Real Estate Valuation and Investment

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Martin Wersing
aus Berlin

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Vorsitzender: Prof. Dr. Frank Heinemann
Berichter: Prof. Axel Werwatz, Ph.D.
Berichter: Prof. Dr. Wolfgang Härdle

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Abstract

Real estate investments are among the most important investment decisions during the life of many private households. This is particular true for residential real estate investments, such as purchasing a single-family house. Uncertainties about future house prices imply that it is difficult to assess the future value of one of the most important sources of wealth for many households. To our understanding of households' investment decisions it is thus essential to measure real estate price risk. A fundamental problem of measuring real estate price risk is the valuation of residential real estate assets. This dissertation empirically analyzes valuation approaches for single-family houses, the measurement of market-wide movements in the price of housing, and the extent to which real estate price risk affects a household's investment decisions into residential real estate. An extensive database on real estate transactions in Berlin, Germany is used for the econometric analysis of different valuation approaches for single-family houses. Furthermore, data from the German Socio Economic Panel Study is used for the measurement of market-wide price movements, as well as the econometric analysis of private households' investment decisions.

Keywords:
Hedonic approach, Forecast accuracy, Real estate price indexes, Tenure mode choice, Dynamic probit models

Zusammenfassung

Immobilieninvestionen sind eine der wichtigsten Anlageentscheidungen im Leben vieler privater Haushalte. Dies gilt insbesondere für den Erwerb von Wohnimmobilien, wie den Kauf eines Eigenheims. Unsicherheiten über zukünftige Hauspreise führen dazu, dass die Wertentwicklung eines Grossteils des privaten Vermögens nur schwierig abzuschätzen ist. Für unser Verständniss des Investionsverhaltens privater Haushalte ist die Messung von Immobilienpreisrisiken daher von fundamentaler Bedeutung. Ein grundlegendes Problem für die Erforschung von Immobilienpreisrisiken ist die Wertermittlung. Die vorliegende Dissertation analysiert empirisch Bewertungsverfahren für Wohnimmobilien, die Messung von den mit Immobilieninvestitionen verbundenen Preisrisiken und wie die Wirtschaftakteure in ihren Investitionsverhalten mit diesen Risiken umgehen. Für die ökonometrischen Analysen zur Wertermittlung wird auf eine umfangreiche Datenbank zu Berliner Einfamilienhaustransaktionen zurückgegriffen. Für die Messung von Immobilienpreisrisiken und für die ökonometrischen Analysen zu dem Investionsverhalten von privaten Haushalten werden die Daten des Sozio-ökonomischen Panels verwendet.

Schlagwörter:
Hedonische Methoden, Vorhersagegüte, Immobilien-Preisindexe, Erwerb von Wohneigentum, Dynamische Probit-Modelle

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Chapter 1

Introduction

1.1 Peculiarities of residential real estate investments

> "Far more important to the world's economies than the stock markets are wage and salary incomes and other nonfinancial sources of livelihood such as the economic value of our houses and apartments. This is where the bulk of our wealth is found."
>
> Robert J. Shiller (2003, p. 9)

In many countries, residential real estate is a large component of aggregate household wealth, and the single most important portfolio component for the majority of households. But residential properties, such as single-family houses, condominiums, or apartments in multi-family houses, are also a quite peculiar investment class. The heterogeneity of houses, their durability, their dual use for consumption and investment purposes, and their non-liquidity distinguishes them from financial assets. These special features of residential properties considerably complicate the valuation of real estate, as well as the investment decisions of households.

The importance of residential properties becomes apparent when looking at figures from households' financial accounts. Eymann and Börsch-Supan (2002) report that residential properties dominated aggregate household portfolios in Germany with a share of about 52% of total wealth in the late 1990s. For the United States, Bertaut and Starr-McCluer (2002) show

that aggregate household portfolios included about one quarter of residential real estate during the same period. Housing wealth is particularly important for middle-class households, and especially homeowners. According to Tracy and Schneider (2001) residential real estate accounted for almost two-thirds of the wealth of the median household in the United States in the late 1990s. In Germany, housing wealth contributed to about 74% of total wealth of the median household (Eymann and Börsch-Supan 2002).

These figures impressively show the importance of residential real estate investments. Shiller (1993a, 2003) has argued that the risks associated with these investment are among the largest economic risk faced by individual and institutional investors. While the price volatility in housing markets may not be greater than for many other assets, house price fluctuations can have great impacts on households' economic well-being, as well as the distribution of wealth. Declining real estate prices, for example, may blot out the savings of households who used their savings on a down-payment on their home. Rising real estate prices, on the other hand, may price those households out of the market who waited to buy a home. Moreover, residential real estate prices are also important for financial institutions who lend to property owners. This is because assets whose value is linked to real estate, such as mortgages or mortgage-backed securities, represent an important component of the portfolio of many banks.

Knowledge of the economic value of residential properties is thus of great importance for investment decisions of households, as well as for lending decisions of financial institutions. The valuation of individual properties and the measurement of their associated price risk, however, is a challenging task. In contrast to financial markets, residential real estate markets are inherently illiquid: Because of the substantial transaction cost of selling and buying a property, houses are seldom traded. Unlike for stocks or bonds, whose prices are quoted on exchanges, one can thus not rely on the market to deliver a continuous signal about the value of a property. But even if transaction prices are observable, the uniqueness of each individual house makes it difficult to figure out the market value of non-traded properties.

Households' investment decisions are further complicated by the fact that residential properties provide their owners with a stream of consumption services. The purchase of a home is thus driven by dual consumption and investment motives. Because equity sharing or partial ownership arrangements are not common in residential real markets, homeowners' real estate holdings are necessarily constrained by their demand for housing services (Brueckner 1997). The non-liquidity of residential properties, on the other hand, inhibits households from changing their desired housing consumption in response to economic shocks. One of the most important decisions every household has

to made with respect to real estate, is the question whether or not to buy or rent a home. When making this decision, households not only need to take the uncertainty about house prices, but also factors such as future income prospects, mobility needs, and the high cost of reversing this decision into account.

Focussing on the investments of private households into residential, this doctoral thesis is dedicated to two related aims: (i) the statistical valuation of single-family houses, as well as the measurement of market-wide movements in the price of housing, (ii) studying the extent to which real estate risk and career concerns affect households' decision whether to rent or buy a home.

1.2 Outline of the study

In Chapter 2 we start by investigating the accuracy of the two most common valuation approaches for single-family houses in Germany, that is the sales comparison approach and the cost approach. Banks and other financial institutions need a long-term forecast of future house prices for lending decisions and risk management purposes. In particular, valuations are often needed during the underwriting or refinancing of mortgage loans, where valuations should provide a fair assessment of the future market value of the property that will serve as collateral for the loan. Furthermore, reassessments of the collateral values for outstanding loans are necessary to value and quantify the risk of the bank's credit portfolio. We use a unique data set of transactions of single-family homes from Berlin, to predict individual house prices observed 1 to 5 years from the present. The cost values, that is the sum of the building cost and the land cost, are appraised values available in our data set. In order to forecast future house prices we adjust these cost values for depreciation and the expected future growth of replacement cost. Sales comparison values are estimated from a hedonic regression. According to this technique, the expected transaction price of a house is a function of the aggregate price level and the house's characteristics. These sales comparison values are adjusted for the expected growth of the future price level over the forecast horizon. The empirical results of our forecast experiment show that sales comparison values provide better long-term forecasts than cost values if the economic loss function is symmetric. Still cost values provide information for better valuations: A weighted average of both sales comparison values and cost values produces smaller losses on average than each of the values alone. However, good arguments can be made that financial institutions face an asymmetric loss function. In valuing the put option of default, an increase in the estimated house price relative to the mortgage value has a smaller effect

on the value of the option than the corresponding decrease. As an inspection of the empirical distribution of the valuation errors reveals, cost values are more likely to underestimate the market value, Thus, they might provide better long-term forecasts if the economic loss function is asymmetric.

While financial institutions are primarily concerned with long-term forecast of house values, home buyers and sellers have a great interest in the current market value of their (prospective) home. In Chapter 3, we investigate the accuracy of the hedonic regression approach for the prediction of current house values. A great advantage of the hedonic regression technique is that it copes easily with large data sets and is suitable for mass appraisals. While hedonic models assume that the market value of a property equals it's expected transaction price, conditional on the property's characteristics, applied hedonic regressions are usually fit to logarithmic transaction prices. This, in turn, requires a retransformation of predicted log prices when the model is used for automated valuations. It is well known, however, that retransformations of a logarithmic dependent variable with the exponential function deliver biased estimates of its expected value. We therefore present consistent predictors for the market values, and evaluate their out-of-sample performance of consistent predictors for the market value using our data of single-family house transactions from Berlin. Here, we consider, both, predictors relying on the assumption of log normally distributed prices and predictors without the imposition of a distributional assumption. The results of our prediction experiment show that the prediction accuracy does not significantly differ between the proposed retransformation techniques. As indicated by predictions obtained for homogenous subgroups of houses in our sample, however, heteroscedasticity in the regression residuals influences the bias reduction of these predictors.

Chapter 4 deals with the measurement of market-wide movements in the price of housing. We particulary focus on the construction of constant-quality rent indexes for Germany, and several German regions. Rental payments account for a large fraction of consumption expenditures for those households who rent their homes. Accurate measures of rent inflation are thus important to our understanding of the housing market risks that renters are exposed to. The construction of such indexes, however, is plagued by the heterogeneity of rental dwellings. To explicitly control for quality differences across and between any two periods of measurement, we consider a panel data variant of the hedonic regression method. Our approach attempts to capture intertemporal changes in rental prices by regressing dwelling characteristics and a set of time dummies on the logarithmic rent. Assuming that the marginal contributions of each attribute to rent stay constant over time, allows to interpret the estimated coefficients on the time dummies as quality-adjusted

price changes. The issue of time-varying regression coefficients on variables not directly related to time is addressed by estimating chained hedonic time dummy indexes. To explore the effect of unobserved dwelling characteristics on the constant-quality rent index, we consider, both, a random effects and fixed effects specification of the hedonic panel model. The models are estimated using data from the German Socio Economic Panel Study. Our empirical results show that omitted dwelling characteristics bias the estimated constant-quality index. A more robust estimation procedure relies on the fixed effects specification of the hedonic regression equation. The presence of time-varying regression parameters does not significantly affect the estimated indexes.

In Chapter 5 we empirically investigate the influence of real estate price risk and it's potential correlation with labor income risk on households' decision whether to rent or buy their home. There are several ramifications of the housing tenure mode decision with labor market career-concerns that imply a relationship between profession-specific income risk and the rent or buy decision. First, renting might be desirable for households in professions where job mobility is important. Renting will lead to lower transaction cost in the likely event of a job change and will shield the household from the resale price risk faced by homeowners. Second, renting may be preferred by members of professions whose labor income is positively correlated with regional housing cost. Then renting allows to diversify some of the systematic income risk. However, renting also exposes the household to rent risk and if this is large it may outweigh the diversification benefit. Using data from the German Socio Economic Panel Study we test these hypotheses regarding the impact of professional career decisions on tenure mode choice at both the profession-region and the household level. Probit regressions for proportions data provide empirical support for the proposed impact of rent and labor income risk and mobility needs on the shares of renters of different professions in the different regions. In order to capture the dynamic nature of households' housing choices, as well as (unobserved) heterogeneity across households within the same profession-region cell, we then turn to the rent or buy decision of individual households. Here we consider, both, a pooled cross-section of recently moved households, that is households facing the rent or buy decision for the time being, and a panel of households regardless of their tenure duration. Pooled probit and dynamic panel probit estimates, that control for the potential state dependence of current housing choices and unobserved heterogeneity, confirm our results from the rental share regressions.

All four Chapters are self-containing and can be read independently. Chapter 2 is based on a joint work with Rainer Schulz, Markus Staiber, and

Axel Werwatz, see also Schulz et al. (2008). Chapter 2 is based on a joint work with Rainer Schulz and Axel Werwatz, see also Schulz et al. (2009).

Chapter 2

The accuracy of long-term real estate valuations

2.1 Introduction

Real estate valuations are important for financial institutions, especially banks, for at least two reasons. First, valuations are often needed during the underwriting or refinancing of mortgage loans, where valuations should provide a fair assessment of the (future) market value of the property that will serve as collateral for the loan. Second, valuations are needed if the institution or bank wants an updated assessment of collateral values for outstanding loans it holds on its balance sheet. Such reassessments might be necessary and required by Basel II if new information arrives or market sentiments change.

The two most common approaches for the valuation of single-family houses are the sales comparison approach and the cost approach. Focussing on a short-term horizon, the studies of Dotzour (1990) and Schulz and Werwatz (2008) have shown that sales comparison values are more accurate than cost values when used as forecasts of current house prices. Further, the latter study finds that a weighted average of sales comparison values and cost values performs best.

In this chapter, we complement the above results by focussing on a long-term horizon and examine the accuracy of single-family house valuations when used as forecasts of future house prices. Here, the future could refer to the date when the borrower is most likely to default. The long-term valuation would then be a forecast of collateral recovery value given default. Informal evidence indicates that the default probabilities are highest in the early years of a mortgage loan, so that a long-term horizon of up to five years seems to

be a reasonable choice.[1]

It should be noted that mortgage banks in several countries are required to compute so-called mortgage lending values for the underwriting process. The rules for the computation of mortgage lending values are binding and defined in detail by the financial market supervisory authorities. This applies to Germany, the country our data comes from. According to the German rules, sales and cost values form the basis for the computation of single-family house mortgage lending values, but further adjustments and deductions are required.[2] Deductions are reasonable if the economic loss function of valuation errors is asymmetric. The long-term valuations we examine and the mortgage lending values are thus not identical, but related. Evaluating the accuracy of long-term valuations might thus also be useful for an understanding of the accuracy of mortgage lending values.

The results of the empirical investigation show that the sales comparison values provide better long-term forecasts than cost values if the economic loss function is symmetric, but a weighted average of sales comparison and cost values performs best. If the economic loss function is asymmetric, however, then—as kernel density estimates of the valuation error distributions reveal—cost values might provide better long-term forecasts. In summary, this chapter proves that it is possible and useful to assess the long-term performance of different valuation techniques empirically. Future work has to provide better understanding of the economic loss function. Moreover, a discussion of the accuracy of the different valuation approaches in a portfolio context seems to be worthwhile (Shiller and Weiss 1999).

The remainder of this Chapter is organized as follows. Section 2.2 discusses the sales comparison and the cost approach in detail and explains how we compute the different valuations. Furthermore our data set is described in detail. Section 2.3 presents the empirical results and the final Section 2.4 concludes.

2.2 Implementation

We explore the accuracy of long-term valuations with single-family house data from Berlin. Our data set allows the computation of sales comparison

[1] Available data on mortgage defaults from the U.S. indicate, that default rates increase substantially after about 3 years of mortgage originating and decline again after 6 to 9 years (Deng et al. 2000). Unfortunately there is no hard evidence available for Germany.

