Three essays on real estate finance

Liu, X.

This thesis outlines several issues related to real estate research. The first chapter relaxes the functional form restriction in the empirical application of the hedonic pricing model, and studies its implication on the house price index construction. The second chapter takes into account both the spatial and temporal correlation among housing transactions, and shows the benefit of doing so contributing to better prediction of future house prices. The third chapter tackles the composition of proxy for market portfolio and its impact on the estimation of REITs risk premium. We show that REITs risk premium estimation is sensitive to both the structural break in the REITs market and the market proxy composition. The inclusion of real estate asset class into the market proxy accounts for a significant portion of the bias in the REITs risk premium estimation arising from using the restrictive market proxy, such as the CRSP equity index.

Xiaolong Liu (1977) obtained his Bachelor degree (with distinction) in Economics and Business from the University of Amsterdam in 2005. He then participated in the M.Phil. program at the Tinbergen Institute, and graduated with M.Phil. in Economics in 2007. Thereafter, he joined the Real Estate Finance Department at the University of Amsterdam for his Ph.D. research. As of September 2010, he will be working as an assistant professor at the School of Finance, Renmin University of China.

Thela Thesis
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481

Three Essays on Real Estate Finance Xiaolong Liu

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Three Essays on Real Estate Finance

Xiaolong Liu

Research Series
Universiteit van Amsterdam

Three Essays on Real Estate Finance

ISBN 978 90 3610 199 8
Cover design: Crasborn Graphic Designers bno, Valkenburg a.d. Geul

This book is no. **481** of the Tinbergen Institute Research Series, established through cooperation between Thela Thesis and the Tinbergen Institute. A list of books which already appeared in the series can be found in the back.

Three Essays on Real Estate Finance

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad van doctor
aan de Universiteit van Amsterdam
op gezag van de Rector Magnificus
prof. dr. D.C. van den Boom
ten overstaan van een door het college voor promoties ingestelde commissie,
in het openbaar te verdedigen in de *Agnietenkapel*
op dinsdag 14 september 2010, te 14:00 uur

door

Xiaolong Liu

geboren te Heilongjiang, China

Promotiecommissie:

Promotor:	Prof. dr. K. G. P. Englund
Overige Leden:	Prof. dr. D. Brounen
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Faculteit Economie en Bedrijfskunde

Acknowledgements

It occurred to me that one decision completely changed the trajectory of my life. Seven years ago, I decided to give up my former job in the tourism industry in China that I had been enjoying so much for the past five years, and chose to study abroad a brand new subject in which I had been interested all along. Seven years later, here I am with a PhD thesis completed in Real Estate Finance, and ready to go back to China to pursue an academic career. Of course, I have been a motivated and hard-working student for, at least, the past seven years, but that would serve as, at best, a necessary condition for what I have achieved so far. It is the opportunity being the sufficient condition, which cannot be taken for granted. At this final stage of my PhD, I would like to take a moment to express my appreciation and extend my gratitude to those who have offered me all kinds of opportunities along the way.

First and foremost, I would like to thank my supervisor Peter Englund for offering me a patient and liberal PhD supervision. I have enjoyed very much during my PhD to do research on topics in which I am most interested, and you have been a dedicated and patient supervisor to give your enlightening insights on those seemingly random topics, and offer advice on further improvements. What I have benefited the most from you is the critical thinking as well as the independent research capability, which will be crucial for a successful and rewarding academic career that I am looking forward to having in the future. As my supervisor, you should also earn the credit as the source of motivation for me to work hard(er) since it has proven that my productivity and work efficiency are significantly positively correlated with your pre-announced schedule and presence in Amsterdam (hope you are not surprised by the strategic timing of revealing this ☺).

I would also like to thank Marc Francke for offering me the opportunity for discussion and valuable comments on my research projects. With a sharp econometric sense, you are able to pick up the most vulnerable part of my paper to make me appreciate, and, at the same time, feel very painful to address later. As a professor next-door, I appreciate you being accessible to my questions by (I am not using the word “through” here ☺) simply knocking on your door every time. Marc, I am truly grateful to your patient explanation as well as critical and constructive comments, which have significantly improved the quality of my papers.

Now, it is the time to thank my "gratis land" buddies, Erik with great imagination and Frans being a hardcore "generalizer", for great companionship and fun. I still recall when I first moved into our office when starting my PhD, the first thing I learnt from you guys was that "this is a free country" until all of us took it literally with respect to the coffee machine. Coffee is indeed free, but I take tea instead every time. Hope the free tea and coffee will not vanish due to the bailout of Greece and the depreciation of the euro. I also enjoy the nice atmosphere offered in the real estate finance department by great colleagues of mine. Marcel, Erasmo, Gerjan, Yolanda and Jolinda, you have been very accommodating and helpful on all occasions. Dion, Betty and Marcel, I cannot imagine what my PhD life would have been like without regularly harassing your office upstairs.

Doing a PhD can bring so much fun if you are lucky to have great friends around you. Chengyang, Joy Sie, Hongliang, Jiajia, Yanjing, Jing, Fangbin, Ning, Yang, Zhengyuan, I am fortunate to have the company of you guys who have made my life in Amsterdam an unforgettable experience. Besides, I would certainly miss the fun and torture on the badminton court with my buddies of this "mind refreshing sport", Tiexi, Qiquan, Hai, Jinhua, Kaikai, Xiaoxiao. Rong, I am deeply thankful for you believing in me and being there for me during a very difficult period of my life prior to the start of my PhD.

My final thanks go to my parents and my brother for their love, support, and being tolerant to leave me enough freedom to pursue my own dreams. This thesis is dedicated to them.

我要感谢我的父母和弟弟给予我的爱与支持，以及宽容的给予我足够的自由去追寻我自己的梦想。谨将此博士论文献给他们。

May 10, 2010 in Amsterdam 2010年5月10日于荷兰阿姆斯特丹

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Chapter 1

Introduction

Real estate, being either residential real estate or commercial real estate, is an important component of the overall investment portfolio for each individual household. It also appears on the balance sheet of many corporations, institutional investors and alike. The high market value weight of the real estate asset class in the overall market portfolio makes the national wealth significantly exposed to the real estate market besides stock market and bond market. As a consequence, any fluctuation in the real estate market will have major repercussions on the overall economy, which has also been evidenced by the recent financial turmoil stemming from the real estate market.

This thesis consists of three chapters in the field of real estate finance. The first chapter tackles the functional form assumption within the popular hedonic regression framework and its consequence on the house price index construction. The second chapter addresses the correlation among housing transactions along both the spatial and temporal dimension and its consequences for the prediction of house prices. The third chapter considers the impact of including real estate assets in the market portfolio and how this affects the market risk premium of real estate investment trusts (REITs). Overall, this thesis contributes to the existing literature on understanding the importance of these issues and establishing the validity of taking them into consideration in empirical real estate research.

Chapter 2 (“Semi-parametric Estimation of House Price Indices”) builds upon the popular hedonic house price index construction approach of Kain and Quigley (1970) where log(transaction price) is taken to be linearly related to various housing attributes and coefficients are interpreted as the implicit attribute prices accordingly. Despite its popularity, such log-linear functional form poses a problem. As Rosen (1974) pointed out, there is no theoretical justification for such a relation to be assumed in empirical applications. Moreover, as shown in Mason and Quigley (1996), it is futile to deduce the precise hedonic specification from the economic theory, and the appropriate functional form in a hedonic regression depends on the data used in practice. To tackle the functional form issue related to the empirical application of hedonic model, Halvorsen and Pollakowski (1981) estimated the functional form of hedonic regression using Box-Cox transformation (Box and Cox, 1964). Nonparametric models have also been adopted to allow more flexibility in the traditional log-linear hedonic regression. See, for example, Pace (1993), Bao and Wan (2004), Martins-Filho and Bin (2005), and Henderson et al. (2007), to name just a few.

In this chapter, we apply the semi-parametric approach to address the hedonic functional form issue and examine its implication on the house price index construction. We apply cubic splines in approximating the unknown functional form, and address the index revision problem by estimating the semi-parametric model on an annual basis. In addition, our index construction is based on the identification of the representative house for each year whose value is predicted according to the semi-parametric model. A Laspeyres chained index is then constructed based on the changes of values of the representative house. We show that the semi-parametric model produces a better fit than the log-linear hedonic model. Moreover, we find consistent divergence between the indices produced by both models. Overall, our results are in line with the previous literature, and we conclude that hedonic equation with less stringent functional form is to be preferred in the empirical house price index construction.

Chapter 3 ("Spatial and Temporal Dependence in House Price Prediction") considers the correlation among housing transactions along both the temporal and spatial dimension and its consequence in house price prediction. Empirical applications of the popular hedonic model often overlook the correlations among housing transactions which leads to inefficient as well as erroneous inference of the parameter estimates. Recognizing this fact, various authors have put emphasis on the model comparison between the default hedonic pricing model and models that account for spatially correlated errors, for example Can (1990, 1992), Basu and Thibodeau (1998), Dubin et al. (1999), and Case et al. (2004). These studies either use a small sample of housing transactions or do not explore the temporal structure in the housing market in making out-of-sample predictions since only early transactions carry pricing information relevant to pricing later transactions and not vice versa.

This chapter builds upon papers by Pace et al. (1998), Pace et al. (2000) and Bourassa et al. (2007). We employ the Spatial and Temporal Autoregressive Model as developed in Pace et al. (1998) and Pace et al. (2000), which assumes the OLS hedonic errors to follow an autoregressive process and models the spatial and temporal dependence in the hedonic errors through spatial and temporal weighting matrices. In making out-of-sample predictions, Bourassa et al. (2007) did not recognize the temporal structure in housing transactions. Moreover, they only used the estimated structural parameters from both the OLS model and the spatial model, and did not exploit the information contained in the spatial weighting matrix. We improve upon Bourassa et al. (2007) in that, for each house in the out-of-sample, we first look for its spatial and temporal neighbors, then combine this information with structural parameter estimates to make out-of-sample predictions. In our empirical analysis we control for time variation of structural parameters through performing the analysis on an annual basis. Further, we control for spatial neighborhood effects or spatial heterogeneity using experience-based submarkets defined by real estate professionals as advocated by Bourassa et al. (2003). We show that, overall, integrating both the spatial and temporal dependence among housing transactions in empirical analysis contributes to a better prediction outcome of future house prices.

Chapter 4 ("The Composition of Market Proxy in REITs Risk Premium Estimation") includes real estate assets into the market portfolio and investigates its impact on the estimation of the risk premium of REITs. Of course, this is a relevant issue to a much broader range of assets, but we limit our analysis to REIT in this chapter due to its increasing popularity among investors looking for either diversification or exposure to the real estate market. By definition, the riskiness of an asset is measured by the risk premium that compensates its undiversifiable market risk exposure. In practice, both academics and practitioners seem complacent to use equity indices for approximating the market portfolio in the estimation of the asset market risk premium, such as S&P 500, and CRSP indices. Using equity indices as market proxies, however, leaves part of the market risk to remain diversifiable as the investment set also includes other assets besides equity. It follows naturally to ask if using a more diversified market portfolio would matter for the estimation of the market risk premium.

In this chapter, we construct a market portfolio in the spirit of Roll (1977) that consists of equity, fixed income securities, and real estate. We test if the REITs risk premium estimated using an equity index as market proxy is robust to alternative broader specifications of the market portfolio. In doing so, we do not attempt to find the true market portfolio that is exhaustive in terms of inclusion of assets, but rather identify a more diversified market portfolio relative to the popular market proxy using equity indices. Our results show that REIT betas are significantly increased as a broader market proxy is used. The market risk premium estimation of REITs is sensitive to both the structural break in the REIT market and market portfolio composition, Moreover, adding real estate in the market portfolio accounts for a significant portion of the bias in the estimated REITs market risk premium. Our results stand after using a survivor-bias free sample of REITs.

Chapter 2

Semi-parametric Estimation of House Price Indices

2.1 Introduction

Housing accounts for the largest proportion of the physical wealth of the average household, but comparing with other assets, it is the least known. This can be attributed to their heterogeneous nature, and infrequent trading. Unlike stocks, bonds, and other assets, houses are not homogeneous in many dimensions and are only traded a few times during their lifetime, normally with significant transaction costs. Practically, it is known that both heterogeneity and illiquidity make the measurement of housing price index a difficult task. Due to the illiquidity nature of housing, few observations of housing transactions within a short time horizon make it hard to estimate a house price index using standard hedonic regression techniques. Moreover, our observations of housing transactions involve houses that differ in quality, for instance, location and design. Therefore, we need to account for the quality difference if we want to filter out the real appreciation of housing in the construction of price index.

With these practical considerations in mind, there are also significant benefits attached to an accurate measure of a housing price index. First, since housing represents a large portion of the investment portfolio of the average household, the price volatility of housing will inevitably exert major implications on the well-being of the household. This calls for either a derivative market for housing or social redistribution to those who are negatively affected by the change of housing price. Through trading these derivatives, the household can shield themselves against housing price volatility. To make the redistribution work, the effect of a shock to prices of housing needs to be measurable. Therefore, both the derivative market for housing and redistribution policies hinges upon an accurate measure of housing price index.

In addition, such housing price index can be used in the case of portfolio choice (Shiller, 1993). When investors are presented with different investment portfolios, some of which contain housing or housing related assets, an accurate housing price index will give the investor a general view on the risk and return profile of these investment opportunities. Investors can thus make their portfolio choice on the basis of this risk return tradeoff and their degree of risk aversion. Housing price index can also be of particular interest to financial institutions which engage in providing mortgage loans to households. As the price of housing fluctuates, the loan-to-value ratio is also changing over time. If the house price drops significantly, meaning a high loan-to-value ratio, households are more likely to default on their mortgage loans, which will inevitably affect the solvency of the financial institutions that provide these mortgage loans. Therefore, an accurate measure of the development of the house price will help these financial institutions to better assess and manage the risks they are facing.

Recognizing the practical challenges in the estimation of housing price index, various estimation methods have been proposed. Among them, the most popular approaches are repeated sales regression (Bailey et al., 1963) and hedonic regression (Kain and Quigley, 1970). Repeated sales regression employs a sub sample of houses that have been sold for at least twice to control for quality change over time. The estimated price difference for the same house is interpreted as the pure appreciation of housing between different points in time, which is used in the construction of the price index. Comparing with the repeated sales regression, hedonic approach uses hedonic regressions to estimate the implicit prices of housing attributes, which can be used in the index construction. Despite their popular application in practice, some of the fundamental flaws associated with these techniques are not negligible (Palmquist, 1979; Wallace, 1996; Meese and Wallace, 1997). Repeated sales regression cannot capture the depreciation of housing over time (Bailey et al., 1963; Palmquist, 1980). Since it only uses a sub-sample of houses that are sold for multiple times, the estimation is not efficient (Case and Quigley, 1991; Hill et al., 1997), and the repeated sales data may be subject to sample selection bias (Clapp and Giaccotto, 1992). Moreover, using repeated sales regressions, unbalanced frequencies of observations can lead to very different weights for the mean returns for each time period (Meese and Wallace, 1997). As Case and Shiller (1987) pointed out, the constant variance assumption in repeated sales regression is not likely to be valid. For hedonic regressions, it normally requires comprehensive attribute variables, which are difficult to obtain in practice. In addition, the usual functional specification poses a problem, since there is no theoretical justification for the log linear functional form (Rosen, 1974). A common assumption in both models is the invariability of implicit prices of attributes. For both methods, the estimated index stability will have practical implications, which can be tackled by constructing a chained index (Clapham et al., 2006).

Variations of these two popular approaches have been proposed to address one or the other of these problems. Case and Shiller (1987) proposed weighted repeated sales method to address the heteroskedasticity problem. Quigley (1995) and Englund et al. (1998) applied the hybrid model to estimate the housing price index for Los Angeles and eight geographical regions in Sweden respectively. Palmquist (1980) used hedonic regression to identify the depreciation of housing, which made it possible to derive depreciation corrected price relatives using repeated sales regression. Due to the increasing popularity of hedonic regression, its functional form assumption has drawn a lot of attention. As shown in Mason and Quigley (1996), it is futile to deduce the precise hedonic specification from economic theory, and that the form of the hedonic model is ultimately an empirical issue, which casted doubts on the conventional log-linear form of the hedonic regression. Halvorsen and Pollakowski (1981) dropped the stringent log linearity restriction and estimated the appropriate functional form of hedonic regression using Box-Cox transformation (Box and Cox, 1964). A number of studies advocate non-parametric modeling of the hedonic equation to make the estimation robust to model misspecification. Hodgson et al. (2006) used kernel method to estimate the error distribution non-parametrically, which fed into the maximum likelihood estimation of the parameters of interest. Their semi-parametric approach addressed possible non-normality of the error terms in the ordinary least squares (OLS) regression, which contributed to precision of index estimation. Martins-Filho and Bin (2005) adopted local polynomial estimators to asses the appropriate functional form of continuous variables in the hedonic regression, and showed superiority of this method over the alternative parametric model in terms of out-of-sample prediction performance. Wallace (1996) applied LOESS estimator, which was a weighted local least squares regression, to approximating the hedonic regression equation non-parametrically. She found significant difference between the price indices estimated using repeated-sales regression that assumed constant quality over time and the non-parametric hedonic equation. Bao and Wan (2004) employed spline smoothing to estimate the non-parametric hedonic equation, and they confirmed that the true functional form was far from smooth and any prior imposed parametric model was likely to result in model misspecification. Henderson et al. (2007) estimated the hedonic equation using OLS, semi-parametric, and non-parametric models. Local linear least squares estimation was used in both the semi-parametric and non-parametric models. They concluded that non-parametric model was able to capture the non-linearity structure of the data, which could produce intuitive and meaningful results. Pace (1993) used the kernel estimation of the non-parametric model, and confirmed the robustness of non-parametric model over its parametric counterparts.

In this chapter, we will investigate the issue of the functional form assumption concerning the hedonic regression and its implication on housing price index estimation using a housing transaction dataset from Amsterdam region, The Netherlands. It differs from previous works on two grounds. First, we employ cubic spline smoothing to approximate the unknown functional form. Second, we address the index revision problem by estimating the hedonic equations year by year and construct a chain index, contrary to standard method of pooling all data and estimating the index through time dummies as is more common in the literature. In particular, we will apply both the parametric OLS and a more general semi-parametric model to the estimation of our hedonic equation. Model fits will be examined, and housing price index constructed using both models are also compared. In the construction of the housing price index, we first find the hypothetical "representative" housing for each year. The values of the "representative" housing are predicted by both models, through which changes of value of the "representative" housing are identified from year to year. A Laspeyres chained index is then constructed on the changes of values of the "representative" housing. The "representative" housing is found by combining the means of the attributes of all housing for a specific year, and we would expect it will change from year to year.

The rest of the chapter is organized as follows. Section 2.2 provides a simple and non-exhaustive overview of our semi-parametric estimation method. Section 2.3 discusses the housing transaction data used in this study. Section 2.4 presents the empirical results. Section 2.5 concludes.

2.2 Semi-parametric Model

2.2.1 Specification

The popular hedonic regression model is given by

$$y = \mu + \varepsilon \qquad \varepsilon_i \sim N(0, \sigma^2) \qquad i = 1, \ldots, n$$

where

$$\mu \equiv E(Y \mid X_1 = x_1, ..., X_D = x_D) = \iota\alpha + \sum_{d=1}^{D} x_d \beta_d \tag{2.1}$$

y, μ and ε are $n \times 1$ vectors and ι is $n \times 1$ vector of ones, and ε_i are i.i.d. error terms. The coefficients are normally interpreted as the implicit attribute prices of housing. The model we use in this chapter generalizes equation (2.1) by making some but not all explicit linear relations to be non-parametrically estimated from the data. Ideally, we would estimate the hedonic equation in the most flexible form

$$\mu \equiv E(Y \mid X_1 = x_1, ..., X_D = x_D) = \iota\alpha + f(x_1, ..., x_D)$$

where f is a smooth function. However, it is not feasible to perform such estimation in a pure non-parametric setting due to the presence of the "curse of dimensionality", meaning that neighborhoods with a fixed number of points become less local as the dimension increases (Bellman, 1961). Therefore, we make an assumption on the structure of $f(x_1, \ldots, x_D)$ that does not include interactions among the independent variables $x_1, \cdots, x_D$, and $f(x_1, \cdots, x_D) = \sum_{d=1}^{D} f_d(x_d)$. The semi-parametric model we use is thus of the form

$$\mu \equiv E(Y \mid X_1 = x_1, ..., X_D = x_D) = \iota\alpha + \sum_{d=1}^{d'} x_d \beta_d + \sum_{d=d'+1}^{D} f_d(x_d) \tag{2.2}$$

2.2.2 Estimation

To estimate this semi-parametric model, we apply the penalized log-likelihood criterion

$$J(\beta_1,\ldots,\beta_{d'}, f_{d'+1},\ldots, f_D) = l(\mu, y) - \frac{1}{2}\sum_{d=d'+1}^{D} \lambda_d \int [f_d''(x_d)]^2 dx \tag{2.3}$$

where $l(\mu, y)$ is the log-likelihood function, λ is the smoothing parameter that attaches the degree of penalty with respect to the roughness of the estimated function $f(x)$, $\int [f''(x)]^2 dx$ denotes the penalty on the roughness of the estimate of $f(x)$, and $f''(x)$ is the second order derivative with respect to x. It is clear that the smoothing parameter λ controls the trade-off between the model fit and smoothness. If $\lambda = 0$, we simply have the maximum likelihood estimation which will lead to data interpolation. On the contrary, if $\lambda \to \infty$, we put all weight on the penalty on wiggliness that leads to $f''(x) = 0$. Therefore, the unknown functions will be estimated to be least square lines. Given smoothing parameters λ_d, functions $f_d(x_d)$ that maximize the criterion (2.3) are cubic splines, because it is a curve made up of piecewise cubic polynomial linked together that is continuous in level as well as first and second order derivatives (Reinsch, 1967).[1] We choose cubic spline over other smoothers to approximate the unknown function primarily for its computational simplicity. Specifically, cubic smoothing spline is not constructed explicitly like kernel smoother, but emerges naturally as the solution to the optimization problem (2.3). As shown in Hastie and Tibshirani (1990), the penalized log-likelihood criterion can be rewritten in the form

$$J(\beta_1,\ldots,\beta_{d'}, f_{d'+1},\ldots, f_D) = l(\mu, y) - \frac{1}{2}\sum_{d=d'+1}^{D} \lambda_d f_d' K_d f_d \tag{2.4}$$

where K_d s are known penalty matrices for each x_d for $d = d'+1,\ldots,D$.

[1] For detailed coverage of the statistical properties of splines, we refer to Wahba (1990) and Gu (2002). Moreover, we take the even spaced knots to be 10 (except for the variable "number_of_room" in 1992, in which case we take the knots to be 5) to approximate the unknown smooth function $f_d(x_d)$. This is motivated by the fact that neither the choice of number of knots and their locations should not have an influence on the model fit, and the estimated shape of $\hat{f}(x)$ is determined by the choice of λ (Wood, 2006).

We apply the local-scoring procedure, maximizing equation (4) with respect to α , β_1 , ... , $\beta_{d'}$, $f_{d'+1}$, ... , f_D , and linearizing around local value of μ_0 in the score equations. Denote

$$U = \frac{\partial l}{\mu} \qquad\qquad H = -\frac{\partial^2 l}{\mu\mu'}$$

where μ is defined according to equation (2.2). we get[2]

$$\begin{pmatrix} \alpha^{i+1} \\ \beta^{i+1} \\ \vdots \\ \beta_{d'}^{i+1} \\ f_{d'+1}^{i+1} \\ \vdots \\ f_D^{i+1} \end{pmatrix} = \begin{pmatrix} S_\alpha[z - \sum_{d=1}^{d'} x_d \beta_d^i - \sum_{d=d'+1}^{D} f_d^i(x_d)] \\ S_{\beta_1}[z - \iota\alpha^i - \sum_{d=2}^{d'} x_d \beta_d^i - \sum_{d=d'+1}^{D} f_d^i(x_d)] \\ \vdots \\ S_{\beta_{d'}}[z - \iota\alpha^i - \sum_{d=1}^{d'-1} x_d \beta_d^i - \sum_{d=d'+1}^{D} f_d^i(x_d)] \\ S_{f_{d'+1}}[z - \iota\alpha^i - \sum_{d=1}^{d'-1} x_d \beta_d^i - \sum_{d=d'+2}^{D} f_d^i(x_d)] \\ \vdots \\ S_{f_D}[z - \iota\alpha^i - \sum_{d=1}^{d'-1} x_d \beta_d^i - \sum_{d=d'+2}^{D-1} f_d^i(x_d)] \end{pmatrix} \tag{2.5}$$

where

$$z = \mu^0 + H^{-1}U$$

$$S_\alpha = (\iota' H \iota)^{-1} \iota' H$$

$$S_{\beta_d} = (x_d' H x_d)^{-1} x_d' H \qquad d = 1, \ldots, d'$$

$$S_{f_d} = (H + \lambda_d K_d)^{-1} H \qquad d = d'+1, \ldots, D$$

We can see that the local scoring procedure is similar a Newton-Raphson algorithm, which provides updates that fit the additive model.

Up-to-now, the smoothing parameters λ_d are taken as given. If λ is set too high, the data will be over smoothed. On the contrary, a too low λ will lead to under smoothing. In both cases, the estimated functions $\hat{f}$ will deviate from the true functions f . This calls for a

[2] See derivation in the Appendix.

criterion for λ to be chosen optimally such that the deviance between $\hat{f}$ and f can be minimized. In the context of model (2.2), this can be achieved as follows. First, define deviance

$$D(y,\hat{\mu}) = 2[l(\mu_{max}, y) - l(\hat{\mu}, y)] \tag{2.6}$$

where $l(\mu_{max}, y)$ denotes the maximized likelihood of the saturated model, and is evaluated by setting $\hat{\mu} = y$. The leave-one-out cross-validated deviance is given by

$$CV = \frac{1}{n}\sum_{i=1}^{n} D(y_i, \hat{\mu}_i^{-i}) \tag{2.7}$$

where $\hat{\mu}_i^{-i}$ is the fitted value at the ith point by leaving the ith point out of the sample (Hastie and Tibshirani, 1990, p.159). In essence, equation (2.7) is the expected deviance evaluated at y and its predicted value based on the model. By minimizing CV with respect to λ_d s, smoothing parameters can be optimally chosen that provide the best out-of-sample forecast.

The theory of inference on additive models is well presented in Hastie and Tibshirani (1990). Wahba (1983) developed the prediction interval for the smoothing spline estimator f from the Bayesian approach, since it can be shown that the smoothing spline estimator is the posterior mean of the Bayesian regression function composed of spline basis functions. A $100(1-\alpha)\%$ prediction interval for the value of the mean function f_d at $x_{d,i}$ is

$$f_d(x_{d,i}) \pm Z_{\frac{\alpha}{2}}\sqrt{Var[f_d(x_{d,i}) \mid y]} \tag{2.8}$$

where $Z_{\alpha/2}$ is the $100(1-\alpha)$th percentage point of the standard normal distribution.

