Stockholm School of Economics

Master's Thesis in Finance

HOUSING MARKET RISK PREMIA: EMPLOYING FAMA AND MACBETH TWO PASS REGRESSION METHODS ON SWEDISH DATA

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Abstract

House returns in most Swedish regions are exposed to changes in real interest rate and in real earnings growth. In some regions house returns are exposed to changes in gross domestic product and in the oil price. We are not able to draw any reliable conclusions regarding risk premia in the Swedish housing market. Nevertheless, we find indications that the real interest rate carries risk premium. Stronger evidence of risk premia could perhaps be found if a larger data set was used in cross section. Furthermore, we find indications of the Swedish housing market being inefficient and our results suggest that there potentially are no considerable risk premia present.

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1 Introduction and Study Outline

1.1 Introduction

For most house owners the house is not just a place to live but it is also the main asset in their investment portfolios. In many countries the largest part of private sector wealth consists of owner occupied houses. The development of house prices is one of the most important determinants of individual wealth in these countries. Case et al (2001) study 15 countries and find that household consumption and savings are more related to the value of house wealth than to the value of other financial assets. They conclude that to be able to explain the financial behaviour of households it is important to understand the house price development. The number of attempts to model the house price development both in Sweden and abroad is limited, although it affects the wealth of individuals considerably.

Knowing which pricing effects to expect from changes in the factors that explain the house price development is relevant for proper valuation. Berry et al (1988) suggest that investors being aware of pricing of relevant risk factors may be able to better forecast the price development and consequently make better investment decisions. The factors investigated in this study are based on macroeconomic time series readily available for most private house investors.[1]

The purposes of this study are to identify a number of factors that jointly can capture the determinants of Swedish house prices and to examine these factors' risk premia. More specifically, we try to specify macroeconomic factors that influenced the time variation of prices and were systematically priced in the Swedish housing market during the years 1981 through 1999 by investigating transaction based house price indices. We employ two versions of the Fama and MacBeth (1973) methodology to estimate time varying risk premia related to the macroeconomic factors specified. House prices are generally investigated with models from economics. The model we use is from the field of finance and in this way our study can be regarded untraditional.

[1] Compare with *Table 1*.

The statistical methods employed in this study involve series of interconnected implementation decisions.[2] These decisions may affect the results of the study. We aspire to describe our model implementation as clearly as possible so as to give the reader an opportunity to evaluate the validity of our findings. Our objective is also to give an accessible and explicit overview of how Fama and MacBeth (1973) two pass regression methods can be put into practice.

1.2 Study Outline

In *Section 2* we present a number of models that are commonly implemented in house pricing research and findings regarding house price dynamics. In this section we also discuss finance asset pricing models and risk premium theory. In *Section 3* the dependent variable, the risk factors and the control variables are defined and motivated. In *Section 4* the statistical models and the criteria used for finding the final model specification are described. In *Section 5* results from the statistical analysis are presented. These results are interpreted in *Section 6*. In *Section 7* we present a discussion of how the results relate to the statistical methods employed. In *Section 8* we give a few suggestions on future research and in *Section 9* we present our references. The appendices in *Section 10* include elaborations of some of the calculations and estimations made in the study. They also include more detailed tables over some data.

2 Theoretical Framework

House prices vary a great deal both in time and in cross section. Case and Quigley (1991) conclude that the cross sectional variation, that is to say local pricing differences, depends on property characteristics like differences in location and housing standards. Schulz and Werwatz (2004) claim that variations in time depend largely on macroeconomic variables, which are variables affecting the conditions for the whole housing market. In this section we first review common house price models and findings from housing research. Then we present research and theory that our finance model is based on. Finally, we discuss how these types of models differ.

[2] *Section 4* includes how the models are implemented and *Section 7* includes a methodological discussion.

2.1 Commonplace House Price Models

Poterba (1984) presents a pioneering attempt to model house return dynamics by developing the asset market model. This model can be categorized as a macroeconomic equilibrium model, where house prices are determined by the intersection of a downward sloping demand curve and an upward sloping supply curve. In this model an increase in demand for houses leads to a shift in the demand curve with a corresponding temporary increase in the price level. The increased price level is followed by new investments until the new equilibrium is reached. This model assumes that the housing market is efficient in the sense that shocks in the market should lead to immediate impact on house prices. At present this fundamental model is used for identifying adjustment paths towards long run equilibria.

The presence of autocorrelation in the housing market is found in numerous studies. Case and Shiller (1990) find strong evidence on house prices being positively autocorrelated for short lags in four metropolitan areas in the U.S.A. For longer lags the autocorrelation is found to be negative. Englund and Ioannides (1997) study house prices in 15 countries and find similar patterns. Expanding the house price model by including contemporary values or lagged values of gross domestic product growth and the real interest rate does not reduce the high first lag autocorrelation in the Englund and Ioannides (1997) study. This indicates that the autocorrelation is persistent.

Hort (1998) investigates whether the autoregressive pattern in Swedish house prices is driven by fundamental demand and supply factors. She employs a restricted error-correction model to capture the impact of deviations from the long run equilibrium on short term house price changes. *Movements in income*, *user cost* and *construction cost* can explain changes in the long run equilibrium. The short term house price development is explained by deviations from the long run equilibrium, positive short term autocorrelation and negative long term autocorrelation.

In a later study Hort (2000) employs a three dimensional vector autoregressive model on Swedish house prices, number of sales and the after-tax mortgage rate to test if the number of sold houses decreases before prices increase when there are shocks in the after-tax mortgage rate. She finds that the number of house transactions is negatively correlated with the price level on the housing market. There is some evidence presented in the article indicating that the number of sales changes before prices change.

Fundamental finance theory suggests that asset returns should not be autocorrelated in efficient markets. Thus, the autocorrelation in house returns is an indication of market inefficiencies. According to the Poterba (1984) model, slow adjustments in the housing market could make house returns autoregressive. This implies that the autocorrelation may be explained by low trading volumes in relation to total number of houses, which causes slow adjustments. Tax considerations and transaction costs can largely explain this illiquidity in the housing market according to Case and Shiller (1989). Meen (2002) views the autocorrelations as a consequence of large transaction costs associated with trading in the housing market. The amount of autocorrelation due to transaction costs, is positively related to, and limited by the size of the transaction costs.

Meen (2002) concludes that many of the contemporary house price models are based on the life cycle model in which the marginal rate of substitution between housing and a composite consumption good is derived. This rate is normally calculated using economic variables like house prices and expected future house prices, marginal tax rates, interest rates, house depreciation rates and inflation. The resulting rate is interpreted as the real housing user cost of capital and this is applied to find the supply and demand elasticities that determine house prices. To summarize this section we conclude that most house pricing models are equilibrium models and a common finding is that returns in housing markets tend to be autocorrelated.

2.2 Financial Asset Pricing and Risk Premium Models

When using a finance model to investigate housing markets we implicitly view houses as pure financial assets. Our model is based on the discounted cash flow (DCF) model, which is commonly used for valuing financial assets. The model discounts expected future cash flows with a risk adjusted discount rate.

If we think of the future utility from owning a house as equivalent to cash flows,[3] then the DCF model can be used in the context of house investments. A house price valuation with this approach is similar to the real estate valuation model used by Ling and Naranjo (1997) and the stock valuation model used by Chen et al (1986).

The original CAPM-model developed by Sharpe (1964) stipulates that the market portfolio should be risk return efficient and that only non-diversifiable risk should be priced. Chen et al (1986) agrees and states that only factors that systematically affect market prices should have risk premia and thus only non-diversifiable risk should be priced. In the CAPM model the expected return of an asset is a linear function of only one factor. This factor is the market portfolio required excess return and it is assumed that all risk but market risk is diversifiable. CAPM was later generalized by Ross (1976) to include more factors that capture economic risk. This multifactor asset pricing model, MAP, rests on the assumption that there is more than one non-diversifiable risk factor. Assets, which prices are affected by these non-diversifiable factors, carry risk premia related to those factors. An asset's risk premium for a certain factor should be proportional to the asset's exposure to that risk factor.

By definition, risk factors are measured as deviations from their expected values. Consequently only variables that are not predetermined can carry risk premia. The multifactor model can be interpreted as explaining differences between realized return and expected return as a multi variable linear function of deviations from expected risk factor values. Risk factors that systematically affect returns should be priced in efficient markets.

Barkham and Geltner (1995) examine a concept called pricing discovery and how it applies to the securitized and unsecuritized commercial property markets in the U.K. and in the U.S.A. The authors define publicly owned real estate investment trusts (REIT's) as securitized property assets. These assets are traded in the stock market and are therefore used as benchmarks for the market prices for property assets. The unsecuritized assets, defined as privately owned commercial property, are related to the securitized assets, but their prices do not adjust to the REIT's prices immediately when new pricing information is available. A finding of the study is

[3] According to Schulz and Werwatz (2004) a proxy for this utility is rent coming from subletting the house minus subletting costs. This is consistent with viewing living in the house as the opportunity cost of subletting it.

that the time for price discovery is one year or more for these asset classes. If this phenomenon is present in the Swedish housing market, then responses to shocks in the risk factors may be delayed and smoothened over a period of time. If the market does not respond swiftly to shocks in risk factors, then it is not unlikely that there is only little risk premia in the market related to those factors.

Chen et al. (1986) employ the MAP model to find factors which have risk premia in the stock market using the two pass Fama and MacBeth (1973) regression. To find factors that explain stock returns ex ante, Chen et al (1986) test a number of factors that may affect stock returns systematically through expected cash flows and/or the discount rate. Their findings are that the *term structure*, *expected* and *unexpected inflation*, *industrial production*, and the *spread between high and low grade bonds* have significant ex ante pricing effects in the stock market, that is to say they carry risk premia.

One important inspiration that we refer to continually in this study is the article "Economic Risk Factors and Commercial Real Estate Returns", written by Ling and Naranjo (1997). They study which risk factors carry risk premia in real estate markets. They use the variables that Chen et al (1986) find significant and add consumption based variables and a market variable to the model. Ling and Naranjo (1997) find that *expected inflation*, *industrial production* and the *spread between high and low grade bonds* variables do not systematically affect returns, whilst the *growth rate of consumption expenditures*, the *real treasury bill rate*, the *term structure premium* and *unanticipated inflation* do affect returns systematically. Furthermore, they find evidence that the *growth rate of consumption expenditures* and the *real treasury bill rate* carry constant risk premia. When risk premia are allowed to vary over time they also find that the *term structure premium* and the *unanticipated inflation* carry risk premia. Ling and Naranjo investigate four different types of real estate data; *stock market return data on REITs*, *appraisal-based returns by geographical division from the National Council of Real Estate Investment Fiduciaries (NCREIF)*, *NCREIF return data disaggregated both by region and property type* and a *combination of division NCREIF data and regional capitalization rate data from the American Council of Life Insurance Companies (ACLI)*. A more thorough and technical discussion of the models employed in this study is presented in *Section 4*.

2.3 Differences Between Finance and Economic Approaches to Investigate House Price Dynamics

When deciding how to practically investigate economic relationships it is important to be aware of that this choice can alter the final results. Meen (2002) shows that discrepancies in research results between the U.K. and the U.S.A. housing markets are largely due to the implementation of different practical models in the two countries. When applying the same models to the two markets, he finds that differences are considerably smaller than previous research suggests. House prices are generally investigated with models from economics and using a financial model for studying house prices is, as previously mentioned, untraditional.

The finance model we employ and the economic models discussed above differ in at least two important ways. Firstly, the finance model cannot include variables that vary between regions in the market, whilst this is possible when employing models from economics. Secondly, many models from economics are equilibrium models based on demand and supply elasticises, whilst the finance model is based on cash flows and discount rates[4].