[2] The German rules are codified by law in the Beleihungswertermittlungsverordnung (BelWertV). In the case of both valuation approaches the appraised market value needs to be deducted by 10% in order to derive mortgage lending values (§16(2) and §19(1) BelWertV).

and cost values over a period of 30 quarters. These valuations are computed for different forecast horizons and are then compared to actual transaction prices. More precisely, we compute valuations for every transaction back-dated up to five years, taking into account only the information that was available that time. These valuations are adjusted for the expected future levels of house prices and replacement costs, respectively, and also for depreciation when necessary. In addition to a direct comparison of sales comparison and cost values, we also compute a equally-weighted combination of both. In practice, appraisers often compute such weighted combinations if two or more valuations of the same property are available.

2.2.1 Computation of the valuations

Sales comparison approach

The sales comparison approach uses transaction prices of comparable houses to estimate the value of the subject house. Several adjustments might be necessary when this approach is applied, either because the recently transactions are not completely comparable to the subject house or because house prices in the aggregate have changed. In this study we use hedonic regression techniques to compute sales comparison values. According to the technique, the observed transaction price of a house is a function of an aggregate price level, the house's characteristics and an unexplained part, assumed to be random.

In this study, we use hedonic regressions to predict sales comparison values given the information available at the time of the valuation. We specifically employ the following hedonic regression model:

$$p_t = \beta_{0t} + \sum_{c=1}^{C} \left\{ \beta_{c1} T_c(x_{ct}) + \beta_{c2} T_c(x_{ct})^2 \right\} + \sum_{d=1}^{D} \gamma_d x_{dt} + \varepsilon_t \ . \tag{2.1}$$

The dependent variable p_t is the log price for a house transacted in period t. The constant β_{0t} captures the general price level in period t. $T_c(\cdot)$ is a Box-Cox type transformation function for the cth continuous characteristic introduced by Bunke et al. (1999). Examples of continuous characteristics x_c are size of the lot, amount of floor space, and age of the building. β_{c1} and β_{c2} are the implicit prices for the respective – possibly transformed – characteristic. x_d is an indicator for the dth discrete characteristic, which could be a location indicator or the type of cellar. γ_d is the implicit price

of the discrete characteristic. The idiosyncratic error term ε_t is assumed to have mean zero and variance σ_ε^2.

Fitting equation (2.1) to transaction data requires the choice of a specific transformation function $T_c(\cdot)$ for each of the continuous characteristics. In principle, these transformation might depend on the sample period used to fit the model. To simplify our analysis, we choose the transformations based on the entire sample and use these transformations throughout. Further details on the choice of the transformation function are given in Appendix 2.5.1.

Table 2.1: The time structure of the forecast experiment.

Valuation Period (t)	Forecast Horizon				
	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$
1995Q1	-	-	-	-	2000Q1
1995Q2	-	-	-	-	2000Q2
1995Q3	-	-	-	-	2000Q3
1995Q4	-	-	-	-	2000Q4
1996Q1	-	-	-	2000Q1	2001Q1
1996Q2	-	-	-	2000Q2	2001Q2
1996Q3	-	-	-	2000Q3	2001Q3
1996Q4	-	-	-	2000Q4	2001Q4
1997Q1	-	-	2000Q1	2001Q1	2002Q1
1997Q2	-	-	2000Q2	2001Q2	2002Q2
1997Q3	-	-	2000Q3	2001Q3	2002Q3
1997Q4	-	-	2000Q4	2001Q4	2002Q4
1998Q1	-	2000Q1	2001Q1	2002Q1	2003Q1
1998Q2	-	2000Q2	2001Q2	2002Q2	2003Q2
1998Q3	-	2000Q3	2001Q3	2002Q3	2003Q3
1998Q4	-	2000Q4	2001Q4	2002Q4	2003Q4
1999Q1	2000Q1	2001Q1	2002Q1	2003Q1	2004Q1
1999Q2	2000Q2	2001Q2	2002Q2	2003Q2	2004Q2
⋮	⋮	⋮	⋮	⋮	⋮
2006Q1	2007Q1	-	-	-	-
2006Q2	2007Q2	-	-	-	-

Notes: Table illustrate the time structure of the forecast experiment. Data prior of 1995Q1 is only used to compute constant-quality house price and land price indexes.

As a by-product of our hedonic regressions, we also obtain constant-quality house price indexes, which we use later for forecasting the expected

future house price level. We start with a regression using the data over the period 1980Q1-1991Q2 to obtain estimates of the price levels β_{0t}. The second regression covers the period 1991Q2-1995Q2 and is used to make valuations based on information up to 1995Q2. The estimated coefficients of the price levels are used to construct the price index series from 1980Q1-1995Q2, which is used to forecast the future price level trend. The procedure continues by shifting the sample by one quarter and fitting a new regression. The last regression is for the period 2002Q2-2006Q2 and we fit 31 regressions in total.

The time structure of our forecast experiment is illustrated in Table 2.1. The individual long-term sales comparison value of a house transacted in $t+h$ is computed in two steps. In the first step, we use a hedonic regression fitted with data up to quarter t to compute the market value of the subject house in the valuation period t. Since the dependent variable in our hedonic regression is measured in logs, a re-transformation of the computed value is necessary. The re-transformation also corrects for any potential bias by using an 'optimal linear correction' factor Theil (1966, pp. 34). In the second step, we adjust the computed period t sales comparison value for the expected future price level over the forecast horizon h, see Section 2.3.1.

As stated above, the hedonic regression technique is only one of many possible ways of implementing the sales comparison approach. A great advantage of the hedonic regression technique is that it copes easily with large data sets and is suitable for mass appraisals (automated valuation). Once the regression is fitted, the value of a house – its expected price – is readily computed. The disadvantage of the hedonic regression technique is that it cannot take into account information that is not systematically recorded in the data set being used to fit the model. Such missing information is often of 'soft' nature, i.e., hard to quantify exactly. Examples are the style of decoration or the appearance of the direct neighborhood. A valuer visiting the subject house would take such soft factors into account. The results presented below on the performance of the sales comparison values might thus be seen as conservative, because the performance could be better if soft factors were taken into account.

Cost approach

The cost approach uses the replacement cost of the subject house as valuation, i.e., the sum of the building construction cost and the land cost. In case where the building of the subject house is not new, the building cost will be adjusted for depreciation. Thus, the cost value C for a building is given by

$$C = \{1 - \delta(a)\}B^{(N)} + L \ , \tag{2.2}$$

where L is land cost, $B^{(N)}$ is the construction cost of a new building, and $\delta(a)$ is the depreciation due to age a. Obviously, $\delta(0) = 0$ and $\delta(a)$ approaches 1 as age a becomes large. Both building cost and land cost are computed by our data provider for the transaction period $t + h$. Further details on these data is given Section 2.2.2.

We compute the cost values in two steps. First, we discount the land cost of the subject house to the valuation period t by using the land cost index. This land cost index is estimated from the time dummies of hedonic land cost regression over the full sample period.[3] The land cost in period t is then adjusted for the expected future land cost growth over the forecast horizon h by using a time series model fitted to the land cost index estimated with information up to period t. In the second step, the observed building cost in period $t + h$ is discounted to the valuation period t. The building cost is then adjusted for the expected future growth over the forecast horizon h by using a time series model fitted to the building cost index up to period t. The building cost for the subject house is finally adjusted for depreciation accrued in period $t+h$. Here, we employ the following depreciation function:

$$\delta(a) = 1 - \left(1 - \frac{a}{l}\right)^{0.65} \quad \text{with} \quad l = \begin{cases} 98 & \text{if } a \leqslant 66 \\ 98 + (a - 66) & \text{if } a > 66 \,, \end{cases} \tag{2.3}$$

where l is the conditional life span of a new building and a is the age of the building. A simpler version of this function was first introduced by Cannaday and Sunderman (1986). Observe that for $a \leqslant 66$ the depreciation accelerates with age. Once a building has reached the age of 66, however, depreciation slows, reflecting superior quality of long-lived buildings (see Figure 2.5). Further details on the depreciation function can be found in Appendix 2.5.2.

The building cost adjusted for depreciation and the land cost are then added together to form replacement cost, i.e., the cost value C. If a valuation is for the short term, it might be advisable to further adjust C for current deviations of prices from cost. Such an adjustment is not necessary for long-term valuations, however, if prices and replacement cost realign quickly over time, as it is the case for the test market (Schulz and Werwatz 2008).[4]

[3]Explanatory variables included in the hedonic land cost regression are lot size, lake side, and location dummies. The continuous variable lot size is transformed in line with the Box-Cox type transformation function applied in equation (2.1).

[4]Using the same data set, Schulz and Werwatz (2008) show that a time series of the ratio of house price to replacement cost, i.e. Tobin's Q, is stationary. Moreover, they show that the Berlin market adjusts back to equilibrium after a demand (supply) shock within about two years.

2.2.2 Data

The data used in the study consists of transactions of single-family houses in Berlin between 1980Q1 and 2007Q2. The data are provided by Berlin's local real estate surveyor commission (Gutachterausschuss für Grundstückswerte, GAA) out of its transaction database (Automatisierte Kaufpreissammlung, AKS). According to German Building Law (Baugesetzbuch, BauGB) surveyor commissions are entitled to request and collect information of all real estate transaction in their respective state. In particular, notaries are obliged to send a copy of the deed to the regional surveyor commission. Surveyor commissions are allowed to collect additional information and must provide information about the local real estate market(BauGB §§192 - 199). Berlin's surveyor commission, for instance, collects additional information on building cost in order to provide adjustment factors for the cost approach.

Our raw data set covers information on all real estate transactions in Berlin. Transactions before 1990 are exclusively from Berlin West. After cleaning our data set we loose about 2% of the observations. All observations have information on the price, appraised land cost, and many different characteristics of the house. Among these are the age of the building, floor space, and lot size. Only transactions from 2000Q1 onwards, however, have current information on new building cost. Between 2000Q1 and 2007Q2, we have 9088 observations, with at least 135, at most 628, and on average 303 transactions per quarter.[5]

Table 2.2 reports summary statistics for the main characteristics of the houses. Obviously, all the characteristics that a appraiser would use for computing a sales comparison value, especially in its hedonic regression variant, are observed. The data relevant to the cost approach are building cost and land cost. The original building construction cost in our data set were computed by the GAA surveyors based on information gathered and published by the German government (Bundesministerium für Raumordnung, Bauwesen und Städtebau 1997, Bundesministerium für Verkehr, Bau- und Wohnungswesen 2000). The published information gives the average building cost for many different house specifications in Germany. The land cost in our data set are the value of land if the site of the subject house were undeveloped. GAA surveyors appraise such land cost using the sales comparison approach and their database of all land transactions.

[5]Observations between 1980Q1 and 1999Q4 are mainly used to estimate constant-quality house price and land cost indexes. Observations between 1995Q1 and 1999Q4 are also used to predict sales comparison values in the valuation period.

Table 2.2: Summary statistics for transacted single-family houses in Berlin between 2000Q1 to 2007Q2.

Panel A: Continuous Characteristics, Prices, and Cost				
	Mean	Median	Std. Dev.	Units
Lot size	566.8	514.0	308.3	Sqm
Floor space	147.7	137.0	53.3	Sqm
Gross volume	657.2	599.0	253.1	Cm
Gross base	247.4	232.0	90.0	Sqm
Year of construction	1961	1962	29.0	Year
Price	228.7	198.5	14.0	(000)
Building cost	185.8	173.4	82.4	(000)
Land cost	120.7	91.1	117.2	(000)
Panel B: House Type				
Detached	52.7%	Semi-detached		22.2%
End-row	16.9%	Mid-row		15.8%
Panel C: Location and Lake Side				
Simple	32.1%	Average		46.5%
Good	18.9%	Excellent		2.0%
Lake side	0.9%			
Panel D: Number of Storeys and Attic				
One	54.3%	Two		43.6%
Three	2.1%	Attic		55.0%
Panel E: Cellar				
Full	77.4%	Part		11.6%
No	10.9%			

Notes: 9088 observations. Gross base is the sum of all base areas in all storeys, gross volume is the corresponding volume. 4017 objects have information on the gross volume and 9063 on the gross base. All euro values in the Table are in real (2000) euros, deflated by the Berlin CPI. Building cost are cost of constructing a new building. Attic in Panel D means that the attic is upgraded for living.

2.3 Empirical results

2.3.1 Characterization of the test market

Figure 2.1 shows the trend of house price, land cost, and construction cost for a constant-quality single-family house in Berlin over the period 1980Q1 to 2007Q2. The index values are computed as

$$100 \exp\{\widehat{\beta}_{0t} - 0.5\widehat{\sigma}_t^2\} \ ,$$

which corrects for small-sample bias Kennedy (1998, p. 37). $\widehat{\beta}_{0t}$ is the estimated coefficient for the house price and land cost level, respectively, in period t and $\widehat{\sigma}_t^2$ is the corresponding estimated (heteroscedasticity) robust variance of the coefficient estimator. The quarterly construction cost index is provided by the Statistical Office Berlin in its Statistical Report M I 4. It measures the change of the construction cost for a new single-family house.

The movement of prices for existing houses and the cost of constructing new houses are closely related. This is in line with economic reasoning because if house prices are above replacement costs, i.e., the sum of land and building construction costs, then it is profitable for developers to construct new houses. The additional supply will increase the housing stock and, given unchanged demand, dampen house price growth. Developers will provide additional supply until prices of existing houses are realigned with replacement cost and no extra profits can be made. In the case that house prices fall below replacement cost, developers will provide no new supply at all and the housing stock will shrink until equilibrium is reached again. This reasoning motivates the use of the cost approach for forecasting long-term house values, because even if prices and replacement cost deviate at the date of valuation, they will move closer in the near future. If replacement cost is a better forecast of the future house price than any function of past prices, then this could put the cost approach at advantage even if the sales comparison approach has been found in previous studies to perform better with respect to short-term valuations.

