Regime shifts in the Swedish housing market
A Markov-switching model analysis

Jakob Stöckel
Niklas Skantz
Master of Science thesis

Title: Regime shifts in the Swedish housing market - A Markov-switching model analysis

Authors: Jakob Stöckel and Niklas Skantz

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Supervisor: Han-Suck Song

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Abstract

Problem statement: Accurate and reliable forecasts of trends in the housing market can be useful information for market participants as well as policy makers. This information may be useful to minimize risk related to market uncertainty. Since the burst of the housing bubble in the early 1990s the price level of single-family houses has risen sharply in Sweden. The Swedish housing market has experienced an unusually long period of high growth rates in transaction prices which has opened up for discussions about the risk of another housing bubble. Business and property cycles have shown to contain asymmetries, which linear models are unable to pick up and therefore inappropriate to analyze cycles.

Approach: Therefore, this study uses non-linear models which are able to pick up the asymmetries. The estimated models are variations of the Markov-switching regression model, i.e. the Markov-switching autoregressive (MS-AR) model and the Markov-switching dynamic regression (MS-DR) model.

Results: Our findings show that the MS-AR(4) model allowing for varying variance across regimes estimated using the growth rate of FASTPI produce superior forecasts over other MS-AR models as well as variations of the MS-DR model. The average expected duration to remain in a positive growth regime is between 6.3 and 7.3 years and the average expected duration to remain in a negative growth regime is between 1.2 to 2.5 years.

Conclusion: The next regime shift in the Swedish housing market is projected to occur between 2018 and 2019, counting the contraction period in 2012 as the most recent negative regime. Our findings support other studies findings which indicate that the longer the market has remained in one state, the greater is the risk for a regime shift.
Regimskiften på den svenska bostadsmarknaden - En analys med Markov-switchingmodeller

Jakob Stöckel och Niklas Skantz

Fastigheter och Byggande

TRITA-FOB-ByF-MASTER-2016:21

Han-Suck Song

Bostadscykler, Markov-switching, regimskifte, MS-AR, övergångssannolikheter, vändpunktsmodell, MS-DR, vändpunkter, svenska bostadsmarknaden, prognos.

Sammanfattning


Resultat: Resultatet visar att MS-AR(4)-modellen som tar hänsyn till varierande varians över regimerna estimerad med tillväxten av FASTPI producerar överlågsna prognoser jämfört med andra MS-AR-modeller samt variationer av MS-DR-modellen. Den genomsnittliga förväntade varaktigheten att befinna sig i en positiv regim är mellan 6,3 och 7,3 år och den genomsnittliga förväntade varaktigheten att befinna sig i en negativ regim är mellan 1,2 till 2,5 år.

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Research on property and housing cycles is currently very hot since prices in many real estate markets worldwide have risen sharply in the past decades. Many researchers also argue that these real estate markets are overheated. Up until now, there has not been any quantitative studies using Markov-switching models, also known as regime-switching models performed on the Swedish housing market. We hope our findings will be useful and provide new insights about housing cycles and how they behave.

We would like to thank our supervisor Han-Suck Song for his valuable input and participation in the process of writing this master thesis. This study would not have been possible without his great knowledge.

Please feel free to contact us if you have any questions regarding our study at jstockel@kth.se (Jakob Stöckel) or nslantz@kth.se (Niklas Skantz).

Jakob Stöckel and Niklas Skantz
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Introduction

The price level of single-family houses in Sweden has risen sharply since the great recession in the early 1990s (Statistics Sweden 2016). The sharp increase has opened up for discussions about the possibility of a housing bubble. Lind (2008) argues that when prices increase sharply and people have strong expectations about future prices, more speculative buyers might enter the market to try to make quick profits and therefore increase the demand and price level. This might be particularly interesting for the Swedish housing market where the current price boom is the lengthiest of 18 industrialized countries according to a major study by Agnello and Schuknecht (2011).

In today’s hot housing market, it is particularly important with reliable and accurate forecasts of regime shifts to reduce the risk of a new major crash in the Swedish housing market. The risk for a contractionary regime shift increases with the duration being in an expansionary regime (Durland and McCurdy 1994; Bracke 2013). Studies have shown that business cycles and housing cycles are interlinked, where the business cycle affect the housing cycle and vice versa (Adams and Füss 2010; Beksin and Abdullahi 2011).

Today many researches worldwide have studied business cycles using especially linear time series models (see e.g. Beveridge and Nelson 1981; Neftçi 1984; Sichel 1993). Nonetheless, non-linear time series models has become much more common recently. However, studies performed on the Swedish housing market using non-linear models are lacking. Accurate predictions of housing cycles can be useful to assess and determine the length of expansions and contractions, as well as to predict regime shifts, which may be valuable information for macroeconomic policy makers and lending institutions.

However, such predictions of future regime shifts or price changes are only meaningful in case where historical information in some way reveal something about the future. Fama (1970) is probably the most famous study within this scope, commonly referred to as the efficient-market hypothesis. Briefly, if the market is any efficient at all, technical analysis such as linear models as well as non-linear models are ineffective because current prices are only affected by new information. Numerous studies have concluded the efficient-market hypothesis to be true for financial assets, where Jensen (1978) is probably one of the most famous. On the other hand, studies in the field of housing prices have shown clear indications of market inefficiency in form of strong autocorrelation in historical housing prices, hence prices are predictable by following trends (see e.g. Case and Shiller 1989, 1990; Englund and Ioannides 1997; Hort 1997). The interest in using sophisticated models to analyze regime shifts in the housing market has increased exponentially in the wake of the U.S. sub-prime mortgage crisis during 2007-2009.

Business and housing cycles can be represented by different regimes, i.e. periods of expansion and contraction. Over these periods the economy react and behave differently, which can be explained by cyclical asymmetries (Kontolemis 1999). To analyze and identify business and housing cycles, researchers often apply various time series models, which can be either linear or non-linear. Linear models are simpler to apply and interpret, but unfortunately unable to pick up the cyclical asymmetries business and housing cycles contain. Lately, the interest to analyze and distinguish regime shifts from expansion and contraction in business cycles has increased (Simpson et al. 2001). The Markov-switching (MS) model proposed by Hamilton (1989) is a popular non-linear approach to analyze business cycles and has the ability to pick up cyclical
asymmetries. The MS model has been widely tested on various macroeconomic variables and economies. The model gained popularity because it does not require any information regarding the length or size of the possible regimes.

Even though the popularity to use MS models to analyze business cycles, the model has not yet been applied to study the Swedish housing market. Hence, there is currently a gap in existing research regarding regime shifts and housing cycles using non-linear time series models in the Swedish housing market. The purpose of this study is to assess the in-sample forecasting performance of the Markov-switching dynamic regression (MS-DR) model and the Markov-switching autoregressive (MS-AR) model; forecast possible out-of-sample regime shifts, including measuring and dating housing cycles in the Swedish housing market.

**Literature review**

Business cycles can be modelled with various time series models, Beveridge and Nelson (1981) measured and dated business cycles in the postwar U.S. economy by using an autoregressive integrated moving average (ARIMA) model. The authors show that at any point in time, the long-run forecasting profile of a time series is asymptotic to a linear function which is a random walk with drift. The difference between this and the actual value is the momentum of the time series and a measure of its transitory and cyclical component. The findings show that the length of expansions and contractions are of similar duration and that the ARIMA model’s ability to date business cycles match the National Bureau of Economic Research (NBER) dating. Similarly, in a study performed in the postwar U.S. economy, an ARIMA model was applied on quarterly real GNP time series data to analyze business cycles. The findings show that in the long run, a 1 percent change in real GNP should change forecasts of real GNP by over 1 percent. The studied time series data showed presence of unit roots and may therefore not be reliable (Campbell and Mankiw 1987). However, studies have provided evidence that time series often contain asymmetries. Findings show that due to the asymmetric behavior in economic time series, linear models such as ARIMA, are not suitable to analyze the different regimes of expansion and contraction over business cycles (Neftçi 1984; Sichel 1993).

