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Thesis for M.Sc. in Financial Economics

Inflation Targeting and Uncertainty in House and Rental Prices

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Preface

Writing a master's thesis has been a challenging and rewarding process. When researching potential topics, I wanted to find a subject that was interesting, made it possible to apply some of the knowledge I have gained through my studies, and that could potentially lead to an interesting conclusion. In the end, I chose to investigate the effect of an inflation targeting monetary policy on uncertainty in house and rental prices. This topic let me combine my interest in the intersection of macroeconomics and financial markets.

This thesis was written using LaTeX, OxMetrics and R. (Ghalanos, 2014; Trapletti and Hornik, 2015; Hlavac, 2015; Leifeld, 2013) The Rugarch-package was invaluable for GARCH-modeling with external regressors. Learning to do econometric analysis in R was one of the most rewarding aspects of writing this thesis.

Finding appropriate data, limiting the scope of the empirical investigation, and writing the thesis itself has been a very educational experience. This would not have been possible without the help of my thesis advisor, Kåre Johansen, who gave valuable advice and ideas and guided me through difficulties with patience and understanding. Hordaland Fylkeskommune also deserves a special thanks for providing office space for me. I would like to thank Professor Paul Van den Noord and Christophe André for answering my questions about their line of study in housing bubbles. I am most grateful to Pernille Løset Skrutvold and Arne Gundersen for proofreading this document. Lastly, I would like to thank my family and friends for their support. I dedicate this thesis to my parents.

Abstract

In 2001 Norway officially implemented a flexible inflation targeting monetary policy. This has coincided with escalated growth in house and rental prices. Studies have shown that, after implementing a flexible inflation target, countries tend to experience two characteristic trends compared to non-inflation targeting countries: house prices tend to increase at a greater rate, and inflation is lower and less volatile. As an addition to this line of research, this thesis investigates how flexible inflation targeting affects uncertainty, or volatility, in the housing market. This study contributes empirical evidence on how implementing flexible inflation targeting has affected volatility in house and rental prices in Norway, from 1979-2015. Using both GARCH and EGARCH models, the results generally suggest that flexible inflation targeting is associated with a decrease in the volatility of house and rental prices. This conclusion is generally robust because it holds for most specifications for the conditional mean and variance, and for both the market for owning and renting residential property in Norway.

Contents

1. Introduction

"It is with regret that we announce the death of inflation targeting. The monetary policy regime, known as IT to friends, evidently passed away in 2008."

- Jeffery Frankel (2012).

In the article following this quote, economist and Harvard professor Jeffery Frankel argues humorously that in the aftermath of the financial crisis, it has become clear that inflation targeting and flexible inflation targeting is not the optimal monetary policy rule. Amongst other things, he argues that flexible inflation targeting leads central banks to become too focused on the price level so that they ignore asset price bubbles and financial imbalances for too long. Others again argue that monetary policy or interest rate policies are not sufficient tools for achieving financial stability, and that regulations and macro-prudential tools are far more efficient (Bernanke and Gertler, 2000). Frankel thus joined an important debate on how, and if, the type of monetary policy regime affects activity in asset markets, and particularly in real estate markets.

Inflation targeting was first implemented in New Zealand in the 1990s and rapidly gained popularity throughout the world, but perhaps particularly in small open economies. The central point of inflation targeting is that the goal of the central bank should be to stabilize inflation around a certain target. When this strict target proved to be sub-optimal in some cases, some countries implemented flexible inflation targeting instead. Flexible inflation targeting dictates that the central bank not only strives to stabilize price levels but also to stabilize output growth (Palmqvist, 2007). A central component of the flexible inflation targeting regime is also transparency. It requires central banks to communicate clearly the inflation target or target range, the future interest rate paths and the rationales behind its decisions. The transparency in policy is often attributed to be one of the key factors in the success of inflation targeting countries. Norway implemented a flexible inflation targeting regime in 2001. Since then, several countries have joined the inflation targeting countries, including emerging economies (Broto, 2011).

As flexible inflation targeting became increasingly prevalent among central banks, so did the disagreements about the consequences of implementing flexible inflation targeting for the economy. One of the major points of concern was the effect the policy would have on financial stability. An important determinant of financial stability is the development of house price, since most purchases of residential property are debt-financed and because housing is often the largest asset in a household's portfolio. One of the central criticisms of inflation targeting is that, while it stabilizes inflation and output, it may neglect the build up of financial imbalances that do not directly affect inflation, but will have a negative effect on the economy in the long run (Borio et al., 2001).

As mentioned above, one such imbalance is that of housing prices. Frappa and Mésonnier (2010) show that inflation targeting countries have experienced a more substantial increase in housing prices than non-inflation targeting countries. However, there is little literature available on the relationship between inflation targeting and the volatility of house prices. When viewing housing mainly as a financial investment, price volatility can be interpreted as market risk. Thus, investigating how inflation targeting affects house price volatility gives indicates if the policy is associated with a change in risk in the housing market.

On the other hand, inflation targeting seems to have had many positive effects on the economy. Some authors argue that inflation targeting countries experience less volatility in output and inflation as a result of implementing the policy (Mishkin and Schmidt-Hebbel, 2007). The reduction in output and inflation uncertainty, along with the volatility of interest rates, are some of the most important determinants of house prices. So, assuming that inflation targeting is associated with periods of more stable price levels and output, then inflation targeting should also be associated with decreased volatility in housing prices.

The goal of this thesis is to investigate how inflation targeting has affected volatility in real house and rental prices. Specifically, I test whether or not there has been a regime shift in the volatility of real house prices and real rental prices in Norway. The Norwegian central bank, Norges Bank, is one of the institutions that has come the closest to the implementation of flexible inflation targeting, as it is dictated by theory (Palmqvist, 2007). The Norwegian economy is therefore an appropriate case study of how monetary policy affects volatility in house prices. I use both prices in market for renting and owning residential property to have several indicators of the development in the level of costs of housing in Norway. Tas (2012) used GARCH models to show that inflation targeting has lead to decreased inflation uncertainty. I use this methodology to investigate the effect of inflation targeting uncertainty in house price inflation, specifically.

In this study, I focus on real prices instead of nominal prices because empirical studies have already shown that inflation targeting countries have experienced lower inflation (Tas, 2012). Therefore, I focus on whether inflation targeting has lead to increased stability in the residential property markets, *beyond* that caused by the stabilization of the general price level. Put a different way: does the effect of inflation targeting on volatility in residential markets exceed its effect on the general price level? Therefore, both house prices and rental prices have been controlled for inflation. I use quarterly data for rental prices, house prices and inflation from the first quarter of 1979 to the first quarter of 2015.

This thesis is organized in the following way: Chapter 2 presents a model comparing the macroeconomic effects of inflation targeting and fixed exchange rates, and then illustrates how the two regimes affect the housing market in different ways. Chapter 3 reviews some recent studies on the impact of monetary policy on the housing market and the methodology used by recent studies to investigate regime shifts in the conditional variance. Chapter 4 describes the datasets used and presents general trends in those data. Chapter 5 discusses the GARCH-methodology and how it is implemented in this paper, while Chapter 6 presents the results of using this methodology. Finally, Chapter 7 comes to a few conclusions, presents some of the limitations of this study and proposes future modes of research.

2. Theory

This chapter first reviews how monetary policy with an inflation target and monetary policy with an exchange rate target compare. I then review how the two different regimes dictate that governments should respond to positive demand and supply shocks. Comparing how the two regimes respond to different shocks reveals how monetary policy was conducted differently before and after inflation targeting was implemented. I then present a model of demand and supply in the housing and real rental market and illustrate how the two different policies affect the housing market in different ways. This finally reveals that the two different regimes impact housing markets in very different ways, and thus makes it possibles to formulate hypotheses about how volatility in the residential property markets may have changed after flexible inflation targeting was first implemented, in the first quarter of 2001 (Gjedrem, 2005).

2.1 Inflation Targeting and Monetary Policy

Inflation targeting has rapidly gained popularity throughout the world since it was first implemented in New Zealand in 1990. The policy entails that central banks set the interest rate so as to keep inflation at a certain target level. However, most countries, including Norway, implement flexible inflation targeting, where the central bank's goal is to keep inflation within some range, but also to keep output somewhat stable. Since this thesis compares a period of a fixed exchange rate regime in Norway (1970-2001) with a period of inflation targeting (2001-2015), this section contains a model that compares how a central bank determines the interest rate under a fixed exchange rate regime with interest rate determination in an inflation targeting regime. This model was first presented by Rødseth (2000) and illustrates how interest rates and output are determined in the two different regimes.

2.1.1 A Static Model of Monetary Policy

Firstly, the model makes certain assumptions about the economic environment. The economy contains two goods: one that is domestically produced and one that is imported from abroad. The economic environment in stationary and free from any autocorrelations, which implies that expectations are constant for all exogenous variables. The citizens expect the central bank not to deviate from the target - the monetary policy is credible. The central bank only has one instrument, interest rates. Capital mobility is high, and aggregate demand is determined by the exchange rate and real interest rates. Employers determine wages before the nature of current shocks is known. The central banks adjusts interest rates after any exogenous shocks have been observed. Lastly, the bank has full knowledge of the economic environment. (Rødseth, 2000, p. 325)

The model can be summed up by the following relationships, where all variables are in log form:

$$y = \beta(p - Ep - w - u) \tag{2.1}$$

$$y = \alpha[i - (Ep - p)] + \gamma e + p_* - p + v \tag{2.2}$$

$$i = i_* + (Ee - e) + z \tag{2.3}$$

$$0 = ap + (1 - a)(e + bp_*) \tag{2.4}$$

Here, equation 2.1 represents aggregate supply, where y is output, p is the price level, Ep is the expected price level for the subsequent period, w and u are an exogenous shock to wages and demand respectively. Equation 2.2 is aggregate demand, where i is the domestic nominal interest rate, e is the exchange rate, and p_* is the price of imported goods. α is a positive constant and can be interpreted as the demand elasticity of the interest rate. γ is also a positive constant and can be interpreted as the demand elasticity of the real exchange rate. 2.3, the equilibrium condition in the foreign exchange market, and illustrates that the domestic interest rate, i, is equal to the foreign interest rate i_* plus the expected rate of depreciation of the exchange rate, $Ee - e$ and a stochastic risk premium. 2.4 represents the price level target of the central bank, where the inflation target is defined by a and b, so that if both $a = 0$ and $b = 0$, then the central bank has an exchange rate target and is not inflation targeting at all. If $a = 1$ and $b = 1$ the target is producer prices. If $a = 0$ and $b = 1$ the target is import prices.

By equating aggregate supply and aggregate demand, we can solve for the price level and output yields:

$$p = \mu[-\alpha(r\_* + z) + (1-b)(\alpha-\lambda)\rho_* + v + \beta(w-u) \quad (2.5)$$

$$y = \beta\mu[-\alpha(r_* + z) + (1-b)(\alpha+\lambda)\rho + v - \frac{\alpha-\lambda}{1-\alpha}(w+u)] \quad (2.6)$$

where μ is the inverse of the sums of all the price elasticities. $\mu = \frac{1-a}{(1-a)\beta+(\alpha)}$ Then, solving for e and i yields the central bank's reaction functions:

$$e = -p_* + \mu[\frac{a}{1-a}[\alpha(r_* + z) - v - \beta(w-u)] + (1-b)(\beta+\alpha+\gamma)p_*] \quad (2.7)$$

$$i = \frac{(i-a)(\beta-\alpha)+\gamma}{(1-a)\beta+\alpha+\gamma}(r_* + z) + \mu[\frac{a}{1-a}[v+\beta(w-u)] - (1-b)(\beta+\alpha-\lambda)p_*] \quad (2.8)$$

:

From equation 2.6 we can see the effects of different shocks given the target of the central bank. If the central bank targets inflation, or the price level, that means that $b = 1$ and a shock to foreign prices has no consequence for aggregate demand. If the central bank has a fixed exchange rate target, that means that $a = 1$ and a change in p_* increases aggregate demand. However, in terms of analyzing the effect of having an inflation target compared to a fixed exchange rate target on the Norwegian economy, the differences are best illustrated looking at shocks to aggregate supply and demand. This is because, depending on the nature of the exchange rate shock, it will to some extent take on the characteristics of a supply or demand shock (Røisland and Sveen, 2005).

2.1.2 Positive Demand Shock

This section illustrates how an exchange rate regime and an inflation targeting regime respond differently to shocks to aggregate supply and demand. The differences in the central bank's interest rate response under the two regimes determines how inflation targeting

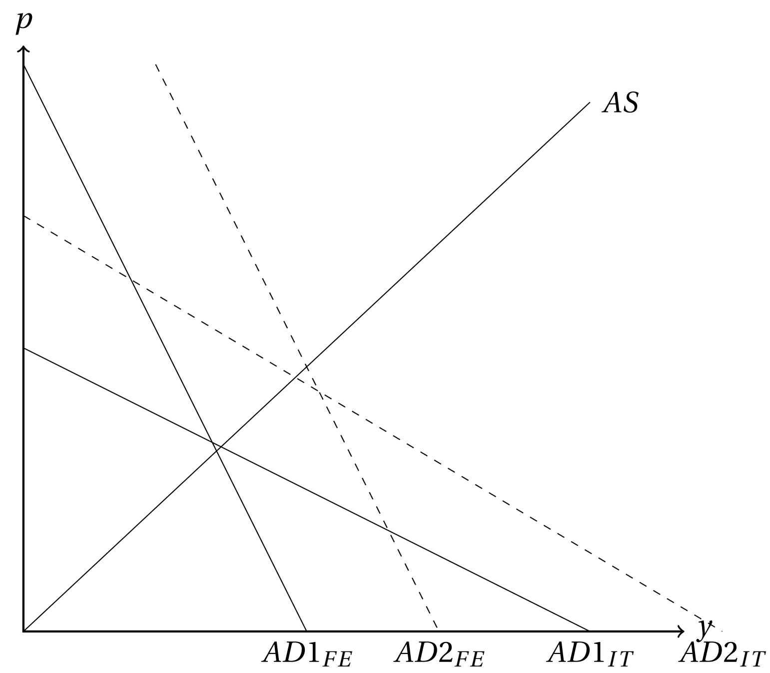

Figure 2.1: Positive demand shock with an inflation target (AD_{IT}) versus an exchange rate target (AD_{FE})

might impact house and rental price volatility.

A positive demand shock can be, for example, a decrease in the domestic savings rate or an increase in demand for the country's exported goods. Figure 2.1 illustrates that the slope of the aggregate demand curve is determined by the central bank's monetary policy. AD_{IT} is the aggregate demand curve of a country with an inflation target. AD_{FE} is the aggregate demand curve of a country with an exchange rate target. A positive demand shock puts upward pressure on inflation. Under an inflation target, to avoid increased inflation, the central bank has to increase interest rates, i. A higher interest rate has a dampening effect on aggregate demand which decreases inflation. Simultaneously, a higher interest rate also leads to appreciation of the exchange rate, causing imported goods to become cheaper and thus also stabilizing inflation (Røisland and Sveen, 2005).