ARMA models for price and cost trends

For the forecast experiment, all three series a treated as difference-stationary time series and ARMA models are fitted to the growth rates. Further details on the time series properties of the index series are given in Appendix 2.5.3. Table 2.3 presents the ARMA specifications for the three different series, the volatility of the growth rates over the full sample and the regression fit. In the case of the two estimated constant-quality series we take the log

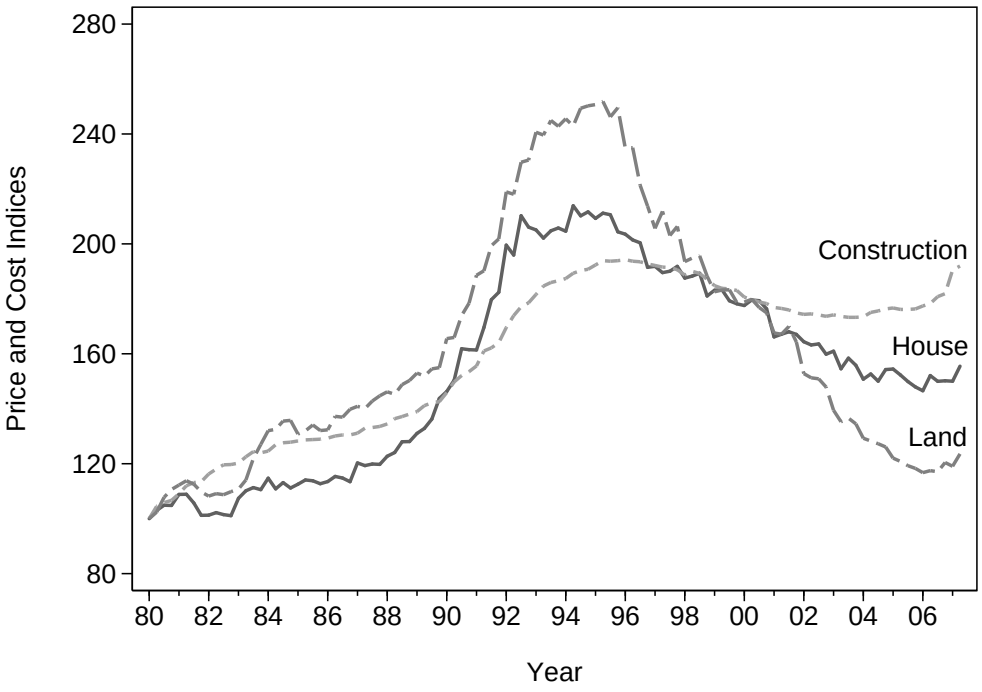

Figure 2.1: Constant-quality house price and land cost indexes, and construction cost indexes for single-family houses in Berlin, 1980Q1-2007Q2. Series are normalized to 100 in 1980Q1.

indexes directly from the hedonic regressions (instead of re-transforming the indexes again). The regression constant c_t of the specifications in Table 2.3 allows for a shift in the respective growth rate after the introduction of the European single market in 1993. The specifications have a parsimonious parametrization and the fitted models have uncorrelated residuals according to the standard Q-test for autocorrelation.

In order to simplify the forecast experiment, we fit the same ARMA specifications to the data of the shorter sample periods. In most cases the residuals of the specifications fitted over shorter sample periods rather than the full sample period are uncorrelated and all the coefficients are statistically significant.

It follows from the specification for the house price growth in Table 2.3 that the house price index follows a random walk. Note that if we were to assume that the required return rate for a housing investment is constant

Table 2.3: Time series model specifications fitted to the three different index series. Volatility, coefficient of determination, and Q-statistics are for the full sample fit with data from 1980Q1 to 2007Q2.

Variable y	Model specification	$\widehat{\sigma}_{\Delta \ln y}$	R^2
House price	$\Delta \ln y_t = c_t + \varepsilon_t$	2.6	13.2
Land cost	$\Delta \ln y_t = c_t + \theta_2 \varepsilon_{t-2} + \theta_3 \varepsilon_{t-3} + \theta_4 \varepsilon_{t-4} + \varepsilon_t$	2.8	44.1
Construction cost	$\Delta \ln y_t = c_t + \phi_4 \Delta \ln y_{t-4} + \theta_3 \varepsilon_{t-3} + \varepsilon_t$	0.9	50.6
	Test for autocorrelation:	Q-statistic	P-value
House price		39.908	0.474
Land cost		51.087	0.112
Construction cost		4.026	1.000

Notes: The constant is $c_t = c_0 + c_1 I_{1993\text{Q}2}(t)$, where $I_{1993\text{Q}2}(t)$ is an indicator function, which is 1 if $t \geqslant 1993\text{Q}2$ and 0 otherwise. ε_t is the residual. The estimated volatility $\widehat{\sigma}_{\Delta \ln y}$ and the coefficient of determination R^2 are expressed in percent. Q-statistic is calculated under the null hypothesis that residuals exhibit no autocorrelation (Ljung and Box 1978). P-value is for a $\chi^2(40)$-distribution.

and the unobserved imputed rent is proportional to the house price, then a random walk would indicate that prices are set in an informational efficient manner.[6] Without the lagged MA terms, the land cost index would follow a random walk as well. It seems reasonable to attribute the moving average terms to the valuation process with which land cost are computed.[7] The growth of construction cost, on the other hand, exhibits a strong seasonal component.

As is obvious from Figure 2.1, the construction cost have a much smaller volatility then the other two series. Moreover, because of the strong seasonal component, the in-sample predictability of the construction cost growth is higher than for the other two series as indicated by the R^2s. Thus, it might be possible to forecast the construction cost with greater accuracy. Compared to prices, the land cost regression has a much better fit, which might indicate that land cost can be forecasted more accurately as well, making a combination of construction and land cost superior to direct forecasting of

[6]This is in contrast to empirical findings for housing markets in the U.S. and U.K.. Since the seminal work by Case and Shiller (1989) it has been repeatedly shown that singly-family house markets in these countries violate standard efficiency criteria.

[7]Since the land values in our database were computed by the GAA surveyors based on current and past information on observed land transactions, the moving average terms are likely to be the result of appraisal smoothing.

the house price index.

Forecasting price and cost trends

Figure 2.2 compares two different price forecasts for the last five years of the full sample period with the full sample house price index. The first forecast is based on the house price specification fitted to the data up to 2002Q2. This is a forecast of the house price index itself and corresponds to the very idea of the sales comparison approach. The second forecast is based on a weighted average of the land and cost indexes, both forecasted in 2002Q2 based on the available information then. We assume that construction costs of the building contribute to 55% of the replacement cost and land cost 45%.[8] Using the forecasted replacement cost index as a forecast of the house price corresponds to the very idea of cost approach. Figure 2.2 reveals that both forecasts seem to perform well.

Although the house price index estimated with the data up to 2002Q2 and the index estimated with the full data sample show a very similar behavior before 2002Q3, they are not identical. This is the results of the rolling window estimation technique we apply. New information due to extension of the estimation sample can influence the estimated index coefficients in preceding quarters. The difference of the two house price indexes in Figure 2.2 before 2002Q2 are not statistically significant, but the point estimates itself differ. The index revision problem is not specific to the constant-quality indexes, but applies also to official indexes like the construction cost index. Consequently, the forecaster has often to work with provisional time series and there is no solution to this problem. There are two additional aspects that have to be considered. First, the full sample house price index itself might not be the best benchmark for assessing forecast accuracy. Second, and closely related, because the time series are normalized indexes, the seemingly good forecasting behavior of the replacement cost in Figure 2.2 should not be misinterpreted: the near equality of the full sample house price and the replacement cost index in period 2002Q2 might be just the result of the arbitrary index normalization. House prices in that period might be larger than replacement cost, in which case forecasted long-term cost values will be below prices during the whole forecasting horizon. If, on the other hand, replacement cost are slightly above house prices in period 2002Q2, then the

[8]The weights have been chosen according to average ratio of construction cost to replacement cost, i.e. construction cost and land cost, in our sample.

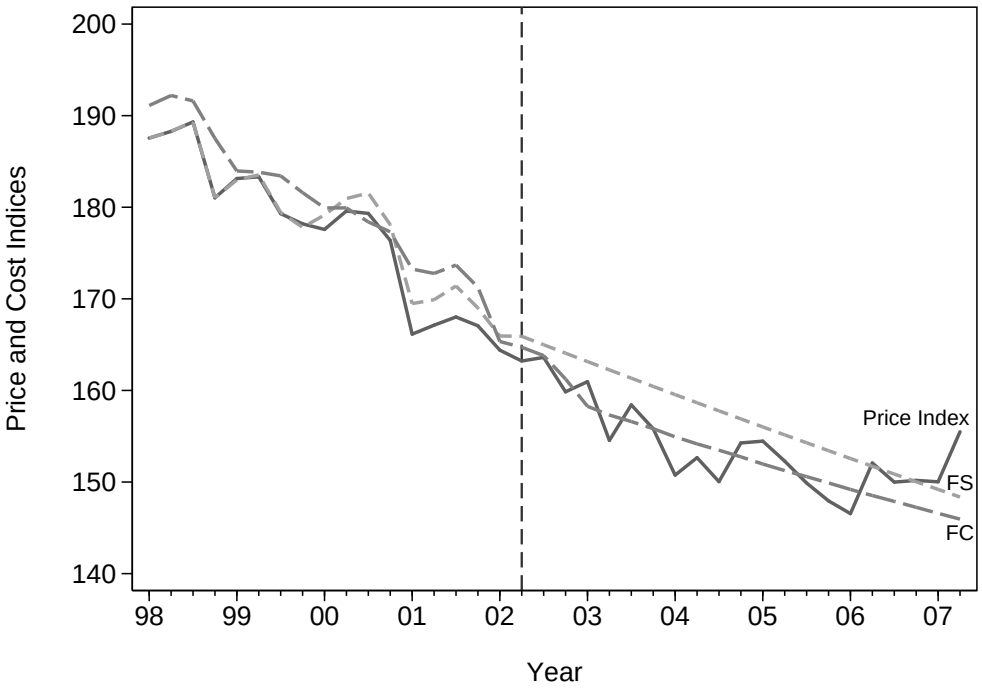

Figure 2.2: Full sample house price index and forecasts for the period 2002Q3-2007Q2 (right from vertical dashed line) based on information up to 2002Q2. The sales comparison approach forecast (FS) is based on the time series model for the price index, the cost approach forecast (FC) is a weighted average of the forecasted land cost and construction cost indexes.

forecasted long-term cost values might be even closer to prices over the forecasting horizon than Figure 2.2 indicates.

Because of these possible estimation and normalization effects, a pure comparison of index series is no substitute for the evaluation of individual house-specific forecast errors. Only a direct comparison of valuations and transaction prices can reveal the accuracy of a valuation technique.

2.3.2 Horse race

In this section, we compare the forecast performance of sales comparison values with the performance of cost values. We first evaluate the forecast ac-

curacy of both approaches using standard (symmetric) loss function. Long-term real estate valuations, however, are of particular interest in the process of mortgage underwriting. Good arguments can be made that the economic loss due to overvaluations are more costly for mortgage originators (Shiller and Weiss 1999). The main problem, however, is to establish the true economic loss function. In order to detect if one approach is more likely to overvalue, we secondly inspect the empirical distribution of valuation errors.

Valuation error and loss function

The figure of interest is the valuation error

$$e_{t+h} = \ln P_{t+h} - \ln V_t \ ,$$

where P_{t+h} is the observed transaction price of a house in period $t+h$ and V_t is the valuation made for this house based on information in period t. We focus on the five forecast horizons $h \in \{4, 8, 12, 16, 20\}$, which correspond to 1, 2, 3, 4, and 5 years, respectively. We use log errors, because they weight over- and undervaluations symmetrically.[9] If the errors are small, then e_{t+h} is a close approximation of the error relative to the valuation

$$\frac{P_{t+h} - V_t}{V_t}$$

and $-e_{t+h}$ is a close approximation of the valuation error relative to the price

$$\frac{V_t - P_{t+h}}{P_{t+h}} \ .$$

Clearly, a valuation technique is the better the smaller the valuations errors are on average and the less dispersed they are. To save on notation, we denote N_h as the number of transactions for which we make valuations with a horizon of h and $e_{h,n}$ as the valuation error for house n with forecast horizon h. The mean error of a valuation technique at the forecast horizon h is then

$$\mathrm{ME}_h = \frac{1}{N_h} \sum_{n=1}^{N_h} e_{h,n} \ ,$$

i.e., the arithmetic average over all errors with the same forecast horizon h. The mean error does not take the dispersion of the errors into account. A

[9]Percentage errors, on the other hand, penalize overvaluations more than undervaluations if the lower limit of a valuation method is bounded by zero. Then evaluating forecast on the basis of percentage errors creates a preference for methods that avoid large overvaluations (Dittman and Maug 2006).

valuation technique might have a small mean error simply because valuations are either far too large or far too small. The following two measures take the dispersion into account. The first is the mean absolute error

$$\mathrm{MAE}_h = \frac{1}{N_h} \sum_{n=1}^{N_h} |e_{h,n}|$$

and the second is the mean squared error

$$\mathrm{MSE}_h = \frac{1}{N_h} \sum_{n=1}^{N_h} e_{h,n}^2 \ .$$

Both measures are symmetric and give positive and negative errors with same absolute magnitude the same weight. In many situations where the economic loss due to under- or overvaluations is unknown, this might be a good compromise. A negative valuation error corresponds to a forecasted value higher than the realized transaction price. In the context of the mortgage underwriting process, such overestimation could lead to underwriting based on a false perception of collateral's value in the case of a default. Overestimation does not necessarily need to lead to an actual loss in the case of default, because the loss also depends on the outstanding loan balance. The sale of the collateral may still be enough to cover borrower's outstanding liabilities. However, from a risk management perspective, it is desirable that loan underwriting is based on a correct assessment of the recovery value of the collateral. Moreover, the initial loan might be directly related the collateral value and overestimation could lead to larger and more risky loans than are perceived during the underwriting process. A positive valuation error corresponds to a forecasted value lower than the the realized price. In this case the collateral will always be sufficient to cover any outstanding loan balance. The economic loss of underestimated collateral values comes from the fact that applications may get declined during the underwriting process. This is foregone business for the mortgage underwriter, because the true value of the collateral could have been more than sufficient to fulfill the underwriting criteria. Using the MSE and the MAE as accuracy measures thus corresponds to the assumption that the economic loss of over- and undervaluation is the same.

Forecast performance under symmetric loss

Table 2.4 presents the forecast evaluation measures for cost and sales comparison values and a equally-weighted combination of both. In addition to the

Table 2.4: Performance of sales comparison and cost values over different yearly forecast horizons. Summary statistics of valuation errors for transactions between 2000:1 to 2007:2.

Valuation method	Horizon	ME	MDE	MSE	MAE	PE25
	1	0.9	1.8	8.8	22.6	65.0
	2	-0.3	0.8	8.8	22.6	65.2
Cost value	3	-2.2	-0.9	9.1	22.8	64.7
	4	-5.6	-4.3	9.5	23.4	63.4
	5	-11.4	-10.3	11.0	25.5	59.5
	1	-3.3	-2.3	6.2	18.7	73.4
	2	-3.3	-2.4	6.7	19.5	71.6
Sales comparison value	3	-4.6	-4.3	7.2	20.2	69.7
	4	-6.6	-5.7	7.9	21.3	67.2
	5	-7.9	-7.3	8.6	22.5	64.3
	1	-1.9	-0.6	6.2	18.7	72.9
	2	-2.5	-1.4	6.4	19.1	72.0
Combination	3	-4.1	-3.0	6.7	19.5	71.2
	4	-6.9	-5.8	7.3	20.5	69.3
	5	-10.6	-9.4	8.2	21.8	66.2

Notes: All reported measures are in percent. Number of observations is 9088 per valuation method and forecast horizon. ME is the mean error, MDE the median error, MSE the mean squared error, MAE the mean absolute error, and PE25 is the relative frequency of valuation errors within ±25% in absolute value. Combination is an equally-weighted average of the cost and the sales comparison values.

measures already discussed above, Table 2.4 also reports the median valuation error and the percentage of observations where the valuation lies within ±25% of the observed transaction price. The first two panels of Table 2.4 show that the sales comparison values perform better than the cost values for each of the five forecast horizons. Although the cost values have smaller mean errors than the sales comparison values for all but the five year horizon, the variation of these errors is larger, as the MSE and the MAE clearly indicate. Moreover, the percentage of valuations that lie within ±25% of the transaction price is larger for the cost values than for the sales comparison values.