Business cycles have periods of different regimes where expansion or contraction occur with asymmetries (Kontolemis 1999). Hamilton (1989) suggests a MS model as a technique for modelling regime shifts in postwar U.S. real GNP. A two regime MS model and an AR(4) model were applied to forecast and date business cycles. The findings show that regime shifts from positive GNP growth rates to negative growth rates is a recurrent feature in business cycles, and therefore the MS model is a useful tool to measure recessions. This suggests that the recurrent pattern of regime shifts in business cycles are better explained with the MS model compared to the AR model. This is due to the fact that the MS model calculates the transition probabilities of being in a specific regime at a given time. However, in a study performed on eight developed economies, findings indicate that the forecasting ability of non-linear MS models only provide slightly improved predictions compared to linear AR models. The study also show evidence that the MS model does not capture all non-linearity and for some economies, outliers are identified as a separate regime (Goodwin 1993). Durland and McCurdy (1994) developed Hamilton’s (1989) MS model further by allowing regime shifts to be duration dependent. In other words, the probability to remain in a certain regime declines the longer the time series has been in the same regime. This extended MS model has been applied on postwar U.S. real GNP. Similar studies support the presence of asymmetry and non-linearity between expansion and recession in
business cycles, as well as recessions to be duration dependent unlike expansions which have been found to not be duration dependent (Diebold and Rudebusch 1990; Diebold et al. 1993; Filardo 1994; Potter 1995). Sichel (1994) found evidence for a “third phase” in business cycles dynamics corresponding to a high-growth recovery phase, taking place in the beginning of expansions and pushes the output back to its previous pre-recession level.

Layton and Katsuura (2001) compared a two regime MS model with probit and logit models to forecast and date U.S. business cycles. These three models are non-linear and their performance to estimate business cycles are in line with the NBER. These models’ forecasting ability to predict regime shifts post-sample was compared and tested. The findings show that the MS model with duration dependent transition probabilities provided better estimates than the probit and logit model. Moolman (2004) studied business cycles in South Africa by using a two regime MS model to capture and distinguish periods of expansion and recession, by dividing real GDP observations into high and low growth regimes. The findings show a strong relationship between interest rates and business cycles. In Malaysia a similar study was performed where Beksin and Abdullahi (2011) applied a two regime MS model on the Malaysian property market. The MS model was used to model and distinguish high and low growth regimes in the Malaysian property cycle and the authors argues that there is a relationship between property cycles and the term structure of interest rates. The property cycles have been modeled using real GDP time series and the term structure of the interest rate to estimate the duration dependent transition probabilities. The findings show a strong relationship between interest rates and property cycles, hence support previous findings from the study performed in South Africa by Moolman (2004). Li et al. (2005) studied a two and a four regime MS model’s performance to distinguish regimes in two industrialized economies, two newly industrialized economies and two developing economies. The data used to test and compare the two models for each economy was the annual industrial production growth rates. The findings show that a two regime MS model works well to distinguish regimes and describe business cycles in industrialized economies and developing economies. The MS model fails to do the equivalent in newly industrialized economies. However, to provide reliable results in newly industrialized economies the sample period should be divided into two sub-periods.

Crawford and Fratantoni (2003) compared the forecasting performance of three different time series models applied on housing prices in the U.S.; two AR models, an ARIMA model, various generalized autoregressive conditional heteroskedasticity (GARCH) models, and a MS model. The findings suggest that the AR models provide best out-of-sample forecasts while the MS model provide best in-sample forecasts. However, Miles (2008) found that a generalized autoregressive (GAR) model, considering the results of Crawford and Fratantoni (2003), in most cases provide better out-of-sample forecasts than ARIMA and GARCH models. Bessec and Bouabdallah (2005) assessed Monte Carlo simulations to examine the reason why MS models provide superior in-sample forecasts compared to linear models, while the opposite applies for out-of-sample. The result shows that the main source of error is related to misclassification of future regimes. Furthermore, Guirguis et al. (2005) presented criticism to numerous of prior studies in the field of assessing forecasts of housing prices, both theoretical and empirical, for not accounting for sub-sample instability of housing prices and constant coefficients. However, to come around this problem, the authors approached a method by testing various of empirical models where the coefficients were allowed to vary in the sample. The results show that the Kalman Filter with autoregressive presentation (KAR) for the parameters’ time variation, and the rolling GARCH model provide best out-of-sample forecasts.
Xiao (2007) investigated if the world’s most volatile property market, i.e. Hong Kong’s residential real estate market, can be explained and changed by only fundamentals. This by using a MS present value model on the Hong Kong Domestic Premise Price index and the Hong Kong Domestic Premise Price-Rent Ratio to capture asymmetries. The findings show evidence that the Hong Kong residential real estate market is not driven by only fundamentals and that the MS present value model capture asymmetries. Park and Hong (2012) assessed two MS models forecasting accuracy and ability to identify trends in the U.S. housing market. This by using time series data variables which has been shown to significantly affect the U.S. housing market, e.g. index of new residential construction, new residential sales and the S&P/Case-Shiller Home Price Index. The U.S. housing market was analyzed by calculating the average month-to-month changes and applying a Markov-switching random walk (MS-RW) model and a MS-AR model. The forecasting performance was tested by using forecasting memory. The findings show that these two MS models’ can be used to analyze housing cycles and provide reliable forecasts in the U.S. housing market. Chen et al. (2013) studied the U.S. housing market to determine feasible regime shifts in housing price cycles and the performance of forecasting housing returns. The authors used a two regime MS model to distinguish a high volatility regime and a low volatility regime. The data consists of time series data of housing returns, real GDP, housing starts, consumption, inflation rate, interest rate and the term spread. The findings show that in a one regime MS model, forecasting housing returns are better explained by using the inflation rate and the federal funds rate. The two regime MS model on the other hand predicts both in-sample and out-of-sample high volatility regimes, or in other words boom-and-bust regimes best using the inflation rate and the federal funds rate.

**Housing cycles**

It is acknowledged that markets in general develops in cycles, commonly with booming periods followed by busts. For instance the booms that busted in the U.S. in the 1930s, in Japan, Sweden, Finland and Ireland in the 1990s, the tech bubble in 2000, and more recently in numerous countries worldwide in 2007 in adjacent to the U.S. sub-prime mortgage crisis. Henceforth, several studies have strived to identify determinants, triggers and consequences of such cycles, while others have focused on assessing regime shifts and durations of the cycles.

Before 2000, housing prices followed the development of the GDP deflator and the effect of housing prices was not considered as individually important to mention in basic macroeconomic theory, such as conventional textbooks (Case et al. 2011). Yet this started to change in the U.S. during the mid-1970s where housing prices began to increase steeper than the GDP deflator. Henceforth a slightly more volatile housing market appeared, but nonetheless rather in line with the development of the GDP deflator. In the early 2000 the U.S. housing market started to boom and grew substantially faster than the GDP deflator. The boom reached its top in adjacent to the U.S. sub-prime mortgage crisis that caused the bust in December 2007 which lasted until June 2009. The bust eliminated the bubble’s price rise and brought the prices back to the pre-boom level. The U.S. crisis that occurred became global as a result of its spillover effects to other markets worldwide, thus the housing market have become a considerable feature in established macroeconomic theory (see e.g. Case et al. 2011; Deniz and Parkash 2012; Harvé Ott 2014)

Aghello and Schuknecht (2011) used a multinomial probit model to examine booms and busts, and the determinants in industrialized countries housing markets over the period 1980-2007. They claim that the duration of the the current booms are unusually lengthy. Furthermore,
their findings indicate domestic credit and short term interest rate to be contributing determinants for booms and busts. While financial deregulations are expected to enhance the probability of booms, regulatory policies are likely to mitigate booms, and banking crises are likely to cause busts. Bracke (2013) performed a similar study by assessing a linear probability model with focus on up- and downturns in OECD countries over the period 1970-2010. In accordance with Agnello and Schuknecht (2011), the current upturns are claimed to be particularly lengthy. Moreover, the result suggests that the duration of upturns in average are longer than downturns (when the last lengthy boom is counted). Furthermore are upturns more likely to end as the duration increase, while the same is not true for downturns (regardless if the last lengthy boom is counted or not). In general terms, housing cycles have shown to last for 2-22 years and are in the long-run commuting around a constant average. Harv´e Ott (2014) is another study examining duration and determinants of housing busts. However, unlike the two other studies, this study focused on European countries that started to experience busts in 2007. This by applying a panel error correction model. In addition, a forecast was assessed to investigate how prices would settle. The result suggests that crucial determinants in the short run are persistent, households’ disposable income, and housing mortgage. While crucial determinants in the long run are dwelling stock and households disposable income. The forecast indicates that housing prices are likely to return to the equilibrium prices in 2014, then gently settle in 2016, and later on continue to increase to new higher equilibriums.

