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PREDICTING A CREDIT CRISIS

HOUSE PRICE INFLUENCE ON THE REAL ESTATE MORTGAGE DEFAULT DECISION

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Abstract

- Title:** Predicting a credit crisis: House price influence on the real estate mortgage default decision.
- Level:** Bachelor's thesis in financial economics, autumn semester 2007.
- Author:** Johannes Forss Sandahl
- Supervisors:** Hossein Asgharian and Hans Byström.
- Purpose:** To evaluate how house price development can indicate risk of mortgage defaults. This leads to conclusions about the capability that the method of the thesis has in predicting mortgage default related crises.
- Questions:** The questions regard which states in the U.S. had the most volatile house prices, which states had unexpectedly high house prices at the end of 2006, and how house prices are affected by changes in interest rates and gross domestic product (GDP). Examination and analysis of the questions above should answer the basic question of this thesis which is: Could house price risk and the expected house price level in relation to interest rate- and GDP development have been used to predict the U.S. credit crisis of 2007?
- Methodology:** The methodology has three main parts. To find out which states that have the highest house price risk, a variance comparison is applied. The states that had the highest unexpected house prices in late 2006 are found by the use of discrete-time simulations. Last, the effect of interest rates and GDP on house prices is examined through an ordinary least squares regression.
- Conclusions:** The conclusion is that house price development work as an indicator of risk of mortgage defaults. However, the method applied does not give a precise picture. The method of this thesis applied on the housing market of the U.S. around 2006 gives examples of two possible reasons for risk of mortgage defaults. These two reasons have to do with housing market characteristics.
- Keywords:** Mortgage default risk, credit risk, mortgage, securitisation, mortgage backed securities, test about two variances, discrete-time simulation, credit crunch, housing market.

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1. Introduction

The introduction establishes an understanding for the objective of the thesis and why that objective is chosen. In order to understand the origination of the topic, the problem background is described. The problem discussion then specifies the questions and the problem. Next, the more general purpose is defined and last the limitations, the target group and the outline of the thesis are given.

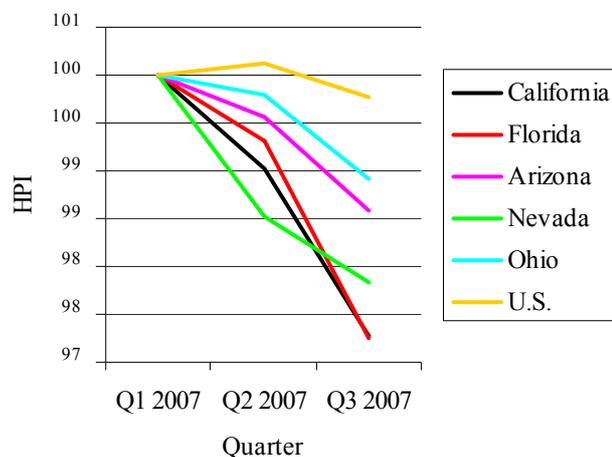
1.1. Background

The United States housing market can be characterised as aggressive with steep price increases for a few years during the very beginning of the 21st century.

Between 1997 and 2007, average U.S. house prices grew by about 106%.¹ A common assumption is that the main reason for this was low interest rates. In late 2006, after two years of official interest rate increases, house prices started

falling. Shortly after these changes, reports started dropping in about heavily increased mortgage default rates around the country.² California, Florida, Arizona and Nevada were the states that fuelled the dark mortgage default statistics of the U.S. in 2007 according to Doug Duncan, the Mortgage Bankers Association's Chief Economist and Senior Vice President of Research and Business Development.³ Another state that also had high mortgage default rates is Ohio.⁴ The 2007 house price falls in the five states mentioned and in the U.S. overall are visualised in chart 1.⁵

Chart 1. House price development 2007.



¹ OFHEO, http://www.ofheo.gov/media/hpi/3q07_hpi_reg.csv. (Nov 08 2007).

² Reuters (2007), p. 1.

³ Waugaman (2007).

⁴ Ibid.

⁵ OFHEO, http://www.ofheo.gov/media/hpi/3q07_hpi_reg.csv and http://www.ofheo.gov/media/hpi/3q07_hpi_sts.csv. (Nov 08 2007). Rebased (Q1 2007 = 100).

Due to widespread securitisation, many financial institutions such as investment banks and hedge funds nowadays rely on securities for which real estate mortgages constitute the underlying assets. Therefore, credit losses and falling values of securities caused many of the institutions and companies that were exposed to these types of securities to suffer. The real estate mortgage default rates rose especially among mortgages that had been given to households with less stable economies.⁶ Securities backed by mortgages with the lowest credit trustworthiness usually have the lowest credit ratings and are placed in the so-called “subprime” rating class.⁷ “Prime” defines loans with top credit ratings because of their high credit trustworthiness.⁸ Loans that have credit ratings that fall between the prime and subprime classes are placed in the “alt-a” class.⁹ The crisis that started to evolve often has been called the “subprime crisis”. However, the most popular name of the crisis and the name that will be used in this thesis is the “credit crunch”.¹⁰

The blame for the credit crunch has been put on many actors in the chain of mortgage lending securitisation. According to many analysts, the state of constantly rising house prices led to mortgage loans being given to households with unfavourable economic conditions. Between 1996 and 2006, the proportion of subprime and alt-a mortgages as underlying assets of private sector mortgage backed securities rose from 47 % to 71 % in the U.S.¹¹ Interestingly, in the middle of 2007, more than one third of the total amount of the adjustable rate subprime mortgages originated in California, Florida, Arizona and Nevada.¹²

During the time of continuous house price increases, lenders used teaser rates to entice borrowers into taking mortgage loans at privileged conditions.¹³ A teaser rate is a low but temporary introductory rate on an adjustable rate mortgage or credit card.¹⁴ Criticism has been directed at this strategy for enabling mortgage loan taking for households that normally could not afford such obligations. For mortgage loans taken at floating teaser rates, increasing interest rates often led to heavily increased costs for the mortgagor. Critics mean that these circumstances contributed to widespread mortgage defaults.¹⁵

⁶ Reuters (2007), p. 1.

⁷ Investopedia, <http://www.investopedia.com/terms/s/subprime.asp>. (Jan 15 2008).

⁸ Ibid., <http://www.investopedia.com/terms/p/prime.asp>. (Jan 15 2008).

⁹ Ibid., <http://www.investopedia.com/terms/a/alt-a.asp>. (Jan 15 2008).

¹⁰ Reuters (2007), p. 1.

¹¹ Rosen (2007), p. 2.

¹² Waugaman (2007).

¹³ Peiser (2007) and Shenn (2007).

¹⁴ Investorwords.com, http://www.investorwords.com/4924/teaser_rate.html. (Jan 12 2008).

¹⁵ Peiser (2007) and Shenn (2007).

Criticism has also been directed at the credit rating agencies. The agencies rating securities backed by mortgages gave high credit ratings to these securities for a long time. Even securities that should have been in the subprime and alt-a classes were sometimes rated with the highest grades. Critics mean that this deceived investors into investing in these securities without realising the credit risks.¹⁶ During 2007 the credit crunch continued and intensified and the subprime and alt-a loans have been given much blame for this.¹⁷

1.2. Problem discussion

From a market perspective the house price can be said to constitute the value of a property. Consider a mortgagor loaning money to finance the purchase of a house. If the house price falls beneath what is left to pay off on the loan the mortgagor suffers a financial loss. The best financial outcome for the mortgagor is then to default the mortgage. In the real world the default behaviour of mortgagors does not follow a simple pattern like that. There are several factors that make the default decision more complex. Examples of these factors are that the mortgagor actually loses the house and that the reputation of the mortgagor worsens. Also, the laws of the most states in the U.S. prohibit the mortgagor from making a free choice to default the mortgage. Still, a bulk of research has proved that house price development and the financial aspect of the mortgagor affect mortgage default risk and the default decision.¹⁸ Therefore, house price development is an interesting perspective when analysing mortgage default risk.

From a house price perspective it is likely that housing markets with high price risk generally have higher risk of mortgage default than housing markets with low price risk. If this is true, the states that had the highest default rates in 2007 should also be the states that had the highest house price risk. An individual state comparison between house price variances¹⁹ answers the first question which is: *Which individual states in the U.S. had the highest house price risk and did these states have the highest rates of mortgage defaults in 2007?*

¹⁶ Rosner (2008).

¹⁷ Scholtes (2007).

¹⁸ Elul (2006), pp. 24-25.

¹⁹ Under the definition of the variance of changes in house prices as the house price risk.

Mortgage default risk is likely to be connected to the financial net of the mortgagor. Falling house prices and decreased financial nets should therefore generate an increased risk of mortgage default. Let us view the credit crunch as a market mechanism adjusting house prices down to the expected level. Then, the states that had the highest rates of defaults in 2007 should be the states that had the highest unexpected house prices in 2006 before house prices dropped. By applying a discrete-time simulation on the housing market, the expected house price level can be calculated and compared to the actual house price level. This answers the second question which is: *Which states in the U.S. had highest unexpected house prices in the end of 2006 and did these states have the highest rates of mortgage defaults in 2007?*

To analyse housing market conditions in relation to mortgage default risk, it is of interest to know how interest rates and the general state of the economy affect house prices. By estimating an equation with the house price level as the dependent variable, it can be tested which variables that significantly affect the house price development. In that way the third question is answered which is: *How are house prices affected by changes in interest rates and gross domestic product (GDP)?*

The problem definition is: *Could house price risk and the expected house price level in relation to interest rate- and GDP development have been used to predict the U.S. credit crunch?* The states in focus are California, Florida, Arizona, Nevada and Ohio.²⁰ The method is successful if it sorts these states out.

1.3. Purpose

The purpose of the thesis is to evaluate how house price development can indicate risk of mortgage defaults. This leads to conclusions about the capability that the method of the thesis has in predicting mortgage default related crises.

1.4. Limitations

Only the United States of America is dealt with. The reason for this choice is mainly that the data concerning house prices and information about the credit crunch is more available from the U.S. than from other economic areas of comparable size.

²⁰ The states that had the highest rates of mortgage default in the first half of 2007. See Waugaman (2007).

When this thesis is written, the world is yet in the credit crunch and the availability of statistics about the crisis is low. Therefore, there is no preciseness regarding for example default rates of the individual states in the U.S.

1.5. Target group

Students of economics and finance are the target group of the thesis. Students learn more about the credit crunch, securitisation, quantitative analysis and simulation models. Chapters 1, 2, 5 and 6 can also be of interest to a person without specific knowledge about economics and finance.

1.6. Outline

Chapter 2: In the second chapter, there are further explanations of the role of securitisation in mortgage lending. This chapter is important in order for the reader to understand the mechanisms that extensive mortgage defaults can cause.

