prices relevant for consumers. Magnussen and Moum (1992) showed that other house price indices moves differently in the period between 1980-87. They used house prices from "Norsk Byggforskningsinstitutt" ("Norwegian Building Research") which includes prices from housing cooperatives and has a less dramatic price increase around the time of the deregulation. They showed, using this house price index, that Brodin and Nymoen's model breaks down in the period right after deregulation.

After this discussion, further research were split into two schools; one following Brodin and Nymoen's example, the other using Magnussen and Moum's strategy with a structural break in 1985. Table 1 summarizes the most relevant research since 1992. The table is from Jansen (2009), and I have added the results from Jansen (2013).

[9]The Lucas critique is a common critique of econometric policy evaluation procedures that points to the failure to recognize that optimal decision rules of economic agents vary systematically with changes in policy.

Paper	Sample	Consumption-variable	Wealth-variable House-price*	Income elasticity	Wealth elasticity	Semi-elasticity real interest	Semi-elasticity age	Adjust-ment-speed
Brodin and Nymoen (1992)	1968(3)-1989(4)	Total consumption	Houses and liquid wealth, BN	0.56 (0.03)	0.27 (0.02)			-0.71 (0.08)
Ekeli (1992)	1976(4)-1991(4)	Total consumption	Total wealth, BN	0.63 t-value=2.1	0.27 t-value=3.2			-0.96 t-value =11.1
Brubakk (1994)	1968(2)-1991(4)	Consumption of non-durable goods	Total wealth, MM	0.59 t-value=5.0	0.13***			-0.49 t-value =5.7
Frøiland (1999)	1967(3)-1997(3)	cpeb**	Total wealth, MM	0.58***	0.21***			-0.71***
Eitrheim et. al. (2002)	1968(3)-1998(4)	Total consumption	Total wealth, BN	0.65 (0.17)	0.23 (0.07)			-0.34 (0.08)
Erlandsen and Nymoen (2008)	1968(3)-2004(4)	Total consumption per capita	Total wealth, BN	0.65 (0.03)	0.17 (0.02)	-0.42 (0.19)	-0.31 (0.08)	-0.47 (0.07)
Jansen (2012)	1971(1)-2008(4)	cpeb*	Total wealth, BN	0.85 (-)	0.15 (0.02)	-0.71 (0.22)		-0.38 (0.08)

*BN indicates that the model uses the house price index from Brodin and Nymoen, while MM indicates the house price index from Magnussen and Moum.
**Consumption less expenditure on health services and on housing.
***Value after shift in 1985. Sum of two coefficients where both are significant.
Standard deviations in parenthesis.

Table 1: Estimated long run coefficients for the Norwegian consumption function.

Ekeli (1992) builds on the research of Brodin and Nymoen (1992) but uses an wider wealth variable that includes wealth components like stocks and bonds. This had little effect on the estimated coefficients. Brubakk (1994) estimates the model with the house prices from Magnussen and Moum (1992) and includes a dummy variable to control for the deregulation of the credit market. His estimated wealth elasticity is less than half of that of Brodin and Nymoen (1992). He also excludes the consumption of durable goods from his analysis. Frøiland (1999) builds on Brubakk (1994), but uses total consumption less health spending and services from housing. Arguing that consumption of services from housing is determined in a large part from house prices and that health spending is more determined by government policy, and that these two are not consumption choices made by households.

Erlandsen and Nymoen (2008) includes an age variable as well as a variable for the real interest rate. They find that when controlling for the age composition, defined as the relative size of the age group between 50-66 years, the real interest rate also becomes significant.[10] Erlandsen and Nymoen finds a negative coefficient for the age variable, which implies that as the age group between 50-66 years increases, this leads to lower consumption. They also estimate consumption per capita, but this should not make a difference, since all the series divided on a per capita basis should not change the coefficients.

Jansen (2013) reestimate the consumption function with the wealth variable from Brodin and Nymoen (1992) and with the real interest rate as a exogenous variable. He finds an income elasticity of 0.85, elasticity on wealth of 0.15 and semi-elasticity of the interest rate of -0.71 on data from the first quarter in 1971 to the last quarter of 2008. We note that the income elasticity is higher than any of the previous models, and the results also differ from earlier research in that the homogeneity restriction is not rejected. Jansen (2013) also finds that the conditional consumption function forecasts better than two alternative Euler equations in the period between 2006 and 2008. The first Euler equation models consumption as a random walk, the other includes the real interest rate.

3.2.1 Research after the financial crisis

The relationship between consumption, income and wealth changed after 2008. Consumption growth weakened substantially and the consumption models at the time failed to predict this. Andersen et al. (2016) finds that consumption as a share of current income has fallen four percentage points since 2009. Several researchers have tried to find an explanation for this development, without finding satisfactory results. Figure 5 shows how the correlation between the consumption to income ratio and the wealth to income ratio has changed from a positive correlation up until 2008 and a negative relationship after 2008. The figure directly shows the cointegration between consumption, income and wealth up until 2008.

[10] Erlandsen and Nymoen (2008) and Jansen (2013) set the real interest rate to zero before quarter 1 in 1984, arguing that it is not relevant before the credit liberalization.

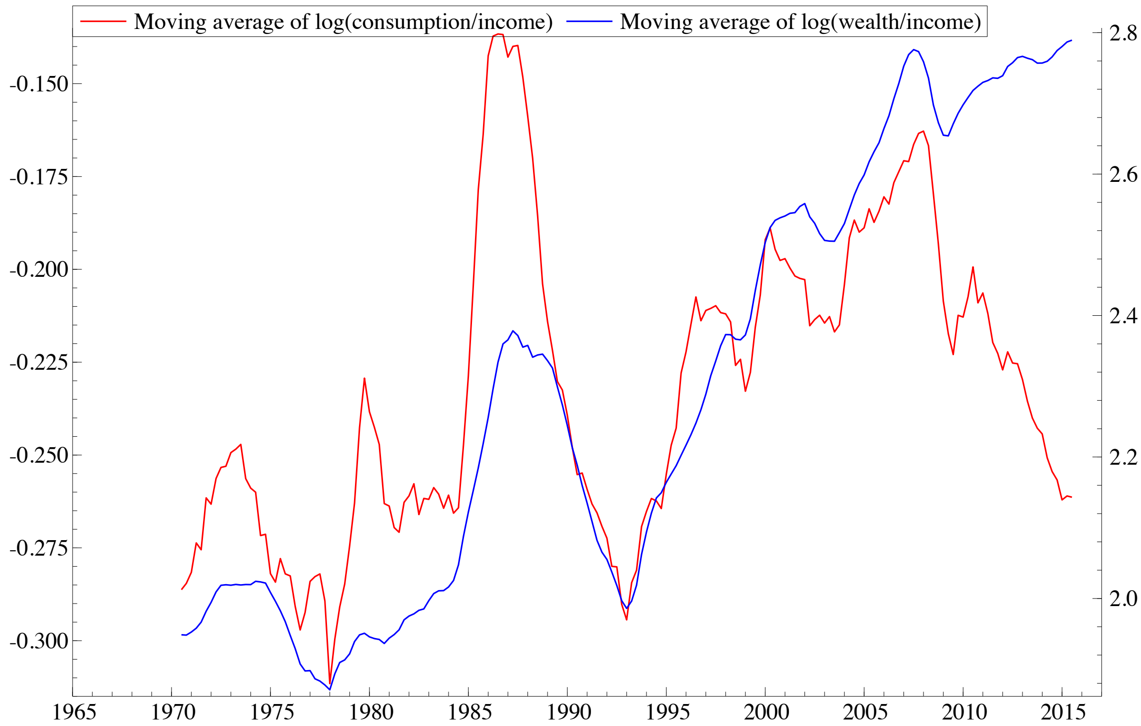

Figure 5: The log of the consumption to income ratio and the log of the wealth to income ratio, both in moving average with 2 lags and 1 lead, in the period 1970-2015.

Gudmundsson and Natvik (2012) investigates the effect of uncertainty on consumption and finds that increasing uncertainty can be one of the reasons of the changed behavior. Using micro data, Fagereng and Halvorsen (2016) finds evidence that households with higher debt has a lower consumption growth. They find that "much of the leveling off in consumption growth after the crisis reflects a regular response by highly indebted households." (Fagereng and Halvorsen, 2016), but they add that precautionary saving probably also played a role.

Jansen (2015) lists several potential reasons for why the fall in the consumption rate, such as the pension reform of 2011, increased immigration, stricter requirements for borrowers, demographic changes in the population, increased saving incentive for youth through "BSU"-accounts, increased immigration, and changes to the income distribution.[11] Andersen et al. (2016) investigates empirically some of these potential reasons, and find that stricter credit conditions and increased uncertainty has been the biggest contributors to the weak development.

Another factor could be the increased house prices. On one side higher house

[11]BSU-accounts are savings accounts with tax-incentives and high interest rates for young people to save towards buying a house. These accounts give young people a large incentive to save.

prices increases housing wealth for house owners, on the other side it makes it increasingly harder for other people to afford a house. This might force people to increase their saving towards buying a house. Higher housing prices might also increase consumption of housing services; this could lead to a “crowding out” of other consumption.

As this and the previous chapter shows, there can be many potential variables affecting consumption. In my further analysis I focus on two areas; income distribution- and wealth effects. I attempt to build a model that can help explain the current movements in consumption, while still being consistent with economic theory and with the historical data. My starting point is the model from Jansen (2013). I replicate this model and show the break-down of the model in the financial crisis in chapter 6. Chapter 7 looks at whether the distribution of income in the population could have an effect on household consumption, while chapter 8 look at the different wealth components. The data used in the analysis is presented in chapter 5, but first I need to introduce the empirical methods, this is done in the following chapter.

4 Method

This chapter gives a brief introduction to time series analysis and the methodologies that are used in my analysis. This includes some basic time series econometrics, cointegration analysis and the equilibrium correction model. The goal is to build a model that can explain the observed variation in Norwegian household consumption and that can be used to forecast consumption in the close future. In my analysis I have used the econometric software OxMetrics developed by Jurgen Doornik and David Hendry, and especially the module PcGive.

In this thesis I use an estimation technique known as general to specific (GETS) modeling. In short, this involves beginning with a large model with many variables and lags (the general model) and then using statistical tests and information criteria when trying to simplify the model. GETS modeling is explained in more detail in section A.3 of the appendix, while a presentation of information criteria is given in section A.4.

I begin with a discussion on time series econometrics and some of the assumptions that need to be fulfilled for our model to be valid. Section 4.2 explains the notion of stationarity of time series. One way of dealing with non-stationary time series is finding cointegrated relationships, which is discussed in section 4.3. Finally I present the equilibrium correction model in section 4.3.1.

The methods presented in this chapter are well known statistical and econometric concepts found in most text books about econometrics and time series, examples are Wooldridge (2015) and Enders (2008). The topics in section 4.3 are thoroughly presented in Bårdsen and Nymoen (2014).

4.1 Time series analysis

A time series is a sequence of data points that are observations measured in a chronological order. Most data relevant in macroeconomics are time series. To be able to do estimation and inference for time series regressions we need to make many of the same assumptions as for cross-sectional data. These include that the series must be linear in parameters ($y_t = \beta_0 + \beta_1 x_{t1} + \beta_2 x_{t2} + ... + \beta_k x_{tk} + u_t$), where x_{ti} can be lagged observations of y_t or some other variable, that we must have zero conditional mean ($E(u_t \mid x_{t1}, ..., x_{tk}) = E(u_t \mid \mathbf{x_t}) = 0$) and that there is no perfect collinearity between variables. All these are necessary to be able to get consistent estimators. Further, we also must assume homoscedasticity and that there is no autocorrelation, two assumptions I dig deeper into in the following subsections. If we also add the assumption that u_t is independent of $\mathbf{x}$, and that $u_t \sim N(0, \sigma^2)$, i.e. normally distributed with mean zero and standard deviation of σ^2, then we can use the standard ordinary least squares also for time series.

When doing an econometric analysis with several variables there is always the possibility of potential feedback effects between the variables. This is especially the case when working with economic series. When these feedback-effects exists, we can use a vector autoregressive (VAR) model. As the name suggests, a VAR model "stacks" the variables in vectors and we can then treat several variables as endogenous.

4.1.1 Homoscedasticity

Homoscedasticity is that the variance of the residuals are independent of the explanatory variables and of time, i.e. that the conditional variance is constant. This is the opposite of heteroscedasticity, where the conditional variance changes over time. Formally, homoscedasticity can be written as

$$Var(u_i \mid x_1,\, x_2,\, ...,\, x_k) = \sigma^2 \tag{4.1}$$

Where u_i is the residuals, $x_1,\, x_2,\, ..., x_k$ are the explanatory variables, and σ is a constant.

Heteroscedasticity does not lead to biased estimators, but makes the variance formulas invalid and therefore affects the statistical inference. This means that the standard errors, t-statistics or F-statistics are invalid under the presence of heteroscedasticity.

There are several ways to test for heteroscedasticity. A simple way to investigate this is to plot the residuals to look for patterns. The most well known formal tests to discover heteroscedasticity are the Breusch-Pagan test and the White test. In my analysis OxMetrics will automatically report test statistics and p-values for heteroscedasticity-tests, and since I do multivariate regressions OxMetrics reports results for vector-tests.[12]

Often in time series, it is possible that the conditional variance itself follows an autoregressive pattern. It is then possible to model the volatility with so-called

[12]Explanations for the different vector tests implemented in OxMetrics is given in Doornik and Hendry (2013b).

ARCH- or GARCH models, however, I do not attempt to model volatility in this thesis.[13]

4.1.2 Autocorrelation

Autocorrelation in the residuals is that we have correlation between residuals in different points in time. Conversely, when we assume that there is no autocorrelation in the residuals, then u_t and u_{t-i} should be independent for all $i \neq 0$. One way of possibly reducing the problem of autocorrelation is by adding lags to the model. We can detect autocorrelation graphically by plotting the residual in time t against the residual from the previous period, or we can conduct statistical tests. OxMetrics report test statistic an p-value for both the vector Portmanteau test and ARCH 1-4 test as tests for autocorrelation.

4.2 Stationarity

A time series is said to be stationary if it has constant mean and variance, and if the covariance between two observations depends only on the distance between them and not at what point we measure them (that they are time invariant). When doing time series analysis it is very important to be aware of the stationarity properties of the series we are working with. Doing regressions without dealing with stationarity can lead us to make false conclusions as we risk doing spurious regressions. More formally we can say that a stochastic process $\{y_t\}_{t=-\infty}^{\infty}$ is (covariance) stationary if, for all t:

$$
\begin{aligned}
E(y_t) &= \mu \\
Var(y_t) &= E(y_t - E(y_t))^2 = E(y_t - \mu)^2 = \sigma^2 \\
Cov(y_t, y_{t-s}) &= E\left[(y_t - E(y_t))(y_{t-s} - E(y_{t-s}))\right] \\
&= E\left[(y_t - \mu)(y_{t-s} - \mu)\right] = \delta_s \, for \, all \, s \neq 0
\end{aligned}
\tag{4.2}
$$

Where μ and σ^2 are constants, and δ_s depends only on s.[14]

[13] ARCH (autoregressive conditional heteroscedasticity) or GARCH (general ARCH) are models that attempt to model the volatility of a series. This depends on volatility following a autoregressive pattern.

[14] Here, I follow the notation from lectures in the course "Time series analysis and prediction" with lecturer Yushu Li.

One example of a process that is non-stationary is a random walk. A simple random walk can be written as $y_t = y_{t-1} + \epsilon_t$, where ϵ_t is white noise.[15] We then see that the first difference of y_t, Δy_t, will be stationary. It is often the case that a non-stationary series can become stationary when differencing. And generally we say that a process is integrated of order d when it is made stationary by taking the difference d times, this is denoted as

$$y_t \sim I(d) \Longleftrightarrow \Delta^d y_t \sim I(0) \tag{4.3}$$

Where $I(0)$ indicates a stationary series. In this thesis I only work with series that are $I(0)$ or $I(1)$. There are large differences in how a stationary and non-stationary series behave. For a stationary series with the characteristics listed above, a shock will only have a temporary effect on the series, i.e. that the autocorrelations will gradually decrease over time. For an $I(1)$ series, the variance will go towards infinity as time goes to infinity, also the effect of a random shock will have a permanent effect on the series and the autocorrelations will stay close to 1, i.e. that each observation depends strongly on the previous observation, or that the series has long memory. Therefore, things that cause a discrete change in y_t can have long-lasting effects. An $I(1)$ series is often said to contain a unit root.

Since an $I(1)$ series will have a variance that goes towards infinity, while a $I(0)$ has finite variance, it will always be true that the sum (or any linear combination) of an $I(1)$ and an $I(0)$ will be an $I(1)$ series. Generally, we can also say that if x_t and y_t are both $I(d)$, then usually, the linear combination $\epsilon_t = x_t - ay_t$, will also be $I(d)$. In special cases however, we might get that $\epsilon_t \sim I(d-b)$, $b > 0$. Which means that it is possible for a linear combination of two $I(1)$ series to be $I(0)$. When this is the case, it is said that the series are cointegrated (Engle and Granger, 1987). Cointegration is a central part of this paper, and something I will explain in more detail in section 4.3.

It is easy to understand the importance of being aware of what kind of series one works with, in the following subsection I will therefore go through how to test for unit-roots.