Local and house specific factors are theoretically diversifiable, but can be regarded practically non-diversifiable.[5] That is to say, there is idiosyncratic risk in the housing market that cannot be diversified away practically. The finance model applied in this study rests on the assumptions that all idiosyncratic risk can be diversified away and that only theoretically non-diversifiable risk factors are priced in efficient markets. Therefore, the idiosyncratic local and house specific risk factors cannot be included as price drivers. Explicitly, the theoretically diversifiable but practically non-diversifiable factors cannot be included in our type of model even though they may affect house prices. Not being able to include local risk factors is one drawback of using finance models on housing data.

Viewing houses as pure financial investments means that demand and supply are no direct price drivers. The reason for this is that risk and return are the only parameters of interest when valuing financial assets. In finance models changes in supply or demand for an asset class do not

[4] Cash flows and discount rates may of course be affected by supply and demand in practice.
[5] It is difficult to diversify house investments because it requires that investors, at the very least, own parts of several houses and preferably also in several regions.

directly change prices of assets in that class. This is because alternative financial investments are substitutes as regards risk and return. Instead of using demand and supply directly, we include factors that affect demand and supply.

Autocorrelation can be viewed as a rather natural phenomenon in equilibrium models, because of non-instantaneous adjustments to new equilibria. In finance models, on the other hand, autocorrelation is a market inefficiency assumed not to be present. The large transaction costs in the housing market may cause considerable autocorrelation as discussed in *Section 2.1*. The presence of autocorrelation indicates that reactions to shocks in risk factors are non-instantaneous. This can be seen as a reason not to expect considerable risk premia in the Swedish housing market.

3 Data and Variables

We study quarterly Swedish house price indices from 1981 through 1999. These indices are based on every house sale in Sweden and are calculated for all A-regions[6] using the method developed by Englund et al (1998). We model time variation in this data using a set of macroeconomic variables. In this section we first present the macroeconomic variables used and sources of data for these variables. Then each variable is described and defined by making necessary transformations. We also motivate why each explanatory variable is included. Thereafter we look for potential correlation problems between our explanatory variables. The section is ended with a table including the explanatory variables and how they are derived from the data.

[6] An A-region is a group of Swedish municipalities. The base for grouping the municipalities is geographical proximity and one A-region is to be one labour market in which the labour force can commute.

Table 1

Summary of untransformed data and sources of data.

Data	Source
Index over nominal house transaction prices for 70 Swedish A-regions.	Provided by Professor Peter Englund at the Stockholm School of Economics.
3 months treasury bill notes measured as yearly returns.	http://www.imfstatistics.org/
Swedish 10 year government bond yield measured as yearly returns.	http://www.imfstatistics.org/
Swedish consumer price index measured as quarterly index values.	http://www.scb.se/templates/tableOrChart____33847.asp
Quarterly nominal values of average hourly earnings in the manufacturing sector. The sample consists of companies in the SNI3 group.	http://www.imfstatistics.org/
Quarterly nominal values of household consumption expenditures excluding durable goods and including expenditures in non-profit institutions serving households.	http://www.imfstatistics.org/
Quarterly nominal values of the Swedish gross domestic product.	http://www.imfstatistics.org/
Quarterly prices of the Rotterdam fuel oil.	http://www.opec.org/library/annual%20statistical%20bulletin/interactive/2003/filez/xl/t74.htm
Affärsvärldens General Index of the Swedish stock market.	http://bors.affarsvarlden.se/afgx/afgxhistory.aspx?settings=afv
Swedish households' 12 month expected inflation at year T-1 regarding year T.	Provided by the Klas-Göran Warginger at the National Institute for Economic Research
Swedish population at year end.	http://www.ssd.scb.se/

3.1 Dependent Variable

The house indices excess returns are used as dependent variable. The variable is derived by deducting the beginning of the quarter known three month treasury bill quarterly rate from the nominal price development in the different A-regions. The nominal price development is measured as quarterly returns in the A-region indices. The three month treasury bill quarterly rate is derived from the three month treasury bill yearly rate using a geometric average.[7]

It is of importance to point out that the return of a house investment is not only the house value appreciation, which the indices we use are based on, but there is also a convenience yield associated with owning a house. This convenience yield includes the value of living in the house. To get more appropriate estimates of house returns, one could add the convenience yield to the dependent variable that we have defined. However, the reasons for not including the convenience yield in the dependent variable in this study is that it can be assumed to have limited variation and thereby not affecting the interpretation of the regression results considerably. Furthermore, it is difficult to estimate the convenience yield with accuracy, so even if it would vary considerably it is not certain that including estimates of this yield would improve the results. *Appendix I* presents average yearly excess returns for all indices during the period 1981Q1–1999Q4. These are all negative, which can be viewed as a consequence of a positive convenience yield over the period. In the same appendix *Figure I* shows the quarterly excess returns of the average index and the average nominal house price development.

3.1.1 Portfolio Construction

Chen et al (1986) argue that the noise in individual asset returns is favourably reduced when assets are grouped into portfolios. Fama and French (1992) agree and conclude that grouping data into portfolios may produce more precise risk premium estimates than if assets are treated individually. This is because portfolio grouping reduces idiosyncratic risk. However, portfolio grouping reduces the degrees of freedom in cross section and should only be used if there are more assets available than there are observations in the time dimension. As we have more indices than time observations[8] and a dependent variable that is likely to be affected by idiosyncratic risk we group the indices into portfolios. We construct 14 portfolios each including 5 A-regions.[9]

[7] The three month treasury bill is hereafter referred to as the treasury bill.
[8] In the second pass regressions.
[9] It is worth pointing out that when choosing the number of portfolios to construct, there is a trade-off between reducing noise and reducing degrees of freedom.

Fama and MacBeth (1973) group the dependent variables into portfolios based on size of estimated betas. These betas are calculated from a regression with only one explanatory variable. This procedure has not been generalized for models with more than one explanatory variable and therefore we cannot use it. There is no theoretical base for grouping house returns discussed in the literature. Chen et al (1986) state that portfolios should be constructed with the objective to spread expected returns. Size has been empirically observed to affect returns for other asset classes and is therefore often used as a base for grouping data.[10] Therefore, as a base for grouping the indices we use the number of citizens in the A-regions on December 31st 1980.[11]

3.2 Explanatory variables

In this study we use the findings of Berry et al (1988), Chen et al (1986) and Ling and Naranjo (1997) as inspiration for finding a set of explanatory variables. Below we motivate and define all explanatory variables investigated. We perform the augmented Dickey Fuller test to examine if each explanatory variable is non-stationary. The variables are transformed into first differences to become stationary when the null hypothesis of a unit root cannot be rejected at the 5% level of significance. [12]

If the explanatory variables and the dependent variable are non-stationary then their residuals will be autocorrelated. This causes errors-in-variables problems in the form of downward biased estimates of the coefficients, as Chen et al (1986) concludes. Transforming a variable into first difference changes the interpretation of its risk premium in the sense that the estimated risk premium will consider shocks to the difference of the factor and not the factor itself. Descriptive statistics of the explanatory variables can be found in *Appendix V*.

3.2.1 Real Interest Rate

The motivation for including a real interest rate in the model is that it can be used as a proxy for capturing conditions for investment opportunities in an economy, as Ferson and Harvey (1991)

[10] For an example see Chen et al (1986).
[11] The portfolios are included in *Appendix I*.
[12] We also perform the augmented Dickey Fuller test on the transformed series. The transformations used as explanatory variables in the final model have all passed this unit root test at the 5 % level of significance.

suggest. Sweeney and Warga (1986) find that stocks in the utility industry are especially sensitive to interest rates and an associated risk premium is strongly indicated. A lower interest rate should decrease the cost of financing and therefore increase asset prices. Thus, an increase in the real interest rate should affect house prices negatively. In accordance with Ling and Naranjo (1997) we use the treasury bill rate and the consumer price index (CPI) to define the real interest rate. RINT is defined as the treasury bill rate over the inflation rate calculated from Swedish quarterly CPI.

3.2.2 Inflation Variables

We estimate the development of future house prices in nominal terms. Shocks to expected inflation will change expected nominal house prices. Copeland et al (2000) state that the valuation of financial assets can be performed either in nominal or in real terms, as long as one is consistent the value will be the same. Theoretically, this implies that inflation is not a value driver, since both cash flows and the cost of capital are equally affected by inflation. However, changed inflation may lead to real effects, such as taxation effects and interasset distortions. Such distortions come into expression as changes in the relative prices of different asset classes. For example, if housing markets are more sensitive to inflation than stock markets, then increases in inflation may raise real values of houses more than real values of stocks are raised. This implies that inflation could be a value driver. Ferson and Harvey (1991) suggest that unanticipated inflation could be a priced factor if inflation is correlated with the marginal utility of wealth and thereby has real economical effects.

The change in households' expected inflation, CEI, is calculated as the change in the Swedish households' inflation expectations. These inflation expectations are based on a survey made by the National Institute for Economic Research with a quarterly frequency. The survey measures households' 12 months inflation expectations, therefore we first transform the expectations into quarterly data by using a geometric average[13] before we take the first difference of the time series. The unanticipated inflation variable, UI, is defined as the difference between the ex post inflation derived from the CPI and the ex ante household expected inflation.

[13] This treatment implies that we assume that the inflation expectations are equally distributed over the quarters. This may bias the results.

A commonly used method to estimate expected inflation was developed by Fama and Gibbons (1984). This method estimates inflation using an ARIMA model and it is therefore not unlikely that these expected inflation estimates, EINFLA, will differ from the households' expected inflation. The method is elaborated in *Appendix II*. We define the change in expected inflation variable, CEIA, as the first difference of the EINFLA time series. The variable unanticipated inflation, UIA, is calculated as the difference between the ex post CPI inflation and the ex ante expected inflation estimates from the Fama and Gibbons (1984) methodology. UIA is transformed into first differences.

3.2.3 Gross Domestic Product

Chen et al (1986) use the variable *change in industrial production* to model stock returns with the motivation that the equity market is related to changes in the industrial production and activity in the long run. We include a gross domestic product variable for similar reasons. The original time series that GDP is based on is quarterly index data. The seasonality in the growth rate of the gross domestic product means that the time series is non-stationary. To circumvent this non-stationarity we transform the data into first difference form. Like Chen et al (1986) and Ling and Naranjo (1997) we lead the GDP one quarter. This is because the variable measures changes in the gross domestic product lagged by at least a partial quarter and because changes in the stock market this quarter probably reflects anticipated changes in gross domestic product at least a quarter into the future. To be precise, the GDP variable is defined as the first difference of the growth rate in the index value of gross domestic product leaded one quarter. We expect that an increase in the GDP variable will have a positive effect on house returns as an effect of the wealth creation represented in gross domestic product growth.

3.2.4 Oil Price

Chen et al (1986) include an oil price variable because the oil price is known to influence stock market returns. Increased oil prices may affect house prices indirectly through decreased consumption power. An increased oil price is thus expected to have a negative impact on house prices. OP is defined as the growth rate of the oil price.

3.2.5 Market Index

The original CAPM model suggests that the market index is important when trying to explain stock returns and wealth creation. Most macroeconomic time series have smoothening and averaging characteristics and they cannot be expected to capture all information available to the market. However, stock market indices do not have these problems as they respond swiftly to new information. The stock market index is included to capture effects of omitted risk factors in accordance with Sweeney and Warga (1986). We use *Affärsvärldens generalindex*[14] as a proxy for the market index because it is a broad index that follows the average development of share prices at the Stockholm Stock Exchange. Dividends paid out are treated as being reinvested and the index is value-weighted, which means that the individual securities are weighted from market capitalization in proportion to total market capitalization. We define the variable AFGX as the spread between the quarterly returns of *Affärsvärldens generalindex* and the three month treasury bill quarterly rate. If one views return growth in the stock market as wealth creation, then house prices are expected to be positively related to AFGX.

3.2.6 Term Structure Change

To capture the effect of the risk associated with changes in the shape of the term structure we use the variable Term Structure Change, TSC. Term structure change is defined as the change in the spread between the quarterly returns of the 10 year government bond and the treasury bill. Changes in the term structure is a risk for house investors because a changed spread between long and short term borrowing rates may change the cost of financing.