One may object that the above comparison is only based on a sample of

transactions and that prices in general may deviate from unobserved market values. It could be that cost values forecast market values perfectly well, but this goes undetected, because observed prices can and will deviate from market values. Diebold and Mariano (1995) proposed several tests for the comparison of different forecast methods that take such uncertainty into account. Table 2.5 presents test results on the relative forecast performance. The test on the MSE uses the $N = 9088$ differences of the squared errors

$$e^2_{C,h,n} - e^2_{S,h,n} \ ,$$

where C stands for the cost valuation error and S for the sales comparison valuation error, and tests if the difference is equal to zero on average (same MSE) or if the difference is at most as large as zero (cost values are at least as good as sales comparison values, possibly even better). The test on the MAE uses

$$|e_{C,h,n}| - |e_{S,h,n}| \ ,$$

but is otherwise identical to the test on the MSE. Applied to our data, we can reject the hypothesis that the cost values values have a MSE at most as large as the sales comparison at the 1% significance level, i.e., we reject $\text{MSE}_C \leqslant \text{MSE}_S$. We can reject the equivalent hypothesis for the MAE at the same level of significance, i.e., we reject $\text{MAE}_C \leqslant \text{MAE}_S$. Another important test is the Sign test, which counts the number of observations where the cost value is closer to the price than the respective sales comparison value, i.e., how often is

$$|e_{C,h,n}| \leqslant |e_{S,h,n}| \ .$$

If both valuation methods were of equal accuracy, then the probability of one being better than the other would be 0.5. If we have N pairwise observations of forecast errors, then we expect under the assumption of equal accuracy that the cost values are better in 50% of the observations and the sales comparison values in the remaining 50%. For our data, however, the cost values are better for only 44.2% of the pairwise observations over all forecast horizons, whereas the sales comparison values are better in 55.8%. Given number of observation, $N = 9088$, these frequencies are unlikely to have been generated by methods with equal accuracy. We can reject the hypothesis that the cost values are at least as accurate as the sales comparison values for each of the forecast horizons at the 1% significance level.

Taking the first two panels of Table 2.4 and the test results in Table 2.5 together, we conclude that the sales comparison values perform better than the cost values based on the MSE and the MAE criteria. If one has to decide in a given situation for either a cost value or a sales comparison value, then

Table 2.5: Tests on the relative valuation performance of cost and sales comparison valuations for all forecast horizons.

	Horizon	Test-Stat.	P-Value two-sided	P-Value one-sided
Test of MSE	1	17.92	0.000	0.000
	2	14.31	0.000	0.000
	3	12.04	0.000	0.000
	4	9.65	0.000	0.000
	5	12.80	0.000	0.000
Test of MAE	1	20.70	0.000	0.000
	2	16.14	0.000	0.000
	3	13.48	0.000	0.000
	4	10.07	0.000	0.000
	5	13.49	0.000	0.000
Sign test	1	5279	0.000	0.000
	2	5115	0.000	0.000
	3	5016	0.000	0.000
	4	4915	0.000	0.000
	5	5051	0.000	0.000
Signed-rank test	1	19.44	0.000	0.000
	2	15.06	0.000	0.000
	3	12.64	0.000	0.000
	4	10.18	0.000	0.000
	5	13.15	0.000	0.000

Notes: Test statistics are computed based on functions $d(e_{C,h}, e_{S,h})$ of the 9088 valuation errors $e_{i,h} = \ln P - \ln V_{i,h}$. P is the transaction price and $V_{i,h}$ is the valuation of technique i for horizon h. In the test on the MSE, $d(e_{C,h}, e_{S,h}) = e^2_{C,h} - e^2_{S,h}$, the null hypothesis is $\mathcal{E}[d] = 0$ in the two-sided version and $\mathcal{E}[d] \leqslant 0$ in the one-sided version. The Test-Stat. is a standard t-Statistic for the average d, which is asymptotically standard-normal distributed. The test on the MAE is similar, but uses $d(e_{C,h}, e_{S,h}) = |e_{C,h}| - |e_{S,h}|$. The Sign and the Signed-rank tests use also $d(e_{C,h}, e_{S,h}) = |e_{C,h}| - |e_{S,h}|$, the null hypothesis of both tests is a zero-median d in the two-sided version and a smaller than zero median in the one-sided version. The Test-Stat. of the Sign test is the number of valuations with $|e_{C,h}| > |e_{S,h}|$. The Test-Stat. under the null follows a binomial distribution with parameter N and probability 0.5. The Signed-rank test is the studentized version of the Wilcoxon test. For details on the tests see Diebold and Mariano (1995).

one should prefer the latter. If both values are computed, as German valuers routinely do, then weighted combination of both value might perform better

than each techniques individually. The third panel of Table 2.4 shows that a equally-weighted average delivers a better performance than stand-alone sales comparison values. Other weights for two values are possible, which might enhance the performance even further.[10] The performance results on the long-term valuation accuracy of sale comparison and cost values is thus identical to the results obtained in previous studies for valuations with a short-term horizon.

Forecast performance under asymmetric loss

Both the MSE and the MAE weigh positive and negative valuation errors symmetrically. In the context of mortgage underwriting, however, it is open to debate if the cost of foregone business due to underestimating the collateral value leads to the same business cost as a loan that is collateralized with a property, which has much lower value than the long-term value indicates. One could argue that positive valuation errors are less costly than negative valuation errors. The true economic loss function would be then asymmetric, putting more weight to negative valuation errors. The main problem with this reasoning is that the true economic loss function is not known and might be complicated to establish. Because of this, Shiller and Weiss (1999) have proposed that an estimate of the distribution of the valuation errors might be a good visual device to assess this.

Figures 2.3 and 2.4 show kernel density estimates for the valuation errors with a horizon of 2 and 5 years. We select the bandwidth according to Silverman's rule of thumb; asymptotic confidence bands are estimated at the 95% level, see Härdle et al. (2004, Chapter 3). The density estimates for the horizons of one, three, and four years are very similar in shape to the density for the two year's horizon in Figure 2.3. It emerges from these density estimates that the valuation error distribution of the sales comparison values is quite symmetric around its mean error, which is -3.3%, but shifted to the right if the an expected error of zero is taken as reference. The distribution of the valuations errors of the cost values, on the other hand, is less symmetric around its mean error of -0.3%. Further, the cost values with 51.3% have a larger probability mass for non-negative errors than the sales comparison values with 45.6%. Compared to the sales comparison values, it is more likely that a cost value underestimates the long-term market value.

[10] Granger and Ramanathan (1984), for instance, present different methods to derive optimal weights from simple linear regressions of observed prices on forecasted values. Using data from Berlin, Schulz and Werwatz (2008) find that these weighted forecast perform better than equally weighted combinations for the prediction of current house prices.

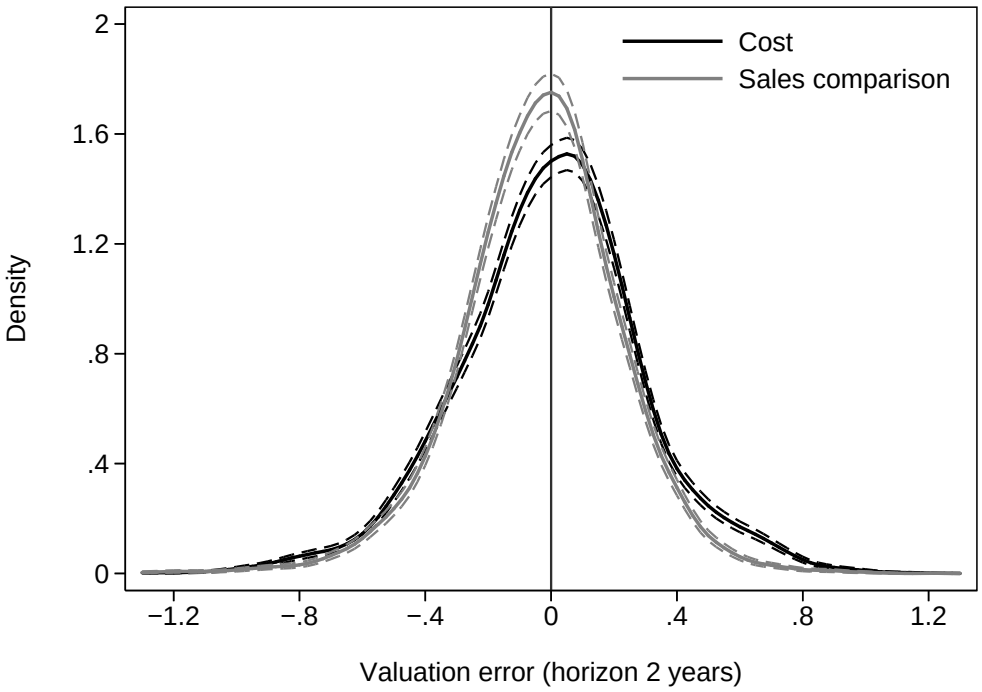

Figure 2.3: Kernel density estimates for the valuation error distributions of the cost and the sales comparison values. The forecast horizon is 2 years. The dashed lines are 95% confidence intervals.

Severe underestimations, where the valuation is only 20-40% of the market value, are much more likely to occur with cost values compared than with sales comparison values. This is shown by the dent of the density function on the right side. If underestimation leads to a lower economic loss than overestimations, then this might indicate an advantage of the cost values. Without an explicitly specified asymmetric economic loss function, however, it is not possible to compute the magnitude of this possible advantage.

A different picture emerges for the distribution of the valuation errors at the five year forecast horizon. Both distributions are shifted to the left and only 35.6% of the cost values produce a positive valuation error compared to 38.5% of the sales comparison values. The dent in the density function for large underestimations of the market value is visible again.

Figures 2.3 and 2.4 are also useful to assess the effect of proportional deductions on valuation errors. Such deductions are required for the compu-

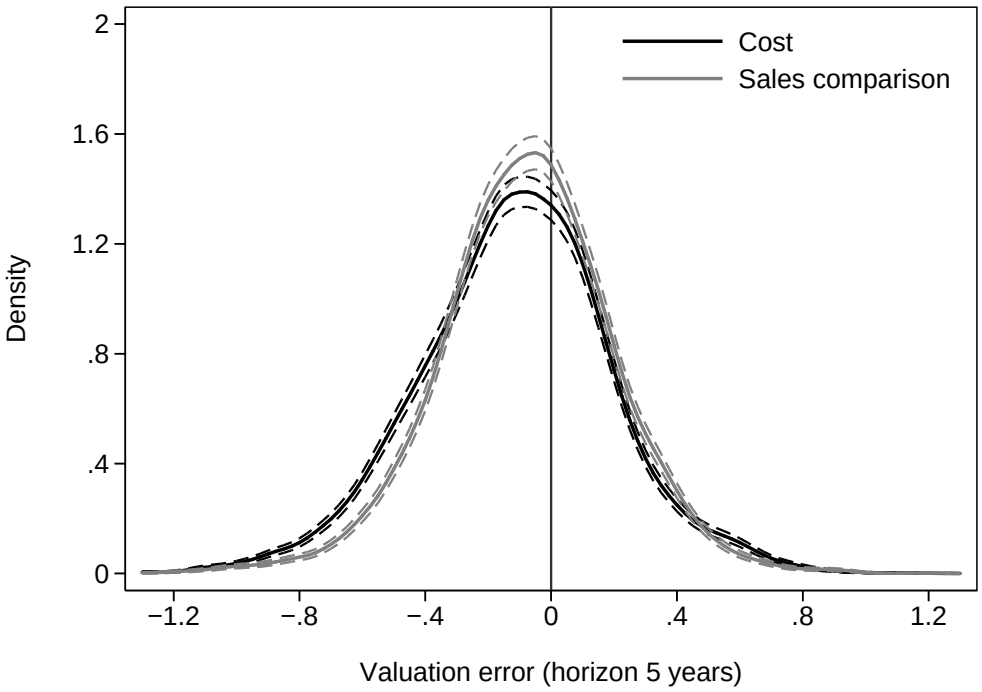

Figure 2.4: Kernel density estimates for the valuation error distributions of the cost and the sales comparison values. The forecast horizon is 5 years. The dashed lines are 95% confidence intervals.

tation of mortgage lending values. Let γ denote the proportional deduction, say 20%, then the resulting mortgage lending value is $(1-\gamma)V$. The corresponding lending valuation error distribution would then simply correspond to the plotted valuation error distributions shifted to the right by approximately γ.

2.4 Conclusion

The direct comparison has shown that sales comparison values perform better than cost values if the economic loss function is symmetric. If both values are available, however, then a equally-weighted average of both cost and sales comparison values produces smaller losses on average than each of the values alone. Pooling the valuations is thus advisable and the cost value, although inferior to the sales comparison values in a direct comparison, still provides

information for better valuations. If the loss function is asymmetric, penalizing overvaluations more than undervaluations, then it might be possible that cost values are better in a direct comparison than the sales comparison values. It is more likely for a cost value to underestimate the market value of a house than it is for a sales comparison value.

Without further knowledge on the economic loss function of valuation errors it is not possible to come to a final assessment. Further work needs to evaluate the specific form of the economic loss function. Varian (1974), for instance, proposed a loss function which varied linear for one sort of deviations and at an exponential rate for the other. Given the deductions required for the computation of mortgage lending values, it seems plausible that losses from overestimation are more problematic in practice than losses from underestimation.

A shortcoming of our study is that over the period 2000Q1 onwards prices were steadily falling, only in the last quarter do prices seemed to have gained some upward momentum. This may explain why the MEs are negative in all but one case. Moreover, our data are for only one region with a large number of comparable sales. The performance of the sales comparison approach might be worse in regions with less active markets. Future research has to make use of longer time periods and should also extend the horizons over which forecasts are made.

2.5 Appendix

2.5.1 Transformation of continuous variables

For the continuous explanatory variables in the regression equation (2.1) we consider the following transformations:

$$T(x_c, \lambda) \quad = \quad \begin{cases} \lambda^{-1}\left[\{\sigma_x^{-1}(x_c + a_\lambda)\}^\lambda - 1\right] & \text{if } \lambda \in \Lambda \\ \ln\{\sigma_x^{-1}(x_c + a_\lambda)\} & \text{if } \lambda = 0 \end{cases} \tag{2.4}$$

with $\Lambda = \{-2, -1, -0.5, 0, 0.5, 1, 2\}$. x_c denotes any of the continuous variables, a_λ is a constant conditional on the parameter λ, σ_x is the sample standard deviation of x_c, and λ determines the functional form of the transformation. A particular value of λ implies a value of the constant a_λ which are computed according to the suggestions made in Bunke et al. (1999).