2.3 Data Description

Before we describe the dataset that is used in this study, it is worthwhile to get a glimpse on the transaction process in the Dutch housing market. In The Netherlands, when a seller wants to sell his dwelling, he will most likely approach a real estate broker for two reasons. First, he asks the broker to market the dwelling that he sells. Second, he can get recommendations on the price of the selling property from the broker. The broker then markets the dwelling on the media, which is normally the local newspaper or *www.funda.nl*. If a buyer is interested in the dwelling, he can contact the broker for a visit of the property. Once the visit is completed, the buyer can give his own bid that kicks off the negotiation process. Sometimes, such bid can be above the list price depending on the market condition. As long as an agreement is reached, the transaction of the dwelling goes through.

In our study, we apply both OLS and the semi-parametric model (2.2) to a dataset of housing transactions within the vicinity of Amsterdam. The dataset is composed by The Dutch Association of Real Estate Brokers and Real Estate Experts (NVM), which possesses several unique attributes. First, it traces the housing transaction in Amsterdam region to as early as 1970. Although the data in these early years may be too few to produce reliable statistical results, it nevertheless gives us the possibility to estimate the housing price index for almost 40 years. Second, the dataset covers a substantial part of the total housing market transactions in the Amsterdam region.[3] This is desirable since a large sample size is beneficial to the accuracy of our estimation. Third, the dataset has an extensive coverage on the characteristics of transacted houses. A large number of housing attributes is a necessary prerequisite for a hedonic regression to be estimated meaningfully in order to mitigate the omitted variable problem. However, in practice, it is hard, if not impossible, to obtain housing transaction data with such comprehensive coverage on these attributes. Table 2.1 gives an overview of the characteristics of the transacted houses in the dataset that are incorporated into this study.

The vicinity of Amsterdam in this study is defined to include Amsterdam, Amstelveen, Diemen, and Ouder-Amstel, although all have their own local authorities. Since there has been a high moving frequency within these four regions of the vicinity of Amsterdam, it is sensible to include all of them in our estimation of the housing price index for Amsterdam region. We have access to a total number of 91,941 housing transactions for the Amsterdam region, spanning a time period from 1970 to 2007. Due to limited number of observations, we delete the data for the early year from 1970 to 1989. We also exclude data

[3] The market share of NVM in the Greater Amsterdam region is shown in Appendix D.

for the year 2007, since the dataset for 2007 is still under construction. Since the variable "square meters" and "volume" are correlated, we construct another variable "height" through dividing "volume" by "square meters", which is also easier for interpretation than "volume". We remove the entries of "height" below 2 meters and above 4.5 meters (think about the average height of the Dutch people!). Moreover, we identify some entries for variables that have either missing or irregular values, which are also excluded from our estimation. After cleaning the dataset, we have a sample consisting of 77,373 observations spanning a period from 1990 to 2006. Among these transactions, roughly 76.5% are apartments. Since most of young and middle-aged people choose to reside in Amsterdam region for stimulating atmosphere and job opportunities, apartments are more popular than houses which typically locate on the outskirts of the city. Table 2.1 shows descriptive statistics of the housing attributes in our transaction dataset.

Table 2.2 provides a description of the distribution of the number of transacted dwellings that are incorporated into our estimation. We can see a clear trend in terms of the number of transactions on a yearly basis. The number of transactions in 2006 is almost 7 times that in 1990. Few possible insights may help to explain such a dramatic increase in terms of the housing transaction volume in Amsterdam region over time. First, it may be due to a booming housing market for the Amsterdam region from the demand side. Second, an increase in transaction volume is the result of an increase of the owner-occupied dwelling of the total housing stock in Amsterdam over time. Third, it may also be the case that the market share of NVM has been increasing over time.

Table 2.1 Descriptive Statistics

Panel A - Continuous variables		
Variable	Mean	Std. Deviation
size	96.85	43.87
number of rooms	3.43	1.49
number of bathrooms	0.93	0.42
height	2.80	0.22

Table 2.1 continued

Panel B - Frequency of binary variables		
Variable	Mean	Observations
storage attic	0.028	2166
balcony	0.490	37933
new	0.023	1806
lift	0.233	18061
parking	0.132	10226
good inside maintenance	0.895	69243
good outside maintenance	0.955	73869
Transaction quarter		
Q1	0.232	17937
Q2	0.252	19476
Q3	0.257	19851
Q4	0.260	20109
Type of dwelling		
row house	0.154	11935
schakelwoning	0.003	263
corner house	0.048	3721
semi-detached house	0.016	1208
detached house	0.013	1017
apartment (ground level)	0.092	7118
apartment (non-ground level)	0.353	27287
apartment (maisonnette)	0.041	3154
apartment (front door in hall)	0.103	7951
apartment (galary)	0.166	12831
apartment (for the elderly)	0.003	232
apartment (ground level with multiple floors)	0.008	656
Building year		
1500-1905	0.143	11064
1096-1930	0.233	18053
1931-1944	0.079	6102
1945-1959	0.061	4745
1960-1970	0.161	12468
1971-1980	0.060	4632

Table 2.1 continued

Panel B - Frequency of binary variables		
Variable	Mean	Observations
Building year		
1981-1990	0.096	7434
1991 and after	0.166	12875
Location		
post codes 1000-1019	0.171	13235
post codes 1020-1025	0.026	2026
postcode1030-1049	0.026	2028
post codes 1050-1059	0.178	13802
postcodes 1060-1069	0.105	8153
postcodes 1070-1079	0.136	10510
postcodes 1080-1087	0.038	2968
postcodes 1090-1099	0.072	5570
postcodes 1100-1108 (1234)	0.054	4190
postcodes 1110-1114	0.029	2240

Table 2.2 Yearly Transactions

Year	Obs.	Year	Obs.
1990	1321	1999	4967
1991	1540	2000	5505
1992	1598	2001	5817
1993	1832	2002	6344
1994	1959	2003	6703
1995	2845	2004	7692
1996	3221	2005	9036
1997	3576	2006	9062
1998	4232		

To improve the statistical properties of our estimations, we transform some of the variables through aggregation over their domain. For example, there are 9 different descriptions of the state of the maintenance within the building ranging from “excellent” to “bad”. Since only few of the dwellings have excellent or bad interior, we transform the variable with only “good” or “bad” descriptions through aggregating from “excellent” to “reasonable” and from “below reasonable” to “bad”. After this transformation, there are still over 89.5% of the transacted dwellings with good interior. We transform altogether three variables following similar lines of reasoning, and they are “maintenance of inside the dwelling”, “maintenance of outside the dwelling” and “parking”.

2.4 Empirical Results

We run separate cross-sectional regression for the yearly data applying both OLS and the semi-parametric model (2.2). The dependent variable in both models is log(transaction price) , and we treat the building year between 1500 and 1905 as the base category for age dummies. We also suppress transaction quarter 1 as the base quarter, detached house as the base dwelling type, and postcode between 1000 and 1019 as the base location. We treat OLS as the null model which imposes the linear functional form restriction and the semi-parametric model as alternative model which is more general in that we do not impose prior functional form for some of the regressors. We follow Hastie and Tibshirani (1990) and perform test on linear model restriction on the basis of the statistic

$$D(\hat{\mu}_1, \hat{\mu}_2) = D(y, \hat{\mu}_1) - D(y, \hat{\mu}_2) \qquad (2.9)$$

which has a χ^2 distribution with degrees of freedom equal to the difference in the dimensions of the two models.

Both models are employed for value prediction of the “representative” dwelling and the estimation results are presented in Appendix B. Table 2.3 gives summary of the results of the parametric model. The coefficients are interpreted as the semi-elasticity of the effects of dwelling attributes on the transaction price except for the coefficients of both the log(size) and log(height) which measures the elasticity of size and height on transaction price respectively.

The signs of the coefficients for log(size) are both positive and significant as expected. The effects of a one-percentage increase in size will lead to an increase of transaction prices ranging from 0.78% to 0.89%. For 14 out of 17 years in our sample, housing transaction in quarter 1 were less favorable compared with other quarters. On the contrary, trading in quarter 4 was more profitable for the seller since the transaction price was generally higher than other quarters, which was the case for 13 out of 17 years in the sample. Therefore, our quarter dummies capture the expected upward intra-year index development trend. The effect of "new" dwelling is not significant and not applicable for some of the years when there were no new dwellings traded. Having "lift" and "storage attic" both would positively affect the transaction price of housing. However, the effect of having a "balcony" is mixed, though insignificant for most of the years, contrary to we expect that a balcony will exert positive impact on the transaction prices. The "number of rooms" has a positive effect on the transaction prices as expected. However, the effect can also be nonlinear, since people may attach different values to an increase of rooms from 2 to 3 and from 4 to 5. This possibility is investigated in the estimation of the semi-parametric model where we estimate the effect of "number of rooms" via a smooth function of unknown form other than the pre-specified linear form. The effect of "number of bathrooms" is positive for all the years. This is in line with our prediction, since more bathrooms will bring more convenience to the household. One extra bathroom will positively affect the transaction price. The constructed variable "height" has significant positive impact on the transaction prices.

The effect of dummy variable "dwelling type" shows that "detached house" is generally valued more than other type of dwellings. Intuitively, a detached house is more costly to build than other type of dwelling, and is normally equipped with private parking and a garden. However, there are also significantly higher operating and maintenance costs associated with owning a house than owning an apartment, which can negatively affect the valuation of a house. In our case, the benefits of owning a detached house clearly outweigh the corresponding costs, which makes detached house more valuable in Amsterdam region. On the contrary, "apartment for the elderly" is found to be the cheapest type of dwelling in Amsterdam region. This is not surprising since this type of dwelling, with large service costs, can only be purchased by people who are above 65, and its price is significantly lower than its comparable type due to government regulation.

The effects of the age dummies are among the most interesting findings of this study. Due to the depreciation of dwelling over time, we expect the impact of age on transaction price to be negative. However, our findings are mixed. Generally, dwellings built in 1960s are cheaper than dwellings built between 1945 and 1959. For some of the years, dwellings built before 1905 are actually more expensive than dwelling built between 1905 and 1990. This counter-intuitive discovery may be an indication of the fact that age may also proxy for other variables that are not included in the estimation which will positively affect the transaction price, for instance, building style and interior design. Postcodes, which proxies for location, have significant effects on the housing transaction price. We find that dwellings within the city center with postcodes ranging from 1000 to 1019 are the most expensive for Amsterdam region. However, dwellings in Amsterdam Zuidoost are significantly cheaper than other areas within the region. This might be due to the fact that immigrants concentrate in Amsterdam Zuidoost and the crime rate there is higher than other parts of Amsterdam region. "Parking" is significantly positive in relation to the transaction price, and both bad interior and outside maintenance are penalized with a lower price.

Table 2.4 presents the results of the alternative semi-parametric estimation. We make explicit linearity assumption for all the dummy variables plus "number of bathrooms", which is the parametric part of this semi-parametric model. The functional forms of three variables "log(size)", "number of rooms" and "log(height)" are estimated non-parametrically that fit the data best according to criterion (2.3).[4] In Table 2.4, the estimated coefficients of the parametric part of the model are reported. However, no explicit coefficients for the smooth functions are available and only the degrees of freedom used in the estimation of the unknown functions are reported, since the smooth functions have non-linear structure by construction.

[4] It is not possible to estimate the functional form of the variable "construction year" since it is recorded using dummy instead of continuous variables.

Table 2.3 OLS Results for Selected Years[5]

	1991		1996		2001		2006	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
log(size)	0.826**	0.025	0.777**	0.020	0.865**	0.014	0.857**	0.013
Q2	0.017	0.018	0.013	0.013	0.019	0.010	0.027**	0.009
Q3	0.028	0.017	0.058	0.013	0.023	0.010	0.048**	0.009
Q4	0.057**	0.018	0.073**	0.013	0.019	0.010	0.077**	0.010
new	0.000	0.000	0.000	0.000	0.054	0.022	0.001	0.019
lift	0.001	0.023	0.020	0.017	0.027	0.011	0.054**	0.011
number rooms	0.010	0.006	0.025**	0.006	0.005	0.004	0.005	0.003
attic	-0.029	0.028	0.005	0.025	0.039	0.023	-0.044	0.035
balcony	0.039**	0.013	-0.014	0.010	0.007	0.008	-0.008	0.007
bathroom	0.118**	0.015	0.098**	0.013	0.011	0.009	0.025**	0.008
log(height)	0.293**	0.095	0.098	0.071	0.405**	0.046	0.342**	0.047
post1020-1025	-0.659**	0.042	-0.438**	0.036	-0.489**	0.026	-0.379**	0.021
post1030-1049	-0.543**	0.051	-0.438**	0.033	-0.531**	0.024	-0.463**	0.021
post1050-1059	-0.326**	0.025	-0.233**	0.020	-0.191**	0.014	-0.133**	0.013
post1060-1069	-0.510**	0.034	-0.416**	0.022	-0.458**	0.015	-0.418**	0.015
post1070-1079	-0.012	0.027	-0.021	0.019	-0.002	0.014	0.062**	0.013
post1080-1087	-0.130**	0.035	-0.165**	0.028	-0.135**	0.022	-0.160**	0.022
post1090-1099	-0.304**	0.033	-0.246**	0.027	-0.219**	0.016	-0.183**	0.015
post1100-1108)	-0.803**	0.033	-0.628**	0.029	-0.611**	0.021	-0.560**	0.018
post1110-1114	-0.470**	0.036	-0.300**	0.028	-0.406**	0.021	-0.359**	0.028
post1180-1183	-0.220**	0.028	-0.228**	0.023	-0.252**	0.018	-0.178**	0.020
post1184-1188	-0.347**	0.029	-0.260**	0.022	-0.327**	0.018	-0.320**	0.020
post1190-1191	-0.258**	0.053	-0.183**	0.051	-0.275**	0.034	-0.190**	0.040
row house	-0.391**	0.044	-0.225**	0.043	-0.330**	0.032	-0.349**	0.034
schakelwoning	-0.183	0.167	-0.133	0.082	-0.208**	0.055	-0.720**	0.071
corner house	-0.347**	0.046	-0.185**	0.045	-0.281**	0.034	-0.322**	0.036
semi-detached	-0.165**	0.056	-0.074	0.052	-0.100	0.042	-0.164**	0.043
ground-level-app	-0.430**	0.054	-0.311**	0.048	-0.301**	0.034	-0.387**	0.035
non-ground-app	-0.507**	0.051	-0.384**	0.049	-0.348**	0.033	-0.430**	0.035
maisonnette	-0.452**	0.057	-0.319**	0.052	-0.365**	0.036	-0.457**	0.038

[5] For the sake of space, not all results are reported. Results for other years are available upon request.

Table 2.3 continued

	1991		1996		2001		2006	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Front-door-in-hall	-0.463**	0.049	-0.295**	0.046	-0.357**	0.035	-0.431**	0.037
galary-app	-0.491**	0.048	-0.348**	0.045	-0.394**	0.036	-0.474**	0.039
for-elderly-app	-0.743**	0.098	-1.052**	0.069	-1.263**	0.065	-1.230**	0.073
ground-more-app	-0.483**	0.067	-0.146	0.063	-0.374**	0.047	-0.366**	0.050
b1906-1930	-0.126**	0.024	-0.024	0.018	-0.041**	0.013	-0.069**	0.012
b1931-1944	-0.075**	0.029	-0.032	0.024	-0.097**	0.016	-0.127**	0.016
b1945-1959	-0.040	0.029	-0.093**	0.023	-0.126**	0.019	-0.170**	0.020
b1960-1970	-0.058	0.028	-0.144**	0.023	-0.179**	0.018	-0.250**	0.018
b1971-1980	0.008	0.029	-0.080**	0.028	-0.145**	0.021	-0.194**	0.022
b1981-1990	0.118**	0.027	0.046	0.023	-0.080**	0.018	-0.148**	0.016
b1991	0.265**	0.057	0.135**	0.021	-0.011	0.015	-0.070**	0.015
parking	0.063**	0.020	0.083**	0.016	0.063**	0.011	0.033	0.012
m-inside-good	0.126**	0.017	0.082**	0.014	0.074**	0.014	0.076**	0.013
m-outside-good	0.106**	0.022	0.114**	0.021	0.073**	0.020	0.011	0.024

** significant at 5% level

We confirm our finding in the OLS estimation of the intra-year appreciation of housing price in Amsterdam region. Both “lift” and “storage attic” will contribute to a higher transaction price. However, the effect of having a balcony is mixed as in the parametric case. The effect of one extra bathroom on the percentage change of transaction price is significantly positive. The effects of “housing type” are significant, and we find that “detached house” is the most expensive and “apartment for the elderly” is the cheapest among all housing types in Amsterdam region. The age dummies still have interesting estimated coefficients. Again, there is no clear cut effect of age on the transaction prices, and our interpretation in the previous parametric model still stands in this semi-parametric model. In terms of the effect of location on transaction price, we confirm our earlier finding that downtown Amsterdam is the most expensive area and Amsterdam Zuidoost is the cheapest area of the whole Amsterdam region.

All of the dummies "parking", good interior and exterior maintenance have the signs as expected. In addition to the parametric results, the approximate significance of the smooth terms is also presented in Table 2.4. The effective degrees of freedom associated with smooth function indicates the amount of smoothing that the smoother does. If the smoothing parameter is very high, we would have close-to-linear estimate of the smooth function which has few degrees of freedom. Therefore, the smoothness is inversely related with degrees of freedom. Figure 2.1 in Appendix B also gives a visualization of the estimated smooth functions for our yearly data with 95% confidence bounds. The estimated function "log(size)" has the expected upward sloping shape, although not strictly monotonic for 1 out of 17 years. Moreover, it is clearly not linear, which demonstrates that our prior linear functional form restriction is not valid.

Table 2.4 Semi-parametric Results for Selected Years[6]

	1991		1996		2001		2006	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Q2	0.013	0.017	0.013	0.013	0.017	0.009	0.028	0.009
Q3	0.027	0.017	0.059**	0.013	0.024**	0.009	0.048**	0.009
Q4	0.052**	0.017	0.073**	0.013	0.019	0.009	0.077**	0.010
new	NA	NA	NA	NA	0.041	0.021	0.003	0.019
lift	0.000	0.022	0.022	0.017	0.031**	0.011	0.055**	0.011
storage-attic	-0.035	0.028	0.003	0.025	0.035	0.022	-0.046	0.035
balkony	0.043**	0.013	-0.012	0.010	0.007	0.008	-0.009	0.007
bathroom	0.115**	0.015	0.097**	0.013	0.015	0.009	0.018	0.008
post1020-1025	-0.670**	0.042	-0.444**	0.036	-0.481**	0.025	-0.377**	0.021
post1030-1049	-0.573**	0.050	-0.448**	0.034	-0.514**	0.023	-0.448**	0.022
post1050-1059	-0.321**	0.026	-0.227**	0.020	-0.185**	0.013	-0.130**	0.013
post1060-1069	-0.513**	0.034	-0.422**	0.023	-0.448**	0.015	-0.413**	0.015
post1070-1079	-0.003	0.026	-0.019	0.019	0.001	0.014	0.064**	0.013
post1080-1087	-0.137**	0.035	-0.174**	0.028	-0.133**	0.021	-0.163**	0.022
post1090-1099	-0.308**	0.033	-0.243**	0.027	-0.213**	0.015	-0.181**	0.015
post1100-1108	-0.815**	0.033	-0.630**	0.029	-0.608**	0.021	-0.553**	0.018
post1110-1114	-0.466**	0.035	-0.304**	0.028	-0.396**	0.020	-0.350**	0.028

[6] For the sake of space, not all results are reported. Results for other years are available upon request.

Table 2.4 continued

	1991		1996		2001		2006	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
post1180-1183	-0.229**	0.028	-0.234**	0.023	-0.241**	0.017	-0.176**	0.020
post1184-1188	-0.359**	0.029	-0.267**	0.022	-0.318**	0.017	-0.315**	0.020
post1190-1191	-0.294**	0.052	-0.190**	0.051	-0.266**	0.033	-0.185**	0.040
row house	-0.389**	0.046	-0.240**	0.043	-0.306**	0.031	-0.323**	0.034
schakelwoning	-0.251	0.164	-0.145	0.083	-0.194**	0.053	-0.703**	0.071
corner house	-0.345**	0.048	-0.202**	0.045	-0.265**	0.033	-0.297**	0.037
semi-detached	-0.170**	0.055	-0.084	0.052	-0.096	0.040	-0.154**	0.043
ground-level-app	-0.443**	0.055	-0.332**	0.049	-0.267**	0.033	-0.347**	0.036
non-ground-app	-0.525**	0.053	-0.411**	0.050	-0.321**	0.033	-0.389**	0.035
maisonnette	-0.488**	0.058	-0.347**	0.052	-0.333**	0.035	-0.413**	0.038
front-door-in-hall	-0.472**	0.050	-0.320**	0.047	-0.333**	0.034	-0.389**	0.037
galary-app	-0.496**	0.050	-0.377**	0.046	-0.371**	0.035	-0.431**	0.039
for-elderly-app	-0.724**	0.098	-1.067**	0.069	-1.243**	0.063	-1.175**	0.074
ground-more-app	-0.481**	0.070	-0.170**	0.063	-0.350**	0.045	-0.329**	0.050
b1906-1930	-0.130**	0.023	-0.030	0.018	-0.042**	0.012	-0.067**	0.012
b1931-1944	-0.077**	0.029	-0.034	0.024	-0.107**	0.016	-0.121**	0.016
b1945-1959	-0.059	0.029	-0.101**	0.024	-0.132**	0.019	-0.159**	0.020
b1960-1970	-0.070	0.028	-0.148**	0.023	-0.186**	0.017	-0.239**	0.018
b1971-1980	0.001	0.029	-0.080**	0.028	-0.153**	0.020	-0.186**	0.022
b1981-1990	0.100**	0.028	0.037	0.023	-0.087**	0.017	-0.141**	0.016
b1991	0.253**	0.056	0.122**	0.022	-0.019	0.014	-0.059**	0.015
parking	0.060**	0.020	0.085**	0.016	0.062**	0.011	0.027	0.012
m-inside-good	0.126**	0.017	0.079**	0.014	0.076**	0.013	0.079**	0.013
m-outside-good	0.102**	0.021	0.111**	0.021	0.078**	0.019	0.015	0.024
Approximate significance of smooth terms (** significant at 5% level)								
	edf		edf		edf		edf	
s(log(size))	7	**	6	**	3	**	4	**
s(number_room)	4	**	5	**	4	**	4	
s(log(height))	6	**	1		9	**	2	**

1. ** significant at 5% level.
2. "edf " is the rounded effective degrees of freedom that is used to estimate the unknown function.

The effect of "log(size)" on transaction price is monotonically increasing as the log(size) of transacted dwelling increases. The smooth function of "log(size)" is also significantly different from zero for all the years in our sample. The effect of "number of rooms" is nonlinear and is significant for 15 out of 17 years, which supports our previous hypothesis in the parametric model that the marginal effect of "number of rooms" on transaction price is not constant. However, the estimated function is difficult to be interpreted. The estimated "log(height)" function is also nonlinear for 15 out of 17 years except 1990, 1996 and significant, and its effect on transaction price is likely to be negative if the housing has a ceiling which is above 3.3 meters or 1.2 in terms of log(height). This is reasonable since it is a waste of living space if the ceiling is way too high.

The model selection test results are reported in Table 2.5 in Appendix B. For all the years in our sample, the semi-parametric model (2.2) performs significantly better than the parametric model (2.1) in terms of the overall model fits. We also perform t-test on the coefficients of the parametric part of this semi-parametric model to examine if these coefficients are significantly different from their counterparts in the parametric model. The t-statistic is calculated by[7]

$$t-\text{statistic}_i = \frac{\hat{\beta}_{i,\text{semi-parametric model}} - \hat{\beta}_{i,\text{parametric model}}}{\text{SE}(\hat{\beta}_{i,\text{semi-parametric model}})}$$

We find in very rare cases that they are significantly different from each other. Therefore, the better fit of the semi-parametric model stems from the unspecified flexible functional forms for the variables which are suppressed to be linear in OLS.

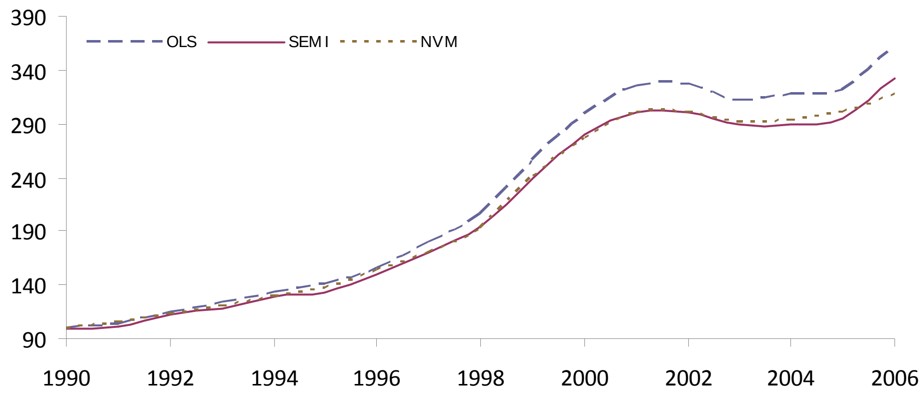
We construct the hypothetical "representative" dwelling for each period by combining the mean of all individual attribute of dwellings in our sample period. The hypothetical "representative" dwellings for selected years are presented in Table 2.6. We apply both the parametric and semi-parametric model to the prediction of values of the "representative" dwellings, which will feed into our construction of the housing price index. The index number measures basically the amount that we need to compensate the "representative" household for the change of cost of purchasing a "representative" dwelling to maintain

[7] The t-test performed here does not take into account the standard errors of the coefficient estimates from the parametric model, and these coefficient estimates are treated as given numbers in the test.

his/her certain standard of living from the reference period to some future period. In other words, it measures the amount that we need to bear in order to shield the household from price fluctuations without affecting their original standards of living. We calculate Laspeyres index for each year, and the index numbers are chained to produce index development over time. The predicted values of the “representative” dwellings for different years are reported in Table 2.7. We treat 1990 as the reference year with value 100, and our calculated index numbers are presented in Table 2.8.