3.2.7 Real Household Consumption Expenditures

Ferson and Harvey (1991) state that consumption variables can help explain asset returns. If one views the household budget as fixed, then there is a trade-off between household consumption in non-durable goods and housing expenditures. On the other hand, if one views the budget as not being fixed and household consumption in non-durable goods as a proxy for wealth, then

[14] A*ffärsvärldens generalindex* is an index of the Swedish stock market calculated by the Swedish business magazine Affärsvärlden.

increased household consumption expenditures may indicate that there could be more money to invest in houses as well. The former would suggest a negative relationship with house prices and the latter would suggest that the relationship is positive. The variable HCONS is defined as the growth rate in aggregated nominal household consumption adjusted for CPI inflation.

3.2.8 Real Earnings Growth

The real growth in average hourly earnings in manufacturing is included as a proxy for changes in consumption power. An increase in the real growth rate of the hourly earnings should affect house prices positively. The variable REG is defined as the growth rate in aggregated nominal average hourly earnings adjusted for CPI inflation.

3.2.9 Population Growth

Hendershott (1996) concludes that population growth is important for explaining the real house price development as it can be used as a proxy for increased demand for houses. The variable POP is defined as the first difference of the growth rate in population. We expect POP to have a positive relationship with house prices.

3.2.10 Correlation Matrix and Summary of Explanatory Variables

Table 2

Correlation matrix for explanatory variables. EXRET is the excess return of the average index.

	EXRET	AFGX	REG	HCONS	OP	GDP	RINT	TSC	CEI	UI	CEIA	UIA
AFGX	-0.1159											
REG	0.0334	-0.0664				1981Q4 - 1999Q4						
HCONS	-0.1362	0.0439	0.4271									
OP	-0.0441	-0.3352	-0.0731	-0.0917								
GDP	0.0915	-0.0721	-0.4875	**-0.9101**	0.1453							
RINT	-0.4338	-0.1163	0.6230	0.2730	-0.0098	-0.2169						
TSC	0.0977	-0.2169	-0.0818	0.0594	0.1238	-0.0303	-0.1371					
CEI	0.2429	0.0249	-0.4574	-0.1957	0.0018	0.2948	-0.4277	0.0177				
UI	0.2697	-0.0056	-0.6637	-0.3180	-0.0258	0.2246	**-0.8886**	0.0608	0.3325			
CEIA	0.0426	-0.0344	-0.3834	-0.4352	0.3073	0.5001	-0.2657	-0.1699	0.1432	0.2907		
UIA	-0.0827	-0.0567	-0.0739	-0.3311	0.3215	0.4204	0.1512	-0.2698	-0.0320	-0.1313	**0.8744**	
POP	0.0216	0.0662	0.0049	0.0218	0.1061	0.0231	0.0226	0.0782	0.0684	-0.0785	-0.0561	-0.0238
AFGX	-0.2051											
REG	0.1838	-0.1274				1992Q1 - 1995Q4						
HCONS	0.0472	0.2065	**0.7579**									
OP	0.1502	-0.3846	0.1842	-0.0739								
GDP	-0.0398	-0.1393	-0.7442	**-0.8769**	-0.0245							
RINT	-0.3699	-0.0453	0.6833	0.5104	-0.1300	-0.4389						
TSC	0.5222	-0.4878	-0.2613	-0.2632	-0.0909	0.2378	-0.5059					
CEI	0.4771	0.0716	-0.2439	-0.0174	0.0352	0.2041	-0.4731	0.2038				
UI	0.0666	-0.0212	**-0.7831**	-0.5699	0.0020	0.4965	**-0.9026**	0.4540	0.3309			
CEIA	-0.1858	0.0464	-0.4373	-0.5038	0.4250	0.5743	-0.3095	-0.3250	-0.0001	0.2873		
UIA	-0.2118	0.1990	-0.1154	-0.2200	0.3536	0.3764	0.0547	-0.5461	-0.0668	-0.1357	**0.8866**	
POP	-0.0161	0.0871	0.0785	0.1618	0.0995	-0.0343	0.0126	0.1400	0.0188	-0.0336	-0.1355	-0.1271
AFGX	-0.2603											
REG	-0.3807	0.2821				1996Q1 - 1999Q4						
HCONS	-0.6185	0.2907	0.5967									
OP	0.0475	-0.0958	-0.6490	-0.1637								
GDP	0.5608	-0.3541	-0.7143	**-0.9444**	0.2613							
RINT	-0.1708	-0.1204	0.4576	0.0392	-0.5051	-0.0331						
TSC	0.0180	0.0165	-0.1226	0.0125	0.5117	0.0508	-0.2033					
CEI	0.0446	-0.2496	-0.1830	0.1868	0.2227	0.0321	0.1967	0.4416				
UI	0.2480	0.0808	-0.3758	-0.1538	0.4820	0.0670	**-0.9158**	0.1344	-0.3341			
CEIA	-0.1821	0.4560	0.1783	-0.0483	-0.3176	-0.0378	0.4016	-0.2954	-0.2096	-0.3313		
UIA	-0.2482	0.3207	0.2460	0.0534	-0.3604	-0.0685	0.6174	-0.3342	-0.1024	-0.5801	**0.8926**	
POP	-0.1209	0.0239	-0.0290	0.2814	0.0322	-0.0909	-0.0995	-0.1101	0.1468	-0.1675	-0.0901	0.0520

In *Table 2* correlations with an absolute value of 0.75 or higher are in bold. The correlation between GDP and HCONS is high. Real household consumption expenditures are intuitively more associated with households' housing expenditures, than the gross domestic product is. However, the GDP variable captures more general effects in the economy that we wish to include in the model. It is not surprising that there is a rather strong correlation between REG and HCONS, higher earnings should be associated with higher consumption. The high correlations between the variables UI and REG and between UI and RINT can to some extent be explained by the fact that CPI inflation is included in all of them. The high correlation between the variables CEIA and UIA can analogously be explained by the fact that they both contain the expected inflation calculated with the Fama and Gibbons (1984) method. It is not desirable to include highly correlated variables in a regression model as this may cause problems with large standard deviations in the estimated coefficients. To eliminate variables at this point one needs to know which variables can substitute the effects of the others. However, we have not found any theoretical arguments for which variables to eliminate and therefore we do not eliminate any of them at this stage. Instead we keep the highly correlated variable pairs in mind when we in *Section 4.3* choose the explanatory variables to be included in the final model specification. Specifically, we will test which of the variables that have high pair wise correlations are better at explaining the house price development together with the other variables.

Table 3

Summary of the explanatory variables tested in the first pass regression.

Variable name	Notation	Derivation	Expected sign
Change in household inflation expectations	CEI	(Household inflation expectations)$_t$ - (household inflation expectations)$_{t-1}$	+/-
Unanticipated inflation	UI	(Inflation derived from the CPI)$_t$ - (Household inflation expectations)$_t$	+/-
Change in inflation expectations with Fama and Gibbons (1984) method	CEIA	Fama and Gibbons (1984) method. See *appendix 2*.	+/-
Unanticipated inflation with Fama and Gibbons (1984) method	UIA	Fama and Gibbons (1984) method. See *appendix 2*.	+/-
Real interest rate	RINT	(1+(Treasury bill rate) $_t$)/(1+(Inflation derived from the CPI)$_t$)-1	-
Gross domestic product	GDP	(Index value of GDP)$_{t+1}$/(Index value of GDP)$_t$ -(Index value of GDP)$_t$/(Index value of GDP)$_{t-1}$	+
Oil price	OP	(Index value of Fuel Oil price)$_t$/(Index value of Fuel Oil price)$_{t-1}$-1	-
Market index	AFGX	(AFGX Index Value)$_t$/(AFGX Index Value)$_{t-1}$-1	+
Term structure change	TSC	(Government Bond Yield)$_t$-(Treasury Bill Rate)$_{t-1}$ -(Government Bond Yield)$_{t-1}$+(Treasury Bill Rate)$_{t-2}$	+/-
Household consumption expenditures	HCONS	(Household cons. exp.)$_t$/(Household cons. exp.)$_{t-1}$ -(Household cons. exp.)$_{t-1}$/(Household cons. exp.)$_{t-2}$	+/-
Real earnings growth	REG	(Average hourly earnings)$_t$/(Average hourly earnings)$_{t-1}$ -(Inflation derived from the CPI)$_t$	+
Population	POP	(Population)$_t$/(Population)$_{t-1}$-(Population)$_{t-1}$/(Population)$_{t-2}$	+

3.3 Control Variables

We use lags of the house indices excess returns as control variables. These variables cannot carry risk premia[15] but they are included to avoid misspecification in the form of omitted variables. More specifically, these lags have explanatory power and including them will make estimations of the other variables' coefficients more accurate.

[15] Only variables that can deviate from their expected value can carry risk premia. Lags are predetermined and therefore they cannot deviate from their expected value. Explicitly, predetermined variables are constants and the expected value of a constant is identically equal to that constant.

Table 4

The proportion of significant lags at the 10% level for the house price indices excess return in the augmented Dickey Fuller test.

LAG 1	LAG 2	LAG 3	LAG 4	LAG 5
32.86%	24.29%	27.14%	15.71%	5.71%

4 Methodology and Model Specification

When attempting to quantify risk premia in the housing market, we first need a model that by using a set of risk factors can explain the return variation in time of the whole market. Then we need a model that can estimate the risk premia associated with the factors from the first model. This procedure may enable us to understand how these factors affect housing returns, both ex ante and ex post. The first model captures which factors affect returns ex post. The risk premia are the ex ante pricing effects from factor exposures.

4.1 Introduction to the Fama and MacBeth Regression Model

We employ a linear multifactor model much alike the MAP developed by Ross (1976). Our model is based on the assumption that a small number of factors determine the general house price development. One of the purposes of the thesis is to investigate the risk premia of the factors discussed in the previous section. To do this we use two versions of the two pass regression model invented by Fama and MacBeth (1973). We call the first type *Original Fama and MacBeth regression*, OFM, and the second type *Ling and Naranjo type of Fama and MacBeth regression*, LNFM. The two versions have the first pass regression in common and differ only in the second pass regression. All regression models are estimated using ordinary least squares.[16]

[16] Although the dependent variable has autoregressive features that may lead to autocorrelation in the error terms, which in turn leads to inefficient OLS estimates, we will not use feasible generalized least squares (FGLS). The reason for this is that the samples are considered small. In small samples the properties of FGLS estimators are not well documented and we do not know if the FGLS estimates would be better or worse than the OLS estimates. Gujarati (2003) gives further details on this topic.

4.2 First pass Fama and MacBeth Regression

In order for a factor to carry risk premia it needs to systematically affect returns. Consequently, in the first pass regression we estimate how sensitive house price index returns are to the factors described in *Section 3.2*. Explicitly, we estimate factor betas[17] for the different indices. These betas vary over time and across indices. The first betas are estimated on year t through year t + N for each index, where N is the length of the estimation window and t is the first year of the data. The second betas are estimated on year $t+1$ through year $t+N+1$. These betas will later on be used for second pass cross sectional regression in the year subsequent of their window. To be precise, we use a rolling data window and estimate a set of betas to be used for each year during the period $t+N+1$ through T, where T denotes the last year in the data set. Thus each index will obtain T-t-N estimated betas for each explanatory variable. This will produce as series of time varying factor betas for each index, which we will use in the second pass cross sectional regressions. Algebraically the model in the first pass can be written as follows for an index i. The model is estimated in the time dimension.

$$\tilde{r}_{it} = \lambda_0 + \sum_{k=1}^{N} \beta_{ikt} \tilde{F}_{kt} + \tilde{\varsigma}_{it} \qquad (1)$$

where

r_{it} is the return for index i at time t minus the risk free interest rate

λ_0 is the return for a zero beta asset minus the risk free interest rate

β_{ikt} is a measure of how sensitive asset i´s return at time t is to factor k

F_{kt} is the value of factor k at time t

ς_{it} is a time and index specific error term

N is the number of factors

~ denotes a random variable

[17] First pass regression coefficients are denoted betas.