Hilbers et al. (2008) examined deviations and the underlying determinants of the housing price development among various European countries. The result shows that a user cost approach combined with demographic factors and output capturing the housing price development for most European countries. Furthermore, fast and average growing countries are mainly driven by income, and trends in user costs (total annual cost of owning a home), and are more sensitive to negative development of fundamentals. On the other hand, falling housing prices in slow growing countries are harder to explain with the usual fundamentals. Another study examining determinants is Goodhart and Hofmann (2008), using a fixed-effects panel vector autoregressive (VAR) model to assess the causality between macroeconomic variables and housing prices in several industrial countries. The result indicates multidirectional causality between housing prices, the macroeconomy and monetary variables. Moreover have shocks related to monetary variables greater impact on housing prices in booming periods. Similar results are shown by Adams and Füss (2010), by using a panel cointegration analysis to assess long- and short-term effects of macroeconomic determinants on housing prices in various countries. Their result suggests that an increase in economic activity by 1 percent corresponds to an increase in housing prices by 0.6 percent, while an increase in construction costs, and interest rate, correspond to a change in housing prices by 0.6, respectively -0.3 percent. Deviation from the long-term equilibrium is argued to take up to 14 years to be completely adjusted. Andrews (2010) found similar results while analyzing determinants for housing prices with focus on the price level and volatility among OECD countries. This by applying a vector error correction (VECM) model. The result suggests housing prices to be linked with income by increasing proportionally, while the opposite occurs when unemployment and interest rates increase. It is moreover suggested that the deregulation on the mortgage market has contributed to higher housing prices. Higher leverage has led to higher volatility, while stricter supervision of banking policies and higher transaction costs will mitigate volatility. Moreover are households’ tax reliefs on mortgages found to amplify the housing price growth, increase the volatility and urge households to take on leverage. Madsen (2012) is another study finding evidence of links between housing prices and various variables. The study strives to explain the increase in housing prices among OECD countries over the period 1995-2007 by proposing a repayment model. The findings reveal that housing prices in the
short run are determined by nominal GDP and nominal mortgage payments. On the other hand acquisition costs are the main determinant in the long run. Furthermore are income elasticity close to 1, and housing prices are claimed to be independent of housing rents.

**Housing cycles in Sweden**

*The boom and bust in the 1980s till the mid-1990s*

Jonung et al. (2005) compared the Swedish and Finnish boom and bust cycles between the 1980s and the mid-1990s against other industrialized countries. Their result shows that the booms and busts were stronger in Sweden and Finland compared to the other countries surveyed in the study. The busts were triggered by two crises; a banking crisis caused by the financial liberalization, and a currency crisis caused by defensive currency policy. Moreover, the crisis affected the two economies as whole, and thereby their commercial real estate and housing markets. The low real interest rates and high capital growth during the booms stimulated the price growth in both the commercial real estate and the housing markets, followed by rapidly increasing real interest rates that completely restored the prices to the pre-boom levels. The falling prices halted when the Riksbank replaced the defensive currency (i.e. the pegged currency) with an inflation target. Henceforth the currency depreciate, which stimulated the exports and economies as whole. Jonung et al. (2008) came to similar conclusions in a study of the same crises in Sweden and Finland. In addition they claim that the favourable tax systems (i.e. deductible interest rate expenses) for borrowing money partly contributed to further over-lending. Furthermore, the over-lending later in the 1990s turned out to have resulted in over-investments, particularly in the housing market. Due to the sharp increase in housing prices, households had the opportunity to increase borrowing since the value of collateral simultaneously was increased, without noting they placed themselves in over-indebtedness positions.

Roszbach (2004) studied financial institutions lending policies in Sweden over the period 1994-1995 by assessing a bivariate tobit model. The result indicates that lending policies were not compatible with default risk minimization and does not favour applicants with longer expected survival times, and thus violates the common idea of a trade-off between default risk and return. However, it cannot be excluded that banks prioritize other aspects such as fees on related products.

*The current boom since the mid-1990s*

Agnello and Schuknecht (2011) estimated the current housing price boom in Sweden to the lengthiest and strongest of all 18 industrialized countries in an international comparison of booms and bust cycles over the period 1980-2007. The Swedish boom was assessed with a persistence of 11 years with an accumulated magnitude of 67.08 percent. Bracke (2013) presented similar results in a study of up- and downturns of 19 OECD countries over the period 1970-2010. Where the current upturn in Sweden was assessed to 56 quarters with an accumulated amplitude of 140.2 percent. Only the Netherlands and Belgium were assessed with longer current upturns and amplitudes. It can be worth noting that both the Netherlands and Belgium also were included in the study by Agnello and Schuknecht (2011), but were considered as “long cyclers” rather than booming markets.

Claussen et al. (2011) argue that there are several indications of that current housing prices in Sweden have increased beyond the long-term trend and can be considered as overvalued based
on only this definition. However, it is argued that the positive trend since the mid-1990s mostly can be explained by the fundamentals; higher incomes, lower real interest rates, and greater preferences of housing consumption, and thus should not be considered as overvalued based on the definition of fundamentals. Similar findings are presented by Englund (2011). Moreover, Claussen et al. (2011) argue that it would be problematic to prevent increasing housing prices by contractive monetary policy since the effect of higher real interest rates and lower income would simultaneously affecting the rest of the economy negatively.

Finocchiaro et al. (2011) reviewed the current literature of households’ leverage, housing prices and macroeconomic implications, and the characteristics of Sweden within this scope. One particular feature raised for Sweden’s housing market is the highly regulated rents. Due to the regulation there is a lacking link between rents and housing prices, thus the otherwise used indicator based on the deviation of the ratio between rents and prices cannot be used to explain fundamental housing prices and a possible bubble. Furthermore, since the regulation complicates to get a rental apartment, particularly in metropolitan areas, households might be forced to buy their residences and thus become exposed to the price fluctuations associated with owning their residences. On the one hand, the highly regulated market in combination with high construction costs have contributed to less new constructed residences in comparison to other European countries. On the other hand, the regulation has reduced speculations of buy and rent out in the housing market. Another particular feature raised is floating mortgage rate contracts, this is by far the most common mortgage contract among Swedish borrowers, which makes them more sensitive to interest fluctuations. Moreover are Swedish borrowers fully responsible of repayment of their mortgages, regardless of the current value of their underlying collateral. This however might have dampened households’ indebtedness, but might also negatively affect their consumption in case of raised interest rates. Other particular Swedish features are that Swedish households’ savings are increasing, but also their home equity withdrawal. The final feature raised is that the support for the debt distribution in Sweden does not pose a serious threat to the financial stability. However, the authors stress that it previously has been difficult to predict bubbles. In the U.S. it was not clear if the market was overvalued before it became obvious that prices started to fall.

Methodology

This is a quantitative study which uses time series models developed by Hamilton (1989) to analyze, forecast, date and distinguish regime shifts in the Swedish housing market. Since time series data and statistical methods are used, a quantitative approach is most suitable to provide reliable results (Saunders et al. 2015). Hamilton’s (1989) Markov-switching model has been chosen because it is one of the most popular non-linear models to analyze business cycles and is commonly applied on economic and financial time series data, with the ability to produce reliable in-sample forecasts. The Markov-switching model also has a reliable theoretical foundation and is commonly used in the field of econometrics as well as in research of business and property cycles (see e.g. Moolman 2004; Li et al. 2005; Chen et al. 2013).