Chapter 3: This is the theory chapter where mortgage default risk research is described. Further explanation is given of the equity model of default, the option theory of mortgage default and the rational choice. These theories are of importance to this thesis as they prove the relationship between mortgage default risk and house prices.

Chapter 4: In this chapter the methodology is explained. The main parts of this chapter are the explanations of the models used. These models are the variance comparison, the discrete-time simulation and the ordinary least squares regression.

Chapter 5: This chapter gives the results and the analysis of the thesis. The results from the models applied are presented and analysed.

Chapter 6: In chapter 6, the conclusions are made. This chapter summarises the inference of the thesis and emphasises its most important points.

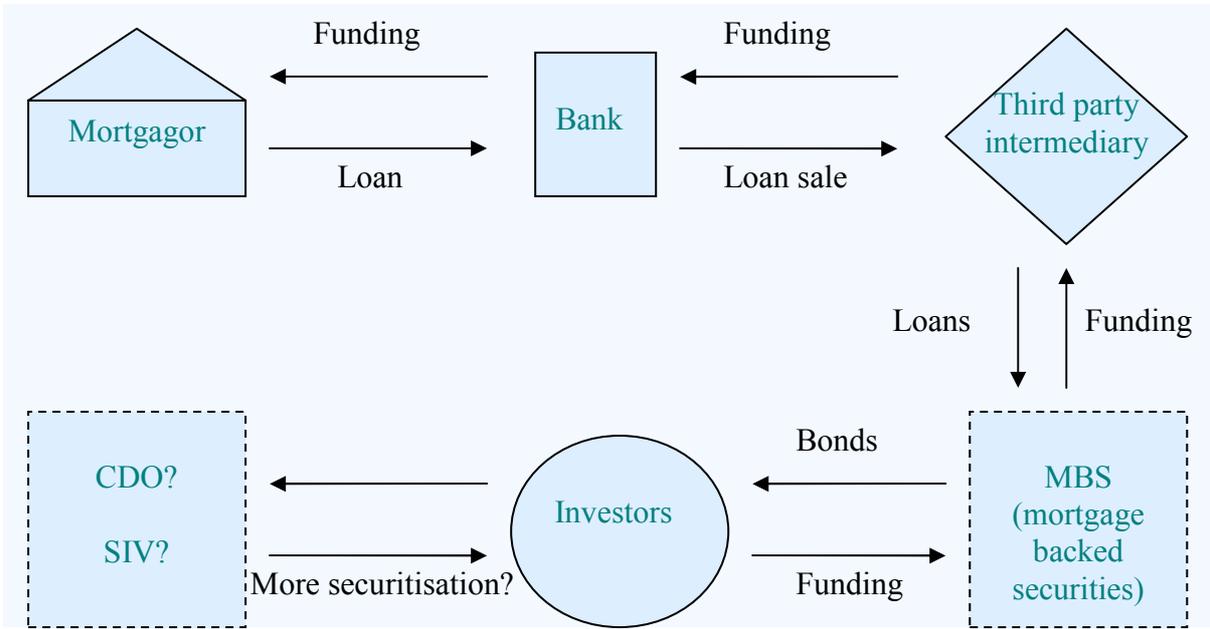
2. Securitisation in mortgage lending

Understanding securitisation in mortgage lending is important to enable wide analysis of mortgage default risk. The securitisation of today can lead to spread effects of mortgage default that magnify the problem significantly. This chapter gives an introduction to the basics of mortgage lending securitisation.

2.1. Structure

Thirty years ago, a mortgage contract usually remained as a deal between the borrower and the lender. As the financial world has advanced so has also the use of mortgages as underlying assets of multiple kinds of securities. Deng, Quigley and van Order (2000) stated that as much as almost half of the outstanding residential mortgages were held in mortgage backed securities (MBS). During the 1990s the outstanding residential mortgaged debt in the U.S. doubled to make up \$ 3 trillion around year 2000. That is to compare with the outstanding government debt which was \$ 5 trillion at that time.²¹

Figure 1. The structure of mortgage lending securitisation.²²



²¹ Deng, Quigley and van Order (2000), p. 275.

²² Rosen (2007), p. 2.

Figure 1 introduces the chain of players in mortgage lending securitisation. The following example explains the basic structure: The borrowers A, B and C borrow money at an interest rate of 6.5 % from bank X. Bank X then sells these mortgages to an intermediary financial institution Y that unifies the mortgages and pools them into one asset. Next, institution Y uses this pooled asset to back bonds with a coupon rate of 6 % that are sold to investor Z. Investor Z does not have to be an individual but can be an organisation like another financial institution. From investor Z the pooled mortgages are often used further to back additional financial solutions for new investors. Examples of additional financial products that can include pools of mortgages and other assets are collateralised debt obligations (CDO) and structured investment vehicles (SIV). It is obvious that securitisation goes deep into the financial system, creating complex financial structures that affect many organisations and individuals.²³

2.2. The risks of mortgage backed securities

There are basically three risks of real estate mortgage backed securities (RMBS). These risks are the prepayment risk, the interest rate risk and the risk of default.²⁴ Even though this thesis deals with the default risk of mortgages only, an introduction of the other two risks is also appropriate.

2.2.1. The risk of prepayment

An investor in an RMBS expects future cash flows that are based on principal and interest payments from the borrower. The prepayment risk derives from the risk that the borrower decides to prepay a part of or the entire principal when interest rates are low. The total income from the RMBS will then be lower than what the investor expected.²⁵

2.2.2. The interest rate risk

The interest rate risk of an RMBS is the same as for any other bond.²⁶ It can be defined as the risk that variations in the general interest rate level cause capital losses or a lower financial

²³ Rosen (2007), pp. 1-4.

²⁴ Ibid., p. 3.

²⁵ Lam (2002), p. 172.

²⁶ Rosen (2007), p. 3.

net.²⁷ The price of a bond is negatively related to the interest rate. This is shown in the general formula for pricing bonds:

$$P_0 = \frac{CF}{(1+r)^t} \quad (\text{Expression 1})^{28}$$

The bond price is equal to the future cash flows divided by the compounded interest rate.

2.2.3. The mortgage default risk – credit risk

The credit risk of an RMBS derives from the situation where the borrower no longer is able to pay off principal and interest. As previously explained in this chapter, the chain of mortgage lending securitisation is complex and has many lines of actors. Credit losses might occur in different lines of the chain depending on how the pooled set of mortgages has been distributed.²⁹

2.3. Credit rating of mortgage backed securities

Credit rating agencies such as Standard & Poor's (also Moody's and Fitch) rate the creditworthiness of mortgage backed securities (MBS). The outlooks of the grades of the different agencies are not equal. However, they follow similar structures. Standard & Poor's for example rate their RMBSs from a top grade of AAA down to AA and so on according to table 1.³⁰ It is obvious that the rate of default rises as the rating falls.

Table 1. RMBS default rate by original rating class.³¹

Initial rating	% of default
AAA	0.04
AA	0.24
A	0.33
BBB	1.09
BB	2.11
B	3.34

²⁷ Söderlind (2001), p. 12.

²⁸ Ibid., p. 139.

²⁹ Lam (2002), p. 172.

³⁰ Tillman (2007), p. 9.

³¹ Ibid., p. 9.

Credit agencies use several models when they rate MBSs. The models calculate default risk and the estimated loss of mortgage default in pools of mortgages. Some models evaluate the availability of cash flow and assets involved in mortgages. They also evaluate legal conditions on which mortgages are founded and the practices and policies involved.³²

2.4. Actors in mortgage lending securitisation

Except for a great number of private firms, the government agency Ginnie Mae and the government-sponsored entities (GSE) Fannie Mae and Freddie Mac issue MBSs.

Ginnie Mae

Ginnie Mae facilitates securitisation of home mortgages for which payments are federally guaranteed or insured. Ginnie Mae also guarantees that interest on mortgage principals are paid in time. However, Ginnie Mae only guaranteed 4 % of all MBSs issued in 2006.³³

Fannie Mae and Freddie Mac

These two organisations accounted for 40 % of all MBSs issued in 2006. They buy conforming mortgages that meet certain borrower quality requirements. For example, Fannie Mae and Freddie Mac have demands on the loan-to-value ratio that is dealt with in chapter 3. The two GSEs then issue MBSs with these conforming mortgages as underlying assets with guarantees that principal and interest on the loans are paid.³⁴

³² Tillman (2007), pp. 7-9.

³³ Rosen (2007), p. 3.

³⁴ Ibid., p. 3.

3. Theoretical framework

In this chapter, established theory in the area of mortgage default is described and explained. Emphasis lies on theories that are of specific importance to the thesis. The objective of the chapter is to clarify the connection between house prices and mortgage defaults. This relationship is what constitutes the foundation of the thesis.

3.1. Earlier research

Since the beginning of the 1960s, a heavy load of research on mortgage defaults has been made.³⁵ According to Quercia and Stegman (1992), the research made until the beginning of the 1990s can be divided into a first-, a second- and a third generation of studies. The first generation of studies had the purpose of assisting lenders in predicting default probabilities of their borrowers.³⁶ Suffering from limits such as only focusing on the risk at loan origination, not considering the time frame of a mortgage and only handling fixed rate mortgages, these early studies were somewhat narrow.³⁷ In the second generation Jackson and Kaserman (1980) are found among others. The studies of this generation had a borrower perspective. The default decision of a borrower maximising utility and net wealth was in focus.³⁸ Also the option theory applied on mortgage default derives from the second generation. In the third generation, the focus was on estimating default probabilities of fractions of pools of mortgages. In general, the third generation contributed with sophisticated methods of research.³⁹ However, the theory of this thesis is based on studies from the second generation models. Hence, the Jackson and Kaserman (1980) optimisation theory and the option theory applied on mortgage default are explained next.

3.2. An optimisation model of mortgage default

Jackson and Kaserman (1980) compared the capability in explaining mortgage default risk of two models. The equity model of default was proven to dominate the alternative ability-to-pay model.⁴⁰

³⁵ Quercia and Stegman (1992), p. 344.

³⁶ Ibid., p. 353.

³⁷ Ibid., p. 351.

³⁸ Ibid., p. 353.

³⁹ Ibid., p. 361.

⁴⁰ Jackson and Kaserman (1980), p. 685.