4.3 First Pass Model Specification

Kan and Zhang (1999) show that misspecified first pass models may produce significant risk premia that do not exist. To avoid this errors-in-variables problem we use the ordinary t-test to test if the betas are equal to zero. Our decision rule is that if we cannot reject the null hypothesis of betas being equal to zero at the 10% level of significance more than 50% of the time, we choose to re-specify the model before continuing with the second pass regressions.

Like Ling and Naranjo (1997) we first use a rolling regression window containing 20 quarters and eliminate variables according to the decision rule above. However, these regressions produce too many insignificant betas for all tested specifications and factors.[18] Plausible reasons for this are that the dependent variable is autocorrelated and noisy and that the number of observations is too small i.e. the rolling window is to short. We expect the noise to be especially high in the smaller regions, as these indices are based on a small number of transactions compared to the larger regions. One can also expect the smaller regions' house markets to be less efficient due to a potential lack of benchmark transactions and a limited number of buyers interested in each house transaction. Also the fact that the house prices are lower in smaller regions may lead to greater relative variation in house prices.

To increase the proportion of significant betas in the first pass and thus decrease the errors-in-variables problems we try two remedial methods. First we disregard the smallest regions from our analysis. As this does not result in any noteworthy improvement of the proportion of significant betas we keep the full set of dependent variables. Secondly we increase the length of the time window to 40 quarters. When choosing window length one has to consider that increasing the window length improves the significance of the beta estimates but it also implies restrictions in the time variation of the betas. The implied restrictions in time variation mean that the number of cross sectional regressions in the second pass is decreased.

[18] We test several specifications. Especially we test which of the variables that have high correlation with each other, as shown in the correlation matrix in *Section 3.2.10*, is better at explaining the house price development together with the other variables.

Table 5

Percentage significant betas at the 10% level of significance in the first pass regression using a 20Q rolling window.

	Constant	LAG 1	LAG 2	LAG 3	REG	RINT	OP	GDP
All 70 indices	23%	29%	13%	10%	24%	33%	11%	13%
56 largest indices	23%	26%	12%	10%	26%	34%	12%	14%
52 largest indices	24%	25%	12%	9%	27%	36%	12%	14%

Table 6

Percentage significant betas at the 10% level of significance in the first pass regression using a 40Q rolling window.

	Constant	LAG 1	LAG 2	LAG 3	REG	RINT	OP	GDP
All 70 indices	27%	42%	15%	21%	54%	72%	15%	19%
56 largest indices	29%	35%	15%	23%	57%	75%	15%	19%

Using the 40 quarter window and the decision rule described above we can without indecision eliminate the variables CEI, UI, CEIA, UIA, TSC, POP, AFGX, HCONS and lags of the dependent variable longer than 3 quarters. The regions are heterogeneous concerning the variables OP and GDP in the sense that in some of the regions these variables have a lot of explanatory power whilst in other regions they have none. Although the proportion of regions in which these variables are significant is less than 50%, which is our rule for discarding first pass regression variables, we keep these variables as control variables. The reason is that discarding these variables could lead to the results being biased due to omitted variables problems in the regions where these variables considerably can help explain the dependent variable. This would in turn lead to unreliable beta estimates in the first pass regressions for these regions.

As stated above we shall keep OP and GDP as control variables in the first pass. This means that we will not analyze their risk premia in the second pass due to the errors-in-variables problem pointed out by Kan and Zhang (1999) as discussed above.[19] The factors included in the final first pass regressions are RINT and REG. As control variables we use OP, GDP and the first 3 lags of the dependent variable. The control variables are included in order to obtain more

[19] It is worth noting that discarding these variables in the first pass would lead to omitted variables in the first pass regression (which would lead to errors-in-variables problem) whilst including them in the first pass but not in the second pass may lead to omitted variables in the second pass. Lastly including them both in the first pass and the second pass would lead errors-in-variables problem.

accurate estimates of the RINT and REG betas. More details on the estimated models are presented in *Section 5.1*.

The indices are grouped into portfolios in the way described in *Section 3.1.1*. In the second pass regression each portfolio will have a beta estimate for each factor and quarter. To get these estimates we take the average of the betas from the indices included in a portfolio and use each estimate during four quarters.

4.4 Original Fama and MacBeth Second Pass Regression

In this section the OFM second pass regression is presented. To give the reader a better understanding of the model we describe how it is practically applied. We first run cross sectional regressions with the portfolio quarterly excess returns during the year *t+N+1* as the dependent variable and the portfolio factor betas estimated in the first pass using the first window from year *t* through year *t+N* as explanatory variables. Then we regress the excess returns during the year *t+N+2* on the portfolio factor betas estimated using the second window and so forth. This produces quarterly time series of time varying risk premium estimates for each explanatory variable, from year *t+N+1* through year *T*. We report the results from these estimation procedures in *Table 8*. Algebraically the second pass OFM risk premium estimating model can be written as follows for time *t*. The model will be estimated in cross section.

$$\tilde{r}_{pt} = \delta_{0t} + \sum_{k=1}^{N} \lambda_{kt} \hat{\beta}_{pkt} + \tilde{\varepsilon}_{pt} \tag{2}$$

where

r_{pt} is the return for portfolio *p* at time *t* minus the risk free interest rate

δ_{0t} is a regression constant

$\hat{\beta}_{pkt}$ is the first pass estimate of portfolio *p*'s *k* factor beta at time *t*. I.e. a measure of how sensitive portfolio *p*'s return at time *t* is to factor *k*

λ_{kt} is the risk premium associated with factor *k* at time *t*

ε_{pt} is a time and portfolio specific error term

N is the number of factors

~ denotes a random variable

The estimate of λ_{kt} in (2) is the estimated risk premium related to factor *k* at time *t*. The return compensation for bearing risk related to factor *k* at time *t* is equal to the risk premium related to factor *k* at time *t*, λ_{kt}, times index *i*'s sensitivity to that factor, β_{ikt}, at time *t*.

4.5 Ling and Naranjo Type of Fama and MacBeth Second Pass Regression

In addition to the OFM regression described above we analyze the data using the slightly different type of Fama and MacBeth second pass regression used by Ling and Naranjo (1997). In the LNFM second pass regression we retain all the variables from the first pass, including the control variables. Even though the LAG variables included cannot carry risk premia we keep them. This is because they can serve as portmanteau variables that are meant to capture unspecified or omitted risk factors. As indicated by the first pass regression results, these lags can help explain housing excess returns. The GDP and OP variables have been included for the same reason. However, as stated above we will only analyze risk premia for the variables RINT and REG.[20] The LNFM second pass cross sectional regression is estimated with the following equation for time *t*.

$$r_{tp}^{\ *} = \alpha_{0t} + \sum_{k=1}^{N} [\lambda_{kt} - E_{t-1}(F_{kt})] \hat{\beta}_{pkt} + \tilde{\vartheta}_{pt} \qquad (3)$$

where

$$r_{tp}^{\ *} = \tilde{r}_{tp} - \sum_{k=1}^{N} \tilde{F}_{kt} \cdot \hat{\beta}_{pkt}$$

and

$\hat{\beta}_{pkt}$ is the first pass estimate of portfolio *p*'s factor *k* beta at time *t*. I.e. a measure of how sensitive portfolio *p*'s return at time t is to factor *k*

[20] We will not analyze the risk premia of GDP and OP because of the errors-in-variables problems in these data as discussed above. We will not analyze the risk premia of the dependent variable lags simple because risk premia on predetermined variables theoretically cannot exist, as discussed above.

$E_{t-1}(Z_t)$	denotes the value expected at time *t-1* of the random variable Z_t at time *t*
α_{0t}	is a regression constant
$\tilde{\vartheta}_{pt}$	is the error term specific to portfolio *p* at time *t*
$[\lambda_{kt} - E_{t-1}(F_{kt})]$	is the gross risk premium for factor *k* at time *t*
F_{kt}	is the value of factor number *k* at time *t*
N	is the number of factors
~	denotes a random variables

Note that by adding $\sum_{k=1}^{N} \tilde{F}_{kt} \hat{\beta}_{pkt}$ on both sides to equation (3) we get:

$$\tilde{r}_{tp} - \sum_{k=1}^{N} \tilde{F}_{kt} \cdot \hat{\beta}_{pkt} + \sum_{k=1}^{N} \tilde{F}_{kt} \hat{\beta}_{pkt} = \alpha_{0t} + \sum_{k=1}^{N} [\lambda_{kt} - E_{t-1}(F_{kt})] \hat{\beta}_{pkt} + \sum_{k=1}^{N} \tilde{F}_{kt} \hat{\beta}_{pkt} + \tilde{\vartheta}_{pt} \quad (4)$$ [21] equals

$$\tilde{r}_{tp} = \alpha_{0t} + \sum_{k=1}^{N} \left[\lambda_{kt} - E_{t-1}(F_{kt}) + \tilde{F}_{kt} \right] \hat{\beta}_{pkt} + \tilde{\vartheta}_{pt} \quad (5)$$ equals

$$\tilde{r}_{tp} = \alpha_{0t} + \sum_{k=1}^{N} [\lambda_{kt} - E_{t-1}(F_{kt})] \hat{\beta}_{pkt} + \sum_{k=1}^{N} \tilde{F}_{kt} \hat{\beta}_{pkt} + \tilde{\vartheta}_{pt} \quad (6)$$ equals

$$\tilde{r}_{tp} = \alpha_{0t} + \sum_{k=1}^{N} \lambda_{kt} \hat{\beta}_{pkt} + \sum_{k=1}^{N} \left[\tilde{F}_{kt} - E_{t-1}(F_{kt}) \right] \hat{\beta}_{pkt} + \tilde{\vartheta}_{pt} \quad (7)$$

The left hand side of (7) is the same as in equation (2) and on the right hand side we have added only $\sum_{k=1}^{N} \left[\tilde{F}_{kt} - E_{t-1}(F_{kt}) \right] \hat{\beta}_{pkt}$ which ex ante is equal to zero. Thus ex ante (7) is equal to (2) and therefore it is obvious that the LNFM second pass regressions and the OFM second pass regressions are estimating the same risk premia, only in different ways.

[21] The term $\sum_{k=1}^{N} \hat{\beta}_{pkt} \tilde{F}_{kt}$ is a constant, even though F has the random variable tilde it is determined when the regression is run, compare with equation (1). We do not want to model (4), (5), (6), (7), as they are, because then $\sum_{k=1}^{N} \hat{\beta}_{pkt} \tilde{F}_{kt}$ would obtain regression coefficients, which would make no sense. Thus, for the model to be regressed with sense we have to move the summation to the left hand side, as in (3).

The risk premium, λ_{kt}, in (3) has the same interpretation as it has in (2). However, running model (3) will produce estimates of time varying gross risk premia $[\lambda_{kt} - E_{t-1}(F_{kt})]$ which in itself is not interesting. To obtain the risk premium we have to add the expected value of the relevant factor to the gross risk premium.

$$\lambda_{kt} = [\lambda_{kt} - E_{t-1}(F_{kt})] + E_{t-1}(F_{kt}) \tag{8}$$

Appendix III includes details on how the expected values of the factors are calculated and *Appendix IV* gives details on how summation (8) is performed. We report the results from these estimation procedures in *Table 9*.

5 Results

5.1 First Pass Fama and MacBeth Regression

In this section we present the results from estimating equation (1) for the variables LAG 1, LAG 2, LAG 3, RINT, REG, OP and GDP. The dependent variable is excess return on the indices.[22]

Table 7

Summary statistics of the first pass regression betas. The means are calculated as averages of the estimated betas of all indices over the period specified. The average standard deviations are calculated as the averages of estimated standard deviations, whilst the beta standard deviations are calculated as the standard deviation of the estimated betas. % significant is the proportion of significant beta estimates on the 10% level and % pos sign is the proportion of significant betas with a positive sign.