In a fixed exchange rate regime, because both a and b are zero, we can see from equation 2.3 that the interest rate is determined by: $i = r_* + p_* + z = i_* + z$. Therefore, the domestic price level is not part of the central banks response function for interest rate and they keep the interest rate at its current level. They have to do this to avoid an appreciation of the exchange rate. As a result, both y and p increase. We can see from figure 2.1 that an inflation target stabilizes y and p more than an exchange rate target. Put a different way, the change

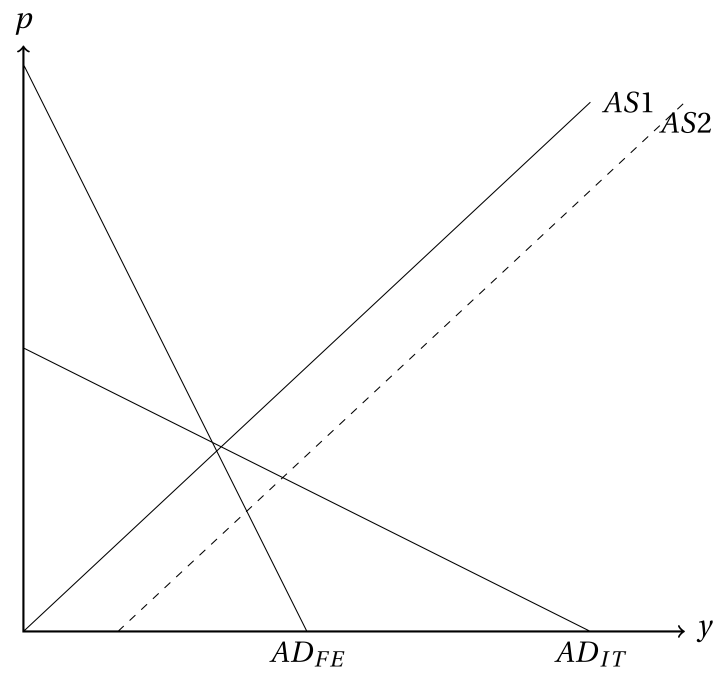

Figure 2.2: Positive supply shock with an inflation target (AD_{IT}) versus an exchange rate target(AD_{FE})

in price level and output is larger when the central bank has a fixed exchange rate target. This is because the slope of the aggregate demand curve is lower (Rødseth, 2000). What determines volatility here is the magnitude of the shifts in output and price level. We see that for a positive demand shock of the same size, the shift in output and price level is larger in an exchange rate regime. Therefore, when faced with demand shocks of the same magnitude, economic theory suggests that a fixed exchange rate regime will have higher volatility in price level and output compared to an inflation targeting regime.

2.1.3 Positive Supply Shock

A positive supply shock is an event that suddenly increases the availability of supply of a product or a service, for example, a decrease in the price of an important intermediate good. In figure 2.2 we see that the positive supply shock shifts the aggregate supply curve to the right. As with a demand shock, we see from the figure that the slopes of the aggregate demand curve determines the impact of the shock on p and y. The intuition behind this is that when supply increases, the price level will decrease because there are more goods available in the market. Compared to an exchange rate target, the inflation target increases the effect of a supply shock on y and decreases its effect on p. In an inflation targeting regime, the central bank is obliged to reduce interest rates when confronted with a positive supply shock. This stimulates demand and exacerbates the effect of the shock on y. In addition, the fall in interest rates also causes the exchange rate to depreciate, thus stimulation demand further (Rødseth, 2000).

From the graph, we see that the shift in output is higher in an inflation targeting regime, compared to an exchange rate regime, but that the shift in price level will be smaller for an inflation targeting regime. Therefore, when the two regimes are faced with an aggregate supply shocks of equal magnitude, the inflation targeting regime will tend to have higher volatility in output and the exchange rate regime will tend to have higher volatility of inflation.

2.1.4 Summary

To sum up, an inflation targeting regime has a lower effect on volatility in income when there is a demand shock, compared to a fixed exchange rate regime. However, when the economy is hit by a supply shock, the inflation targeting regime exacerbates the effect on aggregate output compared to a fixed exchange rate regime. Therefore, an inflation targeting regime will stabilize both price level and income if there is a high volatility of demand shocks on the economy and a low volatility of supply shocks on the economy. At the same time, the volatility of interest rates depends on whether the economy is hit by more shocks that affect the exchange rate or the price level.

2.2 Price Setting in the Real Estate Market

The housing market, whether the market for renting or owning real estate, is most commonly modeled using a stock-flow model. This is because housing is a durable good, that consumers buy once and then own for a longer period of time. Demand for durable goods depends on agents expectations of future income, interest rates, and future consumption in a greater sense than for non-durable goods because consumption can be postponed if the agent already has some stock of the good. [1] For example, if a consumer already owns their home, but would like to buy a new one, then his choice of when to purchase depends on his

[1] Appendix C has a summary of the mean characteristics of demand for durable goods.

expectation of future price and interest rates. If he thinks that he will be able to get a loan at a lower interest rate later or that he will have a higher income later, he can postpone consumption to later (Rødseth, 1992, p. 133). Therefore, demand for durable goods can, in some ways, be even more volatile than demand for non-durables, because consumers have the ability to postpone consumption until market conditions are more favorable (Hess, 1973).

To take into account the special features of durable goods demand, the use of stock-flow models to model housing markets has become increasingly popular. The crux of stock-flow models is that it separates between the stock of housing, which is unchangeable in the short term, and the flow of investment in residential property which reacts quickly to changes in the market. The residential capital stock is defined as the "accumulation of residential investment over time." This does not react quickly to changes in the market conditions. The residential capital stock is linked to the flow of residential investment through housing prices. While the residential housing stock reacts slowly to any changes in its determinants, house prices and investment react quickly (Steiner, 2010). The fact that adjustment of housing stock is slow is reflected by the fact that the construciton of new housing makes up a very little part of total housing supply. In Norway the annual contribution of new construction to the total housing supply, is about 1%, the rest is resale of houses in the "secondhand market" (Nou, 2002). There is many reasons for the slow adjustment of housing stock to change in market factors, one is that it takes a long time to build a new house, another is that housing depreciates at a relatively slow rate.

2.2.1 Demand for Home Ownership

Keeping in mind the special case for demand for durable goods, and the fact that housing is a durable good, we can now look at how to model demand in the housing sector. The basis for my analysis here, is the MODAG model of the Norwegian economy, which is used by Statistics Norway to model developments in the Norwegian macroeconomy. They have a separate model of house price formation (Boug and Dyvi, 2008). In the MODAG-model, demand for total housing stock is defined in the following way:

$$D_t = D^H(HP, Y, i_r) \tag{2.9}$$

where they assume that the demand for residential housing depends on house prices, HP, real disposable household income, Y, and real after tax interest rate, i_r and depreciation, though the latter is omitted to keep the model simple (Boug and Dyvi, 2008, p. 193). They assume that housing price and real interest rate has a negative effect on demand, but that income has a positive effect on demand. Demand has a relatively quick adjustment to a change in any of these factors. We can then invert this expression and solve for HP to find the market clearing price:

$$HP = HP^D(D, Y, i_r) \tag{2.10}$$

2.2.2 Demand for Rental Housing

The MODAG-model is a model for house prices not rental rates. MODAG does not incorporate price setting in the sector for rental rates. While the markets for home-ownership and home renting are strongly intertwined there is some difference in how demand for renting a home forms. While the choice between owning and renting is a complex one, that is beyond the scope of this thesis. The goal here is only to get an impression of what the difference is between formation of demand for renting and owning. While MODAG does not incorporate a model for the setting of prices in the market for renting, several models have been constructed for demand for rent. Rosen (1983) presents a model for stock-flow in the rental market. Here, demand for rentals, D^R is determined by the following prices:

$$D^R = D_t(R, U, Y, P) \tag{2.11}$$

where R is the price of renting one unit of housing services, U is the user cost of owner-occupied housing, Y is real disposable income, and P is the price level. Notice that the main difference in determinants for demand for renting versus owning is that the interest rate no longer is a determinant for rent. At the same time, the cost of the owner occupying the house is incorporated, along with the general price level. We assume there is a negative correlation between demand and rent, and demand and price level, but that the user-cost of owner-occupied housing and income are both positively correlated with demand. Along the same lines as above, we can solve this relation for rent instead of demand, yielding:

$$R^D = R(D, U, Y, P) \tag{2.12}$$

where we assume that there is a negative relationship between demand and rent, a positive relationship between rent and the user-cost of owner occupied housing, a positive relationship between real household disposable income and rent, and a positive relationship between the price-level and rent.

2.2.3 Supply of Housing

In this model, I assume that the supply of homes available for renting and owning is generated in the same way so as to simplify this theoretical discussion. This implies that the rental market is cleared at the end of each period so that there are no vacancies. In the short run, since the speed of adjustment of the housing stock is relatively sluggish, the housing stock is assumed to be fixed. In the MODAG model, investment in new residential housing stock, that is, investment in new construction, is defined as:

$$I_{newstock} = I(HP, P_C, P_L) \tag{2.13}$$

where P_C is the price of construction and P_L is the price of empty lots available for new housing construction. All other factors remaining the same, there is a positive relationship between housing price and investment in new housing stock, and a negative relationship between construction costs and costs of lots. Investment in new housing stock takes a long time and some will not be finished until three years after it started. The total housing stock, S_t can then be defined as:

$$S_t = I_t + (1-d)S_{t-1} \tag{2.14}$$

All together this means that the long run supply of housing stock can be defined by the following relationship:

$$S_t^{LR} = S_t(HP, P_C, P_L) \tag{2.15}$$

where d is the depreciation rate, and S_{t-1} is the housing stock at time $t-1$. There is a positive relationship between house price and long run supply of housing stock, and a negative relationship between the costs of construction and new lots and long run housing stock. In the long run, the equilibrium conditions are as follows:

$$S_t^{LR} = D_t \tag{2.16}$$

$$\Delta HP = HP_t - HP_{t-1} = 0 \tag{2.17}$$

$$\Delta S_t = S_t - S_{t-1} = 0 \tag{2.18}$$

This means that demand has to equal supply, the house prices are stable, and there is new investment to the residential housing stock.

Before moving on to look at the effect of different types of shocks on the housing market, it is important to note that inflation targeting countries in reality do not practice the strict inflation targeting described in section 2.1. Instead, they practice flexible inflation targeting, which means that they seek to stabilize both price levels and output. Depending on how the central bank weights the two targets, they will be able to accept higher inflation to stabilize output and vice versa. Therefore, the cases presented below are extremes. In reality, a flexible inflation targeting central bank will be willing to accept somewhat higher inflation so as to avoid a large destabilization of output. However, the case of strict inflation targeting underscores the main differences between the two regimes and is therefore presented here. Also, in the analysis of how monetary policy affects housing markets, I will not consider the effect on long run housing supply. This is because of the slow adjustment time and the relatively small portion of total housing stock that is new construction.

2.2.4 The Effects of a Positive Aggregate Demand Shock on Real House Prices

Given this model for the Norwegian housing market, we can now look closer at the effect of a change in the monetary policy target on the housing market. An increase in aggregate demand, caused the inflation targeting central bank to increase interest rates to avoid a general

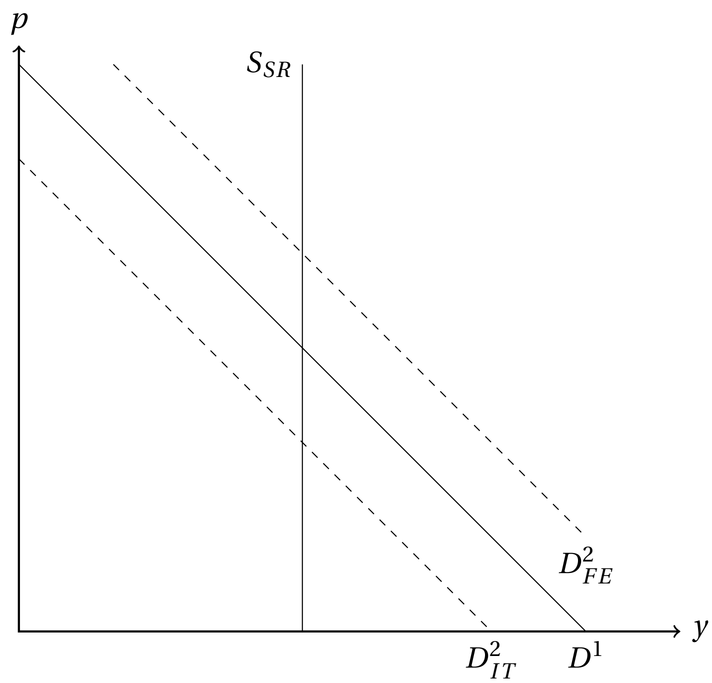

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Figure 2.3: Effect of positive demand shock on housing market. with an inflation target (D_{IT}) versus an exchange rate target(D_{FE})

increase in prices and stabilize output. According to equation 2.10 the increase in interest rates will lead to a decrease in house prices.

For the exchange rate targeting central bank, the increase in aggregate demand lead to a general increase in output and a decrease in price level. This implies an increase in income, and thus according to equations 2.9 and 2.10 this leads to an increase in demand for housing and an increase in house prices.

Figure 2.3 illustrates the effect of the aggregate demand shock combined with two different monetary policies on the housing market. S_{SR} is vertical because supply is constant in the short run as described above. As the figure shows, the demand curve in an inflation targeting regime shifts down as a result of the increase in interest rates, while the demand curve in a fixed exchange rate regime shifts up as a result of the increased income. What determines the volatility of housing prices will here be the magnitude of the shifts. If housing demand is more responsive to shifts in interest rate than to shifts in income, then volatility in housing prices during a demand shock will be higher in an inflation targeting regime than in a fixed exchange rate regime. In addition to the elasticity of housing prices with respect to income and interest rates, which regime leads to greater volatility in housing prices will also be determined by the volatility and persistence of demand shocks.

2.2.5 The Effects of a Positive Aggregate Demand Shock on Real Rental Prices

The main difference between the market for rentals and the market for homeownership in the stock-flow model, is the rental prices are not affected by interest rates. Therefore, in an inflation targeting regime where the central bank completely neutralizes the effect of the positive aggregate demand shock on the price level, the demand curve for rent will not shift at all. However, in a fixed exchange rate regime, both income and the price level increases. Thus, the demand for rentals increases and the price of rentals increases in a fixed exchange rate regime.

2.2.6 The Effects of a Positive Aggregate Supply Shock on Real House Prices

In section 2.1, a positive shock to aggregate supply leads prices and GDP to pull in opposite directions, while GDP increases, prices decrease. Therefore, the central bank has to lower interest rates to stabilize prices, but this further amplifies the increase in output. The decrease in interest rates, and the increase in income both cause house prices and demand for housing to increase. Thus, the demand curve in the housing market under an inflation targeting regime shifts outwards, as illustrated in figure 2.4.

Under an exchange rate regime, however, the positive shock to aggregate supply leads to an increase in output, but no change in the interest rate. Therefore, the increase in output is lower under a fixed exchange rate regime compared to an inflation targeting regime. This is reflected in the relative sizes of the shifts of the curves in figure 2.1.3.

2.2.7 The Effect of a Positive Aggregate Supply Shock on Real Rental Prices

When faced with a positive aggregate supply shock, in the inflation targeting regime, income increases, and therefore so does rental prices. The increase in income causes the demand curve to shift outwards. In an exchange rate regime, income increases, but the price level decreases. Therefore, the effect is ambiguous and whether or not rental prices increases depends on which variable has the greater effect on rental rates.