Time series data is data that has been collected over time and is widely used in many fields, e.g. economics, finance and social sciences. Time series analysis is used to interpret and understand time series data and is frequently used in practice to make forecasts. However, time series data does often contain trends or seasonality, which may cause the estimated time series models to provide unreliable results, leading to imprecise conclusions of the analysis. Time series data con-
taining trends or seasonality are often referred to as non-stationary variables, where a common solution to remove trends or seasonality is to transform the time series into logarithmic form or first difference. A commonly used method to determine whether or not time series are stationary or non-stationary is to test the time series for unit roots with the Augmented Dickey-Fuller (ADF) test (Brockwell and Davis 2002).

This study uses two types of Markov-switching regression models, where the first is the Markov-switching dynamic regression (MS-DR) model and the second is the Markov-switching autoregressive (MS-AR) model. Markov-switching models applied on time series data can be used to identify and analyze business cycles (Hamilton 1989). The beauty of the Markov-switching regression model is that no knowledge of the time or size of different regimes is required (Goodwin 1993). The Markov-switching model proposed by Hamilton (1993) is based on the assumption that the development of \( y_t \) can be explained by regimes, where a two regime Markov-switching regression model can be expressed as:

### Regime 1:
\[ y_t = \mu_1 + \phi y_{t-1} + \epsilon_t \]  
(1)

### Regime 2:
\[ y_t = \mu_2 + \phi y_{t-1} + \epsilon_t \]  
(2)

where \( y_t \) is the dependent variable, \( \mu_1 \) and \( \mu_2 \) represent the intercepts in each regime and \( \phi \) is the autoregressive coefficient and \( \epsilon_t \) is the white noise at time \( t \). In cases where the timing of regime shifts are known, the two regime Markov-switching model can expressed as:

\[ y_t = s_t \mu_1 + (1 - s_t) \mu_2 + \phi y_{t-1} + \epsilon_t \]  
(3)

where \( s_t \) represents the regime and is equal to 1 if the process is in regime 1 and 2 if it is in regime 2. However, in most cases it is not possible to observe in which regime \( s_t \) the process is currently in and therefore unknown. In Markov-switching regression models the regime \( s_t \) follows a Markov chain. A model with \( k \) regime-dependent intercepts, can be expressed as:

\[ y_t = s_t \mu_{st} + \phi y_{t-1} + \epsilon_t \]  
(4)

where \( \mu_{st} = \mu_1, \mu_2, ..., \mu_k \) for \( s_t = 1, 2, ..., k \) regimes. Following Hamilton (1994), the probability of the Markov chain \( s_t \) can be expressed as:

\[ \Pr(s_t = i | s_t = j) = p_{ij} \]  
(5)

This allows the duration of different regimes to differ in length but are forced to be constant over time (Moolman 2004). Possible transition probabilities, which in other words are the probabilities of remaining in or moving between regimes, can be expressed with a \( k \times k \) transition matrix:

\[ P = \begin{bmatrix} \ p_{1,1} & p_{1,2} & \cdots & p_{1,k} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ p_{k,1} & p_{k,2} & \cdots & p_{k,k} \end{bmatrix} \]  
(6)

where the elements of \( P \) are positive and all columns sums to 1. The Markov-switching dynamic regression (MS-DR) model which is a special case of the Markov-switching autoregressive model can be expressed as:
\[ y_t = \mu_s + x_t \alpha + z_t \beta_s + \epsilon_s \] (7)

where \( y_t \) is the dependent variable at time \( t \), \( \mu_s \) is the regime-dependent intercept, \( x_t \) is a vector of regime-invariant coefficients (which can contain lags) \( \alpha \), \( z_t \) is a vector of regime-dependent coefficients (which can contain lags) \( \beta_s \) and \( \epsilon_s \) is the white noise at time \( t \). The Markov-switching dynamic regression model can be expressed as an MS-AR(0) model, i.e. the model does not include any autoregressive lags. Therefore it is more likely to produce more reliable estimates using high-frequency (monthly and higher-frequency) data than low-frequency (quarterly and lower-frequency) data. The Markov-switching autoregressive (MS-AR(p)) model can be expressed as:

\[ y_t = \mu_s + x_t \alpha + z_t \beta_s + \sum_{i=1}^{p} \phi_{i,s} (y_{t-i} - \mu_{s_{t-i}} - x_{t-i} \alpha - z_{t-i} \beta_{s_{t-i}}) + \epsilon_s \] (8)

where \( y_t \) is the dependent variable at time \( t \), \( \mu_s \) is the regime-dependent intercept, \( x_t \) is a vector of regime-invariant coefficients (which can contain lags) \( \alpha \), \( z_t \) is a vector of regime-dependent coefficients (which can contain lags) \( \beta_s \), \( \phi_{i,s} \) is the autoregressive coefficients in regime \( s_t \) and \( \epsilon_s \) is the white noise at time \( t \). This model is more likely to provide more reliable estimates using low-frequency (quarterly and lower-frequency) data.

The unknown Markov-switching model parameters \( \Theta \) can be estimated using the logarithmic likelihood function (Engel and Hamilton 1990) expressed as:

\[ L(\Theta) = \sum_{t=1}^{T} ln f(y_t|y_{t-1}; \Theta) \] (9)

The forecasting performance is assessed both visually and by comparing the root mean squared errors (RMSE) for different forecasting periods estimated using the Markov-switching autoregressive model and the Markov-switching dynamic regression model. RMSE is calculated as:

\[ RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{N} (y_t - \hat{y}_t)^2} \] (10)

where \( n \) is the number of observations, \( y_t \) is the actual value at time \( t \) and \( \hat{y}_t \) is the forecasted value at time \( t \). Smaller RMSE indicate better forecasting accuracy compared to models with larger RMSE. However, models with a good fit to the data does not necessarily provide more accurate forecasts than models with a worse fit (Woschnagg and Cipan 2004).

**Data**

Housing price indexes are frequently used in quantitative studies examining cycles, determinants, regime shifts, durations and similar. Most likely because housing indexes are easily available and provide extensive historical record of data. For instance, the widely used Standard & Poor’s Case–Shiller Home Price Index with historical prices back from the late 1800s. However, in more recent times similar indexes have become available for all developed countries housing markets (see e.g. IMF or BIS for comprehensive lists). Since housing indexes break through, numerous studies have criticized other indexes and claimed to have refined or constructed more sophisticated and reliable indexes by approaching different techniques. Among the most common techniques are the median price method (Mark and Goldberg 1984; Wang and Zorn 1997), the hedonic analysis (Musgrave 1969; Rosen 1974; Gelfand et al. 2004; Song and Wilhelmsson 2010),
repeated sales method (Bailey et al. 1963; Case and Shiller 1989) and the sale price appraisal ratio (SPAR) method (Bourassa et al. 2006; Shi et al. 2009). Commonly, these techniques are based on data either from transactions or appraisals, and more recently also in combination (Bourassa et al. 2006).

This study uses the two publicly available housing price indexes in Sweden. The Real Estate Price Index (FASTPI) by Statistics Sweden and the NASDAQ OMX Valueguard-KTH House Sweden Index (HOXHOUSESWE) by Valueguard. Both indexes are based on transactions; FASTPI by title deeds from the Swedish Cadastral Authority’s official Land Registry, and HOXHOUSESWE by sales reported by real estate brokers. FASTPI is presented quarterly since the first quarter of 1986 and is a median price index, while HOXHOUSESWE is presented monthly since January in 2005 and is a hedonic/quality adjusted index. However, it can be worth noting that data based on housing appraisals is also publicly available in Sweden through the Swedish Tax Agency’s property tax appraisals. But nevertheless, as property taxation of single-family houses is appraised on three years basis with a two years lag, it would not contribute to the purpose of this study in addition to the other two used indexes.

The major advantages of using median price indexes such as FASTPI are that they are easy to understand, assess, and compare with other median indexes. Due to the simplicity of these indexes, they do not consider quality of houses and might perform imprecise results, hence quality of sold houses is likely to differ from the median house over periods, referred to as systematic bias (Hill 2013). A common way to come around this is to use a quality adjusted/hedonic method (i.e. the prices are functions of the houses characteristics (e.g. number of rooms, areas, location etc.) obtained by regression analysis) as the HOXHOUSESWE index does. However, it is argued that the housing markets characteristics contain too many possible variables, hence essential variables might be omitted and cause omitted variable bias. In addition, it cannot be excluded that included variables are strategically chosen to get a desirable result, especially in case where incentives are involved (Shiller 2008). Furthermore, hedonic indexes might be subject to sample selection bias (see e.g. Gatzlaff and Haurin 1998; Hill, Melser and Syed 2009).