4.2.1 Unit root tests

There are several ways to tests if the series are stationary. I will use the most popular test called the Dickey-Fuller test. The starting point for the test is the

[15] A white noise process is a stationary stochastic process with mean zero, constant variance and $cov(\epsilon_t, \epsilon_{t-s}) = 0$ for all s.

general AR(1) model for the time series y_t

$$y_t = \beta y_{t-1} + \epsilon_t \tag{4.4}$$

Where ϵ_t is a random disturbance with zero mean and constant variance σ_ϵ^2. If $\beta = 1$ then the series is a random walk, and it is said to have a unit root. By looking at the variance of such a process, we can show that it is non-stationary. If we assume $\beta = 1$ and that $y_0 = 0$, then, by repeated substitution

$$\begin{aligned}
y_1 &= \epsilon_1 \\
y_2 &= y_1 + \epsilon_2 = \epsilon_1 + \epsilon_2 \\
y_3 &= y_2 + \epsilon_3 = \epsilon_1 + \epsilon_2 + \epsilon_3 \\
&\vdots \\
y_t &= \textstyle\sum_{j=1}^{t} \epsilon_j
\end{aligned}$$

Which has the variance

$$var(y_t) = t\sigma_\epsilon^2$$

Then it is easy to see that the variance is not constant, and that if $t \to \infty$, then $var(y_t) \to \infty$.

We cannot test if $\beta = 1$ directly, therefore we take the first difference of y_t by subtracting y_{t-1} from both sides. We then get

$$\Delta y_t = (\beta - 1)y_{t-1} + \epsilon_t$$

and now we can test if the coefficient $(\beta - 1)$ is equal to zero. This is very similar to a t-test of the coefficient, but under the null-hypothesis of the series being a random walk the distribution does not follow a standard t-distribution. Therefore we need to use the critical values found by David Dickey and Wayne Fuller, this is the standard Dickey-Fuller test of stationarity.

The standard Dickey-Fuller test assumes that the residuals of the model are uncorrelated with residuals in earlier periods, i.e. no autocorrelation, this is often not the case. The *Augmented* Dickey-Fuller test includes lagged variables of Δy_t to make the residuals uncorrelated over time. We often use information criteria (explained in appendix section A.4) to determine the number of lags to include in the test.

The critical values of the test also depends on whether we include a constant term and/or deterministic trend. Therefore, we need to determine if the series has a constant or a trend before running the test.

4.3 Cointegration

As explained in section 4.2, there can exist linear combinations of two $I(1)$ series that will have residuals that exhibit $I(0)$ behavior. This implies that even though both series has increasing variance, they will not drift too far from each other. If we have two $I(1)$ series, we can have the regression

$$y_t = \alpha + \beta x_t + \epsilon_t \tag{4.5}$$

where α and β is constant. If y_t and x_t are cointegrated, then we will get an error term that is $I(0)$. The formal definition of cointegration given in Engle and Granger (1987) is

> "The components of the vector x_t are said to be co-integrated of order d, b, denoted $x_t \sim CI(d, b)$, if (i) all components of x_t are $I(d)$; (ii) there exists a vector $\alpha(\neq 0)$ so that $z_t = \alpha' x_t \sim I(d-b), b > 0$. The vector is called the co-integrating vector."

For ϵ_t to be $I(0)$ when both y_t and x_t are $I(1)$, the long run relationship between the $I(1)$ variables is stable so it is the short run components that dominate ϵ_t. ϵ_t can then be interpreted as deviations from equilibrium in period t, and when $\epsilon_t \neq 0$, then there will be forces pulling the system back to equilibrium. However, note that the empirical equilibrium found in cointegrated relationships are the average relationship between two, or more, series over the sample period, which is not the same as equilibrium used in economic theory. But the two are not unrelated, if we cannot find evidence for cointegration, then we should question whether the theoretical equilibrium really exists in practice.

If equation 4.5 consists of two $I(1)$ series, then the long run coefficient β can be estimated consistently with OLS if it exists and if x_t and y_t cointegrates. Then

ϵ_t will be a stationary process only reflecting the short run dynamics (Engle and Granger, 1987). If there are more than two variables in the cointegration equation, then there can exist more than one cointegration vector between these variables. Johansen (1988) developed a method to find the number of cointegrated vectors, which I explain in more detail section 4.3.3.

4.3.1 Error correction model

There is a close relationship between cointegration and the error correction model (ECM). The ECM shows the adjustment process when the variables deviate from their long run relationship. An example of a ECM representation is

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \alpha\beta X_{t-k} + \epsilon_t \tag{4.6}$$

Where the short run coefficients are in the Γ-matrix, the long run relations are the β-vector, and the adjustment coefficients are in the α-vector.

The error correction model explains short run fluctuations while still being consistent with the long run relationship. The idea is that a proportion of the disequilibrium from the long run relationship from one period is corrected in the next period. For example if consumption is too low compared to the long run relationship, this will be corrected back to equilibrium over several periods, not immediately (Engle and Granger, 1987).

The *Granger representation theorem* states that cointegrated variables will have a ECM representation, and that cointegration gives a statistical reason to use ECM representation. Engle and Granger (1987) suggests the following two-step approach to model cointegrated variables. First, one needs to estimate the cointegration equation. Then one estimates a error correction model that includes the residuals of the cointegration equation (lagged one period) instead of the level-variables. The main challenge when building a ECM is often to find the cointegration equation, and then to find the relevant variables in explaining the short run fluctuations.

4.3.2 Weak exogeneity

A central assumption behind building a single equation ECM, is weak exogeneity. This is related to which variable that adjusts to maintain the long run relationship. Estimation of the conditional consumption function implicitly assumes that consumption is the only variable that equilibrium corrects. We can test this assumption by testing if the coefficients in the α-vector, related to the other variables, also called the loadings, are significantly different from zero. The way we do this is to restrict these variables to zero when doing an analysis of the relevant cointegrated VAR, and then doing an likelihood-ratio test on the restrictions.[16] If the restrictions pass the test, then we have statistical support for estimating the conditional consumption function (Bårdsen and Nymoen, 2014).

4.3.3 Johansen-method

One way of testing for cointegration is to test if the residuals of a ECM-model is stationary. However, this method is not able to test for more than one cointegrating relationship. I will therefore use the Johansen-method, introduced by Søren Johansen in his paper from 1988.

We start with a general VAR model where the residuals (ϵ_t) are well behaved. Again, I write the general ECM model from equation 4.6, but writing $\alpha\beta = \Pi$, where Π is a matrix with the coefficients for the lagged variables in levels

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-k} + \epsilon_t \tag{4.7}$$

Here, X_t is a vector of the variables and the coefficients will be matrices with dimensions equal to the number of variables. The coefficients of interest when testing for cointegration are in the Π-matrix, since this catches the long run relationships between the variables, while coefficients in the Γ-matrix model the short run dynamics.

The way we test for cointegration is by testing if the eigenvalues of the Π-matrix is significantly different from zero.[17] This is the same as determining the rank of the matrix since the rank is given as the number of non-zero eigenvalues in a matrix. To find the matrix' rank OxMetrics will use the trace test which has the following test statistic

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{K} ln(1 - \hat{\lambda}_i) \tag{4.8}$$

[16] The likelihood ratio test (LR test) is a statistical test to compare the goodness of fit of two models. The first (null) model usually includes special restrictions on the general (alternative) model.

[17] Eigenvalues are a special set of scalars associated with a linear system of equations (i.e., a matrix equation) that are sometimes also known as characteristic roots.

where T is the number of observations, $\hat{\lambda}_i$ is the estimated value of the i'th eigenvalue, r is the rank we test for, and K is the is the number of estimated eigenvalues. The critical values depend on the number of endogenous and exogenous variables, as well as the inclusion of deterministic terms like trend and constant. OxMetrics does not report the correct p-values, so instead of relying on the p-values from OxMetrics I use the critical values estimated by Doornik (2003).

We rank the estimated eigenvalues and test the largest one first. For the first test the null hypothesis is that the rank of the matrix is zero, while the alternative hypothesis is that the rank is strictly larger than zero. If we reject the null hypothesis, we can test for rank smaller or equal to one against the alternative hypothesis of rank strictly larger than one. We continue in this way until we can not reject the null hypothesis. If we, for example, reject the null hypothesis of rank zero, but cannot reject the null hypothesis of rank smaller or equal to one, this points to the rank being one, which means that there is one cointegrating equation.

With this in mind, I turn to the analysis. First, I present the data series and their properties with regards to transformations and stationarity. I explain how some of them are constructed and their sources. In several instances the series have been constructed from different sources and I then explain the reasoning behind the choices made.

5 Data

This chapter presents the data series used in the analysis. When doing the analysis it is important to be familiar with the data, to know how the series are constructed, and the different sources. The series used, together with the sources are listen in appendix section A.1. I use a dataset with quarterly data, beginning in the first quarter of 1970, with the last observation in the fourth quarter of 2015, with some exceptions that I return to below. I use the real values of the variables, deflated by the price index for consumption goods (PC).[18] I log-transform the series for consumption, income and the different series for wealth because the log-transformed series are more likely to be difference stationary. I keep the interest rate, age variable and the different measures for inequality in levels.

In chapter 6 I use the same dataset as in Jansen (2013). Since his analysis we have had several revisions of the data series, so in chapter 7 and 8 I use the revised data series. It is also the revised series that are presented in this chapter.

5.1 The data series

The main focus in this thesis is the consumption variable. In my analysis I use total consumption exclusive of health services and services from housing (C). The rationale behind excluding expenditures on health services is that this is mostly determined by public policy decisions and not by the households themselves. Consumption of housing services follow the movements in the housing capital, which is how this is calculated in the national accounts. In other words it depends greatly on the housing market, and therefore does not always reflect consumer choices. (Frøiland, 1999) Another factor is that this definition of private consumption is the endogenous variable in Statistics Norway's KVARTS-model.

As discussed in the theory chapter, including durable goods in household consumption is problematic since we really would like to measure the consumption of the services from these goods, but measuring the use of durable goods is very difficult. In total, the consumption variable included in the analysis accounts for about 75% of total private consumption in the national accounts.

The income variable (Y) is total disposable income less dividend income which has been taken out because of a large spike in dividend payouts around 2005. This

[18]The only exception is the consumption variable that is deflated by $PCPEB$. This is a price deflator related to the consumption variable that I use, i.e. excluding prices of health services and services from housing.

was a consequence of changes in taxation and did probably not affect household consumption since most of the dividend payouts were reinvested.

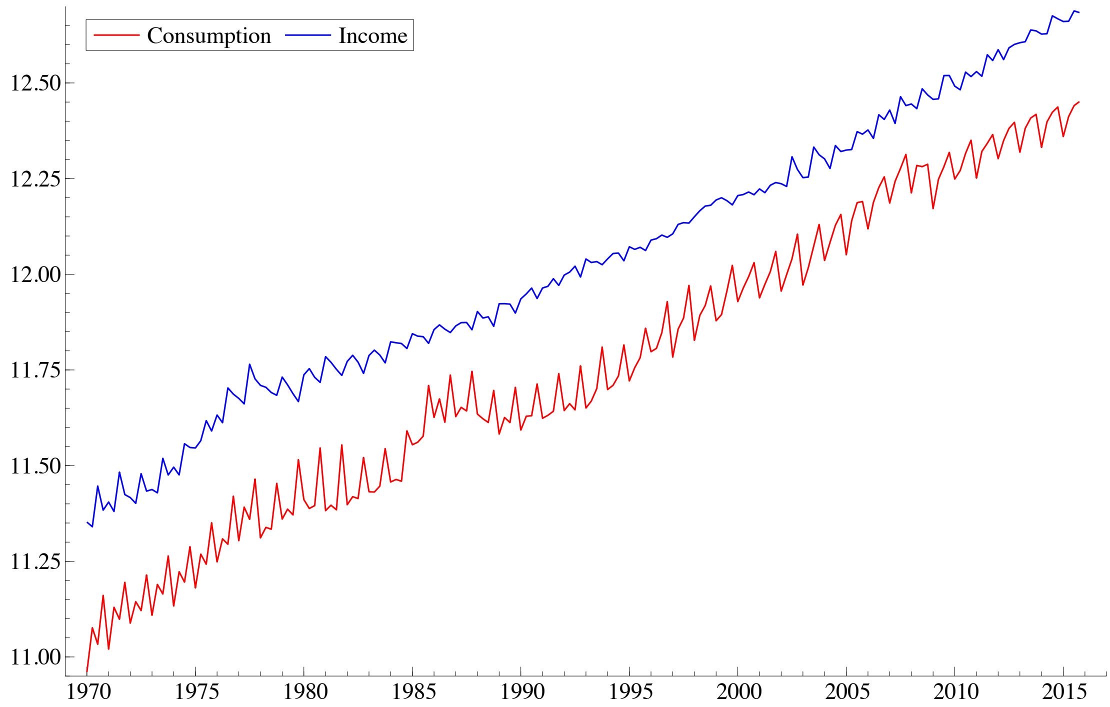

Figure 6: Series for consumption and income, deflated and log-transformed.

The different ways to measure household wealth (W) was discussed in section 3.2. I build on Brodin and Nymoen (1992) and use their wealth variable for net household wealth. A criticism of the wealth variable from Brodin and Nymoen (1992) is that it undervalues housing wealth. However, finding better series that reflect market value, available for the whole sample period, is difficult. The most important feature of the series is that it reflects the changes in market value, even though the value is on a lower level than market value.

In chapter 8 I use the different wealth components separately. The house wealth variable is, as mentioned, the same as in Brodin and Nymoen (1992). The series for financial wealth and debt is collected from two data sources, I briefly go through the construction of these series in section 5.1.2

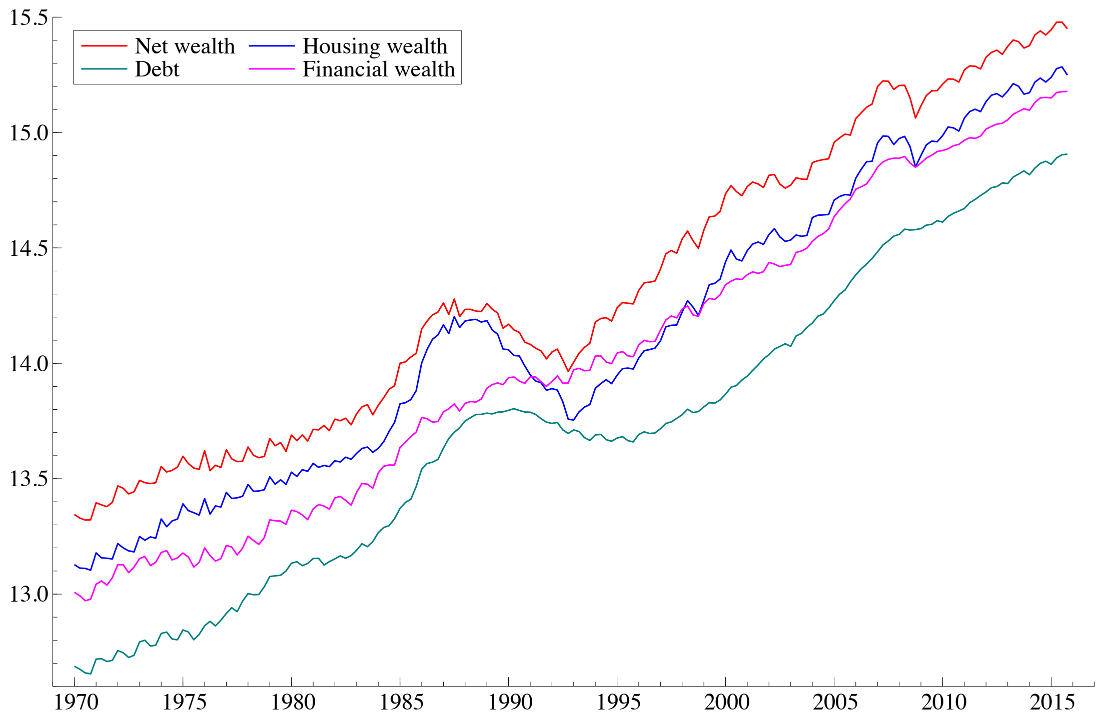

Figure 7: Wealth variables, deflated and log-transformed.

In addition, I also use the two exogenous variables from Jansen (2013), the after-tax real interest rate and a variable for the age-composition. These are shown in figure 8.

The after-tax real interest rate is constructed as follows

$$r = i * (1 - t) - \pi \tag{5.1}$$

Where i is the average interest rate paid on house loans (the nominal interest rate), t is the average tax rate, and π is the inflation rate.

The age-variable is defined as the number of people aged 50-66 divided by the number of people between 20 and 49, and 67 years and up.