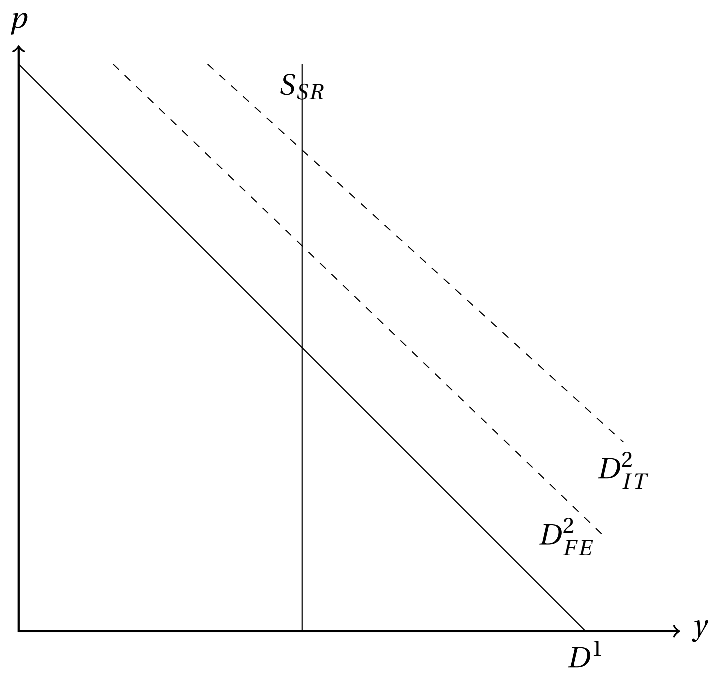

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Figure 2.4: Effect of positive supply shock on housing market. with an inflation target (D_{IT}) versus an exchange rate target(D_{FE})

2.3 Formulating Hypotheses: Connecting Theory to the Research Question

To sum up, economic theory predicts that monetary policy mainly impacts housing prices through income and interest rates. Monetary policy affects rental prices through the general price level and income. The two different regimes that Norway has had in the period this paper investigates - an exchange rate regime and an inflation targeting regime - imply that interest rates would respond to demand and supply shocks differently. An inflation targeting regime stabilizes prices and output when faced with a demand shock, while it may destabilize output when faced with a supply shock. Thus, the impact of the shocks on the housing and rental markets ultimately depends on *the central bank's response* to shocks. In section 2.2 we saw that monetary policy affects house prices through real disposable income, interest rates and price level. What determines whether or not inflation targeting increases or decreases volatility in the housing market is therefore: what effect does inflation targeting have on income, interest rates and the price level compared to an exchange rate regime? Theory and empirical evidence provides some indication of whether inflation targeting stabilizes or destabilizes these factors. [2]

To reiterate from the introduction, the goal of this thesis is to investigate whether or not the implementation of a flexible inflation targeting regime has affect volatility, or uncertainty, in the residential property market. The research question can be formulated has follows:

How does a flexible inflation targeting monetary policy affect uncertainty in the real house prices and real rental prices?

The next step in the analysis is to formulate some hypotheses based on how economic theory predict that a flexible inflation targeting regime will impact residential property prices.

As section 2.1 illustrated, how the monetary policy target affects output depends on the type of shock the economy faces. In general an interest rate target stabilizes output when faced with an aggregate demand shock, and destabilizes output when faced with an aggregate supply shock. An exchange rate regime cannot change the interest rate in response to these shocks, and therefore output is affected in both cases. However, when faced with a supply shock, the fixed exchange rate regime does not amplify the destabilizing effect of the shock by reinforcing it with an interest rate change. Therefore, a fixed exchange rate regime should destabilize income to a lesser extent than an inflation targeting regime when faced with an aggregate supply shock. Either way, the fixed exchange rate regime destabilizes income in both cases, but inflation targeting destabilizes income only in the case of a supply shock. If the economy is faced with a relatively equal amount of both types of shocks, theory suggests that inflation targeting should lead to less volatility in output and disposable incomes. Table 2.1 shows that in general, the time period after inflation targeting was implemented in Norway has been characterized by lower volatility in the growth rate of GDP for mainland Norway.

From economic theory it is clear that the volatility of the interest rates set by the central bank is determined by the frequency and magnitude of shocks the economy faces, as well as the aggressiveness of the central bank in responding to shocks, and how the shocks affect the target. From the section 2.1, it is evident that the central bank changes interest rates when

[2] Here it is important to note that Norway's exchange rate regime was not uniform from 1979 to 2001. After 1992, Norway abandoned a formally fixed exchange rate, devalued its currency, and the monetary policy target was to keep interest rates stable compared to a basket of European currencies (Gjedrem, 2005). However, the main target of monetary policy was still to stabilize the exchange rate. Therefore, for the purposes of this thesis, the two different regimes are treated as one "exchange rate regime."

	Entire Period	pre IT	post IT
Interest Rates	4.10	1.89	0.51
GDP growth	3.51	2.21	0.50
Inflation	1.91	1.18	0.49

Table 2.1: Standard deviations of central banks' interest rate, GDP growth and inflation. (Norges Bank, 2015; Statistics Norway, 2015b,a)

prices face upwards or downwards pressure in an inflation targeting regime. In an exchange rate regime, interest rates must match foreign interest rates, and interest rates therefore depend on foreign economies. As table 2.1 and figure 2.5 shows, volatility in the nominal interest rates set by the Norwegian Central bank has generally been lower after inflation targeting was implemented. This is not to argue that this is a direct results of inflation targeting - that is beyond the scope of this thesis. This simply indicates that the period after inflation targeting was implemented in Norway, has been marked by decreased volatility in interest rates (Statistics Norway, 2015a; Norges Bank, 2015; Statistics Norway, 2015b).[3]

Similarily, and perhaps most obviously, theory suggests that inflation targeting should succeed in stabilizing inflation compared to an exchange rate regime. This is simply because the central bank prioritizes stable prices more than a stable exchange rate. Table 2.1 confirms that the period after inflation targeting in Norway has been marked by a decrease in the variablility of inflation. The “post inflation targeting” period in Norway has been marked by decreased inflationary volatility. Therefore, real rental prices should also be less volatile since the general price level has become less volatile, but also since the difference between nominal and real household disposable income has become less volatile.

However, there is conflicting empirical evidence on whether or not the decreases in volatility of output, interest rates and inflation can be attributed to inflation targeting. It is therefore important to underline the fact that just because the “post inflation targeting” period in Norway has been marked by decreases in these variables, that does not mean that these decreases were *caused* by the change in monetary policy regime. This debate is discussed in more detail in section 3.2 Nevertheless, these are the main channels through which monetary policy affects house prices and rental prices and they therefore indicate how inflation targeting can have affected house prices.

[3] In the data for interest rate, Norges Bank's interest rate (“styringsrenten”) is used after Q2-1993, while the overnight loans rate is used before Q2-1993 since the central bank changed key rates at that time.

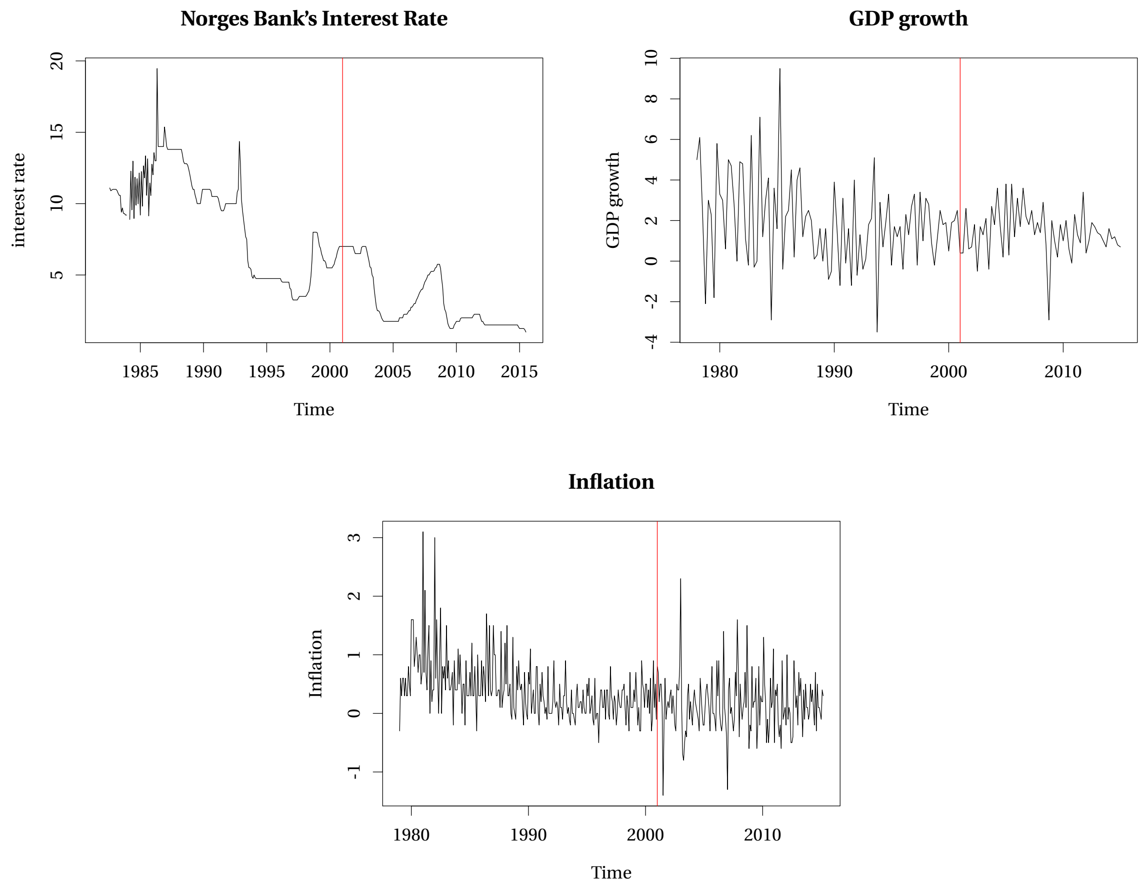

Figure 2.5: Plots of interest rate, GDP growth and inflation in Norway. The red line marks the start of flexible inflation targeting, that is, Q1 2001.

To sum up, to some extent economic theory and macroeconomic indicators from Norway indicate that inflation targeting should decrease house price volatility in Norway compared to an exchange rate regime because output, interest rates and inflation have become less volatile since inflation targeting was implemented. Economic theory suggests that it is through these variables that monetary policy affects house prices. Accordingly, if these variables have become more stabile, then that is a good indicator of what effect flexible inflation targeting will have on the Norwegian economy.

Given these development in interest rates, output and inflation, and what economic theory predicts about the housing market, I suggest the following hypotheses about the Norwegian housing market.

- **Hypothesis I:** After implementing a flexible inflation targeting regime in Norway, volatility in real house prices has decreased, so that there has been a regime shift in the volatility of real house prices.

- **Hypothesis II:** After implementing a flexible inflation targeting regime in Norway, volatility in real rental prices has decreased, so that there has been a regime shift in the volatility of real rental prices.

To investigate these hypotheses further, the next chapter looks at some of the more relevant empirical studies on the relationship between monetary policy and inflation targeting, and regime shifts in volatility.

3. Empirical Review

This chapter reviews some of the more central empirical studies that have been done concerning inflation targeting, house prices and GARCH-models. The chapter first reviews some of the empirical literature on how inflation targeting impacts the determinants of house and rental prices and then illustrates how other studies have modeled regime shifts in the conditional variance.

3.1 Inflation Targeting and House Prices

To this author's knowledge, there is not much literature on the relationship between inflation targeting and the volatility of house prices. However, evidence shows that inflation targeting countries tend to have higher growth in real estate market prices than countries that do not target inflation. Frappa and Mésonnier (2010) find that "on average, the adoption of inflation targeting is associated with an increase in the level of annual house price inflation of roughly 2.0 percentage points." This suggests that countries that follow an inflation targeting regime tend to have higher growth in real estate market prices, than countries that do not. He includes both countries with a flexible inflation targeting regime and a strict inflation targeting regime.

Along similar notes, Akram and Eitrheim (2008) look at the effectiveness of different interest rate rules in stabilizing financial market volatility. They experiement with housing price rules and stock market rules and find that all rules contribute to lower variance in the underlying inflation and output growth relative to their observed variances over the simulation horizon. However, the relative stability seems to be achieved at the expense of substantially higher volatility in interest rates, exchange rates and house prices. This indicates that which interest rate rule a central bank chooses has a profound effect on the volatility in other markets.

3.2 Inflation Targeting and the Determinants of House Prices

The empirical evidence is contradictory on whether or not inflation targeting has any effect on output volatility. There is a plethora for studies investigating the impact of inflation targeting on output volatility. For example, Ball and Sheridan (2004) find no difference in output stability between targeting and non-targeting countries. However, Mishkin and Schmidt-Hebbel (2007) compare inflation targeting countries' macroeconomic performance over time and with non-targeting countries, and find that inflation targeting in general is associated with a decrease in output variability. Their study also controls for any effect explained by fewer and smaller supply shocks.Thus, while the empirical evidence is contradictory on whether or not inflation targeting stabilizes output compared to an exchange rate regime, the "post-IT" period in Norway has been marked by lower output volatility in general. This indicates that the period should also be marked by lower volatility in house prices.

In addition, in a study comparing inflation targeting and non-targeting countries, Ball and Sheridan (2004) found that in general inflation targeting has no impact on the volatility of short-term or long-term interest rates, but that most countries have seen a decline in interest rates volatility regardless of monetary policy target. However, whether or not the decrease in interest rate volatility is a result of a changed monetary policy target or not, inflation targeting in Norway has coincided with a period of lower interest rate volatility. As a results, the inflation targeting period should also be characterized by decreased volatility in house prices.

It is important to note that in this case there are also some dissenting views in the empricial studies about whether or not inflation targeting is the *cause* of this decrease in variability. Again, Ball and Sheridan (2004) find that overall inflation targeting has no effect on inflation volatility while Mishkin and Schmidt-Hebbel, 2007 find that inflation targeting decreases inflation volatility.

In section 2.3, I argued that inflation targeting affects real house and rental prices through interest rates, real disposable income and the price level. It is important to underline that most of the empirical literature notes a general decrease in the volatility of these variables in many countries, but that the disagreement lies in whether or not this decrease is associated with inflation targeting or not. It is beyond the scope of this thesis to investigate the causal effect of inflation targeting on these variables, and I therefore do not control for the relationship between inflation targeting and these variables in the methodology.

3.3 Regime Shifts and GARCH Models

The goal of this paper is to investigate whether or not there has been a regime shift in volatility in residential property markets as a results of inflation targeting. One of the most common ways to investigate the properties of volatility is using the GARCH model.

This study is inspired by the methods used in Tas (2012). Tas investigates whether or not inflation targeting has had a significant impact on volatility for inflation targeting countries using GARCH and PGARCH models for panel data. He models the inflation targeting regime as a dummy variable that takes the value before inflation targeting was implemented, and one after inflation targeting was implemented. By including this dummy variable in the conditional variance, he is able to prove that there has been a signficant regime shift in the conditional volatility of inflation.

Other studies also use GARCH-models to estimate regime shifts in the conditional volatility. Elyasiani and Mansur (1998) use a GARCH-M model and dummy variables for the implementation of new monetary policy regimes to investigate whether the regime shifts have a signficant impact on bank stock returns. They find that regime shift generally do impact bank stock returns. Dummy variables have also been used to account for the effect of monetary policy regime shifts on exchange rates. (Lastrapes, 1989).

Thus, GARCH models and dummy variables make it possible to model any changes to the conditional volatility. This is a commonly used technique when investigating the effect of a change in monetary policy target on the economy. The next chapter details how I use GARCH models to investigate the effect of inflation targeting on volatility in real house and rental prices.

4. Data and Descriptive Statistics

Variable	Data Set	Source	Time Period
House Price Index	Long series of Property Indexes	Bank of International Settlements (BIS)	Q1 1979 - Q1 2015
Rent	Rental expenditure from CPI	Statistics Norway	M01 1979 - M03 2015
Consumer Price Index	CPI	Statistics Norway	M01 1979 - M03 2015

Table 4.1: The sources and definitions of the various datasets used in this thesis.