Figure 1: Real estate price indexes in Sweden between the first quarter of 1986 and the first quarter of 2016 (FASTPI), and between January 2005 and January 2016 (HOXHOUSESWE) (Statistics Sweden 2016; Valueguard 2016).
Table 1: Descriptive statistics of FASTPI and HOXHOUSESWE and their growth rates (Statistics Sweden 2016; Valueguard 2016).

<table>
<thead>
<tr>
<th>Statistic</th>
<th>FASTPI</th>
<th>HOXHOUSESWE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>121</td>
<td>133</td>
</tr>
<tr>
<td>Starting point</td>
<td>Q1 1986</td>
<td>Jan 2005</td>
</tr>
<tr>
<td>Ending point</td>
<td>Q4 2015</td>
<td>Jan 2016</td>
</tr>
<tr>
<td>Frequency</td>
<td>Quarterly</td>
<td>Monthly</td>
</tr>
<tr>
<td>Mean</td>
<td>323.96</td>
<td>140.28</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>160.63</td>
<td>20.24</td>
</tr>
<tr>
<td>Minimum</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Maximum</td>
<td>683</td>
<td>194.55</td>
</tr>
<tr>
<td>A. Dickey-Fuller</td>
<td>(1.00) ns</td>
<td>(0.98) ns</td>
</tr>
</tbody>
</table>

Note: *** = reject the null hypothesis of a unit root at 1% significance level; ns = non-significant; p-values in parentheses.

As can be seen in table 1, the two indexes are non-stationary while the quarterly and monthly growth rates are stationary. Thus, the models in this study are estimated using the growth rates. FASTPI is expected to provide more reliable results using the MS-AR model, due to its less frequent data. HOXHOUSESWE is expected to provide more reliable results using the MS-DR model, due to its more frequent data. However, FASTPI contain the 1990s housing bubble which may be necessary for the models to be able to distinguish expansionary and contractionary regimes.

Housing prices are assumed to be linked to population growth, real disposable income and urbanization. The population in Sweden has increased by 17.5 percent and the real disposable income per capita has increased by 78.6 percent between 1986 and 2015 (Statistics Sweden 2016). This might explain the sharp increase in demand for centrally located housing. The Swedish housing market move in long cycles and has well defined regime shifts, where regime shifts can be defined as a switch from positive to negative growth rate in housing prices and vice versa (Agnello and
Studies of housing prices have shown signs of cyclical and are therefore said to be predictable in the short and medium run. Englund and Ioannides (1997) performed a study on the Swedish housing market and their findings show a strong autocorrelation in housing price changes compared to exchange traded assets. Their findings also show that housing prices tend to return to its trend in the long run.

Housing prices in Sweden have risen sharply since the mid-1990s, as can be seen in figure 1 and table 1 (Statistics Sweden 2016). The price level has increased by over 207 percent between the first quarter of 1996 and fourth quarter of 2015 which corresponds to an average yearly increase of 20.8 percent. By visually inspecting figure 1 and figure 2, regime shifts and trends can be clearly distinguished. Between 1986 and 1990, housing prices increased by 42 percent, the late 1980s price increase might be explained by lower real mortgage rates and the deregulation of the credit market. However, this price increase reached its peak in 1990, where the price level started falling in 1991, which might be explained by the increase in real mortgage rates. This price decrease of 28.9 percent between 1991 and 1995 is known as the burst of the Swedish housing bubble caused by the banking and currency crises.

Housing prices started to rise sharply again in 1996 until the global financial crisis in 2007. The price level increased by 139.6 percent between 1991 and 2007 and might be explained by declining real mortgage rates, increasing real disposable income as well as increasing real financial wealth. The global financial crisis resulted in a slight decrease of 5.8 percent in housing prices between 2007 and 2009 followed by a short period of increasing prices. Between the third quarter of 2010 and first quarter of 2012 the price level decreased by 6.3 percent.

From the first quarter of 2012 and the fourth quarter of 2015 housing prices increased by 29.6 percent. According to a study performed by Claussen et al. (2011), changes in housing prices can be explained by a number of various variables. However, the only statistical significant variables in their model was households real disposable income, real mortgage rate and real financial wealth which explained almost all variations in the model. Their findings also show that exogenous variables, or in other words, variables which are not explained inside the model affect housing prices. Thus, the recent increase in housing prices might be explained by an increased preference for housing compared to other consumption, all time low real mortgage rates, increased real disposable income and increased real financial wealth. Their findings also show that monetary policy might be used to affect housing prices. However, they argue that monetary policy has only limited effect on housing prices, as a 1 percentage point change in the repo rate (which is currently -0.5 percent) results in a 3 percent change in housing prices.

Empirical results

In this section, the results are presented from the best performing MS-AR and MS-DR model estimated using the growth rates of FASTPI and HOXHOUSESWE. The models have been tested using various characteristics. The first is to include one to four autoregressive lags, where one lag is usually the optimal number of lags in yearly time series data and four lags are usually the optimal number of lags in quarterly time series data and so forth. The second characteristic is to allow for varying variance across regimes instead of assuming a constant variance. This is useful in case where it is unreasonable to assume that the variance is constant over periods.
of high and low volatility. As can be seen in figure 2, the growth rate of FASTPI have some
periods of high volatility and some of low volatility. The growth rate of HOXHOUSESWE on
the other hand indicates a more constant volatility and that it might contain seasonality. The
third characteristic is to include or exclude regime-dependent autoregressive parameters, which
can be used to analyze how fast or slow shocks in each regime will die out.

Model selection has been carried out in accordance to Burnham and Anderson (2002), where
the model with the lowest Akaike information criterion (AIC) is most probable to minimize
the information loss, hence most suitable to represent the true model. Similarly the Schwarz
Bayesian information criterion (SBIC) can be used to distinguish the most suitable model. The
selected models presented in table 2 and 5 have the lowest AIC and SBIC.

Figure 2 shows that the growth rate of FASTPI was negative in 19 out of 120 quarters be-
tween 1986 and 2016, while HOXHOUSESWE was negative in 48 out of 132 months between
2005 and 2016, all other periods had positive or unchanged growth rate. These periods of posi-
tive and negative growth rate can be divided into two distinct regimes (Agnello and Schukneht
2011), i.e. one negative (regime 1) and one positive (regime 2).

In some cases it might be useful to determine more than two regimes, e.g. one regime with
high positive growth rate, one regime with moderate growth rate and one with negative growth
rate. However, three-regime MS models estimated with the growth rate of FASTPI and HOX-
HOUSESWE provide higher AIC and SBIC and therefore indicate higher information loss and
worse fit to the data compared to the two-regime MS models. Therefore only the results of the
two regime models will be presented in this study.

Results FASTPI

Table 2: Results of parameter estimates from the MS-AR(4) model allowing for varying variance across
regimes and the MS-DR model estimated using the growth rate of FASTPI.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>FASTPI MS-AR(4) model</th>
<th>FASTPI MS-DR model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_1$</td>
<td>-1.9270 (0.7396) ***</td>
<td>-0.3556 (0.5731) ns</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>1.7963 (0.3381) ***</td>
<td>2.5545 (0.2806) ***</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>0.5793 (0.0694) ***</td>
<td>N/A</td>
</tr>
<tr>
<td>$\sigma_1^2$</td>
<td>2.3015 (0.4850)</td>
<td>1.9835 (0.1464)</td>
</tr>
<tr>
<td>$\sigma_2^2$</td>
<td>1.3927 (0.1225) N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>$p_{11}$</td>
<td>0.7959 (0.1212)</td>
<td>0.8998 (0.0736)</td>
</tr>
<tr>
<td>$p_{21}$</td>
<td>0.0343 (0.0219)</td>
<td>0.0340 (0.0271)</td>
</tr>
<tr>
<td>AIC</td>
<td>4.0128</td>
<td>4.4888</td>
</tr>
<tr>
<td>SBIC</td>
<td>4.1789</td>
<td>4.6049</td>
</tr>
</tbody>
</table>

Note: $\mu_1$ = negative regime (regime 1); $\mu_2$ = positive regime (regime 2); $\phi_1$ = AR parameter; $\sigma_1^2$ = variance in regime 1; $\sigma_2^2$ = variance in regime 2; $p_{11}$ = transition probability to remain in regime 1 the next period given it is in regime 1; $p_{21}$ = transition probability to move from regime 2 to regime 1 in the next period; AIC = Akaike information criterion; SBIC = Schwartz Bayesian information criterion; *** = reject the null hypothesis that the coefficient is different from 0 at 1% significance level; ns = non-significant; standard errors in parentheses.