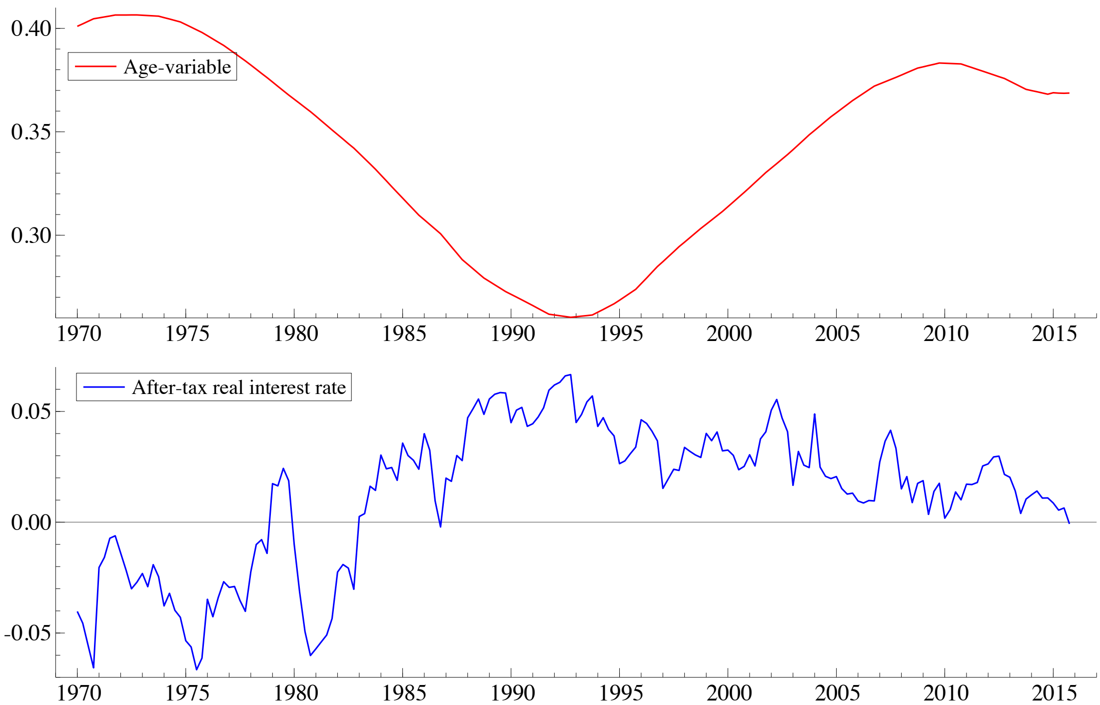

Figure 8: Age-variable and the after-tax real interest rate.

I have now presented the variables that are used in chapter 6. In the following two subsections I present the variables that are added to the model. First, I present the series for economic inequality, then the financial data series.

5.1.1 Income distribution

Economic inequality is a complex notion and capturing a country's inequality with a single measure is, to say the least, optimistic. I have chosen to focus in the income distribution, and focus on two different variables that may capture changes to the income distribution in Norway. The first is an adjusted version of the well-known Gini coefficient, the other is the wage share of the economy.

The Gini coefficient measures inequality on a scale from 0 to 1, where 0 is complete equality (everyone earning the same amount) and 1 is complete inequality (one person earning all of the nation's income). One can use the Gini coefficient for both income and wealth, here I will use the Gini for the distribution of income.

In Aaberge (2007), Rolf Aaberge shows how he constructs two new variables that are "close relatives" to the standard Gini coefficient. He created Gini coefficients that are more sensitive to changes in the upper or lower end of the distribution curve. The theory behind including the income distribution in my analysis states that individuals with a higher income will have a lower MPC, I therefore use the version of the Gini coefficient most sensitive to changes in the upper end of the income distribution. However, the development in the different Gini series is very similar so this should not affect my results. As for the income-variable described above, the Gini is estimated on the income distribution where dividend payments have been taken out.

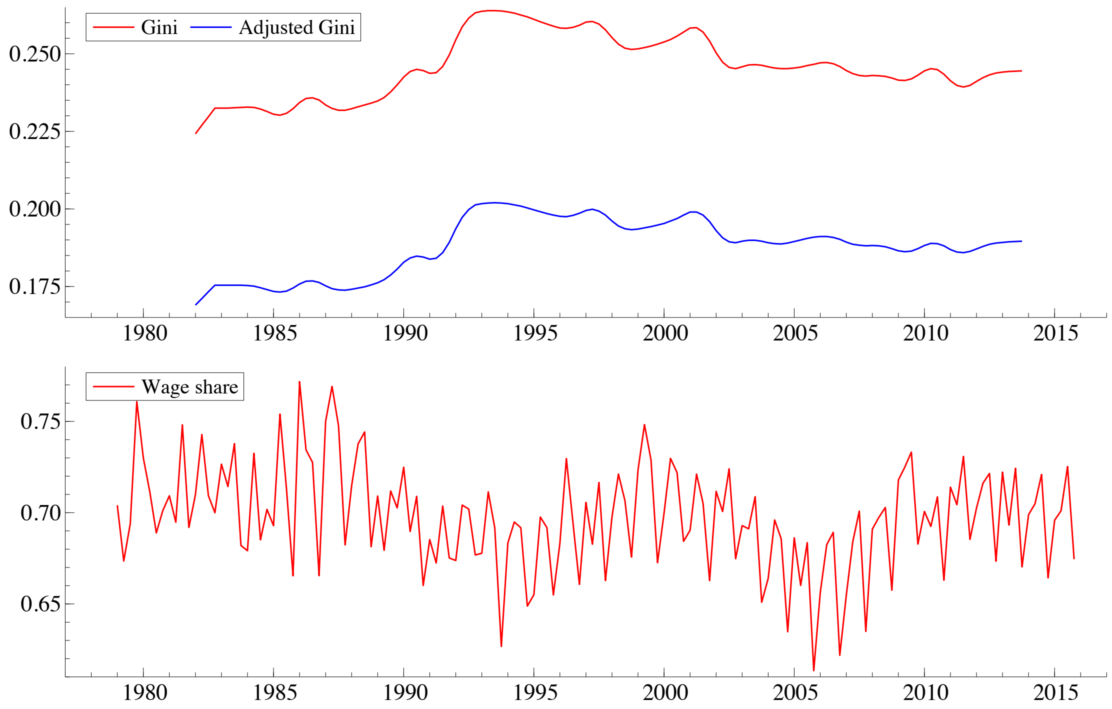

Figure 9: Time series for the income distribution.

A problem with using the Gini coefficient is that it is estimated in yearly frequency. To be able to use the series together with quarterly data, the series was transformed so that the average of the growth rates of each quarter with respect to the corresponding quarter of the previous year, is equal to the annual growth rate of the original series.[19]

The second measure of inequality that is used is the wage share of the economy. This is calculated as total wages divided by total income. The relationship between inequality and the wage share is complex, and the wage share is not a direct measure of inequality, but one can expect that there is correlation between the two. The wage share measures the share of national income going to wages as

[19]This was done in a statistical software called Troll, using the function “spatq”.

opposed to capital-owners.[20] It is reasonable to assume that income from wages are more equally distributed than the income going to capital owners. If the capital owners are more concentrated in the top of the income distribution, then a smaller wage share would, ceteris paribus, lead to more inequality. Empirically, this seems to be the case. There seems to be evidence suggesting that the inequality is greater between owners of capital and non-capital owners, than inequality within the group of non-capital owners. Therefore the aggregate effect should be that a larger wage share reduces inequality.

Checchi and García-Peñalosalosa (2010) argues that there is a close relationship between the wage share and income inequality, after studying a panel of OECD countries for the period 1960-2000. Francese and Mulas-Granados (2015) claims that the most important determinant of income inequality is not the share of national income that goes to labor or capital, but the dispersion of wages, which should be picked up by the Gini.

5.1.2 Financial data series

In chapter 8 the goal is to analyze if the different components of wealth could be used to improve the model for consumption. Using data from households' financial balances gives us the opportunity to separate the variable for financial wealth into different categories, depending on the degree of liquidity. Here, I follow in the footsteps of Krogh (2008), which did a project on this in Statistics Norway in 2008.

We have two different sources for the data of households' financial balances, FINDATR and FINSE. FINDATR was a database held by Norges Bank and contains data from fourth quarter of 1975 up until the first quarter of 2003. In 2003 the quarterly financial accounts were revised and the new database FINSE (FINancial SEctor accounts) replaced FINDATR. FINSE contains data from the fourth quarter of 1995.

Both FINSE and FINDATR contains data on the financial balance sheet of households. I divide the financial wealth into three different series by the degree of liquidity. The first, and most liquid category, contains cash and bank deposits, the second is less liquid and contains stocks, bonds and other financial assets, the final category contains insurance claims.

[20]This is a simplification. Capital income (total income minus wages) does not go directly to capital owners as profit. There are several costs that the capital income must cover. For example; capital income must cover depreciation of capital and cost of capital. However, wage share can still be a measure of how much of the income that goes to labor.

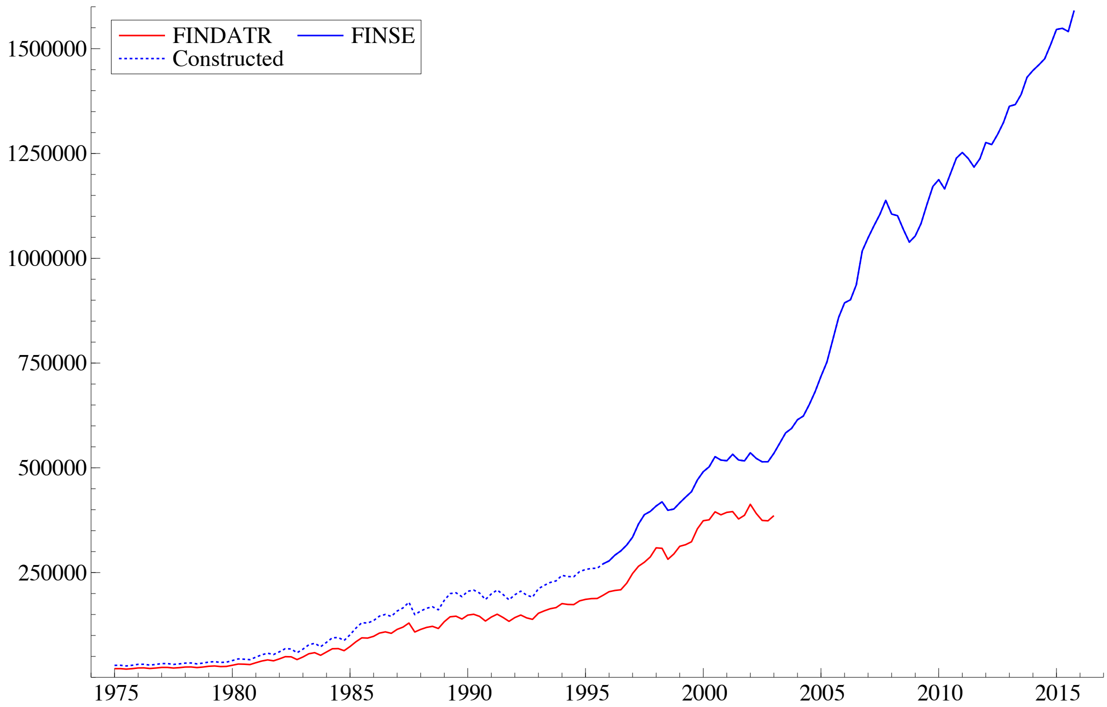

Figure 10: Nominal series from FINSE and FINDATR for stocks, bonds and other financial assets.

Since FINSE only have data back to 1995, we use the data in FINDATR to construct a series going back to 1975. I compute the growth rates for each of the three categories in FINDATR, and then use these to construct FINSE backwards. So from the fourth quarter in 1995 I use the series from FINSE, while earlier observations will follow the growth rates from FINDATR. Figure 10 shows the original series from FINSE and FINDATR together with the constructed series back to 1975 for the category containing stocks, bonds and other financial wealth (the conclusion is the same for the other categories). We see that the two series follow each other closely for the period where we have observations from both databases, but being on different levels. It is therefore reasonable to assume that the growth rates of FINDATR are representative for the actual developments in the financial balance sheet for households up until 1995. Figure 11 shows the three series for financial wealth that are used in my analysis.

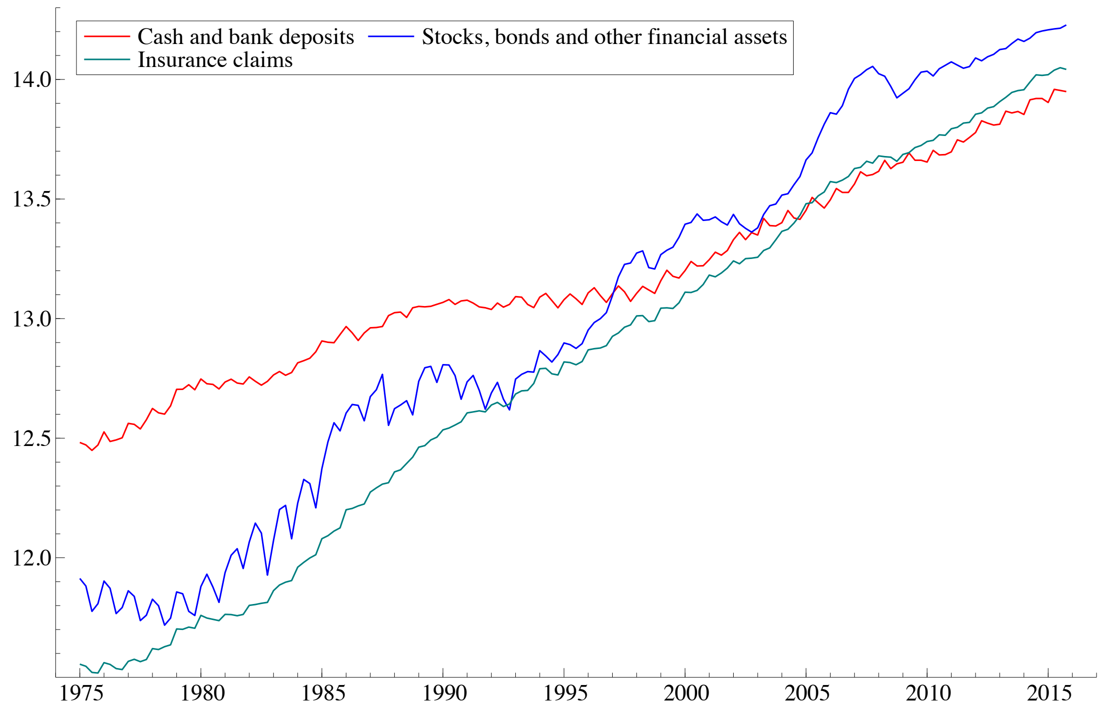

Figure 11: The different components of financial wealth, deflated and log-transformed.

5.2 Stationarity of the series

It is important to know if the series are stationary or not. I have therefore conducted augmented Dickey-Fuller (ADF) tests on the series that are used in the analysis. These test are documented in section A.5 of the appendix. The log-transformed variables of consumption, income, and all financial variables are $I(1)$ variables, i.e. they become stationary when taking the first difference. The same is true for the interest rate and the wage share in levels. The Gini coefficient is clearly not stationary in levels, but the results are more ambiguous for the first difference series. The AGE-variable is more uncertain, it passes some tests in levels, but not when differenced. In my analysis I will treat all variables as $I(1)$.

6 Replication of previous results

This chapter begins the analysis by presenting the replicated model from Jansen (2013), and by illustrating the break-down that happened during the financial crisis. The first section goes trough the replication of the model, section 6.2 shows the dismal forecasting performance of the model since the financial crisis. Jansen (2013) forecasted up until the last quarter of 2009, and noted already then that the model seemed to overpredict consumption in the last quarters. This chapter will be the backdrop for the following chapters which attempt to improve the model presented here.

6.1 Replication of Jansen (2013)

I follow the analysis in Jansen (2013) and build a VAR with five lags in the endogenous variables consumption (c), income (y) and wealth (w), all in logs.[21] I include one lag of the age-variable (AGE) and the real interest rate (RR), which is allowed to enter the cointegration space. This implies that the real interest rate is considered a policy variable, that varies exogenously and is not affected by variation in the other variables. I also include a time trend, centered seasonal dummies, and an event-dummy ($CPSTOP$). $CPSTOP$ is included to pick up the effects from a wage price freeze in 1978-79.[22] The real interest rate is set to zero up until the fourth quarter of 1983. This is because it most likely had a very modest relevance in this period because of credit constraints.

Eigenvalue	Hypotheses on rank		Trace tests (λ_{trace})	
λ_i	H_0	H_A	λ_{trace}	5% critical value*
0.1910	$r = 0$	$r \geq 1$	59.31	57.32
0.1052	$r \leq 1$	$r \geq 2$	27.74	35.96
0.0723	$r \leq 2$	$r = 3$	11.18	18.16

Tests of the VAR(5) system
Sample period: 1970(2) - 2008(2)
Vector AR 1-5 test: $F(45, 312) = 1.04\,(0.406)$
Vector normality test: $\chi^2(6) = 2.85\,(0.828)$
Vector heteroscedasticity test: $F(270, 592) = 1.09\,(0.195)$
*Critical values are from Doornik (2003)

Table 2: Johansen test for replication model.

[21] I do not get exactly the same results as Jansen (2013), this is most likely due to differences in transformations of the variables (for example in constructing the real interest rate). However, the differences are small and do not change the qualitative results.

[22] In fact, two sets of seasonal dummies are included. The second set is to account for a change in the way the quarterly income statistics is constructed that happened in 2001.

The VAR is well-behaved, meaning it passes tests for autocorrelation, heterogeneity and normality. The Johansen-analysis concludes that there is one cointegrating relationship. The test results are shown in table 2.

These results let us condition on one cointegration vector in the further analysis, we can then test further restrictions on the long run equation. I begin with an identifying restriction (setting the coefficient for $c = 1$). The first thing we observe is that the trend is insignificant, so I can restrict this to zero. In the next step, AGE is restricted to zero, this also passes the statistical test. Restricting the loadings of income and wealth is also accepted, meaning that they are weakly exogenous. Finally, we find that the homogeneity-restriction is accepted. The results are given in table 3.