Given the empirical literature on the subject, it is clear that it is possible and relevant to investigate regime shifts in volatility. This chapter presents the data and descriptive statistics for the two main variables used in this paper, real house price inflation and real rental inflation. I use graphs and descriptive statistics as an initial indication of whether or not there has been a decrease in volatility in the real house and rental prices. Table 4.1 summarizes the most vital information about each dataset used, including the consumer price index data set that has been used to calculate real prices (BIS, 2015; Norges Bank, 2015; Statistics Norway, 2015a).

For each variable, I look at both change from quarter to quarter, and change from year to year. I include both measures of inflation so that I can control for seasonal effects in two different ways, and thus increase the robustness of any conclusions I reach. The quarter to quarter series can be controlled for seasonal effects by using seasonal dummies, while the year to year growth rate removes any seasonal effects by subtracting the first quarter one year form the corresponding quarter in the subsequent year. This chapter first presents descriptive statistics for real house price inflation and then for real rental price inflation.

4.1 Real House Price Inflation

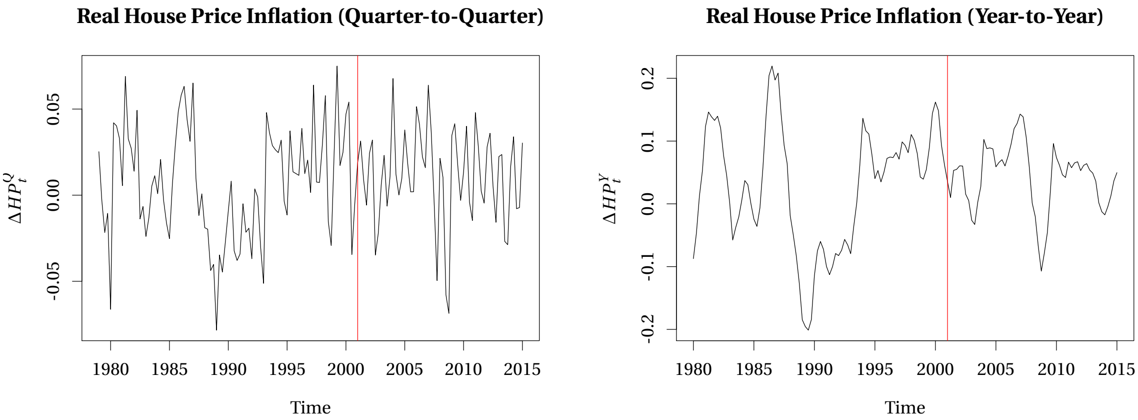

Figure 4.1: Plots of the change in real house price inflation. The red line indicates the start of inflation targeting, i.e. Q2 2001.

To measure real house price I use Norwegian house price index as provided by the Bank of International Settlements. The index is a measure of the average nominal price per square meter of residential property. It does not include property used for business purposes. The index is compiled by the Bank of International Settlements from several different time series provided by Statistics Norway. It has been adjusted for structural breaks. However, one drawback of using these data is that the underlying time series can make use of different methodologies and may cover different types of dwelling and geographic areas.

I define the quarter to quarter growth rate of real house prices, ΔHP_t^Q, and year to year growth rate, ΔHP_t^Y ,in the following way:

$$\Delta HP_t^Q = \frac{HP_t - HP_{t-1}}{HP_{t-1}} - i_t \approx (ln(HP_t) - ln(HP_{t-1})) - i_t \tag{4.1}$$

$$\Delta HP_t^Y = \frac{HP_t - HP_{t-4}}{HP_{t-4}} - i_t \approx (ln(HP_t) - ln(HP_{t-4})) - i_t \tag{4.2}$$

Figure 4.1 illustrates how real house price inflation has changed since 1979. The graphs indicates that since inflation targeting was introduced, both the quarter to quarter and year to year growth rates might have become less volatile, since the magnitude of the fluctuations appears to be somewhat smaller. This reduction in volatility from one monetary policy regime to another is confirmed by table 4.2. The table shows that the average standard deviation of both series has decreased substantially since inflation targeting was introduced. In the year to year series, it has almost been reduced by half. This reduction corroborates the hypotheses proposed in section 2.3, where I hypothesized that inflation targeting should lead to decreased variability in real house price and real rental prices.

I also test for stationarity in the first difference of real house prices, using the Augmented Dickey Fuller test. The test indicates that for up to six autocorrelation lags of real house price growth, we can reject the null hypothesis that real house price growth is a non-stationary stochastic white noise process. (Trapletti and Hornik, 2015) This suggests that the series is suited for GARCH modeling and that we can avoid spurious regressions.

An interesting observation is that price volatility or risk in the market, has decreased, while the average price has increased. This is surprising because with financial assets, we expect there to be a positive relationship between risk and return. That is, if volatility decreases, all other things remaining the same, we would expect prices to decrease.

In addition, figure 4.1 also illustrates that there seem to be significant seasonal effects at work in the quarter to quarter growth rate. The graph for HP_t^Q seems to have far more frequent fluctuations. Simultaneously, the graph for HP^Y seems to be far "smoother" than HP_t^Q, suggesting that this series eliminates the seasonal effects. This is confirmed by the data in table 4.3. This table illustrates the results of a regression of seasonal dummies on both series. While two of the three seasonal dummies are significant in the quarter to quarter growth rate, none are significant for the year to year growth rate. These results confirm that the HP_t^Q should be corrected for inflation but HP_t^Y should not.

Time Period	Mean	Min	Max	Std. Dev.
Real house price inflation, quarter to quarter growth				
Q1 1979 - Q1 2015	0.846%	-7.837%	7.497%	0.03082
Q1 1979 - Q1 2001	0.693%	-7.837%	7.497%	0.032632
Q2 2001 - Q1 2015	1.566%	-7.264%	7.173%	0.026736
Real house price inflation, year to year growth				
Q1 1980 - Q1 2015	3.405%	-20.12%	21.951%	0.082906
Q1 1980 - Q1 2001	2.848%	-20.12%	21.951%	0.09788
Q2 2001 - Q1 2015	4.239%	-10.717%	14.296%	0.051911
ADF-Test (lag length 6)	Test statistic	p-value		
Real house price inflation (Q-to-Q)	-3.962	0.01309		
Real house price inflation (Y-to-Y)	-3.666	0.02985		

Table 4.2: Descriptive statistics for real house price inflation, both change from quarter to quarter and year to year. The Augmented Dickey Fuller test is included at the bottom. Std. Dev. stands for standard deviation.

	Dependent variable:	
	ΔHP_t^Q	ΔHP_t^Y
	(1)	(2)
Q1	0.016**	−0.001
	(0.007)	(0.020)
Q3	0.032***	−0.001
	(0.007)	(0.020)
Q4	0.003	−0.00003
	(0.007)	(0.020)
Constant	−0.004	0.034**
	(0.005)	(0.014)
Observations	145	141
R^2	0.173	0.00002
Adjusted R^2	0.156	−0.022
Residual Std. Error	0.028 (df = 141)	0.084 (df = 137)
F Statistic	9.853*** (df = 3; 141)	0.001 (df = 3; 137)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4.3: Regression of seasonal dummies on real change in house price and year-on-year real change rental price.

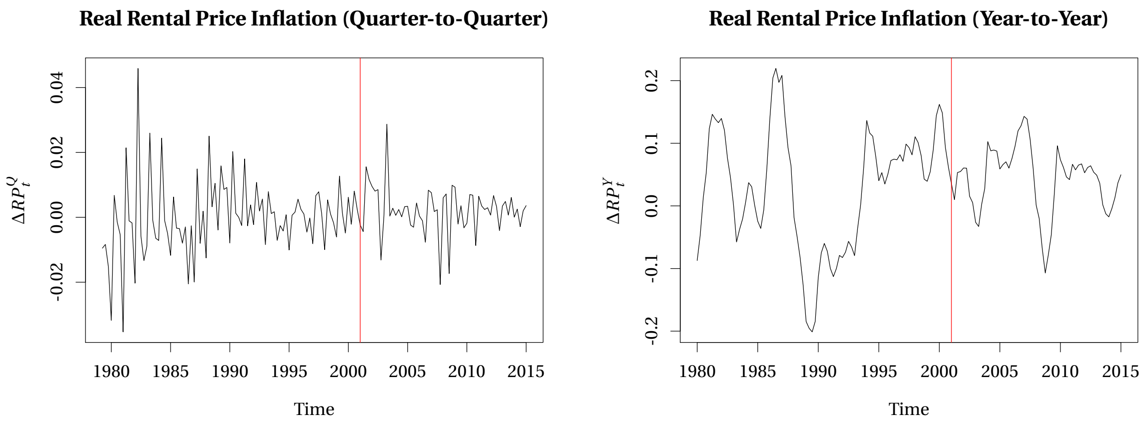

Figure 4.2: Plots of the change in real rental price inflation. The red line indicates the start of inflation targeting, i.e. Q2 2001.

4.2 Real Rental Price Inflation

I define the quarter to quarter real rental price growth rate, ΔRP_t^Q, and the year to year real rental price growth rate, ΔRP_t^Y in the following way:

$$\Delta RP_t^Q = \frac{RP_t - RP_{t-1}}{RP_{t-1}} - i_t \approx (ln(RP_t) - ln(RP_{t-1})) - i_t \tag{4.3}$$

$$\Delta RP_t^Y = \frac{RP_t - RP_{t-4}}{RP_{t-4}} - i_t \approx (ln(RP_t) - ln(RP_{t-4})) - i_t \tag{4.4}$$

The graphs of real rental price in figure 4.2 generally show the same trend as noted for house price inflation. Both the quarter to quarter and year to year growth rates appear to slightly less volatile after infation targeting than before, as marked by the red line. These results are confirmed by table 4.4, where each variable's standard deviation is lower after inflation targeting than before inflation targeting. The Augmented Dickey Fuller test suggests that the first difference of real rental prices is stationary.

The data for rental price used in this study are part of the Consumer Price Index collected every year in Norway. The data details the average expenses of a household on renting housing services. For households that do not rent, but own their homes, the rental price is extrapolated from the average rent in the area. One drawback of the data is therefore that it is not necessarily an exact measure of the average price of renting a home, but it is nonetheless a adequate indicator of the price level for purchasing housing services(Boug and Dyvi, 2008).

The graph for year to year growth also appear far more “smooth” than the graph for quarter to quarter growth, indicating that there are significant seasonal effects at work in the quarter to quarter growth rate. This is confirmed by the results in table 4.5, where all but one quarterly dummy is significant for the quarter to quarter growth rate, while none are significant for the year to year growth rate. The year to year growth rate therefore appears to eliminate seasonal effects.

Time Period	Mean	Min	Max	Std. Dev.
Real rental price inflation, quarter to quarter growth				
Q1 1979 - Q1 2015	0.085%	-3.532%	4.59%	0.010
Q1 1979 - Q1 2001	-0.006%	-3.532%	4.59%	0.012
Q2 2001 - Q1 2015	0.219%	-2.068%	2.87%	0.0075
Real rental price inflation, year to year growth				
Q1 1980 - Q1 2015	0.38%	-5.055%	4.557%	0.017
Q1 1980 - Q1 2001	0.041%	-5.055%	3.223%	0.018
Q2 2001 - Q1 2015	0.892%	-1.683%	4.557%	0.011
ADF-test (lag length 6)	Test statistic	p-value		
Real rental price	-4.0295	>0.01		
Real rental price Y-on-Y	-3.8282	0.01964		

Table 4.4: Descriptive statistics for real rental price inflation, both change from quarter to quarter and year to year. The Augmented Dickey Fuller test is included at the bottom. Std. Dev. stands for standard deviation.

In general, the average volatility, or standard deviation, of both real house price and real rental prices have decreased since inflation targeting was implemented in 2001 in Norway. If we think about volatility in the market as an independent stochastic process, the decrease in standard deviations indicate that there may have been a permanent change in this process at the time when inflation targeting was implemented. However, to test whether there has been a significant change in the “volatility process,” we need a more rigorous modeling approach. As discussed in chapter 3, a common way to investigate regime shifts in volatility is using GARCH models, which make it possible to model the time varying volatility of any model exhibiting time-varying volatility. The next chapter therefore describes the GARCH models implemented in this thesis to investigate whether or not there has been a significant regime shift.

	Dependent variable:	
	ΔRP_t^Q	ΔRP_t^Y
	(1)	(2)
Q1	-0.004^{*}	-0.001
	(0.002)	(0.004)
Q2	0.009^{***}	-0.001
	(0.002)	(0.004)
Q3	0.0001	
	(0.002)	(0.004)
Constant	-0.0004	0.004
	(0.002)	(0.003)
Observations	144	141
R^2	0.224	0.0004
Adjusted R^2	0.208	-0.022
Residual Std. Error	0.009 (df = 140)	0.016 (df = 137)
F Statistic	13.488^{***} (df = 3; 140)	0.017 (df = 3; 137)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4.5: Regression of seasonal dummies on real rental price and year-on-year real rental price.

5. Methodology

The thesis uses generalized autoregressive heteroscedastic (GARCH) models to investigate whether or not there has been a regime shift in the conditional volatility of real house prices and real rental rates. The advantages of GARCH regressions are firstly that they make it possible to take advantage of any serial correlation in the dependent variable to model volatility as a separate process. This makes it possible to investigate if there has been any persistent and significant change, or a regime shift, in the stochastic volatility process. In chapter 3, we saw several examples of how researchers have used GARCH-models in combination with dummy variables to account for the effects of a regime shift on conditional volatility. This chapter illustrates how I use GARCH models to check if there has been a regime shift in the volatility. It explains the two different GARCH-models used in this paper, the GARCH-model and the EGARCH-models, and illustrates how the hypotheses outlined in the hypotheses section can be tested using these models.

5.1 Modeling Flexible Inflation Targeting as a Regime Shift

To be able to test my hypotheses, I will model flexible inflation targeting as a dummy variable that takes the value 1 in a period after the first quarter of 2001, when inflation targeting was introduced. And the value 0, if not. Formally, the dummy variable is defined in the following way:

$$IT = \begin{cases} 1, & \text{if } t > Q1,2001 \\ 0, & \text{otherwise} \end{cases} \tag{5.1}$$

The base value for the regression then becomes a fixed exchange rate regime for monetary policy. That is, all coefficients will show the value under an exchange rate regime, and any changed value of the intercept will be reflected by the value on the coefficient of IT_t. This is equivalent to the methodology used in Tas (2012) to estimate regime shifts in the conditional variance of inflation.

5.2 GARCH-models

One of the key assumptions of basic econometric models estimated using Ordinary Least Squares (OLS), is that the variance of the regression is constant or that the model exhibits homoskedasticity. However, many financial variables exhibit volatility clustering or periods with very high and very low volatility. In 1982, Engle introduced the Autoregressive Conidi-tional Heteroskedasticity model (ARCH) that exhibit heteroskedasticity, but they also make it possible to estimate and forecast the variance of such time series (Enders, 2010). It is these properties that have made GARCH- and ARCH-models increasingly popular in the past 15 years.