Figure 2.2 shows the index development of the Amsterdam housing market for the period 1990-2006, which are constructed separately with the OLS and the semi-parametric models. Moreover, we also add published NVM housing index that have been widely used by real estate practitioners. The methodology behind the NVM index is simple since only the median transaction prices are used in the index construction. All indices share similarities in their respective development paths. The housing price steadily increased from 1990 to 1996, but the speed of increase accelerated after 1996 up to 2001 when the housing price reached its peak. The housing market tumbled after 2001, and the recovery started roughly in late quarters of 2004. Figure 2.2 demonstrates divergence of index numbers estimated by OLS and semi-parametric model respectively, and the divergence is widened as time proceeds. In addition, the index numbers constructed by OLS is consistently overstating their semi-parametric counterparts. Moreover, the published NVM index is less volatile as compared with other two indices. Although the NVM index resembles the development paths of the indices estimated by both the OLS and the semi-parametric model, its theoretical soundness is not well founded. First of all, the dwelling corresponds to the median transaction price is not necessarily representative of the housing market. Second, the NVM index does not contribute to the understanding of the change of implicit prices of housing attributes from time to time.

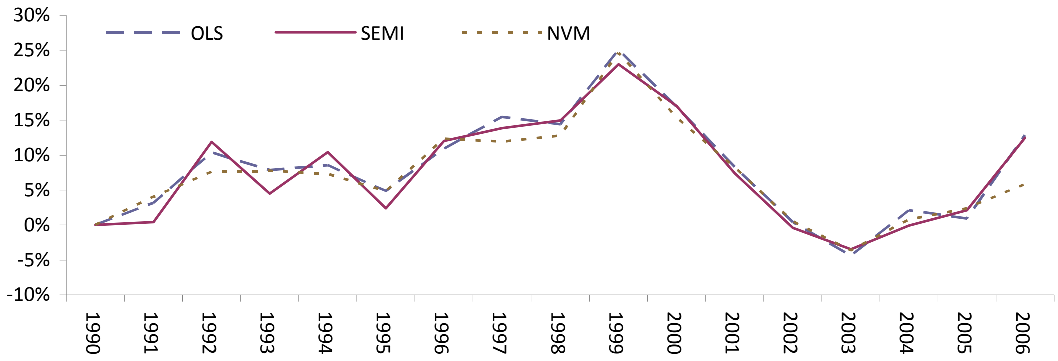
Figure 2.2 House Price Index Development



We investigate further the consistent divergence between OLS and semi-parametric estimates of the housing price index by examining the yearly change of housing prices. Figure 2.3 illustrates the yearly change of housing prices as published by NVM together with estimation by both methods. We observe similar pattern of the estimated yearly change of housing prices between OLS and the semi-parametric model, except for 1990 and 1997. However, the OLS estimation normally records higher yearly change of housing prices than that of the semi-parametric model, which sheds light on the consistent divergence in terms of index levels as estimated by both methods. The overestimation of index returns by OLS can be potentially explained by the implicit non-linear nature of the three smooth functions of “log(size)”, “number of rooms”, and “log(height)”.

It is not hard to discern that the development path of the indices resembles closely to that of the Dutch nominal GDP of the period as shown in Figure 2.4 in Appendix C. Two possible explanations are put forward. When the economy is doing well, there are more job opportunities and better remuneration, which will translate into a surging demand for big and better housing from residential households. Furthermore, when there is a booming economy, inflation will pick up, and households may reshuffle their investment portfolio in order to mitigate the impact of inflation on their portfolio return. Since housing is believed to a good hedge against inflation, households will invest in new or existing housing as part of their portfolio adjustment. However, the exact cause of the similarity between the housing price index and temporal economic development deserves further research, and is thus beyond the scope of this chapter.

Figure 2.3 Yearly Change of House Price Index



2.5 Conclusion

In this chapter, we assess the functional form assumptions concerning the popular hedonic regression, and its implications on the index construction. We apply both traditional hedonic model and the semi-parametric models to a unique housing transaction dataset for the Amsterdam region. Our model selection test results support using less stringent functional form for the hedonic equation, which is line with the findings of a number of studies mentioned in this chapter. In the construction of index, we implicitly tackle the index revision problem by estimating hedonic regression cross-sectionally, which implies that, when new information becomes available, past index numbers are not subject to change, contrary to standard time series estimates of price index with pooled data and time dummies used to capture the temporal house price development. Moreover, we allow variations of quality and implicit prices of housing attributes over time, which runs counter to repeated sales methodology. We apply the flexible functional form in our semi-parametric model to address the assumption of linear hedonic functional form problem. Chained Laspeyres index is applied in our index estimation, which measures the change of value between the base year and future period for the same "representative" housing of the base year.

The resulting indices based on the parametric and semi-parametric models share some similarities in terms of their development paths. However, the OLS index numbers are generally overstating their semi-parametric counterparts. Therefore, we conclude that OLS can be a useful first step to have a general view over the index development path due to its practical simplicity. However, hedonic equation with less stringent functional form is still preferred for its robustness to model misspecification and better model fits if we aim to produce accurate and consistent estimates of the housing price index that can be used for practical purposes.

Appendix A Derivation of Equation (5)

We use a simpler model than model (2.3) to show how equation (2.5) is derived. Consider

$$\mu = \alpha + x_1\beta_1 + f_2(x_2)$$

Maximizing criterion (2.4) with respect to α , β and f_2 , we have

$$\iota' \frac{\partial l}{\partial \mu} = 0$$

$$x_1' \frac{\partial l}{\partial \mu} = 0$$

$$\frac{\partial l}{\partial \mu} - \lambda_2 K_2 f_2(x_2) = 0$$

Linearize the equations above around μ_0 , we have

$$\iota' \frac{\partial l}{\partial \mu}|_{\mu_0} + \iota' \frac{\partial^2 l}{\partial \mu \mu'}|_{\mu_0} \iota(\alpha - \alpha_0) + \iota' \frac{\partial^2 l}{\partial \mu \mu'}|_{\mu_0} x_1(\beta_1 - \beta_1^0) + \iota' \frac{\partial^2 l}{\partial \mu \mu'}|_{\mu_0} [f_2(x_2) - f_2^0(x_2)] = 0$$

$$x_1' \frac{\partial l}{\partial \mu}|_{\mu_0} + x_1' \frac{\partial^2 l}{\partial \mu \mu'}|_{\mu_0} \iota(\alpha - \alpha_0) + x_1' \frac{\partial^2 l}{\partial \mu \mu'}|_{\mu_0} x_1(\beta_1 - \beta_1^0) + x_1' \frac{\partial^2 l}{\partial \mu \mu'}|_{\mu_0} [f_2(x_2) - f_2^0(x_2)] = 0$$

$$(\frac{\partial l}{\partial \mu}|_{\mu_0} - \lambda_2 K_2 f_2^0(x_2) + \frac{\partial^2 l}{\partial \mu \mu'}|_{\mu_0} \iota(\alpha - \alpha_0) + \frac{\partial^2 l}{\partial \mu \mu'}|_{\mu_0} x_1(\beta_1 - \beta_1^0) + (\frac{\partial^2 l}{\partial \mu \mu'}|_{\mu_0} - \lambda_2 K_2)[f_2(x_2) - f_2^0(x_2)] = 0$$

In matrix form

$$\begin{pmatrix} \iota' U \\ x_1' U \\ U - \lambda_2 K_2 f_2^0(x_2) \end{pmatrix} = \begin{pmatrix} \iota' H \iota & \iota' H x_1 & \iota' H \\ x_1' H \iota & x_1' H x_1 & x_1' H \\ H \iota & H x_1 & H + \lambda_2 K_2 \end{pmatrix} \times \begin{pmatrix} \alpha - \alpha_0 \\ \beta_1 - \beta_1^0 \\ f_2(x_2) - f_2^0(x_2) \end{pmatrix}$$

where U and H are the same as defined in the chapter. After rearranging, we have

$$\begin{pmatrix} \alpha^1 \\ \beta_1^1 \\ f_2^1(x_2) \end{pmatrix} = \begin{pmatrix} S_\alpha [z - x_1\beta_1^1 - f_2^1(x_2)] \\ S_{\beta_1} [z - \alpha^1 - f_2^1(x_2)] \\ S_{f_2} [z - \alpha^1 - \beta_1^1 x_1] \end{pmatrix}$$

with z, S_{α}, S_{β_1} and S_{f_2} defined similarly in the chapter.

Appendix B Other Estimation Results

Table 2.5 Model Selection Test Results

Year	P value	Year	P value
1990	0.00	1999	0.00
1991	0.00	2000	0.00
1992	0.00	2001	0.00
1993	0.00	2002	0.00
1994	0.00	2003	0.00
1995	0.00	2004	0.00
1996	0.00	2005	0.00
1997	0.00	2006	0.00
1998	0.00		

Table 2.6 Characteristics of "Representative" Dwelling for Selected Years

	1991	1996	2001	2006
size	102.901	98.292	98.570	92.119
Q2	0.259	0.236	0.251	0.269
Q3	0.281	0.255	0.271	0.264
Q4	0.268	0.256	0.246	0.209
new	0.000	0.000	0.029	0.045
lift	0.194	0.274	0.256	0.203
number_room	3.705	3.476	3.432	3.320
storage_attic	0.047	0.036	0.024	0.010
balkony	0.240	0.315	0.587	0.546
bathroom	0.857	0.914	0.960	0.942
height	2.925	2.850	2.790	2.727
post1020-1025	0.026	0.020	0.023	0.037
post1030-1049	0.017	0.025	0.028	0.034

Table 2.6 continued

	1991	1996	2001	2006
post1050-1059	0.176	0.144	0.168	0.195
post1060-1069	0.058	0.104	0.117	0.100
post1070-1079	0.111	0.137	0.126	0.147
post1080-1087	0.052	0.052	0.040	0.036
post1090-1099	0.047	0.042	0.074	0.095
post1100-1108	0.055	0.050	0.046	0.070
post1110-1114	0.043	0.039	0.040	0.018
post1180-1183	0.142	0.116	0.075	0.051
post1184-1188	0.106	0.101	0.074	0.045
post1190-1191	0.015	0.010	0.012	0.008
row house	0.204	0.152	0.162	0.128
schakelwoning	0.001	0.004	0.006	0.003
corner house	0.073	0.058	0.046	0.039
semi-detached	0.025	0.019	0.013	0.013
ground-level-app	0.045	0.054	0.099	0.109
non-ground-app	0.065	0.042	0.413	0.529
maisonnette	0.029	0.025	0.051	0.040
front-door-in-hall	0.156	0.143	0.104	0.066
galary-app	0.362	0.472	0.081	0.049
for-elderly-app	0.005	0.007	0.004	0.003
ground-more-app	0.013	0.010	0.010	0.008
b1906-1930	0.234	0.201	0.220	0.266
b1931-1944	0.075	0.063	0.076	0.075
b1945-1959	0.099	0.079	0.056	0.048
b1960-1970	0.240	0.237	0.162	0.117
b1971-1980	0.100	0.069	0.067	0.044
b1981-1990	0.110	0.107	0.075	0.108
b1991	0.012	0.104	0.205	0.206
parking	0.145	0.123	0.150	0.112
m inside good	0.812	0.853	0.915	0.915
m outside good	0.897	0.938	0.963	0.976

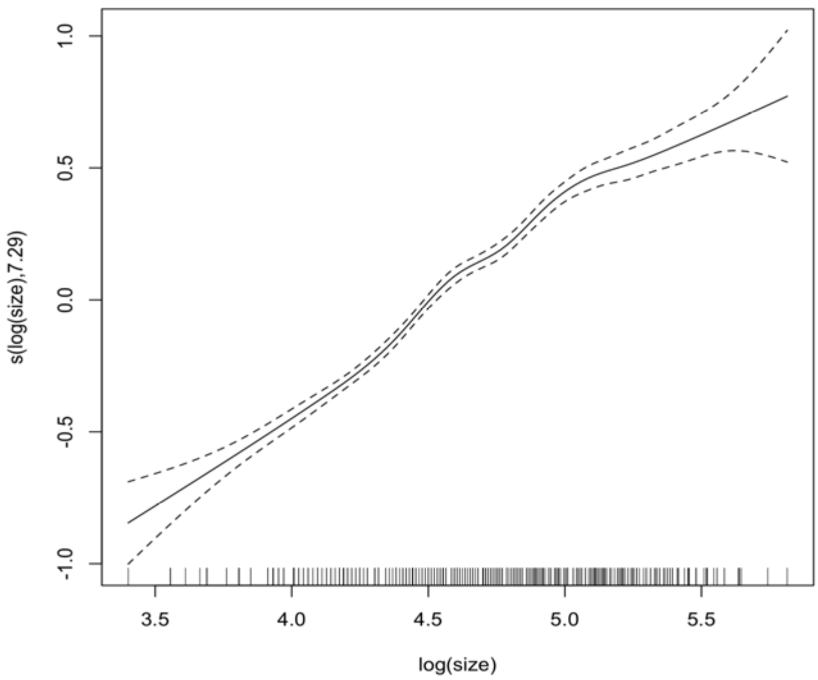
Table 2.7 Predicted Value of "Representative" Dwelling

Year	OLS Model	Semi-parametric Model	Year Model Used
1990	11.207	11.276	1990
	11.238	11.280	1991
1991	11.274	11.309	1991
	11.373	11.421	1992
1992	11.354	11.405	1992
	11.430	11.449	1993
1993	11.431	11.451	1993
	11.513	11.550	1994
1994	11.513	11.551	1994
	11.560	11.575	1995
1995	11.548	11.562	1995
	11.652	11.676	1996
1996	11.644	11.666	1996
	11.788	11.795	1997
1997	11.795	11.801	1997
	11.930	11.941	1998
1998	11.937	11.948	1998
	12.160	12.155	1999
1999	12.195	12.189	1999
	12.351	12.346	2000
2000	12.348	12.343	2000
	12.428	12.415	2001
2001	12.417	12.410	2001
	12.421	12.406	2002
2002	12.416	12.401	2002
	12.371	12.366	2003
2003	12.373	12.371	2003
	12.394	12.370	2004
2004	12.371	12.346	2004
	12.380	12.367	2005
2005	12.361	12.347	2005
	12.482	12.465	2006

Table 2.8 House Price Index Numbers

Year	OLS Model	Semi-parametric Model
1990	100	100
1991	103.15	100.41
1992	113.88	112.33
1993	122.84	117.37
1994	133.33	129.62
1995	139.83	132.72
1996	155.12	148.70
1997	179.12	169.30
1998	204.91	194.65
1999	256.24	239.45
2000	299.61	280.24
2001	324.62	301.01
2002	325.96	299.77
2003	311.67	289.45
2004	318.24	289.24
2005	321.14	295.31
2006	362.39	332.26

Figure 2.1 Visualizing Smoothing Results for Selected Year - 1991



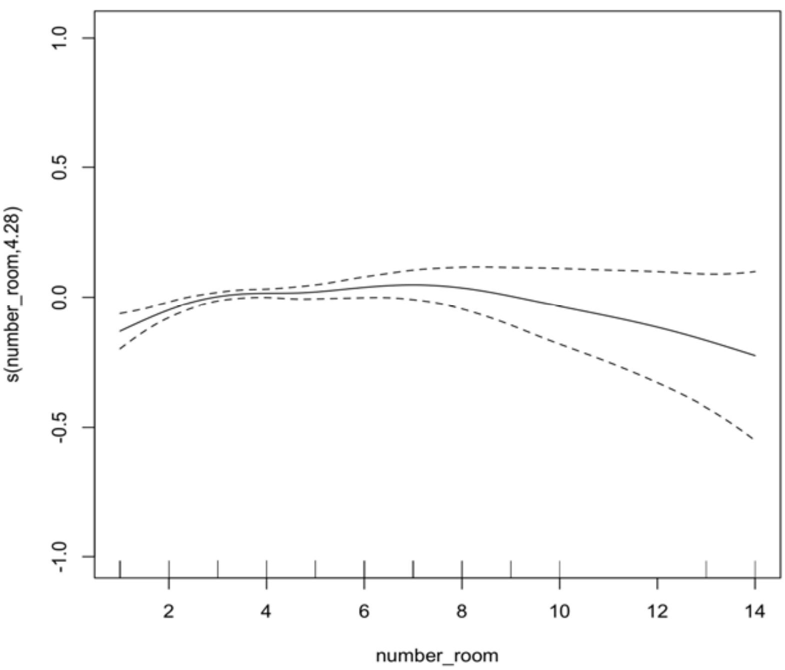
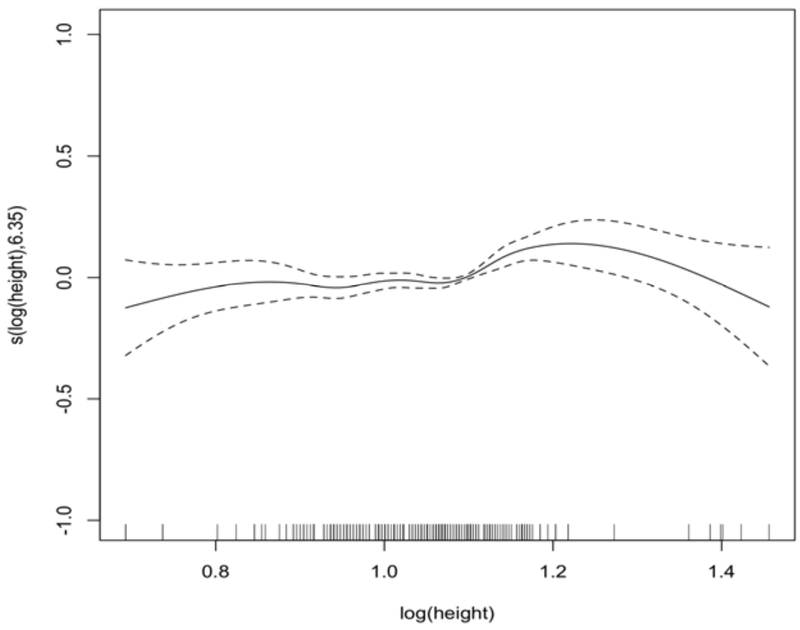
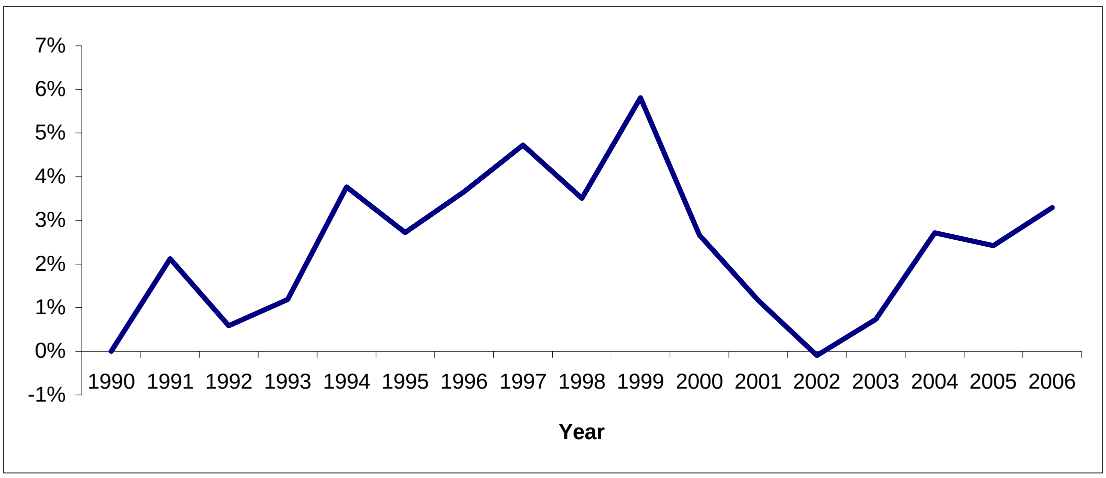


Figure 2.1 continued



Appendix C Dutch GDP Index

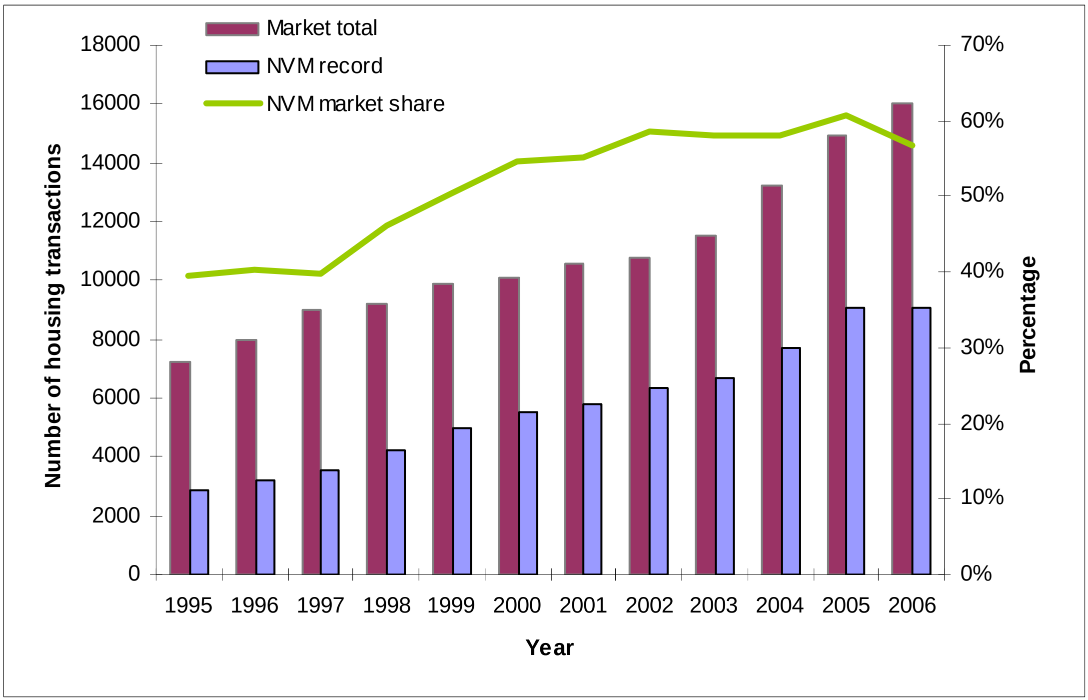
Figure 2.4 Yearly Change of Dutch GDP



Source: Dutch Central Bureau of Statistics (CBS) and author's own calculation

Appendix D NVM Market Share 1995-2006

This graph shows the market share of NVM in terms of housing transactions within the Greater Amsterdam region. The Greater Amsterdam region classified by Dutch CBS includes more municipalities than the Amsterdam region in this study. As a result, the NVM market share with reference to the Greater Amsterdam region in this graph is a conservative measure of the true market share of NVM within the Amsterdam region in this study.



Source: NVM, Dutch Central Bureau of Statistics (CBS), and author's own calculation

Chapter 3

Spatial and Temporal Dependence in House Price Prediction

3.1 Introduction

Predicting property values is of great interest to various parties in an economy. Individuals are interested in knowing the values of their properties before setting up their list prices. Tax authorities rely on the estimates of the properties' value as the basis for levying property taxes. Banks and mortgage providers conduct housing collateral valuation to qualify the borrowers for their mortgage applications. When the underlying mortgages are repackaged as securitized products which are ready to be sold in the marketplace, rating agencies scrutinize respective loan-to-value ratios to assess the risk profile associated with these structured products (Standard & Poor's, 2005, 2007). Real estate investors and portfolio managers devise and carry out their investment decisions based on periodic evaluations of their real estate portfolios.

Due to the heterogeneous nature of housing and the thin housing market with infrequent transactions, the house price determination process has traditionally been modeled within the hedonic framework, following the pioneer work by Rosen (1974). Within this framework, houses can be viewed as bundles of attributes that offer utilities to their users, and the market equilibrium dictates house prices to be determined by the amount of utility-generating attributes possessed by these houses. The observable housing transaction prices are thus the value realization of heterogeneous bundles with varying amounts of different attributes which these houses contain. Within the hedonic framework, hedonic regression techniques, normally taking the log-linear functional form, are widely applied using real housing transaction data to filter out the implicit attributes' prices and make house price predictions. The hedonic regression specification takes structural as well as location attributes as explanatory variables with log(transaction price) as the dependent variable, and the coefficients can be interpreted as either elasticities or semi-elasticities. A notable problem with this standard ordinary least squares (OLS) specification is that errors may not be independent from one another, and such error correlation will lead to inefficient as well as erroneous inference of these parameter estimates. This is of particular concern in the housing market due to the spatial and temporal feature of housing transactions. Spatial dependence occurs when houses close in proximity tend to be correlated which violates the assumption that the housing transactions are independent in traditional hedonic regressions. According to Basu and Thibodeau (1998), house prices are spatially correlated for two reasons. First, neighborhoods tend to be developed at the same time so that neighborhood properties have similar structural characteristics. Second, neighborhood residential properties share location amenities. The inclusion of location indicators in the hedonic regression specification does not necessarily remove the spatial dependence among the properties within the neighborhoods since they only capture the spatial effects that are shared by all the properties within certain geographical boundaries. Therefore, hedonic regressions that control for well-defined spatial locations may still have house price residuals exhibiting spatial dependence (Pace et al., 1998; Dubin, 1998).

Another source that causes correlated error structure in traditional hedonic regression specification is that housing transactions tend to be correlated temporally. Such temporal dependence could arise due to earlier housing transactions containing information that is relevant to the pricing of the target property. Past housing transactions may proxy for the market trend of general house price development, and can also capture changes in institutional setting, such as changes in tax laws, as well as local amenities, all of which could lead to temporal correlation among housing transaction prices. Consequently, both the spatial and temporal dependence need to be accounted for if one aims to address the correlated errors in the traditional hedonic regression specification. Such exercise is not only beneficial to improving estimation efficiency and inference accuracy, but also having implication on house price prediction which is one of the most important tasks of empirical application of hedonic price models.

The purpose of this chapter is thus to integrate the spatial and temporal dependence within the traditional hedonic regression specification, and assess if accounting for spatial and temporal effects in the housing market improves prediction performance relative to hedonic regression specification with such effects neglected. Given our focus on the empirical applications of hedonic price models, we limit our analysis to the spatiotemporal autoregressive (STAR) model of Pace et al. (1998) that corrects for both the spatial and temporal correlations in the error structure. In addition, the sparse structure of spatial and temporal weight matrices in the STAR model offers computational efficiency especially when dealing with large datasets (Pace, 1997; Pace and Barry, 1997a, 1997b). This computational advantage is of particular relevance to the empirical analysis of this chapter since the working dataset has over 400,000 housing transactions covering the Dutch Randstad region for the period from 1997 to 2007.

Most of the prior research has put emphasis on the model comparison between the default hedonic pricing model and various models that account for spatial correlated errors (Can, 1990, 1992; Basu and Thibodeau, 1998; Dubin et al., 1999; Gelfand et al., 2004; Militino et al., 2004; Case et al., 2004; Bourassa et al., 2007). These studies either employ small samples of housing transactions or do not explore the temporal structure in the housing market in making out-of-sample predictions since only early housing transactions convey information relevant to the pricing of later transactions and not vice versa. Moreover, as shown in a recent study by Nappi-Choulet and Maury (2009), the temporal heterogeneity, which refers to the time variation of the structural as well as spatial and temporal dependence parameters, may well exist when using property transaction data extending over a long period of time. This chapter contributes to the existing literature on the following grounds. First, we employ a large non-U.S. dataset, which, to our knowledge, is one of the first papers studying the prediction performance of spatiotemporal hedonic model in the Dutch housing market. Second, to account for temporal heterogeneity in the housing market, we perform the analysis on an annual basis. Third, the prediction exercise recognizes the time structure in the housing market such that only earlier housing transactions are taken for predicting future house values. Our findings show that accounting for spatial and temporal dependence in traditional hedonic pricing model is not only theoretically warranted, but also contributing to better prediction performance. As a natural application of the spatial and temporal model in the context of house price index construction due to its better predictive power, we show that the house price index constructed using the OLS model consistently understates the more accurate house price development as captured by the spatial and temporal model on the basis of the single random sample that is used to represent the overall housing market.