(1) Model without testable restrictions $c = \beta_y y + \beta_w w + \beta_{RR} RR + \beta_{AGE} AGE + \gamma Trend$ Log L: 1163.19
(2) Restricting $\gamma = 0$ $c = 0.73y + 0.24w - 0.22RR + 0.14AGE$ (0.04) (0.02) (0.27) (0.14) $\alpha_c = 0.53$, $\alpha_y = -0.06$, $\alpha_w = -0.11$ (0.11) (0.10) (0.15) Log L: 1162.97; $\chi^2(1) = 0.44$ (p-value = 0.508)
(3) Restricting $\gamma = 0$ and $\beta_{AGE} = 0$ $c = 0.71y + 0.24w - 0.42RR$ (0.04) (0.02) (0.18) $\alpha_c = 0.55$, $\alpha_y = -0.08$, $\alpha_w = -0.09$ (0.12) (0.11) (0.15) Log L: 1162.43; $\chi^2(2) = 1.51$ (p-value = 0.471); $\chi^2(1) = 1.07$ (p-value = 0.301)
(4) Restricting $\gamma = 0$, $\beta_{AGE} = 0$, $\alpha_y = 0$ and $\alpha_w = 0$ $c = 0.72y + 0.24w + 0.48RR$ (0.04) (0.02) (0.19) $\alpha_c = 0.59$ (0.11) Log L: 1161.96; $\chi^2(4) = 2.46$ (p-value = 0.651); $\chi^2(2) = 0.96$ (p-value = 0.620)
(5) Restricting $\gamma = 0$, $\beta_{AGE} = 0$, $\beta_y + \beta_w = 1$, $\alpha_y = 0$ and $\alpha_w = 0$ $c = 0.78y + 0.22w - 0.71RR$ (−) (0.02) (0.17) $\alpha_c = 0.52$ (0.11) Log L: 1160.13; $\chi^2(5) = 6.11$ (p-value = 0.296); $\chi^2(1) = 3.64$ (p-value = 0.056)

Standard errors in parenthesis.
Sample period: 1970(2) - 2008(2)
Small letters indicate log-transformed variable.

Table 3: Testing restrictions on the cointegration vector for replication model.

This gives us the following long run relationship between consumption, income, wealth and the real interest rate

$$ecm = c - 0.78y_t - 0.22w_t + 0.71RR_{t-1} \tag{6.1}$$

Figure 12 shows the beta-coefficients estimated recursively, we can see that these are stable from the mid-1990s onwards.[23]

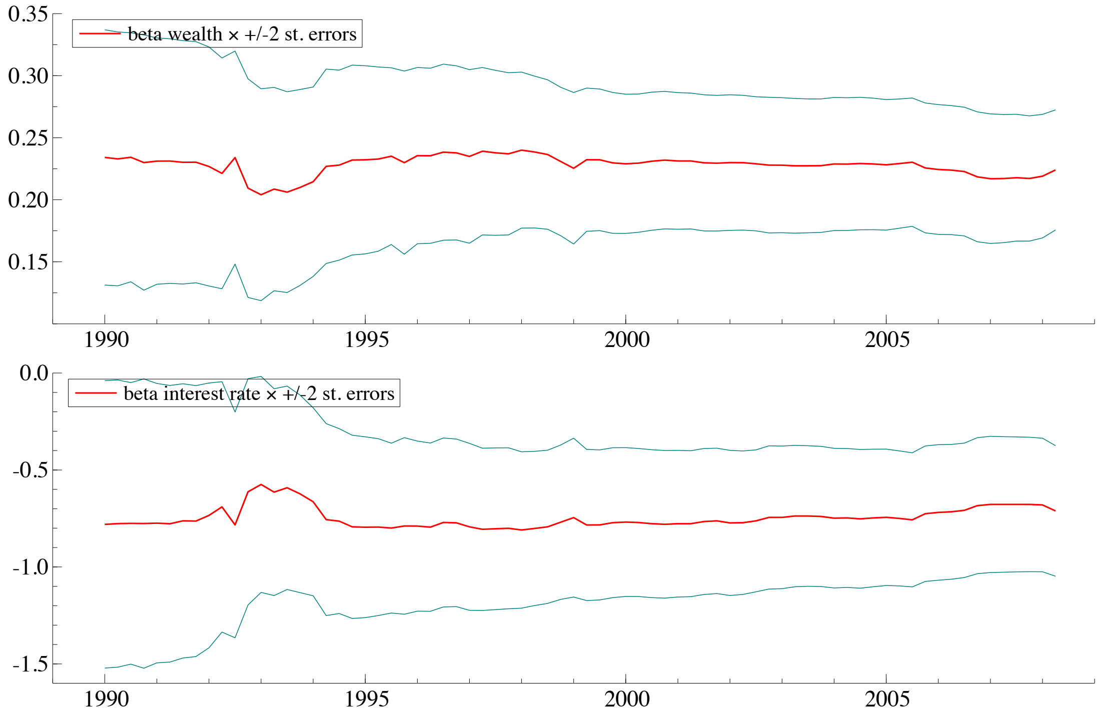

Figure 12: Long run coefficients for wealth and interest rate.

We are now ready to estimate the conditional consumption function. This is a ECM-model including the *ecm* variable from equation 6.1 as the long run solution (lagged one period). I now specify a rich model including four lags of the first-differenced series in consumption, income, wealth, and the interest rate, and use the GETS-modeling tool *Autometrics* to end up with a parsimonious model.[24] [25] Seasonal dummies are still included, but not $CPSTOP$.

[23]Because we have imposed the homogeneity-restriction, we only get the standard errors and the recursive graphics for the wealth coefficient, and not for income.

[24]The estimated general model is given in table 12 in the appendix.

[25]Autometrics is a computer implementation of general-to-specific modeling, for more information see appendix or Doornik and Hendry (2013a,b).

Model:	(1): 1971(2)-2008(4)		(2): 1971(2)-2008(4)	
	coefficient	t-value	coefficient	t-value
Δc_{t-4}	0.2615	3.93	0.2706	4.07
constant	-0.4272	-7.93	-0.1072	-0.726
Δy_t	0.2091	2.34	0.1998	2.22
Δy_{t-1}	-0.2855	-3.36	-0.2878	-3.36
Δy_{t-2}	-0.3164	-3.81	-0.3272	-3.91
Δw_t	0.1606	2.67	0.1924	3.13
Δw_{t-1}	0.2046	3.17	0.1913	2.89
ecm_{t-1}	-0.5569	-8.05		
c_{t-1}			-0.5878	-8.19
y_{t-1}			0.4251	7.48
w_{t-1}			0.1330	6.14
RR_{t-2}			-0.2294	-2.00
SE regression	1.89%		1.89%	
Tests:	Statistics	Value (p-value)	Statistics	Value (p-value)
AR 1-5 test:	F(5,131)	0.89 (0.493)	F(5,128)	1.16 (0.332)
ARCH 1-4 test:	F(4,143)	0.58 (0.676)	F(3,143)	0.31 (0.868)
Normality test:	$\chi^2(2)$	0.11 (0.946)	$\chi^2(2)$	0.16 (0.922)
Heteroscedasticity test:	F(21,129)	1.43 (0.115)	F(27,123)	1.20 (0.252)
Reset test:	F(2,134)	0.08 (0.923)	F(2,131)	0.18 (0.832)

Seasonal dummies not reported

Sample period: 1971(2) - 2008(4)

Table 4: Replication of ECM for Δc.

Table 4 shows the coefficients of the ECM model. I estimate the model both with the *ecm* as a variable, and with the level variables separately (model (2)). We see that the coefficients of the level variables in model (2) corresponds well with the ones implied in model (1). All variables in the table are significant at a 5% significance level. As figure 13 shows, the model fits the data well during the sample period.

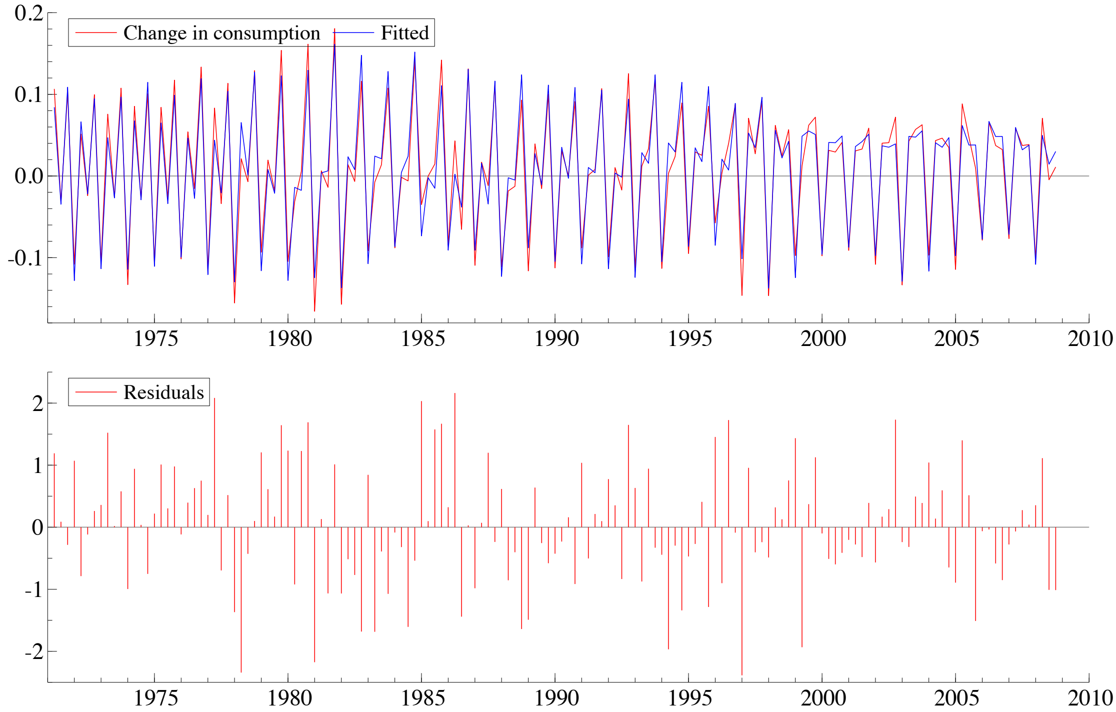

Figure 13: Replication model fit with residuals.

In the next section I use model (1) estimated on data up until the last quarter of 2008 to forecast future growth in consumption and show how the model consistently over-estimates this growth.

6.2 Break-down during the financial crisis

I now use model (1) in the previous section to forecast growth in consumption after 2008, i.e. *ex post* forecasts. These are dynamic 1-step ahead forecasts up until the second quarter of 2014, 22 quarters in total. Figure 14 shows the forecasts against the realized values. The figure also shows confidence bands equal to two standard errors. It is easy to see that the forecasts consistently fail to predict the growth in consumption. Another illustration of the break is to estimate the model on a larger sample and then plot the recursively estimated coefficients of the ECM-model, this is figure 20 in the appendix. This shows a clear break of the ECM-coefficient and the constant around 2009, the other coefficients are more stable, which points to a break especially in the long run relationship.

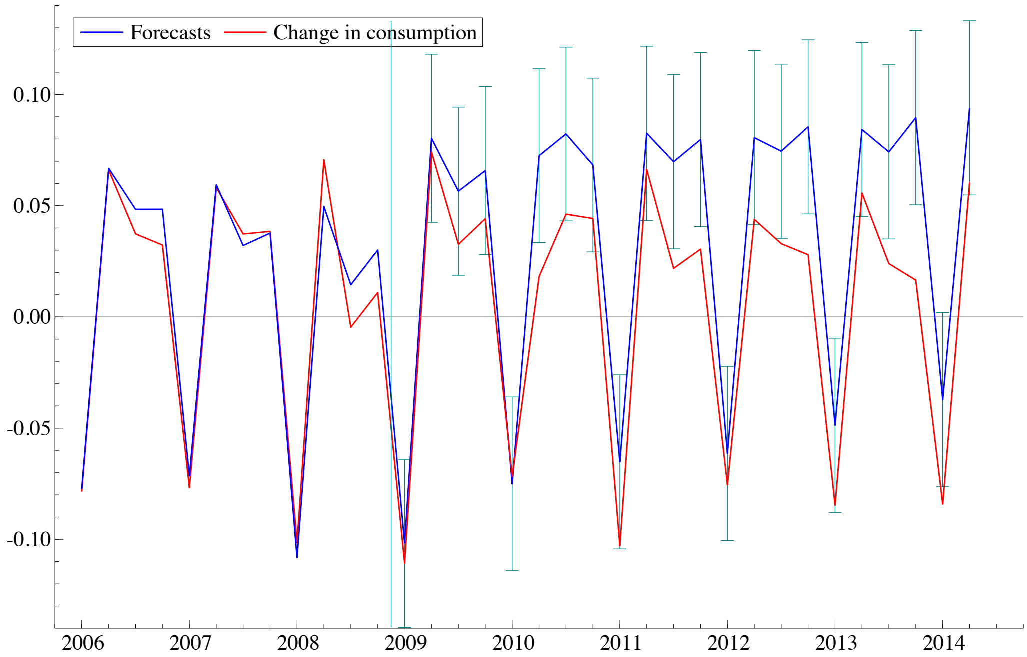

Figure 14: Dynamic one-step forecasts for the replication model.

6.3 Progress since 2008

Since the break was clear, there has been attempts of improving the model. In their KVARTS-model, Statistics Norway has solved the problem by including a step-dummy from the second quarter of 2009. This improves the forecasting, but is not satisfactory as an explanation of the weak development of household consumption. Other papers has tried to explain the weakening of household consumption in Norway, as discussed in section 3.2, but no improved model has emerged.

Since Jansen (2013) there has been revisions to the data series. The revisions should result in a better quality of the data, but may also impact the results. The revisions were small for most series, but for the series of financial wealth, the changes were more substantial. Reestimating the model with the new dataset gives no improvement in forecasting and the break is still present. In addition we get problems with the diagnostic tests in the cointegration analysis. I also find that the AGE-variable is significant in the cointegration vector, while the interest rate has become insignificant. The homogeneity-restriction is also rejected with the new dataset.

In the rest of this thesis, I use the most current dataset with the revised series. The following chapter presents my analysis of the income distribution effect on consumption.

7 Income distribution

This chapter presents the investigation into the effect of the income distribution on private consumption. I use two separate variables for the income distribution. The first is an adjusted version of the standard Gini coefficient, as explained in section 5.1.1 (from now on I often refer to this as Gini for short), and the latter variable is the wage share of the economy.

The intuition behind looking at economic inequality as a variable for consumption is that people tend to spend a smaller portion of their income on consumption as they become more wealthy, i.e. they have a lower MPC. We would therefore expect that if a larger share of the economy's income went to those in the upper end of the income distribution, then aggregate consumption would be lower than it would be if the income was evenly spread out across the population. This notion is nothing new, Keynes (1936) discussed how the income distribution would affect consumption through the lower MPC of wealthy individuals, but even if Keynes argued for this relationship it has not been widely included in consumption functions. However, with several countries experiencing changes to their income distributions, together with an increased focus on inequality both in the public and among researchers, there is more research focusing on the relationship between income inequality and private consumption.

7.1 Using the adjusted Gini variable

I begin with a large VAR, then use tests for model reduction and information criteria to end up with a VAR with four lags in the endogenous variables. I include consumption, income and wealth as endogenous variables, and the real interest rate, AGE and Gini as exogenous variables, all of which may enter the cointegration space, as well as a trend. I include lagged, differenced variables for the exogenous series to pick up autocorrelation, I include three lags of the first differenced variables unrestricted, this is to go as far back as the endogenous variables (because $\Delta x_{t-3} = x_{t-3} - x_{t-4}$). The deterministic terms are a constant and two sets of seasonal dummies (as in the replication analysis). The sample period is between the first quarter of 1986 up until the first quarter of 2014, since this is the last observation for the Gini-series. 1986 is a natural starting point as it is right after the credit liberalization in Norway.

The test statistics do not detect autocorrelation and the residuals are normally distributed, but there seems to be some problems with heteroscedasticity, but

I still continue with the analysis. When testing for cointegration we find one cointegrating relationship in our analysis. Results from the Johansen analysis is given in table 5.

Eigenvalue	Hypotheses on rank		Trace tests (λ_{trace})	
λ_i	H_0	H_A	λ_{trace}	5% critical value*
0.2831	$r = 0$	$r \geq 1$	66.69	64.48
0.1294	$r \leq 1$	$r \geq 2$	29.08	40.95
0.1120	$r \leq 2$	$r = 3$	13.43	20.89

Tests of the VAR(4) system

Sample period: 1986(1) - 2014(1)

Vector AR 1-5 test: $F(45, 199) = 1.18\,(0.222)$

Vector normality test: $\chi^2(6) = 9.81\,(0.133)$

Vector heteroscedasticity test: $F(306, 343) = 1.2366\,(0.028)$

*Critical values are from Doornik (2003)

Table 5: Johansen test for cointegration when including Gini coefficient.

Further, I condition on there being one cointegration relationship, we can then test more restrictions on the long run relationship. I begin with an identifying restriction to the system (setting the coefficient for consumption to 1), and then stepwise adding more restrictions, this process is shown in table 6.