The GARCH models are defined in the following way:

$$y_t = a_0 + \gamma_1 IT_{t-1} + \sum_{i=0}^{5} a_i y_{t-i} + \varepsilon_t \tag{5.2}$$

$$\varepsilon_t = v_t \sqrt{h_t} \tag{5.3}$$

$$h_t = \alpha_0 + \gamma_2 IT_{t-1} + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{5.4}$$

where 5.2 is the conditional mean, 5.3 is the residual error term which is spit into two parts - a white noise process, v_t, and a serially correlated term h_t. The h_t term is modeled as a AR(1) model, or a GARCH(1, 1) process, which is described by equation 5.4. y_t is the depen-dent variable, whether real house prices or real rental prices. The IT dummy is included in both the conditional mean and the conditional volatility. This is to control for the effect that inflation targeting might have on the general price level, before estimating volatility (Enders, 2010).

Taking advantage of any serial correlation in the residual, it is possible to think about the current fitted variance, h_t as a weighted function of some relevant information. Specifically, α_0, and γ_2 after flexible inflation targeting was implemented, are the long-term average volatilities. Notice that the implementation of a flexible inflation targeting regime is modeled as a shift in the intercept of the the conditional volatility. $\alpha_1 \varepsilon_{t-1}^2$ is information about the volatility in the previous period and $\beta_1 h_{t-1}$ is information about the fitted variance in the previous period (Brooks, 2014, p. 428).

In GARCH-models, it is most common to estimate the conditional mean and variance simultaneously. These are estimated using maximum likelihood since the models are non-linear. It is also important to note that the GARCH-model imposes a non-negativity constraint on α_0, α_1 and β_1, because the variance of y_t by definition can never be negative (Brooks, 2014, p. 439). [1]

In this paper, for both real house price inflation and real rental price inflation, I estimate the mean model as an AR(5) process with various restrictions on the mean. I start by holding all the coefficients on the autoregressive terms equal to zero so that $a_1 = a_2 = a_3 = a_4 = a_5 = 0$, and I then incrementally let remove the restriction on each coefficient. I do this to increase the robustness of my hypothesis-test, and to see if they hold when accounting for an increased amount of autocorrelation in the prices. I estimate the mean for up to five lags because the partial autocorrelation function indicates that this is where any autocorrelations stop being significant for both variables.

While my methodology is very similar to that used by Tas (2001) to check for a regime shift in inflation uncertainty, it differs in that Tas uses panel data, while I use data for a single country, but two different segments of the housing market, the market for owning and renting. While there are advantages to both approaches, the advantage of using only one country, but two different markets, is that it makes it possible to test how robust the hypothesis is for several specifications of the mean and across different segments of the residential property market.

The GARCH-model has become increasingly popular in the economic and financial literature, exactly because it not only makes it possible to avoid serial correlation in models, but also because it is possible to investigate the patterns of time-dependent volatility them-

[1] When estimating the models, I restricted the value of γ_2 to be between -1 and 1, as is recommended in the manual for the rugarch statistics package (Ghalanos, 2014).

selves. This makes it easier to, for example, forecast risk in the market, but also to find explanations for why market risk has changed by investigating whether there have been any regime shifts or not.

5.3 EGARCH models

As a sensitivity test, I then proceed to estimate exponential GARCH (EGARCH) models to further test any conclusions reached from the GARCH models. This model makes it possible to allow negative shocks to volatility to have a greater effect on volatility than positive shocks. The conditional mean is defined in the same was as in equation 5.2. The conditional variance is defined in the following way:

$$ln(h_t) = \alpha_0 + \alpha_1 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \lambda_1 |\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}| + \beta_1 ln(h_{t-1}) + \gamma_2 IT_{t-1} \tag{5.5}$$

One of the big drawbacks of the regular GARCH-model is that it imposes non-negativity constraints on the coefficients when estimating the conditional variance, as mentioned above. The EGARCH model estimates $ln(h_t)$ so that even if the estimated value of $ln(h_t)$ is negative h_t can never be negative. Another difference is that the EGARCH-model makes use of the standardized residuals, which some argue makes for a more natural interpretation of the size and persistence of shocks. (Enders, 2010, p. 156)

Another advantage of the EGARCH model is that it makes it possible to account for any asymmetric effects of stochastic shocks to the conditional variance, that is if negative shocks have a different effect than postive shocks. This is accounted for through the λ_1 in equation 5.5 (Brooks, 2014, p. 439). If the term $\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$ is negative the effect of the shock on $ln(h_t)$ is $-\alpha_1 + \lambda_1$, and if the same term is positive the effect will be $\alpha_1 + \lambda_1$. ((Enders, 2010, p. 156)) Therefore, I use the EGARCH(1, 1)) model to check if the conclusions from the GARCH(1, 1) model hold when accounting for asymmetric effects and relaxing the non-negativity constraint. However, a disadvantage of the model is that it is more complicated than the GARCH(1, 1) model.

The EGARCH models I estimate are identical in the mean to the GARCH models. The difference is in the specification of how h_t is generated, as in 5.5. The model removes any non-negativity restrictions imposed in regular GARCH models because h_t now is in log-form. In addition, the term behind λ_1 makes it possible to capture any asymmetry in the conditional variance process. That is, the strength of the EGARCH model is that it makes it possible to let negative shocks have a higher impact on conditional volatility than positive shocks (Enders, 2010).

Several authors have documented the tendency for housing markets to exhibit asymmetric effects of shocks on the conditional volatility in housing markets. For example, Lee (2009) documents significant asymmetric effects in the Australian housing market (Lee, 2009). Similarly, Morley and Wei (2012) document significant asymmetric effects in the conditional variance of house prices in the US housing market. Along the same lines, Tas (2012) also uses both a regular GARCH and a GARCH model that accounts for asymmetries in the conditional variance to confirm his hypothesis of decreased inflation uncertainty as a result of inflation targeting. Therefore, controlling for asymmetric effects of shocks makes it possible for this paper to test for a regime shift in house price volatility using a similarly robust environment to Tas.

5.4 Testing Hypothesis 1 and 2

Using these models, I can test both hypothesis 1 and hypothesis 2 in increasingly robust models and thus estimate whether or not there has been a regime shift in the volatility process. This can be done using a simple t-test. However, it is important to note that when estimating the standard errors, I use the Bollerslev-Wooldridge standard errors instead of regular standard errors, since the model is heteroscedastic. The hypotheses can be formulated as follows:

$$H_0{:}\gamma_2 = 0 \tag{5.6}$$

$$H_1{:}\gamma_2 \neq 0 \tag{5.7}$$

Here, equation 5.6 is the null hypothesis that there has been no regime shift in the conditional volatility. 5.7 is the alternative hypothesis. Accepting the alternative hypothesis indicates that there has been a regime shift. In this thesis, I use various specification of the conditional mean and the conditional volatility to test these hypotheses in as robust an environment as possible. In general, if the hypotheses hold for several different specifications, this indicates that there has been a regime shift.

The test statistic is given by $t_{\gamma_2} = \frac{\gamma_2}{se(\gamma_2)}$. The null hypothesis is rejected if $t_{\gamma_2} > c$. Here, c is a critical value for the students t-distribution, at a given significance level.

To sum up, using a dummy variable for flexible inflation targeting and a GARCH(1, 1) model, it is possible to test whether or not inflation targeting is correlated with a regime shift in the conditional variance of real house and rental prices in Norway. I add several modifications to the models to test whether the regime shift is significant in an increasingly robust environment. Firstly, I estimate the mean model with up to five autoregressive terms. Any variation in real prices that can be explained by prices in preceding periods will then be removed from the residual, ε_t. This makes it possible to test if the hypothesis holds as the conditional mean explains more of the variation in the residual. Secondly, I use the EGARCH(1, 1) model to account for any asymmetric effects of shocks to conditional volatility. It is possible that negative shocks have a greater impact on volatility than positive shocks. Therefore, including the EGARCH(1, 1) model as a sensitivity test, makes it possible to see if the hypotheses hold when the volatility process becomes increasingly complex. Lastly, I test the hypotheses across both the markets for renting and owning residential property. This is to see the regime shift is consistent for the two main residential property markets in Norway. The goal of adding these complexities to the original model is to reach as robust a conclusion as possible. The next chapter discusses the results of estimating these models.

6. Analysis

This chapter contains the results for estimating real house price and real rental price volatility using the models described in the methodology chapter. I first review and comment on the results from the GARCH models, and then the EGARCH models. In general, the GARCH models confirm the hypotheses by predicting that flexible inflation targeting has had a significant and negative impact on the volatility of both real house and rental prices. The EGARCH models also estimate that inflation targeting has a negative effect on the volatility of real house and rental prices. However, this effect is generally not significant.

6.1 GARCH-models

6.1.1 Real House Price Inflation

The results from the GARCH model estimation can be found in table 6.1. The table contains results both for year-on-year and quarter-to-quarter growth rates, and with various restrictions on the mean model.[1] Firstly, I note that γ_2, the coefficient on the flexible inflation targeting dummy variable is estimated to be negative in all the models. In the models for quarter-to-quarter growth in real house price inflation, γ_2 is significant in all the models but AR(5). This seems reasonable since the AR(5) model includes the most autocorrelating lags, and therefore decreases the size and variation in the residual substantially.

For the quarter-to-quarter growth rate the "stationary white noise" model, which does not include autoregressive lags, γ_2 is significant and negative. This trend continues as the num-

[1]Appendix A contains the results from several estimations of the mean models, with and without the the IT_{t-1} dummy in the mean, and both controlled and not controlled for seasonal effects. In general, the results align with those presented in tables 6.1 and 6.2.

ber of autoregressive lags is increased, however, there is a large drop in the magnitude of the coefficient from the model with no autoregressive lags to the AR(1) model. This is expected, since the GARCH-model technically estimates the variance of the residuals, and not the volatility of the real house price itself. Thus, when no autoregressive lag is included, the residual contains any variation of real house prices beyond its mean. Put a different way, when not including any autoregressive lags the residual contains all the variation of real house prices. As the number of autoregressive lags in the mean model increases, the magnitude of γ_2 tends to decrease. This is also expected, as the residual variance becomes smaller as the mean explains more of the variation in real house prices. The AR(5) model is the only model where flexible inflation targeting does not have a significant effect on the variance of the residual. This is likely because the mean model now explains more of the variation in real house prices. The AR(5) model is most likely somewhat over-specified since there are few significant variables in the conditional mean and variance.

When it comes to the interpretation of the results, it is important to note that the dependent variable is in percent. Thus, when interpreting γ_2 in the "stationary white noise" model for the quarter to quarter growth rate, it indicates that after the flexible inflation targeting regime was implemented, in general, the variance in real house prices decreased by about 0.06 percentage points. But, when interpreting γ_2 when the mean includes autoregressive lags, the interpretation changes slightly. For example, in the AR(1) model for quarter to quarter growth the value of γ_2 suggests that after the implementation of the flexible inflation targeting regime, residual volatility was decreased by 0.0013 percentage points, if the mean is modeled as an AR(1) process.

In general, for the quarter-to-quarter growth rate it is also clear that γ_1 is not significant in any of the model specifications for the mean. While not central to the hypotheses, this indicates that flexible inflation targeting did cause a significant regime shift in the *level* of real house prices. However, the results clearly indicate that even when accounting for the potential effect of flexible inflation targeting on the general level of real house prices in the mean model, flexible inflation targeting still had a negative impact on the conditional variance of the residual.

On the other hand, for the year-to-year growth rate, in the "stationary white noise model" the coefficient in the flexible inflation targeting dummy is negative, but not significant, nor is it significant in the AR(1) model. This indicates that when removing variance in real house prices that can be explained by real house prices in previous periods, flexible inflation targeting is correlated with a regime shift in the residual variance. The main difference between the results is that the year to year growth rate removes seasonal effects, not by using quarterly dummies, but by calculating the growth rate from quarter to quarter. It is not clear which method adjusts for seasonality in a better way than the other, but the results indicate that the method of seasonal adjustment affects the results in a significant way.

In comparison to the quarter-to-quarter growth rate, there are more significant autoregressive lags in the mean model, and γ_1 is significant in the AR(2) and AR(4) models. Thus, when removing seasonal effects by calculating the year-to-year growth rate, the autoregressive mean model appears to explain more of the variation in real house price than otherwise.

Nevertheless, the general trend in the results is that flexible inflation targeting is correlated with a decrease in the volatility when modeling real house prices as a stationary white noise process. When accounting for any serial correlation between current and previous lags of real house prices, the effect of a flexible inflation targeting consequently remains negative and is significant in most cases. This result is robust both when controlling for seasonal effects using seasonal dummies and when calculating the year-to-year growth rate. Depending on the specification of the conditional mean, the effect of the presence of a flexible inflation targeting regime on residual variance ranges from about 0.06 percentage points to 0.0013 percentage points. Thus, the results from the GARCH(1, 1) estimations strongly support hypothesis 1, or that the presence of a flexible inflation targeting regime is correlated with a decrease in volatility in real house prices.

	Real House Price Inflation (Quarter to Quarter)						Real House Price Inflation (Year to Year)					
	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
a_0	−0.0101294	−0.0123421*	−0.0127115*	−0.0144242	−0.0133862*	−0.0155020	0.0703329***	−0.0630997***	−0.0473259	−0.0066621	0.0044496	0.0172447
	(0.0080153)	(0.0072301)	(0.0070071)	(0.0121882)	(0.0079960)	(0.3264027)	(0.0150725)	(0.0091802)	(0.0485759)	(0.0318509)	(0.0737185)	(0.0309966)
γ_1	0.0047086	0.0048143	0.0051982	0.0085253	0.0076277	0.0082989	−0.0109218	−0.0405727***	−0.0150057	0.0291780	0.0270608***	0.0040391
	(0.0075324)	(0.0079562)	(0.0090770)	(0.0349125)	(0.0095701)	(1.3331201)	(0.0140878)	(0.0034565)	(0.1080126)	(0.0438089)	(0.0103054)	(0.0252132)
a_1		0.4579320***	0.4591817***	0.4630756	0.4336735***	0.4953202		0.9744873***	1.5344200***	1.4120421***	1.3981292**	1.3866479***
		(0.0823182)	(0.0826522)	(0.2818356)	(0.0834884)	(5.5808395)		(0.0176812)	(0.2418291)	(0.0975217)	(0.6001479)	(0.0488868)
a_2			0.0015208	−0.0668520	−0.0433901	−0.0301999			−0.5849397**	−0.4286631***	−0.4029902***	−0.3666258***
			(0.0793213)	(0.1632894)	(0.0718296)	(0.2604771)			(0.2640209)	(0.1328815)	(0.0286150)	(0.0943490)
a_3				0.1415305	0.0553107	−0.0060432				−0.1194400	−0.1845870***	−0.0141705
				(0.6040449)	(0.0740764)	(0.1569192)				(0.0831994)	(0.0694927)	(0.1026270)
a_4					0.1723018***	0.2941035					0.0385674	−0.4429870***
					(0.0505211)	(1.8892298)					(0.4435357)	(0.1227414)
a_5						−0.3410198						0.3428493***
						(2.9300207)						(0.0907458)
α_0	0.0008691**	0.0000000	0.0000000	0.0000003	0.0000000	0.0000012	0.0006308	0.0005413***	0.0000023	0.0000014	0.0000006	0.0000000
	(0.0003816)	(0.0000051)	(0.0000049)	(0.0000180)	(0.0000052)	(0.0036721)	(0.0019023)	(0.0001629)	(0.0000065)	(0.0000014)	(0.0000275)	(0.0000136)
α_1	0.2164182**	0.0013344***	0.0013652***	0.0052270***	0.0012874***	0.0060201	0.8381192***	0.6898462***	0.0000000	0.0020297***	0.0023185***	0.0000088
	(0.1103289)	(0.0003418)	(0.0002403)	(0.0001540)	(0.0001791)	(0.0454837)	(0.1570905)	(0.2208392)	(0.0003750)	(0.0003657)	(0.0000008)	(0.0002556)
β_1	0.0000000	0.9998093***	0.9997465***	0.9961333***	0.9999707***	0.9946006***	0.2005795	0.0000000	1.0000000***	0.9997853***	0.9999688***	0.9999997***
	(0.2929585)	(0.0000620)	(0.0007871)	(0.0005904)	(0.0000142)	(0.3152365)	(0.2812267)	(0.1408637)	(0.0026566)	(0.0010078)	(0.0656636)	(0.0000722)
γ_2	−0.0005823*	−0.0000130***	−0.0000129***	−0.0000145***	−0.0000115***	−0.0000142	−0.0005613	−0.0002436	−0.0000161**	−0.0000201***	−0.0000199***	−0.0000132***
	(0.0003185)	(0.0000000)	(0.0000013)	(0.0000024)	(0.0000002)	(0.0005457)	(0.0018535)	(0.0001641)	(0.0000064)	(0.0000010)	(0.0000004)	(0.0000005)
Hannan-Quinn	-4.2375151	-4.4305863	-4.4105417	-4.4003839	-4.4133697	-4.5331970	-2.7712415	-4.0614826	-4.3140309	-4.2936597	-4.2468436	-4.2523933

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6.1: Results of AR(p)-GARCH(1, 1) estimations for real house price inflation. The quarter-to-quarter series has been estimated using seasonal dummies. Lag length in mean model varies from 0 to 5. Bollerslev-Woolridge robust standard errors are in the parentheses below the coefficient.