1992Q1 - 1999Q4	Constant	LAG 1	LAG 2	LAG 3	REG	RINT	OP	GDP
Means	0.01	-0.21	0.01	0.13	1.06	-2.28	0.00	0.03
Average std. dev.	0.01	0.16	0.17	0.16	0.62	0.98	0.03	0.06
Beta std. dev.	0.02	0.24	0.20	0.16	0.59	1.24	0.04	0.07
% significant	27%	42%	15%	21%	54%	72%	15%	19%
Max	0.07	0.46	0.51	0.66	3.13	1.51	0.12	0.26
Min	-0.06	-1.02	-0.62	-0.35	-1.15	-7.01	-0.08	-0.18
% pos sign	94%	8%	53%	93%	100%	0%	52%	93%

1992Q1 - 1995Q4	Constant	LAG 1	LAG 2	LAG 3	REG	RINT	OP	GDP
Means	0.01	-0.19	0.03	0.15	0.90	-1.93	0.00	0.03
Average std. dev.	0.01	0.16	0.17	0.16	0.53	0.87	0.03	0.06
Beta std. dev.	0.02	0.24	0.21	0.16	0.58	1.05	0.03	0.07
% significant	25%	36%	18%	24%	55%	71%	18%	20%
Max	0.07	0.46	0.51	0.66	2.77	1.51	0.11	0.24
Min	-0.06	-1.02	-0.62	-0.35	-1.15	-6.40	-0.08	-0.18
% pos sign	88%	8%	68%	93%	100%	0%	32%	97%

1996Q1 - 1999Q4	Constant	LAG 1	LAG 2	LAG 3	REG	RINT	OP	GDP
Means	0.01	-0.23	-0.02	0.11	1.21	-2.64	0.00	0.03
Average std. dev.	0.01	0.16	0.17	0.16	0.70	1.08	0.03	0.07
Beta std. dev.	0.02	0.24	0.18	0.16	0.57	1.32	0.04	0.08
% significant	29%	48%	13%	18%	53%	73%	13%	18%
Max	0.07	0.44	0.51	0.42	3.13	0.23	0.12	0.26
Min	-0.03	-0.90	-0.45	-0.34	0.12	-7.01	-0.08	-0.16
% pos sign	100%	8%	39%	93%	100%	0%	72%	90%

[22] This model has 32 degrees of freedom. We estimate 8 parameters on 40 data points in each time series regression.

Table 7 shows the quality of the first pass beta estimates. It is crucial that the accuracy of the first pass beta estimates is sufficient, since the quality of the risk premium estimates in the second pass regression largely depends on this. We can see that the proportions of significant betas at the 10% level of the RINT and the REG variables do not change much between the two sub-periods. The signs of the RINT, REG and GDP variables are in accordance with our expectations. The high proportions of significant lags indicate that the dependent variable is autocorrelated. *Figure 1* provides more details on the yearly development of the proportion of significant beta estimates, which together with the development of the beta estimates in *Figure 2* give an indication of that the beta estimates are stable over the time period studied. The proportions of significant REG and RINT betas are well in line with the proportions that Ling and Naranjo (1997) deem adequate. In that study the proportions of significant betas in the first pass regression span from 47.9% to 97.9%. We end this section by concluding that the betas seem accurate enough not to seriously distort the risk premium estimates in the second pass regression.

Figure 1

The yearly proportions of significant betas estimated for the years 1992 through 1999.

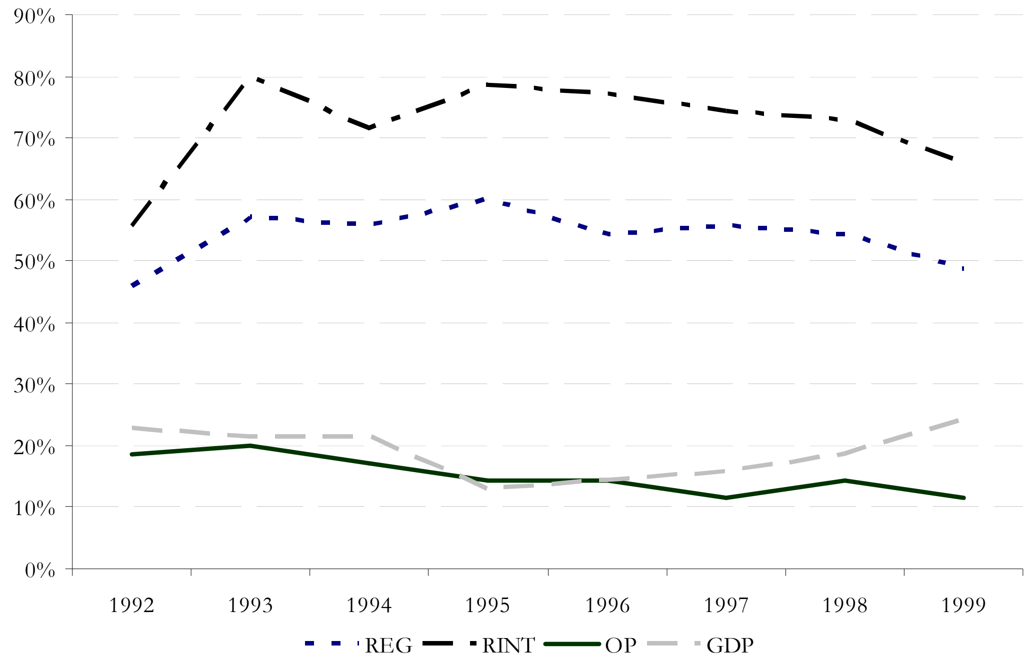
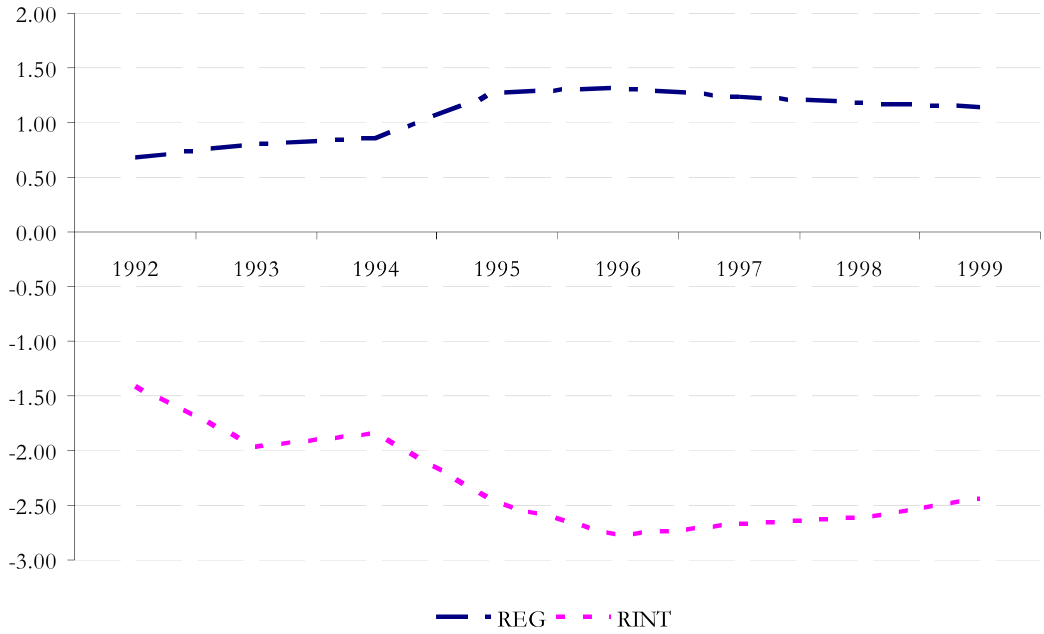


Figure 2

The yearly averages of estimated REG and RINT betas for the years 1992 through 1999.



5.2 Original Fama and MacBeth Second Pass Regressions

In this section we present the results from estimating equation (2) for the estimated betas of RINT and REG. The dependent variable is excess return on portfolios of the indices.[23]

The proportions of risk premia significant at the 10% level reported in *Table 8* are low. The intercept has the highest proportion of significant risk premia when looking at the whole 1992Q1-1999Q4 period. The proportions of significant RINT risk premia are higher than the REG proportions. When splitting the data into two equally long sub-periods, where the first period is 1992Q1-1995Q4 and the second period is 1996Q1-1999Q4, we find that RINT is more often significant in the later period whilst the opposite is true for the REG and intercept risk premia. The means of the risk premia for REG and RINT change signs to minus in the second period, whilst the average intercept premium becomes positive.

[23] This model has 11 degrees of freedom. We estimate 3 parameters on 14 data points in each cross sectional regression.

Table 8

Summary statistics for risk premia estimated using the original Fama and MacBeth method.

1992Q1 - 1999Q4	REG	RINT	Intercept
Means	-0.006	-0.001	-0.013
Average Std. Dev	0.050	0.020	0.031
Risk premia std dev	0.055	0.026	0.054
% significant	9%	22%	28%
Max	0.087	0.076	0.054
Min	-0.115	-0.055	-0.143

1992Q1 - 1995Q4	REG	RINT	Intercept
Means	0.002	0.001	-0.038
Average Std. Dev	0.050	0.024	0.035
Risk premia std dev	0.055	0.032	0.055
% significant	13%	19%	38%
Max	0.087	0.076	0.034
Min	-0.104	-0.055	-0.143

1996Q1 - 1999Q4	REG	RINT	Intercept
Means	-0.014	-0.003	0.012
Average Std. Dev	0.049	0.017	0.027
Risk premia std dev	0.054	0.020	0.040
% significant	6%	25%	19%
Max	0.059	0.023	0.054
Min	-0.115	-0.040	-0.094

5.3 Ling and Naranjo Type of Fama and MacBeth Second Pass Regressions

In this section we present the results from estimating equations (3) and (8) for the estimated betas of LAG 1, LAG 2, LAG 3, RINT, REG, OP and GDP. The dependent variable is a transformation of the excess return on portfolios of the indices.[24]

The proportions of risk premia significant at the 10% level reported in *Table 9* are low. The intercept has the most frequent significant risk premia. When splitting the data into two equally long sub-periods, where the first period is 1992Q1-1995Q4 and the second period is 1996Q1-1999Q4, we find that the REG and RINT risk premia are more frequently significant in the first period whilst the opposite is true for the intercept. The means of the REG and RINT risk premia are larger in the second period, whilst the intercept mean risk premium is smaller in the second period. The average sign of the REG risk premia is negative during both sub-periods.

[24] This model has 6 degrees of freedom. We estimate 8 parameters on 14 data points in each cross sectional regression.

The average sign of the RINT risk premia is negative during the first period and positive during the second period.

Table 9

Summary statistics for risk premia estimated using the LNFM method.

1992Q1 - 1999Q4	REG	RINT	Intercept
Means	-0.003	0.072	-0.053
Average Std. Dev	0.070	0.407	0.100
Risk premia std dev	0.073	0.630	0.328
% significant	6%	9%	25%
Max	0.239	2.137	0.650
Min	-0.150	-1.025	-1.601

1992Q1 - 1995Q4	REG	RINT	Intercept
Means	-0.004	-0.002	-0.034
Average Std. Dev	0.072	0.040	0.069
Risk premia std dev	0.085	0.051	0.074
% significant	13%	13%	19%
Max	0.239	0.140	0.111
Min	-0.150	-0.094	-0.152

1996Q1 - 1999Q4	REG	RINT	Intercept
Means	-0.002	0.146	-0.072
Average Std. Dev	0.067	0.774	0.131
Risk premia std dev	0.063	0.897	0.089
% significant	0%	6%	31%
Max	0.130	2.137	0.328
Min	-0.098	-1.025	0.033

5.4 Analysis of the Proportions of Significant Risk Premia

The intercept premium is statistically significant in 28% of the periods using OFM and in 25% using LNFM. The relatively high significance of the intercept may indicate that the model is flawed in some way, perhaps due to an omitted variables bias. Considering that the probability of making a Type I error[25] is 10%[26], we would expect that 10% of estimated risk premia on purely unrelated variables should be significant. Using this as a benchmark, it is not at all satisfactory to find that only the RINT risk premia estimated in the OFM second pass regression are significant more often than this 10% level when the whole period is considered. Moreover, this proportion of RINT risk premia significant is only 22%.