Table 2 shows the parameter estimates from the best performing two-regime MS-AR model and
two-regime MS-DR model. The best performing MS-AR model contains 4 autoregressive lags and allow for varying variance across regimes. This model will be referred to as MS-AR(4) in this study. The best performing MS-DR model estimated using the growth rate of FASTPI is a regular MS-DR model. As expected due to the lower frequency of FASTPI, the MS-AR(4) model provides lower AIC and SBIC compared to the MS-DR model. The MS-AR(4) model provides the lowest AIC (4.0128) and SBIC (4.1789) compared to the other tested models, as well as the lowest AIC and SBIC MS-DR model with an AIC of 4.4888 and an SBIC of 4.6049. Thus, the MS-AR(4) model allowing for varying variance across regimes is assumed to have the lowest information loss compared to the other models estimated using the growth rate of FASTPI.

The two-regime MS-AR(4) model distinguishes a negative regime (regime 1) and a positive regime (regime 2). The average growth rate in each regime is presented by the parameters $\mu_1$, with an average growth rate of -1.9270 percent in contraction periods respectively $\mu_2$, with an average growth rate of 1.7963 percent in expansion periods. The AR parameter $\phi_1$ is estimated at 0.5793, which means that the Swedish housing market is positively correlated with previous quarter’s data. The variance in each regime $\sigma^2_1$ estimated at 2.3015 and $\sigma^2_2$ estimated at 1.3927 indicate higher volatility in periods of contraction (regime 1) than in periods of expansion (regime 2).

The estimated transition probability $p_{11}$ is 0.7959 while $p_{21}$ is 0.0343, where $p_{11}$ is the probability to remain in regime 1 the next quarter given it is regime 1, and $p_{21}$ is the probability to for the process to move from regime 2 to 1 in the next quarter. The probability to transition from regime 1 to regime 2 in the next quarter is $1 - 0.7959 = 0.2041$ and the probability to remain in regime 2 the next quarter given it is in regime 2 is $1 - 0.0343 = 0.9657$. This means that the process is more likely to remain in a regime of expansion (regime 2) and move from a regime of contraction (regime 1) to a regime of expansion (regime 2).

The two-regime MS-DR model also distinguish a negative regime (regime 1) and a positive regime (regime 2). However, the average growth rate in each regime is slightly different compared to the MS-AR(4) model. Regime 1 has an average growth rate of -0.3556 percent in contraction periods, which is a bit lower, and an average growth rate of 2.5545 percent in expansion periods, which is a bit higher than what the MS-AR(4) model estimates. The MS-DR model can be expressed as an MS-AR(0) model and hence does not contain any AR parameters. The MS-DR model does only have one variance parameter $\sigma^2_1$ estimated at 1.9835 and is similar to the MS-AR(4) model.

The estimated transition probability $p_{11}$ is 0.8998 while $p_{21}$ is 0.0340, where $p_{11}$ is the probability to remain in regime 1 the next quarter given it is regime 1, and $p_{21}$ is the probability to for the process to move from regime 2 to 1 in the next quarter. The probability to transition from regime 1 to regime 2 in the next quarter is $1 - 0.8998 = 0.1002$ and the probability to remain in regime 2 the next quarter given it is in regime 2 is $1 - 0.0340 = 0.9600$. This means that the process is even more likely to remain in a regime of expansion (regime 2) and move from a regime of contraction (regime 1) to a regime of expansion (regime 2) compared to the MS-AR(4) model.
Figure 3: Transition probabilities over time for the MS-AR(4) model (left) and the MS-DR model (right) estimated using the growth rate of FASTPI.

Figure 3 shows how the transition probabilities develop over time for the MS-AR(4) model and the MS-DR model estimated using the growth rate of FASTPI. The MS-AR(4) model indicates that the transition probabilities were close to 1 (regime 1) between the second quarter of 1992 and the second quarter of 1994, followed by a stable period with probabilities close to 0 (regime 2) until the global financial crisis in 2007. During the global financial crisis the transition probabilities were then again close to 1 between the second quarter of 2008 and the second quarter of 2010, followed by a short stable period with another high probability period between the first quarter of 2012 and the fourth quarter of 2012. The estimated transition probabilities seem reasonable in accordance to fundamentals described by (e.g. Jonung et al. 2005; Jonung et al. 2008; Claussen et al. 2011; Finocchiaro et al. 2011).

The transition probabilities estimated with the MS-DR model show a similar pattern as the MS-AR(4) model but with longer periods of transition probabilities close to 1. The probability to be in regime 1 is close to 1 between the second quarter of 1992 and the third quarter of 1997 followed by a less stable period until the global financial crisis and then again two longer periods close to 1. Comparing the results of transition probabilities estimated with the MS-AR(4) model and MS-DR model, the MS-AR(4) model seem to capture regime shifts more accurately than the MS-DR model.
Figure 4: One-step-ahead forecasts for the MS-AR(4) model (left) and the MS-DR model (right) estimated using the growth rate of FASTPI.

Figure 4 shows the one-step-ahead forecasts estimated using the growth rate of FASTPI. The one-step-ahead forecast of the MS-AR(4) model captures fluctuations quite well even though with some lag, which is expected since the model includes four AR lags. However, the forecasted values are less volatile than the actual growth rate. The MS-DR model on the other hand fails to capture fluctuations in the growth rate and may thus not be suitable to distinguish regimes and forecast regime shifts.

Figure 5: Fitted values, residuals and the actual growth rate for the MS-AR(4) model (left) and the MS-DR model (right) estimated using the growth rate of FASTPI.

Figure 5 shows the fitted values of the growth rate, the residuals and the actual growth rate. This can be used to assess the MS-AR(4) model’s and the MS-DR model’s fit. As can be seen the residuals explain much of the variation in growth rates. Hence, neither of the two models have a very good fit to the data. However, the models can still be useful to forecast regime shifts and determine the average expected duration to remain and move between each regime.
Figure 6: In-sample forecasts for the MS-AR(4) model (left) and the MS-DR model (right) estimated using the growth rate of FASTPI.

Figure 6 shows the 12 quarter in-sample forecasts of the MS-AR(4) model and the MS-DR model. As can be seen in the figure, the MS-AR(4) model forecasts fluctuations quite accurate while the MS-DR model fails to forecast any of the fluctuations. However, the forecasted growth rate in the MS-AR(4) model is less volatile than the actual growth rate but forecast the first four quarters growth rate changes very well. The results indicate that the MS-DR model might not be suitable to forecast regime shifts in the Swedish housing market.

Table 3: Forecasting performance test results for the MS-AR(4) model and the MS-DR model estimated using the growth rate of FASTPI.