The chapter is structured as follows. The next section briefly reviews relevant literature. Section 3.3 illustrates the STAR model and highlights some estimation issues. Section 3.4 focuses on the empirical analysis and estimation results are discussed. Section 3.5 concludes.

3.2 Literature Review

3.2.1 Spatial Heterogeneity and Housing Submarkets

Spatial dependence and spatial heterogeneity are distinct phenomena in the housing market. Spatial heterogeneity refers to low degree of substitutability of houses on the basis of both observable and unobservable characteristics, which occurs across well-defined submarkets. Houses within each of the submarkets exhibit high degree of homogeneity and are highly substitutable with similar implicit attributes' prices. In this context, spatial dependence still exists due to the substitutability of houses within each submarket. Therefore, if the housing submarkets are inappropriately defined, it would aggravate the problem of spatial correlated error terms in hedonic equations. Recognizing this fact, we give special consideration to the inclusion of well defined submarkets into our regression analysis to control for the spatial heterogeneity effect.

Can (1990) was among the first to address both the spatial heterogeneity and spatial dependence in the modeling of spatial data. She used Casetti's (1972) spatial expansion method where the structural parameters of the hedonic pricing model were allowed to vary over space. Spatial dependence in the error structure was treated using the so-called mixed regressive-autoregressive model which incorporated a spatially lagged dependent variable into the hedonic regression specification. Using a sample of 577 single family transactions in Columbus, Ohio MSA, she showed that accounting for both the spatial heterogeneity and spatial dependence could explain the urban house price variations better than the traditional hedonic model on the basis of some in-sample statistics.

A number of studies advanced in the search of well-defined housing submarkets such that spatial heterogeneity could be optimally controlled for within an OLS setup, and results were mixed. Bourassa et al. (1999) applied the statistical method that using principal component analysis to first extract a set of factors and performing cluster analysis on the basis of these factors to identify the composition of housing submarkets. Hedonic price equations were estimated using a priori classified submarkets and statistically generated submarkets. Using a survey data with 4661 observations from Sydney and Melbourne, they found that submarkets based on the statistical procedures, with one exception, did not produce results that were much better than the a priori submarket classification.

Dunse et al. (2000) followed the same statistical procedures as Bourassa et al. (1999) to derive submarkets for the office market in two cities, Glasgow and Edinburgh. They showed that different factors were important in influencing the structure of the office market in Scotland's major centers. In a follow-up study, Dunse et al. (2002) tested parameter stability across different submarkets with both a priori and statistical definitions. They found little evidence of spatial heterogeneity of parameter estimates on the basis of Chow test. In addition, the test results did not differ between two submarket definitions. Put it differently, there was little difference in the submarket defined using agent's knowledge as compared to that constructed through complex statistical procedures.

A similar result was also found in Bourassa et al. (2003), in which they explored the effects of alternative definitions of submarkets on the accuracy of predictions for mass appraisal purposes. Using 8421 residential transactions in the city of Auckland, they compared submarkets based on small geographical areas defined by the real estate appraisers with a set of submarkets that were generated via statistical procedures. They found more accurate price prediction based on the housing market segmentation used by appraisers.

These previous research shed light on the validity of using submarkets defined by real estate professionals rather than those produced otherwise through statistical procedures. Two notes are put forward for the empirical unsuccessful application of statistically derived submarkets. First, the cluster analysis that has been widely applied in deriving the submarkets empirically implicitly gives equal weights to the housing attributes. It seems likely that some attributes are more important than others. For instance, location may well conform to the ideal sense of submarket more precisely than do other factors in the clustering process to derive submarkets (Bourassa et al., 2003). Second, taking factors from supply side alone is not sufficient in classifying submarkets in practice. One can think of one good and one bad neighborhood that are contiguous with similar housing attributes. The two neighborhoods are treated as one submarket if only housing attributes are considered in the statistical process. However, the result would change if, for example, household income and education are considered as well. The submarkets defined by the real estate professionals, on the contrary, correct for these issues related to statistically generated submarkets since their submarket classification is experience-based that incorporates the usual confidential demand side factors as well as observable housing attributes.

3.2.2 Spatial and Temporal Dependence Modeling and Applications

The spatial nature of housing data has attracted significant amount of attention in the academic literature regarding the optimal way to model the spatial data. As summarized in Dubin (1998), there are two common ways to address the spatial dependence in the error structure of traditional hedonic pricing models. The first method is to model the process itself through using a spatial lag structure, and the second approach is to model the spatial error covariance matrix explicitly.[8] However, the current literature does not endorse the use of one approach over the other, which may depend on the working data at hand and the complexity involved in the implementation process. Nevertheless, model comparison exercises generally show better performance of spatial models relative to the traditional hedonic specification (Can, 1990, 1992; Pace et al., 1998; Pace et al., 2000; Case et al., 2004; Militino et al., 2004) except Bourassa et al. (2007).

[8] For the details of these two modeling approaches, please refer to Dubin (1998).

Can (1992) advanced Can (1990) by applying rigorous testing of the presence of spatial effects. Similar models as in Can (1990) were estimated using 563 single-family houses for 1980 sold in the Franklin County of the Columbus metropolitan area. Results indicated the spatial models that incorporated both spatial dependence and spatial heterogeneity were better than traditional hedonic specification that included neighborhood effects in terms of explaining house price variations. She also showed that neighborhood quality variable seemed to be capable of capturing the spatial heterogeneity without introducing spatially varying marginal prices of structural housing attributes.

Miltino et al. (2004) compared four spatial models as well as OLS without out of sample prediction. They estimated these four spatial models using 293 property transactions from Pamplona, Spain, and found that most inferences seemed robust with respect to the spatial technique. In addition, between the two commonly used spatial models, the spatial autoregressive model (SAR) and conditional autoregressive model (CAR), CAR offered better performance than SAR on the basis of AIC or BIC values.

Bourassa et al. (2007) was an exception to an overwhelming favor of the spatial models over the OLS hedonic pricing model. They used submarket defined by valuers and applied alternative methods of controlling for the spatial dependence of house prices to a housing transaction database with 4,880 observations in Auckland. Without recognizing the temporal structure in the housing market, they applied repeated random sampling of 100 times to obtain prediction results. Moreover, their prediction exercises only considered the estimated structural parameters without fully exploring the spatial information in the spatial models. Their prediction outcome favored the inclusion of submarket variables in OLS specification over alternative spatial models.

There has been few studies that address both the spatial and temporal features inherent in modeling housing data with exceptions such as Pace et al. (1998), Pace et al. (2000), Case et al. (2004), Gelfand et al. (2004) and Nappi-Choulet and Maury (2009).

Pace et al. (1998) investigated the best way to model spatial and temporal effect by comparing two models. One model used indicators of time and location, and the other incorporated the spatiotemporal dependence in the error specification such that the target house price was affected not only by the early transactions in the housing market but also by prior transactions of neighbors. Using a large dataset with 70,822 observations from 1969 to 1991 from Fairfax County Virginia, they demonstrated improved goodness of fit of using the STAR model to account for both the spatial and temporal dependence than the indicator based hedonic model. They concluded that the house price variations were strongly influenced by the sales prices of previously sold, neighboring properties.

Case et al. (2004) applied the standard hedonic model and three spatial models to a similar sample as used in Pace et al. (1998), and out-of-sample prediction accuracy was used for comparison purposes. Their final results showed that two out of three spatial models outperformed OLS with residuals from 15 nearest neighbors included in out of sample prediction. Moreover, their prediction results indicated the importance to incorporate the nearest neighbor transactions for predicting housing values.

Nappi-Choulet and Maury (2009) adopted the STAR model as in Pace et al. (1998) in the analysis of Paris office market while incorporating temporal heterogeneity to control for the time varying structural parameters as well as spatial and temporal dependence coefficients. Applying Paris office transaction dataset with 2,587 observations between 1991 and 2005, they found that spatial and temporal dependence parameters differed strongly according to the transaction date, which implicated the assessment of price changes from 1991 to 2005 for the Paris office market.

Overall, previous literature demonstrate the need to account for spatial effects to address the correlated error in an OLS setup, but the optimal way of doing so remains blur up to date. In addition, the intrinsic temporal structure in housing transactions deserve attention when making out of sample predictions such that recent observations would not be used in predicting house values that are transacted in the past. Spatial heterogeneity should be modeled on the basis of experience based definition of submarkets rather than those derived through statistically complex procedures, while temporal heterogeneity is of concern when the dataset includes housing transactions over a long period of time.

3.3 Spatiotemporal Model and Estimation Procedure

We proceed to present the STAR model by Pace et al. (1998) which models the spatial and temporal dependence in the hedonic error structure through using a weight matrix. The STAR model is favored in this study due to its implementation advantage, especially in dealing with large dataset as in the empirical analysis of this chapter. The traditional hedonic regression is specified as follows,

$$Y = X\beta + u \tag{3.1}$$

where Y is a $n\times1$ vector with log transaction prices, X denotes a $n\times k$ matrix, which normally includes time dummies, location indicator variables, and housing structural characteristics, β is a $k\times1$ vector of parameters corresponding to k independent variables, and u refers to a $n\times1$ vector of error terms. However, such specification overlooks the correlated errors. To account for this, we follow Pace et al. (1998) to subsume an autoregressive error process such that

$$u = Wu + \epsilon \tag{3.2}$$

where W is a $n\times n$ weighting matrix, and ε is a $n\times1$ vector of white noise. If W consists of only spatial weighting matrix, the model is essentially a SAR model. However, as noted in Pace et al. (1998), in a temporal context, simply multiplying the dependent and the independent variables by the spatial weighting matrix does not remove all the autocorrelation effects, since neighboring transactions may well have taken place far back in time that do not contain too much information in the pricing of the property in question. In addition, as mentioned above, earlier housing transactions may convey other relevant information to the pricing of the target property. Therefore, there is a need to take into account the previous transactions which are not necessarily close in proximity relative to the target property. Within our model specification, it boils down to the inclusion of a temporal weighting matrix into W besides a spatial weighting matrix. The spatial and temporal elements in W thus generalize the SAR model to be the STAR model.

Following Pace et al. (1998), we structure all observations to be ordered according to time, such that first element in Y and first row of W correspond to the oldest housing transaction with the first row in X containing its attributes. Therefore, the implicit temporal feature of the housing transactions is recognized and accounted for in the STAR model. Moreover, it will be shown later that such time ordering of W contributes to computational efficiency in estimating the model. Combining (3.1) and (3.2), we arrive at a compact form of the STAR model as

$$(I-W)Y=(I-W)X\beta+\epsilon \tag{3.3}$$

A general specification of W, as in Pace et al. (1998), would be

$$W=\phi_S S+\phi_T T+\phi_{ST}ST+\phi_{TS}TS \tag{3.4}$$

where S and T are spatial and temporal weighting matrices while ϕ_S and ϕ_T are spatial and temporal dependence parameters. ST and TS are the interaction matrices that allow for the modeling of potentially compound spatiotemporal effects with ϕ_{ST} and ϕ_{TS} as their coefficients.[9] As a further generalization of (3.3) and (3.4), we write the unrestricted STAR model as follows,

$$\begin{aligned} Y &= \alpha + X\beta_1 + SX\beta_2 + TX\beta_3 + STX\beta_4 + TSX\beta_5 \\ &\quad +\phi_T TY + \phi_S SY + \phi_{TS} TSY + \phi_{ST} STY + \epsilon \end{aligned} \tag{3.5}$$

where β_1, β_2, β_3, β_4, β_5 are $k\times 1$ vectors of coefficients that correspond to independent variables as well as the spatial, temporal and spatial-temporal lagged independent variables. Our empirical analysis will be based on the unrestricted form of the STAR model (3.5).

The spatial weighting matrix S is generally structured on the basis of cardinal distances among housing transactions, for example, in Can (1990), Can (1992), and Militino et al. (2004). Another specification of the spatial weighting matrix is based on ordinal distances, which is equivalent to the use of a fixed number of neighbors in space as in Pace et al. (1998), which reduces the problems posed by uneven densities of housing. We follow Pace et al. (1998) in the specification of matrix, and we limit the existence of spatial dependence within 30 ($m_S=30$) neighbors which are identified on the basis of Euclidean distance d_{ij} between every pair of observations j and i for every prior observation j relative to the ith observation ($j<i$). Consequently, we are able to sort these calculated distances, and find our required number of neighbors relative to every housing transaction. We form neighbor matrices S_i ($i\in[1,m_S]$), where S_1 includes the closest previously sold

[9] As noted in Pace et al. (1998), the interaction terms essentially account for the order of filtering both the dependent and the independent variables, especially when we do not have prior knowledge on which, space or time, to filter first.

neighbor, S_i stores the ith closest previously sold neighbor relative to every observation. The overall spatial weighting matrix S is computed as follows,

$$S = \frac{\sum_{i=1}^{m_s} \rho^i S_i}{\sum_{i=1}^{m_s} \rho^i} \tag{3.6}$$

where ρ is the spatial decay parameter capturing the impact of neighboring transactions based on proximity and falls between 0 and 1. By construction, S matrix is row standardized and lower triangular with zeros on its diagonal.

The temporal weighting matrix is structured in a similar fashion. We take the temporal dependence to be within 150 ($m_t = 150$) previously sold houses relative to the current transaction. The ith row in the temporal matrix T contains m_t prior observations which are equally weighted with weight $\frac{1}{m_t}$.[10] Therefore, the T matrix is structured to be lower triangular and contains zeros on its diagonal with the ijth element as

$$T_{ij} = \frac{1}{m_t} \tag{3.7}$$

only if $i > j$ and $i - j \le m_t$, and $T_{ij} = 0$ otherwise.

Since we are taking ordinal distances in both space and time in specifying the S and T matrices, both S and T are sparse with densities $\frac{m_s}{n}$ and $\frac{m_t}{n}$ respectively. The low densities in S and T matrices avoid the time consuming calculation of the determinant in maximizing the log-likelihood function and contribute to the computational efficiency (Pace, 1997; Pace and Barry, 1997a, 1997b). Taking the spatial and temporal weighting matrix W as specified in (3.4) and substituting it into (3.3), we arrive at our working model which can be estimated using maximum likelihood. The concentrated log-likelihood function in parameters ϕ is shown by Pace et al. (1998) and Pace et al. (1998) to be

[10] Pace et al. (1998) discuss the choice of the equal weight attached to each of the prior transaction to the current transaction which is based on an acceptable performance from preliminary fitting.

$$L(\phi) = \ln | I - \phi_s S - \phi_t T - \phi_{st} ST - \phi_{ts} TS | - (\frac{n}{2}) \ln[SSE(\phi)] \quad (3.8)$$

where SSE is the sum of squared errors. Given the structure of S and T matrices, the log-determinant term drops out in the calculation of the log-likelihood, which greatly speeds up the estimation of the STAR model especially when using large dataset.

The implementation of the STAR model requires the specification of the optimal spatial decay parameter ρ. In this study, the optimal ρ is set through maximizing the likelihood function, and we implement this with a rough grid search process. Specifically, we take the optimal ρ to be falling within 0.2 and 0.85, and preliminary fitting is carried out for different ρ values with an interval 0.05 within the pre-specified range, for instance, 0.2, 0.25, 0.3, 0.35, ... , 0.85. The optimal ρ is chosen such that the log-likelihood of the STAR model is maximized. This process of choosing the optimal ρ does not necessarily produce the true optimal spatial decay parameter that corresponds to the global maximum of the log-likelihood, but it is adopted as a trade-off between computational feasibility and bias arising from a priori subjective choice.

We pay special attention to several issues that have been widely discussed in the previous literature related to the application of the hedonic pricing model. First, when using housing transaction data that extend over a long period of time, we should account for temporal heterogeneity of the parameters in the model. It is reasonable to assume that parameters such as marginal housing attribute prices are also time varying. In the short-run, the supply of reproducible housing attributes is inelastic, which underlies the fluctuation of housing attribute prices as the demand for certain attributes changes. However, in the long run, the housing attributes prices will be driven by the supply of these reproducible attributes with non-constant production costs. For irreproducible housing attributes such as lake view and highway access, the prices of these attributes will be determined by demand both in the short run and in the long run. For example, as people become better well-off over time, houses with lake view simply appreciate in prices since the lake view is irreproducible and there is no supply to accommodate the increasing demand of such housing attribute over time. Knight et al. (1995) relaxed the temporal parameter stability assumption, and applied seemingly unrelated regressions (SUR) to account for the time variation of implicit housing attribute prices in the context of housing price index construction. Munneke and Slade (2001) focused on the commercial real estate price construction, and controlled for the temporal heterogeneity through running hedonic regressions for each of the sub periods. Besides the time varying structural parameters, both the temporal and spatial dependence terms are also subject to temporal heterogeneity as established in Nappi-Choulet and Maury (2009). In this study, we perform both estimation and prediction on an annual basis, which is similar to Munneke and Slade (2001), to take into account temporal heterogeneity.

The second issue related to the empirical application of hedonic price model is the existence of spatial heterogeneity such that parameters of interest in a hedonic model may differ according to the submarkets where the property belongs. Can (1990) modeled the spatial heterogeneity via interactions between neighborhood quality variable and housing structural attributes. Can (1992) found that hedonic model without such interactions performed equally well as the hedonic model estimated in Can (1990). In this chapter, we model the spatial heterogeneity through incorporating submarkets defined by real estate professionals. Using the spatial drift terms to capture the spatial heterogeneity has been applied in Bourassa et al. (2007) and Nappi-Choulet and Maury (2009). The validity of adopting the experience-based submarket definition over deriving the submarket statistically has been briefly discussed above and supported by the existing literature, such as Palm (1978), Michaels and Smith (1990), Dunse et al. (2000, 2002) and Bourassa et al. (2003, 2007).

Our main prediction exercise is performed on an annual basis as follows. For every year, we sort the housing transaction data from the earliest to the latest, and we use the first 80% of all observations as the in-sample for estimation, and the other 20% as the out-of-sample. In doing so, we recognize the intrinsic temporal structure in housing transactions, since only previous transactions are relevant for predicting the current house value and not vice verse. As a robustness check to see if our prediction results are driven by a particular out-of-sample specification, we specify two other out-of-samples that are composed of 80% - 90%, and 90% - 100% of all temporally ordered observations respectively. In addition, as a further robustness check, we retain 90% of all observation as in-sample, and observations within 90% - 100% range as out-of-sample to check if our results are sensitive to different specifications of in-sample. It is to note that, in predicting future house values, we not only utilize the estimated structural parameters as in Bourassa et al. (2007) but also explore information contained in the spatial and temporal neighbors relative to these transactions. Put it differently, for each observation in our out-of-sample, we first identify its spatial and temporal neighbors from a pool of temporally ordered housing transactions within the in-sample, and this information will be combined with parameter estimates from the in-sample in predicting the value of each house in the out-of-sample. Our main prediction exercise also guarantees that identical information set is taken for predicting house value using both the OLS model and the STAR model, so that model comparison on the basis of predictive power is performed on a level ground.

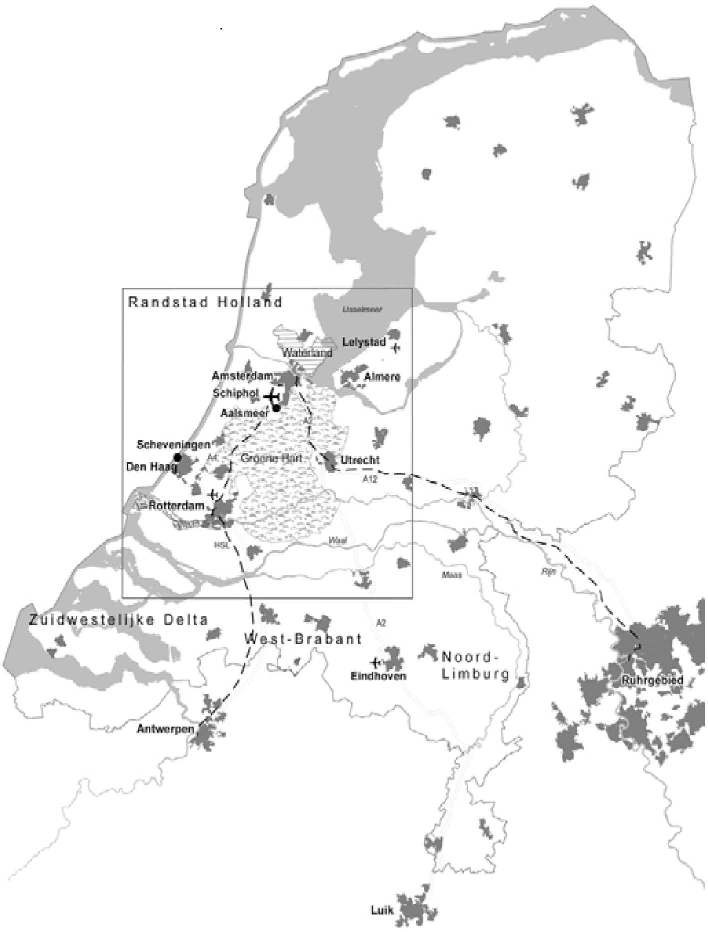
To check the robustness of our prediction results as to an alternative definition of submarket, we also examine the prediction performance of an OLS model that includes submarkets using pre-specified geographical areas represented by postcodes which are more refined as compared to the submarket defined by real estate brokers. This is a relevant issue since using more refined submarkets or an alternative definition of submarket may alleviate the spatial dependence among housing transactions, which makes the explicit modeling of hedonic errors to account for the spatial dependence be less of a concern.

3.4 Data and Empirical Results

3.4.1 Randstad Housing Transaction Data

Our working dataset comprises housing transactions from the Dutch Randstad region. The Dutch Randstad region is a conurbation in the Netherlands, which consists of parts of four Dutch provinces, North Holland, South Holland, Utrecht and Flevoland. The country's largest cities, Amsterdam, Rotterdam, The Hague and Utrecht are all in Randstad, as well as the world's largest port in Rotterdam, one of the European busiest airports at Schiphol, and the major railway terminal in Utrecht. It has a population of seven million which is around 46% of the total Dutch population on 26% of the country's land area, making it one of the most densely populated areas in Europe. The region hosts a wide range of economic activities with 45% of total employment and accounts for a significant share of the Dutch economy with nearly half of the total Dutch GDP generated. Due to its affluence of employment opportunities and limited land area, the Randstad region faces a strong housing demand with 15% at any growth rate and, if rapid growth should occur, even 30% of the current housing supply (van der Burg and Vink, 2008). Such a high competition on the demand side of the housing market makes the Randstad region the most vibrant housing market in The Netherlands.

Figure 3.1 The Dutch Randstad Region



Source: van der Burg and Vink, 2008

The housing transactions in our dataset span a period from 1997 to 2007. These transaction data are collected by the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) which represent approximately 70% of total housing transactions in the Dutch housing market in recent years. The NVM transaction database has also been applied by Francke and Vos (2004) and Theebe (2004), where they control for the spatial dependence in addressing different issues in the Dutch housing market. Francke and Vos (2004) modeled spatial dependence among housing clusters or neighborhoods by spatial error structure with submarket dummy variables in the study of house price index construction. Theebe (2004) adopted the SAR model to control for spatial dependence in the analysis of the impact of traffic noise on house prices.

After removing transactions with missing or unreliable attributes' values, we have access to 437,734 housing transactions, which is one of the largest real estate working dataset in the existing literature. Moreover, our dataset is very comprehensive in its coverage of housing structural attributes and related information. Specifically, as shown in Table 3.1, for each transaction, we have information on the transaction price, transaction date, exact location, housing quality, housing attributes, and the submarket, to where it belongs. The submarkets are classified on the basis of any region where at least 80% of the moving taking place within itself. This definition of the submarket takes into account the substitutability or homogeneity of houses with respect to their attributes within each submarket as well as consumer tastes and preferences which are normally clustered as well and influenced by unobservable demand side factors. As indicated in Table 3.1, housing transactions in each of the four broker regions exceed 10% of our total observations. Unsurprisingly, these four submarkets, being broker region 34, 42, 46, and 49, include the four largest cities in the Randstad as well as the whole country, which are Amsterdam, Utrecht, The Hague, and Rotterdam respectively. The house type variable provides detailed information regarding the type of transacted owner occupied dwellings. Houses are classified into 5 different categories from detached house to houses sharing one roof or row house, while apartments are divided into 6 types, ranging from apartments on the ground floor to apartments on the ground floor with front door in the hallway.

Table 3.1 Descriptive Statistics

Panel A - Continuous variables		
Variable	Mean	Standard Deviation
Size in Square Meters	108.73	42.99
Number of Rooms	4.05	1.40
Log Transaction Price	12.09	0.51
Panel B - Yearly Observations		
Year	Proportion in the Sample	Observations
1997	5.4%	23838
1998	7.3%	31744
1999	7.7%	33569
2000	8.3%	36123
2001	9.3%	40609
2002	9.5%	41645
2003	9.6%	41840
2004	10.0%	43770
2005	10.9%	47584
2006	11.2%	48832
2007	11.0%	48180
Panel C - Binary Variable Frequency		
Variable	Proportion in the Sample	Observations
Parking Possibility	18.5%	80930
Lift	13.9%	60665
Attic	14.9%	65064
Living Room with Sunlight	9.9%	43378
Building Year		
1500 to 1905	7.5%	32696
1906 to 1930	16.9%	74136
1931 to 1944	12.2%	53595
1945 to 1959	7.5%	32685
1960 to 1970	12.3%	53804
1971 to 1980	11.7%	51081
1981 to 1990	13.3%	58381
After 1991	18.6%	67353
House / Apartment Type		
Detached House	2.4%	10492
House In Between	30.6%	133960
Schakelwoning	1.1%	4854
Corner House	10.5%	45889
Houses with Shared Roof	4.3%	19031

Table 3.1 continued

Panel C - Binary Variable Frequency		
Variable	Proportion in the Sample	Observations
Ground Level Apartment	7.4%	32229
Non-Ground Level Apartment	15.3%	67099
Maisonnette	4.3%	18795
Front Door In Hall Apartment	14.6%	64000
Galary Apartment	9.0%	39535
Ground Floor With Front Door In Hall	0.4%	1850
House Quality		
Inside Good	89,90%	393600
Outside Good	93.9%	411080
NVM Submarkets Classification		
Broker Region 31	1.8%	8034
Broker Region 32	3.0%	13185
Broker Region 33	4.7%	20767
Broker Region 34	16.1%	70289
Broker Region 35	1.0%	4392
Broker Region 36	3.2%	13968
Broker Region 37	5.2%	22778
Broker Region 38	2.5%	11084
Broker Region 39	3.7%	16198
Broker Region 41	2.5%	10870
Broker Region 42	10.4%	45649
Broker Region 44	1.9%	8142
Broker Region 45	3.0%	13314
Broker Region 46	18.8%	82201
Broker Region 47	2.1%	9004
Broker Region 48	1.8%	7832
Broker Region 49	13.0%	56798
Broker Region 50	0.5%	2170
Broker Region 51	1.7%	7514
Broker Region 52	3.1%	13545

We have applied aggregation over the domain of some categorical variables in the creation of dummies due to limited observations within some detailed classifications. For instance, there are nine different descriptions of housing maintenance status ranging from “bad” to “excellent”. Since there are very few observations with bad or excellent inside and outside maintenance, we create only "good" or "bad" housing quality indicator variables through aggregating from "excellent" to "reasonable" and from "below reasonable" to "bad" respectively. After the transformation, there are around 90% of total observations having good interior and exterior. The same reasoning applies to the transformation of other variables as well, such as "parking possibility" and "living room with sunlight".