[25] Committing a Type I error means rejecting a true null hypothesis.

[26] As stated above, the null hypothesis of no risk premia has been rejected if it can be rejected at the 10 % significance level.

Ling and Naranjo (1997) interpret the proportions 18.8%, 37.5%, 50.0% and 54.2% for their different types of real estate data as evidence for a significant risk premium associated with a certain factor. These proportions are calculated at the 5% level. Our best finding is 25% significant risk premia on the 10% level. Explicitly, we have not found enough evidence to be able to draw any robust and statistically reliable conclusions regarding risk premia in the Swedish housing market. The proportions of significant risk premia for RINT can only be considered an indication of that it carries risk premium.

5.5 Analysis of the Real Interest Rate Risk Premium

Table 10

The Mean Betas are the RINT estimates from the first pass regression. The Quarterly Risk Premia are the mean OFM second pass estimates of RINT. The Quarterly Risk Premium Components are calculated as the products of Mean Beta and Risk Premium. This is geometrically annualized in the yearly risk premium component.

	1992Q1-1999Q4	1992Q1-1995Q4	1996Q1-1999Q4
Mean Beta	-2.28	-1.96	-2.64
Quarterly Risk Premium	-0.10%	0.10%	-0.30%
Quarterly Risk Premium Component	0.23%	-0.20%	0.79%
Yearly Risk Premium Component	0.92%	-0.78%	3.21%

The RINT risk premium component is a measure of the ex ante average return compensation demanded by investors for carrying real interest rate risk associated with house investments during the specified periods. We expect this component to be positive as investors normally demand additional return for carrying risk. However, in the first sub-period we find that the risk component is negative. This is probably due to insignificant observations biasing the risk premia.[27]

[27] The negative risk premium component could theoretically stem from investors hedging their asset portfolios with house investments. If house returns are negatively correlated with the rest of an investor investment portfolio, the investor could demand lower returns on the house investments as these would lower the risk of the whole portfolio. Considering the type of investors owning houses, hedging behaviour seems quite unlikely on an aggregated level.

Ling and Naranjo (1997) find that the mean beta of the real interest rate is approximately -0.5, that its risk premium is 2.4% and that the risk premium component is -1.2%. The negative risk premium component is explained by investors hedging their portfolios with property assets.

6 Conclusions

We conclude that most regions in the Swedish housing market are exposed to the changes in real interest rate and in real earnings growth. Also some regions are exposed to changes in gross domestic product and in the oil price. However, we cannot with certainty determine whether these factors are priced or not. More specifically, we cannot draw any reliable conclusions regarding the size, sign or even existence of risk premia in the Swedish housing market.

In spite of a reasonably accurate first pass regression model and two different approaches to estimate risk premia in cross section, all we find is an indication of that real interest rate carries risk premium in the Swedish housing market. The high proportion of insignificant risk premia may to some extent be explained by the few degrees of freedom in cross section. It also indicates that our model may suffer from omitted variables or that the data is plagued by idiosyncratic movements. A larger data set in cross section would increase the degrees of freedom, which in turn would make point estimates statistically more reliable.

The autocorrelation in house returns, which in line with numerous studies was found significant, is an indication of inefficiencies in this market. Furthermore, if price discovery[28] is present in the Swedish housing market, then it would not, on an aggregated level, respond swiftly to shocks in risk factors. Instead the effect of changes in the risk factors would be delayed and smoothened over a period of time. Given that the housing market is inefficient and that price discovery may be present, it is not unlikely that risk factors are less influential on house prices ex ante compared to how risk factors influence prices ex ante in more efficient markets. More precisely, the reason why we find little evidence of risk premia may be that there are no considerable risk premia present.

[28] Price discovery is discussed in *Section 2*.

7 Methodological Discussion

The statistical methods employed in this study are associated with a series of interconnected implementation decisions. Continuing the statistical investigation by using different variables, portfolio constructions, decision rules, window lengths, other forecasting models for expected values and different model specifications in both first and second pass could change the results and give evidence of risk premia. In this section we present a number of alternatives at hand regarding the empirical model implementation. The alternatives presented should not be considered exhaustive.

One option available regarding portfolio construction is increasing the number of portfolios by reducing the number of indices in each portfolio to increase the degrees of freedom in cross section. Another option is changing the base for portfolio grouping, which for example may be geographical proximity. The decision rules can be changed regarding significance levels and/or proportions of significant betas. Structural models can be used to estimate expected factor values for the LNFM model.

8 Suggestions for Further Research

- In our model GDP and OP can explain house returns only in some regions. Without doing separate estimations for the regions with the same set of explanatory variables, how can risk premia be estimated when explanatory variables are not the same for all regions?

- After reading this study one might be inclined to believe that the inefficiencies in the Swedish housing market means that there is some kind of arbitrage opportunity at hand. However, if one would include the large transaction costs associated with buying or selling a house this might not be true. Develop a model that, taking transaction costs into account, identifies potential arbitrage opportunities.

- Fama and MacBeth (1973) group the dependent variables into portfolios based on the sizes of beta estimates. These betas are calculated from a regression with only one explanatory variable. We have several explanatory variables and we cannot use this procedure as it cannot easily be generalized to include more variables. Find a way to generalize it. One suggestion is to first standardize the factor betas so their values can be compared. Secondly find a way to optimize the difference in portfolio expected returns by allocating the dependent variables into portfolios using their standardized factor betas.

- Examine how the concept of pricing discovery applies to the Swedish housing market compared to the housing markets in the other Nordic countries, to the Swedish real estate market and to Swedish real estate stocks.

- Develop a risk premia estimating model which includes effects of price discovery.

- Hendershott (1996) concludes that interregional migration is important when explaining house market returns. Develop a model that includes such effects.

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10 Appendices

I Portfolio Structure[29] and index excess returns

Table I

Specification of the A-regions included in the portfolios used in the second pass regressions.

The A-region excess returns are the average yearly index excess returns over the period 1981Q1–1999Q4.

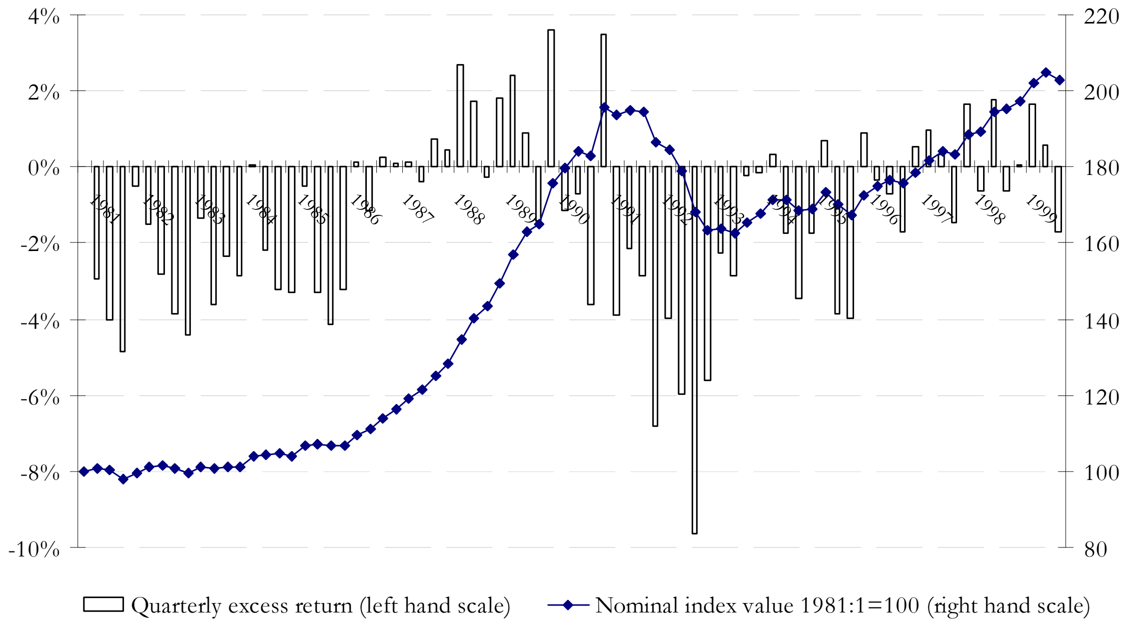
Portfolio	Included A-regions	Population on 31 Dec. 1980	A-region excess return
I	A-01 Stockholms/Södertälje A-region	1487358	-3.2%
	A-33 Göteborgs A-region	732376	-4.0%
	A-28 Malmö/Lunds/Trelleborgs A-region	453337	-3.6%
	A-27 Helsingborgs/Landskrona A-region	217717	-4.2%
	A-36 Borås A-region	188266	-5.6%
		Average:	-4.1%
II	A-56 Gävle/Sandvikens A-region	180421	-5.4%
	A-45 Örebro A-region	172533	-4.7%
	A-42 Karlstads A-region	171780	-5.1%
	A-04 Uppsala A-region	167220	-4.3%
	A-10 Norrköpings A-region	164622	-5.6%
		Average:	-5.0%
III	A-52 Borlänge/Faluns A-region	151396	-5.6%
	A-48 Västerås A-region	147163	-4.5%
	A-09 Linköpings A-region	136122	-4.7%
	A-63 Östersunds A-region	134934	-6.0%
	A-16 Växjö A-region	134484	-5.2%
		Average:	-5.2%
IV	A-11 Jönköpings A-region	134285	-4.4%
	A-59 Sundsvalls A-region	126963	-5.5%
	A-34 Uddevalla A-region	121804	-4.3%
	A-20 Kalmar/Nybro A-region	117372	-5.1%
	A-64 Umeå A-region	115497	-4.7%
		Average:	-4.8%
V	A-07 Eskilstuna A-region	114059	-4.5%
	A-35 Trollhättan/Vänersborgs A-region	112406	-5.3%
	A-31 Halmstads A-region	108312	-4.6%
	A-68 Luleå/Bodens A-region	102769	-4.2%
	A-24 Kristianstads A-region	96376	-5.0%
		Average:	-4.7%
VI	A-13 Eksjö/Nässjö/Vetlanda A-region	90340	-5.9%
	A-22 Karlskrona A-region	90300	-5.4%
	A-37 Lidköpings/Skara A-region	88776	-5.3%
	A-08 Mjölby/Motala A-region	87683	-5.2%
	A-29 Ystads/Simrishamns A-region	84339	-4.5%
		Average:	-5.2%

[29] The population data used for sorting the A-region indices into portfolios is taken from the Statistics Sweden database. http://www.ssd.scb.se.