<table>
<thead>
<tr>
<th>Forecast period</th>
<th>FASTPI</th>
<th>MS-AR(4) model</th>
<th>MS-DR model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 quarter</td>
<td>1.2841</td>
<td>0.1724</td>
<td></td>
</tr>
<tr>
<td>2 quarters</td>
<td>1.3502</td>
<td>1.0645</td>
<td></td>
</tr>
<tr>
<td>3 quarters</td>
<td>1.6354</td>
<td>1.4263</td>
<td></td>
</tr>
<tr>
<td>4 quarters</td>
<td>1.4601</td>
<td>1.2475</td>
<td></td>
</tr>
<tr>
<td>5 quarters</td>
<td>1.3236</td>
<td>1.3509</td>
<td></td>
</tr>
<tr>
<td>6 quarters</td>
<td>1.6608</td>
<td>1.8538</td>
<td></td>
</tr>
<tr>
<td>7 quarters</td>
<td>1.7668</td>
<td>1.9577</td>
<td></td>
</tr>
<tr>
<td>8 quarters</td>
<td>1.7780</td>
<td>1.8246</td>
<td></td>
</tr>
<tr>
<td>9 quarters</td>
<td>1.7054</td>
<td>1.7245</td>
<td></td>
</tr>
<tr>
<td>10 quarters</td>
<td>1.6268</td>
<td>1.6954</td>
<td></td>
</tr>
<tr>
<td>11 quarters</td>
<td>1.5930</td>
<td>1.5774</td>
<td></td>
</tr>
<tr>
<td>12 quarters</td>
<td>1.4728</td>
<td>1.3825</td>
<td></td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.1649</td>
<td>0.4608</td>
<td></td>
</tr>
</tbody>
</table>

Note: RMSE calculated using equation 10.

Table 3 shows the calculated RMSE in each forecast period for the MS-AR(4) model and the MS-DR model. As can be seen the MS-AR(4) model produces lower RMSE in six periods, while the MS-DR model produces lower RMSE in the other six periods. However, as can be seen in figure 6 the forecasting performance of the MS-DR model is poor compared to the MS-AR(4) model. Therefore the MS-AR(4) model is assumed to provide more reliable forecasts than the
MS-DR model.

Figure 7: Out-of-sample forecasts for the MS-AR(4) model (left) and the MS-DR model (right) estimated using the growth rate of FASTPI.

Figure 7 shows the out-of-sample forecasts of the MS-AR(4) model and the MS-DR model. The dashed line represent the out-of-sample forecast, which begin after the first quarter of 2016 and spans over an eight quarter period until the first quarter of 2018. As can be seen the MS-AR(4) model forecasts four fluctuations with a downward trend in the growth rate but no regime shifts in the short run. However, as mentioned earlier the out-of-sample forecasting performance of MS models have been shown to be less accurate than linear forecasting models, such as ARIMA and GARCH. Forecasts estimated with the MS-DR model performs poorly and does not predict any fluctuations or regime shifts until the first quarter of 2018. Comparing these results with the in-sample forecasts, the actual growth rate is expected to be much more volatile than the MS-AR(4) model predicts but with accurate predictions of when fluctuations occur.

Table 4: Results of expected durations estimated using the growth rate of FASTPI.

<table>
<thead>
<tr>
<th>FASTPI</th>
<th>Expected duration</th>
<th>MS-AR(4) model</th>
<th>MS-DR model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime 1</td>
<td>4.8989 (2.9089)</td>
<td>9.9791 (7.3323)</td>
<td></td>
</tr>
<tr>
<td>Regime 2</td>
<td>29.1298 (18.5985)</td>
<td>25.0076 (16.9693)</td>
<td></td>
</tr>
</tbody>
</table>

Note: average expected duration (quarters) to remain in each regime; standard errors in parentheses.

Table 4 shows the average expected duration to remain in each regime. The expected durations differ substantially between the MS-AR(4) model and the MS-DR model. Since the time series data is quarterly, the expected duration to remain in regime 1 (contraction) is approximately 1.2 years; respectively an expected duration of 7.3 years to remain in regime 2 (expansion) according to the MS-AR(4) model. While the expected duration according to the MS-DR model is estimated to approximately 2.5 years to remain in regime 1 (contraction) and 6.3 years to remain in regime 2 (expansion). Thus, the next predicted regime shift is expected to occur between 2018 and 2019, counting the contraction period in 2012 as the most recent negative regime.
Results HOXHOUSESWE

Table 5: Results of parameter estimates from the MS-AR(1) model with regime-dependent AR parameters and MS-DR model allowing for varying variance across regimes estimated using the growth rate of HOXHOUSESWE.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>MS-AR(1) model</th>
<th>MS-DR model</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_1 )</td>
<td>0.0320 (0.1720) ns</td>
<td>0.2890 (0.2252) ns</td>
</tr>
<tr>
<td>( \mu_2 )</td>
<td>1.8857 (0.3821) ***</td>
<td>1.2814 (0.9355) ns</td>
</tr>
<tr>
<td>( \phi_1 )</td>
<td>0.4125 (0.0888) ***</td>
<td>N/A</td>
</tr>
<tr>
<td>( \phi_2 )</td>
<td>-0.9886 (0.2263) ***</td>
<td>N/A</td>
</tr>
<tr>
<td>( \sigma^2_1 )</td>
<td>1.3436 (0.9387)</td>
<td>1.3897 (0.1975)</td>
</tr>
<tr>
<td>( \sigma^2_2 )</td>
<td>N/A</td>
<td>2.7355 (0.6336)</td>
</tr>
<tr>
<td>( p_{11} )</td>
<td>0.7471 (0.0792)</td>
<td>0.7695 (0.1720)</td>
</tr>
<tr>
<td>( p_{21} )</td>
<td>1 (9.16 × 10^{-7})</td>
<td>0.7494 (0.4894)</td>
</tr>
<tr>
<td>AIC</td>
<td>3.9142</td>
<td>4.0929</td>
</tr>
<tr>
<td>SBIC</td>
<td>4.0678</td>
<td>4.2240</td>
</tr>
</tbody>
</table>

Note: \( \mu_1 \) = low growth regime (regime 1); \( \mu_2 \) = high growth regime (regime 2); \( \phi_1 \) = AR parameter in regime 1; \( \phi_2 \) = AR parameter in regime 2; \( \sigma^2_1 \) = variance in regime 1; \( \sigma^2_2 \) = variance in regime 2; \( p_{11} \) = transition probability to remain in regime 1 the next period given it is in regime 1; \( p_{21} \) = transition probability to move from regime 2 to regime 1 in the next period; AIC = Akaike information criterion; SBIC = Schwarz Bayesian information criterion; *** = reject the null hypothesis that the coefficient is different from 0 at 1% significance level; ns = non-significant; standard errors in parentheses.

The results of parameter estimates for the MS-AR(1) with regime dependent AR parameters and the MS-DR model allowing for variance switching estimated using the growth rate of HOXHOUSESWE are presented in Table 5. Unexpectedly, the MS-AR(1) model provided lower AIC and SBIC compared to the MS-DR model even though the higher frequency data. The MS-AR(1) model provided lower AIC (3.9142) and SBIC (4.0678) compared to the other tested models including more lags as well as to the best performing MS-DR model with AIC (4.0929) and SBIC (4.2240). Thus, the MS-AR(1) model with 1 regime-dependent AR parameter is assumed to have the lowest information loss compared to the other models estimated using the growth rate of HOXHOUSESWE.

The two-regime MS-AR(1) model distinguish a low growth regime (regime 1) and a high growth regime (regime 2). The average growth rate in each regime is 0.0320 percent respectively 1.8857 percent. The AR parameters \( \phi_1 \) and \( \phi_2 \) is estimated at 0.4125 respectively -0.9886, which means that the Swedish housing market is positively correlated with previous month’s data in low growth rate periods and vice versa in high growth rate periods. The estimated transition probability \( p_{11} \) is 0.7471 while \( p_{21} \) is approximately 1. This means that the process is almost certain to remain in the high growth regime.

The two-regime MS-DR model also distinguish a low growth regime (regime 1) and a high growth regime (regime 2). The average growth rate in each regime is similar to the MS-AR(1) model. Regime 1 has an average growth rate of 0.2890 percent in low growth periods and an average growth rate of 1.2814 percent in high growth periods. The estimated transition probability \( p_{11} \) is 0.7695 while \( p_{21} \) is 0.7494. This means that the process is more likely to remain in the low growth regime.
Figure 8: Transition probabilities over time for the MS-AR(1) model (left) and the MS-DR model (right) estimated using the growth rate of HOXHOUSESWE.