3.4.2 Estimation Results

In our empirical analysis, we estimate the unrestricted STAR model as in (3.5), and X matrix is structured as $X = \begin{pmatrix} D_S & \tilde{X} \end{pmatrix}$, where D_S is a $n \times i$ matrix storing submarket dummies, and $\tilde{X}$ is a $n \times j$ matrix of housing structural attributes. We specify the OLS hedonic regression and estimate

$$\log(\text{Price}) = \alpha + \sum_{i=1}^{I} D_{S,i}\gamma_i + \sum_{j=1}^{J} \tilde{X}_j \beta_j + \epsilon \qquad (3.9)$$

where we explain the variation of $n \times 1$ log(transaction price) using J housing structural attributes represented by $n \times 1$ vectors of $\tilde{X}_j$ while controlling for spatial heterogeneity via the inclusion of I submarket dummy variables $D_{S,i}$ with broker region 31 as the base case. For building year dummy, we use houses built between 1500 and 1905 as the base, and, for dwelling type dummy, detached house serves as the base. In addition, to control for the possibility of nonlinear relationship between the log price and size and number of rooms, we add size squared and number of rooms squared into the regression.

Our main goal of this chapter is to examine the prediction performance of the STAR model as compared to the traditional hedonic pricing model. Before our prediction exercise, we first perform analysis based on both models using the full annual sample from 1997 to 2007 to examine their descriptive power. For the sake of space, we present only one example result for the year 1997 in Table 3.2.[11] Moreover, since we include the submarket dummies as control variables for spatial heterogeneity, we do not report them in the table. The reported standard errors are heteroskedastic robust standard errors following White (1980). We first turn to the OLS results. For the OLS model as a whole, the explanatory

[11] Results for other years are available upon request.

power is satisfactory with R squared over 77%. For 1997, one square meter increase in the size of the dwelling will cause the transaction price to rise by roughly 1.3% and the effect is statistically significant. With the coefficient of the size squared term is zero, it seems that the log linear relationship between the log transaction price and size is adequate for this transaction sample. Having a lift in the building will positively affect the transaction by approximately 1.3%, which is reasonable since people are willing to pay for convenience in their living surroundings. Both the number of rooms and its squared term do not have a significant impact on the housing transaction prices. The building year of the dwellings, on the other hand, is an important factor in explaining house price variations. With reference to houses built prior to 1905, all houses built in other years except after 1991 are transacted with a lower price. This is a bit confusing if we take the building year as a benchmark for housing depreciation, and we would expect the oldest houses trading with a significant discount. Our findings seem to suggest that other omitted quality variables which are highly correlated with building time cause such offsetting effects. For example, houses built long time ago may have been artistically designed and decorated which are appreciated nowadays. Generally, relative to the base case, houses built between 1960 and 1970 are the cheapest in the market, while modern constructions are traded with significant premium.

As expected, dwelling types also significantly influence the transaction prices. The detached houses, which serve as the base case, are the most expensive in the market. This makes perfect sense since detached houses are normally associated with garden and spacious parking, which become a luxury in highly concentrated urban areas with mostly apartment buildings. Moreover, the building costs are high for detached houses as well which naturally lead to higher transaction prices. Comparing with other house types, normal apartments, which are not on the ground floor, are the cheapest. It is a bit puzzling to find a negative sign of the attic dummy, since having an attic provides convenience for storage purposes which should have added value. However, if such utility is not valued, for instance, due to poor design with multiple storage possibilities within the dwelling, or such storage function needs to be shared with others in the case of apartment buildings, we would find a negative effect of having an attic on house prices, which seems likely to be the case here. Unsurprisingly, having a sun-through living room increases the house value, and the same holds for good maintenance for both the interior and exterior of the dwelling. Parking possibility is valued at 9.4% of the house value, which is quite significant. Nonetheless, it seems reasonable if we take into account the high population density within the Randstad region.

Next, we turn to the estimation results of the STAR model. We do not report coefficients of TX, SX, STX, and TSX, which are estimated through our specification of the autoregressive process of the hedonic error terms, but do not have a straightforward interpretation as the OLS coefficients (Nappi-Choulet and Maury, 2009). A first look at the STAR model results reveal much better in-sample fit with R squared over 87% as compared with less than 78% for the traditional hedonic model. Since we control for spatial heterogeneity in both models using dummies of submarkets defined by real estate brokers, it seems to suggest the existence of spatial and temporal dependence within housing transactions, which contribute to explaining house price variations. Most of the signs of coefficients are consistent with our findings using the OLS model. However, there are few notable exceptions. First, the effect of the number of rooms becomes significant, and its squared term is able to capture the nonlinear relationships between the number of rooms and log transaction price. Second, the order of the impact of building year on the transaction price is changed. In the OLS model, where error terms are taken as independent, we find houses with building year prior to 1905 are the second most expensive in the housing market next to the most recent constructions. This is no longer the case once we incorporate the spatial and temporal dependence in the housing transactions. The STAR model results show that houses built after 1971 are more expensive as compared with older houses. Overall, neglecting the error correlation in the OLS model leads to larger estimates of the effect of housing construction period on the transaction prices. Third, having an attic is no longer significantly affecting the house prices as compared to the puzzling finding using the OLS model.

We now focus on the spatial and temporal dependence parameter estimates as well as their interactions. All of these parameter estimates are statistically significant, with the spatial dependence parameter ϕ_S exhibiting the greater magnitude than the temporal dependence parameter ϕ_T. The statistical significance of the interaction terms TS and ST suggests

Table 3.2 Example Result for Year 1997

Year 1997	OLS Model		STAR Model	
Structural Variable	Coeff.	SE	Coeff.	SE
Size	0.013**	0.0003	0.009**	0.0002
Size Squared	0.000	0.000	0.000	0.000
Lift	0.013**	0.006	0.040**	0.004
NRooms	0.013	0.007	0.072**	0.005
NRooms Squared	0.000	0.001	-0.005**	0.001
Age1906 to 1930	-0.104**	0.008	-0.035**	0.006
Age1931 to 1944	-0.117**	0.008	-0.009	0.006
Age1945 to 1959	-0.127**	0.009	-0.033**	0.007
Age1960 to 1970	-0.171**	0.008	-0.039**	0.006
Age1971 to 1980	-0.123**	0.008	0.019**	0.006
Age1981 to 1990	-0.029**	0.008	0.104**	0.006
After 1991	0.070**	0.008	0.193**	0.006
House In Between	-0.332**	0.013	-0.337**	0.011
Schakelwoning	-0.232**	0.016	-0.226**	0.013
Corner House	-0.294**	0.013	-0.296**	0.011
Houses With One Roof	-0.169**	0.013	-0.177**	0.011
Ground Level	-0.367**	0.015	-0.398**	0.013
Non Ground Level	-0.432**	0.015	-0.474**	0.013
Maisonnette	-0.387**	0.015	-0.451**	0.012
Front Door In Hall	-0.373**	0.014	-0.458**	0.012
Galary	-0.392**	0.014	-0.469**	0.012
Ground Front Door In Hall	-0.359**	0.034	-0.340**	0.027
Attic	-0.018**	0.004	0.002	0.003
Living Room Sun	0.017**	0.004	0.012**	0.003
Inside Good	0.099**	0.006	0.104**	0.004
Outside Good	0.107**	0.007	0.076**	0.005
parking	0.094**	0.004	0.085**	0.003
$ø_T$			-0.162**	0.038
$ø_S$			0.875**	0.005
$ø_{ST}$			-0.110**	0.039
$ø_{TS}$			0.469**	0.049
R Squared	0.777		0.877	
Loglik	-82420		-75425	
k	47		235	
F Statistic			101	
ρ			0.75	

** Statistically significant at 5% level their significant impact on the house price determination process. For our 1997 transaction data, the large magnitude of ϕ_{TS}, as compared to ϕ_{ST}, implies the need to filter space first and subsequently for time and not vice versa, contrary to the findings in Pace et al. (1998) and Pace et al. (2000). A priori, if there is no spatial and temporal dependence in housing transactions such that $\phi_S = \phi_T = \phi_{ST} = \phi_{TS} = 0$, the STAR model would be reduced to the OLS model. We perform a F-test on the joint significance of the spatial and temporal dependence parameter estimates in the STAR model, and the large F statistic in Table 3.2 clearly rejects the null hypothesis that these dependence terms are jointly zero. This confirms the existence of both the spatial and temporal dependence in the Randstad housing market.

Our STAR model results implicate the necessity to take into account the previous neighboring transactions in determining the value of the current house in the Randstad region. Our finding of large spatial dependence parameter, which is 0.875, is consistent with those found in other studies being 0.811 in Pace et al. (1998), 0.886 in Pace et al. (2000), and above 0.9 in Militino et al. (2004). On the contrary, Nappi-Choulet and Maury (2009) found the spatial dependence coefficient to be 0.5 in Paris office market. It seems to indicate that the residential housing market exhibits stronger spatial dependence than that in the office market. As compared to the spatial dependence parameter, the temporal parameter is of relatively smaller magnitude. This is not surprising, since part of the temporal effect has been absorbed through the specification of the spatial weighting matrix with implicit temporal structure where only previously sold neighbors are considered. In other words, the explicit temporal ordering in the spatial weighting matrix dampens the temporal effect which is supposed to be captured through the specification of the temporal weighting matrix.

Table 3.3 presents the summary of estimation results using full annual sample for other years from 1998 to 2007. For all the other years, we find large spatial dependence coefficients, all of which are larger than that in 1997. This consistent finding reinforces our earlier conclusion that it is necessary to take into account the previous neighboring transactions in pricing the current house in the Randstad housing market. The temporal dependence parameter estimates, on the other hand, exhibit much greater variations over time as compared to the spatial dependence parameter estimates, ranging from -0.209 in 2004 to 0.289 in 1999, which seems to suggest that the temporal heterogeneity is more relevant to the temporal dependence parameter than to the spatial dependence parameter. We find the optimal spatial decay parameter ρ is not constant over time, but concentrated between 0.75 and 0.8, which are in line with Pace et al. (1998) and Pace et al. (2000). With respect to the standard error of the regression, the STAR model outperforms the OLS model in terms of in-sample fit during our entire sampling period in a consistent manner. The STAR model, on average, reduces the regression standard error by 27% relative to the alternative OLS model.

Table 3.3 Summary of Estimation Results from 1998 to 2007

This table shows the results of in-sample estimates using full sample. We do not report the coefficients of housing attributes here but only the parameters of interest.

	1998		1999		2000		2001		2002	
	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR
$ø_T$		0.088		0.289		0.007		-0.071		-0.069
$ø_S$		0.900		0.901		0.890		0.883		0.878
ρ		0.75		0.75		0.75		0.75		0.75
SE	0.230	0.164	0.252	0.179	0.245	0.178	0.227	0.163	0.215	0.159
	2003		2004		2005		2006		2007	
	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR
$ø_T$		-0.084		-0.209		-0.045		-0.158		-0.163
$ø_S$		0.890		0.896		0.892		0.933		0.933
ρ		0.75		0.75		0.80		0.80		0.75
SE	0.206	0.155	0.215	0.159	0.225	0.172	0.231	0.168	0.234	0.163

In addition to examining the in-sample fits using annual full sample as shown in Table 3.2 and Table 3.3, we also undertake one-step ahead forecast for both the OLS model and the unrestricted STAR model (3.5) as in Pace et al. (1998) and Pace et al. (2000). It is to note that the one-step ahead forecast is essentially a robustness check of the in-sample fits using a subset of the full sample.[12] Specifically, for every year, we use the first 30%, 60% and

[12] See, for example, Plackett (1950).

90% of all temporally ordered observations respectively as the in-sample to start one-step ahead forecast for the next 500 observations. The one-step ahead forecast results are summarized in Table 3.4, Table 3.5 and Table 3.6 in the Appendix, which consistently demonstrate better in-sample fits of the STAR model relative to the OLS model.

3.4.3 Prediction Results

Our previous analysis demonstrates satisfactory performance of the STAR model relative to the OLS model in terms of in-sample fits. However, what matters more in practice is not how well a model is capable of describing the past, but rather how the model is going to improve our prediction accuracy into the future. Therefore, our main goal is to examine if the STAR model adds to the prediction power relative to the OLS model in predicting future house values. The prediction exercise is performed using first 80% of temporally sorted housing transaction as in-sample, and other 20% as the out-of-sample.

Table 3.7 summarizes the prediction results for every individual year from 1997 to 2007 obtained using the OLS model, and the unrestricted STAR model respectively. The prediction performance is evaluated using the mean absolute error, the median absolute error, the mean squared error (MSE) and the root mean squared error (RMSE) criterion. All of these criteria penalize prediction error in both directions in the prediction error distribution.

On the basis of mean absolute prediction error, the STAR model consistently outperforms the OLS model. On average, the STAR model reduces the OLS mean absolute prediction error by 27.6%. Relative to the OLS model, the best prediction outcome of the STAR model is found to be in 1999 with 32.4% decline in the OLS mean absolute prediction error. For the STAR model, 1998 corresponds to the year with the smallest reduction, which is 22.3%, in the OLS mean absolute prediction error. These findings indicate that the incorporation of both the spatial and temporal dependence in the traditional hedonic price model pays off in obtaining more accurate prediction of future housing values.

We explore further into other prediction performance measures to check the consistency of our findings. For all the years in our sampling period, the STAR model is capable of reducing the standard deviation of the prediction error which is measured by RMSE substantially as compared to the OLS model, ranging from a drop of 21.5% in 1998 to 27% in 2000. On average, the RMSE for the OLS model is 0.23, and is 0.17 for the STAR model. The OLS model produces much larger variation of the prediction error which is between 0.204 and 0.274 than that generated using the STAR model which falls within the range of 0.158 and 0.2. The mean reduction of the prediction error variation using the STAR relative to the OLS model is around 24.2%. Prediction performance based on the median absolute error also favors the STAR model over the OLS model. The average median prediction error for the OLS model is 0.134 as compared to that of the STAR model, which is 0.094.

Overall, our main prediction exercise illustrates that integrating both the spatial and temporal dependence among housing transactions in the empirical analysis is not only a warranted theoretical concept but also contributing to a better prediction outcome of future house values. It is to note that our findings run counter to Bourassa et al. (2007) which favors the OLS model over the spatial on the basis of their prediction outcome. This may be attributed to the amount of information used in undertaking house price prediction. In their prediction exercises, they only utilize the in-sample parameter estimates, and do not explore the information contained in spatial weighting matrices. On the contrary, we do not only use the in-sample parameter estimates, but also take into account the spatial and temporal weighting matrices in making out-of-sample predictions.

We undertake two robustness checks of our main prediction results. In the first robustness check, we include an alternative specification of submarkets defined by postcode areas in the OLS model and repeat our main prediction exercise to examine if our prediction results are sensitive to a different and more refined submarket definition. The results are incorporated in Table 3.7. It is interesting to note that the prediction performance of the OLS model including submarkets defined by postcode areas is better than that of the OLS model using experience based submarket definitions, which is consistent across the entire sampling period. It suggests that, at least for the Dutch Randstad housing market, using

Table 3.7 Main Prediction Results

After temporal ordering of housing transactions, using the first 80% as the in-sample and 80%-100% as the out-of-sample.

Prediction Error	1997			1998			1999			2000		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1732	0.1256	0.1539	0.1824	0.1418	0.1489	0.2024	0.1369	0.1537	0.1854	0.1303	0.1453
Median |error|	0.0164	0.0226	0.1134	0.0570	0.0792	0.1141	0.0780	0.0280	0.0542	0.0415	0.0307	0.0395
MSE	0.0533	0.0297	0.0449	0.0565	0.0348	0.0404	0.0749	0.0401	0.0558	0.0598	0.0317	0.0405
RMSE	0.2310	0.1722	0.2119	0.2376	0.1866	0.2011	0.2737	0.2002	0.2363	0.2446	0.1781	0.2013
N(Postcode Regions)			246			319			321			367

Prediction Error	2001			2002			2003			2004		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1662	0.1201	0.1350	0.1544	0.1157	0.1274	0.1555	0.1169	0.1276	0.1613	0.1176	0.1268
Median |error|	0.0201	0.0019	0.0998	0.0019	0.0143	0.0969	0.0084	0.0133	0.0965	0.0092	0.0110	0.0956
MSE	0.0487	0.0273	0.0355	0.0418	0.0249	0.0301	0.0436	0.0267	0.0309	0.0484	0.0293	0.0329
RMSE	0.2207	0.1653	0.1884	0.2046	0.1576	0.1735	0.2088	0.1635	0.1757	0.2199	0.1712	0.1813
N(Postcode Regions)			359			368			381			379

Prediction Error	2005			2006			2007		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1635	0.1193	0.1266	0.1721	0.1231	0.1299	0.1759	0.1204	0.1310
Median |error|	0.0122	0.0164	0.0929	0.0157	0.0296	0.0985	0.0100	0.0157	0.0961
MSE	0.0506	0.0310	0.0349	0.0545	0.0307	0.0347	0.0576	0.0319	0.0375
RMSE	0.2250	0.1761	0.1868	0.2334	0.1753	0.1863	0.2400	0.1786	0.1936
N(Postcode Regions)			400			409			409

submarket defined by real estate professionals performs worse in terms of predicting future house value than the alternative submarket definition of postcode areas. However, the STAR model consistently out-performs the OLS model including postcode submarket dummies for all the years from 1997 to 2007. In general, our first robustness check implies that including more refined postcode submarket dummies within the OLS model reduces the effect of spatial dependence among housing transactions within the Randstad region in predicting future house values to a certain extent. Accounting for spatial dependence among housing transactions is still a valid exercise for a better prediction outcome.

In the second robustness check, we check if our prediction results are driven by different in-sample and out-of-sample specifications. First, we alter the out-of-sample used for prediction. We split the original 80% - 100% out-of-sample into two out-of-samples containing 80% - 90% and 90% - 100% of total temporally ordered yearly observations. The results are shown in Table 3.8 and Table 3.9 in the Appendix. The out-performance of the STAR model in the predicting future house values relative to both OLS models with different submarket proxies is confirmed using both out-of-samples on the basis of all three evaluation criterion. Second, we focus on the in-sample specification. We extend our in-sample from using the first 80% of all yearly observations with temporal ordering to using the first 90% of all observations. Prediction performance is evaluated using 90% - 100% of all observations out-of-sample.

Table 3.10 in the Appendix presents the results. Again, the STAR model demonstrates better performance in house value prediction relative to both OLS models. In sum, our second robustness check results reinforce our earlier findings regarding the better prediction ability of the STAR model which are not driven by the specifications of either out-of-sample or in-sample.

3.4.4 A Parsimonious Model and House Price Index Construction

As a natural application that exploits the better predictive power of the STAR model, we extend our analysis into the house price index construction. For practical purposes, we need to search for a parsimonious model that balances the performance and the reduction of dimensionality.

In light of the discrepancy in terms of the magnitude and consistency between the spatial and temporal dependence terms as shown in Table 3.11, we examine the performance of a simpler model that only includes the spatial dependence term as compared to the full blown STAR model on the basis of both in-sample fits and out-of-sample predictions. The parsimonious model consists of 94 variables relative to 235 variables in the STAR model. As shown in Table 3.11, the parsimonious model performs satisfactorily though marginally worse in terms of the in-sample fits than that of the STAR model across all the individual years in our sampling period as expected. However, the performance of the parsimonious model in terms of out-of-sample prediction power is better than that of the STAR model for most of the years in our sampling period except 2000 and 2004. Overall, the reduction of dimensionality and the increase of the degrees of freedom of the parsimonious model loses its in-sample fits, but gains in out-of-sample predictions.

Table 3.11 Performance of the Parsimonious Model

This table shows the performance of the parsimonious model for both the in-sample fits and the out-of-sample prediction. The out-of-sample prediction is performed using the first 80% of temporally ordered yearly housing transactions as the in-sample and the remaining 20% as the out-of-sample.

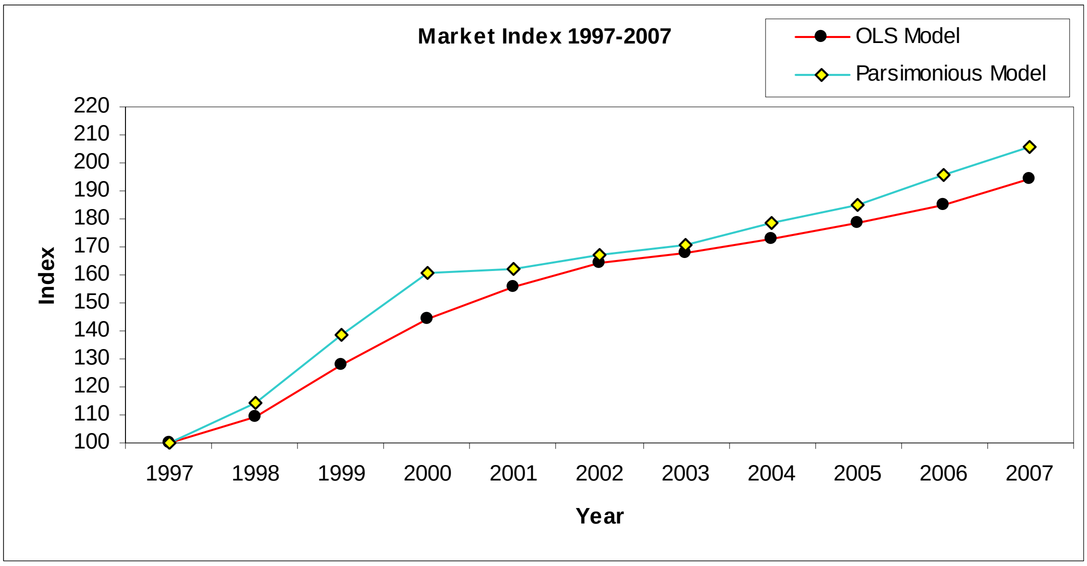
	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
In-sample R Squared											
Parsimonious Model	0.8752	0.8742	0.8734	0.8740	0.8828	0.8809	0.8808	0.8803	0.8619	0.8790	0.8917
STAR Model	0.8766	0.8763	0.8765	0.8780	0.8836	0.8814	0.8814	0.8808	0.8624	0.8797	0.8923
Out-of-sample RMSE (80% In-Sample and 80% - 100% Out-of-Sample)											
Parsimonious Model	0.1717	0.1690	0.1987	0.2077	0.1651	0.1573	0.1627	0.1716	0.1755	0.1730	0.1781
STAR Model	0.1722	0.1866	0.2002	0.1783	0.1653	0.1576	0.1635	0.1712	0.1761	0.1753	0.1786

We construct the market house price index following a two-step procedure as follows. First, we randomly sample 1,000 properties from transactions within 1997. Second, we predict each of the 1,000 properties in our random sample on the basis of the parsimonious model (3.10) at the end of each year in our sampling period,

$$\hat{Y}_t = \hat{\alpha} + X\hat{\beta}_1 + \hat{\phi}_S S_t X\hat{\beta}_2 + \hat{\phi}_S S_t Y_t \tag{3.10}$$

where $\hat{Y}_t$ is the predicted log house price at the end of each year, and S_t is the spatial matrix storing the updated spatial neighbors of the predicted house with the reference point at the end of each year. The house price index is constructed through chaining the average predicted price changes of the properties in the random sample. Figure 3.2 demonstrates the market price indices built using both the parsimonious model and the OLS model. As expected, the OLS market index exhibits less volatility relative to the market index constructed using the parsimonious model. This is largely attributed to the fact that, in addition to the updating of the estimated structural parameters in predicting the property value in the random sample as the case for the OLS model, the parsimonious model also updates the spatial weighting matrix storing the spatial neighbors on a yearly basis. Since the spatial neighbors of a particular property differs from one year to another, the standard deviation of the rate of price change in the random sample is larger for the parsimonious model than that for the OLS model.

Figure 3.2 Market House Price Index



In terms of the index level, the OLS model reports smaller index numbers relative to the parsimonious model across the years. As demonstrated above, the better predictive power of the parsimonious model implicates consistent understatement of the housing market price development that is derived using an OLS model for the period from 1997 to 2007. Through dividing our random sample on the basis of location and property type, we construct local house price indices as well as price indices for different property types using the parsimonious model. For the local indices, we report house price indices for four broker regions that include the four largest cities in the Randstad.[13] These indices are shown in Figure 3.3 and 3.4 in the Appendix. Among the four local indices, broker region 34, where Amsterdam is included, has experienced much more volatile house price development over the period from 1997 to 2007, as compared to other three broker regions. Moreover, it is also the region that has enjoyed the largest price increase within the 10-year period. In view of the price indices by property type, the price development for apartment is the largest and the least volatile among five property types. To a great extent, there is synchronization of the price indices between the row and the corner houses, and between the detached and the semi-detached houses, which demonstrates substitutability between these two pairs of property type.

It is to note that one should not over-emphasize and generalize the house price indices produced using only one random draw to obtain a sample of properties to represent the entire Randstad housing market as shown in this chapter. If one is interested in the reliability of the house price indices produced above, which is not a focal point of this chapter, multiple random sampling of housing transactions will make it possible to establish confidence bounds around these index numbers.

3.5 Conclusion

This chapter studies the impact of accounting for error correlations within the setup of traditional hedonic price model on predicting future house prices using a large non-U.S. housing transaction dataset. We follow the STAR model in Pace et al. (1998) which

[13] Broker region 34 includes Amsterdam. Broker region 42 includes Utrecht. Broker 46 includes The Hague. Broker region 49 includes Rotterdam.

subsumes the errors in the hedonic regression following an autoregressive process. Both the spatial and temporal dependence in the error structure are taken into account via explicit incorporation of spatial and temporal weighting matrices and their interactions. We control for spatial heterogeneity using experience-based definition of submarkets, and for temporal heterogeneity through performing analysis on an annual basis. Moreover, in our prediction exercise, we recognize the temporal nature in the housing market, and integrate the information contained in both the spatial and temporal neighbors in predicting the future house values. As a natural extension, we exploit our findings in the context of house price index construction.