6.1.2 Real Rental Price Inflation

The results for the estimation of the GARCH(1, 1) model for real rental prices is illustrated in table 6.2. For the quarter to quarter growth rate in real house prices, in the stationary white noise model γ_2 is significant and negative. For this model, γ_2 indicates that the presence of an inflation targeting regime leads to a decrease in the variance of real house prices of about 0.00010 percentage points. Here, when adding autoregressive lags γ_2 remains at about the same size and is negative up to an AR(3) model. However, for the AR(4) and AR(5) models, the coefficient is very small in magnitude and estimated to be positive. Therefore, as the mean model explains an increasing amount of the variation in the residual, the results indicate that flexible inflation targeting may have had a positive effect on the remaining volatility in the residual.

In the conditional mean specifications for the real rental price, it is important to note that very few of the autoregressive lags are significant. In fact, only when the lagging the real rental price by four, is the lag significant. This coincides with the shift in the sign of γ_2, and indicates that when accounting for any significant autocorrelation in the real rental price γ_2 becomes positive. Nevertheless, the “stationary white noise” model and the models with fewer autoregressive lags than four confirm that there has been a regime shift in the volatility of real rental prices, and that this shift has been negative.

Along the same lines, for the year to year growth rate in real rental prices, γ_2 is negative and significant for all specifications of the mean model. In the “stationary white noise” model the effect of the presence of a flexible inflation targeting regime is estimated to be -0.00018 percentage points, but then drops as autoregressive lags are included. Notice that there are more significant autoregressive lags in the specifications of the mean compared to the results for the quarter to quarter growth. As opposed to for the quarter to quarter growth rate, however, when including significant autoregressive lags in the mean, γ_2 remains negative and significant.

Therefore, the results for the real rental price overall support the hypothesis that the presence of a flexible inflation targeting regime is correlated with a regime shift in the conditional volatility of the real house price, although there are some exceptions. This conclusions is robust when controlling for seasonal effects using two different methods, when controlling for the effect of flexible inflation targeting on the general rental price level, and when controlling for autocorrelation in the real rental price.

	Real Rental Price Inflation (Quarter to Quarter)						Real Rental Price Inflation (Year to Year)					
	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
a_0	0.0000086	−0.0000757	−0.0001205	−0.0001037	−0.0008862	−0.0012355	0.0077754***	−0.0446272***	−0.0424598***	−0.0406055***	−0.0369393***	−0.0375799***
	(0.0010522)	(0.0010634)	(0.0009799)	(0.0009686)	(0.0030300)	(0.0029174)	(0.0000994)	(0.0025911)	(0.0019770)	(0.0018921)	(0.0032380)	(0.0029337)
γ_1	0.0011666	0.0011565	0.0011569	0.0012396	0.0019967	0.0032976	0.0003917	−0.0191918***	−0.0206906***	0.0032992	0.0036851	−0.0128068
	(0.0011375)	(0.0010705)	(0.0011906)	(0.0010961)	(0.0032514)	(0.0043221)	(0.0010297)	(0.0021160)	(0.0018038)	(0.0025965)	(0.0029297)	(0.0096624)
a_1		−0.1519711	−0.1573336**	−0.1487583	−0.1407899	−0.0879986		0.9908146***	1.1187378***	1.1330411***	1.1323601***	1.0525710***
		(0.1497988)	(0.0782228)	(0.1579578)	(0.1291831)	(0.1260108)		(0.0059230)	(0.0683083)	(0.0894170)	(0.1021801)	(0.0216507)
a_2			−0.0369501	−0.0249995	0.0122282	0.0054629			−0.1274775*	−0.2133345**	−0.2264802***	−0.1864495***
			(0.1395555)	(0.1265160)	(0.1424043)	(0.1248313)			(0.0677292)	(0.0964868)	(0.0860256)	(0.0455986)
a_3				0.0151457	0.0543203	0.0537881				0.0680192	0.0519226	0.1440296**
				(0.0830544)	(0.1105628)	(0.1018700)				(0.0528964)	(0.0664997)	(0.0660804)
a_4					0.3789133**	0.4475062***					0.0291440	−0.2464228*
					(0.1720786)	(0.1369575)					(0.0396688)	(0.1390321)
a_5						−0.0802997						0.2277461**
						(0.1111313)						(0.1095640)
α_0	0.0000021	0.0000022	0.0000022	0.0000022	0.0000031	0.0000044***	0.0000331***	0.0000255***	0.0000281***	0.0000280***	0.0000282***	0.0000088***
	(0.0000106)	(0.0000132)	(0.0000127)	(0.0000130)	(0.0000155)	(0.0000004)	(0.0000091)	(0.0000005)	(0.0000024)	(0.0000099)	(0.0000089)	(0.0000000)
α_1	0.1943247*	0.2086034	0.2128390*	0.1973230	0.0975574***	0.0358845***	0.9491678***	0.5634240**	0.6693757***	0.6718892***	0.6622514***	0.2363015***
	(0.1102653)	(0.1343167)	(0.1176411)	(0.1457312)	(0.0239442)	(0.0054686)	(0.1298538)	(0.2595300)	(0.1963126)	(0.2109222)	(0.2342452)	(0.0785072)
β_1	0.7911942***	0.7783358***	0.7748570***	0.7855702***	0.8397489***	0.8669738***	0.0000000	0.2046474	0.0743538	0.0785496	0.0868070	0.6443308***
	(0.1167496)	(0.1663034)	(0.1438957)	(0.1681588)	(0.1555846)	(0.0175390)	(0.0135057)	(0.1615251)	(0.0611388)	(0.1857280)	(0.1928560)	(0.0694911)
γ_2	−0.0000010***	−0.0000011***	−0.0000011***	−0.0000010***	0.0000005***	0.0000022***	−0.0000175***	−0.0000126***	−0.0000097***	−0.0000117***	−0.0000130***	−0.0000039***
	(0.0000001)	(0.0000000)	(0.0000000)	(0.0000000)	(0.0000000)	(0.0000001)	(0.0000001)	(0.0000000)	(0.0000001)	(0.0000000)	(0.0000001)	(0.0000000)
Hannan-Quinn	-6.5672919	-6.5610301	-6.5279067	-6.5058537	-6.5628431	-6.5260864	-6.0973538	-6.7725104	-6.7802877	-6.7652813	-6.7352325	-6.7287020

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

Table 6.2: Results of AR(p)-GARCH(1, 1) estimations for real rental price inflation. The quarter-to-quarter series has been estimated using seasonal dummies. Lag length in mean model varies from 0 to 5. Bollerslev-Woolridge robust standard errors are in the parentheses below the coefficient.

6.2 EGARCH-models

The previous section illustrated that the results from the GARCH(1, 1) model generally support the hypothesis that flexible inflation targeting is associated with decreased volatility in real house and rental prices. This section extends the analysis using an EGARCH(1, 1) model. The use of the EGARCH(1, 1) model in this thesis is meant as a sensitivity analysis of the results from the GARCH(1, 1) model. The goal is to answer the question: How robust is the conclusion when accounting for the potential asymmetric effects of shocks to volatility?

6.2.1 Real House Price Inflation

Table 6.3 illustrates the results of estimating real house price inflation using an EGARCH(1, 1) model. For the quarter-to-quarter growth rate in real house price inflation, γ_2 is negative but not significant for all specifications of the mean model. The magnitude of γ_2 also fluctuates between a minimum of about -0.20 to a maximum of about -1.22 and does not seem to increase as the number of autoregressive lags increases. While the negative sign of the coefficient supports the conclusions drawn from the GARCH(1, 1) model, the standard errors indicate that when using an EGARCH model, I cannot reject the null hypothesis that flexible inflation targeting has no effect at all on the conditional variance of the residuals.

It is interesting to see that λ_1 is significant for all but one specification of the mean model, the AR(2) model. This indicates that shocks to volatility have asymmetric effects on the conditional variance of real house prices, and that negative shocks have a greater effect than positive shocks. In the specifications of the mean model, γ_1 is significant for some, but not all specifications of the mean model, but it generally indicates that the presence of a flexible inflation targeting regime is correlated with an overall increase in the level of real house prices. Most of the autoregressive lags also tend to be significant for the specifications of the mean model.

In the results for year to year growth rate in real house prices, on the other hand, γ_2 starts off as negative and significant in the stationary white noise model. This result corroborates the conclusion drawn from the GARCH(1, 1) model. When adding autoregressive lags, γ_2

is insignificant for the AR(1), AR(2), AR(3), and AR(5) models, but significant in the AR(4) model, and negative in all models. Thus, both the sign and in some models, the significance of γ_2 support hypothesis 1.

As opposed to the results for the quarter on quarter growth rate, for the year to year growth rate, λ_1 is significant in all but the AR(5) model specification, futher supporting the presence of asymmetric effects of shocks in the market for owning residential property. It is also interesting to note that γ_1 is negative in all the model specifications for the year to year growth rate, suggesting that flexible inflation targeting has a negative impact on the overall real house price level.

Thus, in general the EGARCH model estimates the effect of the flexible inflation targeting dummy on the conditional variance of the residual to be negative. However, for the majority of specifications of the mean model, the effect is not significantly different from zero. Before refuting the conclusion from the GARCH(1, 1) model, it is nonetheless important to note that EGARCH models are far more complicated than GARCH models. EGARCH models therefore require more variation in the data to produce significant results. Thus, the lack of significance in γ_2 for some specifications in the mean may be an indicator that the model needs more data. Therefore, the results from the EGARCH model do not directly reject the hypothesis that flexible inflation targeting has a negative impact on volatility in real house prices. They all estimate the effect to be negative, however, when accounting for asymmetries in shocks, γ_2 is significant in far fewer cases than for the GARCH(1, 1) model.

	Real House Price Inflation (Quarter to Quarter)						Real House Price Inflation (Year to Year)					
	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
a_0	-0.0049096^{***}	-0.0091435	-0.0094261^{***}	-0.0131282^{***}	-0.0082971	-0.0151664^{***}	0.0743797^{***}	-0.0689313^{***}	-0.0292508^{***}	-0.0247828	-0.0050806^{***}	0.0164599
	(0.0011697)	(0.0057039)	(0.0014877)	(0.0025925)	(0.0089442)	(0.0022711)	(0.0247431)	(0.0089901)	(0.0083238)	(0.0643945)	(0.0003486)	(0.0498507)
γ_1	0.0004253	0.0094994	0.0099009^{*}	0.0123687^{***}	0.0136666	0.0197000^{***}	-0.0156994	-0.0424294^{***}	-0.0302757	-0.0357709	-0.0122022^{**}	-0.0097295
	(0.0083210)	(0.0069678)	(0.0055913)	(0.0012244)	(0.0083576)	(0.0067365)	(0.0386161)	(0.0002699)	(7.3437673)	(0.6744690)	(0.0049651)	(0.0330220)
a_1		0.5079736^{***}	0.5097377^{***}	0.4887694^{***}	0.4500500^{***}	0.5511865^{***}		0.9811272^{***}	1.6030986^{*}	1.5511772^{***}	1.5649298^{***}	1.3475750^{***}
		(0.1185060)	(0.0494862)	(0.0779167)	(0.0876890)	(0.0412906)		(0.0195013)	(0.8922783)	(0.5415229)	(0.0025315)	(0.2526310)
a_2			0.0013799^{***}	-0.0180021^{*}	-0.0052513	0.0201139^{***}			-0.6492868	-0.6008893^{**}	-0.5781563^{***}	-0.2710832^{***}
			(0.0003963)	(0.0094793)	(0.0572906)	(0.0027973)			(0.5972234)	(0.2599710)	(0.0028151)	(0.0985230)
a_3				0.1231697^{***}	0.0160576	0.0157071^{***}				-0.0108549	-0.1794620^{***}	-0.0375561
				(0.0433086)	(0.0730987)	(0.0024006)				(0.0464484)	(0.0012727)	(0.1464191)
a_4					0.1959065^{***}	0.3626100^{***}					0.1162680^{***}	-0.4755008^{***}
					(0.0664022)	(0.0521115)					(0.0003964)	(0.1616775)
a_5						-0.3245624^{***}						0.3828851^{*}
						(0.0347571)						(0.2006442)
α_0	-2.0844133	-10.8337521^{***}	-10.9330216^{***}	-10.6170870^{***}	-11.3302785^{***}	-6.7336892^{***}	-1.3568772^{**}	-4.1081754	-0.8925876	-0.9504141^{*}	-0.8064724^{***}	-1.5753167
	(2.5072344)	(1.1937111)	(0.9531750)	(2.5188339)	(0.9801401)	(2.4901966)	(0.6050789)	(3.4603164)	(0.5549313)	(0.4867023)	(0.0045341)	(1.3456194)
α_1	-0.1362047	-0.0831458	-0.0827137	-0.0373601	-0.0652704	-0.0760588	-0.0835324	0.0376511	0.1238526^{***}	0.0044656	0.0413817^{***}	-0.0149322
	(0.0943185)	(0.1074869)	(0.0911728)	(0.0922494)	(0.0949429)	(0.1164991)	(0.1305881)	(0.1369203)	(0.0231645)	(0.7191293)	(0.0001490)	(0.0631953)
β_1	0.7040292^{*}	-0.4989340^{***}	-0.5144851^{***}	-0.4610431	-0.5765348^{***}	0.1120550	0.7643806^{***}	0.4037561	0.8786169^{*}	0.8686640	0.8876553^{***}	0.7879815^{***}
	(0.3665974)	(0.1355917)	(0.1298753)	(0.2964063)	(0.1428664)	(0.3348858)	(0.1178141)	(0.5034355)	(0.5250676)	(1.1846991)	(0.0011516)	(0.1792386)
λ_1	0.2818359^{**}	0.3714592	0.3714820^{**}	0.3168885^{**}	0.3295143^{*}	0.4805916^{***}	1.3988354^{***}	0.7890204^{***}	-0.4694108	-0.4640999^{***}	-0.3584411^{***}	0.2779994
	(0.1317524)	(0.2493145)	(0.1812289)	(0.1384171)	(0.1791476)	(0.1762082)	(0.3064011)	(0.1903417)	(0.3206590)	(0.0209914)	(0.0027861)	(0.2117149)
γ_2	-0.2137158	-1.0275991	-1.0377221	-0.8938427	-1.2254012	-0.2802986	-0.4083120^{**}	-0.2807324	-0.0383295	-0.0500676	-0.0510220^{***}	-0.1071313
	(0.4406353)	(0.9411242)	(0.9182237)	(1.0316439)	(0.7790237)	(0.3321227)	(0.2043054)	(0.3199909)	(19.7252416)	(2.0449484)	(0.0073225)	(0.0991709)
Hannan-Quinn	-4.2313897	-4.4134344	-4.3956234	-4.3750031	-4.4024780	-4.5016965	-2.7979609	-4.0302360	-4.3453175	-4.3187852	-4.2428480	-4.2062296

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6.3: Results of AR(p)-EGARCH(1, 1) estimations for real house price inflation. The quarter-to-quarter series has been estimated using seasonal dummies, but these are not included for brevity.. Lag length in mean model varies from 0 to 5. Bollerslev-Woolridge robust standard errors are in the parentheses below the coefficient.