(1) Model without testable restrictions $c = \beta_y y + \beta_w w + \beta_{RR} RR + \beta_{AGE} AGE + \beta_{Gini} Gini + \gamma Trend$ Log L: 944.18
(2) Restricting $\gamma = 0$ $c = \underset{(0.13)}{0.80}y - \underset{(0.07)}{0.12}w - \underset{(0.43)}{0.89}RR + \underset{(0.55)}{2.20}AGE + \underset{(2.07)}{1.74}Gini$ $\alpha_c = \underset{(0.07)}{0.27},\ \alpha_y = \underset{(0.05)}{-0.04},\ \alpha_w = \underset{(0.10)}{-0.37}$ Log L: 943.38; $\chi^2(1) = 1.60$ (p-value = 0.21)
(3) Restricting $\gamma = 0$ and $\beta_{RR} = 0$ $c = \underset{(0.16)}{0.83}y - \underset{(0.09)}{0.16}w + \underset{(0.63)}{2.65}AGE + \underset{(2.46)}{1.98}Gini$ $\alpha_c = \underset{(0.06)}{0.26},\ \alpha_y = \underset{(0.05)}{-0.03},\ \alpha_w = \underset{(0.09)}{-0.27}$ Log L: 941.34; $\chi^2(2) = 5.63$ (p-value = 0.06); $\chi^2(1) = 4.02$ (p-value = 0.045)
(4) Restricting $\gamma = 0$, $\beta_{RR} = 0$, $\alpha_y = 0$ and $\alpha_w = 0$ $c = \underset{(0.11)}{0.67}y + \underset{(0.06)}{0.04}w + \underset{(0.42)}{1.54}AGE + \underset{(1.64)}{1.42}Gini$ $\alpha_c = \underset{(0.10)}{0.48}$ Log L: 937.61; $\chi^2(4) = 13.13$ (p-value = 0.01); $\chi^2(2) = 7.33$ (p-value = 0.026)

Standard errors in parenthesis.
Sample period: 1986(1) - 2014(1)
Small letters indicate log-transformed variable.

Table 6: Testing restrictions on the cointegration vector when including Gini coefficient.

Even when restricting the other insignificant variables (trend and interest rate), and laying restrictions on the loadings, the Gini stays insignificant and positive, which is clearly in contradiction to the theory because it implies that higher inequality gives higher consumption.

The fact that the Gini coefficient is insignificant and positive is a strong argument that the Gini is not a long-term determinant of private consumption, and should not be included in the long-run equation used in the ECM-model. Including the Gini in the short run dynamics would not be appropriate, both because the income distribution changes relatively slow, and because the Gini-series used in this thesis is constructed from yearly data so they do not really include information about changes in the income distribution between quarters. The negative results are discussed in more detail in the final section of this chapter.

7.2 Using wage share

As the previous section showed, the Gini coefficient did not give any significant effect on consumption. The second variable that could pick up the effect of unequal distribution of income is the wage share of the economy. The intuition behind this is that the ownership of capital is *less* equally distributed than the income of labour. Since capital also earns income which inevitably ends up to the owners of that capital, there is likely to be a different propensity to consume out of the capital income compared to wages. My hypothesis is that when wages get a larger share of the income in the economy, then the aggregate consumption would also increase.

I conduct the analysis in the same way as in the previous section, but with data until the fourth quarter of 2015. I find that a VAR in consumption, income and wealth with four lags is well specified. With one lag in the interest rate, the age variable and wage share as exogenous variables, with the same dummies as the previous chapter and a trend.

Eigenvalue	Hypotheses on rank		Trace tests (λ_{trace})	
λ_i	H_0	H_A	λ_{trace}	5% critical value*
0.2302	$r = 0$	$r \geq 1$	64.57	64.48
0.1647	$r \leq 1$	$r \geq 2$	33.96	40.95
0.1044	$r \leq 2$	$r = 3$	12.90	20.89

Tests of the VAR(4) system
Sample period: 1986(4) - 2015(4)
Vector AR 1-5 test: $F(45, 211) = 1.10\,(0.323)$
Vector normality test: $\chi^2(6) = 8.80\,(0.185)$
Vector heteroscedasticity test: $F(306, 366) = 1.279\,(0.012)$
*Critical values are from Doornik (2003)

Table 7: Johansen test for cointegration when including wage share.

As table 7 shows, there is support for one cointegrating vector with a test statistic slightly larger than the critical value for 5% significance value. As in the previous section, I condition on one cointegration vector and an identifying restriction, before imposing more restrictions on the long run equation. Table 8 summarizes this process.

(1) Model without testable restrictions $c = \beta_y y + \beta_w w + \beta_{RR} RR + \beta_{AGE} AGE + \beta_{Gini} WageShare + \gamma Trend$ Log L: 986.51
(2) Restricting $\gamma = 0$ $c = 0.92y - 0.13w + 1.35RR + 1.62AGE + 0.11WageShare$ (0.09) (0.07) (0.45) (0.47) (0.26) $\alpha_c = 0.23$, $\alpha_y = -0.03$, $\alpha_w = -0.33$ (0.06) (0.05) (0.10) Log L: 986.47 ; $\chi^2(1) = 0.08$ (p-value = 0.775)
(3) Restricting $\gamma = 0$ and $\beta_{RR} = 0$ $c = 0.89y - 0.10w + 1.74AGE + 0.08WageShare$ (0.09) (0.08) (0.49) (0.28) $\alpha_c = 0.28$, $\alpha_y = -0.01$, $\alpha_w = -0.19$ (0.07) (0.06) (0.11) Log L: 982.76; $\chi^2(2) = 7.51$ (p-value = 0.023); $\chi^2(1) = 7.09$ (p-value = 0.008)
(4) Restricting $\gamma = 0$ and $\beta_{RR} = 0$, $\alpha_y = 0$ and $\alpha_w = 0$ $c = 0.76y + 0.15w + 1.30AGE + 0.03WageShare$ (0.07) (0.06) (0.39) (0.22) $\alpha_c = 0.37$ (0.09) Log L: 981.39; $\chi^2(4) = 10.23$ (p-value = 0.037); $\chi^2(2) = 3.26$ (p-value = 0.194)

Standard errors in parenthesis.
Sample period: 1986(4) - 2015(4)
Small letters indicate log-transformed variable.

Table 8: Testing restrictions on the cointegration vector when including wage share.

Again, we see that the coefficient for wage share is insignificant independently of the imposed restrictions, but now the coefficient has the "correct" sign. When including the wage share we are not able to restrict the interest rate coefficient to be zero, nor can we restrict the loadings to zero. We also note that the coefficient for the age-variable is positive and significant. The sum of the income and wealth coefficient is 0.91, not far from homogeneity.

Given that the wage share, nor the Gini was significant in the long run solution, I do not continue with building an ECM-model that includes the income distribution.

7.3 Is the income distribution insignificant?

There can be several reasons for the lack of positive results from including variables of income inequality. It may be due to the inability of the series included in measuring income inequality. We know that there are several weaknesses from these measures. As mentioned, the Gini is originally a series with yearly frequency, this may pose several problems when including it as quarterly data. The wage share is not a direct measure of inequality *per se*, but rather a proxy which could be disputed. It could also be the case that income inequality is not the best measure of *economic* inequality between households, wealth also plays an important role.

Another reason for why income inequality does not seem to have an effect on consumption could be that the changes in inequality in Norway since 1986 are not big enough. It could be that larger shifts in inequality would have a more profound effect on consumption, but Norway is still a relatively equal society with regards to income.

A better way to research the relationship between the income distribution and private consumption could be to look at microdata. By looking at data for the different income cohorts, it might be possible to estimate how much of their income that goes to consumption. However, estimating this effect on aggregate consumption would still be difficult and is a topic for future research.

8 Investigation of wealth effects

While chapter 7 looked at the income distribution, this chapter builds a new consumption function where the different wealth components can have separate effects on consumption. The different components were thoroughly presented in chapter 5. In the long run, I separate housing wealth and financial wealth, while in the short run I split financial wealth according to liquidity, and include debt as a separate variable.

The first section presents a new long run relationship that builds on Eilev Jansen's research on the consumption function in the spring of 2016. Then I continue with an ECM model where I estimate the separate wealth effects. The last section of this chapter shows that the new ECM model forecasts better than the model presented in chapter 6.

8.1 A new long run equation

The methods for finding the long run equation is the same as for the previous chapters. I build a VAR with consumption (c), income (y) and net housing wealth (w_H) as the endogenous variables, with five lags. As exogenous variables, I include one lag of the after-tax real interest rate (RR) and net financial wealth (w_F), and a step dummy for the financial crisis.[26] As in the previous analyses I include two sets of seasonal dummies, as well as a constant and trend. The seasonal dummies and the constant are unrestricted to enter the cointegration space. I begin the sample in the first quarter of 1985.

Model reduction down to four lags in the endogenous variables was accepted by the LR-test (p-value of 0.15), but gives a problem of autocorrelation, therefore it is better to continue with five lags.

To avoid having to include too many variables in the cointegration analysis, I have constructed series for net housing wealth and net financial wealth, these were constructed by subtracting a portion of the total debt from each. Because it is difficult to know the exact portion of debt that is connected to housing or financial assets, I use the average relative size of the two components in the sample period. The portions assigned was 58% of the debt to housing wealth, and 42% to

[26]The step-dummy $FCRISIS$ takes the value 1 from the third quarter of 2009 to the final observation.

financial wealth.[27] The relative size has been stable over the period. It is important to account for debt in the long run analysis, thereby not allowing debt-financed consumption in the long run.

The model passes tests for autocorrelation and heterogeneity, but not for normally distributed residuals. Still, it is unlikely that this poses problems for the further analysis. The results of the Johansen analysis are given in table 9, we find support for rank equal to one, but we see that the test for rank equal to two fails by a small margin with a 5% significance level.

EIGENVALUE	HYPOTHESES ON RANK		TRACE TESTS (λ_{trace})	
λ_i	H_0	H_A	λ_{trace}	5% critical value*
0.2070	$r = 0$	$r \geq 1$	69.04	64.48
0.1662	$r \leq 1$	$r \geq 2$	40.28	40.95
0.1333	$r \leq 2$	$r = 3$	17.74	20.89

Tests of the VAR(5) system
Sample period: 1985(1) - 2015(4)
Vector AR 1-5 test: $F(45, 241) = 1.36\,(0.076)$
Vector normality test: $\chi^2(6) = 15.74\,(0.015)$
Vector heteroscedasticity test: $F(264, 449) = 1.05\,(0.311)$
*Critical values are from Doornik (2003)

Table 9: Johansen test with two wealth variables.

I condition on one cointegration relationship and add the identifying restriction that the coefficient for consumption is equal to one. We see from table 10 that restricting the coefficients of the trend and for the $FCRISIS$-dummy to zero is accepted with a wide margin (p-value for both restrictions of 0.574). Testing for weak exogeneity of income and housing wealth is also accepted. We therefore have support for building a conditional consumption function.

[27]The relative sizes are found after correcting for the size of housing wealth. The level of the housing wealth in the dataset from Jansen (2013) is most likely too low compared to market value. To correct for this, the housing wealth variable has been multiplied with a factor of 1.25. This ratio is the assessed value of housing wealth found in tax returns, to the housing market variable from Jansen (2013) in 2014. The assessed housing wealth found from tax returns is expected to be closer to the market value.

(1) Model without testable restrictions $c = \beta_y y + \beta_{wH} w_H + \beta_{wF} w_F + \beta_{RR} RR + \beta_{FCRISIS} FCRISIS + \gamma Trend$ Log L: 971.11
(2) Restricting $\gamma = 0$ $c = 0.47y + 0.11w_H + 0.20w_F - 0.24RR - 0.01FCRISIS$ (0.18) (0.02) (0.10) (0.29) (0.02) $\alpha_c = 0.42$, $\alpha_y = -0.02$, $\alpha_w = -0.41$ (0.10) (0.06) (0.23) Log L: 970.67 ; $\chi^2(1) = 0.87$ (p-value = 0.351)
(3) Restricting $\gamma = 0$ and $\beta_{FCRISIS} = 0$ $c = 0.36y + 0.10w_H + 0.26w_F - 0.24RR$ (0.12) (0.02) (0.07) (0.29) $\alpha_c = 0.42$, $\alpha_y = 0.01$, $\alpha_w = -0.37$ (0.10) (0.06) (0.22) Log L: 970.55; $\chi^2(2) = 1.11$ (p-value = 0.574); $\chi^2(1) = 0.24$ (p-value = 0.626)
(4) Restricting $\gamma = 0$ and $\beta_{FCRISIS} = 0$, $\alpha_y = 0$ and $\alpha_{w_H} = 0$ $c = 0.37y + 0.08w_H + 0.27w_F - 0.64RR$ (0.13) (0.02) (0.07) (0.31) $\alpha_c = 0.46$ (0.09) Log L: 970.10; $\chi^2(4) = 2.01$ (p-value = 0.734); $\chi^2(2) = 0.90$ (p-value = 0.637)

Standard errors in parenthesis.
Sample period: 1985(1) - 2015(4)
Small letters indicate log-transformed variable.

Table 10: Testing restrictions on the cointegration vector when including two wealth variables.

Table 10 gives us the following long run relationship between consumption, income, housing wealth, financial wealth and the after-tax real interest rate

$$ecm = c - 0.37y - 0.08w_H - 0.27w_F + 0.64RR \tag{8.1}$$

The first thing to note is the small coefficient for income. It is doubtful that the marginal propensity to consume out of income is only 0.36 for households in the long run. This equation also imply that households consume less out of housing wealth than they do from financial wealth. This is interesting since it points different behavior of households from changes in housing wealth, relative to financial wealth. A potential weakness of this long run equation is that we are far from homogeneity, the sum of the coefficients of income, housing wealth and financial wealth is 0.72.[28]

[28] Testing for homogeneity by restricting the sum of the coefficients to one, gives a p-value of 0.0003, i.e. homogeneity is strongly rejected.

The interest rate effect is negative, as predicted. A lower interest rate will *ceteris paribus* lead to higher consumption. With a coefficient of -0.64, the effect is of similar magnitude to the long run effect found by Jansen (2013) (-0.71) and by Erlandsen and Nymoen (2008) (-0.42). By looking at the recursively estimated coefficients for the interest rate (beta RR) in figure 15 we see that the coefficient for the interest rate has fallen since the mid 1990s.

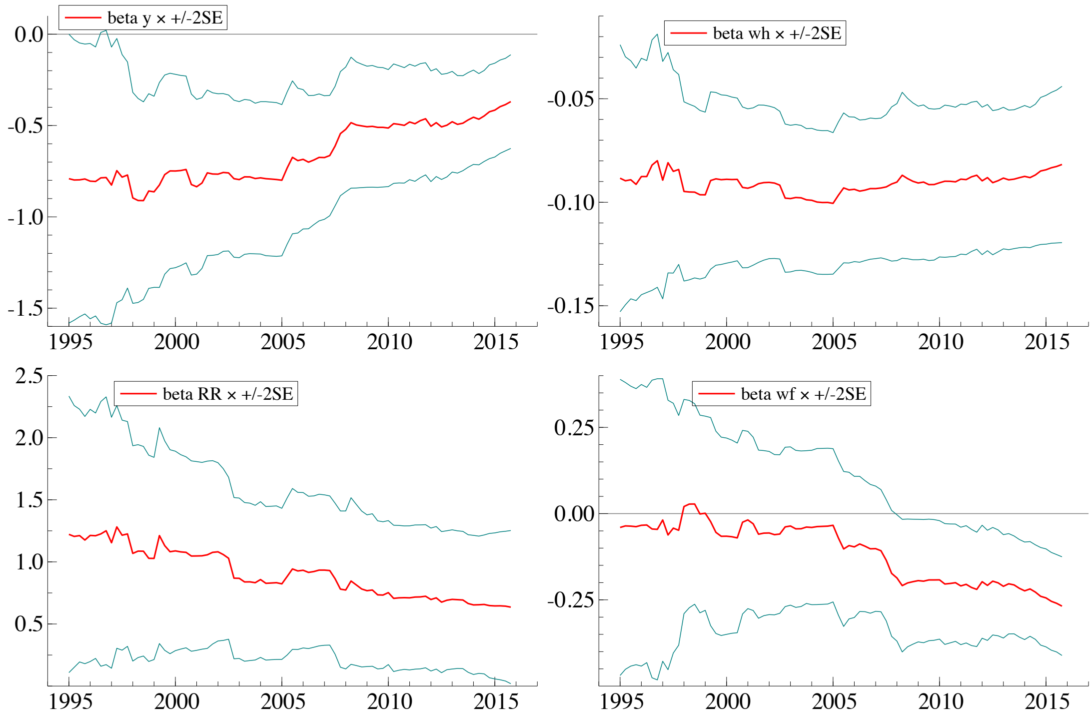

Figure 15: Recursive plots of the beta coefficients of the cointegration vector.

Figure 15 shows the coefficients of equation 8.1 recursively estimated. We see that the coefficients of income (beta y) has declined over the period and that something happened around the time of the break of the previous model around late 2007, beginning of 2008. While the coefficient of housing wealth (beta wh) has been relatively stable in the period, the financial wealth coefficient has gone from insignificant to more and more significant in later years. The fact that we see these unstable coefficients points to that there is still something happening outside the model that affects consumption, this is a weakness of the model.

We see from figure 16, which plots the error correction variable, that this looks stationary. This is the variable included in the error correction model in the following section.