We choose λ_i simultaneously for each of the $I = 5$ continuous variables (see Table 2.2, Panel A) by the following leave-one-out cross-validation cri-

terion:

$$\boldsymbol{\lambda}^* = \arg\max_{\lambda} 1 - \left\{ \frac{\sum_{t=1}^{T} \sum_{n=1}^{N_t} \left(p_{n,t} - \widehat{p}_{t,-n}(\lambda^*)\right)^2}{\sigma_p(N-1)} \right\}, \tag{2.5}$$

where the vector $\boldsymbol{\lambda}^*$ collects all λ_is, T denotes the number of periods, N_t is the number of observations in t, and N is the total number of observations. $\widehat{p}_{t,-n}$ is the predicted value for observation $p_{n,t}$ from an OLS regression of log-prices on all explanatory variables, including the continuous variables, that have been transformed according to the particular value of λ under consideration. Here, the subscript $(t, -n)$ denotes the leave-one-out estimator of observation $p_{n,t}$. More specifically observation $p_{n,t}$ has been omitted from the regression used to predict the price of house n at time t. By leaving out the observation used for evaluating the model fit the cross validated choice of $\boldsymbol{\lambda}^*$ is optimal in the sense of minimizing an estimate of the expected squared prediction error (Bunke et al. 1999). Note, that in the context of OLS the prediction error of the leave-one-out estimator can be obtained by the ratio of the OLS residuals and the diagonal elements of the hat matrix, see e.g. Myers (1990, pp. 133).

2.5.2 Depreciation function

We have estimate the depreciation function defined in equation (2.8) from our data on observed transaction prices and the corresponding replacement cost. Recall that very idea of the cost approach states that in steady-state house prices equal replacement cost adjusted for depreciation. In the short-run, however, house prices and replacement cost may deviate from equilibrium values. We thus model the relationship between observed transaction prices and replacement cost by

$$\begin{aligned} P &= Q\left[B^{(N)}\left\{1-\delta(a)\right\} + L\right] U \\ &= Q\left[C^{(N)} - B^{(N)}\delta(a)\right] U \end{aligned} \tag{2.6}$$

where Q captures short-run deviations of replacement cost from price, and U is an idiosyncratic error term with mean zero. Note that in a standard stock-flow model of housing investment the variable Q can be interpreted as Tobin's Q which captures deviations from equilibrium (Schulz and Werwatz 2008).

Dividing both sides of equation 2.6 with the replacement cost for a new house, $C^{(N)}$, and taking logs yields

$$q^{(N)} = q + \ln\left\{1 - w\delta(a)\right\} + u \tag{2.7}$$

where $q^{(N)} \stackrel{\text{def}}{=} \ln(P/C^{(N)})$ and w is building cost share of replacement cost, i.e. $w \stackrel{\text{def}}{=} B^{(N)}/C^{(N)}$. Given a parameteric specification of the depreciation function, $\delta(a)$, in equation (2.7) one can easily estimate the unknown parameters of the depreciation function with nonlinear least squares (NLS). We specifically employ a modified version of the depreciation function introduced by Cannaday and Sunderman (1986):

$$\delta_{CS}(a) = 1 - \left(1 - \frac{a}{l}\right)^{\beta} \quad \text{with} \quad l = \begin{cases} \underline{l} & \text{if } a \leqslant a_K \\ \underline{l} + (a - a_K) & \text{if } a > a_K \end{cases}, \tag{2.8}$$

where l is the life span of a building, conditional on the building's age a, and $\underline{l}$ the unconditional life span in years. For $a \leqslant a_K$, the depreciation accelerates with age if $0 < \beta < 1$, remains constant if $\beta = 1$, and declines if $\beta > 1$. In order to account for the superior quality of long-lived buildings (vintage effects), the function has a kink at the age of a_K. In particular, the rate of depreciation increases relative to the building value for $a > a_K$. Because of the three free parameters β, $\underline{l}$, and a_K, the function is very flexible for modelling the depreciation of houses. Note that, the original specification employed by Cannaday and Sunderman (1986) did not consider a kink, i.e. $a_K = \underline{l}$.

We consider equation (2.8) both without and with a kink and call these functions CS and CS kink, respectively. For the CS function we estimate the coefficient β separately for each $\underline{l} \in \{\underline{a}, \ldots, 300\}$. $\underline{a}$ is the age of the oldest house in the database and is 130. For the CS Kink function, we estimate the coefficient β separately for all possible combinations of $\underline{l} \in \{70, \ldots, 110\}$ and $a_K \in \{50, \ldots, 70\}$. As a benchmark case we consider the depreciation function used by the GAA surveyors:

$$\delta_{GAA}(a) = \frac{a}{2l}\left(1 + \frac{a}{l}\right) \quad \text{with} \quad l = \begin{cases} 80 & \text{if } a < 65 \\ a + 15 & \text{if } a \geqslant 65 \end{cases}, \tag{2.9}$$

where l denotes the life span in years. Equation (2.9) implies the following form of depreciation: While the rate of depreciation accelerates until a building reaches age 65. At the age of 65 the function has a kink and the rate of depreciation decreases relative to the building value. As all the parameters are already given in equation (2.9), we only need to estimate the time dummy coefficients, q, in equation (2.7) with OLS.

Table 2.6 summarizes the estimation results for the three different depreciation functions. The coefficients reported in the table produced highest R^2 on, both, the level of the dependent variable, $q^{(N)}$, and the price level. The latter measure is calculated using the predicted house price

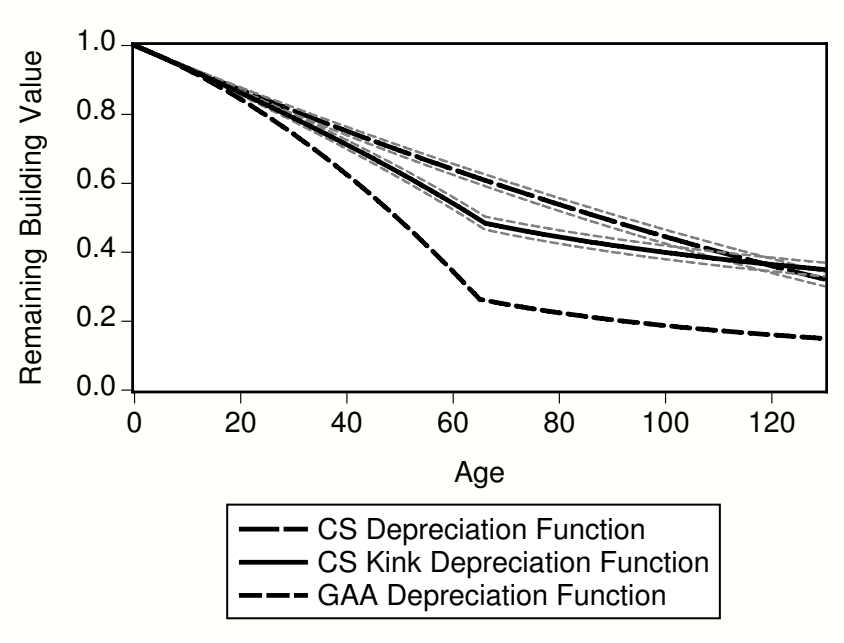

Figure 2.5: Figure shows three depreciation functions $\delta(a)$. Upper and middle functions are estimated, dash lines around the solid lines are confidence bands at the 95% level. Confidence bands are calculated using the delta method. Lower function is the depreciation function applied by GAA surveyors.

$\widehat{P} = \exp\{\widehat{q}^{(N)}\}C^{(N)}$ The resulting depreciation functions are depicted in Figure 2.5. According to our measures of goodness-of-fit the CS kink function suits or data best. While the CS function copes well with relatively young buildings, it has problems with older buildings. Thus, the allowance of a kink to control for vintage effects is justified by the estimation results. The fit of the GAA function, on the other hand, is poor. This is because building values depreciate less in the first 65 years than is assumed by the GAA surveyors.

2.5.3 Unit root test for index series

A well known problem with (augmented) Dickey-Fuller type unit root test is their potential confusion of structural breaks in the series with nonstationarity (Perron 1989, 1990). We therefore apply Perron's testing procedure to establish stationarity of the difference index series. This procedure first removes the deterministic trend of the time series, and then conducts an

Table 2.6: Model fit for optimal specification of different depreciation functions.

	$\underline{l}$	a_K	$\widehat{\beta}$	S.E.$(\widehat{\beta})$	$R^2_{q^{(N)}}$	R^2_P
GAA function	80	65	.	.	-0.064	0.694
CS function	300	.	1.997	0.057***	0.139	0.739
CS Kink function	98	66	0.648	0.018***	0.153	0.741

Notes: Table reports least squares estimates of equation (2.7). Dependent variable is the log of the price replacement cost ratio. Replacement cost are for a new house, i.e. land cost plus cost of a new building. Depreciation function is either (2.9) (GAA) or (2.8) (CS and CS Kink). Time dummies and constant are not reported. $R^2_{q^{(N)}}$ is the R^2 from the regression (2.7). R^2_P refers to a R^2-type measure on the price scale. *** significant at 1%-level ** significant at 5%-level * significant at 10%-level

ADF-type test for the residuals. In particular, the first step employs the following regression:

$$y_t = \beta_0 + \beta_1 DU_t + \widetilde{y}_t \tag{2.10}$$

where DU_t is 1 if $t > T_B = 1993Q2$ and 0 else, under the null hypothesis of a unit root. The residuals, $\widetilde{y}_t$, are then regressed on their lagged values, a number of lagged differences and a set of dummy variables needed to make the distribution of the test statistic tractable:

$$\widetilde{y}_t = \rho\widetilde{y}_{t-1} + \sum_{j=0}^{K} \omega_j DTB_t + \sum_{k=1}^{K} \phi_k \Delta\widetilde{y}_{t-k} + \varepsilon_t \tag{2.11}$$

where DTB_t is 1 if $t = T_B + 1$ and 0 else, and the number of lags K is selected so that residuals behave like white noise. The autocorrelation parameter on the dependent variable, ρ, is analogous to the augmented Dickey-Fuller coefficient, thus the null hypothesis may be rejected if ρ is significantly smaller than unity. Critical values are tabulated in Perron (1990).

Table 2.7 present results of the two step test procedure for each series of log growth rates. While the house price and land cost series are stationary, we can not reject the null hypothesis of nonstationarity for the construction cost series. This is mainly due to the seasonal component of the series, which is not captured well by lagged differences in the second step ADF-type test regression. Using the same data Schulz and Werwatz (2008) show that growth rate of construction cost is modelled well with $\Delta y_t = \mu + \rho\Delta y_{t-4} + \varepsilon_t$, where the null hypothesis of a seasonal unit root is rejected at the 1% significance

Table 2.7: Unit root test for the three different index series.

	First Stage		Second Stage	
	β_0	β_1	K	ρ
House price				
Coefficient	0.013	-0.018	0	-1.141
t-statistic	4.07***	-3.943***		-11.719***
Land cost				
Coefficient	0.017	-0.029	6	-1.019
t-statistic	5.02***	-6.233***		-4.897**
Construction cost				
Coefficient	0.011	-0.011	5	-0.193
t-statistic	9.20***	-6.210***		-1.375

Notes: Table reports results of Perron (1990) unit root test. Each series has 109 observations and 1993Q2 corresponds to 53rd observation. β_0 and β_1 are coefficients from first step regression (2.10). K is number of lags and ρ autocorrelation parameter from second step regression (2.11). The critical values for the unit root test t-statistic are -4.12 (*** significant at 1%-level), -3.34 (** significant at 5%-level), and -3.03 (* significant at 10%-level) with $T = 200$ and $\lambda = 0.5 \approx 52/109$, see Perron (1990, Table 4).

level. We thus treat all three series as difference stationary. Note, that the first step regression results support the view that the introduction of the single market impacted on price and cost growth.

Chapter 3

Predicting market values for single-family houses

3.1 Introduction

The previous Chapter 3 has presented empirical evidence that the hedonic regression variant of the sales comparison approach outperforms the cost approach for long-term real estate valuations. Moreover, the hedonic regression techniques provides a statistical tool that can be readily used for the automated valuation of single-family properties. In fact, numerous companies in the U.S. have developed Automated Valuation Systems (AVM) based on hedonic models (Pace et al. 2002).[1]

Whereas the long-term value of residential real estate assets is of particular interest for mortgage investors, accurate predictions of current market values are crucial for (potential) home buyers and sellers. In an applied hedonic regression, however, it is common to use the logarithmic transformation of observed transaction prices as the dependent variable (e.g. Palmquist (1980), Engle et al. (1985), Case and Quigley (1991), Hill et al. (1997) and Schulz and Werwatz (2004)). This is done for two reasons.

First, observed transaction prices are strictly positive and usually skewed to the right. A standard linear regression with the price as the dependent

[1] In Germany, on the other hand, statistical valuation models for real estate are not wide spread. A notable exception is the online house price prediction service MD*immo (Schulz 2003, Chapter 4). MD*immo has been developed has a cooperation between the Center for Applied Statistics and Economics (CASE) at the Humboldt-Universität zu Berlin and Berlin's local Surveyor Commission for Real Estate (GAA). The service is implemented on the website of GAA Online, www.gutachterausschuss-berlin.de, and delivers real time predictions of market values for Berlin single-family houses given the current state of the market and characteristics of the subject property.

variable is, thus, not an appropriate model for the conditional mean function of the underlying population. Second, the logarithmic transformation may also helps to dampen the substantial heteroscedasticity frequently observed in house price data (Goodman and Thibodeau 1995, 1997, Stevenson 2004).

Estimating a hedonic model with a log dependent variable might not pose a problem if the main goal of the analysis is to estimate relative changes of aggregate house prices over time. In that case, differences between estimated time-dummies from consecutive periods are unbiased estimators for relative price changes. As the literature on hedonic price models has been primarily concerned with the measurement of constant-quality house price indexes, it is not surprising that the retransformation of estimated log house prices has not attracted much attention.

Things have changed with the advent of AVMs, where the goal is to predict expected transaction prices, that is the market value of the property. It is well known, that the naive retransformation of a logarithmic dependent variable with the exponential function delivers a biased estimator of its expected value (see e.g. Neyman and Scott (1960)). An impression of the bias' potential magnitude can be given with reference to the hedonic regression presented in Thibodeau (2003, Table 3). The estimated variance of the residuals in his model is about 0.05, which leads under the assumption of log normally distributed prices to a downward bias of predicted market values of about 2.5%.

In this Chapter, we evaluate the out-of-sample performance of consistent predictors for the market value at the hand of a large database with transactions of single-family houses. Here, we consider, both, predictors relying on the assumption of log normally distributed prices and predictors without the imposition of a distributional assumption (e.g. Brown and Mariano (1984), van Garderen (2001)).

The results of our prediction experiment show that the prediction accuracy does not significantly differ between the proposed retransformation techniques. As indicated by predictions obtained for homogenous subgroups of houses in our sample, however, heteroscedasticity in the regression residuals influences the bias reduction of these predictors.

The remainder of this Chapter is organized as follows. Section 4.2 defines the problem. Furthermore, we present consistent predictors for the market value. Section 4.3 describes the empirical implementation of a horse race between the different retransformation techniques. The empirical results are presented in Section 4.4 and the final Section 3.5 concludes.