3.2.1. The equity model of default

In the following theory, the value of the mortgaged property is defined as the house price. The equity model of default holds that the mortgagor makes a default decision based on a rational comparison between the financial gains and losses that the mortgage and the mortgaged property yield over time. This hypothesis is based on the assumption of a strict optimising financial behaviour of mortgagors. It implies the following definition of mortgage default risk:

$$\Pr(D_t) = \Pr(V_t \leq M_t) \quad (\text{Expression 2})$$

where V_t is the house price at time t and M_t is the outstanding mortgage balance at time t . The outstanding mortgage balance is the total principal and interest that the mortgagor has left to pay off and depends on the terms of the mortgage contract.⁴¹

By definition of a cumulative density function, expression 2 can be rewritten as:

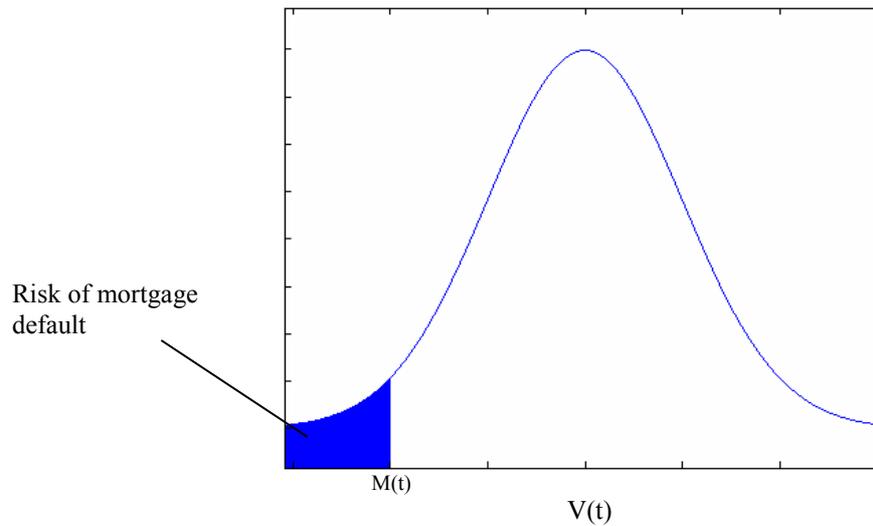
$$\Pr(D_t) = \int_0^{M_t} f_t[V_t] dV_t \quad (\text{Expression 3})$$

where V_t is the variable of possible outcomes of the house price at time t . The expression $f_t[V_t]$ is a probability density function.⁴²

⁴¹ Ibid., p. 679.

⁴² Ibid., p. 680.

Chart 2. The distribution of possible outcomes of the house price according to the equity model of default.



The risk of mortgage default is found in the left-hand tale of the outstanding mortgage balance in the distribution of possible house price outcomes. This is visualised in chart 2.

The outstanding mortgage balance is defined as:

$$M_t = V_0 \left[\frac{L}{V_0} \right] \left[\frac{1 - (1+r)^{t-T}}{1 - (1+r)^{-T}} \right] \quad (\text{Expression 4})$$

where V_0 is the house price at mortgage origination and r is the contract rate of interest of the mortgage obligation. $\frac{L}{V_0}$ is the loan-to-value ratio determining the proportion of payment obligations left to pay off in relation to the house price at mortgage origination. T is the contract life of the mortgage obligation from origination to maturity. M_t is positively related to both the loan-to-value ratio and to the contract interest rate.⁴³

3.2.2. Model quality

Jackson and Kaserman (1980) note that the explanatory capability of the equity model of default is fairly low when the regression is based on individual data. The use of individual data only gives a goodness of fit of 1 % in the study. For this, Jackson and Kaserman give two explanations. First, the use of individual loans as the unit of observation is said to typically lead to a low predictive capability. Second, the low goodness of fit is said to be a result of the

⁴³ Ibid., pp. 679-680.

wide existence of loans insured by the Federal Housing Agency in the sample. According to Jackson and Kaserman, the existence of insurances eliminates the stochastic variation of default probabilities in the sample. This variation accounts for a large fraction of the individual default risk and is what generates the demand for mortgage loan insurances.⁴⁴

Jackson and Kaserman solved the problem by dividing the sample into groups of observations with similar characteristics and using the group means as the unit of observation. This method increased the goodness of fit of the equity model of default to 46 %. According to Jackson and Kaserman, this emphasises the influence of the stochastic element on the individual mortgage default risk.⁴⁵

The significance and explanatory capability of the equity model of default strongly connects the house price to mortgage default risk. Jackson and Kaserman even imply that their study well may constitute the foundation of mortgage default studies based on simulations of house prices.⁴⁶

3.2.3. The use of the equity model of default

There are two important aspects to remember from this section. The first is that the higher the variance of the distribution of possible outcomes of the house price, the higher the mortgage default risk. That is because the distribution of possible outcomes of house prices in chart 2 becomes wider. The variance of possible house price outcomes can be defined as the house price risk. According to the equity model of default, this means that mortgage default risk is positively correlated with house price risk.

The second important aspect is that the mortgage balance is positively related to the house price at mortgage origination. Even though this is obvious it is of great importance to the assumptions of the thesis. A mortgage loan taken at an unexpectedly high house price gives a high loan balance that the house price could fall short of if house prices should fall. According to the equity model of default this causes the mortgagor to default. However, in this thesis the equity model of default is not used strictly. Instead, it is used as empirical evidence that house

⁴⁴ Ibid., pp. 683-684.

⁴⁵ Ibid., pp. 684-685.

⁴⁶ Ibid., p. 687.

prices affect mortgage default risk. In that way it constitutes a foundation for using house price development as an indicator of mortgage default risk.

3.3. Option theory of mortgage default

According to the option theory, mortgagees are writers of call options on long-term debts and put options on real estate prices.⁴⁷

The call option gives the mortgagor the right to pay off the entire mortgage at any point in time. This option is in favour for the mortgagor when alternative contract rates of interest fall⁴⁸ and make alternative loans cheaper.⁴⁹ From the perspective of the investor this is where the prepayment risk derives.

The put option becomes a fact because of the risk that the mortgagor defaults and gives the mortgagee no other alternative than to turn his or her claim into ownership of the real estate.⁵⁰

This choice is favourable to the mortgagor when the price of the real estate falls.

Theoretically, the mortgagor exercises the put option as soon as the value of the property plus any costs that are included with exercising the option falls below the payment obligations. In the same way as in the equity model of default, default is also here seen as a purely financial matter.⁵¹

3.3.1. Model quality

Deng, Quigley and van Order (2000) showed that the probability of a mortgagor exercising the put option to default is strongly correlated with the house price being lower than the loan balance. In terms of option theory this situation is called the put option being “in the money”.⁵² It was also shown that the option theory of mortgage default does not give a complete picture but is rather simple. Research made on the option theory of mortgage default has, for example, shown that mortgagors do not default as soon as the house price falls beneath the loan balance.⁵³ Instead, mortgagors are very likely not to default the mortgage

⁴⁷ Case, Shiller and Weiss (1995), p. 2.

⁴⁸ Long term bond prices rise.

⁴⁹ Case, Shiller and Weiss (1995), p. 2.

⁵⁰ Ibid., p. 2.

⁵¹ Quercia and Stegman (1992), p. 358.

⁵² Deng, Quigley and van Order (2000), p. 303.

⁵³ The equity of the mortgagor goes negative.

until the equity of the mortgagor is significantly negative.⁵⁴ Deng, Quigley and van Order also showed that the call option to prepay and the put option to default depend on each other. For example, a mortgagor that is likely to default is less likely to prepay.⁵⁵ The option theory of default also lacks consideration of the so-called “transaction costs” involved with exercising the put option to default. Examples of transaction costs are that the mortgagor actually loses the house when defaulting and that the mortgagor gets a bad reputation from defaulting.⁵⁶ However, evidence still remains that the option theory of mortgage default has a significant explanatory power on default behaviour.

3.3.2. The use of the option theory of mortgage default

According to the option theory, the value of the default put option rises with a higher house price volatility. That is because the risk of the underlying asset price is high. In other words, the option of the mortgagor to default the mortgage is more valuable and therefore more likely to be exercised when house prices are volatile.⁵⁷

The option theory of mortgage default says that the put option is exercised when the house price falls short of the loan balance. This is the same conclusion as in the equity model of default. In this thesis, the option theory, in the same way as the equity model of default, is not used strictly. It is used as a foundation enabling the use of house price development as an indicator of mortgage default risk.

3.4. Rationality and a strict decision criterion

The rational choice is fundamental in all economics and in the theories above the importance of the rational choice is obvious. “Preference” is a popular word among economists. In economics, when an individual says that “A is preferred to B”, it means that the individual rather has A than B, all scenarios and circumstances considered. The rational choice has three fundamental assumptions:⁵⁸

1. Completeness: The individual is always able to specify which situation is preferred.

⁵⁴ Elul (2006), p. 23.

⁵⁵ Deng, Quigley and van Order (2000), p. 303.

⁵⁶ Elul (2006), p. 24.

⁵⁷ Ibid., p. 23.

⁵⁸ Nicholson (2005), p. 69-70.

For example: “A is preferred to B” or “B is preferred to A” or “A and B are equally preferred”. An individual cannot be inconsistent by saying that “A is preferred to B” and “B is preferred to A”.

2. Transitivity: The choices of an individual are internally consistent. In other words, if “A is preferred to B” and “B is preferred to C” then “A is preferred to C”.
3. Continuity: If an individual specifies that “A is preferred to B” then situations similar to A are also preferred to B.

In the explanation of the equity model of default in section 3.2 the strict decision criterion is mentioned. In economics, the strict preference signifies that the individual definitely prefers a situation more than other possible situations. For example, if an individual says that “A is strictly preferred to B” it implies that the individual with no doubt prefers situation A to situation B.⁵⁹ In other words, the strict decision criterion mentioned in the equity model of default emphasises the criterion of the default decision.

⁵⁹ Varian (2006), p. 34.

4. Methodology

From the problem discussion it is known that a variance comparison model is used to compare house price risk between individual states. Then, a discrete-time simulation model is used to enable a comparison of each state's actual house price level of late 2006 to the expected house price level. Last, a regression is run on the house price development with interest rate and gross domestic product as explanatory variables. The objective of this chapter is to explain why and how these models are used. The methodological approach, criticism of the methodology and thesis reliability and validity are also given.

4.1. A quantitative methodology with an inductive approach

A quantitative methodology is adopted in this thesis. This is the choice since a massive amount of data needs to be used in order to find relationships to base conclusions on.

Induction is a methodological approach based on empirical data whilst deduction is an approach based on logical relationships.⁶⁰ Using an inductive approach means making research based on data retrieved from reality and interpreting the collected data through theories, models and concepts. With the inductive approach one can go from the specific to the general.⁶¹ Induction leads to conclusions based on probabilities. One cannot draw 100 % certain conclusions based on an inductive approach. Instead the inductive approach gives probabilities of different scenarios.⁶² Using the deductive approach means interpreting relationships and validating theories through a logical discussion. One goes from the general to the specific.⁶³ For example one could make conclusions based on combinations of mathematical and logical formulas.

In the analysis of this thesis, empirical data from the U.S. housing market is used. In other words, the approach of the thesis is inductive. It may be stated that the theoretical framework also has a deductive approach. This framework is used as a foundation with a set of assumptions to enable a quantitative methodology with an inductive approach.