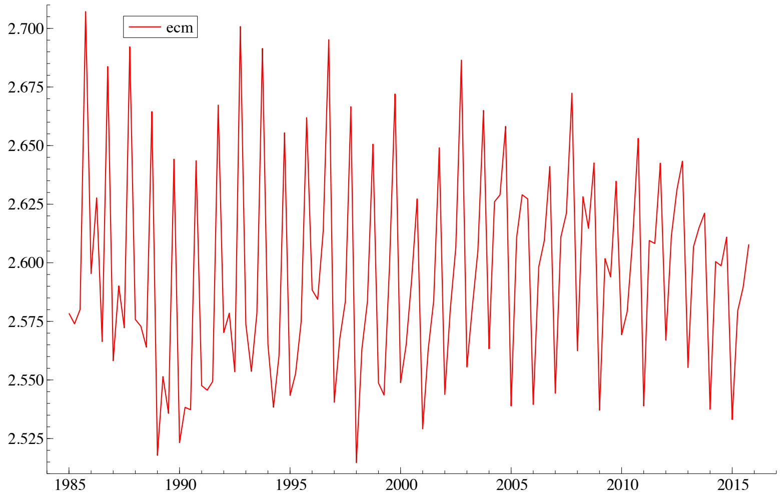

Figure 16: Stationarity of the ecm variable.

8.2 Short run dynamics with separate wealth variables

Now that we have found a long run equation that passes the statistical tests, I can go on to build an error correction model. To analyze the short run effects a bit deeper, I now split the wealth variables further. In the short run, it is possible that the wealth variables have different effects on consumption because of differences in liquidity or consumers willingness to consume out of that wealth category. I also want to allow debt to have an independent effect on consumption; a motivation for this is that highly indebted households could be more cautious and behave differently than if they did not have debt. Therefore, I now include two variables for gross financial wealth, gross housing wealth and debt as separate variables.

Three different variables for financial wealth are available, but only $finwealth1$ (which consists of cash and bank deposits) and $finwealth2$ (stocks, bonds and other financial wealth) are included. This means that I do not include the last category of financial wealth which consists of insurance claims. Insurance claims are very illiquid and it is unlikely that they affect households' consumption decisions.

Housing wealth and total debt is also included in the model, thus opening up for the fact that debt can have asymmetric effects on consumption. In addition to the wealth variables, I also include disposable income, the interest rate and the unemployment rate. I first estimate the model in its general form, these results are reported in table 13 of the appendix. Using the *Autometrics* software available in OxMetrics, I reduce the model to its specific form. The final model is reported in table 11.

Model:	(1): 1986(1)-2013(4)	
	coefficient	t-value
Δc_{t-1}	-0.2467	-2.81
Δc_{t-4}	0.1758	2.38
constant	0.8291	3.42
$\Delta_2 y_t$*	0.3512	3.15
$\Delta housewealth_{t-1}$	0.2121	3.35
$\Delta housewealth_{t-3}$	-0.1581	-2.55
$\Delta finwealth2_{t-3}$	0.1257	2.61
ecm_{t-1}	-0.3196	-3.42
SE regression	1.64%	
Tests:	Statistics	Value (p-value)
AR 1-5 test:	F(5,93)	1.27 (0.283)
ARCH 1-4 test:	F(4,104)	2.20 (0.074)
Normality test:	$\chi^2(2)$	4.93 (0.085)
Heteroscedasticity test:	F(21,90)	0.97 (0.510)
Reset test:	F(2,96)	1.22 (0.299)

*$\Delta_2 y_t = y_t - y_{t-2}$
Sample period: 1986(1) - 2013(4)
Seasonal dummies not reported.

Table 11: ECM for Δc with separate wealth variables.

The model passes diagnostic tests, but the normality and ARCH-test passes only slightly with p-values of 0.085 and 0.074 respectively. Standard errors of the regression are relatively low with 1.64% and all coefficients are significant. The reduced model from *Autometrics* included both the contemporaneous first difference of income, as well as the first lag, with basically the same coefficients. It was therefore possible to reduce the model further by including the second difference of income; this did not change any of the results.

As a robustness check, the model was estimated with the level variables in the error correction term included separately, this did not change much in the model; all the variables still had the same sign and magnitude, and the coefficients of the *ecm* variable corresponded well to the coefficients of equation 8.1 found by the long run analysis.

Housing wealth has a significant positive effect after one quarter, then a negative effect after three quarters, the total effect is positive. This suggests that higher house prices initially increases consumption, but that the total impact effect is small. Since the consumption variable in the model excludes consumption of housing services, this small impact effect seems likely. Also, higher house prices could have the effect of "crowding out" consumption of other goods, which again suggests that the impact effect of changes to housing wealth on the consumption variable in the model, should be relatively small.

The only financial wealth variable that comes out as significant is $finwealth2$, i.e. stocks, bonds, and other financial wealth. The fact that $finwealth1$ do not pass the model reduction suggests that cash and bank deposits are kept mostly as transaction means, not as a store of wealth, so changes in this type of financial wealth has no direct effect on consumption. It seems like less liquid financial wealth is a more significant driver for consumption and that households want to consume a portion of the increased wealth. Financial wealth is only included in the third lag in the model, so it takes time before households react to changes in financial wealth. A reason for this could be that households do not react immediately to changes in this wealth, but rather wait to see if the change is more permanent.

The finding that the most liquid financial wealth has no impact on consumption is somewhat controversial. It is in direct contradiction to the conclusions of Ekeli (1992). He finds that the most liquid wealth has a *bigger* effect on consumption than the less liquid financial wealth. An explanation for this could be cultural and technological changes since 1992. It has become much easier for regular savers to buy stocks and bonds and to move money between asset classes. This will also affect the relative significance of the different classes of financial wealth on consumption.

Debt falls out of the model during model reduction. This might be because debt follows the wealth variables closely and therefore becomes insignificant when wealth already is included, but it could also be because debt has no significant independent effect on consumption in the short run. If housing and financial wealth has short term effects on consumption, but not debt, this points to asymmetric effects between wealth and debt. However, there are several effects from debt to consumption, and the decreased disposable income from increased interest payments are already accounted for in the disposable income variable. Since we use net wealth variables in the long run analysis, the model includes debt effects in the long run.

In the general model I also included the first difference of the after-tax real interest rate with four lags, these were not significant, and were dropped during the model reduction process. The lack of short run interest rate effects has also been found earlier by Jansen (2013), and implies that changes in the interest rate does not directly affect household consumption in the short run.

The unemployment rate was also dropped from the final model. This was included as a proxy for the business cycle. Business cycle developments will affect private consumption through several channels, most notably through income and wealth, which is already accounted for in the model. Other effects could be that greater uncertainty in downturns lead to higher saving, or that the consumption share of income will increase, because unemployed individuals typically will consume a larger share of their income because the income has fallen. Since the unemployment rate is dropped, we find no support for such effects in the model.

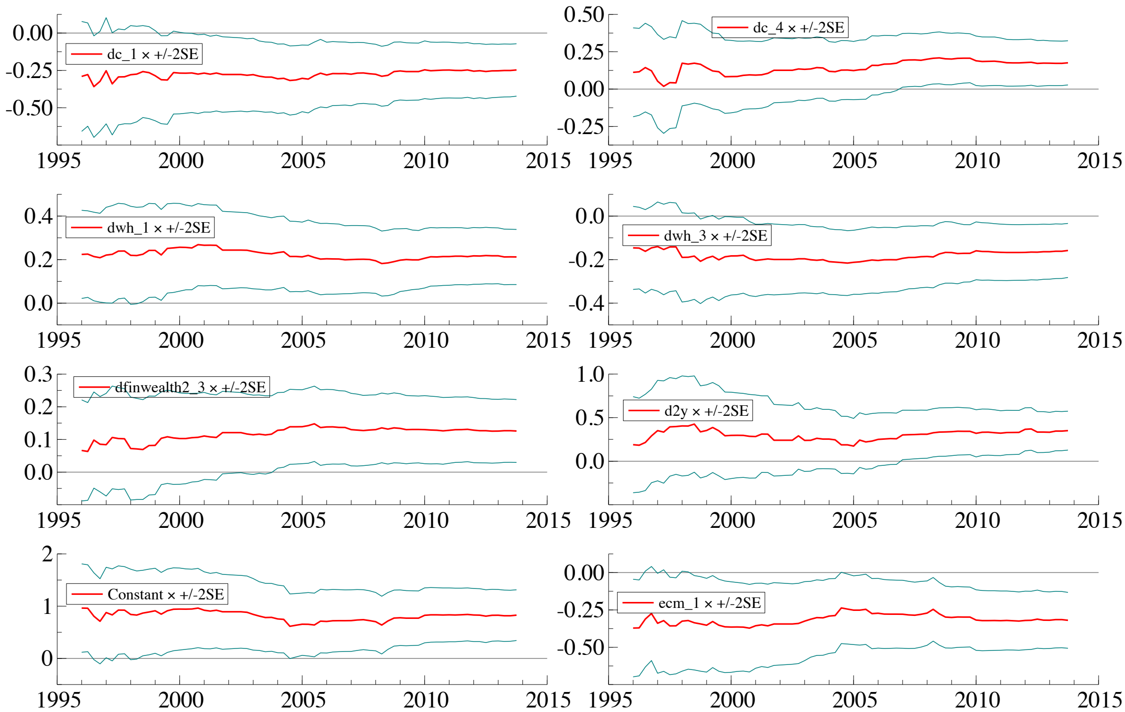

Figure 17: Recursive graphics of the estimated coefficients in the ECM.

Recursive graphics of the estimated coefficients in figure 17 show that both the estimated constant and coefficient of the error correction term (*ecm*) is stable in the estimated period.

8.3 Forecasting performance

For the model in table 11, both the structure (the model reduction) and the estimated coefficients were estimated on a sample up until the fourth quarter of 2013. So we can use the model to perform *ex post* one-step forecasts for the change in consumption. I forecast eight quarters ahead, up until the last quarter of 2015. Figure shows the forecasts with confidence bars, together with the realized values.

The model passes parameter constancy tests. The Chow-test passes with a p-value of 0.92, and the forecast $\chi^2(8)$ test has a p-value of 0.87. Also, we see that the realized values are within the confidence bars for all quarters, but that the model still seem to over-predict consumption growth in the third and fourth quarter in both years. The confidence bars represent two standard errors.

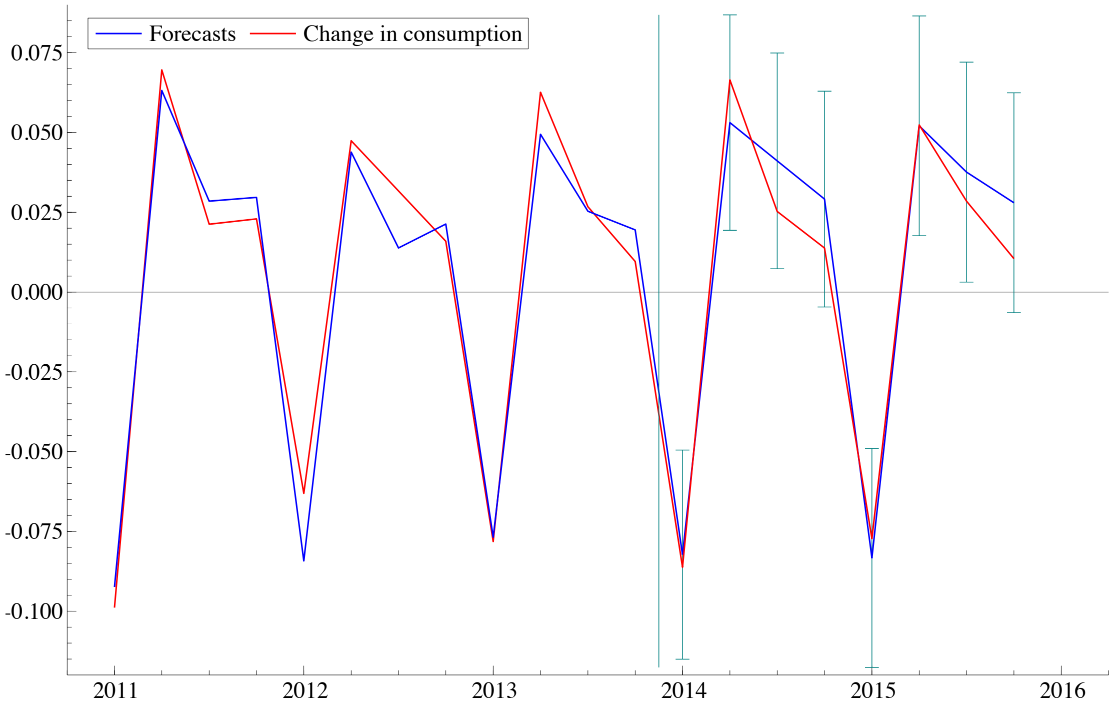

Figure 18: Forecasts for the change in consumption.

Finally, I want to convince the reader that the current model is an improvement from the model in chapter 6. To do this, I estimate the ECM from chapter 6 on a sample up until the last quarter of 2013 with the "old" cointegration vector, and perform the same forecasts as in figure 18. To do the forecasts on the same data, I estimate the "old" model on the revised dataset, the model is presented in table 14 in the appendix, and the forecasts are given in figure 19.

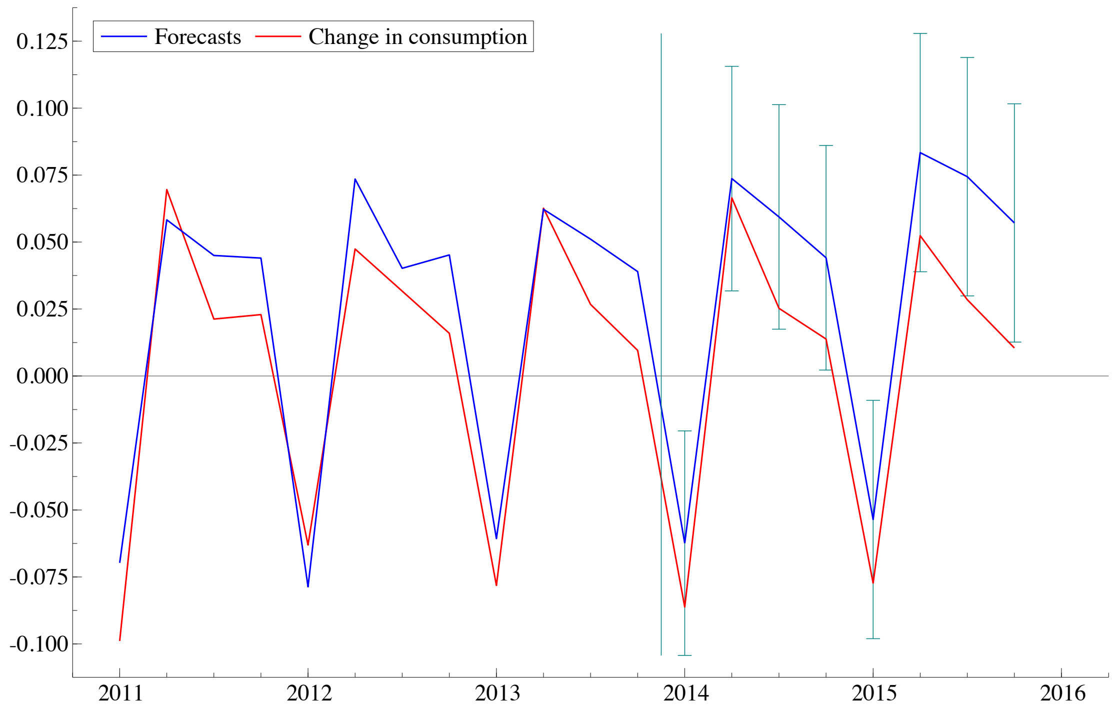

Figure 19: Forecasts from replicating model.

It is easy to see that the forecasts in figure 18 are a big improvement from those in figure 19. The old model consistently over-predict consumption growth, and in the last two quarters, the realized values are outside the confidence bars. Looking at the test statistics confirms this, the p-value from the $\chi^2(8)$-test is 0.08, and the Chow-test has p-value of 0.29, far below that of the "new" model.

The numerical values of the forecasts are given in table 15 and 16 in the appendix. In the table we also see that the new model does better on every metric. The Root Mean Squared Error (RMSE) is almost three times as big for the replication model compared to the new model (0.012 vs. 0.033).

To recap, this chapter has shown that by including separate wealth variables in the model, we find a model that deals better with the break around the financial crisis. We find that housing wealth and financial wealth has different effects on consumption both in the long and short run. We have also found that the financial wealth most relevant when modeling consumption is the category containing stocks, bonds and other financial assets.

9 Conclusion

The goal of this master's thesis was to improve the current consumption function in Statistics Norway's KVARTS model by testing two different hypotheses. The first was to see whether the income distribution could explain some of the feeble growth in consumption after the financial crisis, the second was to see if splitting the wealth variable into different components could improve the model.

Two variables were found to capture developments in the income distribution. The first variable is the well-known Gini coefficient, which was modified to be more sensitive to changes in the upper end of the income distribution. The second was the wage share of the economy. While the Gini is a direct measure of the income distribution, the connection between the wage share and the income distribution is not as abvious. However, none of these variables had a significant effect on aggregate consumption. There are several possible reasons for why the income distribution is insignificant, it could be that the variables do not pick up the real developments in the income distribution, that the changes in the income distribution has not been large enough to affect consumption or that income inequality does not have the suggested effect on consumption. Future research might be able to shed more light on this relationship.