6.2.2 Real Rental Price Inflation

Table 6.4 illustrates the results from estimating real rental price inflation using an EGARCH(1, 1) model. For the quarter to quarter growth rate, γ_2 is negative for all specifications of the mean model, but not significant in any of them. Here it is important to note that, of the autoregressive lags included in the mean model, very few of are significant. This indicates that the models might be somewhat over or underspecified. On the other hand, λ_1 is significant in all specifications but the AR(5) model, suggesting the presence of asymmetric effects of shocks on the real rental price volatility.

Similarly, for the year to year growth rate γ_2 is estimated to be negative but not significant in any of the specifications of the conditional mean. Here, λ_1 is also significant throughout all the model specifications, further strengthening the evidence for asymmetric effects of shocks in the real rental price market.

In general, the results from EGARCH(1, 1) estimation of the real rental price indicate that the presence of a flexible inflation targeting regime is correlated with a negative regime shift in the volatility of the residuals for all specifications of the mean. However, we cannot reject the null hypothesis that flexible inflation targeting has no effect at all on the conditional variance of the residual when using an EGARCH(1, 1) model. It is important to note that also in this case, this may not be direct rebuttal of the conclusions reached when using a GARCH(1, 1) model. It may simply indicate that the use of a more complicated model requires more variation in the data than provided.

	Real Rental Price Inflation (Quarter to Quarter)						Real Rental Price Inflation (Year to Year)					
	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
a_0	−0.0002364***	−0.0003366	−0.0003872	−0.0002511	−0.0014413	−0.0006222***	0.0055165***	−0.0473089***	−0.0432321***	−0.0408301***	−0.0375658***	−0.0379076***
	(0.0000565)	(0.0018833)	(0.0003167)	(0.0015867)	(0.0021574)	(0.0000691)	(0.0010483)	(0.0023429)	(0.0020782)	(0.0021629)	(0.0027149)	(0.0022338)
γ_1	0.0011199***	0.0011806	0.0011867***	0.0011795	0.0014766	0.0062804	0.0017715	0.0024515	0.0008461	0.0013307	0.0011855	0.0025249***
	(0.0001562)	(0.0013438)	(0.0003129)	(0.0009528)	(0.0020826)	(0.0040518)	(0.0012763)	(0.0055415)	(0.0041800)	(0.0054488)	(0.0047342)	(0.0006893)
a_1		−0.0955613	−0.0906216	−0.0902216	−0.1006336	−0.0322195***		0.9874598***	1.1100523***	1.1068256***	1.1037257***	1.0295095***
		(0.1058763)	(0.0950400)	(0.1217505)	(0.1085004)	(0.0038083)		(0.0121276)	(0.0094412)	(0.0551646)	(0.0090978)	(0.0108030)
a_2			−0.0155244	−0.0301991	0.0072237	0.0347599***			−0.1202395***	−0.1765289***	−0.1854739***	−0.1627474***
			(0.0189931)	(0.1363736)	(0.1084553)	(0.0134489)			(0.0024994)	(0.0413447)	(0.0028338)	(0.0018572)
a_3				−0.0348852	0.0120906	0.0175945***				0.0556234***	0.0963271***	0.0897347***
				(0.0790654)	(0.0816847)	(0.0015413)				(0.0059829)	(0.0031497)	(0.0012189)
a_4					0.3173634*	0.4707955***					−0.0306591***	−0.2395680***
					(0.1727014)	(0.0403135)					(0.0028409)	(0.0038942)
a_5						−0.1120640***						0.2719873***
						(0.0375321)						(0.0058553)
α_0	−0.5547987	−0.5347028	−0.5511777	−0.5466377	−0.6858572*	−1.4341495***	−3.3338927***	−2.0186967	−2.1664035	−2.0483591	−1.8543741	−0.9927935
	(0.3472631)	(0.3321218)	(0.3486792)	(0.3878184)	(0.3655042)	(0.0135273)	(0.5087120)	(1.5050442)	(1.4149194)	(1.4922532)	(1.3023682)	(0.7629823)
α_1	−0.1962098***	−0.1831804***	−0.1940017***	−0.1886174***	−0.1550558***	−0.1501360***	0.0090413	0.0381032	0.0340998	0.0235060	0.0142397	−0.0013414
	(0.0495340)	(0.0534035)	(0.0528383)	(0.0683170)	(0.0533241)	(0.0227545)	(0.0927314)	(0.1148311)	(0.1191177)	(0.1227650)	(0.1168340)	(0.0898492)
β_1	0.9420067***	0.9442895***	0.9421433***	0.9427960***	0.9290500***	0.8570173**	0.6283393***	0.7916192***	0.7772647***	0.7891560***	0.8093711***	0.8977010***
	(0.0357256)	(0.0339298)	(0.0364588)	(0.0411525)	(0.0367258)	(0.3364525)	(0.0533719)	(0.1525448)	(0.1424776)	(0.1501897)	(0.1312445)	(0.0764727)
λ_1	0.3132569***	0.3186462***	0.3318689***	0.3485140***	0.2290041	−0.4964996***	1.2912859***	0.4574675***	0.4759241***	0.4628952***	0.4511065***	0.3934324***
	(0.1020336)	(0.1011164)	(0.1004219)	(0.1172089)	(0.1774391)	(0.0306053)	(0.1705197)	(0.1616701)	(0.1687725)	(0.1721168)	(0.1435240)	(0.1164772)
γ_2	−0.0233239	−0.0236143	−0.0268042	−0.0256583	−0.0087609	0.0207106	−0.3970041	−0.0361729	−0.0156138	−0.0282413	−0.0238953	−0.0492934
	(0.0529834)	(0.0689089)	(0.0533087)	(0.0655769)	(0.0696737)	(0.0340138)	(0.2774128)	(0.1187997)	(0.1253924)	(0.1197325)	(0.1113671)	(0.0639608)
Hannan-Quinn	-6.6136597	-6.5998268	-6.5698683	-6.5438274	-6.5702535	-6.6673938	-6.0478526	-6.7305841	-6.7323793	-6.7086043	-6.6787457	-6.7138495

$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

Table 6.4: Results of AR(p)-EGARCH(1, 1) estimations for real rental price inflation. The quarter-to-quarter series has been estimated using seasonal dummies but these are not included for brevity. Lag length in mean model varies from 0 to 5. Bollerslev-Woolridge robust standard errors are in the parentheses below the coefficient.

7. Conclusion

This thesis has investigated if implementing flexible inflation targeting in Norway is correlated with a regime shift in the volatility of real house and rental prices. Real house prices and real rental prices were estimated using GARCH and EGARCH models. Controlling for autocorrelation, seasonal effects and the effects of flexible inflation targeting, the results from the GARCH-estimation supported the hypothesis that flexible inflation targeting has lead to a negative shift in the volatility of house and rental prices.

The results from the EGARCH model also confirm that flexible inflation targeting has had a negative effect on the conditional variance of the residuals in the regression, however, for the different models of the mean there was large variation in the level of significance[1]. Either way, given the added informational demands of the EGARCH model, and the general robustness of the conclusion in other settings, the evidence generally shows that flexible inflation targeting is associated with a reduction in house price volatility.

A possible implication of this finding is that the presence of a flexible inflation targeting regime in the Norwegian economy is correlated with decreased risk in the markets for both real house price and real rental prices. This development has happened simultaneously with an unprecedented rise in house prices in the Norwegian market. Many pundits claim that there is a housing bubble in the Norwegian market, or that the rise in residential property prices is caused by low interest rates.(Homsnes et al., 2015) Studies have also documented that although many industrialized countries have experienced unprecedented rises in house prices over the past few years, the increases in house prices tend to be higher for flexible inflation targeting countries. (Frappa and Mésonnier, 2010) Thus, while inflation targeting tends to be associated with an increase in house prices, it has also, at least in the Norwegian

[1] For real house price inflation, the p-value of γ_2 ranged from 0.02 to 0.91. For real rental price inflation, the p-value of γ_2 varied from 0.002 to 0.89

case, been associated with decreased risk in the market.

There are many reasons why flexible inflation targeting might lead to less fluctuation in the housing market, while the housing market persists in experiencing very high price increases. First of all, the manner in which flexible inflation targeting is conducted by most central banks purports being predictable and communicating the policy stance clearly. This leads to decreased uncertainty about interest rates amongst consumers. Thus, trusting that interest rates are somewhat predictable, consumers are more willing to engage in the debt-financed purchase of residential property. Another possible explanation is that while rental prices are included in the Norwegian CPI, house prices are not, since they are not a consumer good but a household financial asset. Therefore, the central bank might decrease fluctuations in the market through more stable output, price level and interest rates, while house prices are driven upwards by immigration and easier access to debt.

Others might argue that another possible explanation for the decrease in volatility in the Norwegian housing market, is that an asset price bubble is currently building up in the Norwegian housing market. When the bubble "bursts" and prices decrease, the decrease will be substantial enough to eliminate any regime shift caused by the dummy variable. Therefore, it is important to further investigate the nature, causes and characteristics of the effects of flexible inflation targeting on the housing market.

A possible extension of this study is that I implicitly assume that in the periods before and after flexible inflation targeting, the Norwegian economy experienced similar frequencies and magnitudes for shocks to demand and supply. Thus, controlling for difference in supply and demand shocks would be an interesting line of future research. Similarly, the use of the flexible inflation targeting dummy variable can assert the presence of a regime shift, but not how and in what way flexible inflation targeting affected volatility in house price markets. To investigate this, a multivariate approach is needed. Furthermore, it would be interesting to see if the conclusion holds using panel data for several countries.

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A. AR(p) - GARCH(1, 1)

A.1 Real House Price Inflation: Various Estimations of the Mean Model

A.2 Real Rental Price Inflation: Various Estimations of the Mean Model

	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
a_0	0.0071278	0.0076615	0.0074481	0.0068125	0.0047300	0.0032916
	(0.0060317)	(0.0058628)	(0.0058787)	(0.0067112)	(0.0088249)	(0.0082011)
γ_1	0.0031191	0.0026056	0.0029898	0.0033856	0.0065659	0.0083276
	(0.0071122)	(0.0074986)	(0.0089002)	(0.0131756)	(0.0106312)	(0.0152436)
a_1		0.3882391***	0.4323623***	0.4696788***	0.3736450***	0.5118521***
		(0.0865215)	(0.0802286)	(0.0818533)	(0.0814360)	(0.1212862)
a_2			−0.1282891	−0.2844021**	−0.1995145***	−0.1762419
			(0.0849379)	(0.1178908)	(0.0751607)	(0.2215220)
a_3				0.2838219***	0.1307007*	0.0505067
				(0.0798240)	(0.0757253)	(0.1293040)
a_4					0.3432155***	0.5144601***
					(0.0750318)	(0.1336231)
a_5						−0.3996335**
						(0.1578179)
α_0	0.0000010	0.0000004	0.0000006	0.0000009	0.0000005	0.0000006
	(0.0000013)	(0.0000005)	(0.0000064)	(0.0000016)	(0.0000087)	(0.0000113)
α_1	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0005936
	(0.0000088)	(0.0000033)	(0.0000563)	(0.0002025)	(0.0001232)	(0.0006204)
β_1	0.9999999***	0.9999997***	0.9999999***	1.0000000***	1.0000000***	0.9999652***
	(0.0009323)	(0.0000397)	(0.0000361)	(0.0004298)	(0.0000893)	(0.0002732)
γ_2	−0.0000092***	−0.0000024	−0.0000057***	−0.0000100**	−0.0000088***	−0.0000103*
	(0.0000000)	(0.0000018)	(0.0000014)	(0.0000049)	(0.0000004)	(0.0000055)
Akaike	-4.0570903	-4.2005982	-4.2027915	-4.2618864	-4.3699954	-4.5407207
Bayes	-3.9339151	-4.0568938	-4.0385579	-4.0771236	-4.1647034	-4.3148995
Shibata	-4.0603369	-4.2049795	-4.2084657	-4.2690079	-4.3787147	-4.5511848
Hannan-Quinn	-4.0070400	-4.1422063	-4.1360578	-4.1868110	-4.2865783	-4.4489619

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

Table A.1: AR(p)-GARCH(1, 1) models for real house price inflation without seasonal effects in the mean variable. p varies from 0 to 5. *** means $\alpha \leq 0.01$, ** means $\alpha \leq 0.05$ * means $\alpha \leq 0.1$. Bollerslev-Woolridge robust standard errors are in the parantheses below the coefficient.

	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
a_0	0.0703329***	−0.0630997***	−0.0473259	−0.0066621	0.0044496	0.0172447
	(0.0150725)	(0.0091802)	(0.0485759)	(0.0318509)	(0.0737185)	(0.0309966)
γ_1	−0.0109218	−0.0405727***	−0.0150057	0.0291780	0.0270608***	0.0040391
	(0.0140878)	(0.0034565)	(0.1080126)	(0.0438089)	(0.0103054)	(0.0252132)
a_1		0.9744873***	1.5344200***	1.4120421***	1.3981292**	1.3866479***
		(0.0176812)	(0.2418291)	(0.0975217)	(0.6001479)	(0.0488868)
a_2			−0.5849397**	−0.4286631***	−0.4029902***	−0.3666258***
			(0.2640209)	(0.1328815)	(0.0286150)	(0.0943490)
a_3				−0.1194400	−0.1845870***	−0.0141705
				(0.0831994)	(0.0694927)	(0.1026270)
a_4					0.0385674	−0.4429870***
					(0.4435357)	(0.1227414)
a_5						0.3428493***
						(0.0907458)
α_0	0.0006308	0.0005413***	0.0000023	0.0000014	0.0000006	0.0000000
	(0.0019023)	(0.0001629)	(0.0000065)	(0.0000014)	(0.0000275)	(0.0000136)
α_1	0.8381192***	0.6898462***	0.0000000	0.0020297***	0.0023185***	0.0000088
	(0.1570905)	(0.2208392)	(0.0003750)	(0.0003657)	(0.0000008)	(0.0002556)
β_1	0.2005795	0.0000000	1.0000000***	0.9997853***	0.9999688***	0.9999997***
	(0.2812267)	(0.1408637)	(0.0026566)	(0.0010078)	(0.0656636)	(0.0000722)
γ_2	−0.0005613	−0.0002436	−0.0000161**	−0.0000201***	−0.0000199***	−0.0000132***
	(0.0018535)	(0.0001641)	(0.0000064)	(0.0000010)	(0.0000004)	(0.0000005)
Akaike	-2.8222319	-4.1209714	-4.3820181	-4.3701453	-4.3318275	-4.3458756
Bayes	-2.6967527	-3.9745791	-4.2147125	-4.1819266	-4.1226956	-4.1158305
Shibata	-2.8256602	-4.1255970	-4.3880073	-4.3776606	-4.3410270	-4.3569137
Hannan-Quinn	-2.7712415	-4.0614826	-4.3140309	-4.2936597	-4.2468436	-4.2523933

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

Table A.2: Estimation of AR(p)-GARCH(1, 1) models for real house price inflation without seasonal effects and the inflation targeting dummy in the mean equation. Lag length varies from 0 to 5. *** means $\alpha \le 0.01$, ** means $\alpha \le 0.05$ * means $\alpha \le 0.1$. Bollerslev-Woolridge robust standard errors are in the parantheses below the coefficient.