Our results indicate the existence of both the spatial and temporal dependence in the Randstad housing market. Moreover, the spatial dependence is of much larger magnitude as compared to the temporal dependence, which is consistent over all the individual year during our sampling period. This finding is comparable to a number of previous spatial studies using housing transaction data from other countries, such as the U.S. and Spain. Our prediction results show better prediction capability of the STAR model relative to the OLS model, which are robust to alternative specifications of in-sample as well as out-of-sample. Therefore, it is necessary to correct for both the spatial and temporal dependence among housing transactions in the empirical applications of the hedonic pricing model for predictive purposes. Examining the consequence of exploiting the better predictive power of the STAR model in constructing house price indices on the basis of single random sample of housing transactions used to represent the overall Randstad housing market, we show that the OLS index consistently understates the more accurate house price development as captured using the parsimonious model.

Our results have implications in practice if the aim is to produce better forecast of house values, and accounting for the effect of both the spatial and temporal dependence among housing transactions can substantially reduce the prediction error. In addition to constructing house price indices, this is relevant to, for example, banks providing mortgage which need to access the associated risk via loan-to-value ratio, and rating agencies to improve the rating accuracy of structured products, such as mortgage backed securities.

Appendix

Table 3.4 One-step Ahead Prediction Result 1

This table shows the results using first 30% observations to start 1-step ahead prediction for the next 500 observations.

Error	1997		1998		1999		2000	
	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR
Mean |error|	0.1555	0.1163	0.1666	0.1238	0.1972	0.1443	0.1898	0.1356
RMSE	0.2074	0.1622	0.2173	0.1688	0.2581	0.1990	0.2555	0.1828
Error	2001		2002		2003		2004	
	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR
Mean |error|	0.1747	0.1223	0.1637	0.1223	0.1525	0.1188	0.1500	0.1082
RMSE	0.2347	0.1691	0.2182	0.1703	0.2110	0.1749	0.1970	0.1453
Error	2005		2006		2007			
	OLS	STAR	OLS	STAR	OLS	STAR		
Mean |error|	0.1636	0.1208	0.1622	0.1206	0.1726	0.1140		
RMSE	0.2147	0.1619	0.2145	0.1670	0.2263	0.1559		

Table 3.5 One-step Ahead Prediction Result 2

This table shows the results using first 60% observations to start 1-step ahead prediction for the next 500 observations.

Error	1997		1998		1999		2000	
	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR
Mean |error|	0.1626	0.1110	0.1751	0.1206	0.1858	0.1236	0.1619	0.1106
RMSE	0.2168	0.1513	0.2278	0.1655	0.2352	0.1616	0.2098	0.1480
Error	2001		2002		2003		2004	
	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR
Mean |error|	0.1820	0.1149	0.1637	0.1033	0.1588	0.1119	0.1524	0.1037
RMSE	0.2466	0.1578	0.2124	0.1400	0.2170	0.1559	0.2027	0.1439
Error	2005		2006		2007			
	OLS	STAR	OLS	STAR	OLS	STAR		
Mean |error|	0.1609	0.1096	0.1656	0.1158	0.1751	0.1113		
RMSE	0.2330	0.1749	0.2437	0.1838	0.2280	0.1466		

Table 3.6 One-step Ahead Prediction Result 3

This table shows the results using first 90% observations to start 1-step ahead prediction for the next 500 observations.

Error	1997		1998		1999		2000	
	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR
Mean |error|	0.1731	0.1102	0.1820	0.1223	0.1879	0.1254	0.1873	0.1120
RMSE	0.2214	0.1439	0.2383	0.1628	0.2404	0.1744	0.2433	0.1546
Error	2001		2002		2003		2004	
	OLS	STAR	OLS	STAR	OLS	STAR	OLS	STAR
Mean |error|	0.1571	0.1130	0.1504	0.1013	0.1561	0.1061	0.1562	0.1030
RMSE	0.2045	0.1552	0.2012	0.1418	0.2166	0.1568	0.2229	0.1637
Error	2005		2006		2007			
	OLS	STAR	OLS	STAR	OLS	STAR		
Mean |error|	0.1607	0.1064	0.1737	0.1028	0.1673	0.1106		
RMSE	0.2207	0.1581	0.2207	0.1396	0.2447	0.1871		

Table 3.8 Robustness Check of Different Out-of-Sample 1

After temporal ordering of housing transactions, using the fist 80% as the in-sample and 80% - 90% as the out-of-sample

Prediction Error	1997			1998			1999			2000		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1736	0.1274	0.1541	0.1828	0.1412	0.1470	0.2037	0.1375	0.1506	0.1855	0.1316	0.1452
Median |error|	0.0218	0.0246	0.1157	0.0557	0.0820	0.1138	0.0750	0.0313	0.0000	0.0429	0.0295	0.0368
MSE	0.0529	0.0294	0.0437	0.0571	0.0331	0.0401	0.0769	0.0417	0.0543	0.0610	0.0329	0.0407
RMSE	0.2300	0.1714	0.2091	0.2390	0.1818	0.2002	0.2773	0.2043	0.2329	0.2469	0.1815	0.2016
N(Postcode Regions)			246			319			321			367

Prediction Error	2001			2002			2003			2004		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1667	0.1188	0.1351	0.1550	0.1168	0.1280	0.1536	0.1173	0.1274	0.1605	0.1182	0.1266
Median |error|	0.0229	0.0012	0.1017	0.0009	0.0153	0.0973	0.0053	0.0131	0.0955	0.0141	0.0097	0.0948
MSE	0.0482	0.0259	0.0349	0.0420	0.0257	0.0303	0.0431	0.0274	0.0315	0.0470	0.0284	0.0318
RMSE	0.2195	0.1609	0.1867	0.2048	0.1602	0.1741	0.2077	0.1655	0.1775	0.2169	0.1684	0.1782
N(Postcode Regions)			359			368			381			379

Prediction Error	2005			2006			2007		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1616	0.1191	0.1269	0.1704	0.1212	0.1287	0.1761	0.1203	0.1309
Median |error|	0.0113	0.0168	0.0941	0.0168	0.0301	0.0987	0.0083	0.0136	0.0949
MSE	0.0488	0.0306	0.0345	0.0534	0.0299	0.0340	0.0583	0.0315	0.0378
RMSE	0.2209	0.1749	0.1858	0.2311	0.1728	0.1843	0.2416	0.1774	0.1943
N(Postcode Regions)			400			409			409

Table 3.9 Robustness Check of Different Out-of-Sample 2

After temporal ordering of housing transactions, using the first 80% as the in-sample and 90%-100% as the out-of-sample.												
Prediction Error	1997			1998			1999			2000		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1728	0.1237	0.1536	0.1821	0.1425	0.1507	0.2011	0.1362	0.1568	0.1852	0.1290	0.1455
Median |error|	0.0116	0.0196	0.1104	0.0595	0.0765	0.1145	0.0816	0.0257	0.0542	0.0402	0.0316	0.0421
MSE	0.0538	0.0300	0.0461	0.0558	0.0366	0.0408	0.0730	0.0384	0.0574	0.0587	0.0304	0.0406
RMSE	0.2319	0.1731	0.2146	0.2362	0.1912	0.2019	0.2702	0.1960	0.2396	0.2423	0.1745	0.2014
N(Postcode Regions)			246			319			321			367
Prediction Error	2001			2002			2003			2004		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1657	0.1213	0.1349	0.1539	0.1146	0.1268	0.1575	0.1166	0.1277	0.1620	0.1169	0.1269
Median |error|	0.0166	0.0038	0.0986	0.0054	0.0137	0.0967	0.0125	0.0136	0.0979	0.0031	0.0121	0.0966
MSE	0.0492	0.0287	0.0361	0.0417	0.0240	0.0299	0.0440	0.0261	0.0302	0.0497	0.0303	0.0340
RMSE	0.2218	0.1695	0.1900	0.2043	0.1550	0.1729	0.2098	0.1615	0.1739	0.2230	0.1740	0.1843
N(Postcode Regions)			359			368			381			379
Prediction Error	2005			2006			2007					
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)			
Mean |error|	0.1654	0.1195	0.1263	0.1738	0.1250	0.1310	0.1757	0.1205	0.1310			
Median |error|	0.0127	0.0158	0.0918	0.0151	0.0290	0.0982	0.0121	0.0175	0.0972			
MSE	0.0524	0.0315	0.0352	0.0556	0.0316	0.0354	0.0568	0.0323	0.0372			
RMSE	0.2289	0.1774	0.1877	0.2358	0.1778	0.1883	0.2384	0.1799	0.1929			
N(Postcode Regions)			400			409			409			

Table 3.10 Robustness Check of Different In-Sample

After temporal ordering of housing transactions, using the first 90% as the in-sample and 90%-100% as the out-of-sample.

Prediction Error	1997			1998			1999			2000		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1713	0.1222	0.1493	0.1803	0.1280	0.1477	0.1981	0.1382	0.1160	0.1845	0.1273	0.1444
Median |error|	0.0118	0.0157	0.1076	0.0524	0.0308	0.1135	0.0725	0.0399	0.0083	0.0346	0.0246	0.0378
MSE	0.0525	0.0297	0.0438	0.0549	0.0307	0.0394	0.0712	0.0392	0.0459	0.0584	0.0307	0.0401
RMSE	0.2291	0.1723	0.2093	0.2344	0.1753	0.1986	0.2668	0.1981	0.2141	0.2417	0.1752	0.2003
N(Postcode Regions)			266			336			341			367
Prediction Error	**2001**			**2002**			**2003**			**2004**		
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)
Mean |error|	0.1653	0.1227	0.1329	0.1535	0.1131	0.1259	0.1573	0.1156	0.1262	0.1620	0.1160	0.1242
Median |error|	0.0146	0.0269	0.0968	0.0040	0.0059	0.0960	0.0116	0.0067	0.0971	0.0023	0.0130	0.0940
MSE	0.0490	0.0289	0.0349	0.0416	0.0237	0.0296	0.0439	0.0252	0.0296	0.0497	0.0300	0.0323
RMSE	0.2215	0.1701	0.1867	0.2039	0.1538	0.1719	0.2096	0.1588	0.1720	0.2229	0.1733	0.1797
N(Postcode Regions)			374			379			395			401
Prediction Error	**2005**			**2006**			**2007**					
	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)	OLS	STAR	OLS (Postcode)			
Mean |error|	0.1652	0.1178	0.1252	0.1737	0.1216	0.1299	0.1756	0.1227	0.1302			
Median |error|	0.0120	0.0116	0.0910	0.0134	0.0167	0.0981	0.0100	0.0315	0.0965			
MSE	0.0523	0.0309	0.0348	0.0555	0.0306	0.0350	0.0568	0.0329	0.0368			
RMSE	0.2287	0.1759	0.1865	0.2355	0.1750	0.1872	0.2383	0.1814	0.1918			
N(Postcode Regions)			412			421			421			

Figure 3.3 Local House Price Indices (Parsimonious Model)

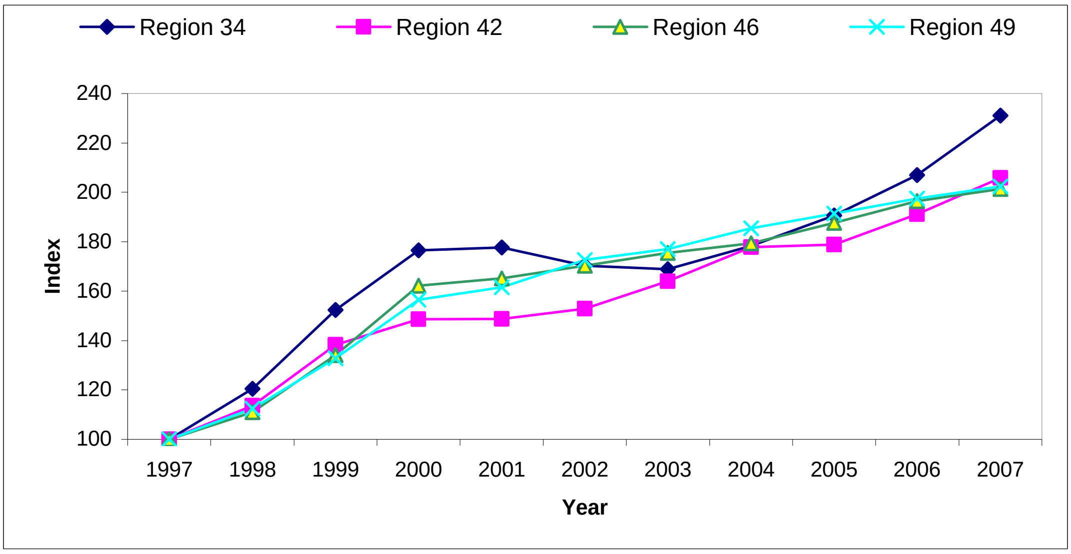
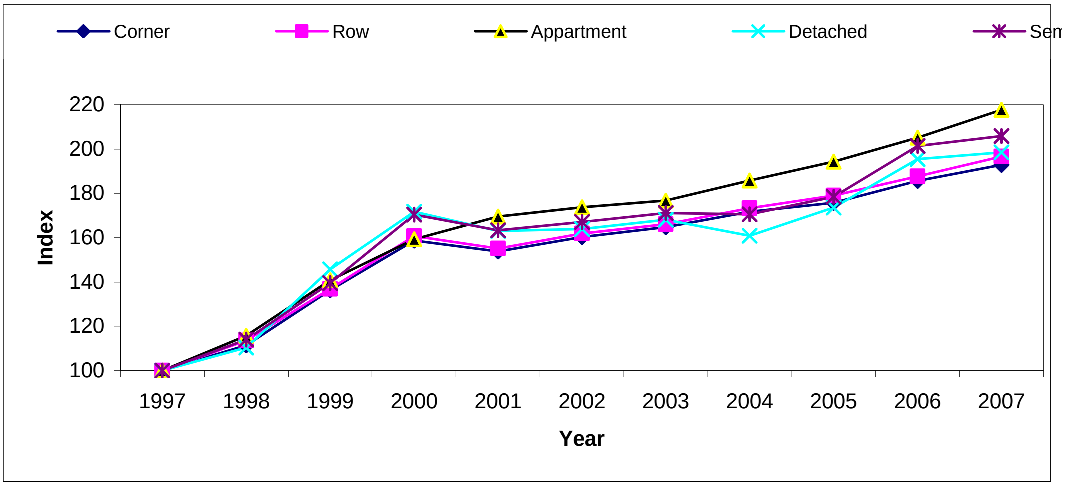


Figure 3.4 House Price Indices by Property Type (Parsimonious Model)



Chapter 4

The Composition of Market Proxy in REITs Risk Premium Estimation

4.1 Introduction

The 1990s marks the boom of real estate investment trusts (REITs) as a popular investment vehicle among both the individual and institutional investors. During this period, both the market capitalization and liquidity of REITs were significantly boosted which sparked the interests among practitioners as well as academics to better understand the risk and return profile of this investment class through applying the standard capital asset pricing model (CAPM) and its multi-factor extensions. As a well defined asset pricing model, CAPM stipulates that investors should only concern about the undiversifiable market risk of their investments other than some ad hoc risk factors. In other words, it is the systematic risk exposure for which investors would be compensated. Therefore, the market risk premium, which is the product of beta and the expected market excess return, provides informative measure of risk exposure that underline the REITs investments. Ex ante, investors can rely on an accurate measure of the market risk premium to make capital budgeting decisions by allocating an appropriate portion of funds into REITs. Ex post, market risk premium is relevant to assessing the performance of REITs investments.

In CAPM theory, the market risk premium is determined by the true market portfolio's expected excess return and the systematic risk of the asset with respect to the market portfolio. The market portfolio is thus the key to an accurate estimation of the market risk premium of a given asset. It also gives beta a sensible interpretation as the systematic risk exposure to “the” market portfolio. By definition, the true market portfolio is unique and should include all investable assets in the asset universe, which is not observable in practice. In consequence, ambiguities exist in the empirical application of CAPM to estimate the market risk premium concerning the appropriate market proxy to use. By far, both the practitioners and the academics seem complacent about using equity indices, such as S&P 500 and CRSP indices, to proxy for the true market portfolio in their empirical works. Using these equity market indices, recent studies have consistently shown that REITs have low betas (Chan et al., 1990; Han and Liang, 1995; Peterson and Hsieh, 1997; Lee et al., 2008). Although these findings seem to confirm the low or moderate market risk compensation of REITs, investors should be wary about the robustness of these results to an alternative specification of a more diversified market portfolio that is more in line with the true market portfolio as prescribed by CAPM theory. There are also established empirical evidence demonstrating that the risk exposures of REITs are beyond equities (Chan et al., 1990; Ling and Naranjo, 1997; Peterson and Hsieh, 1997; Clayton and Mackinnon, 2001, 2003; Lee et al., 2008). In fact, using equity indices alone as market proxy is rather restrictive in the sense that it only captures the asset's risk exposure to the equity market and leaves part of the market risk to remain to be diversified away as the market portfolio becomes more complete that incorporates various assets besides equity. As a result, estimation of the required rate of return to compensate REITs' exposure to the systematic risk is likely to be erroneous, and the omission of asset classes from the market proxy may have lead to the findings that bond and real estate factors contribute to the systematic risk compensation of REITs.[14]

Due to the unobservability of the true market portfolio as dictated in theoretical CAPM, the implication of using equity market proxies in empirical works is not about the exclusion of certain asset classes from the market portfolio per se, rather lies on whether inferences based on CAPM are sensitive to the misspecification of the market portfolio. In the context of REITs market risk premium estimation, it pertains to whether the composition of the market portfolio matters for assessing the riskiness of REITs. This is a critical issue to investors who are prone to misallocation of funds and erroneous performance evaluation due to misstated riskiness underlying their investments.

[14] See, for example, Chan et al. (1990), Ling and Naranjo (1997), Clayton and MacKinnon (2001), Lee et al. (2008).

The purpose of this chapter is to address this issue by constructing a more comprehensive market portfolio that incorporates not only equity but also fixed income securities and real estate, and test if the REITs market risk premium estimation is sensitive to market portfolio composition. It is to note that we do not attempt to build an exhaustive market portfolio in this chapter that ultimately includes all asset classes, but rather identify a broader market proxy than the restrictive equity market proxy for our testing purpose. Our findings include that REITs betas are significantly increased when a more diversified market portfolio is used, indicating REITs are not as conservative as investors perceive them in terms of their systematic risk exposure with respect to a more diversified market proxy. Moreover, the REITs market risk premium estimation seems sensitive to both the structural break in the REITs market in terms of REITs return as well as market proxy composition. Adding real estate in the market proxy accounts for a significant portion of the bias in the estimation of REITs market risk premium.

The rest of the chapter is organized as follows. Section 4.2 reviews relevant literature. Section 4.3 illustrates the U.S. data used in this study. Section 4.4 discusses the methodology and some estimation issues. An analysis of the results is presented in section 4.5. Section 4.6 concludes.

4.2 Literature Review

As a popular and novel investment vehicle, REITs provide investors with exposure to the real estate market while maintaining a high level of liquidity. Past research, mostly in the field of REITs performance evaluation and REITs risk exposure analysis, has consistently shown that REITs have low market risk exposure that are evidenced by low betas with respect to various equity market proxies. These studies also shed light on the inadequacy of using equity market proxy by showing REITs returns are compensated for their exposures to not only equity market, but also bond and real estate markets. Chan et al. (1990) studied the risk and return on equity REITs (EREITs). They constructed an equally weighted index of 18 to 23 EREITs that were traded on major exchanges over the 1973-1987 period. When equally and value weighted NYSE indices were applied to proxy for the market portfolio, REITs betas were below 0.7 for both cases. When adopting a multi-factor model, they found that REITs returns were compensated for the exposure to credit risk, term structure, and unexpected inflation. However, their results suffered from using a small sample of survivor REITs.

Peterson and Hsieh (1997) studied risk exposures of REITs using the monthly returns of a value weighted REITs portfolio from 1976 to 1992. Applying the NYSE/ASE/NASDAQ monthly value weighted index as the market proxy, they found the betas of equity and mortgage REITs to be equal to 0.62 and 0.70 respectively. Moreover, they showed that, besides the market portfolio, risk premiums on equity REITs can be explained by size and book-to-market equity factors in common stock return, and risk premiums on mortgage REITs are related to bond market factors.

Clayton and MacKinnon (2001) analyzed the time varying nature of the link between REITs, real estate and other financial assets. They employed multi-factor model which included stock, bonds, and real estate factors. Using quarterly data from 1978 to 1998, they illustrated REITs risk exposure to large and small cap stocks, bonds and real estate. Moreover, their results also showed the asymmetric nature of REITs during different market conditions. As an extension of this study, Clayton and MacKinnon (2003) demonstrated that the REITs market went from being driven largely by the same economic factors that drive large cap stocks through the 1970s and 1980s to being more strongly related to both the small cap stocks and real estate related factors in 1990s.

Lee et al. (2008) studied the real estate risk exposure of equity REITs by applying the multifactor model which included Fama-French stock and bond factors (Fama and French, 1993) plus a real estate factor proxied by Russell-NCREIF property index. They showed that the beta of NAREIT equity REITs index on value weighted CRSP index covering the period from 1978 to 2003 was below 0.6. Their results confirmed that REITs had risk exposure to unsecuritized real estate market.

A number of studies documented the asymmetric nature of REITs beta with respect to stock market portfolio that REITs betas were lower during the boom than other market circumstances (Sagalyn, 1990; Goldstein and Nelling, 1999; Chatrath et al., 2000). Sagalyn

(1990) examined the risk and return performance of both the securitized and unsecuritized real estate for the period 1973 to 1987. Using quarterly return data on a portfolio of REITs, she found REITs beta was around 0.8 with reference to S&P 500 index. Her results also indicated the time dependence of REITs beta during the business cycle. REITs beta was high (1.16) during GNP low growth period, while low (0.45) during GNP high growth period. Nonetheless, caution should be raised regarding these findings due to the small sample size (20 REITs) and possible survivor bias.

Goldstein and Nelling (1999) pointed to the return-dependence of REITs to the general stock market. The authors utilized monthly returns on portfolios of EREITs and MREITs from 1972 to 1998 and S&P 500 index as the market proxy, and they found that the beta estimate of EREITs was significantly lower during advancing market than that during the declining market. In addition, due to the low betas of REITs, they concluded that REITs can be useful to in reducing the overall portfolio risk.

Chatrath et al. (2000) provided further evidence on the nature of the return dependence in REITs betas and investigated its origins. Their study employed monthly returns of EREITs index from NAREIT and monthly return series of a number of stock indices, including S&P 500, spanning the interval 1972-1998. They found similarity in terms of beta patterns between REITs and small cap stocks, but failed to satisfactorily describe the beta pattern of REITs after controlling the variance effects.

Chiang et al. (2004) and Chiang et al. (2005) attempted to resolve the issue of asymmetric REITs beta by incorporating Fama-French factors next to the conventional equity market proxy, such as CRSP value weighted index and S&P 500 index. Chiang et al. (2004) sampled NAREIT index monthly return from 1972 to 2001. Using CRSP index and S&P 500 index respectively, they confirmed the persistence of REITs beta asymmetry phenomenon as well as small REITs beta. However, such return dependence disappeared when both the size and book-to-market factors were controlled for. Chiang et al. (2005) arrived at similar conclusions that detecting regime shifts in REITs market betas was sensitive to both the nature of the data and asset pricing model that was applied.

Studies of Han and Liang (1995) and Corgel and Djoganopoulos (2000) provided evidence that using a restrictive market proxy could lead to biased estimates of cost of capital and performance evaluation of REITs. Han and Liang (1995) examined the issues of benchmark selection and survivor bias in the REITs performance evaluation. They assembled survivor bias free portfolios of REITs for the period of 1970 and 1993, and used equally weighted CRSP index to proxy for the market portfolio. They found that both the use of S&P 500 index and survivor sample of REITs lead to over-estimation of REITs performance. The beta estimates in their study ranged from 0.68 to 0.87 when the equally weighted CRSP index was used to proxy the market. Their findings shed light on the fact that, if the riskiness of REITs is understated due to using less diversified S&P 500 index as the market other than the small stock-inclusive CRSP index, a better performance will likely to emerge ex post. The caveat of their study, however, is that the equally weighted CRSP index in their study tends to have an over-representation of small caps in the equity market portfolio which leads to enhanced market returns.

Similar results were also found by Corgel and Djoganopoulos (2000). Their REITs sample consisted of more than 60 REITs companies that possessed the return series spanning the period from January 1993 through November 1997. They found that the mean cost of capital estimation using S&P 500 index was generally understated by 0.8% on an annual basis as compared with using an alternative Russell 2000 index.

All of the aforementioned empirical studies on risk and return of REITs seem to take equity portfolios as the “default” market proxy irrespective of their limited inclusion within the asset universe. Roll (1977) highlighted the issue of choosing the right market portfolio empirically in the context of CAPM testing. He argued the market portfolio should include all individual assets, while he also conceded that such endeavor might not succeed in reality. Stambaugh (1982) was the first to address the Roll's critique by constructing a broad market portfolio that incorporated not only equity but also fixed income securities, consumer durables and real estate. He concluded that CAPM testing seemed insensitive to the market portfolio composition. In spite of the rough measures of asset returns, his market portfolio was the most comprehensive at the time when data was not readily available.

Liu et al. (1990) tackled the issue of the composition of the market portfolio and REITs performance evaluation. Their sample included 18 EREITs for the period 1978 and 1986. They expanded the market portfolio by including fixed income securities, equities, and real estate. Using quarterly data, they demonstrated that the composition of the market proxy did not necessarily lead to different inferences on REITs performance. However, their results should be taken with caution. First, the survivor bias might arise due to their sampling scheme that REITs in their sample should possess continuous return series covering the whole study period. Second, as the authors acknowledged, there can be double counting issue involved by simply taking the outstanding market values of assets, while neglecting multiple financial claims on the same underlying assets.

Along the same vein, Benefield et al. (2007) examined a similar issue as Liu et al. (1990) while focusing on post-1986 REITs performance. They included REITs that had price information through 1995 to 2002. The chosen market proxies were equally and value weighted CRSP index, S&P 500 index and the small cap decile of the CRSP index. Adopting different performance measures and quarterly return data, their results showed the insensitivity of REITs performance measure to the market proxy composition. Apart from suffering from the survivor bias problem as the case for Liu et al. (1990), the authors failed to address the breath of the market proxy issue by applying very restrictive equity indices rather than synthesizing among different asset classes to approximating various market proxy composition.