The second part of the analysis was to include different wealth variables separately in the model. In the long run I found that consumption is determined by the following equation

$$c = 0.37y + 0.08w_H + 0.27w_F - 0.64RR \tag{9.1}$$

We see that housing wealth has a smaller effect on consumption than financial wealth and that the effect of the real interest rate is negative. The small income effect and lack of homogeneity in income and wealth are potential weaknesses of the model, but for forecasting up to three years ahead, which is the objective of the KVARTS-model, this is not necessarily a problem.

In the short run analysis, two categories of financial wealth were included. The first, and most liquid, consists of cash and bank deposits, the second, less liquid category consists of stocks, bonds and other financial assets. The analysis show that the latter category has the largest effect on consumption, confirming the assumption that cash and bank deposits are held more as a means of transactions instead of as a store of wealth. I also find that housing wealth has a short run effect, but that this is small.

When reducing the ECM model, debt does not “make the cut”. This suggests that short term changes in debt do not affect consumption. However, interest payments on debt are included in the variable for disposable income, and debt is also accounted for in the long run equation, where the wealth variables are net wealth.

While the current consumption function in KVARTS needs to include a step-dummy for the financial crisis, I end up with a new conditional consumption function that forecasts well *ex post*, even without such a dummy. I find stable coefficients in the ECM model, but unstable coefficients in the cointegration analysis.

Even if the estimated model performs better after the financial crisis, the changed behavior of consumers is still a puzzle. The conclusion so far seems to be that there are several effects working at the same time. The increased uncertainty during the financial crisis certainly played a role, the same for the pension system which both increased the working populations incentive to save, as well as giving certain age groups the possibility of working while still collecting their pension. Also the increased immigration might have increased the aggregate savings rate. Future research might be able to incorporate these factors in an empirical model, but this thesis has shown that splitting wealth can at least take us a part of the way.

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A Appendix

A.1 Data definitions and sources

Most of the data used in this thesis are collected from Statistics Norway's KVARTS database.

AGE	Variable for the relative size of the population age between 50 and 66 years. The variable is constructed as P50-66 / (P20-49 + P67up). Source: Statistics Norway.
C	Consumption expenditure in households and ideal organizations less expenditure on health services and housing. Nominal value deflated by PCPEB. Source: Statistics Norway
CPI	Consumer price index. Source: Statistics Norway.
CPSTOP	Dummy-variable constructed to catch the price freeze in 1978. Its value is 1 for the period from 1978(1) to 1980(1), zero elsewhere.
DEBT	Total debt for households. Nominal value deflated by PC. Source: Statistics Norway.
FINWEALTH1	The most liquid financial wealth, containing cash and bank deposits. Nominal value deflated by PC. Source: FINSE database, Norges Bank.
FINWEALTH2	Less liquid financial wealth. This category contains stocks, bonds and other financial wealth. Nominal value deflated by PC. Source: FINSE database, Norges Bank.
FINWEALTH3	The least liquid category of financial wealth. This category contains insurance claims. Nominal value deflated by PC. Source: FINSE database, Norges Bank.
Gini	Variable measuring the income distribution. Series from Aaberge (2007).
HOUSEWEALTH	Nominal value of house wealth deflated by PC. Source: Statistics Norway.
i	Nominal interest rate. Average interest rate on households' bank loans. Source: Norges Bank.

INF Inflation, constructed as the fourth difference of the log-transformed CPI.

PC Price deflator for total consumption expenditure. Source: Statistics Norway.

PCPEB Price deflator for consumption expenditure less spending on housing services and health services.

RR Marginal after-tax real interest rate for households. Constructed as $RR = i * (1 - \tau) - INF$. Zero for the period before 1984. Source: Statistics Norway.

UNEMPL Norwegian unemployment. Labour force survey, seasonally-adjusted figures. Source: Statistics Norway.

W Net total wealth. Nominal value deflated by PC. Defined as

$$W_t = (L_{t-1} - CR_{t-1} + (PH/PC)_t * K_{t-1}) \tag{A.1}$$

Where L_t is household sector liquid assets, CR_t is household sector loans by banks and financial institutions, PH_t is housing prices, PC_t is private consumption expenditure deflator, and K_t is the volume of the residential housing stock. Source: Statistics Norway and Norges Bank. This series was first introduced in Brodin and Nymoen (1992) and later used in Jansen (2013).

Wage share Wage income as a share of total income. Constructed as wage/(wage+capital income). Source: Statistics Norway.

Y Disposable income for households excluding equity income. Nominal value deflated by PC. Source: Statistics Norway.

A.2 Supplementary figures and tables

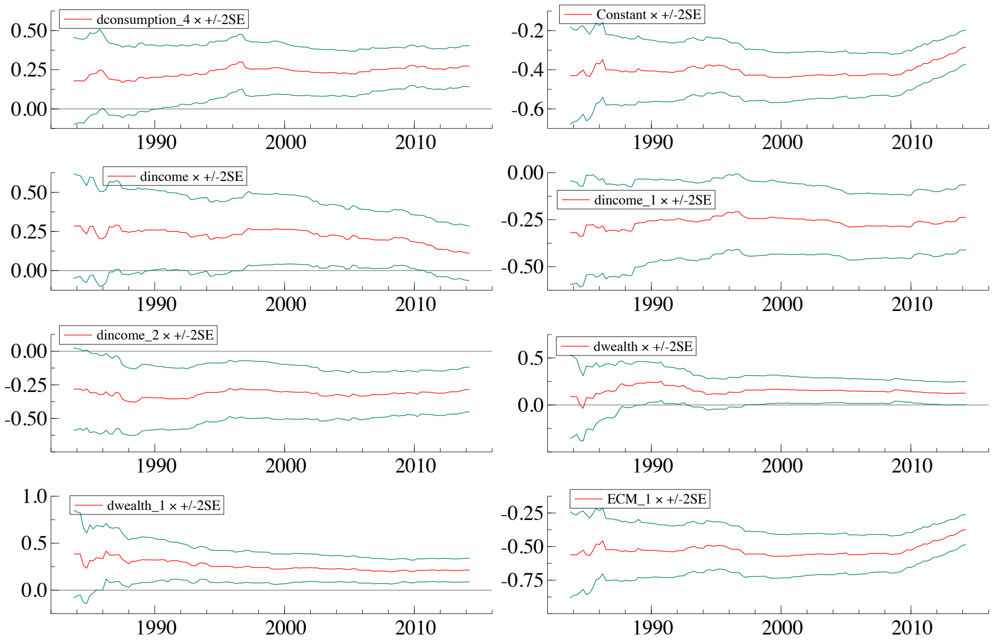

Figure 20: Recursive estimated coefficients of ECM from replication.

```
EQ(40) Modelling dc by OLS
       The dataset is: C:\Users\jla\Dropbox\Skole\Masteroppgave\Datafiler\Data replication\Analysedata nov 2014.in7
       The estimation sample is: 1971(2) - 2008(2)

                  Coefficient  Std.Error  t-value  t-prob Part.R^2
dc_1                -0.142946     0.1240    -1.15  0.2512   0.0109
dc_2              -0.00537163     0.1151  -0.0467  0.9629   0.0000
dc_3                0.0798458     0.1094    0.730  0.4670   0.0044
dc_4                 0.278848    0.08967     3.11  0.0023   0.0740
Constant            -0.343984    0.08855    -3.88  0.0002   0.1109
dy                   0.241338     0.1025     2.35  0.0202   0.0438
dy_1                -0.168194     0.1361    -1.24  0.2189   0.0125
dy_2                -0.228029     0.1310    -1.74  0.0843   0.0244
dy_3                0.0826661     0.1213    0.682  0.4967   0.0038
dy_4                0.0661800    0.09844    0.672  0.5027   0.0037
dnetwealth           0.166087    0.07239     2.29  0.0235   0.0417
dnetwealth_1         0.208876    0.07348     2.84  0.0053   0.0626
dnetwealth_2        0.0700868    0.07174    0.977  0.3305   0.0078
dnetwealth_3       0.00144320    0.07243   0.0199  0.9841   0.0000
dnetwealth_4        -0.182487    0.07210    -2.53  0.0127   0.0503
CSeasonal           -0.100458    0.01840    -5.46  0.0000   0.1976
CSeasonal_1        -0.0959001    0.01556    -6.16  0.0000   0.2390
CSeasonal_2        -0.0965911    0.01742    -5.54  0.0000   0.2026
ECM_Jansen_1        -0.447747     0.1138    -3.94  0.0001   0.1135
DK1step02          -0.0266315    0.01007    -2.64  0.0093   0.0546
DK2step02          -0.0100030   0.009875    -1.01  0.3131   0.0084
DK3step02           0.0113098   0.009722     1.16  0.2470   0.0111
DK4step02          -0.0425538   0.009898    -4.30  0.0000   0.1325
dRR                  0.164970     0.1802    0.915  0.3618   0.0069
dRR_1              -0.0882892     0.1583   -0.558  0.5779   0.0026
dRR_2              -0.0574464     0.1621   -0.354  0.7236   0.0010
dRR_3               0.0945548     0.1602    0.590  0.5562   0.0029
dRR_4               0.0976668     0.1622    0.602  0.5482   0.0030

sigma               0.0189813  RSS             0.0435951951
R^2                  0.954911  F(27,121) =   94.91 [0.000]**
Adj.R^2               0.94485  log-likelihood        394.766
no. of observations       149  no. of parameters          28
mean(dc)           0.00843107  se(dc)              0.0808262

AR 1-5 test:      F(5,116)   =  0.24902 [0.9396]
ARCH 1-4 test:    F(4,141)   =   1.0245 [0.3969]
Normality test:   Chi^2(2)   =   1.6223 [0.4443]
Hetero test:      F(47,101)  =   1.2455 [0.1794]
RESET23 test:     F(2,119)   = 0.062706 [0.9393]
```

Table 12: General model of replication.

EQ(92) Modelling dc by OLS
The dataset is: C:\Users\jla\Dropbox\Skole\Masteroppgave\Datafiler\Oppdaterte data\Data til analysen2.in7
The estimation sample is: 1986(1) - 2013(4)

		Coefficient	Std.Error	t-value	t-prob	Part.R^2
dc_1		-0.503731	0.1575	-3.20	0.0021	0.1360
dc_2		-0.274930	0.1663	-1.65	0.1031	0.0404
dc_3		-0.110716	0.1437	-0.771	0.4437	0.0091
dc_4		0.118521	0.1194	0.993	0.3245	0.0149
dy		0.183708	0.1761	1.04	0.3008	0.0165
dy_1		0.508168	0.2068	2.46	0.0167	0.0850
dy_2		0.276319	0.1986	1.39	0.1689	0.0289
dy_3		0.0953519	0.2071	0.461	0.6467	0.0033
dy_4		0.125491	0.1855	0.677	0.5010	0.0070
dhousewealth		0.0132105	0.09843	0.134	0.8937	0.0003
dhousewealth_1		0.103078	0.09687	1.06	0.2912	0.0171
dhousewealth_2		0.159961	0.09995	1.60	0.1143	0.0379
dhousewealth_3		-0.135940	0.1037	-1.31	0.1943	0.0258
dhousewealth_4		-0.0730009	0.09590	-0.761	0.4493	0.0088
ddebt		0.508573	0.2847	1.79	0.0787	0.0468
ddebt_1		0.132541	0.2578	0.514	0.6089	0.0041
ddebt_2		-0.358073	0.2566	-1.40	0.1677	0.0291
ddebt_3		0.268082	0.2780	0.964	0.3385	0.0141
ddebt_4		-0.657962	0.2566	-2.56	0.0126	0.0919
dfinwealth1		-0.0565477	0.1614	-0.350	0.7273	0.0019
dfinwealth1_1		0.151470	0.1540	0.984	0.3289	0.0147
dfinwealth1_2		0.167441	0.1572	1.06	0.2908	0.0172
dfinwealth1_3		-0.124548	0.1673	-0.744	0.4594	0.0085
dfinwealth1_4		0.258201	0.1817	1.42	0.1601	0.0301
dfinwealth2		0.0587998	0.07409	0.794	0.4303	0.0096
dfinwealth2_1		0.00969235	0.07252	0.134	0.8941	0.0003
dfinwealth2_2		0.0605386	0.07322	0.827	0.4113	0.0104
dfinwealth2_3		0.0352085	0.06938	0.507	0.6135	0.0039
dfinwealth2_4		0.0150796	0.06743	0.224	0.8237	0.0008
CSeasonal		-0.0770202	0.03015	-2.55	0.0130	0.0912
CSeasonal_1		-0.0874558	0.02877	-3.04	0.0034	0.1245
CSeasonal_2		-0.0830809	0.02596	-3.20	0.0021	0.1361
DC1step02		0.0214005	0.02335	0.917	0.3628	0.0128
DC2step02		0.0610123	0.02402	2.54	0.0135	0.0903
DC3step02		0.0616357	0.02340	2.63	0.0105	0.0964
dUNEMPL		0.00313719	0.008126	0.386	0.7007	0.0023
dUNEMPL_1		-0.00979402	0.007537	-1.30	0.1984	0.0253
dUNEMPL_2		0.00163755	0.006801	0.241	0.8105	0.0009
dUNEMPL_3		0.00241269	0.006821	0.354	0.7247	0.0019
dUNEMPL_4		-0.0192597	0.006828	-2.82	0.0063	0.1091
dRR		-0.309051	0.2358	-1.31	0.1946	0.0257
dRR_1		-0.233941	0.2116	-1.11	0.2729	0.0185
dRR_2		0.121025	0.2184	0.554	0.5813	0.0047
dRR_3		0.163725	0.2259	0.725	0.4711	0.0080
dRR_4		-0.123278	0.2303	-0.535	0.5942	0.0044
Constant	U	0.791871	0.3583	2.21	0.0306	0.0699
ecm_1	U	-0.305619	0.1388	-2.20	0.0312	0.0694

sigma	0.0159884	RSS	0.016615968
R^2	0.967573	F(46,65) =	42.16 [0.000]**
Adj.R^2	0.944625	log-likelihood	334.769
no. of observations	112	no. of parameters	47
mean(dc)	0.00632725	se(dc)	0.0679439

1-step (ex post) forecast analysis 2014(1) - 2015(4)
Parameter constancy forecast tests:

Forecast	Chi^2(8)	=	5.5589 [0.6965]
Chow	F(8,65)	=	0.48055 [0.8656]

AR 1-5 test:	F(5,60)	=	0.89106 [0.4929]
ARCH 1-4 test:	F(4,104)	=	2.9461 [0.0237]*
Normality test:	Chi^2(2)	=	2.9618 [0.2274]
Hetero test:	F(87,24)	=	1.3858 [0.1834]
RESET23 test:	F(2,63)	=	0.49269 [0.6133]

Table 13: General model with separate wealth variables.

```
// ECM_replication = c-0.77596*y-0.22404*husformue+0.71102*RR_Jansen;

EQ(27) Modelling dc by OLS
       The dataset is: C:\Users\jla\Dropbox\Skole\Masteroppgave\Datafiler\Oppdaterte data\Data til analysen2.in7
       The estimation sample is: 1971(2) - 2013(4)

                     Coefficient  Std.Error  t-value  t-prob Part.R^2
dc_4                 0.356188   0.06838     5.21  0.0000   0.1473
Constant               -0.169623    0.03625    -4.68  0.0000   0.1224
dy                    -0.0519193    0.09079   -0.572  0.5682   0.0021
dy_1                   -0.199738    0.08563    -2.33  0.0209   0.0335
dy_2                   -0.294721    0.08678    -3.40  0.0009   0.0684
dwealth                0.0965313    0.06736     1.43  0.1538   0.0129
dhwealth_1              0.180174    0.06993     2.58  0.0109   0.0406
ecm_replication_1      -0.229134    0.04751    -4.82  0.0000   0.1290
CSeasonal              -0.108555    0.01529    -7.10  0.0000   0.2430
CSeasonal_1           -0.0611517   0.008855    -6.91  0.0000   0.2330
CSeasonal_2           -0.0538827   0.008948    -6.02  0.0000   0.1876
DC1step02              0.0470909    0.01244     3.79  0.0002   0.0836
DC2step02              0.0463909    0.01293     3.59  0.0004   0.0758
DC3step02              0.0492988    0.01277     3.86  0.0002   0.0868

sigma                0.0209542  RSS                0.0689356249
R^2                   0.928687  F(13,157) =   157.3 [0.000]**
Adj.R^2               0.922782  log-likelihood        425.651
no. of observations        171  no. of parameters          14
mean(dc)         0.0081721  se(dc)            0.0754073

1-step (ex post) forecast analysis 2014(1) - 2015(4)
Parameter constancy forecast tests:
Forecast  Chi^2(8)  =    14.057 [0.0803]
Chow      F(8,157)  =    1.2201 [0.2905]
CUSUM     t(7)      =   -2.913 [0.0226]*  (zero forecast innovation mean)

AR 1-5 test:      F(5,152)  =   3.2967 [0.0074]**
ARCH 1-4 test:    F(4,163)  =  0.51727 [0.7231]
Normality test:   Chi^2(2)  =  0.66984 [0.7154]
Hetero test:      F(21,149) =  0.81652 [0.6963]
Hetero-X test:    F(84,86)  =   1.0440 [0.4212]
RESET23 test:     F(2,155)  =   4.3142 [0.0150]*
```