⁶⁰ Thurén (2007), p. 22 and p. 28.

⁶¹ Reinecker and Stray Jørgensen (2002), p. 160.

⁶² Thurén (2007), p. 26.

⁶³ Reinecker and Stray Jørgensen (2002), p. 160.

4.2. Data

The variables of data series that are used in the analysis are:

- U.S. and individual state specific house price indices.
- The U.S. one year secondary market Treasury bill interest rate.
- The U.S. gross domestic product.
- Information about models and U.S. mortgage default statistics

House price index

The house price index (HPI) is used as the measure of house prices and house price levels. All HPI data has been collected from *The Office of Federal Housing Enterprise Oversight (OFHEO)*.⁶⁴ OFHEO is an independent entity within the U.S. Department of Housing and Urban Development.⁶⁵

The HPI of the OFHEO is a measure of single-family house price development. The index is a so-called weighted repeat-sales index that measures the quarterly average price changes in repeat sales or refinancings on the same mortgaged properties. The HPI is based on mortgages that have been purchased or securitised by Fannie Mae or Freddie Mac since January 1975.⁶⁶

Interest rate

The source of the interest rate is Datastream. The time series used is quarterly observations of the *U.S. Treasury bill 2nd market 1 year – middle rate*. The time series of this interest rate goes from Q2 1980 to Q3 2001. Therefore the regression includes data from this period.

Gross domestic product

The source of the gross domestic product (GDP) measure is the *OECD Economic Outlook* and is found in Datastream. The GDP measure used is the *GDP (NOMINAL) (AR)* scaled in millions with quarterly observations.

Models and U.S. mortgage default statistics

Information about models and methods is gathered from course books and acknowledged research journals. Information about which states that had the highest rates of default in 2007

⁶⁴ OFHEO, <http://www.ofheo.gov/>. (Nov 08 2007).

⁶⁵ Ibid., <http://www.ofheo.gov/about.aspx>. (Jan 18 2008).

⁶⁶ Ibid., <http://www.ofheo.gov/hpi.aspx?Nav=269>. (Jan 02 2008).

is collected from an announcement of mortgage statistics for the second quarter of 2007 made by Doug Duncan, the Mortgage Bankers Association's Chief Economist and Senior Vice President of Research and Business Development.⁶⁷ Duncan announced that California, Florida, Arizona and Nevada had the highest mortgage default rates in 2007 and that Ohio also had high rates of mortgage defaults.⁶⁸

4.3. Variance comparison

The volatility of house prices can be used a measure of house price risk.⁶⁹ It can be defined as the square root of the variance of changes in house price.⁷⁰ From the equity model of default and the option theory of mortgage default it is known that the house price risk is positively correlated with mortgage default risk. The variance comparison shows which states that had the most risky house prices between 1997 and 2007. It compares each individual state of the U.S. to the entire country. Quarterly observations of changes in HPI are used to calculate the sample variance, s_i^2 . The tests are two-tailed and test the following hypotheses on the 95 % level of significance:

$$H_0 : s_1^2 = s_2^2$$

$$H_1 : s_1^2 \neq s_2^2$$

The test statistic is defined as:

$$TS = \frac{s_1^2}{s_2^2} \text{ has an F distribution with } (79, 79) \text{ degrees of freedom.} \quad (\text{Expression 5})^{71}$$

When all test statistics are calculated the individual states are ranked descending by the test statistics for the period 1997-2007.

4.3.1. Amount of historical data used

As already explained, HPI change observations from ten years back are used in the variance calculations. The reason for this choice is that the latest trends on the housing markets should

⁶⁷ Waugaman (2007).

⁶⁸ Ibid. (2007).

⁶⁹ Hull (2006), p. 758.

⁷⁰ Ibid., p. 252.

⁷¹ Thomas (2005), p. 209.

be captured. In chart 3, the U.S. house prices seemed to enter a new trend around 1997. This motivates why 1997 should be the start point of historical data used here.

4.4. Discrete-time simulation

The equity model of default and the option theory of mortgage default explain that the mortgagor defaults when the house price falls beneath the loan balance. An unexpectedly high house price level could be expected to be adjusted down by the market which could cause mortgage defaults to occur. The discrete-time simulation gives a measure of the expected house price level in each state at the end of 2006. This expected level is then compared to the actual house price level which gives a measure of how close to expected the actual house price level of late 2006 was.

100 potential HPI developments for each state are simulated from 1997 to the last quarter of 2006. Then the actual HPI of each state in the fourth quarter of 2006 is compared to the spectrum of simulated HPIs. The comparison takes place as a test about the mean of the spectrum of simulations.

4.4.1. Assumptions – the Markov property and the Wiener process

The Markov property, usually called the Markov process, states that no historical information about the price helps determining the future price. Therefore, predictions about the future are doubtful and must be expressed in terms of probability distributions. Neither is the probability of a certain price at a certain point in time dependent on price movements of the past.⁷²

The Wiener process is built on a Markov stochastic process with a mean change of 0 and a variance of 1. This process is used to simulate many types of motions and is often referred to as the *Brownian motion*.⁷³ To use the Wiener process for a variable z the assumption is made that the change Δz during a short time interval Δt is $\Delta z = \varepsilon\sqrt{\Delta t}$ where ε is standard normally distributed, $\phi(0, 1)$. Also, it is assumed that the values of Δz in different time intervals are independent.⁷⁴ The Wiener process for a variable x can be expressed as:

⁷² Hull (2006), pp. 263-264.

⁷³ Ibid., p. 265.

⁷⁴ Ibid., p. 265.

$$dx = adt + bdz \quad (\text{Expression 6})$$

where adt is the expected drift per unit of time and bdz is the stochastic process. This is a modification of the Wiener process called the *generalised Wiener process*.⁷⁵

4.4.2. Calculation

In the discrete-time simulation model the relative HPI change in each period is defined as:

$$\frac{\Delta HPI}{HPI_0} = \mu \Delta t + \sigma \varepsilon \sqrt{\Delta t} \quad (\text{Expression 7})^{76}$$

This model is said to follow a *geometric Brownian motion*. The HPI of the next period is calculated as:

$$HPI_1 = HPI_0 \cdot \left(1 + \frac{\Delta HPI}{HPI_0} \right) \quad (\text{Expression 8})^{77}$$

The basic assumption of the model is:

$$\frac{\Delta HPI}{HPI_0} \sim \phi(\mu \Delta t, \sigma \sqrt{\Delta t}) \quad (\text{Expression 9})^{78}$$

This means that the HPI change is assumed to be standard normally distributed with a mean of $\mu \Delta t$ and a standard deviation of $\sigma \sqrt{\Delta t}$. The mean and standard deviation of the HPI changes are also assumed to be constant. The stochastic element ε is generated by the Microsoft Office Excel *Random Number Generator*. For each time period, 100 simulations are made. This generates 100 time series of simulated HPI developments. The simulations are made on a quarterly basis.

⁷⁵ Ibid., pp. 267-268.

⁷⁶ Ibid., p. 271.

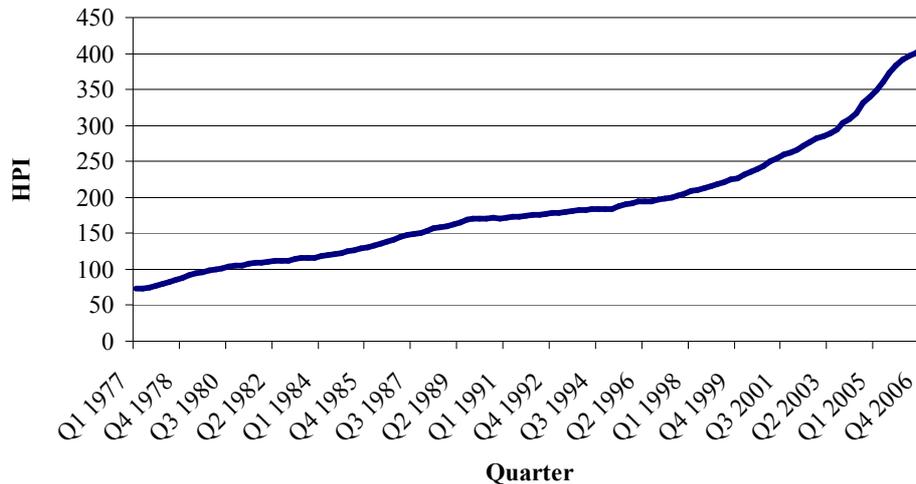
⁷⁷ Ibid., p. 271.

⁷⁸ Ibid., p. 271.

4.4.3. Amount and frequency of data

A critical issue in the simulations is how much data to base the mean and the standard deviation of the HPI change on. The simulation should not give a result based on a temporary trend but on a long run market trend.

Chart 3. U.S. HPI development.⁷⁹



Looking at the U.S. HPI in chart 3, the trend seems to break slightly around 1990 where the growth slows down. The trend also seems to break around 1997 where the HPI starts growing faster. In late 2006 a break is once again found as the HPI growth decreases radically. From this analysis it seems like U.S. house prices develop in cycles of about 5-10 years. Test simulations have been made by using 10 years of data. These did, however, rarely fall in line with the actual HPI development which is an evidence of the need for more data. In the simulations, quarterly data from 20 years back is used to calculate the mean and standard deviation of HPI change.

4.4.4. Test about the mean

In quarter four 2006 a spectrum of 100 possible HPis is retrieved from the simulations. First, the following hypotheses for the two-tailed test are formulated:

H_0 : HPI expected

H_1 : HPI not expected

Second, the arithmetic mean \overline{HPI} and standard deviation s of the possible outcomes are calculated. Third, the right-hand side probability distribution of the actual HPI is calculated

⁷⁹ OFHEO, http://www.ofheo.gov/media/hpi/3q07_hpi_reg.csv. (Nov 08 2007).

using the Microsoft Office Excel function NORMDIST(). Alternatively one could calculate the standardised value of the actual HPI level in the distribution as:

$$Z = \frac{HPI_{actual} - \overline{HPI}}{s} \text{ which has an } N(\overline{HPI}, s) \text{ distribution.} \quad (\text{Expression 10})^{80}$$

Fourth, the states are ranked descending by their right-tale probabilities. This shows which states that had the most extreme HPI developments until 2007. The tests are analysed on the 95 % level of significance.

Together with the probabilities a so-called “actual-to-mean ratio” is presented. This ratio is simply another way of comparing the actual HPI level to the expected HPI level. It is calculated as:

$$\text{Actual-to-mean ratio} = \frac{HPI_{actual}}{HPI} \quad (\text{Expression 11})$$

This gives the following possibilities:

Actual-to-mean ratio < 1 : Actual HPI lower than expected.