3.2 Hedonic price equations and market values

3.2.1 The problem

Hedonic models assume that the market value of a property at time t can be represented as a function $V(\mathbf{x}_t)$ of its implicitly valued characteristics, where the characteristics like age, floor space, and lot size are collected in the row vector $\mathbf{x}_t$. However, during observed market transactions the market value is never observed but rather the transaction price P_t. In hedonic models – and the practise of valuation – it is assumed that the observed transaction price is the market value influenced by unsystematic influences during the business dealing:

$$P_t = V(\mathbf{x}_t)U_t \ , \tag{3.1}$$

where the error term U_t is defined as

$$U_t \stackrel{\text{def}}{=} \frac{\exp(u_t)}{\Theta} \quad \text{with} \quad \Theta \stackrel{\text{def}}{=} E[\exp(u_t)] \ .$$

Assuming that u_t is distributed with $u_t \sim \text{i.i.d.}(0, \sigma_u^2)$ it immediately follows that $E[U_t] = 1$ and

$$E[P_t|\mathbf{x}_t] = V(\mathbf{x}_t) \ . \tag{3.2}$$

Thus, the market value for a property with characteristics $\mathbf{x}_t$ equals its expected transaction price.

Instead of directly estimating the multiplicative regression model (3.1), hedonic price equations are frequently log-linearized to infer the implicit prices of the properties' characteristics. Denoting the logs of price, market value and Θ with the lower case letters p, v and θ, one easily obtains

$$\begin{aligned} p_t &= v(\mathbf{x}_t) - \theta + u_t \\ &= w(\mathbf{x}_t) + u_t \ , \end{aligned} \tag{3.3}$$

where $w(\mathbf{x}) \stackrel{\text{def}}{=} v(\mathbf{x}_t) - \theta$. Given an estimate of the function $w(\mathbf{x}_t)$ the prediction of expected log prices is usually straightforward. Users of automated valuation models, however, are interested in predictions of market values rather than log prices. Then a retransformation of predicted log prices is necessary.

For the sake of the argument assume that we know $w(\mathbf{x}_t)$. In that case the market value of the property is given by

$$V(\mathbf{x}_t) = \exp\{w(\mathbf{x}_t)\}\,\Theta \ . \tag{3.4}$$

Even if $\exp\{w(\mathbf{x}_t)\}$ can be estimated consistently, the simple exponential retransformation leads to an inconsistent estimator for the market value. The direction of the bias immediately follows from Jensen's inequality:

$$\Theta = E[\exp(u_t)] > \exp\{E[u_t]\} = 0 \ .$$

Thus, the naive retransformation with the exponential function leads to a downward biased estimate of $V(\mathbf{x}_t)$. For an unbiased, or at least consistent, estimate of the market value, one needs to know the factor Θ for retransformation.

However, it is obvious from equation (3.4) that the log-linearization of a multiplicative regression model does not impose any difficulties if one is solely interested in the relative changes of market values over time. This is because the bias is proportional and cancels out when taking the ratio of estimated market values for consecutive periods. A further discussion of this result can be found in Appendix 3.6.1.

Table 3.1: Overview of different predictors for the market value in the log-linear model.

Naive Predictor	Bias	Consistent	Source
– $\widehat{V}_1 = \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}$	yes	no	-
Log normal Predictors			
– $\widehat{V}_2 = \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}\exp\left\{0.5\sigma_u^2\right\}$	yes	yes	Goldberger (1968)
– $\widehat{V}_3 = \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}\exp\left\{0.5(\sigma_u^2 - \sigma_{\hat{w}}^2)\right\}$	yes	yes	Meulenberg (1965), Kennedy (1983)
– $\widehat{V}_4 = \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}{}_0F_1\left(m; 0.5m(\hat{\sigma}_u^2 - \hat{\sigma}_{\hat{w}}^2)\right)$, with ${}_0F_1(m;x) = \sum_{i=0}^{\infty} x^i/i!(m)_i$	no	yes	van Garderen (2001)
Robust Predictors			
– $\widehat{V}_5 = \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}\widehat{\Theta}$, with $\widehat{\Theta} = \mathrm{N}^{-1}\sum_{n=1}^{N} P_n\widehat{V}_{1,n}/\widehat{V}_{1,n}^2$	yes	yes	Theil (1966), Mincer and Zarnowitz (1969)
– $\widehat{V}_6 = \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}\widehat{\Theta}$, with $\widehat{\Theta} = \mathrm{N}^{-1}\sum_{n=1}^{N} P_n/\widehat{V}_{1,n}$	yes	yes	Duan (1983), Brown and Mariano (1984)
– $\widehat{V}_7 = \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}/(1 + 0.5\sigma_{\hat{w}}^2)\widehat{\Theta}$, with $\widehat{\Theta} = \sum_{n=1}^{N} P_n/\sum_{n=1}^{N}\widehat{V}_{1,n}$	yes	yes	Aigner (1974)

To consistently predict the market value according to equation (3.4), on the other hand, we need both a consistent estimator of $\exp\{w(\mathbf{x}_t)\}$ and a

consistent estimator of the transformation factor Θ.[2] Table 3.1 gives an overview of predictors for the market value that we briefly discuss in the following section (for a rigorous treatment of their properties we refer to cited sources). Here, we assume that the log price function is linear in the implicit prices (see below). The predictors can be categorized into two broad groups. The first group of predictors relies on the assumption of log normally distributed prices. Then a closed-form solution for the conditional mean function (3.2) is available and both consistent and unbiased predictors can be derived. The second group does not impose distributional assumptions. Here, the transformation factor Θ is estimated using the empirical distribution of the residuals u_t.

3.2.2 Estimation of market values

While the problem of retransforming predicted log prices occurs for any specification of the price equation (3.1), we take the semi-logarithmic functional form as an example. That is, we assume that the log price function is given by

$$w(\mathbf{x}_t) = \mathbf{x}_t \boldsymbol{\beta} \ ,$$

where the column vector $\boldsymbol{\beta}$ collects the implicit prices of the respective – possibly transformed – property characteristics.

The main advantage of the log-linear specification is that the implicit prices of property characteristics are easily estimated and can be readily used for automated valuations. More precisely, an estimate of the the vector of implicit prices can be obtained by least squares regressions of observed transaction prices on the corresponding property characteristics. Given the estimated parameters $\widehat{\boldsymbol{\beta}}$, it is straightforward to predict the log price of a subject property by plugging-in its characteristics, $\mathbf{x}_t$, in the estimated log price equation

$$\widehat{w}(\mathbf{x}_t) = \mathbf{x}_t \widehat{\boldsymbol{\beta}} \ .$$

The naive predictor for market values is then given by

$$\widehat{V}_1(\mathbf{x}_t) \quad = \quad \exp\{\mathbf{x}_t \widehat{\boldsymbol{\beta}}\} \ , \tag{3.5}$$

While equation (3.5) delivers biased and inconsistent predictions of market values, it will lead to consistent estimates of median transaction prices if log prices are symmetrically distributed. This is because any order statistic of a monotonic function equals the function of the order statistic.

[2] By the product rule of probability limits, it then holds that $\operatorname{plim}\left(\exp\{\widehat{w}(\mathbf{x})_t\}\widehat{\Theta}\right) = \exp\{w(\mathbf{x}_t)\}\,\Theta$.

Given the fact, that we need to estimate the parameters $\boldsymbol{\beta}$, however, introduces an additional small sample bias problem. Even if the estimator of $\widehat{w}(\mathbf{x}_t) = \mathbf{x}_t\widehat{\boldsymbol{\beta}}$ is unbiased, it holds that

$$\exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\} = \exp\{E[\mathbf{x}_t\widehat{\boldsymbol{\beta}}]\} \neq E[\exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}] \ .$$

With $\widehat{w}(\mathbf{x}_t) \sim (\mathbf{x}_t\widehat{\boldsymbol{\beta}}, \sigma^2_{\widehat{w}})$, a second order Taylor approximation yields

$$E[\exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}] \approx \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}\left(1 + 0.5\sigma^2_{\widehat{w}}\right) \ .$$

Thus, the small sample bias is proportional to the variance of the prediction, $\sigma^2_{\widehat{w}}$, and approaches zero asymptotically. The bias, though, can be substantial if one attempts to predict market values of houses that are far outside the data sample. This is because the variance of the prediction is smallest at the sample mean and grows with the square of the distance from this mean (see e.g. Myers (1990, pp. 41)).

Prediction under log normal assumption

The first group of consistent predictors for market values relies on the assumption that log transaction prices, conditional on house characteristics $\mathbf{x}_t$, are normally distributed. More precisely, let's assume that $p_t \sim N(\mathbf{x}_t\boldsymbol{\beta}, \sigma^2_u)$ and $u \sim N(0, \sigma^2_u)$. This, in turn, implies that $\exp\{u_t\}$ is log normally distributed $\exp\{u_t\} \sim LN(0, 0.5\sigma^2_u)$ with mean $\Theta = 0.5\sigma^2_u$ (see Aitchison and Brown (1957)). The market value of a property with characteristics $\mathbf{x}_t$ is thus given by

$$E[P_t|\mathbf{x}_t] \quad = \quad \exp\{\mathbf{x}_t\boldsymbol{\beta} + 0.5\sigma^2_u\} \ . \tag{3.6}$$

Given the closed-form solution for the expected transaction price (3.6), consistent predictors for the market value can be constructed by replacing the unknown parameters, $\boldsymbol{\beta}$ and σ^2_u, with their estimates. This approach, however, ignores the sampling error in the parameters discussed above.

In fact, under the assumptions made an exact solution for the small sample bias of the naive predictor can be derived. Since the estimated parameters $\widehat{\boldsymbol{\beta}}$ are joint normally distributed, the log price prediction is normal distributed with $\widehat{w}(\mathbf{x_t}) \sim N(\mathbf{x}_t\boldsymbol{\beta}, \sigma^2_{\widehat{w}})$. The variance of the prediction is given by $\sigma^2_{\widehat{w}} = \mathbf{x}_t\Sigma\mathbf{x}_t^\top$, where $\Sigma \stackrel{\text{def}}{=} V(\widehat{\boldsymbol{\beta}})$ denotes the covariance matrix of the estimated parameters. Thus, the expected value of the exponential retransformation is given by

$$E[\exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}] = \exp\{\mathbf{x}_t\boldsymbol{\beta} + 0.5\sigma^2_{\widehat{w}}\} \ .$$

For our prediction experiment, we consider, both, predictors that do not and that do correct for small sample bias. The log normal predictors are:

i. Closed-form predictor The simple closed-form predictor is given by

$$\widehat{V}_2(\mathbf{x}_t) \quad = \quad \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}} + 0.5\widehat{\sigma}_u^2\} \ . \tag{3.7}$$

where $\widehat{\boldsymbol{\beta}}$ are the least squares estimates of the implicit prices that are obtained from the regression of log prices on house characteristics. $\widehat{\sigma}_u^2$ is the estimated variance of the respective (log) residuals. As both, the estimates $\exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}$ and $\exp\{0.5\widehat{\sigma}_u^2\}$ are consistent estimates of $\exp\{\mathbf{x}_t\boldsymbol{\beta}\}$ and Θ, the closed-form predictor (3.7) is consistent, as well. By ignoring the sampling error in estimating both $\widehat{\boldsymbol{\beta}}$ – and $\widehat{\sigma}_u^2$ – , the closed-form predictor (3.7) is, however, biased upwards (see e.g. Goldberger (1968), Kennedy (1983)).

ii. Corrected closed-form predictor Given the expression for the expected value of the naive predictor, a corrected closed-form predictor is given by

$$\widehat{V}_3(\mathbf{x}_t) \quad = \quad \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}} + 0.5(\widehat{\sigma}_u^2 - \widehat{\sigma}_{\widehat{w}}^2)\} \tag{3.8}$$

where $\widehat{\sigma}_{\widehat{w}}^2 = \mathbf{x}_t\widehat{\Sigma}\mathbf{x}_t^\top$ is the estimated variance of the prediction. While the corrected closed-form predictor (3.8) is consistent, it is still biased upward. In particular, the expected value of the bias correction, $E[\exp\{0.5(\widehat{\sigma}_u^2 - \widehat{\sigma}_{\widehat{w}}^2)]$, exceeds $\exp\{0.5(\sigma_u^2 - \sigma_{\widehat{w}}^2)$ because of the convexity of the exponential function. However, $\widehat{V}_3(\mathbf{x}_t)$ converges to $V(\mathbf{x}_t)$ in quadratic mean, which is a stronger property than consistency (see Meulenberg (1965, pp. 865-866)).

iii. Exact Unbiased Predictor Under the assumption of normally distributed log errors, it is also possible to derive exact unbiased predictors for market values (Goldberger 1968, Bradu and Mundlak 1970). We specifically consider the unbiased predictor derived by van Garderen (2001).[3] The predictor is given by

$$\widehat{V}_4(\mathbf{x}_t) = \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}{}_0F_1\left(m; 0.5m(\widehat{\sigma}_u^2 - \widehat{\sigma}_{\widehat{w}}^2)\right) \ , \tag{3.9}$$

where ${}_0F_1(m;x)$ denotes the hypergeometric function

$${}_0F_1(m;x) = \sum_{i=0}^{\infty} \frac{x^i}{i!(m)_i} \ ,$$

[3]Compared to the solutions given in Goldberger (1968) and Bradu and Mundlak (1970), this approach has the advantage that the bias correction can be calculated without numerical integration.

with $m = (N-K)/2$. Here, N is the number of observations used to estimate the log price equation and K is the number of parameters $\boldsymbol{\beta}$. The exact predictor (3.9) is not only unbiased, but also superior to the closed-form predictor in terms of relative mean squared error efficiency (van Garderen 2001).

Predictions with no distributional assumption

The second group of predictors for the market value dose not impose distributional assumptions on transaction prices. Naturally closed-form solutions for the expected transaction price are not available in this case. The robust predictors rather adjust the naive predictor by a nonparametric estimate of the transformation factor Θ. The resulting predictors are generally consistent, but biased. For our prediction experiment, we consider the following robust predictors:

i. Linear corrected predictor Based on an 'optimal linear correction' for biased forecasts (see Mincer and Zarnowitz (1969) and Theil (1966, pp. 34)) Wooldridge (2006, pp. 218) suggests to retransform log price predictions by

$$\widehat{V}_5(\mathbf{x}_t) \quad = \quad \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}\widehat{\Theta} \ , \tag{3.10}$$

where the transformation factor $\widehat{\Theta}$ is estimated from an ordinary least squares regression of observed (in-sample) prices on their naive predictions

$$P_n = \Theta\widehat{W}_n + \varepsilon_n \ . \tag{3.11}$$

Here, $\widehat{W}_n = \exp\{\mathbf{x}_n\widehat{\boldsymbol{\beta}}\}$ is the naive predictor of house n in the estimation sample and $\varepsilon_n \stackrel{\text{def}}{=} \Theta W_n(U_n - 1)$. While the OLS estimate $\widehat{\Theta}$ is a consistent estimate for Θ, it is inefficient. This is because the estimator $\widehat{\Theta}$ ignores the heteroscedastic variance of the error term ε_n. Moreover, the linear corrected predictor (3.10) is not corrected for small sample bias, however it approaches $V(\mathbf{x})_t$ asymptotically.

ii. Residual-based predictor Duan (1983) and Brown and Mariano (1984) suggest to directly use the arithmetic mean of the retransformed log residual, $\exp\{\widehat{u}_t\}$ as an estimate of Θ. Their residual-based predictor can then be written as

$$\widehat{V}_6(\mathbf{x}_t) \quad = \quad \exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}\mathrm{N}^{-1}\sum_{n=1}^{N} P_n/\widehat{W}_n \ . \tag{3.12}$$

where $\widehat{W}_n$ is defined as above. Notably, the estimator $\mathrm{N}^{-1}\sum_{n=1}^{N} P_n/\widehat{W}_n$ is the weighted least squares estimator for Θ in the regression (3.11). It is, thus, not only consistent, but also more efficient. The residual-based predictor (3.12) approaches $V(\mathbf{x})_t$ asymptotically, but is biased (see Duan (1983)).

iii. Corrected residual-based predictor Given the expression for the small sample bias of $\exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}$ derived from a Taylor series expansion, one can also correct for small sample bias in a setting without distributional assumptions. In particular, Aigner (1974) proposes to adjust the naive predictor by $(1+0.5\sigma^2_{\widehat{w}})^{-1}$ and a nonparametric estimate of Θ. Specifically the corrected residual-based predictor is given by

$$\widehat{V}_7(\mathbf{x}_t) \quad = \quad \frac{\exp\{\mathbf{x}_t\widehat{\boldsymbol{\beta}}\}}{1+0.5\mathbf{x}_t\widehat{\boldsymbol{\Sigma}}\mathbf{x}_t^\top}\sum_{n=1}^{N} P_n/\sum_{n=1}^{N}\widehat{W}_n \ . \tag{3.13}$$

where $\widehat{\boldsymbol{\Sigma}}$ denotes the estimated covariance matrix of the estimated coefficients $\widehat{\boldsymbol{\beta}}$, and $\widehat{W}_n$ is defined as above. Since $\sum_{n=1}^{N} P_n/\sum_{n=1}^{N}\widehat{W}_n$ is a consistent estimator for Θ, the corrected residual-predictor (3.13) approaches $V(\mathbf{x})_t$ asymptotically (see Aigner (1974)).