This chapter distinguishes itself from earlier works on the following three grounds. First, we address the impact of the market portfolio composition on assessing the riskiness of REITs. This is a more fundamental issue as compared with ex ante capital allocation and ex post REITs performance evaluation. Second, the analysis is performed on the basis of individual REITs rather than REITs portfolios, which is motivated by the fact that aggregating stocks into portfolios conceals important information contained in individual stock betas and reduces the cross-sectional variation in betas (Ang, Liu and Schwarz, 2008). Ferson and Harvey (1999) noted that stock grouping only works when the characteristics used for portfolio formation are good proxies for risk shared by stocks within the portfolio. Bauer et al. (2009) demonstrated strong heterogeneity within portfolios that were formed based on Fama and French (1993). Third, we tackle the survivor bias problem explicitly by including REITs that are short-lived in our analysis as opposed to Liu et al. (1990) and Benefield et al. (2007).

4.3 U.S. Data Sources

The purpose of this chapter is to check the robustness of estimating the market risk premium of REITs using the restrictive equity index to an alternative market proxy which is more diversified across various asset classes besides equity.[15] To this end, we use the popular CRSP equity index, which synthesizes the stocks traded on NYSE, AMEX, and NASDAQ, as the "default" market proxy. The CRSP equity index is more representative of the U.S. equity market in the sense that it incorporates large as well as small cap stocks, and has been used in various studies so that we can draw parallel with results of these earlier research.[16] The alternative market portfolio is constructed by taking into account not only equities but also asset classes such as fixed income securities and real estate, which is similar to Stambaugh (1982) and Liu et al. (1990). The construction of this comprehensive market portfolio requires (i) rate of return series of each candidate asset class in the portfolio and (ii) the market values to compute the weights in order to construct the composite market index. Our sample consists of monthly asset return series from January 1990 to June 2008. Assuming annual rebalancing of the market portfolio at the beginning of the year, we assemble the market capitalization data of the individual asset class from the end of 1989 to the end of 2007.

4.3.1 Asset Market Value and Weights

Our market portfolio is composed of four asset classes, which are equity, fixed-income securities, real estate, and time and saving deposits. Equity asset class mainly concerns corporate equity. Fixed-income securities can be divided into treasury securities, municipal

[15] The aim of this study does not attempt to find such a market portfolio that is exhaustive in its coverage of assets. Therefore, our market portfolio omits consumer durables and human capital due to the complexity and validity in estimating their market values as well as returns.
[16] It should be noted that CRSP equity index contains REITs such that it is not the "pure" equity index representing the U.S. equity market.

securities, and corporate bonds. Real estate asset class is distinguished between residential and commercial real estate. In estimating the market value of each of the individual asset, we pay special attention to the double counting issue involved, as noted by Stambaugh (1982) and Liu et al. (1990). Double counting of asset market value could arise when we naively take the outstanding market value of the asset. For example, there can be cross holding of firm shares or bonds, or multiple claims on the same underlying assets, such as mortgage and asset/mortgage backed securities.

We obtain end-of-year market value of assets except commercial real estate from flow-of-funds accounts composed by the U.S. Federal Reserve.[17] The details are as follows.

1. Equity. Gross corporate equity portion from the flow-of-funds accounts excludes ADRs and mutual fund shares.[18] In addition, it does take into account of inter-corporate holdings to avoid double counting. Due to the fact that REITs shares are part of the gross corporate equity, we, therefore, subtract the REITs portion from the corporate equity to avoid double counting equity and commercial real estate.

2. Fixed income securities. Treasury securities comprise U.S. government securities with different maturities, such as treasury bill, treasury notes and treasury bonds. Municipal securities include both the short and long term municipal bonds, and exclude the trade debt of state and local governments and U.S. government loans to them. In the calculation of corporate bond market capitalization, we consider the direct and indirect holdings of corporate bonds. Direct holdings of corporate bonds are taken from the household sector, while indirect holdings are obtained from holdings through mutual funds and pension funds, etc. Moreover, we take into account of the cross holdings among issuers. For example, we do not count holdings of corporate bonds by local governments who are also the issuers of municipal bonds. We also exclude ABS issuers to avoid double counting due to multiple claims on the same underlying asset. For instance, ABS issuers securitize mortgage loans, but it is a double counting since we also include real estate in our market portfolio.

[17] The source details from the flow-of-funds accounts to retrieve the asset market value are displayed in Table 4.12 in the Appendix.
[18] Mutual funds shares are excluded to avoid double counting of the corporate equity.

3. Time and saving deposits. The market value figure is retrieved from direct holdings of the household sector and indirect holdings through funds.

4. Residential real estate. Holdings of the residential real estate concentrate within the household sector and can be taken from the balance sheet of U.S. households from the flow-of-funds accounts. It consists of all types of owner-occupied housing including farm houses and mobile homes, as well as second homes that are not rented, vacant homes for sale and vacant land. The calculation of the market value of residential real estate excludes real estate held by non-profit organizations, such as hospitals and museums.

5. Commercial real estate. In measuring the market value of the commercial real estate, we discriminate between the securitized and unsecuritized commercial real estate holdings. Holdings of securitized commercial real estate relate to investment in commercial real estate through purchasing REITs shares, while the unsecuritized commercial real estate holdings refer to gaining the exposure to the commercial real estate market through funds under fiduciary setting, such as pension funds holdings of commercial real estate. The market capitalization data of REITs is obtained from the National Association of Real Estate Investment Trusts (NAREIT). The aggregate market value of unsecuritized commercial real estate is provided directly by National Council of Real Estate Investment Fiduciaries (NCREIF). We acknowledge the fact that data deficiency precludes a more accurate measure of the commercial real estate since NCREIF members are only a small subset of firms holding unsecuritized income generating commercial real estates.

Table 4.1 presents the estimates of year-end market value and weights of the assets in the market portfolio. Over our sampling period from 1990 to 2008, corporate equity portion of the asset market ranges from 19% in 1991 to 44% in 2000 in terms of market value. More than half of the asset market in terms of value is represented by fixed income securities and residential real estate. In comparison, commercial real estate accounts for a small value weight in the asset market, ranging from 0.3% in 1990 to 1.3% in 2007.[19] Overall, using equity market assets to proxy for the market portfolio is rather restrictive and inadequate

[19] Due to data limitations on the market value of the commercial real estate, these figures should not be generalized to be representing the market value of the entire unsecuritized commercial real estate asset class in reality.

Table 4.1 Asset Weights and Aggregate Market Value

Asset Class	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Corporate Equity (excl. REITs)	0.2061	0.1880	0.2334	0.2461	0.2596	0.2511	0.3010	0.3302	0.3792	0.4008	0.4424	0.4042	0.3513	0.2743	0.3068	0.3015	0.2849	0.2863	0.2772
Corporate Bonds	0.0707	0.0775	0.0754	0.0777	0.0846	0.0887	0.0897	0.0889	0.0851	0.0872	0.0810	0.0846	0.0950	0.1048	0.0984	0.0976	0.0952	0.0979	0.1012
Gov. Bonds	0.1251	0.1367	0.1383	0.1443	0.1464	0.1506	0.1389	0.1317	0.1169	0.1042	0.0900	0.0841	0.0844	0.0936	0.0910	0.0905	0.0904	0.0875	0.0898
Muni. Bonds	0.0553	0.0571	0.0564	0.0539	0.0534	0.0503	0.0421	0.0377	0.0347	0.0334	0.0304	0.0315	0.0345	0.0394	0.0373	0.0364	0.0373	0.0374	0.0399
Time saving and deposits	0.1561	0.1534	0.1356	0.1214	0.1086	0.1055	0.1004	0.0980	0.0923	0.0875	0.0799	0.0879	0.0971	0.1079	0.1008	0.1016	0.1045	0.1060	0.1134
Residential Real Estate	0.3841	0.3845	0.3582	0.3538	0.3440	0.3499	0.3236	0.3082	0.2850	0.2808	0.2708	0.3014	0.3305	0.3722	0.3571	0.3625	0.3772	0.3721	0.3671
Commercial Real Estate																			
Securitized - REITs	0.0007	0.0005	0.0007	0.0008	0.0015	0.0020	0.0023	0.0033	0.0046	0.0041	0.0032	0.0037	0.0041	0.0044	0.0054	0.0067	0.0067	0.0082	0.0057
Unsecuritized - Pension Funds	0.0019	0.0022	0.0020	0.0020	0.0019	0.0019	0.0020	0.0020	0.0022	0.0020	0.0021	0.0026	0.0030	0.0034	0.0032	0.0032	0.0038	0.0046	0.0056
Total Market Value ($ Trillion)	16.86	17.11	18.95	20.12	21.43	21.82	24.64	27.09	30.72	33.96	38.51	37.73	37.47	36.48	41.79	46.01	49.46	53.26	54.61

due to its negligence of important asset classes that have significant value weights in the asset market.

4.3.2 Asset Returns

We retrieve the monthly asset returns as follows.

1. REITs. The individual REITs return series is obtained from CRSP/Ziman Real Estate Database which includes all REITs traded on the NYSE, AMEX and NASDAQ exchanges. Our REITs sample contain not only the survivor REITs that possess return information spanning the whole sampling period but also REITs that are terminated prior to the end of the sampling period. Moreover, in order to reduce the noise in the estimation process, we retain REITs that have return series for more than 30 months. Based on the indicator of REITs types provided by CRSP/Ziman, we also identify equity RIETs which are used for our estimation next to using all REITs.

2. Corporate equity. We obtain the CRSP value weighted equity index from CRSP U.S. Indices Database. Since REITs are included in the construction of the CRSP index, we filter REITs out from the CRSP equity index in order to have a "clean" proxy for the corporate equity performance. To do this, we collect the data from CRSP database on the market capitalization of both the CRSP value weighted index and CRSP/Ziman REITs index as well as the total return on CRSP/Ziman REITs index. Applying the following formula to calculate the value weighted CRSP equity index returns, we can back out the "cleaned" value weighted equity index that excludes REITs.

$$R_{REITs} \times weight_{REITs} + R_{Clean} \times weight_{Clean} = R_{CRSP} \tag{4.1}$$

3. Corporate bond. On the basis of credit ratings, corporate bonds are classified into investment grade and junk bonds. Therefore, a representative corporate bond index should take into account of both of these two classes of bonds. We retrieve Lehman investment grade and high yield corporate bonds indices from Datastream, and the market values of these two indices are provided directly by Barclays Capital. Therefore, we are able to construct a value weighted corporate bond index which incorporates both the investment grade and junk corporate bonds.

4. Treasury securities. Along the same vein as constructing a representative corporate bond index, we include both the short and long term treasury securities in assembling a representative treasury index. We obtain both the Lehman U.S. short treasury index and Lehman U.S. treasury index excluding treasury bills from Datastream, alongside their respective market capitalization. We then compute the value weighted U.S. composite treasury index that contain treasury securities with different maturities.

5. Municipal bond. Lehman municipal index is used to proxy for the returns of municipal bonds, and is accessible through Datastream. It involves both the investment grade and high yield municipal issues, and covers the US dollar denominated long term (longer than one year) tax exempt bond market. The index covers four main sectors, state and local general obligation bonds, revenue bonds, insured bonds, and prerefunded bonds.

6. Residential real estate. To find a good return proxy for the residential real estate, we resort to S&P/Case-Shiller Home Price Index which is calculated on a monthly basis and made available on S&P website. The S&P/Case-Shiller index employs repeat sales methodology to measure the changes in house prices given that the quality attributes remain unchanged over time. The index covers 20 major metropolitan areas, and the value weighted composite house price index is used to impute the return series that represents the performance of the U.S. residential real estate market. Essentially, we are only considering the capital gains on residential real estate without taking into account the imputed rents (net of maintenance) in calculating the total return of residential real estate, which is largely due to data limitations.

7. Commercial real estate. As mentioned in the previous subsection, we break up commercial real estate into securitized and unsecuritized commercial real estate holdings. Returns on securitized commercial real estate investment through REITs shares are obtained from CRSP/Ziman real estate database. The CRSP/Ziman REITs index is representative with respect to the performance of the REITs market in that it incorporates

REITs traded in all major exchanges in the U.S.. Unsecuritized commercial real estate investment returns are taken from transaction based index (TBI) provided by MIT Center for real estate. The MIT/TBI is based on the transaction prices of property sold from the NCREIF property index (NPI) database, and is available on a quarterly basis. In comparison with the alternative popular NPI, the MIT/TBI is more transparent and objective and does not suffer from the issues related to appraisal based indices (Geltner et al., 2003). The obvious drawback of the MIT/TBI for this study is that it is only available quarterly. Therefore, in order to match the data frequency with other assets in the construction of the market portfolio, we apply intra-quarter linear interpolation on MIT/TBI to get monthly return series. One natural consequence of the linear interpolation is that the overall return volatility of the weighted market portfolio is reduced. However, this is not a serious concern here, since the market value of unsecuritized commercial real estate holdings is small as compared with other asset classes, the impact of such treatment on our value weighted market portfolio is negligible.

8. Risk-free rate. The one month Treasury bill rate is used to proxy the risk free rate, and it is retrieved from CRSP database.

Table 4.2 displays the descriptive statistics as well as correlations among these assets on the monthly basis over our entire sampling period from January 1990 to June 2008. It is noted that the securitized commercial real estate in the form of REITs exhibits high correlations with fixed income securities and corporate equity. This is consistent with early findings that there are relationships between REIT returns and the returns of stocks and bonds.[20] The fixed income characteristic of REITs is derived from stable payout ratio of their taxable income, which is a minimum of 90% annually. REITs also resemble equity in nature due to the fact that they are publicly traded shares. Moreover, since REITs normally have relatively small market capitalization, they behave similarly to small cap stocks, which have been evidenced in the previous studies such as Chan et al. (1990), Han and Liang (1995) and Peterson and Hsieh (1997). As a result, the volatility of the equity market has substantial bearing on the REITs performance. In contrast, REITs appear to have low correlation with unsecuritized commercial real estate as well as residential real estate,

[20] See, for example, Chan et al. (1990), Liang et al. (1995) and Sanders (1998).

which indicates that REITs cannot be treated as the perfect substitutes for unsecuritized real estate. The low correlations of the unsecuritized real estate with respect to other asset class, however, suggest that adding unsecuritized real estates in the market portfolio brings diversification potential.

Table 4.2 Correlations and Descriptive Statistics of Monthly Asset Returns (1990.01-2008.06)

	1	2	3	4	5	6	7	8
1. Corporate Equity	1.000							
2.Corporate Bonds	0.353	1.000						
3.Muni Bonds	0.126	0.719	1.000					
4.Time Saving Deposits	0.036	0.253	0.248	1.000				
5.Gov. Bonds	-0.020	0.756	0.736	0.431	1.000			
6.Secu. Commer. R. E.	0.435	0.345	0.225	-0.048	0.049	1.000		
7.Unsecu. Commer. R. E.	0.037	0.014	-0.026	-0.146	-0.049	0.046	1.000	
8.Residential R. E.	-0.055	-0.047	-0.008	-0.327	-0.085	0.061	0.378	1.000
Mean[21]	0.0086	0.0062	0.0052	0.0038	0.0052	0.0095	0.0254	0.0036
Standard Deviation	0.0414	0.0130	0.0121	0.0018	0.0092	0.0394	0.0326	0.0084

4.4 Methodology and Estimation Issues

On the basis of CAPM, the market risk premium of an individual asset can be calculated as follows.

$$\beta_i \times E(R_m - R_f) \tag{4.2}$$

where β_i measures the systematic risk exposure of asset i with reference to the market portfolio, and $E(R_m - R_f)$ is the unconditional expectation of the market excess return. Therefore, the estimation of the market risk premium involves two steps. First, beta is estimated using the historical return series of both the REITs and the market portfolio.

[21] The large average return of unsecuritized real estate is found to be due to large outliers in the monthly return series. The exclusion of imputed rents from total returns of residential real estate explains the lowest return of residential real estate as compared to other asset classes.

$$(R_{i,t} - R_{f,t}) = \alpha_i + \beta_i \times (R_{m,t} - R_{f,t}) + \epsilon_{i,t} \tag{4.3}$$

where $(R_{i,t} - R_{f,t})$ is the excess return of REITs i at month t, $(R_{m,t} - R_{f,t})$ is the excess return on the market portfolio at month t, and $\epsilon_{i,t}$ is the standard error term. The second step requires estimating the expected market excess return. Controversy exists with respect to the appropriate estimation procedures of the expected market excess return. On the one hand, using a long history of market returns improves the estimation precision.[22] On the other hand, it is more likely that some important structural breaks within the long time series are neglected than otherwise relying on more recent data (Pástor and Stambaugh, 2001). In this study, we estimate the expected market excess return by averaging over the historical market return series that matches with the time span of the return information for each individual REIT. For example, suppose a REIT has a return series from 1992 to 2004, we employ the market information during the 1992-2004 period in formulating the expectation of the market excess return in our estimation of the market risk premium of this particular REITs. By following this procedure, on one hand, we lose the estimation accuracy due to averaging over a short period of time. On the other hand, it is less probable that the calculated expectation of the market excess return subjects to the possible structural breaks in the REITs market.[23]

Our REITs sample includes both the survivor REITs and REITs that have short lives. In order to reduce the noise in our estimation, we exclude those REITs that have return information less than or equal to 30 months so that the degrees of freedom in our regression specification (4.3) are at least 30. Our analysis is performed on all REITs that include equity REITs, mortgage REITs, and hybrid REITs, as well as equity REITs alone, which dominate our REITs sample. We utilize three market proxies which are progressively broader in the calculation of the market risk premiums of REITs on the basis of equation (4.2). The first market proxy (No.1) is the "default" CRSP equity index. The second market proxy (No.2) encompasses the first market proxy plus fixed income securities. The third market proxy (No.3) includes the second market proxy as well as both

[22] The equity return series that dates back to 19th century is constructed in Schwert (1990).
[23] Another practical issue that motivates us to use short time series of the market returns is the data limitation. Some assets within our market portfolio possess return information only after 1980s or even later, which prohibits us to estimate the expected market excess return through averaging over a long time horizon.

commercial and residential real estate. Therefore, for each individual REIT, we have three estimated market risk premiums corresponding to the respective market proxies used. To assess the significance of the issue whether market composition matters in the estimation of the market risk premium for REITs, we resort to paired-sample t test.

Our sampling period is from January 1990 till June 2008, which covers the "new REITs era" when REITs have experienced significant boost in both the market capitalization and liquidity.[24] In order to evaluate the stability of our results, we take into account the possible structural break in the REITs industry in 2001 when the REITs Modernization Act was put into effect. Specifically, the Act permits a REIT to own up to 100% controlling stake in a taxable REIT subsidiaries (TRS) that can provide services to REIT tenants without disqualifying the tax exempt status of the rents that a REIT receives from its tenants. However, the Act puts an upper limit on the TRS securities holdings of REITs which may not exceed 20% of their total assets. Moreover, the dividends from TRS are not classified as tax-exempt income of REITs. The consequence of the adoption of the Act is that REITs will be more like operating firms than funds, which has been evidenced by the inclusion of a number of REITs by the S&P in its market indices in October 2001 (Chan et al., 2003). The results from the Chow test on the structural break in the REITs market with respect to the REITs returns shown in Table 4.3 support the notion that REITs market has experienced structural break around 2001.[25] Therefore, besides the whole sampling period, we also repeat our analysis focusing on two subperiods from January 1990 to December 2000 and from January 2001 to June 2008 respectively.

Table 4.4 displays the descriptive statistics and correlations of various market proxies for the whole sampling period as well as two subperiods. From Table 4.4, the diversification effect is obvious as the market proxy becomes broader progressively. The monthly stock returns are rather volatile for all the periods. However, the market portfolio standard deviation is dramatically reduced by almost 50% as we include fixed-income securities in

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[24] One of the contributing factors to the growth of REITs after 1990 is the passage of the Omnibus Budget Reconciliation Act of 1993, which has stimulated pension funds investments in REITs, leading to growth of REITs market capitalization and increased liquidity of the REITs market.

[25] The Chow test is performed using total returns of all-REITs portfolio and equity REITs portfolio that represent the overall REITs market and the equity REITs market respectively. The return data are obtained from NAREIT.

addition to equity, and is decreased further as we incorporate both the commercial and residential real estate in the market portfolio. The correlations between the pairs of three market proxies are rather high, which are on an order of 0.95 or higher. The high correlations suggest that the equity market proxy tracks closely the movement of monthly returns of the broader market proxies. Overall, Table 4.4 sheds light on the inadequacy of using equity alone as the market proxy as to capturing the magnitude and dispersion of returns of alternative market proxies that are more complete.

Table 4.3 Chow Tests on the Stability of REITs Beta

This table shows the result of the structural break test around the introduction of the REITs Modernization Act. No.1 market proxy is the CRSP equity index. No.2 market proxy is No.1 market proxy plus fixed income securities. No.3 market proxy includes No.2 market proxy and real estate.

1990.01-2000.12 vs. 20001.01-2008.06		F statistics	
Market Proxy	No.1	No.2	No.3
All REITs	2.754*	3.084**	3.376**
Equity REITs	2.285	2.527*	2.747*

* 10% significance level, ** 5%significance level

The detail of our REITs sample used in this analysis that satisfies the inclusion criteria is shown in Table 4.5. During the whole sampling period as well as the two subperiods, equity REITs dominate the REITs sample. Therefore, few mortgage REITs and hybrid REITs are available for independent analysis next to equity REITs. Moreover, the survivor REITs are only a small portion of the full REITs sample that includes REITs with short lives in addition to survivor REITs. For the whole sampling period, the number of REITs in the survivor sample is roughly 10% of that in the full sample, which climbs to around 50% during the period 2001-2008. In particular, more than 80% of REITs perished during the period 1990-2000 as compared with less than 50% for the period 2001-2008. The under-representation of REITs in the survivor sample casts doubt on getting unbiased estimation results based on using surviving REITs exclusively in the analysis. Table 4.5 demonstrates that, on average, survivor REITs outperform those in the full REITs sample on a risk adjusted basis for both the full sampling period and the two sub-periods.

Table 4.4 Descriptive Statistics of Monthly Returns of Market Proxies and Their Correlations

This table shows the descriptive statistics of three market proxies and correlation among them. No.1 market proxy is the CRSP equity index. No.2 market proxy is No.1 market proxy plus fixed income securities. No.3 market proxy includes No.2 market proxy and real estate.

Market Proxy	Mean	Standard Deviation	Correlations between Market Proxies	
1990.01-2008.06			No.2	No.3
No. 1	0.0086	0.0412	0.977	0.952
No. 2	0.0063	0.0215		0.977
No. 3	0.0053	0.0148		
1990.01-2000.12				
No. 1	0.0126	0.0416	0.974	0.953
No. 2	0.0087	0.0218		0.988
No. 3	0.0065	0.0150		
2001.01-2008.06				
No. 1	0.0027	0.0401	0.981	0.950
No. 2	0.0029	0.0207		0.961
No. 3	0.0037	0.0144		

Table 4.5 REITs Sample Statistics

This table shows the sample statistics of the REITs in both the survivor sample and the full sample that includes REITs with short lives.

	1990.01-2008.06	1990.01-2000.12	2001.01-2008.06
Survivor Sample			
Number of all REITs	39	50	115
Mean nominal return	0.0125	0.0115	0.0129
Standard Deviation of return	0.0060	0.0084	0.0071
Number of equity REITs	31	40	95
Mean nominal return	0.0120	0.0112	0.0132
Standard Deviation of return	0.0063	0.0087	0.0063

Table 4.5 continued

	1990.01-2008.06	1990.01-2000.12	2001.01-2008.06
Full Sample			
Number of all REITs	370	300	223
Mean nominal return	0.0086	0.0082	0.0107
Standard Deviation of return	0.0140	0.0122	0.0146
Number of equity REITs	299	249	183
Mean nominal return	0.0100	0.0089	0.0131
Standard Deviation of return	0.0122	0.0120	0.0098

4.5 Estimation Results

4.5.1 REITs Beta

Following the two-step estimation procedure as outlined above, we first estimate the beta for each individual REIT on the basis of the regression specification (4.3). Table 4.6 displays the summary statistics of estimated betas based on the survivor REITs sample. It is interesting to note that the mean REITs beta exhibits a systematic tendency to increase as the market proxy becomes broader. Specifically, the mean REITs beta rises by more than 2 folds when the market proxy moves from using CRSP index alone to including fixed-income securities as well as commercial and residential real estate. Caution should be raised when interpreting the result that one should not compare betas on absolute terms as the market proxy is changed from one to another, which is similar to rescaling the beta as we adjust the reference market portfolio. In other words, beta can only be interpreted sensibly with respect to “the” market portfolio. Therefore, the upward trend of mean REITs beta implies that REITs have more systematic risk exposure to a more diversified market portfolio.

When comparing the means of REITs beta with reference to the same market proxy using all REITs and equity REITs alone, it is shown that the mean REITs beta is higher for all REITs than that for equity REITs for the periods January 1990-June 2008 and January 1990-December 2000. This finding indicates relatively high systematic risk exposures of mortgage REITs and hybrid REITs included in the all REITs sample in addition to equity REITs, which is in line with the findings of Goldstein and Nelling (1990). However, the picture is reversed for the period January 2001-June 2008 when equity REITs are marginally riskier than mortgage REITs. During the whole sampling period, the systematic risk exposure of REITs is below unity with respect to all market proxies, indicating REITs are rather conservative investments relative to the market. Table 4.6 also provides evidence of the asymmetric pattern of REITs beta over the two subperiods. In particular, the mean REITs beta is lower during the period January 1990-December 2000 than that during the period January 2001-June 2008 for both the all REITs sample and equity REITs sample. Over the period January 2001-June 2008, for both the all REITs sample and equity REITs sample, the mean REITs beta is around 1.3 when the most diversified market portfolio is employed in beta estimation, which demonstrates that REITs are not as conservative as investors used to perceive them with reference to a broad market portfolio.

Table 4.6 Summary Statistic of Survivor REITs Beta Estimates

This table shows the beta estimates using survivor REITs sample for the whole sampling period as well as the two subperiods with respect to various market proxies. No.1 market proxy is the CRSP equity index. No.2 market proxy is No.1 market proxy plus fixed income securities. No.3 market proxy includes No.2 market proxy and real estate.