Actual-to-mean ratio = 1 : Actual HPI expected.

Actual-to-mean ratio > 1 : Actual HPI higher than expected.

4.5. Regression

In order to analyse mortgage default risk from a house price perspective it is important to know how house prices are affected by general market conditions. The regression shows how the HPI is affected by changes in interest rate and GDP.

The regression is run on changes in U.S. HPI using changes in interest rate and changes in GDP as explanatory variables. In the regression, quarterly observations from 1980 to 2000 are used. The ordinary least squares method is used to estimate the parameters of the equation. Eviews 5 performs the estimation and calculates all test statistics. The estimated equation has the following structure:

$$\Delta HPI = a + b\Delta GDP + c\Delta r \quad (\text{Expression 12})$$

⁸⁰ Thomas (2005), p. 76.

where a is the constant and b and c are the estimated coefficients of the explanatory variables.⁸¹ In connection to the regression, two-tailed t-tests are made of the significance of the influence of the coefficients, b and c , of the explanatory variables. The hypotheses of the tests are:

$$H_0 : b, c = 0$$

$$H_1 : b, c \neq 0$$

In other words, the tests enable to reject or not to reject the hypothesis of a significant influence of changes in interest rate and GDP on the U.S. house price development.

4.5.1. Heteroscedasticity and autocorrelation

White's heteroscedasticity test with no cross terms is used in Eviews to test the estimated equation for heteroscedasticity. To test for autocorrelation, a Bruesch-Godfrey test is used in Eviews.

4.6. Criticism of sources and methods

A couple of factors that can have an effect on the outcome of the three models have been identified. In this section, these factors are explained and the choices of how to deal with those factors are motivated. Thereby, the reliability of the thesis is strengthened.

4.6.1. Standard normally distributed HPI change

Chiong-Long Kuo (1995) criticised the use of the geometric Brownian motion for simulating future house prices. Kuo means that applying the geometric Brownian motion on the housing market has not given a good fit with the actual outcome.⁸² However, much research has otherwise settled with the geometric Brownian motion. For example Daglish, Garfinkel and Sa-Aadu (2007) said that "The assumption that house prices follow a geometric Brownian motion is a simple one, and is a similar assumption to that commonly used in financial option pricing".⁸³ The geometric Brownian motion is the choice of model in this thesis. However, one factor in the model can be questioned further and that is the standard normally distributed changes in HPI.

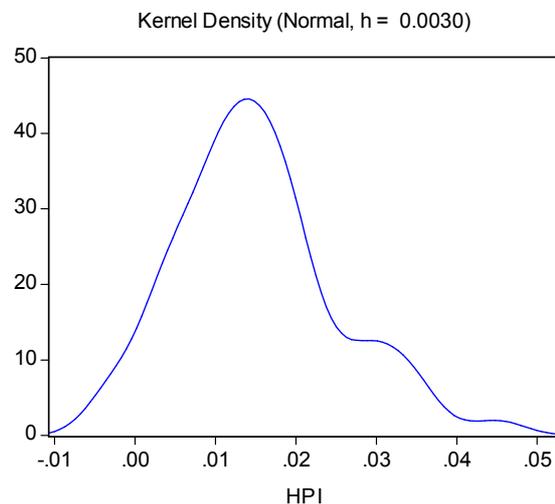
⁸¹ Ibid., p. 262.

⁸² Kuo (1995), p. 19.

⁸³ Daglish, Garfinkel and Sa-Aadu (2007), p. 3.

In chart 4 the probability distribution of the quarterly changes in HPI from 1977 to 2007 is presented.

Chart 4. Probability distribution of HPI change.⁸⁴



The HPI change probability distribution does have the shape of a normal distribution. The right-hand tale of the distribution is somewhat larger than the left-hand tale but overall the judgement is that the assumption of changes in HPI being normally distributed holds. The assumption of the normally distributed changes in HPI is therefore accepted.

4.6.2. Inflation

Inflation is not accounted for in the HPI development in the calculations. There are two major reasons for this.

The first and main reason is that the equity model of default and the option theory of mortgage default relate to the nominal financial net of the mortgagor. Because of that, the use of real values instead of nominal values would give an incorrect result. This could be an interesting subject of further research. That is, to more deeply look into the risk of mortgage default in connection to real house prices.

The second reason for not adjusting for inflation is the nature of the relative comparison. Both in the variance comparison and in the simulations, states are compared relatively and not absolutely. Therefore, an adjustment for inflation would have no effect on the results.

⁸⁴ OFHEO, http://www.ofheo.gov/media/hpi/3q07_hpi_reg.csv. (Nov 08 2007).

4.7. Reliability and validity

The reliability and validity of a quantitative and inductive thesis is critical for its quality.⁸⁵ Therefore, these two properties are now evaluated.

The reliability measures to what extent calculations are correct and that all possible factors affecting the calculations are considered.⁸⁶ To maximise the reliability, the calculations are standardised. Only one formula is typed in for each calculation and then used for all observations. The occurrence of numbers typed in by hand is minimised or not existing. All typed in formulas are checked at least twice to minimise the risk of them being incorrect. Both inflation and the assumption about normally distributed HPI change have been discussed. These are two factors that are identified to have a possible effect on the reliability of the calculations.

Thesis validity means that only examinations and calculations that are supposed to be made are made.⁸⁷ The purpose of this thesis is to evaluate how house price development can be used to indicate risk of mortgage defaults. This leads to conclusions about the capability that the method of the thesis has in predicting mortgage default related crises. Theories of mortgage default risk are explained to provide a theoretical framework. Then, the variance comparison, the simulations and the regression deal with the behaviour of house prices and the parameters affecting house price development. The validity of the examinations is motivated through the connections made between house prices and mortgage default risk in chapter 3.

⁸⁵ Thurén (2007), p. 26.

⁸⁶ Ibid., p. 26.

⁸⁷ Ibid., p. 26.

5. Results and analysis

This chapter evaluates the methodology as to its capability of indicating mortgage default risk. First, the results from the variance comparison between individual states are shown and analysed. Second, the results retrieved from the discrete-time simulations are presented and analysed. Third, the regression results are shown, answering how house prices are affected by interest rates and GDP. Last, possible inferences of the thesis are presented.

5.1. The variance comparison

In table 2 the twenty individual states that had the most volatile house prices between 1997 and 2007 are presented. The variance of changes in HPI is here the HPI volatility. Table 2 presents the twenty states with the riskiest housing markets.

Table 2. Top 20 test statistics.⁸⁸

	Test statistic
Nevada	10.52
Hawaii	10.33
Arizona	7.69
District of Columbia	5.46
California	5.22
Florida	5.16
Maryland	4.75
Rhode Island	4.27
Idaho	3.55
Utah	3.21
Oregon	3.20
Virginia	3.18
Vermont	2.90
New Jersey	2.67
Alaska	2.64
Washington	2.34
Delaware	2.34
New Mexico	2.31
Massachusetts	2.24
Wyoming	1.95

⁸⁸ Complete results from tests about two variances are found in appendix 1. On the 95 % level of significance, the lower critical value of the tests is 0.64 and the upper critical value of the tests is 1.56 as all tests have (79, 79) degrees of freedom. The null hypothesis of having equal price risk as to that of the entire U.S. is rejected for all states in the top twenty.

California, Florida, Arizona and Nevada are found in the top ten. They are, according to Doug Duncan, the states that had the highest rates of mortgage default in the first half of 2007.⁸⁹ Interestingly, Ohio is the third last in the ranking.⁹⁰ For the period 1997 to 2007, the null hypothesis of Ohio having an equal house price risk to that of the U.S. can be rejected. Ohio had a house price risk significantly lower than the entire U.S. during this period. Meanwhile, Ohio also has experienced high mortgage default rates during 2007.⁹¹ This result deviates from the other states and might be a sign of different kind of circumstances affecting the housing market in Ohio. This matter is discussed further in the inference section 5.4.

5.2. The discrete-time simulations

Every state's actual HPI of quarter four 2006 is compared to the spectrum of simulated HPIs. The test about the mean is used as a measure of comparison. The actual-to-mean ratios are also calculated. In table 3, the individual states with the lowest probabilities of having such high HPIs in quarter four 2006 are ranked ascending.

Table 3. Top 20 states – actual HPI probability.⁹²

	Probability	Actual-to-mean ratio
Florida	0.00%	1.7
California	0.00%	1.7
Maryland	0.00%	1.4
Virginia	0.05%	1.4
Arizona	0.12%	1.5
District of Columbia	0.94%	1.7
Minnesota	1.02%	1.3
Nevada	1.27%	1.4
New Jersey	4.95%	1.2
Rhode Island	5.36%	1.3
Delaware	11.66%	1.2
New Hampshire	11.81%	1.3
Wyoming	13.87%	1.3
Louisiana	16.24%	1.1
Pennsylvania	19.90%	1.1
Kansas	21.49%	1.1
Georgia	21.72%	1.1
New York	22.45%	1.2
Massachusetts	23.97%	1.1
Connecticut	24.69%	1.1

⁸⁹ Waugaman (2007).

⁹⁰ See appendix 1.

⁹¹ Waugaman (2007).

⁹² Right-hand probability distributions of actual HPIs in quarter four 2006 in the distribution of simulated HPIs. The null hypothesis of the HPI being expected is rejected on the 95 % level of significance when the probability distribution is higher than or equal to 97.5 % or lower than or equal to 2.5 %. The complete results from the simulations are found in appendix 2.

Also in table 3 the states that according to Doug Duncan had the highest mortgage default rates in the first half of 2007 are found.⁹³ It should also be mentioned that these states⁹⁴ are ranked in the top 10. This means that the probabilities of the house prices in these states being that high in late 2006 were very low. For the four states mentioned the probabilities are all below 2.5 %. Therefore, the null hypothesis of the house price level of late 2006 being expected can be rejected on the 95 % level of significance for these states.

At the same time as Ohio had high mortgage default rates, the house price development of the state does not follow the pattern which other states with high mortgage default rates follow. In fact, the Ohio house price level has developed in the opposite direction. Ohio has experienced lower house price growth than expected. In table A2⁹⁵ Ohio lies in the very bottom of the simulated HPIs with a 94.35 % right-hand side probability distribution. The Ohio house price level of quarter four 2006 was very low even though the null hypothesis of the HPI not being expected cannot be rejected on the 95 % level of significance.⁹⁶

In order to create a better understanding of this matter, the simulations from California, Florida, Arizona, Nevada and Ohio are presented in appendix 4.⁹⁷ It is obvious that the HPI grew aggressively from around 2000-2004 until 2006 in California, Florida, Arizona and Nevada. It is also clear that the actual HPI lied in the upper part of the spectrum of simulated HPIs or even outside the spectrum at the end of the period. A breaking trend with falling HPI growth is noticed in many states from around 2006 as the housing market slowed down.