3.3 Prediction experiment

In this section, we describe the implementation of a prediction experiment in order to examine the empirical performance of the estimators for the market value. The criterion used to evaluate the alternative retransformation techniques is their out-of-sample prediction accuracy. We specifically estimate market values over a period of 24 quarters and compare these predictions with observed transaction prices for single-family houses from Berlin. More precisely, we fit the hedonic log price equation (3.3) using only data observed four years prior to the evaluation period $t+1$. We start with the period 1996Q1 to 1999Q4 and use the estimated model to predict market values for houses that were transacted in 2000Q1. The estimation sample is then shifted by one quarter to fit a new regression and obtain out-of-sample predictions for 2000Q2. This procedure continues until the last regression is fitted for 2002Q2 to 2005Q3 and predict market values for houses transacted in 2005Q4.

Note that, our rolling window procedure defines out-of-sample observations as those houses which are sold up to one quarter after the latest transactions in our estimation sample. As our primary interest lies in the evaluation of the different retransformation methods, we abstain from forecasting the

future expected price level. By using the estimated price level in period t when predicting market values, the predictions are lagged by one quarter. Given the downward trend of aggregate house prices during our period of observation (see the empirical results in Chapter 2), the naive predictor might perform better than one would expect in an environment with no price growth. The consistent predictors, on the other hand, might tend to overestimate observed transaction prices.

In addition, we investigate how heteroscedasticity in the regression residuals influences the performance of the predictors. While the prediction of expected log prices does not critically depend on the homoscedasticity of the error term, the presence of heteroscedasticity should influence the discussed retransformation techniques. In the case of log normally distributed prices, for instance, one could model the error variance as function of the characteristics and derive corresponding predictors based on a weighted least squares procedure (Manning 1998, Ai and Norton 2000). Calculating the robust predictors conditional on house characteristics, however, is aggravated by the high dimensionality of the data. To inspect the influence of heteroscedasticity, we therefore estimate price predictions by employing separate regressions for more homogenous groups of houses, i.e. detached, semi-detached, and row houses, and compare their performance with predictions from a single regression model for all houses.

3.3.1 Model specification

The empirical specification for the hedonic price equation (3.3) is the regression model introduced in Chapter 2:

$$p_t = \beta_{0t} + \sum_{c=1}^{C} \left\{ \beta_{c1} T_c(x_{ct}) + \beta_{c2} T_c(x_{ct})^2 \right\} + \sum_{d=1}^{D} \gamma_d x_{dt} + u_t \ . \tag{3.14}$$

Here, p_t is the log price for a house transacted in period t. The constant β_{0t} captures the general price level in period t. $T_c(\cdot)$ is a Box-Cox type transformation function for the cth continuous characteristic (Bunke et al. 1999). We specifically consider the age, floor space, and lot size of the property. x_{dt} is an indicator for the dth discrete characteristic, such as the number of storeys, the type of house, and the district the property is located. The parameters β_{c1}, β_{c2}, and γ_d are the implicit prices of the respective characteristics and need to be estimated. We assume that the error term u_t is distributed with mean zero and constant variance σ_u^2.

Given the least squares estimates of the parameters $\widehat{\beta}_{c1}$, $\widehat{\beta}_{c2}$, and $\widehat{\gamma}_d$, we can easily calculate predictions of the expected log transaction price by

plugging-in the characteristics of the subject property in equation (3.14). To obtain predictions of the market value, the predicted log price are then re-transformed to the natural scale according the respective technique (see Table 3.1). Our reference predictor is the naive retransformation with the exponential function.

Estimating the hedonic price equation (3.14) requires the choice of a specific transformation function $T_c(\cdot)$ for each of the continuous variables. Here, we follow the same procedure as described in Chapter 2. As the transformations might depend on the sample period used to fit the model, we conduct the model choice for each of our estimation periods separately. For each optimal model specification, we further select the specific set of explanatory variables by a backward selection procedure (Myers 1990, pp. 186).

3.3.2 Data

We obtain our data from Berlin's local real estate surveyor commission (Gutachterausschuss für Grundstückswerte, GAA) out of its transaction database (Automatisierte Kaufpreissammlung, AKS). According to German Building Law (Baugesetzbuch, BauGB) surveyor commissions are entitled to request and collect information of all real estate transaction in their respective state. In particular, notaries are obliged to send a copy of the deed to the regional surveyor commission. The commission can further request additional information from buyers and sellers, and must use the data to provide information on the real estate market (BauGB §§192 - 199).

Our data set consists of 14,674 transactions of single-family houses in Berlin between 1996 and 2005. Observations between 1996Q1 and 1999q4 are solely used to fit in-sample hedonic regressions up to the out-of-sample period 2003Q4. Observations from 2000Q1 onwards are used both for fitting in-sample regressions and out-of-sample predictions. Between 2000Q1 and 2005Q4 – our evaluation period – we have 8,756 observations with at least 235, at most 488, and on average 364 transactions per quarter.

Table 3.2 reports summary statistics for the main characteristics of all houses transacted between 2000Q1 and 2005Q4. About half the observations are detached single-family houses. The remaining 50% of observations are either semi-detached (22.3%) or row houses (26.4%). All observations have information on the transaction price, age of the building, floor space, lot size, and numerous discrete characteristics. The average price across all house types is $227,600$ Euros, while the median price is only $196,800$ Euro. As expected the distribution of prices is skewed to the right.

Figure 3.1 shows kernel density estimates of the (marginal) distribution of log transaction prices for all house types and by house type. In all cases,

Table 3.2: Summary statistics for transacted single-family houses in Berlin between 2000Q1 to 2005Q4.

Panel A: Continuous Characteristics and Prices				
	Mean	Median	Std. Dev.	Units
Lot size	556.4	500	322.1	Sqm
Floor space	145.7	135	54.1	Sqm
Year of construction	1961	1961	29.4	Year
Price	227.6	196.8	148.2	(000)
Panel B: House Type				
Detached	50.3%	Semi-detached		22.3%
End-row	9.5%	Mid-row		17.9%
Panel C: Location and Lake Side				
Simple	34.0%	Average		44.2%
Good	18.6%	Excellent		2.1%
Lake side	0.7%			
Panel D: Number of Storeys and Attic				
One	53.5%	Two		43.8%
Three	2.7%	Attic		54.6%
Panel E: Cellar				
Full	74.6%	Part		12.2%
No	13.2%			

Notes: 8756 observations. Price is in real (2000) euros, deflated by the Berlin CPI. Attic in Panel D means that the attic is upgraded for living.

we select the bandwidth according to Silverman's rule of thumb. The dashed lines depict asymptotic confidence bands, that are estimated at the 95% level, see Härdle et al. (2004, Chapter 3). The blue lines depict the normal density evaluated at the respective sample mean and standard deviation. The empirical distribution of log prices is unimodal centered around their mean and closely resembles the normal. However, the confidence bands reveal that the kernel density estimates deviate statistically significant from the normal density.[4] This might indicate an advantage of the robust predictors over

[4]The standard tests for normality, in particular the Kolmogorov-Smirnov test, Shapiro-Wilk test (Shapiro and Wilk 1965) and D'Agostino test (D'Agostino et al. 1990), confirm the visual inspection. All three tests reject the null hypothesis of normally distributed log prices at the 1% level.

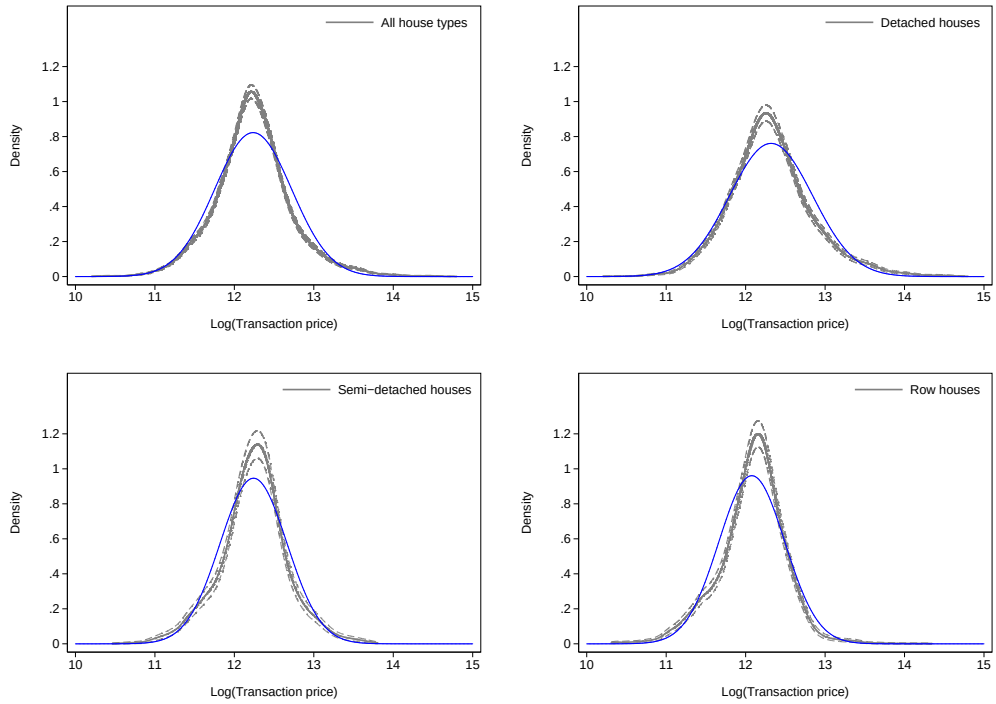

Figure 3.1: Kernel density estimates for the marginal distribution of log transaction prices. The dashed lines are 95% confidence intervals. The blue line is the normal density evaluated at corresponding sample mean and standard deviation.

the retransformation techniques relying on the normality assumption of log prices.

To illustrate the (conditional) distribution of transaction prices and the three continuous dwelling characteristics – age, floor space, and lot size – by house type, Figure 3.2 shows box plots of the four respective variables. Compared to semi-detached and row houses, detached houses are sold for higher (median) prices and exhibit a larger dispersion. These differences in the conditional distribution of transaction prices, however, stem mostly from the differences in property characteristics. Detached houses are generally larger (floor space and lot size) and older than semi-detached and row houses, respectively. Thus, conditioning the estimation sample on the type of house is likely to remove only part of the heteroscedasticity observed in the regression

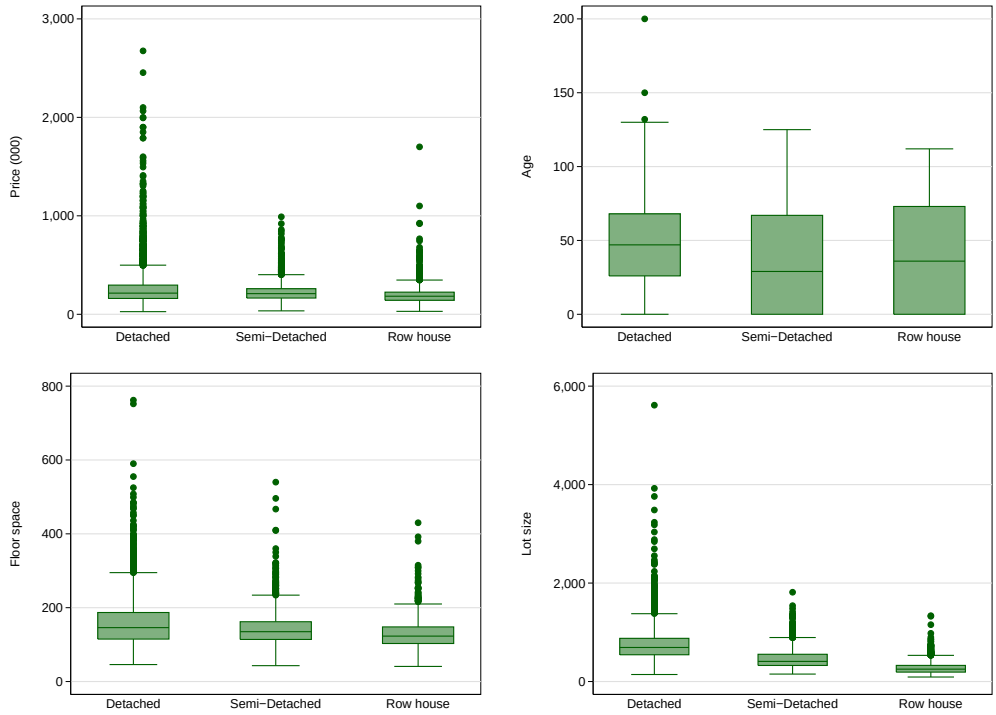

Figure 3.2: Box plot of transaction price and continuous characteristics by house type. Price is in real (2000) euros. Floor space and lot size is in square meters.

residuals.[5]

3.4 Empirical results

The figure of interest is the prediction error relative to the prediction

$$e_{t+1,j} = \frac{P_{t+1} - \widehat{V}_{t,j}}{P_{t+1}}$$

where P_{t+1} is the observed transaction price in the evaluation period $t+1$ and $\widehat{V}_{t,j}$ the predicted market value according to the estimator $j \in \{1, \ldots, 7\}$.

[5]The Breusch-Pagan test for heteroscedasticity (Breusch and Pagan 1979) indeed rejects the null hypothesis of a constant conditional variance of the residuals in all our regressions. A visual inspection of the regression residuals, however, indicates that estimating equation (3.14) by house type helps to reduce heteroscedasticity considerably.