Figure 8 shows how the transition probabilities develop over time for the MS-AR(1) model and the MS-DR model estimated using the growth rate of HOXHOUSESWE. The presentation of transition probabilities appears more dynamic corresponding to higher likelihood of transition between regimes compared to the transition probabilities estimated using the growth rate of FASTPI. However, these models might capture effects of seasonality in the housing market, rather than actual periods of contractions and expansions. Since the periods seems to, more or less, repeat in a yearly pattern. The reason for this is likely to be that HOXHOUSESWE does not include the Swedish housing bubble in early 1990s.

Figure 9: One-step-ahead forecasts for the MS-AR(1) model (left) and the MS-DR model (right) estimated using the growth rate of HOXHOUSESWE.

Figure 9 shows the MS-AR(1) model’s and the MS-DR model’s one-step-ahead forecasts estimated using the growth rate of HOXHOUSESWE. Both models fail to capture fluctuations and regime shifts and does not provide reliable one-step-ahead forecasts. These results indicate that MS models estimated using the growth rate of HOXHOUSESWE are not suitable to distinguish regimes and forecast regime shifts in the Swedish housing market.
Figure 10: Fitted values, residuals and the actual growth rate for the MS-AR(1) model (left) and the MS-DR model (right) estimated using the growth rate of HOXHOUSESWE.

Figure 10 shows the fitted values of the growth rate, the residuals and the actual growth rate. As can be seen the residuals explain almost all of the growth rates variation. Hence, both of the models have a very bad fit to the data and neither of the models produce reliable forecasts.

Figure 11: In-sample forecasts for the MS-AR(1) model (left) and the MS-DR model (right) estimated using the growth rate of HOXHOUSESWE.

Figure 11 shows the 12 months in-sample forecasts of the MS-AR(1) model and the MS-DR model. As can be seen in the figure, both models provide similar forecasts and fail to forecast any of fluctuations or regime shifts. Comparing these results with the results estimated using the growth rate of FASTPI, HOXHOUSESWE is clearly not suitable to analyze housing cycles in the Swedish housing market.
Table 6: Forecasting performance test results of the MS-AR(1) model and the MS-DR model estimated using the growth rate of HOXHOUSESWE.

<table>
<thead>
<tr>
<th>Forecast period</th>
<th>HOXHOUSESWE</th>
<th>MS-AR(1) model</th>
<th>MS-DR model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>3.7550</td>
<td>3.3910</td>
<td></td>
</tr>
<tr>
<td>2 months</td>
<td>2.6312</td>
<td>2.5230</td>
<td></td>
</tr>
<tr>
<td>3 months</td>
<td>2.2545</td>
<td>2.1797</td>
<td></td>
</tr>
<tr>
<td>4 months</td>
<td>1.9911</td>
<td>1.9276</td>
<td></td>
</tr>
<tr>
<td>5 months</td>
<td>1.7843</td>
<td>1.7308</td>
<td></td>
</tr>
<tr>
<td>6 months</td>
<td>2.0028</td>
<td>1.8860</td>
<td></td>
</tr>
<tr>
<td>7 months</td>
<td>1.8719</td>
<td>1.7461</td>
<td></td>
</tr>
<tr>
<td>8 months</td>
<td>1.7867</td>
<td>1.7009</td>
<td></td>
</tr>
<tr>
<td>9 months</td>
<td>1.6844</td>
<td>1.6045</td>
<td></td>
</tr>
<tr>
<td>10 months</td>
<td>1.6411</td>
<td>1.5617</td>
<td></td>
</tr>
<tr>
<td>11 months</td>
<td>1.6628</td>
<td>1.5610</td>
<td></td>
</tr>
<tr>
<td>12 months</td>
<td>1.6383</td>
<td>1.5323</td>
<td></td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.5833</td>
<td>0.5172</td>
<td></td>
</tr>
</tbody>
</table>

Note: RMSE values calculated using equation 10.

Table 6 shows the calculated RMSE in each forecast period for the MS-AR(1) model and the MS-DR model. The RMSE for the MS-AR(1) model and the MS-DR model estimated using the growth rate of HOXHOUSESWE are higher than the RMSE for the MS models estimated using the growth rate of FASTPI, in all periods. Thus, MS models estimated using the growth rate of FASTPI are much more accurate when forecasting the Swedish housing market in-sample.

Figure 12: Out-of-sample forecasts for the MS-AR(1) model (left) and the MS-DR model (right) estimated using the growth rate of HOXHOUSESWE.

Figure 12 shows the out-of-sample forecasts of the MS-AR(1) model and the MS-DR model. The dashed line represents the out-of-sample forecast, which begin after January 2016 and spans over an eight months period until September 2016. As can be seen the two models provide similar forecasts and no regime shifts. However, the forecasts are in line with the forecasts of the MS-AR(4) model and MS-DR model estimated using the growth rate of FASTPI, which predicts a declining growth rate in the near future.
Table 7: Results of expected durations estimated using the growth rate of HOXHOUSESWE.

<table>
<thead>
<tr>
<th>Regime</th>
<th>HOXHOUSESWE</th>
<th>MS-AR(1) model</th>
<th>MS-DR model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expected duration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regime 1</td>
<td>3.9545 (1.2388)</td>
<td>4.3375 (3.3862)</td>
<td></td>
</tr>
<tr>
<td>Regime 2</td>
<td>1 (9.16×10⁻⁷)</td>
<td>1.3344 (0.8714)</td>
<td></td>
</tr>
</tbody>
</table>

Note: average expected duration (months) to remain in each regime; standard errors in parentheses.

Table 7 shows the average expected duration to remain in each regime. The expected durations are similar in the MS-AR(1) model and the MS-DR model. Since the time series data is monthly, the expected duration to remain in the low growth regime is approximately 4 months; respectively 1 month to remain in the high growth regime. These results indicate that the MS-AR(1) model and the MS-DR model estimated using the growth rate of HOXHOUSESWE much likely captures seasonality instead of actual regimes.

Conclusion

Reliable and accurate forecasts of trends in the Swedish housing market are crucial to prevent and minimize the risk of a recurrence of the housing bubble in the early 1990s. Today forecasts of trends in the Swedish housing market are carried out either by using fundamental analysis or technical analysis. However, technical analysis forecasts in the Swedish housing market are often performed using linear models, which have been proven to not capture asymmetries cycles contain.

In this study, forecasts of trends have been carried out using non-linear models which can pick up asymmetries. These models are variations of Hamilton’s Markov-switching regression model, i.e. a Markov-switching aggressive model and a Markov-switching dynamic regression model. Advantages of these models are their ability to estimate average durations being in a certain regime and transition probabilities to move and stay in each distinguished regime.

The results show that trends and cycles in the Swedish housing market can be accurately determined using the growth rate of FASTPI. The selected MS-AR model and MS-DR model distinguish one negative growth regime and one positive growth regime, these models also provide similar results. The MS-AR(4) model allowing for varying variance across regimes produce superior forecasts compared to the MS-DR model and it also captures fluctuations accurately, although being less volatile than the actual growth rate. The results also show that MS models estimated using the growth rate of HOXHOUSESWE perform poorly and most likely distinguish seasonality in the data rather than actual regimes.

Validating fundamental analysis of trends in the Swedish housing market with forecasts estimated and identified using Markov-switching models can provide useful information to market participants as well as policy makers, to minimize risks related to market uncertainty. However, analysis of trends and cycles in the Swedish housing market carried out in this study are based on historical time series data and does not include future structural changes which might affect the market.

The MS models estimated using the growth rate of FASTPI show that the Swedish housing market is more likely to remain in a positive growth regime which have an average duration of
6.3 to 7.3 years, while an average duration of 1.2 to 2.5 years to remain in a negative growth regime. The next regime shift in the Swedish housing market is projected to occur between 2018 and 2019, counting the contraction period in 2012 as the most recent regime shift.

Our findings show that the two most recent negative growth regimes was slightly shorter than the housing bubble in the early 1990s. These two negative growth regimes occurred 2009 and 2012, which are most likely a lagging effect from the global financial crisis (where Sweden is one of the countries that managed the crisis well), or effects of the debt crisis in the Eurozone in 2010-2012. At the moment the Swedish housing market is in an unusually long period of high growth rates. The results of this study supports earlier studies findings that the longer the market has remained in one regime, the greater is the risk for a regime shift.

References


Electronic references