⁹³ Waugaman (2007).

⁹⁴ California, Florida, Arizona and Nevada.

⁹⁵ Appendix 2.

⁹⁶ On the 90 % level of significance the null hypothesis could be rejected.

⁹⁷ An explanation on how to interpret the simulation charts is found in appendix 3.

5.3. The regression

The objective of the regression is to understand the effect of changes in interest rate and gross domestic product (GDP) on house price development.

5.3.1. Test for heteroscedasticity

In Eviews, a white test with no cross terms is used to test for heteroscedasticity in the estimated equation. The test statistic has a probability distribution of 26 % and therefore the null hypothesis of homoscedasticity cannot be rejected on the 95 % level of significance. In other words, the existence of heteroscedasticity is rejected.

5.3.2. Test for autocorrelation

The Durbin-Watson test statistic of the original estimation output is about 0.90 which gives a somewhat uncertain measure of the existence of positive autocorrelation in the estimation.⁹⁸ A Bruesch-Godfrey serial correlation Lagrange multiplier test is used to ensure the existence or non-existence of autocorrelation in the estimated equation.

It was found that the use of three lags gives the most complete information about the autocorrelation.⁹⁹ The results from the Bruesch-Godfrey test enable rejecting the null hypothesis of no autocorrelation on the 99 % level of significance. It is therefore clear that autocorrelation exists in the estimation output.

Several attempts have been made to tackle the autocorrelation by using generalised least squares estimation (GLS). In the GLS method, the parameter creating the systematic disturbance has to be estimated. The attempts made to erase the autocorrelation using GLS have not been successful. A possible reason for this could be a more complex disturbance than estimated. Estimations have also been made including lags of the variables. This has not generated any positive effects on the results.

Therefore, the Newey-West robust standard errors procedure is applied to the equation. This improves the model as it makes the standard errors asymptotically correct, that is, consistent.

⁹⁸ Thomas (2003), p. 480.

⁹⁹ Please contact the author for a full specification.

Table 4. Estimation output with Newey-West robust standard errors.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP	0.195549	0.087377	2.237985	0.0281
R	-0.026244	0.007147	-3.671850	0.0004
C	0.007448	0.002153	3.459057	0.0009
R-squared	0.198810	Mean dependent var		0.010673
Adjusted R-squared	0.178000	S.D. dependent var		0.007172
S.E. of regression	0.006502	Akaike info criterion		-7.196515
Sum squared resid	0.003256	Schwarz criterion		-7.107189
Log likelihood	290.8606	F-statistic		9.553542
Durbin-Watson stat	0.900086	Prob(F-statistic)		0.000197

5.3.3. The coefficient t-tests

The coefficient b of the GDP change ΔGDP has a value of about 0.20 which means that changes in GDP are positively correlated with HPI development. The test statistic of the t-test on coefficient b is 2.24, which equals a probability distribution of about 2.8 %. Thus, the null hypothesis of there being no influence of changes in GDP on U.S. house prices can be rejected on the 95 % level of significance. The relationship between GDP- and house price development is significant and positive.

The coefficient c of the interest rate change Δr has a value of about -0.03 which means that changes in interest rate are negatively correlated with HPI development. The test statistic of the t-test on coefficient c is -3.8 which equals a probability distribution of 0.04 %. Thus, the null hypothesis of there being no influence of changes in interest rate on U.S. house prices can be rejected on the 95 % level of significance. The relationship between the interest rate- and house price development is strongly significant and negative.

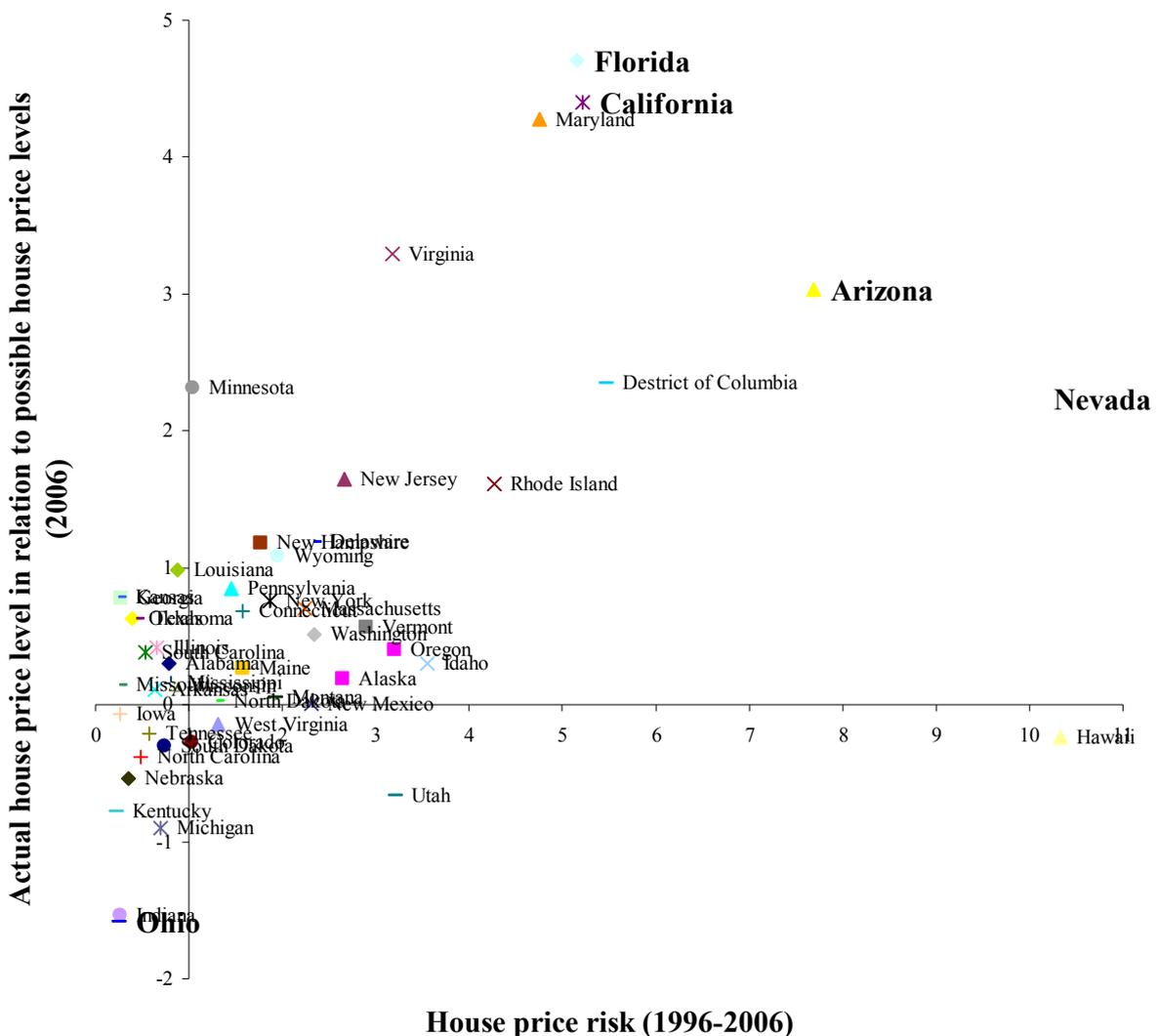
5.3.4. Model quality

The regression has an R-squared of almost 20 % which is a rather satisfying result for this regression. It must be emphasised that a regression on HPI using only two explanatory variables is far from perfect. It is highly doubtful that the HPI is only correlated with the interest rate and the GDP. This, on the other hand, does not prohibit from making conclusions based on the regression. The influences of changes in interest rate and GDP on house prices are clearly significant.

5.4. Inference

According to both the equity model of default and the option theory of mortgage default high house price volatility implies high default risk. The variance comparison sorts out the states that had the most volatile house prices between 1997 and 2007. Both the equity model of default and the option theory of mortgage default also state that mortgage default risk rises as house prices fall. The discrete-time simulations were made to examine which states that had the highest unexpected house prices in late 2006. Mortgage loans given to mortgagors in these states should be the most affected if the market was to adjust the house prices down. In chart 5 the results of from the variance comparison and the discrete-time simulations are presented together.

Chart 5. Box plot of states.



California, Florida, Arizona and Nevada are placed the furthest out in the upper right hand corner of the box plot. They had the most volatile house prices and the highest unexpected house prices at the end of 2006. They also had the highest mortgage default rates during 2007.¹⁰⁰ This is proof that the models enable the use of house prices as an indicator of risk of mortgage defaults.

In the states that had the highest unexpected house prices during late 2006, loans were still given to house buyers. If these house buyers were creditworthy or not is an interesting question but does not belong in this thesis. The assumption can be made that mortgage loans were given as usual or even on a more frequent basis. This assumption is backed by the fact that the house prices grew radically from around 2000 until late 2006. If there was no demand, prices would not rise and loans would not be given. But because the house prices rose as much as they did, demand must have been high and mortgage loans must have been given to finance house purchases.

Unexpectedly and possibly unconditionally high prices of an asset are likely to be adjusted down by the market at some point. In the housing market this means that the market at some point does not drive house prices further up but down instead. Based on the equity model of default by Jackson and Kaserman (1980), falling house prices is a serious matter for mortgage loans. Especially those loans that have outstanding mortgage balances that are not much lower than the house price.¹⁰¹ Reasonably, the situation of a high loan-to-value ratio is the case for mortgagors that recently went into debt to finance house purchases. Let us assume that all mortgage loans are given at the same loan-to-value ratio at mortgage origination. Then the default risk of recent mortgagors is higher than the default risk of mortgagors that have been paying off their loans for a longer time.

Therefore, drastic house price growth indicates two things where the first causes the second. It indicates that the demand for houses is high and possibly rising which in its turn indicates that many mortgage loans are given at high house prices. In times of house price increases, the judgement of lenders might even be that the favourable conditions make it possible to entice possible borrowers further by using sales methods such as teaser rates. This market condition is therefore likely to work as a spiral were house prices are pushed up further and further. It is likely that house prices alike other asset prices follow a long-run trend. At some point the

¹⁰⁰ Waugaman (2007).

housing market adjusts prices to a normal growth rate or down. According to the option theory of mortgage default falling house prices cause mortgagors to exercise their put options on the real estate price to default the mortgage.