Portfolio	Included A-regions	Population on 31 Dec. 1980		A-region excess return
VII	A-65 Skellefteå A-region	84241		-5.8%
	A-32 Falkenbergs/Varbergs A-region	79076		-4.5%
	A-05 Nyköpings A-region	78219		-4.4%
	A-39 Skövde A-region	74197		-5.1%
	A-57 Bollnäs/Söderhamns A-region	72848		-5.9%
			Average:	-5.1%
VIII	A-58 Hudiksvalls/Ljusdals A-region	71095		-5.7%
	A-25 Hässleholms A-region	70145		-5.5%
	A-14 Värnamo A-region	67881		-4.7%
	A-23 Karlshamns A-region	63242		-4.8%
	A-70 Kiruna/Gällivare A-region	63179		-3.2%
			Average:	-4.8%
IX	A-62 Örnsköldsviks A-region	60552		-6.0%
	A-67 Piteå A-region	60459		-5.7%
	A-06 Katrineholms A-region	60258		-5.0%
	A-21 Visby A-region	55346		-4.2%
	A-60 Härnösands/Kramfors A-region	54367		-5.7%
			Average:	-5.3%
X	A-47 Lindesbergs A-region	52749		-5.0%
	A-26 Ängelholms A-region	51210		-4.0%
	A-49 Köpings A-region	50751		-5.5%
	A-30 Eslövs A-region	50355		-4.7%
	A-43 Säffle/Åmåls A-region	50035		-5.4%
			Average:	-4.9%
XI	A-46 Karlskoga A-region	49074		-6.4%
	A-19 Oskarshamns A-region	48972		-5.1%
	A-41 Kristinehamns A-region	47091		-5.5%
	A-55 Mora A-region	47049		-6.2%
	A-44 Arvika A-region	46214		-5.3%
			Average:	-5.7%
XII	A-03 Enköpings A-region	46021		-4.4%
	A-54 Ludvika A-region	45084		-4.6%
	A-38 Falköpings A-region	44944		-5.4%
	A-66 Lycksele A-region	44118		-5.6%
	A-53 Avesta/Hedemora A-region	43439		-5.8%
			Average:	-5.2%
XIII	A-40 Mariestads A-region	41491		-5.4%
	A-17 Västerviks A-region	41263		-5.5%
	A-02 Norrtälje A-region	40842		-4.0%
	A-69 Haparanda/Kalix A-region	40647		-4.2%
	A-15 Ljungby A-region	39207		-5.0%
			Average:	-4.8%
XIV	A-51 Sala A-region	34314		-5.9%
	A-18 Hultsfreds/Vimmerby A-region	33974		-5.8%
	A-12 Tranås A-region	29615		-5.1%
	A-50 Fagersta A-region	27310		-6.4%
	A-61 Sollefteå A-region	26053		-6.3%
			Average:	-5.9%

Figure I

Quarterly excess return of the average house price index and the average index development.



II Fama and Gibbons Estimation of Expected Inflation

The Fama and Gibbons (1984) method estimates the expected inflation from the real interest rate by using an ARIMA(0,1,1) model. This model produces expected values that capture inflation trends. Deviations from these trends, which we try to capture in the CEIA and UIA variables, can be relevant for the house price development. The ARIMA forecasting model extracts expected inflation from the treasury bill real rate. According to Fama and Gibbons (1984) the first difference of the real interest rate[30] can be described by an ARMA(0,1) process with a constant which is described by the equation:

$$DRINT_t = u_t - \theta u_{t-1} + \hat{\zeta}_t$$

[30] That is, the first difference of RINT which we denote DRINT.

According to the output from running this regression presented in *Table II* below, the estimated coefficient, θ, has the value -1.000 and a t-probability of 0.000.

Table II

Fama and Gibbons (1984) time series estimation of the expected inflation.

1981Q1-1999Q4	Coefficient	Std.Error	t-value	t-prob
MA-1	-1.000	0.046	-21.9	0.000
Constant	2.22E-05	5.52E-05	0.403	0.688
log-likelihood	232.8			
no. of observations	75			
AIC.T	-459.6			
AIC	-6.13			
mean(DRINT)	0.0002			
var(DRINT)	0.0003			

Algebraically the output in *Table II* can be expressed as:

$$DRINT_t = u_t - (-1.000)u_{t-1} = u_t + 1.000u_{t-1} = u_t + u_{t-1}$$

By saving the residuals, $\hat{\zeta}_t$, when running the regression we can calculate the expected inflation as:

$$EINFLA_t = TB_{t-1} - CPI\_INFLATION_{t-1} + \hat{\zeta}_{t-1}.$$

III Time Series Estimation of Expected Values

Expected values of the factors can be estimated using the Box-Jenkins methodology. To produce the values ex ante we use the 1980Q1–1990Q4 time period for finding an ARMA[31] model that can produce forecasts for the first quarter in 1991. We then study the 1980Q1–1991Q1 period for finding a new ARMA model that can produce forecasts for the second

[31] We only consider ARMA models as we have performed the augmented Dickey Fuller test and found the series to be stationary.

quarter in 1991 and so forth. This procedure produces one quarter horizon expected values for the 1991Q1–1999Q4 period. In the two figures below we visualize how the data patterns change as more data is added.

Figure II

The ACF and PACF functions for the REG (top) and RINT (bottom) variables during the period 1980Q1–1990Q4.

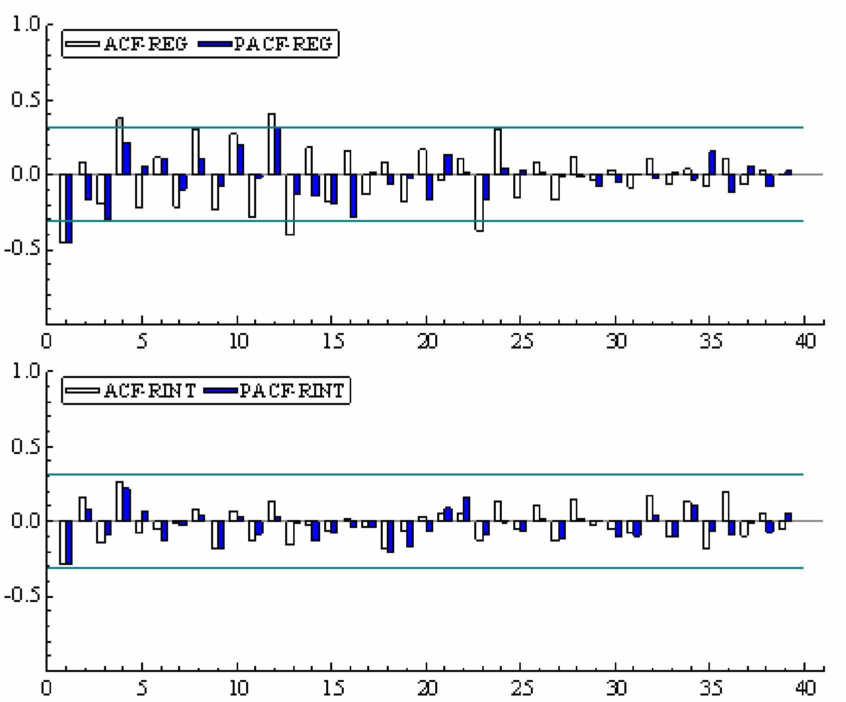
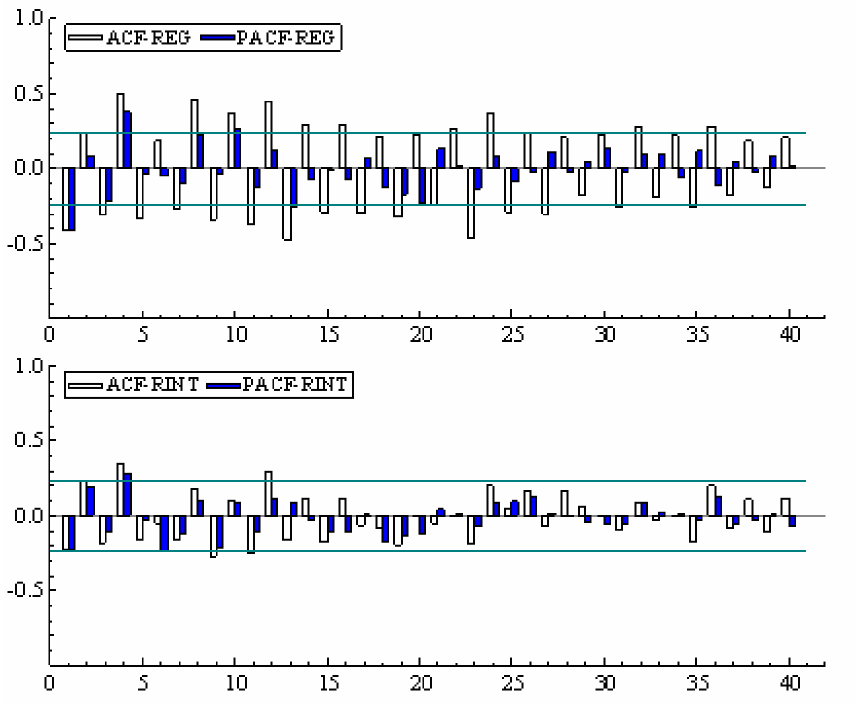


Figure III

The ACF and PACF functions for the REG (top) and RINT (bottom) variables during the period 1980Q1–1999Q4.



By using the Box-Jenkins methodology and trying different specifications we find a set of reasonably good models, which are summarized in *Table III* and *Table IV*. As criteria for finding a good model we want a low AIC value and a high log-likelihood value.

Table III

Specification of the ARMA models that are used to forecast REG.

Period	Type of model	MA terms set to zero	AR terms set to zero
1991Q1–1992Q2	ARMA(4.4)	2,3	2,3
1992Q3–1999Q4	ARMA(1,4)	1,2,3	-

Table IV

Specification of the ARMA models that are used to forecast RINT.

Period	Type of model	MA terms set to zero	AR terms set to zero
1991Q1–1991Q4	ARMA(1,1)	-	-
1992Q1–1999Q4	ARMA(0,4)	1,2,3	-

In *Table V* and *Table VI* below two model estimations for each of REG and RINT are presented. The model estimations are used for making one quarter forecasts, which are shown in *Table VII* and *Table VIII*.

Table V

Estimation of different ARMA models for REG.

1981Q1-1991Q4	Coefficient	Std.Error	t-value	t-prob
AR-1	-0.0591	0.2088	-0.2830	0.7790
AR-4	0.6374	0.3474	1.8300	0.0740
MA-1	-0.3107	0.3036	-1.0200	0.3130
MA-4	-0.2455	0.4694	-0.5230	0.6040
Constant	0.0006	0.0025	0.2410	0.8110
log-likelihood	115.97			
no. of observations	44.00			
AIC.T	-219.94			
AIC	-5.00			
mean(REG)	0.0013			
var(REG)	0.0005			

1981Q1-1999Q3	Coefficient	Std.Error	t-value	t-prob
AR-1	-0.3460	0.1132	-3.0600	0.0030
MA-4	0.2766	0.0952	2.9100	0.0050
Constant	0.0033	0.0018	1.8300	0.0710
log-likelihood	199.88			
no. of observations	75			
AIC.T	-391.76			
AIC	-5.22			
mean(RINT)	0.0033			
var(RINT)	0.0004			

Table VI

Estimation of different ARMA models for RINT.

1981Q1-1990Q4	Coefficient	Std.Error	t-value	t-prob
AR-1	-0.965	0.071	-13.60	0.000
MA-1	0.802	0.173	4.63	0.000
Constant	0.011	0.001	7.43	0.000
log-likelihood	127.949392			
no. of observations	40			
AIC.T	-247.90			
AIC	-6.20			
mean(RINT)	0.0106			
var(RINT)	0.0001			

1981Q1-1991Q4	Coefficient	Std.Error	t-value	t-prob
MA-4	0.753	0.155	4.86	0.000
Constant	0.011	0.002	4.52	0.000
log-likelihood	142.19			
no. of observations	44			
AIC.T	-278.39			
AIC	-6.33			
mean(RINT)	0.0104			
var(RINT)	0.0001			

IV Risk Premia Calculations in LNFM

To get the LNFM risk premia point estimates we add the one quarter horizon estimated forecast values for REG and RINT respectively to the estimated gross risk premia:

$$\lambda_{kt} = [\lambda_{kt} - E_{t-1}(F_{kt})] + E_{t-1}(F_{kt})$$

The risk premium standard deviations are calculated by adding the squared standard deviations of the forecasts to the squared standard deviations of the gross risk premia and taking the square root of that sum:

$$s_{Risk\_premium\_t} = \sqrt{s^2_{Forecast\_t} + s^2_{Gross\_risk\_premium\_t}}$$

Next, we standardize the estimated risk premia and use the student's t-distribution with 6 degrees of freedom to perform a two sided test on the 10% level of significance with the null hypothesis that the individual risk premium is not different from zero. We report the proportion of significant risk premia in the results section.

Table VII

Calculation of the LNFM REG risk premia. The residual sum of squares for the REG forecasts is 0.0074.