Table 14: Replicated ECM-model estimated on new sample to make forecasts.

```
Dynamic (ex ante) forecasts for dc (SE based on error variance only)
   Horizon      Forecast         SE        Actual       Error   t-value        -2SE        +2SE
   2014(1)    -0.0822830    0.01638    -0.0862234  -0.0039404    -0.240    -0.11505   -0.049514
   2014(2)     0.0530967    0.01688     0.0664933    0.013397     0.794    0.019346    0.086848
   2014(3)     0.0411043    0.01690     0.0252606   -0.015844    -0.937   0.0072946    0.074914
   2014(4)     0.0291258    0.01691     0.0137993   -0.015327    -0.907  -0.0046875    0.062939
   2015(1)    -0.0833173    0.01716    -0.0772705   0.0060468     0.352    -0.11764   -0.048996
   2015(2)     0.0520856    0.01722     0.0523747  0.00028905     0.017    0.017644    0.086527
   2015(3)     0.0375893    0.01723     0.0284883  -0.0091010    -0.528   0.0031318    0.072047
   2015(4)     0.0279710    0.01723     0.0104761   -0.017495    -1.015  -0.0064882    0.062430
   mean(Error) =   -0.0052468    RMSE =     0.011760
   SD(Error)   =     0.010525    MAPE =       50.728
```

Table 15: Forecasts from ECM with separate wealth.

```
Dynamic (ex ante) forecasts for dc (SE based on error variance only)
   Horizon      Forecast         SE        Actual       Error   t-value        -2SE        +2SE
   2014(1)    -0.0623967    0.02095    -0.0862234   -0.023827    -1.137    -0.10431   -0.020488
   2014(2)     0.0736942    0.02095     0.0664933  -0.0072010    -0.344    0.031786     0.11560
   2014(3)     0.0593911    0.02095     0.0252606   -0.034130    -1.629    0.017483     0.10130
   2014(4)     0.0441363    0.02095     0.0137993   -0.030337    -1.448   0.0022278    0.086045
   2015(1)    -0.0535749    0.02224    -0.0772705   -0.023696    -1.065   -0.098063  -0.0090873
   2015(2)     0.0833941    0.02224     0.0523747   -0.031019    -1.395    0.038907     0.12788
   2015(3)     0.0744152    0.02224     0.0284883   -0.045927    -2.065    0.029928     0.11890
   2015(4)     0.0571422    0.02224     0.0104761   -0.046666    -2.098    0.012655     0.10163
   mean(Error) =    -0.030350    RMSE =     0.032626
   SD(Error)   =     0.011970    MAPE =       136.25
```

Table 16: Forecasts from replicated ECM.

A.3 General to specific modeling

Defined by Muellbauer and Lattimore (1995), the principle of general to specific modeling, or *GETS*, is beginning with a general, congruent model and testing a series of simplifications to reduce it a parsimonious model that is consistent with the data.

An important criticism of GETS has been that the model you end up with is dependent on the “path” you choose to reduce the model, so called path-dependence. This has been solved by building algorithms (see Hoover and Perez (1999)) that automates the reduction process, examining multiple search paths and therefore avoiding the path dependency issue. In the reduction process it is important to only consider models passes diagnostic tests in order to retain congruence.

The basic steps of such an algorithm is; 1. Make sure that the general statistical model is congruent by diagnostic testing. 2. Eliminate on or several variables that satisfies the simplification criteria (e.g. significance of the variable). 3. Check if the simplified model passes diagnostic tests. 4. Continue steps 2 and 3 until no further simplification is possible (Campos et al., 2005).

Often we can find that searches lead to different model selections, if we have several competing models then we will use encompassing tests and information criteria to choose the final model.

OxMetrics includes a GETS modeling tool named *Autometrics*, this what is used in this thesis.

A.4 Information criteria

One of the difficult choices that an econometrician must take when working with time series, is to determine the number of lags to include in the model. A useful method is to look at the so-called information criteria which aims to measure the fit of the model relative to the number of parameters estimated. In the time series setting one can always include many lags to achieve better fit and to get rid of autocorrelation, but this also consumes degrees of freedom, and increases the standard deviation.

The most known are the Akaike information criterion (AIC) and the Schwarz’s Bayesian information criterion (SBIC and BIC). They are defined as:

$$AIC = -2ln(L)/T + 2N/T \tag{A.2}$$

$$BIC = -2ln(L)/T + Nln(T)/T \tag{A.3}$$

Where T is the sample size, L is the maximized value of multivariate maximum likelihood, and N is the total number of parameters in all equations in the VAR. A lower information criteria indicates a better model. We can see that the BIC gives more punishment for the number of parameters included in the model (N), as long as

$$ln(T) > 2 \rightarrow T > e^2 \rightarrow T > 7.389 \tag{A.4}$$

The sample size will for all my models be larger than 7.389 and the BIC will therefore often prefer fewer lags than AIC. It is also often the case that the information criteria will leave us without a clear answer. According to Lütkepohl (2005), the AIC will overestimate the lag order with a positive probability, while the BIC is a consistent estimate of the true lag order.

A.5 Tests of stationarity

Here follows the augmented Dickey-Fuller tests that I have conducted on the data series. I have used the sample period from the first quarter of 1986 until the latest observation for each variable (this means 2015(4) for every variable except the Gini, which has its last observation in 2014(1)), since this is the sample period for my analysis in chapters 7 and 8.

c: ADF tests (T=120, Constant+Trend+Seasonals; 5%=-3.45 1%=-4.04)							
D-lag	t-adf	betaY_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-2.639	0.87998	0.02006	4.898	0.0000	-7.738	
3	-1.995	0.90076	0.02204	-4.688	0.0000	-7.558	0.0000
2	-2.409	0.87050	0.02402	-4.131	0.0001	-7.394	0.0000
1	-3.278	0.81717	0.02567	-1.783	0.0773	-7.268	0.0000
0	-3.969*	0.78703	0.02591			-7.257	0.0000

Table 17: ADF test for consumption

dc: ADFtests (T=120, Constant+Seasonals; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-4.572**	-0.30718	0.02024	-2.187	0.0308	-7.728	
3	-5.762**	-0.54699	0.02058	-4.599	0.0000	-7.702	0.0308
2	-12.85**	-1.4740	0.02234	4.868	0.0000	-7.546	0.0000
1	-13.14**	-0.74669	0.02446	4.745	0.0000	-7.372	0.0000
0	-14.07**	-0.24798	0.02665			-7.209	0.0000

Table 18: ADF test for first difference of consumption

y: ADFtests (T=120, Constant+Trend+Seasonals; 5%=-3.451%=-4.04)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-2.103	0.86197	0.01301	1.269	0.2071	-8.604	
3	-2.042	0.86580	0.01305	-7.441	0.0000	-8.607	0.2071
2	-2.723	0.78486	0.01590	-6.287	0.0000	-8.219	0.0000
1	-4.788**	0.59517	0.01841	-0.03630	0.9711	-7.933	0.0000
0	-5.389**	0.59380	0.01833			-7.950	0.0000

Table 19: ADF test for income

dy: ADFtests (T=120, Constant+Seasonals; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-5.648**	-1.2616	0.01338	-0.9617	0.3383	-8.556	
3	-7.685**	-1.4880	0.01338	-1.686	0.0945	-8.564	0.3383
2	-17.09**	-1.9513	0.01349	7.401	0.0000	-8.556	0.1569
1	-16.16**	-0.89118	0.01636	7.647	0.0000	-8.177	0.0000
0	-13.16**	-0.20166	0.02004			-7.780	0.0000

Table 20: ADF test for first difference of income

netwealth: ADFtests (T=120, Constant+Trend+Seasonals; 5%=-3.451%=-4.04)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-2.549	0.95269	0.02425	1.520	0.1313	-7.359	
3	-2.286	0.95812	0.02440	1.121	0.2647	-7.355	0.1313
2	-2.135	0.96132	0.02442	2.179	0.0314	-7.360	0.1715
1	-1.834	0.96652	0.02483	3.388	0.0010	-7.335	0.0434
0	-1.501	0.97146	0.02594			-7.255	0.0008

Table 21: ADF test for net total wealth

dnetwealth: ADFtests (T=120, Constant+Seasonals; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-3.978**	0.45392	0.02471	1.260	0.2103	-7.329	
3	-3.763**	0.50735	0.02477	-1.038	0.3013	-7.332	0.2103
2	-4.462**	0.45707	0.02478	-0.7843	0.4345	-7.339	0.2671
1	-5.391**	0.41437	0.02474	-1.916	0.0579	-7.350	0.3537
0	-7.986**	0.29156	0.02503			-7.335	0.1457

Table 22: ADF test for first difference of net total wealth

RR: ADFtests (T=120, Constant; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-1.917	0.89417	0.008687	-0.9029	0.3685	-9.443	
3	-2.213	0.88175	0.008680	0.3641	0.7164	-9.453	0.3685
2	-2.200	0.88667	0.008647	-0.2010	0.8410	-9.468	0.6238
1	-2.345	0.88394	0.008612	-0.7581	0.4499	-9.485	0.8042
0	-2.670	0.87339	0.008596			-9.496	0.8168

Table 23: ADF test for the after-tax real interest rate

dRR: ADFtests (T=120, Constant; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-6.093**	-0.52244	0.008792	0.9308	0.3539	-9.419	
3	-6.593**	-0.40001	0.008787	1.409	0.1616	-9.428	0.3539
2	-6.908**	-0.23786	0.008824	0.1978	0.8435	-9.428	0.2449
1	-8.753**	-0.21560	0.008788	0.7958	0.4277	-9.444	0.4130
0	-12.39**	-0.13250	0.008774			-9.455	0.4782

Table 24: ADF test for first difference of the after-tax real interest rate

AGE: ADF tests (T=120, Constant; 5%=-3.45 1%=-4.04)							
D-lag	t-adf	betaY_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-3.290*	0.99773	0.000297	0.8690	0.3867	-16.20	
3	-3.178*	0.99790	0.000297	1.120	0.2650	-16.21	0.3867
2	-2.977*	0.99812	0.000297	1.887	0.0617	-16.21	0.3698
1	-2.556	0.99842	0.000300	60.69	0.0000	-16.20	0.1411
0	0.883	1.0031	0.001703			-12.73	0.0000

Table 25: ADF test for AGE

dAGE: ADF tests (T=120, Constant; 5%=-3.45 1%=-4.04)							
D-lag	t-adf	betaY_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-1.908	0.96980	0.000298	3.124	0.0023	-16.19	
3	-1.848	0.96965	0.000309	0.0764	0.9392	-16.12	0.0023
2	-1.857	0.96964	0.000308	-0.1941	0.8465	-16.14	0.0092
1	-1.864	0.96965	0.000307	-1.135	0.2586	-16.16	0.0239
0	-1.873	0.96946	0.000307			-16.16	0.0295

Table 26: ADF test for first difference of AGE

adjGini: ADFtests (T=112,Constant; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-2.074	0.992690	.0002806	3.529	0.0006	-16.31	
3	-1.790	0.993370	.0002952	3.186	0.0019	-16.21	0.0006
2	-1.731	0.993320	.0003075	-13.48	0.0000	-16.14	0.0000
1	-2.939*	0.981960	.0005014	19.18	0.0000	-15.17	0.0000
0	-2.114	0.97306	0.001044			-13.71	0.0000

Table 27: ADF test for adjusted Gini

dadjGini: ADFtests (T=112, Constant; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-2.374	0.911490	.0002792	-2.326	0.0219	-16.32	
3	-3.114*	0.886540	.0002849	-3.369	0.0010	-16.28	0.0219
2	-4.726**	0.835830	.0002982	-3.161	0.0020	-16.20	0.0003
1	-8.073**	0.768850	.0003103	14.08	0.0000	-16.13	0.0000
0	-2.790	0.870840	.0005185			-15.11	0.0000

Table 28: ADF test for first difference of adjusted Gini

wageshare: ADFtests (T=120, Constant+Seasonals; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-1.867	0.83207	0.01693	-1.773	0.0790	-8.085	
3	-2.216	0.80237	0.01709	-2.351	0.0205	-8.074	0.0790
2	-2.853	0.74905	0.01743	-2.862	0.0050	-8.042	0.0147
1	-3.928**	0.66447	0.01797	-2.517	0.0132	-7.989	0.0010
0	-5.657**	0.56353	0.01839			-7.952	0.0002

Table 29: ADF test for wage share

dwageshare: ADFtests (T=120, Constant+Seasonals; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-6.356**	-1.5946	0.01713	-0.9226	0.3582	-8.062	
3	-9.237**	-1.8418	0.01712	2.135	0.0349	-8.071	0.3582
2	-10.77**	-1.3767	0.01739	2.962	0.0037	-8.048	0.0715
1	-12.92**	-0.87203	0.01797	3.935	0.0001	-7.989	0.0034
0	-16.35**	-0.39824	0.01907			-7.879	0.0000

Table 30: ADF test for first difference of wage share

finwealth1: ADFtests (T=120, Constant+Trend+Seasonals; 5%=-3.451%=-4.04)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-1.398	0.97459	0.01545	6.428	0.0000	-8.260	
3	-0.6389	0.98651	0.01804	-3.341	0.0011	-7.958	0.0000
2	-0.8499	0.98132	0.01884	-3.844	0.0002	-7.879	0.0000
1	-1.280	0.97044	0.01996	-1.577	0.1175	-7.772	0.0000
0	-1.504	0.96538	0.02009			-7.767	0.0000

Table 31: ADF test for financial wealth 1 (cash and bank deposits)

dfinwealth1: ADFtests (T=120, Constant+Seasonals; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-3.678**	0.17735	0.01584	0.01094	0.9913	-8.219	
3	-3.905**	0.17815	0.01577	-7.127	0.0000	-8.235	0.9913
2	-9.714**	-0.82482	0.01892	2.524	0.0130	-7.878	0.0000
1	-11.22**	-0.47984	0.01937	3.517	0.0006	-7.840	0.0000
0	-12.36**	-0.13290	0.02030			-7.754	0.0000

Table 32: ADF test for the first difference of financial wealth 1

finwealth2: ADFtests (T=120,Constant+Trend; 5%=-3.451%=-4.04)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-3.587*	0.87815	0.03729	7.857	0.0000	-6.522	
3	-1.772	0.92671	0.04616	-0.5841	0.5603	-6.102	0.0000
2	-1.919	0.92225	0.04603	-1.598	0.1127	-6.116	0.0000
1	-2.279	0.90901	0.04634	-0.2758	0.7832	-6.111	0.0000
0	-2.395	0.90676	0.04615			-6.127	0.0000

Table 33: ADF test for financial wealth 2 (stocks, bonds and other financial assets)

dfinwealth2: ADFtests (T=120, Constant; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-5.163**	0.10689	0.03699	3.756	0.0003	-6.545	
3	-4.056**	0.28918	0.03904	-6.982	0.0000	-6.445	0.0003
2	-7.812**	-0.37022	0.04639	0.9233	0.3578	-6.109	0.0000
1	-9.540**	-0.26422	0.04636	2.019	0.0458	-6.118	0.0000
0	-11.69**	-0.068205	0.04696			-6.100	0.0000

Table 34: ADF test for the first difference of financial wealth 2

debt: ADFtests (T=120,Constant+Trend; 5%=-3.451%=-4.04)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-3.173	0.97786	0.01076	9.834	0.0000	-9.007	
3	-1.318	0.98766	0.01460	2.740	0.0071	-8.405	0.0000
2	-1.012	0.99031	0.01500	0.6632	0.5085	-8.358	0.0000
1	-0.9521	0.99095	0.01497	4.894	0.0000	-8.371	0.0000
0	-0.5377	0.99443	0.01637			-8.200	0.0000

Table 35: ADF test for debt

ddebt: ADFtests (T=120, Constant; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-2.448	0.79065	0.01109	1.775	0.0785	-8.955	
3	-2.222	0.80973	0.01119	-9.135	0.0000	-8.944	0.0785
2	-4.097**	0.56439	0.01464	-2,642	0.0094	-8.415	0.0000
1	-5.766**	0.43828	0.01501	-0.6302	0.5298	-8.373	0.0000
0	-7.302**	0.40486	0.01497			-8.378	0.0000

Table 36: ADF test for the first difference of debt

housewealth: ADFtests (T=120,Constant+Trend; 5%=-3.451%=-4.04)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-2.973	0.95356	0.02797	7.851	0.0000	-7.097	
3	-1.552	0.97027	0.03462	1.269	0.2071	-6.678	0.0000
2	-1.417	0.97295	0.03471	-1.034	0.3032	-6.681	0.0000
1	-1.559	0.97047	0.03472	2.446	0.0159	-6.688	0.0000
0	-1.298	0.97501	0.03545			-6.654	0.0000

Table 37: ADF test for housing wealth

dhousewealth: ADFtests (T=120, Constant; 5%=-2.891%=-3.49)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
4	-3.387*	0.55913	0.02789	2.976	0.0036	-7.110	
3	-2.703	0.64555	0.02882	-7.305	0.0000	-7.052	0.0036
2	-5.543**	0.21684	0.03473	-1.134	0.2593	-6.688	0.0000
1	-7.539**	0.12521	0.03477	1.187	0.2378	-6.693	0.0000
0	-8.717**	0.21173	0.03483			-6.698	0.0000

Table 38: ADF test for the first difference of housing wealth

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