There is one outlier though. Ohio was one of the states to have extensive mortgage defaults in the credit crunch.¹⁰² In chart A6 in appendix 4 it is visualised how the house price development of Ohio has been rather modest. In the models used in this thesis, Ohio is found among the bottom ranked states. In chart 5 Ohio is found the furthest out in the lower left-hand corner. There are two possible reasons for this. The first reason would be that Ohio might have experienced a different kind of house price development than the other states with high mortgage default rates. In this case, demand did not drive prices up to levels where house buyers were given mortgage loans at unexpectedly high house prices. Instead, the reserved house price development in Ohio indicates that demand for houses was falling. In this case, the extensive mortgage defaults can have been caused by conditions that also caused the low demand. Examples of these conditions can be a regionally worsened economy, increasing unemployment or the area being an unattractive place of living. The second possible reason for Ohio not being sorted out in the same way as California, Florida, Arizona and Nevada is that the models used in this thesis do not give a complete picture of risk of mortgage defaults. In that case, the house price perspective might have to be complemented with analyses for example regarding variables such as measures of creditworthiness of pools of mortgages.

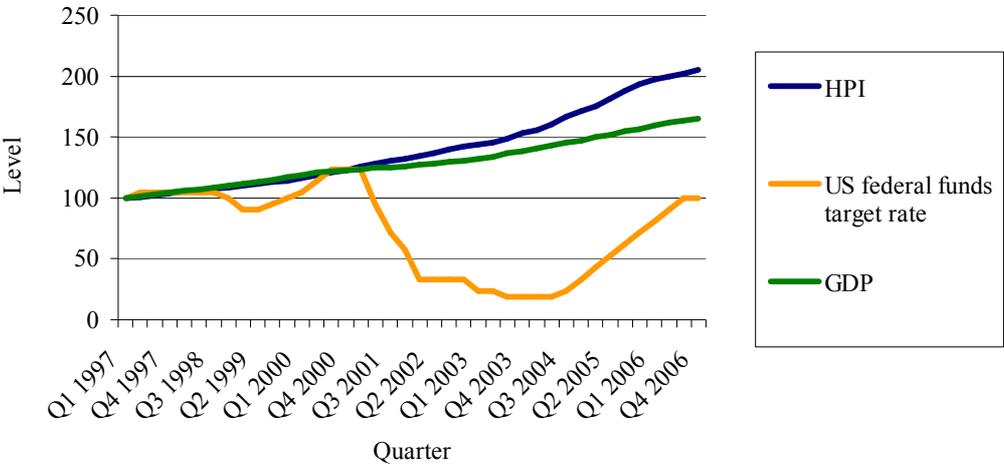
Risk of mortgage defaults indicated by the models of the thesis is only realised if house prices fall. Therefore, knowledge about how house prices react to general economic conditions is needed in order to use house price development as an indicator of mortgage default risk. The regression presented in this thesis shows a negative relationship between interest rates and house prices and a positive relation between GDP and house prices. In chart 6 the U.S. HPI, the U.S. GDP and the U.S. federal funds target rate from 1997 to 2007 are shown.¹⁰³

¹⁰¹ That is, a high loan-to-value ratio.

¹⁰² Ibid.

¹⁰³ The 1Y secondary market Treasury bill interest rate used in the regression is not available for the period of time shown in chart 6. Therefore the *U.S. federal funds target rate* (Datastream) is used as an approximation of the 1Y Treasury bill rate. The assumption is made that these two interest rates are closely correlated.

Chart 6. HPI-, target rate- and GDP development from 1997 to 2007.¹⁰⁴



In chart 6 it is visualised how the target rate of the U.S. Federal Reserve fell between 2000 and 2004 and then rose between 2004 and 2007. A somewhat decreasing GDP growth is noticed from the middle of 2006. These facts give reason to believe that the house prices in the U.S. were going to have a decreased- or even negative growth.

Many factors indicated a coming credit crisis from a house price perspective before the crisis was realised. High house price variance and extreme house price growth in combination with increasing interest rates and a slightly falling GDP growth strongly indicated that heavy risk of mortgage defaults in some states was likely to be realised. Now, consider mortgage lending securitisation. It is a fact that securities backed by mortgages from areas burdened by heavy risk of mortgage defaults constitute large parts of balance sheets of banks, companies and institutions. Therefore, an indication of the kind generated by the models of the thesis should be taken most seriously. A possible fall in house prices could cause massive mortgage defaults and great credit losses. This in turn would decrease the value of mortgage backed securities and therefore weaken the balance sheets of banks, companies and institutions holding these securities. In other words, market conditions such as those investigated in this thesis clearly indicate a possible credit crisis.

¹⁰⁴ OFHEO, http://www.ofheo.gov/media/hpi/3q07_hpi_reg.csv. (Nov 08 2007). *U.S. federal funds target rate* (Datastream) and OECD Economic Outlook, *GDP (NOMINAL) (AR)* (Datastream). Rebased time series (Q1 1987 = 100).

6. Conclusion

Risk of mortgage defaults can be indicated by house price development through the models of this thesis. A variance comparison gives a measure of the house price risk. The method also includes a discrete-time simulation that enables a comparison between the expected and the actual house price level. The results from the models can indicate different reasons for risk of mortgage defaults. In this examination, two examples of reasons for risk of mortgage defaults are generated.

The first reason for default risk is a housing market having high house price volatility and an unexpectedly high house price level. This indicates a high demand for houses causing many mortgage loans to be given at high house prices. A negative financial net of the mortgagor is realised when the payment obligations of the mortgage loan exceed the house price. In connection to established theory of mortgage default, a negative financial net causes the mortgagor to make a decision to default the mortgage. The thesis shows that there is a negative relationship between interest rates and house prices and a positive relationship between gross domestic product (GDP) and house prices. Rising interest rates and falling GDP growth indicate falling house prices. If house prices start falling in a housing market with high price risk and unexpectedly high house prices this housing market is likely to experience extensive mortgage defaults.

The second reason for default risk is a housing market with low house price volatility and unexpectedly low house prices. This market is likely to have a lowered demand for houses and is likely to experience mortgage default because of unfavourable market conditions.

The method applied to this thesis does not give a precise or a complete picture of mortgage default risk. It is supposed to be used as an indicator of the risk based on a house price development analysis. It can for example be used to screen the distribution of mortgage default risk in a country. The method of the thesis is applied on the U.S. housing market. However, the judgement is that the method is appropriate to apply on other housing markets such as the one in Sweden.

6.1. Future research on the subject

This thesis shows that the house price development in Ohio has differed from that of other states in the U.S. This discovery is not further investigated in the thesis. However, learning more about the housing market of Ohio might complement the method and extend the understanding of it. Therefore, the housing market of Ohio is an interesting object of further investigation.

It is also of interest to compare the actual 2007 default rates of the individual states in the U.S. to the results of the thesis. In that way, the usefulness of the method would be further examined. For example, an equation estimation of mortgage default risk explained by house price variance and the relation between actual and expected house prices could be estimated and analysed.

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Appendix 1

*Table A1. Test statistics from
tests about two variances
ranked descending.*

	Test statistic
Nevada	10.52
Hawaii	10.33
Arizona	7.69
District of Columbia	5.46
California	5.22
Florida	5.16
Maryland	4.75
Rhode Island	4.27
Idaho	3.55
Utah	3.21
Oregon	3.20
Virginia	3.18
Vermont	2.90
New Jersey	2.67
Alaska	2.64
Washington	2.34
Delaware	2.34
New Mexico	2.31
Massachusetts	2.24
Wyoming	1.95
Montana	1.92
New York	1.87
New Hampshire	1.76
Connecticut	1.58
Maine	1.57
Pennsylvania	1.45
West Virginia	1.31
North Dakota	1.31
Minnesota	1.03
Colorado	1.03
Louisiana	0.88
Wisconsin	0.83
Mississippi	0.81
Alabama	0.79
South Dakota	0.74
Michigan	0.70
Illinois	0.65
Arkansas	0.64
Tennessee	0.57
South Carolina	0.54
North Carolina	0.48
Texas	0.44
Oklahoma	0.40
Nebraska	0.36
Georgia	0.28
Iowa	0.27
Indiana	0.26
Missouri	0.26
Ohio	0.25
Kansas	0.25
Kentucky	0.23

Appendix 2

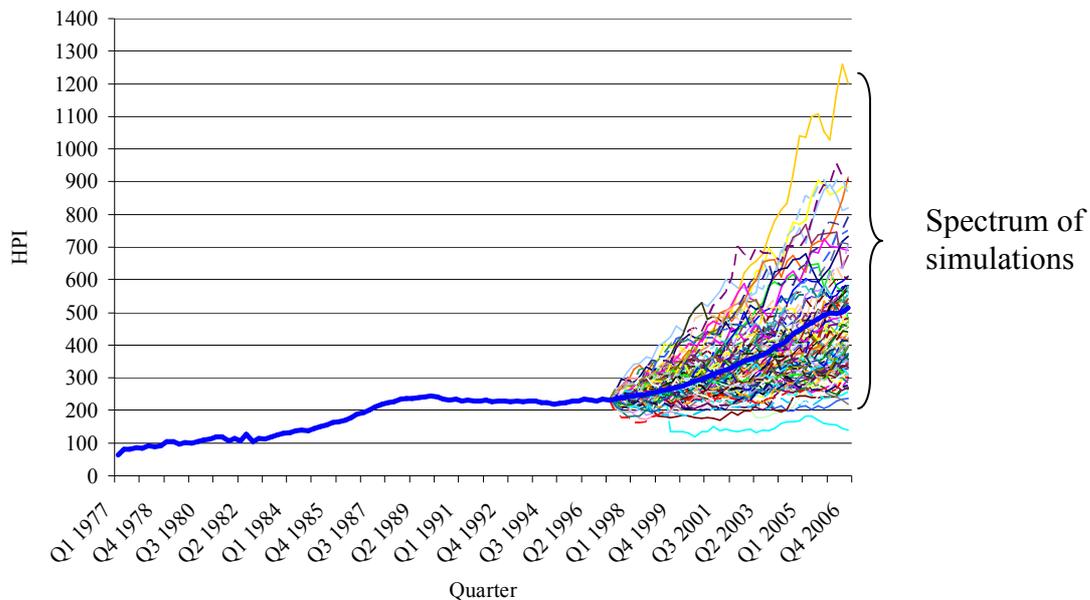
Table A2. Actual-to-mean ratios and left-hand side distributions of actual HPIs in each state in quarter four 2006. Ranked by left-hand side distributions.