	Forecast	Forecast st.dev.	Actual RINT value	Residual	Residual squared	Gross risk premium	Gross risk premium st.dev.	Risk premium	Risk premium st.dev.	t-value	t-prob
1992-1	-0.0228	0.0171	-0.0013	0.0215	0.0005	0.09756	0.09169	0.0747	0.0933	0.8013	0.4535
1992-2	0.0050	0.0172	0.0292	0.0242	0.0006	-0.06042	0.09673	-0.0554	0.0983	-0.5637	0.5934
1992-3	-0.0065	0.0180	-0.0100	-0.0035	0.0000	0.24561	0.08358	0.2391	0.0855	2.7964	0.0313
1992-4	0.0096	0.0178	0.0082	-0.0014	0.0000	-0.08590	0.10330	-0.0763	0.1048	-0.7281	0.4940
1993-1	0.0031	0.0176	-0.0294	-0.0325	0.0011	-0.04172	0.07167	-0.0386	0.0738	-0.5231	0.6196
1993-2	0.0243	0.0181	0.0162	-0.0081	0.0001	0.01759	0.07189	0.0419	0.0741	0.5653	0.5924
1993-3	-0.0052	0.0179	-0.0114	-0.0062	0.0000	-0.04615	0.03500	-0.0514	0.0393	-1.3065	0.2392
1993-4	0.0060	0.0178	0.0120	0.0060	0.0000	-0.07674	0.05168	-0.0708	0.0546	-1.2950	0.2429
1994-1	-0.0131	0.0176	0.0009	0.0140	0.0002	0.04884	0.04321	0.0358	0.0467	0.7669	0.4722
1994-2	0.0003	0.0175	0.0139	0.0142	0.0002	-0.01974	0.07403	-0.0195	0.0761	-0.2557	0.8067
1994-3	-0.0051	0.0175	-0.0092	-0.0041	0.0000	-0.00721	0.06354	-0.0123	0.0659	-0.1867	0.8581
1994-4	0.0073	0.0173	0.0162	0.0088	0.0001	-0.02294	0.04347	-0.0156	0.0468	-0.3333	0.7503
1995-1	0.0005	0.0172	-0.0047	-0.0042	0.0000	0.01196	0.07047	0.0124	0.0725	0.1713	0.8696
1995-2	0.0081	0.0171	0.0106	0.0025	0.0000	0.00972	0.08501	0.0178	0.0867	0.2054	0.8441
1995-3	-0.0030	0.0169	0.0023	0.0053	0.0000	0.00704	0.06866	0.0040	0.0707	0.0570	0.9564
1995-4	0.0040	0.0168	0.0279	0.0239	0.0006	-0.15446	0.06752	-0.1505	0.0696	-2.1626	0.0738
1996-1	-0.0094	0.0169	0.0104	0.0198	0.0004	0.06849	0.14900	0.0591	0.1500	0.3940	0.7072
1996-2	0.0000	0.0170	0.0439	0.0439	0.0019	-0.01368	0.04856	-0.0137	0.0514	-0.2659	0.7992
1996-3	-0.0102	0.0177	-0.0110	-0.0008	0.0000	0.05454	0.02250	0.0444	0.0286	1.5486	0.1724
1996-4	0.0145	0.0176	0.0173	0.0028	0.0000	-0.05867	0.02979	-0.0442	0.0346	-1.2779	0.2485
1997-1	0.0033	0.0175	0.0117	0.0084	0.0001	0.04246	0.04619	0.0457	0.0494	0.9260	0.3902
1997-2	0.0131	0.0174	0.0074	-0.0056	0.0000	0.00753	0.04333	0.0206	0.0467	0.4409	0.6747
1997-3	0.0014	0.0172	-0.0155	-0.0169	0.0003	-0.04729	0.02558	-0.0459	0.0308	-1.4871	0.1876
1997-4	0.0102	0.0172	0.0209	0.0107	0.0001	-0.04352	0.04047	-0.0333	0.0440	-0.7581	0.4771
1998-1	0.0008	0.0171	0.0123	0.0131	0.0002	-0.07531	0.04964	-0.0745	0.0525	-1.4192	0.2056
1998-2	-0.0015	0.0171	0.0216	0.0231	0.0005	0.13161	0.06704	0.1302	0.0692	1.8813	0.1090
1998-3	-0.0074	0.0172	-0.0082	-0.0008	0.0000	-0.09009	0.06206	-0.0975	0.0644	-1.5141	0.1808
1998-4	0.0104	0.0171	0.0193	0.0089	0.0001	-0.10298	0.11020	-0.0926	0.1115	-0.8305	0.4381
1999-1	0.0018	0.0170	-0.0018	-0.0036	0.0000	0.03714	0.02378	0.0389	0.0292	1.3320	0.2312
1999-2	0.0118	0.0169	0.0093	-0.0025	0.0000	-0.01516	0.05657	-0.0034	0.0590	-0.0568	0.9565
1999-3	0.0014	0.0168	-0.0178	-0.0192	0.0004	-0.01687	0.11280	-0.0155	0.1140	-0.1358	0.8964
1999-4	0.0132	0.0168	0.0192	0.0061	0.0000	0.04186	0.12960	0.0550	0.1307	0.4211	0.6884

Table VIII

Calculation of the LNFM RINT risk premia. The residual sum of squares for the RINT forecasts is 0.0041.

	Forecast	Forecast st.dev.	Actual RINT value	Residual	Residual squared	Gross risk premium	Gross risk premium st.dev.	Risk premium	Risk premium st.dev.	t-value	t-prob
1992-1	0.0058	0.0092	0.0268	0.0210	0.0004	0.0156	0.0499	0.0214	0.0507	0.4216	0.6880
1992-2	0.0148	0.0083	0.0272	0.0124	0.0002	-0.0529	0.0526	-0.0382	0.0533	-0.7167	0.5005
1992-3	0.0201	0.0093	0.0222	0.0021	0.0000	0.1202	0.0455	0.1403	0.0464	3.0223	0.0233
1992-4	0.0148	0.0092	0.0285	0.0137	0.0002	-0.0656	0.0562	-0.0508	0.0569	-0.8924	0.4066
1993-1	0.0275	0.0093	-0.0092	-0.0367	0.0013	-0.0148	0.0426	0.0128	0.0436	0.2927	0.7796
1993-2	0.0220	0.0106	0.0231	0.0011	0.0000	-0.0301	0.0427	-0.0081	0.0440	-0.1836	0.8604
1993-3	0.0135	0.0105	0.0098	-0.0037	0.0000	-0.0142	0.0208	-0.0007	0.0233	-0.0299	0.9771
1993-4	0.0242	0.0104	0.0183	-0.0059	0.0000	-0.0495	0.0307	-0.0253	0.0324	-0.7796	0.4653
1994-1	-0.0224	0.0103	0.0068	0.0292	0.0009	0.0432	0.0256	0.0208	0.0276	0.7532	0.4798
1994-2	0.0140	0.0110	0.0106	-0.0034	0.0000	-0.0570	0.0439	-0.0430	0.0452	-0.9510	0.3783
1994-3	0.0094	0.0109	0.0091	-0.0003	0.0000	0.0234	0.0377	0.0328	0.0392	0.8370	0.4347
1994-4	0.0116	0.0108	0.0207	0.0091	0.0001	-0.0463	0.0258	-0.0347	0.0279	-1.2420	0.2606
1995-1	0.0150	0.0108	0.0083	-0.0067	0.0000	-0.0053	0.0340	0.0097	0.0356	0.2714	0.7951
1995-2	0.0102	0.0107	0.0144	0.0042	0.0000	-0.0067	0.0410	0.0035	0.0423	0.0833	0.9363
1995-3	0.0114	0.0106	0.0177	0.0063	0.0000	0.0076	0.0331	0.0190	0.0348	0.5469	0.6042
1995-4	0.0151	0.0106	0.0220	0.0069	0.0000	-0.1095	0.0325	-0.0943	0.0342	-2.7574	0.0330
1996-1	0.0093	0.0105	0.0146	0.0053	0.0000	0.0144	0.0751	0.0237	0.0758	0.3130	0.7649
1996-2	0.0135	0.0105	0.0177	0.0041	0.0000	0.0509	0.5763	0.0644	0.5764	0.1117	0.9147
1996-3	0.0145	0.0104	0.0138	-0.0007	0.0000	-0.6652	0.2670	-0.6508	0.2672	-2.4355	0.0508
1996-4	0.0147	0.0103	0.0150	0.0003	0.0000	0.5189	0.3535	0.5336	0.3537	1.5088	0.1821
1997-1	0.0141	0.0102	0.0085	-0.0056	0.0000	-0.5967	0.7033	-0.5826	0.7034	-0.8283	0.4392
1997-2	0.0136	0.0102	0.0014	-0.0122	0.0001	-0.5979	0.6598	-0.5843	0.6599	-0.8854	0.4100
1997-3	0.0116	0.0102	0.0008	-0.0108	0.0001	0.1631	0.3895	0.1747	0.3896	0.4484	0.6696
1997-4	0.0118	0.0102	0.0134	0.0016	0.0000	0.9934	0.6163	1.0052	0.6164	1.6307	0.1541
1998-1	0.0096	0.0101	0.0191	0.0096	0.0001	0.0182	0.7046	0.0278	0.7047	0.0394	0.9698
1998-2	0.0073	0.0101	0.0084	0.0012	0.0000	-1.0322	0.9516	-1.0249	0.9517	-1.0770	0.3229
1998-3	0.0077	0.0101	0.0134	0.0057	0.0000	1.0104	0.8809	1.0181	0.8810	1.1557	0.2917
1998-4	0.0124	0.0037	0.0117	-0.0006	0.0000	2.1245	1.5640	2.1369	1.5640	1.3663	0.2208
1999-1	0.0152	0.0036	0.0036	-0.0116	0.0001	-0.4558	0.3417	-0.4406	0.3417	-1.2893	0.2448
1999-2	0.0120	0.0100	0.0018	-0.0102	0.0001	-0.4960	0.8129	-0.4841	0.8130	-0.5955	0.5733
1999-3	0.0134	0.0100	0.0048	-0.0086	0.0001	1.6135	1.6220	1.6269	1.6220	1.0030	0.3546
1999-4	0.0113	0.0100	0.0075	-0.0038	0.0000	-0.5182	1.8620	-0.5069	1.8620	-0.2722	0.7946

V Descriptive Statistics for Explanatory Variables

Table IX

Descriptive statistics for the explanatory variables

Sample period	Variables	Means	Standard deviations
1981Q4 - 1999Q4	AFGX	0.0342	0.1319
	REG	0.0039	0.0197
	HCONS	0.0095	0.0708
	OP	0.0197	0.2330
	GDP	-0.0027	0.1462
	RINT	0.0117	0.0105
	TSC	0.0001	0.0033
	CEI	-0.0002	0.0015
	UI	-0.0003	0.0106
	CEIA	-0.0005	0.0329
	UIA	-0.0002	0.0250
	POP	0.0000	0.0002
1992Q1 - 1995Q4	AFGX	0.0265	0.1364
	REG	0.0045	0.0154
	HCONS	0.0022	0.0619
	OP	0.0365	0.1874
	GDP	-0.0015	0.1314
	RINT	0.0160	0.0098
	TSC	0.0001	0.0037
	CEI	-0.0007	0.0016
	UI	-0.0003	0.0094
	CEIA	0.0002	0.0298
	UIA	0.0006	0.0219
	POP	-0.0001	0.0004
1996Q1 - 1999Q4	AFGX	0.0694	0.1238
	REG	0.0087	0.0162
	HCONS	0.0120	0.0600
	OP	0.0322	0.2098
	GDP	-0.0010	0.1450
	RINT	0.0097	0.0060
	TSC	0.0004	0.0016
	CEI	-0.0002	0.0008
	UI	-0.0036	0.0051
	CEIA	-0.0016	0.0125
	UIA	-0.0017	0.0131
	POP	0.0000	0.0001