All REITs

Market Proxy	No.1		No.2		No.3	
1990.01-2008.06	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.319	0.146	0.578	0.280	0.829	0.405
Standard Deviation	0.192	0.093	0.355	0.179	0.506	0.259
Minimum	-0.090	0.051	-0.237	0.097	-0.301	0.141
Maximum	0.845	0.596	1.659	1.143	2.581	1.653
N	39		39		39	
Mean Adjusted R Squared	0.031		0.027		0.026	
1990.01-2000.12	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.354	0.203	0.623	0.388	0.837	0.564
Standard Deviation	0.258	0.137	0.451	0.262	0.636	0.379
Minimum	-0.414	0.069	-0.279	0.131	-0.526	0.190
Maximum	1.055	0.902	2.032	1.723	2.667	2.499
N	50		50		50	
Mean Adjusted R Squared	0.030		0.023		0.019	

Table 4.6 continued

Market Proxy	No.1		No.2		No.3	
2001.01-2008.06	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.435	0.196	0.835	0.379	1.284	0.538
Standard Deviation	0.279	0.102	0.546	0.197	0.795	0.281
Minimum	-0.933	0.072	-1.953	0.137	-2.560	0.196
Maximum	1.456	0.630	2.675	1.218	3.870	1.736
N	115		115		115	
Mean Adjusted R Squared	0.074		0.072		0.082	

Equity REITs

Market Proxy	No.1		No.2		No.3	
1990.01-2008.06	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.284	0.134	0.510	0.257	0.732	0.372
Standard Deviation	0.160	0.099	0.272	0.190	0.374	0.274
Minimum	-0.090	0.051	-0.237	0.097	-0.301	0.141
Maximum	0.623	0.596	1.041	1.143	1.462	1.653
N	31		31		31	
Mean Adjusted R Squared	0.033		0.028		0.027	
1990.01-2000.12	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.301	0.186	0.511	0.356	0.673	0.518
Standard Deviation	0.228	0.142	0.349	0.272	0.478	0.394
Minimum	-0.414	0.069	-0.279	0.131	-0.526	0.190
Maximum	0.821	0.902	1.317	1.723	1.677	2.499
N	40		40		40	
Mean Adjusted R Squared	0.029		0.022		0.017	
2001.01-2008.06	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.453	0.173	0.861	0.336	1.313	0.476
Standard Deviation	0.277	0.078	0.544	0.151	0.771	0.216
Minimum	-0.933	0.072	-1.953	0.137	-2.560	0.196
Maximum	1.456	0.630	2.675	1.218	3.870	1.736
N	95		95		95	
Mean Adjusted R Squared	0.085		0.082		0.094	

In order to assess the robustness of the findings relating to REITs betas using the survivor REITs only, we repeat the beta estimation procedure using the full REITs sample that takes into account REITs with short lives next to survivor REITs. The beta estimation results are summarized in Table 4.7. We have similar findings regarding the mean REITs beta with those using the survivor REITs sample. The mean REITs beta is monotonically increasing as the market portfolio becomes more diversified. Relatively high systematic risk exposures of mortgage REITs and hybrid REITs as compared with equity REITs are also evident when contrasting the mean REITs beta using all REITs sample to that using equity REITs sample. The asymmetric nature of the mean REITs beta is present over the two subperiods. To evaluate the degree of survivor bias in terms of beta estimation, we compare the estimated mean REITs beta across Table 4.6 and Table 4.7 while controlling for the market proxy used in the estimation. Over the whole sampling period, using the survivor REITs sample understates the systematic exposure of REITs to the market for both the all REITs sample and equity REITs sample. Interesting results emerge as we examine the survivor bias over the two subperiods. During the period January 1990-Decemebr 2000, the mean REITs beta using the survivor REITs marginally overstates that using the full REITs sample. However, over the following subperiod, the survivor bias turns to be negative as the case over the whole sampling period.

In general, our findings regarding REITs beta when using equity index as the market proxy confirms the results from early studies that REITs have low beta relative to the equity market proxy (Chan et al., 1990; Peterson and Hsieh, 1997; Lee et al., 2008). However, contrary to these studies, for the period January 2001-June 2008, the mean REITs beta are well above unity (1.3 or higher) when taking the most diversified market proxy in the estimation, which persists for both the survivor and the full REITs samples. Our result of asymmetric nature of REITs betas is in line with prior findings of varying REITs betas during different market circumstances (Sagalyn, 1990; Goldstein and Nelling, 1999; Chatrath et al., 2000; Chiang et al., 2004, 2005). In the context of this chapter, the asymmetric REITs betas seem to suggest that the systematic risk exposure of REITs is sensitive to the structural break in the REITs market.

Exploring further into our findings, we find that rising REITs beta relative to broader market proxy is, to a large extent, due to the addition of other asset classes in the market proxy next to equities that substantially reduces the overall volatility of the market proxy. Table 4.8 illustrates the return correlations of CRSP/Ziman REITs index with other asset classes as well as market proxies. It is shown that the correlations of REITs with various market proxies are quite close to one another for all the periods under consideration. Therefore, the source that drives REITs betas to increase as the market proxy becomes broader is the diversification effect through the inclusion of other assets in the market proxy, which is evidenced by the standard deviations of the market proxies in Table 4.8. Examining the correlations of REITs with different asset classes over the two sub-periods, it is interesting to note that REITs returns are more correlated with returns of fixed income securities and less correlated with returns of unsecuritized real estate for the period January 1990-December 2000 than those for the subsequent period. Overall, correlations of REITs with three market proxies are close to 0.5 over January 2001- June 2008 period, while they are below 0.41 for the period prior to 2001. Given similar return volatilities of REITs and three market proxies over the two sub-periods, the time dependence of REITs beta finding seem to be attributed to the time dependence of return correlation structure between REITs and various market proxies.[26]

Table 4.7 Summary Statistic of Full REITs Beta Estimates

This table shows the beta estimates using full REITs sample including REITs with short lives next to survivor REITs for the whole sampling period as well as the two subperiods with respect to various market proxies. No.1 market proxy is the CRSP equity index. No.2 market proxy is No.1 market proxy plus fixed income securities. No.3 market proxy includes No.2 market proxy and real estate.

All REITs

Market Proxy	No.1		No.2		No.3	
1990.01-2008.06	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.431	0.253	0.847	0.512	1.214	0.748
Standard Deviation	0.470	0.207	0.975	0.465	1.488	0.696
Minimum	-0.944	0.051	-1.617	0.097	-2.757	0.141
Maximum	3.113	1.330	6.473	2.948	12.060	4.730
N	370		370		370	
Mean Adjusted R Squared	0.049		0.047		0.047	
1990.01-2000.12	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.287	0.249	0.531	0.022	0.754	0.735
Standard Deviation	0.292	0.178	0.585	0.044	0.865	0.659
Minimum	-1.006	0.069	-1.968	-0.032	-2.950	0.190
Maximum	1.426	1.207	2.956	0.253	4.450	4.730
N	300		300		300	
Mean Adjusted R Squared	0.024		0.022		0.020	

[26] The time dependence of return correlation between REITs and market portfolio worths further exploration, and is thus out of the scope of this paper.

Table 4.7 continued

Market Proxy	No.1		No.2		No.3	
2001.01-2008.06	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.571	0.262	1.150	0.086	1.672	0.731
Standard Deviation	0.545	0.190	1.127	0.102	1.748	0.529
Minimum	-0.944	0.072	-1.953	-0.028	-2.562	0.196
Maximum	3.113	1.330	6.473	0.579	12.060	3.698
N	223		223		223	
Mean Adjusted R Squared	0.087		0.086		0.091	

Equity REITs

Market Proxy	No.1		No.2		No.3	
1990.01-2008.06	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.382	0.222	0.733	0.442	1.014	0.649
Standard Deviation	0.423	0.174	0.858	0.390	1.156	0.598
Minimum	-0.944	0.051	-1.617	0.097	-2.757	0.141
Maximum	3.113	1.156	6.473	2.619	8.117	4.150
N	299		299		299	
Mean Adjusted R Squared	0.050		0.048		0.047	
1990.01-2000.12	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.261	0.229	0.469	0.445	0.661	0.661
Standard Deviation	0.265	0.168	0.516	0.381	0.767	0.602
Minimum	-1.006	0.069	-1.968	0.131	-2.950	0.190
Maximum	1.124	1.156	2.804	2.619	4.409	4.150
N	249		249		249	
Mean Adjusted R Squared	0.024		0.022		0.021	
2001.01-2008.06	Beta	SE	Beta	SE	Beta	SE
Mean Beta	0.518	0.221	1.026	0.436	1.439	0.619
Standard Deviation	0.490	0.127	0.999	0.262	1.335	0.211
Minimum	-0.944	0.072	-1.953	0.137	-2.562	0.196
Maximum	3.113	0.889	6.473	1.771	8.117	2.511
N	183		183		183	
Mean Adjusted R Squared	0.091		0.090		0.093	

4.5.2 REITs Market Risk Premium

With estimated beta for each individual REIT, we can calculate its corresponding market risk premium with respect to various market proxies by following equation (4.2). The summary statistics of estimated market risk premium using the survivor REITs sample is shown in Table 4.9. For the whole sampling period, the estimated mean REITs market risk premium using the all REITs sample does not differ across the choices of the market proxy. On average, REITs are compensated with 17 basis points monthly for their exposure to the general market risk.

Table 4.8 Correlations of REITs with Other Asset Classes and Market Proxies

This table shows the correlation between REIT and various asset classes that are used to construct three different market proxies. No.1 market proxy is the CRSP equity index. No.2 market proxy is No.1 market proxy plus fixed income securities. No.3 market proxy includes No.2 market proxy and real estate.

	1990.01-2000.12	2001.01-2008.06	1990.01-2008.06
Corporate Bonds	0.396	0.293	0.345
Muni Bonds	0.284	0.163	0.225
Time Saving Deposits	0.067	-0.149	-0.048
Gov. Bonds	0.222	-0.132	0.049
Corporate Equity	0.403	0.497	0.435
Unsecu. Commer. R. E.	-0.151	0.057	0.046
Residential R. E.	-0.097	0.161	0.061
Market Proxy			
No.1	0.409	0.513	0.446
No.2	0.368	0.499	0.415
No.3	0.341	0.524	0.415
Standard Deviation			
REITs	0.036	0.044	0.039
Market Proxy			
No.1	0.0416	0.0401	0.0412
No.2	0.0218	0.0207	0.0215
No.3	0.0150	0.0144	0.0148

Similar results hold when we focus only on the equity REITs sample. However, the marginally lower mean market risk premium of equity REITs suggests that, on average, mortgage REITs and hybrid REITs are riskier than equity REITs. Overall, using the CRSP equity index as the market portfolio seems robust to the issue of market portfolio composition. Nonetheless, when we take into account the structural break in the REITs market around 2001, the estimated mean REITs market risk premium exhibits systematic tendency to decrease as the market portfolio becomes more diversified over the period January 19900-December 2000. Significant portion of such decrease is driven by the inclusion of real estate assets into the market portfolio. For instance, for the all REITs sample, 9 out of 10 basis points reduction of the estimated monthly market risk premium is the result of altering the market portfolio to incorporate real estate assets. On the contrary, over the period January 2001-June 2008, we observe an upward trend in the mean estimated REITs market risk premium as the market portfolio gets broader progressively, which is mostly accounted for as the real estate assets enter the market portfolio composition. Using the CRSP index as the default market portfolio, the degree of bias is small on an order of 1 to 3 basis points monthly in absolute terms as compared to the alternative market portfolio that consists of fixed income securities in addition to equity. When real estate assets are considered in the market portfolio composition as well as equity and fixed income securities, the degree of bias is more pronounced, which, in absolute terms, ranges from 10 to 16 basis points monthly.

Since the results shown in Table 4.9 are obtained through applying only the survivor REITs, they maybe subject to survivor bias. To examine the robustness of these results, we follow the identical estimation procedure while using the full REITs sample. The results are displayed in Table 4.10. We find similar patterns of estimated REITs market risk premium as compared to those in Table 4.8 when we apply various market proxies. Over the whole sampling period, the mean estimated REITs market risk premium does not vary significantly as the market portfolio becomes more complete. On average, there is a mere 1 basis point difference between using market proxy No.1 and No. 3 for both the all REITs sample and equity REITs sample. For the subperiod from January 1990 to December 2000, using CRSP equity index as the market portfolio causes an upward bias in the estimation of the REITs market risk premium which is between 5 and 10 basis points monthly relative to the most diversified market portfolio. However, the bias turns negative when we focus on the period January 2001-June 2008, and the degree of the downward bias using CRSP equity index is from 14 to 15 basis points monthly with respect to the market portfolio that consists of equity, fixed income securities and real estate. In absolute terms, large portion of the bias is attributed to the inclusion of real estate assets in the market portfolio, which is consistent with the findings using only the survivor REITs sample.

Table 4.9 Summary Statistic of Market Risk Premium of Survivor REITs

This table shows the statistics of the market risk premium of survivor REITs. No.1 market proxy is the CRSP equity index. No.2 market proxy is No.1 market proxy plus fixed income securities. No.3 market proxy includes No.2 market proxy and real estate.

	All REITs			Equity REITs		
Market	No.1	No.2	No.3	No.1	No.2	No.3
1990.01-2008.06						
Mean	0.0017	0.0017	0.0016	0.0015	0.0015	0.0014
Standard Deviation	0.00100	0.00105	0.00099	0.00083	0.00081	0.00073
N	39	39	39	31	31	31
1990.01-2000.12						
Mean	0.0030	0.0029	0.0020	0.0026	0.0024	0.0016
Standard Deviation	0.00219	0.00208	0.00152	0.00194	0.00161	0.00114
N	50	50	50	40	40	40
2001.01-2008.06						
Mean	0.0002	0.0005	0.0017	0.0002	0.0005	0.0018
Standard Deviation	0.00011	0.00031	0.00106	0.00011	0.00030	0.00103
N	115	115	115	95	95	95

Comparing the mean estimated market risk premium while controlling the market proxy across Table 4.9 and Table 4.10, survivor REITs, on average, have lower market risk premium than that of the full REITs sample, which holds true for the full sampling period as well as the period from January 2001 to June 2008. This indicates that survivor REITs have less market risk exposure as compared to REITs that have short lives.

Overall, Table 4.9 and Table 4.10 demonstrate that bias arises in the estimation of REITs market risk premium as the market portfolio composition varies. However, the direction of the bias seems sensitive to the structural break in the REITs market, which is positive over the sub period January 1990-December 2000 and turns negative for the period from

January 2001 to June 2008. In addition, when we look into the degree of bias as different market portfolios are used in the estimation of REITs market risk premium, we find that adding real estate assets into the market portfolio accounts for a significant portion of the bias. Over the period January 1990-December 2000, including real estate in the market proxy accounts for more than 80% of the total bias, which is more than 75% for the following period from January 2001 to June 2008.

Table 4.10 Summary Statistics of Market Risk Premium of Full REITs

This table shows the statistics of the market risk premium of REITs using the full REITs sample that includes REITs with short lives next to survivor REITs. No.1 market proxy is the CRSP equity index. No.2 market proxy is No.1 market proxy plus fixed income securities. No.3 market proxy includes No.2 market proxy and real estate.

	All REITs			Equity REITs		
Market	No.1	No.2	No.3	No.1	No.2	No.3
1990.01-2008.06						
Mean	0.0023	0.0025	0.0022	0.0022	0.0023	0.0021
Standard Deviation	0.00289	0.00312	0.00415	0.00273	0.00291	0.00317
N	370	370	370	299	299	299
1990.01-2000.12						
Mean	0.0027	0.0026	0.0020	0.0025	0.0023	0.0021
Standard Deviation	0.00261	0.00277	0.00230	0.00257	0.00291	0.00317
N	300	300	300	249	249	249
2001.01-2008.06						
Mean	0.0011	0.0015	0.0026	0.0009	0.0012	0.0023
Standard Deviation	0.00266	0.00285	0.00535	0.00219	0.00242	0.00405
N	223	223	223	183	183	183

To evaluate the statistical significance of the difference in the estimated market risk premium of REITs using different market portfolio, we perform paired sample t-tests.[27] The test results are displayed in Table 4.11. For the whole sampling period, the difference

[27] The paired sample t-test statistic = $\frac{\bar{d}}{se_{\bar{d}}}$, where $\bar{d}$ is the mean difference between the pairs, and $se_{\bar{d}}$ is the standard error of the mean difference between the pairs.

in the estimation of REITs market risk premiums with respect to any pair of market proxies does not appear to be significantly different from zero. Moreover, the mean differences are small in absolute terms, ranging from 0.4 to 2.7 basis points monthly. Therefore, for the whole sampling period, the market portfolio composition does not significantly affect the estimation of REITs market risk premium. In other words, using equity index alone is robust to the estimation of REITs market risk premium. However, when we take into account the structural break in the REITs market, the mean REITs market risk premium differs significantly across pairs of market proxies used in the estimation. During the period January 1990-December 2000, using a less diversified market proxy significantly overstates the REITs market risk premium, and the bias turns negative when focusing on the subsequent period from January 2001 to June 2008. Most of the paired differences are significant at 5% level. In addition, using survivor sample of REITs, on average, overstates the degree of the significant positive bias as compared with that using the full REITs sample.

Table 4.11 Results of Paired Sample t-test of the Mean Risk Premium Difference

This table shows the t-test results examine if the mean risk premium with respect to three market proxies are significantly different from each other. The test is conducted for both the survivor REITs as well as full REITs sample including REITs with short lives next to the survivor REITs. No.1 market proxy is the CRSP equity index. No.2 market proxy is No.1 market proxy plus fixed income securities. No.3 market proxy includes No.2 market proxy and real estate.

Market Proxy	Survivor REITs Sample		Full REITs Sample	
	All REITs	Equity REITs	All REITs	Equity REITs
1990.01-2008.06				
No.1 - No.2	-0.00006	-0.00004	-0.00017**	-0.00009**
	(0.00004)	(0.00004)	(0.00003)	(0.00004)
No.2 - No.3	0.00010**	0.00008**	0.00027	0.00019
	(0.00003)	(0.00003)	(0.00016)	(0.00013)
No.1 - No.3	0.00004	0.00004	0.00010	0.00009
	(0.00004)	(0.00005)	(0.00015)	(0.00013)

Table 4.11 continued

Market Proxy	Survivor REITs Sample		Full REITs Sample	
	All REITs	Equity REITs	All REITs	Equity REITs
1990.01-2000.12				
No.1 - No.2	0.00013	0.00019**	0.00004	0.00011**
	(0.00008)	(0.00009)	(0.00004)	(0.00004)
No.2 - No.3	0.00088**	0.00076**	0.00059**	0.00042**
	(0.00009)	(0.00009)	(0.00009)	(0.00008)
No.1 - No.3	0.00101**	0.00095**	0.00064**	0.00053**
	(0.00013)	(0.00015)	(0.00007)	(0.00007)
2001.01-2008.06				
No.1 - No.2	-0.00029**	-0.00030**	-0.00035**	-0.00033**
	(0.00002)	(0.00002)	(0.00003)	(0.00003)
No.2 - No.3	-0.00125**	-0.00127**	-0.00106**	-0.00106**
	(0.00007)	(0.00007)	(0.00027)	(0.00025)
No.1 - No.3	-0.00154**	-0.00157**	-0.00141**	-0.00138**
	(0.00009)	(0.00009)	(0.00028)	(0.00026)

** 5%significance level

4.6 Conclusion

Estimation of asset risk premium is potentially subject to the bias that may arise due to the omission of asset classes from the market portfolio proxy according to CAPM. In practice, popular market proxies, such as S&P 500 and CRSP equity index, are prone to such bias due to their restricted inclusion of assets from the asset universe. This chapter empirically examines the degree and significance of the bias in the estimation of REITs market risk premium that results from excluding asset classes, such as fixed income securities and real estate, from the market proxy.

Our interesting findings are three folds. First, the mean REITs beta estimation is positively related to the breath of market proxy used. As the market proxy becomes broader progressively, the mean REITs beta is also rising accordingly. This indicates that REITs investments are not as conservative as investors used to perceive them when equity indices are used to proxy for the market portfolio. Second, the market risk premium estimation of REITs is sensitive to both the structural break in the REITs market and the composition of market proxy. The composition of the market proxy does not seem to matter for the estimation of REITs market risk premium over the entire sampling period. However, when the structural break in the REITs market around 2001 is taken into consideration, we find REITs market risk premium is overstated significantly by 5 to 10 basis points monthly when using the most restrictive market proxy as compared to the most diversified market proxy over the pre-2001 period. The bias turns significantly negative, ranging from 14 to 15 basis points monthly, over the post-2001 period. Third, a substantial portion of the bias in REITs market risk premium estimation arising from using the most restrictive market proxy can be attributed to the exclusion of real estate in the market proxy, which is more than 80% during the period January 1990-December 2000 and 75% over the following period respectively.

Our findings are relevant to both the institutional and individual investors who are interested in having real estate exposure through investing in REITs due to its increasing market capitalization and liquidity. The composition of the market proxy matters for REITs market risk premium estimation, ignoring which can potentially lead to erroneous capital budgeting decisions as well as performance evaluation.

Appendix

Table 4.12 Flow of Funds Source for Retrieving Asset Market Value

This table shows the source of data that are used for this study to retrieve the asset market value of various asset classes.

Asset Class	Flow of Funds Account Source
Corporate Equity	L.213 Account No. 20 − REITs
Treasury Securities	L.209 Account No. 3
Muni. Securities	L.211 Account No. 2
Corporate Bonds	L.212 Account No. 13 + 20 + ... +27
Time and Saving Deposits	L.205 Account No. 17 + 27 + 28 + 29
Residential Real Estate	B.100 Account No. 4

Chapter 5

Conclusion

In conclusion, this thesis outlines three important issues related to real estate research. Chapter 2 addresses the functional form assumption related to the application of the popular hedonic pricing model and its implication on the house price index construction. We apply both the standard hedonic model and the semi-parametric model to a unique housing transaction dataset from Amsterdam region for the period 1990 to 2006. Our results are in line with the earlier studies that support a less stringent functional form of the hedonic model. In the construction of house price index, we first identify the representative house that combines the mean of housing attributes for each year in our sampling period. Both the traditional hedonic model and the semi-parametric model are used to predict the value of the representative house, which leads to chained Laspeyres indices. We find the index produced using the traditional hedonic model consistently overstates its semi-parametric counterpart.

Chapter 3 studies the effect of accounting for spatial as well as temporal correlation among housing transactions in predicting house prices. We follow the STAR model as in Pace et al. (1998), which subsumes the errors in the hedonic regression to follow an autoregressive process. We use a housing transaction dataset from Randstad region in The Netherlands spanning a period from 1997 to 2007, and control for spatial heterogeneity using submarkets defined by Dutch real estate brokers. We recognize the temporal order of housing transactions and integrate both the spatial and temporal neighbors in predicting future house prices. Our results show large magnitude of spatial correlation as compared to temporal correlation, which is consistent over our sampling period and in line with earlier studies using housing transaction data from other countries, such as U.S. and Spain. Moreover, we show that accounting for both the spatial and temporal correlation can substantially reduce the prediction error of future house prices, which is robust to alternative in-sample as well as out-of-sample specifications.

Chapter 4 tackles the issue of market portfolio composition in estimating REITs risk premium. Estimation of asset risk is potentially subject to bias arising from omission of asset classes from the market portfolio proxy according to CAPM. In practice, popular equity indices, such as S&P 500 and CRSP equity index, are prone to such bias. Using U.S. data, we construct a more diversified market portfolio that includes not only equity but also other asset classes, such as bonds and real estate, and test if the market proxy composition matters for REITs risk premium estimation. We show that REITs risk premium estimation is sensitive to both the structural break in the REITs market and market proxy composition. Moreover, a substantial portion of the bias in REITs risk premium estimation arising from using the popular equity indices as market proxy can be attributed to the exclusion of the real estate asset class in the market proxy. The results are robust to a survivor bias free sample of REITs.

Chapter 6

Samenvatting (Summary in Dutch)

Deze dissertatie beschrijft drie belangrijke onderwerpen in vastgoedonderzoek. Hoofdstuk 2 behandelt de aannamen die ten grondslag liggen aan de wiskundige formulering van het populaire hedonische prijs model en de daaruit voortvloeiende implicaties voor het construeren van huizenprijsindices. We gebruiken zowel het standaard hedonische model als een semi-parametrisch model op een unieke huizentransactie-dataset van de regio Amsterdam over de periode van 1990 tot 2006. Onze resultaten zijn in lijn met eerder onderzoek dat een minder strikte wiskundige formulering dan die van het hedonisch model ondersteunt. In de constructie van een huizenprijsindex identificeren we eerst de representatieve woning die de gemiddelde woningkenmerken van ieder jaar van onze onderzoeksperiode combineert. Zowel het traditionele hedonische model als het semi-parametrische model worden gebruikt om de waarde van het representatieve huis te voorspellen, wat resulteert in geketende Laspeyres indices. Wij vinden dat de index die geconstrueerd wordt met het traditionele hedonische model consistent de index gebaseerd op het semi-parametrische model overschat.

Hoofdstuk 3 bestudeert het effect van het rekening houden met ruimtelijke en tijdsgebonden autocorrelatie tussen woningtransacties in het voorspellen van huizenprijzen. We volgen het STAR-model van Pace et al. (1998), wat de storingstermen in de hedonische regressie toestaat een autoregressief proces te volgen. We gebruiken een huizentransactie-dataset van de Randstad over de periode van 1997 tot 2007 en corrigeren voor ruimtelijke heterogeniteit door gebruik te maken van submarkten die door Nederlandse makelaars zijn onderscheiden. Wij doen onze voorspellingen rekening houdend met de tijdgebonden volgorde van woningtransacties. Verder houden we in onze voorspellingen rekening met de dichtstbijzijnde transacties in zowel ruimtelijk als in tijdgebonden opzicht.

Onze resultaten tonen een grote hoeveelheid ruimtelijke autocorrelatie vergeleken met tijgebonden autocorrelatie. Dit is consistent het geval over onze gehele onderzoeksperiode en is in lijn met eerdere onderzoeken op basis van woningtransacties in andere landen, zoals de V.S. en Spanje. Bovendien vinden we dat het rekening houden met zowel ruimtelijke als tijdgebonden autocorrelatie de voorspellingsfouten voor toekomstige woningprijzen substantieel kan verminderen; deze resultaten zijn robuust voor verschillende alternatieve binnen- en buiten-steekproef specificaties.

Hoofdstuk 4 adresseert het thema van de markt portfolio samenstelling in het schatten van de risicopremie van REITs. Volgens de CAPM kan het schatten van het risico van activa kan mogelijk systematisch beïnvloed worden door het ontbreken van bepaalde klassen van activa uit de markt portfolio schatting. In de praktijk blijken populaire aandelenindices, zoals de S&P 500 en de CRSP, vatbaar voor zulke invloeden. Gebruikmakend van data uit de V.S. construeren we een beter gediversificeerde markt portfolio die niet alleen aandelen, maar ook andere vermogensbestanddelen als obligaties en vastgoed bevat. We testen of de samenstelling van de markt portfolio schatting invloed heeft op de schatting van risico premies van REITs. We tonen aan dat de schatting van risico premies van REITs gevoelig is voor zowel structurele veranderingen in de REITs-markt en de markt portfolio schatting. Bovendien kan een belangrijk deel van de afwijking veroorzaakt door het gebruik van de populaire aandelenindices worden toegeschreven aan het ontbreken van vastgoed in de markt portfolio schatting. De resultaten zijn robuust voor de overlevingsbias.

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