	Probability	Actual-to-mean ratio
Florida	0.00%	1.7
California	0.00%	1.7
Maryland	0.00%	1.4
Virginia	0.05%	1.4
Arizona	0.12%	1.5
District of Columbia	0.94%	1.7
Minnesota	1.02%	1.3
Nevada	1.27%	1.4
New Jersey	4.95%	1.2
Rhode Island	5.36%	1.3
Delaware	11.66%	1.2
New Hampshire	11.81%	1.3
Wyoming	13.87%	1.3
Louisiana	16.24%	1.1
Pennsylvania	19.90%	1.1
Kansas	21.49%	1.1
Georgia	21.72%	1.1
New York	22.45%	1.2
Massachusetts	23.97%	1.1
Connecticut	24.69%	1.1
Oklahoma	26.50%	1.1
Texas	26.54%	1.1
Vermont	28.56%	1.2
Washington	30.41%	1.1
Illinois	33.91%	1.1
Oregon	34.31%	1.1
South Carolina	35.11%	1.1
Alabama	38.12%	1.0
Idaho	38.23%	1.1
Maine	39.39%	1.1
Alaska	42.43%	1.1
Mississippi	43.76%	1.0
Missouri	44.16%	1.0
Wisconsin	44.40%	1.0
Arkansas	45.67%	1.0
Montana	47.75%	1.0
North Dakota	48.97%	1.0
New Mexico	49.67%	1.0
Iowa	52.77%	1.0
West Virginia	55.62%	0.9
Tennessee	58.33%	1.0
Hawaii	59.44%	0.7
Colorado	60.67%	1.0
South Dakota	61.66%	0.8
North Carolina	64.94%	1.0
Nebraska	70.46%	0.9
Utah	74.59%	0.9
Kentucky	78.24%	0.9
Michigan	81.64%	0.9
Indiana	93.76%	0.9
Ohio	94.35%	0.9

Appendix 3

Simulation specifics and interpreting the simulation charts

Chart A1. Example of simulation of an individual state.



Remember:

- The thick blue line represents the actual HPI development.
- The simulation process of each individual state consists of 100 individual time series of simulations.
- The mean and standard deviation of each simulation is calculated on quarterly observations from 1977 to 1997.
- The mean and standard deviation are assumed to be constant in the simulations.

Appendix 4

Simulations from California, Florida, Arizona, Nevada and Ohio.

Chart A2. California – HPI simulations.

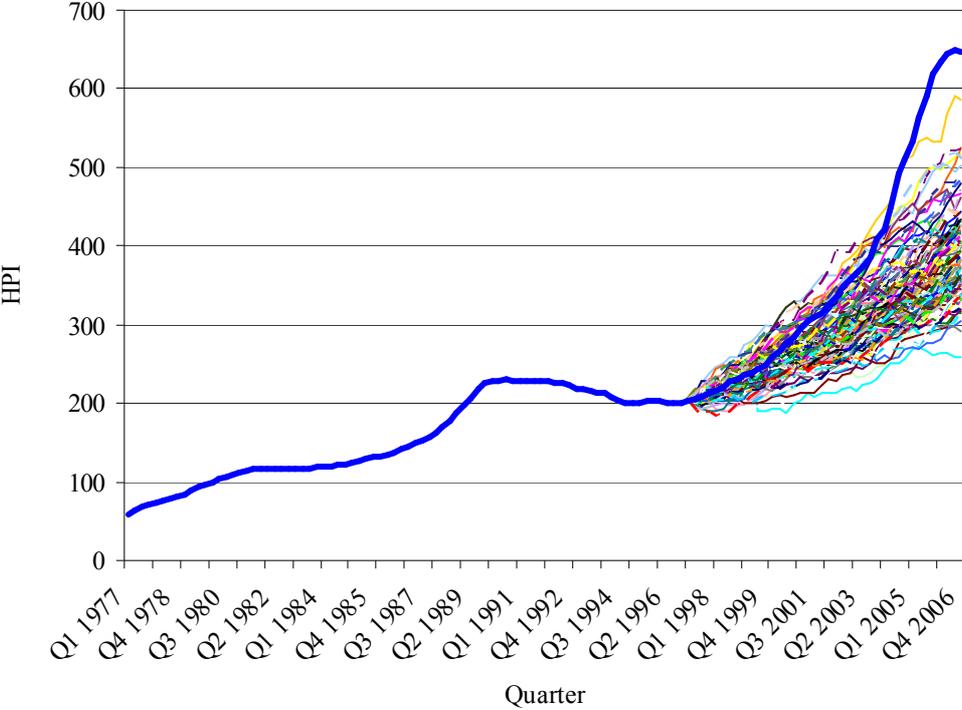


Chart A3. Florida – HPI simulations.

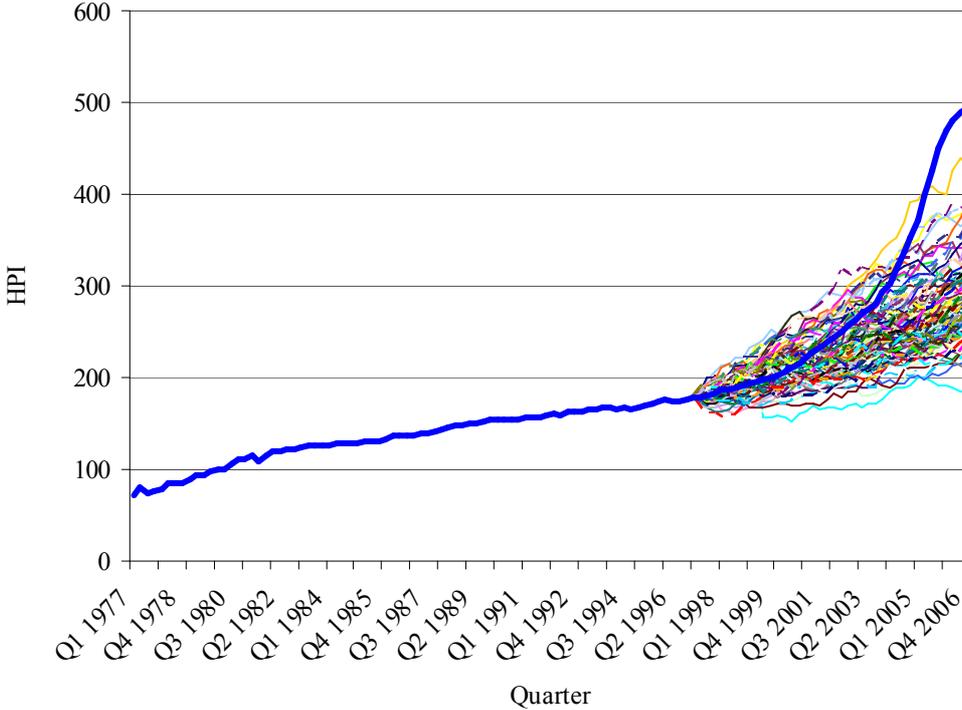


Chart A4. Arizona – HPI simulations.

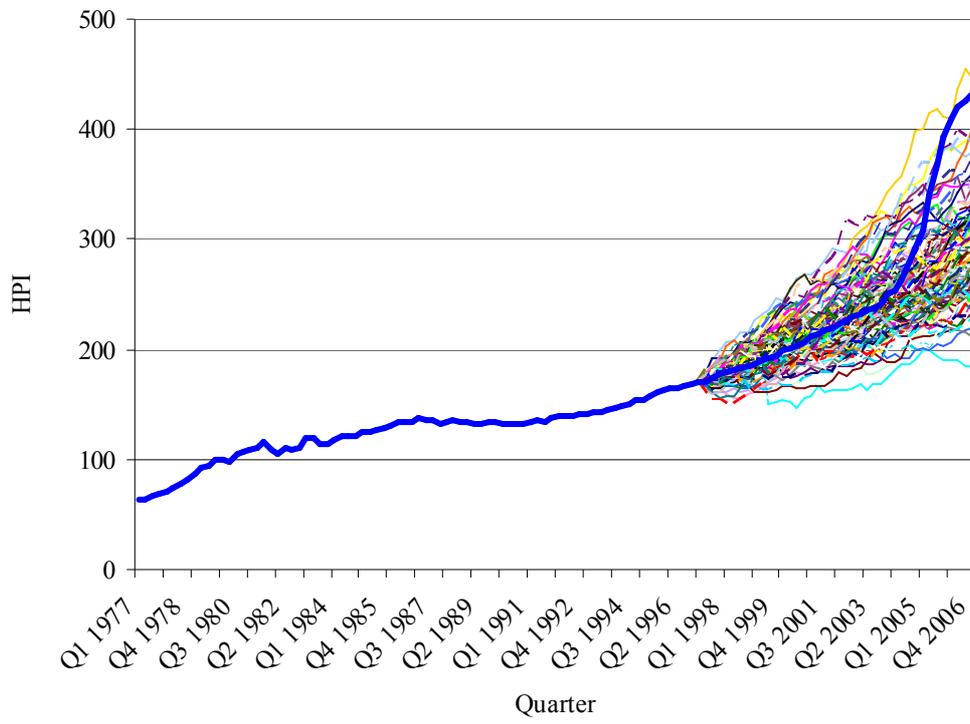


Chart A5. Nevada – HPI simulations.

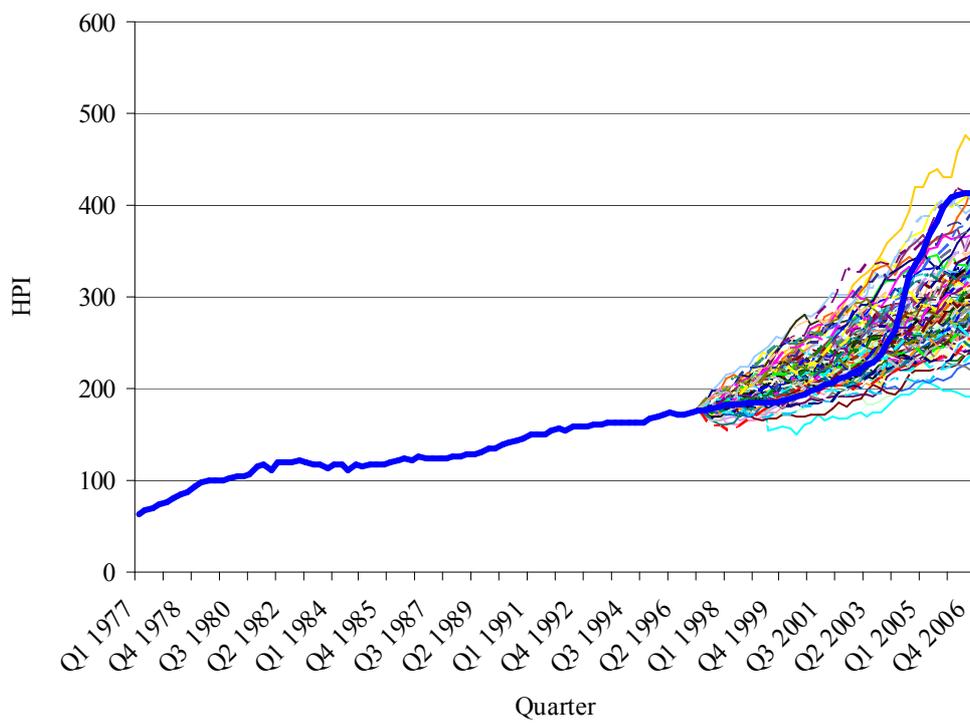


Chart A6. Ohio – HPI simulations.