	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
a_0	0.0703329^{***}	-0.0630997^{***}	-0.0473259	-0.0066621	0.0044496	0.0172447
	(0.0150725)	(0.0091802)	(0.0485759)	(0.0318509)	(0.0737185)	(0.0309966)
γ_1	-0.0109218	-0.0405727^{***}	-0.0150057	0.0291780	0.0270608^{***}	0.0040391
	(0.0140878)	(0.0034565)	(0.1080126)	(0.0438089)	(0.0103054)	(0.0252132)
a_1		0.9744873^{***}	1.5344200^{***}	1.4120421^{***}	1.3981292^{**}	1.3866479^{***}
		(0.0176812)	(0.2418291)	(0.0975217)	(0.6001479)	(0.0488868)
a_2			-0.5849397^{**}	-0.4286631^{***}	-0.4029902^{***}	-0.3666258^{***}
			(0.2640209)	(0.1328815)	(0.0286150)	(0.0943490)
a_3				-0.1194400	-0.1845870^{***}	-0.0141705
				(0.0831994)	(0.0694927)	(0.1026270)
a_4					0.0385674	-0.4429870^{***}
					(0.4435357)	(0.1227414)
a_5						0.3428493^{***}
						(0.0907458)
α_0	0.0006308	0.0005413^{***}	0.0000023	0.0000014	0.0000006	0.0000000
	(0.0019023)	(0.0001629)	(0.0000065)	(0.0000014)	(0.0000275)	(0.0000136)
α_1	0.8381192^{***}	0.6898462^{***}	0.0000000	0.0020297^{***}	0.0023185^{***}	0.0000088
	(0.1570905)	(0.2208392)	(0.0003750)	(0.0003657)	(0.0000008)	(0.0002556)
β_1	0.2005795	0.0000000	1.0000000^{***}	0.9997853^{***}	0.9999688^{***}	0.9999997^{***}
	(0.2812267)	(0.1408637)	(0.0026566)	(0.0010078)	(0.0656636)	(0.0000722)
γ_2	-0.0005613	-0.0002436	-0.0000161^{**}	-0.0000201^{***}	-0.0000199^{***}	-0.0000132^{***}
	(0.0018535)	(0.0001641)	(0.0000064)	(0.0000010)	(0.0000004)	(0.0000005)
Akaike	-2.8222319	-4.1209714	-4.3820181	-4.3701453	-4.3318275	-4.3458756
Bayes	-2.6967527	-3.9745791	-4.2147125	-4.1819266	-4.1226956	-4.1158305
Shibata	-2.8256602	-4.1255970	-4.3880073	-4.3776606	-4.3410270	-4.3569137
Hannan-Quinn	-2.7712415	-4.0614826	-4.3140309	-4.2936597	-4.2468436	-4.2523933

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.3: Estimation of AR(p)-GARCH(1, 1) models for year-on-year real house price inflation without seasonal effects but with the inflation targeting dummy in the mean equation. Lag length varies from 0 to 5. *** means $\alpha \leq 0.01$, ** means $\alpha \leq 0.05$ * means $\alpha \leq 0.1$. Bollerslev-Woolridge robust standard errors are in the parantheses below the coefficient.

	Stationary White Noise	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
a_0	0.0592493***	−0.0607486***	−0.0417359***	−0.0145808	0.0041676	0.0177736
	(0.0049104)	(0.0131391)	(0.0110825)	(0.0328328)	(0.0409647)	(0.0255339)
a_1		0.9603001***	1.5265045***	1.4602810***	1.4346388***	1.3910606***
		(0.0216622)	(0.2216322)	(0.1197235)	(0.0931462)	(0.1919227)
a_2			−0.5880692**	−0.4864955***	−0.4344439***	−0.3709589
			(0.2363367)	(0.0038821)	(0.0983706)	(0.2403253)
a_3				−0.0682419	−0.1682682	−0.0117589
				(0.1815655)	(0.1347706)	(0.1602068)
a_4					0.0525645	−0.4448764***
					(0.1157376)	(0.1259686)
a_5						0.3453621***
						(0.0914075)
α_0	0.0007429	0.0005768***	0.0000024***	0.0000021***	0.0000016	0.0000000
	(0.0009946)	(0.0001754)	(0.0000000)	(0.0000000)	(0.0000020)	(0.0000065)
α_1	0.7925963***	0.5973162***	0.0000000	0.0000004	0.0000000	0.0000083
	(0.0989790)	(0.1899011)	(0.0000368)	(0.0000160)	(0.0009288)	(0.0010356)
β_1	0.2084433*	0.0000000	1.0000000***	0.9999998***	1.0000000***	0.9999955***
	(0.1218423)	(0.1727347)	(0.0006127)	(0.0042536)	(0.0019015)	(0.0001211)
γ_2	−0.0006547	−0.0001917	−0.0000170***	−0.0000163***	−0.0000164***	−0.0000131***
	(0.0010373)	(0.0001844)	(0.0000047)	(0.0000002)	(0.0000000)	(0.0000039)
Akaike	-2.8311199	-4.0963997	-4.3948603	-4.3795605	-4.3383437	-4.3597925
Bayes	-2.7265539	-3.9709205	-4.2484680	-4.2122550	-4.1501250	-4.1506606
Shibata	-2.8335219	-4.0998280	-4.3994859	-4.3855498	-4.3458590	-4.3689920
Hannan-Quinn	-2.7886279	-4.0454093	-4.3353715	-4.3115734	-4.2618581	-4.2748085

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

Table A.4: Estimation of AR(p)-GARCH(1, 1) models for year-on-year real house price inflation without seasonal effects and without the inflation targeting dummy in the mean equation. Lag length varies from 0 to 5. *** means $\alpha \leq 0.01$, ** means $\alpha \leq 0.05$ * means $\alpha \leq 0.1$. Bollerslev-Woolridge robust standard errors are in the parantheses below the coefficient.

B. R-code for GARCH models

```
num_arma_models <- function(max_p, max_q){
     num_list_entries <- 0
     if (max_p == 0) {
          num_list_entries <- (max_q+1)
     } else if (max_q == 0) {
          num_list_entries <- (max_p+1)
     } else {
          num_list_entries <- (max_p+1)*(max_q+1)
     }
     return(num_list_entries)
}

#Create function for making a list of increasing p, q, d:
#Note that d is always 0.
gen_pdq_list <- function(max_p, max_q, num_list_entries) {

     #Generate vectors of possible values of p, d, and q, (d is always 0), in the correct
          order.
     p_vector <- c()
     for (i in 0:max_p) {
          p_vector <- c(p_vector, rep(i, num_list_entries/(max_p+1)))
     }
     if (max_q>0) {
     q_vector <- rep(0:max_q, num_list_entries/(max_p+1))
     } else {
     q_vector <- rep(0, max_p+1)
     }
     #Combine vectors in a matrix
     pdq_matrix <- matrix(data = c(p_vector, q_vector), nrow=num_list_entries, ncol=2,
         byrow=FALSE)

     #Add each row of the matrix as an entry to a list
     pdq_list <- list()
     for (i in 1:num_list_entries) {
          pdq_list[[i]] <- pdq_matrix[i, ]
     }
```

```
return(pdq_list)
}

gen_spec_garch_rhpinf<- function(arma_order) {
     ugarchspec(    variance.model      =    list(model = "sGARCH", external.regressors = IT_1),
                mean.model =  list(armaOrder = arma_order, include.mean = TRUE, external.regressors = rhpinf_allvars[, 4:7]))
}

gen_spec_e_rhpinf<- function(arma_order) {
     ugarchspec(    variance.model      =    list(model = "eGARCH", external.regressors = IT_1),
                mean.model =  list(armaOrder = arma_order, include.mean = TRUE, external.regressors = rhpinf_allvars[, 4:7]))
}

gen_fit_realhpinf <- function(spec) {ugarchfit(spec, real_hpinf)}

gen_spec_g_rhpinfq_woSOm<- function(arma_order) {
     ugarchspec(    variance.model      =    list(model = "eGARCH", external.regressors = IT_1),
                mean.model =  list(armaOrder = arma_order, include.mean = TRUE, external.regressors = IT_1))
}

gen_spec_e_rhpinfq_woSOm<- function(arma_order) {
     ugarchspec(    variance.model      =    list(model = "eGARCH", external.regressors = IT_1),
                mean.model =  list(armaOrder = arma_order, include.mean = TRUE, external.regressors = IT_1))
}

gen_fit_rhpinfq <- function(spec) {ugarchfit(spec, rhpinfq)}

gen_spec_garch_rrinf <- function(arma_order) {
     ugarchspec(    variance.model      =    list(model = "sGARCH", external.regressors = IT_1),
                mean.model =  list(armaOrder = arma_order, include.mean = TRUE, external.regressors = rrinf_allvars[, 4:7]))
}

gen_spec_e_rrinf <- function(arma_order) {
     ugarchspec(    variance.model      =    list(model = "eGARCH", external.regressors = IT_1),
                mean.model =  list(armaOrder = arma_order, include.mean = TRUE, external.regressors = rrinf_allvars[, 4:7]))
}

```

```
gen_fit_rrinf <- function(spec) {ugarchfit(spec=spec, data=rrinf)}

gen_spec_gwos_rrinfq <- function(arma_order) {
     ugarchspec(    variance.model     =    list(model = "sGARCH", external.regressors =
          IT_1),
                mean.model =  list(armaOrder = arma_order, include.mean = TRUE, external.
                    regressors = IT_1))
}

gen_spec_e_rrinfq <- function(arma_order) {
     ugarchspec(    variance.model     =    list(model = "eGARCH", external.regressors =
          IT_1),
                mean.model =  list(armaOrder = arma_order, include.mean = TRUE, external.
                    regressors = IT_1))
}

gen_fit_rrinfq <- function(spec) {ugarchfit(spec=spec, data=rrinfq)}

max_models_5 <- num_arma_models(5, 0)
models_5 <- gen_pdq_list(5, 0, max_models_5)
rhpinf_g_specs_5 <- lapply(models_5, gen_spec_garch_rhpinf)
for (i in 1:length(rhpinf_g_specs_5)) {
     setbounds(rhpinf_g_specs_5[[i]]) <- list(vxreg1=c(-1, 1))
}
rhpinf_g_results_5 <- lapply(rhpinf_g_specs_5, gen_fit_realhpinf)

max_models_5 <- num_arma_models(5, 0)
models_5 <- gen_pdq_list(5, 0, max_models_5)
rhpinfq_gwoS_specs_5 <- lapply(models_5, gen_spec_garch_rhpinfq_woSOm)
for (i in 1:length(rhpinfq_gwoS_specs_5)) {
     setbounds(rhpinfq_gwoS_specs_5[[i]]) <- list(vxreg1=c(-1, 1))
}
rhpinfq_gwoS_results_5 <- lapply(rhpinfq_gwoS_specs_5, gen_fit_rhpinfq)

rrinf_g_specs_5 <- lapply(models_5, gen_spec_garch_rrinf)
for (i in 1:length(rrinf_g_specs_5)) {
     setbounds(rrinf_g_specs_5[[i]]) <- list(vxreg1=c(-1, 1))
}
rrinf_g_results_5 <- lapply(rrinf_g_specs_5, gen_fit_rrinf)

rrinfq_gwos_specs_5 <- lapply(models_5, gen_spec_gwos_rrinfq)
for (i in 1:length(rrinfq_gwos_specs_5)) {
     setbounds(rrinfq_gwos_specs_5[[i]]) <- list(vxreg1=c(-1, 1))
}
rrinfq_gwos_results_5 <- lapply(rrinfq_gwos_specs_5, gen_fit_rrinfq)
```

C. Demand for Durable Goods

Microeconomic theory provides some powerful insights into how demand for housing can be determined. A durable good is one that does not need to be purchased frequently because it is made to last for a long time. Housing can therefore easily be defined in the cateogry for durable goods. An agent's demand for durable goods is determined in a slightly different way than demand for a non-durable good. This appendix summarizes the model for demand for durable goods from Rødseth (1992, p.133). These characteristics of demand for durable goods form t

Demand for a durable good depends on the current stock the agent has of the durable good, or how much of the durable good he bought in the previous period. (Rødseth, 1992, p. 133) The utility function can then be expressed as follows:

$$U = U(c_1, c_2, j_1, j_2) \tag{C.1}$$

Where c_1 and c_2 ar the quantity consumed of non-durable goods, and k_1 and k_2 are the stocks of one durable good in periods 1 and 2 respectively. The agent's budget constraint at the end of period 1 can then be defined by as:

$$p_1 c_1 + \pi_1 k_1 + (p_2 c_2 + \pi_2 k_2)\frac{1}{1+i_2} = y_1 + y_2 \frac{1}{1+i_2} \tag{C.2}$$

where y_1 and y_2 are income at $t = 1$ and $t = 2$, and i_1 and i_2 are interest rates in the same periods. We discount income and consumption in period to by the interest rate. Thus, the left hand side of the equation can be viewed as the present value of consumption and the right hand side is the present value of income. (Rødseth, 1992, p. 134)π_1 is the *implicit rental price* and is defined as:

$$\pi_t = q_t[(1+i_t)\frac{q_{t-1}}{q_t} - (1-\delta)] \tag{C.3}$$

where q_t and q_{t-1} are the prices of durable goods purchased in periods t and $t-1$ respectively, and consumed in the subsequent period. This implict rental price is a result of the assumption that agent's borrow money to buy durable goods. This is the rent that the agent implicitly pays to himself for using the good. It can also be interpreted as the opportunity cost of using it, which is what he could make by renting the good another agent.

It is evident that interest rates are an important determinant of demand for durable goods. As with non-durable goods, an increase in the interest rate will have a substitution effect that leads to reduced consumption now and more in the future. Another consequence of an interest rate hike is the wealth effect which can lead to both increased and decreased consumption, depending on the agent's future income and position in hte life cycle. In addition, an increase in the interest rate leads to higher implicit rental price for the durable good and therfore substituion to consumption of a non-durable good. A short term increase in income can also have a profound effect on demand for durable goods. (Rødseth, 1992, p. 136)

Similarly, if we assume that agents would like to smooth consumption throughout their life-cycle as much as possible, then there will always be a tendency that the purchase of durable goods with occur early in an agents life-cycle. This implies that consumer undertake more debt early in life than later on. It is important to note that this model does not take transaction costs into account.

These basic insights have powerful implications for the demand for housing and therefore also for house prices. Demand for durable goods depends on agents expectations of future income, interest rates, and future consumption in a greater sense than for non-durable goods because consumption can be postponed if the agent already has some stock of the good. For example, if a consumer already owns their home, but would like to buy a new one, then his choice of when to purchase depends on his expectation of future price. If he expects housing prices to decrease then he will postpone purchase and live in his current home longer. Similarily, the choice of how much money to spend on a new home depends on future income - the buyer is willing to spend more, and has access to more credit, the higher his future income is expected to be.