Note, that negative errors imply overestimations of the market value, while positive errors imply underestimations. We use relative errors because the we are primarily interested in the performance of predictions on the natural scale.Ideally, price predictions should be unbiased and have a small variance. To save on notation, let N denote the number of observations for which we make out-of-sample predictions, and $e_{n,j}$ the prediction error for house n and predictor j. The mean error of a predictor is then

$$\text{ME} = \frac{1}{N} \sum_{n=1}^{N} e_{n,j} \ ,$$

that is the arithmetic average over all errors of the respective predictor. It is obvious that the mean error should converge to zero for a consistent predictor. The different predictors, however, might also differ with respect to the dispersion of prediction errors. We therefore also calculate the mean absolute error

$$\text{MAE} = \frac{1}{N} \sum_{n=1}^{N_h} |e_{n,j}|$$

and the mean squared error

$$\text{MSE} = \frac{1}{N} \sum_{n=1}^{N_h} e_{n,j}^2 \ .$$

Both measures are symmetric and give positive and negative errors with same absolute magnitude the same weight. This corresponds to the assumption of a symmetric loss function. From the standpoint of (potential) buyers and sellers, who need an unbiased estimate of the market value of the property, the assumption of a symmetric losses is reasonable (Pace et al. 2002).

As the above evaluation measures are calculated using a sample of transacted houses, the statistics are subject to sampling variation. Thus, even if a predictor is, for instance, consistent the ME might be different from zero. Moreover, one would ideally perform test of sampling significance in order to ascertain whether the prediction performance of the different estimators indeed differs. As we are interested in more than one pairwise comparison a formal statistical testing procedure as described in Chapter 2 encounters the problem of multiple testing (see e.g. Miller (1985)). In order to make inference, we therefore calculate bootstrap confidence intervals for the evaluation measures. We specifically consider 10000 replications from the each set of statistics, and based on the resulting bootstrap sample estimate percentile based confidence intervals (Efron and Tibshirani 1986).

Table 3.3: Performance of retransformation techniques for hedonic regression. Summary statistics of prediction errors for single regressions for all house types.

	ME	MED	MSE	MAE	PE25
naive					
V_1	2.387	0.313	7.471	18.471	74.794
	[1.821 2.983]	[-0.307 0.832]	[6.083 9.471]	[18.067 18.908]	[73.892 75.697]
log normal					
V_2	-0.224	-2.260	7.038	18.100	75.300
	[-0.775 0.358]	[-2.811 -1.777]	[5.731 8.909]	[17.713 18.521]	[74.400 76.182]
V_3	-0.151	-2.227	7.055	18.110	75.286
	[-0.702 0.431]	[-2.769 -1.704]	[5.745 8.935	[17.723 18.532	[74.383 76.176]
V_4	-0.161	-2.197	7.044	18.106	75.297
	[-0.712 0.421]	[-2.753 -1.715]	[5.738 8.920]	[17.719 18.528]	[74.395 76.188]
robust					
V_5	-1.789	-3.789	6.862	18.011	75.240
	[-2.333 -1.216]	[-4.343 -3.286]	[5.595 8.686]	[17.636 18.424]	[74.338 76.119]
V_6	-0.108	-2.137	7.051	18.112	75.251
	[-0.660 0.475]	[-2.704 -1.657]	[5.743 8.929]	[17.725 18.533]	[74.360 76.142]
V_7	-0.425	-2.451	7.011	18.084	75.274
	[-0.976 0.156]	[-3.012 -1.964]	[5.711 8.878]	[17.698 18.503]	[74.378 76.153]

Notes: All reported measures are in percent. Number of observations is 8753 per retransformation method. ME is the mean error, MDE the median error, MSE the mean squared error, MAE the mean absolute error, and PE25 is the relative frequency of valuation errors within ±25% in absolute value. Non-parametric bootstrap confidence intervals are reported in parenthesis. Confidence intervals are calculated as $[\theta^*_{j,\alpha/2}, \theta^*_{j,1-\alpha/2}]$, where $\theta^*_{j,p}$ is the pth percentile of the bootstrap distribution $(\widehat{\theta}_{j,1}, \ldots, \widehat{\theta}_{j,k})$ for statistic j. Number of bootstrap replications is $k = 10000$. For details on the percentile based bootstrap confidence intervals see Efron and Tibshirani (1986).

Prediction performance for all house types

Table 3.3 presents the prediction evaluation measures for the different predictors of the market value (see Table 3.1). Here, all predictions have been obtained from a single hedonic regression for all house types. In addition to the measures already discussed above, Table 3.3 also reports the median prediction error (MED) and the percentage of predictions which lies within ±25% of the observed transaction price (PE25).

The first Panel of Table 3.3 shows that the naive predictor is on average

biased downwards by about 2.3%. For the average single-family house in Berlin this bias implies that the market value is underestimated by about 5400 Euros. The median error of the naive predictor, on the other hand, is indistinguishable from zero. The exponential retransformation consistently estimates median market values. The second and third Panel of Table 3.3 show that the different retransformation techniques are quite successful in removing the downward bias of the naive predictor. In fact, all predictors – but the linear corrected predictor $\widehat{V}_5$ – have mean errors that are indistinguishable from zero. Moreover, it is striking that the performance of the predictors relying on the log normal assumption is not worse than the robust retransformation techniques. The rather small deviations from the normal distribution observed in our data do not put the robust retransformation techniques at advantage.

As indicated by the MSE and MAE, the variation of prediction errors for the consistent predictors is slightly smaller than for the naive predictor. Furthermore, the percentage of predictions that lies within ±25% is larger for these predictors. The differences in the prediction accuracy between the consistent predictors, however, are minor. Even though, the linear corrected predictor ($\widehat{V}_5$) has both the lowest MSE and MAE, the bootstrap confidence interval indicate that the differences in these evaluation measures is not statistically significant. Moreover, the smaller dispersion of the prediction errors is attributable to the relative large upward correction for the linear corrected predictor. Therefore, the effect of large under predictions for log transaction prices in the right tail of the price distribution is dampened.

Prediction performance by house type

As discussed above, we repeated our prediction experiment by estimating separate regressions for each house type, i.e.´detached houses, semi-detached houses and row houses. Table 3.4 presents the corresponding prediction evaluation measures. Here, the statistics are calculated using all out-of-sample observation regardless of the type of house.[6]

Compared to the results in Table 3.3, the separate estimation of price equations for each house type does not qualitatively change our conclusions. Whereas the consistent retransformation techniques outperform the naive predictor with respect to all evaluation measures, there are only insignificant differences between these predictors. It is striking, however, that the mean error of the different predictors reduces considerably compared to the re-

[6] A comparison of the evaluation measures separately for each house type in Table 3.3 and Table 3.4 has lead to the same qualitative conclusions.

Table 3.4: Performance of retransformation techniques for hedonic regression. Summary statistics of prediction errors for separate regression models for each house type.

	ME	MED	MSE	MAE	PE25
naive					
V_1	2.241	-0.369	7.724	18.608	75.320
	[1.665 2.840]	[-0.905 0.122]	[6.476 9.439]	[18.189 19.048	[74.418 76.222]
log normal					
V_2	-0.220	-2.644	7.288	18.286	75.662
	[-0.782 0.364]	[-3.160 -2.003]	[6.112 8.908]	[17.885 18.708]	[74.760 76.541]
V_3	-0.029	-2.490	7.353	18.320	75.571
	[-0.592 0.556]	[-2.995 -1.834]	[6.166 8.981]	[17.918 18.744]	[74.680 76.450]
V_4	-0.110	-2.473	7.268	18.209	72.464
	[-0.690 0.493]	[-3.005 -1.815]	[6.042 8.952]	[17.800 18.649]	[71.528 73.390]
robust					
V_5	-0.695	-2.851	7.218	18.248	75.674
	[-1.252 -0.117]	[-3.453 -2.349]	[6.050 8.823]	[17.849 18.671]	[74.760 76.542]
V_6	-0.042	-2.475	7.314	18.301	75.617
	[-0.605 0.543]	[-2.998 -1.845]	[6.132 8.940]	[17.900 18.725]	v74.714 76.500]
V_7	-0.143	-2.449	7.300	18.291	75.651
	[-0.704 0.442]	[-3.013 -1.879]	[6.117 8.920]	[17.891 18.714]	[74.749 76.530]

Notes: All reported measures are in percent. Number of observations is 8753 per retransformation method. ME is the mean error, MDE the median error, MSE the mean squared error, MAE the mean absolute error, and PE25 is the relative frequency of valuation errors within ±25% in absolute value. Non-parametric bootstrap confidence intervals are reported in parenthesis. Confidence intervals are calculated as $[\theta^*_{j,\alpha/2}, \theta^*_{j,1-\alpha/2}]$, where $\theta^*_{j,p}$ is the pth percentile of the bootstrap distribution $(\widehat{\theta}_{j,1}, \ldots, \widehat{\theta}_{j,k})$ for statistic j. Number of bootstrap replications is $k = 10000$. For details on the percentile based bootstrap confidence intervals see Efron and Tibshirani (1986).

sults in Table 3.3. Thus, calculating the retransformation factors conditional on house type can improve the bias reduction. Estimating separate price equations for each house type, however, comes at a cost. More precisely, all predictors exhibit a larger dispersion of prediction errors than in Table 3.3. The lower prediction performance, measured with the MSE and MAE, is attributable to the decreased size of the respective estimation sample. This in turn increases the sampling error and thus the accuracy of the predictors.

3.5 Conclusion

Hedonic price equations are commonly specified in a semi-logarithmic parametric functional form. The main advantage of such a specification is that implicit prices of property characteristics are easily estimated and can be readily used for automated valuations. While, the use of the log transaction price as the dependent variable in hedonic price equation does not pose any difficulties for the prediction of expected log transaction prices, the users of AVMs are primarily interested in predictions on the natural scale. However, the simple retransformation with the exponential function leads to biased estimates of the expected transaction price, i.e. the market value. To obtain consistent estimates of the market value, one needs to adjust the naive predictor.

In this chapter, we have presented consistent predictors of market values under both the assumption of log normally distributed prices and without imposing a distributional assumption. In addition, we have evaluated their out-of-sample prediction performance at the hand of a large data set on single-family house transactions from Berlin. The empirical results have shown that these predictors outperform the naive retransformation of predicted log transaction prices with the exponential function. Though, the choice of a particular retransformation technique does not significantly affect prediction performance. As indicated by predictions obtained for homogenous subgroups of houses in our sample, heteroscedasticity in the regression residuals, however, influences the performances of the different retransformation techniques.

3.6 Appendix

3.6.1 Estimation of market returns

It is obvious from equation (3.4) that the relative common change in market values for consecutive periods can be consistently estimated if $w_t(\mathbf{x})$ for period t can be estimated consistently. Then we have

$$\begin{aligned} \exp\{w_t(\mathbf{x}) - w_{t-1}(\mathbf{x})\} - 1 &= \exp\{v_t(\mathbf{x}) - v_{t-1}(\mathbf{x})\} - 1 \\ &= \frac{V_t(\mathbf{x})}{V_{t-1}(\mathbf{x})} - 1 \,. \end{aligned}$$

Implicitly assuming, that the hedonic prices for the houses' characteristics $\mathbf{x}$ are time invariant, we can use estimated coefficients of time dummy variables to consistently measure changes of market wide price trend. Note, that the

exponential retransformation of estimated time-dummies, however, leads to upward biased estimates of the market-wide price level. A simple corrections for this small sample bias can be found in Kennedy (1981).

On the other hand, the retransformation of repeat-sales (log) price estimators deliver downward biased estimates of market returns (Shiller 1991, Goetzmann 1992, Goetzmann and Peng 2002). This is because transaction prices are influenced by unusual circumstances, whereas market values are not. The repeat-sales approach assumes, that the log-return of an individual house n is given by

$$\ln\left(\frac{P_{n,t}}{P_{n,t-1}}\right) = \mu_t + \varepsilon_{n,t} \ ,$$

where μ_t denotes the market wide return and $\varepsilon_{n,t}$ is an i.i.d error term. Under the assumption of normally distributed error terms the unbiased maximun-likelihood estimator is

$$\widehat{\mu}_t = \frac{1}{N}\sum_N \ln\left(\frac{P_{n,1}}{P_{n,0}}\right) \ . \tag{3.15}$$

Now, by Jensen's inequality, the average over logs is less then log of the average, when there is any variance in the prices. That is

$$\ln\left(\frac{1}{N}\sum_N \frac{P_{n,1}}{P_{n,0}}\right) \geq \frac{1}{N}\sum_N \ln\left(\frac{P_{n,1}}{P_{n,0}}\right)$$

and the exponential retransformation of the repeat sales estimator (3.15) is a downward biased estimator for the arithmetic mean of market wide returns. In fact, the repeat sales estimator estimates the geometric mean of returns (Goetzmann and Peng 2002).

Chapter 4

Hedonic repeated measures indexes: Application to rental prices in Germany

4.1 Introduction

In the previous chapters, we have concentrated on the statistical valuation of individual properties. To our understanding of the investment behavior in residential real estate markets it is also important, though, to have an accurate picture of market wide changes in the price of housing. By combining information on a population, or sample, of dwellings, price and rent indexes try to infer the general tendency of (rental) prices, as well as the volatility of the market. The construction of indexes of housing inflation, however, is aggravated by the heterogenous nature of real estate.

The rental value of a dwelling, for instance, is determined by various physical characteristics of the building, as well as its location. Moreover, depreciation and maintenance changes the quality of individual dwellings, as well as the composition of the housing stock over time. Therefore, it has been widely acknowledged that elementary price indexes – based on average prices or rents – are misleading indicators of housing inflation (Diewert 2003a, 2007). The construction of real estate indexes rather necessitates statistical methods that explicitly control for quality differences across and between any two periods of price measurement.

Two such methods, hedonic time dummy and repeated sales, have been frequently employed for the construction of constant-quality real estate indexes (see e.g. Palmquist (1980), Case and Quigley (1991), Gatzlaff and Ling (1994), Meese and Wallace (1997), Englund et al. (1998)). The traditional

hedonic time dummy method attempts to capture inter-temporal changes in (rental) prices by regressing quality related dwelling characteristics and a set of time dummies on the logarithmic rent or price. Assuming that the marginal contributions of each attribute to the (rental) price stay constant over time, allows then to interpret the estimated coefficients on the time dummies as quality-adjusted price changes. The measurable set of structural and location characteristics, however, may only be insufficient controls for the relevant quality differences.

The repeated sales method, as first proposed by Bailey et al. (1963), confines the statistical analysis to repeated, though not necessarily consecutive, observations of presumably identical dwellings. Given that dwelling characteristics, as well as their regression coefficients are stable over time, there is no need to estimate the individual contribution of each attribute to rent or price. Any quality differences can be eliminated by a "first difference" transformation. Shiller (1993a,b) has further extended the repeated sales method to include changes in observed characteristics to the regression equation (see also Clapp and Giaccotto (1998)). The resultant hedonic repeated measures model may be described as a variant of the traditional hedonic time dummy regression using unbalanced panel data.

The goal of this Chapter is to present the theoretical basis to the hedonic repeated measures model, as well as to empirically apply this approach to the estimation of constant-quality rent indexes for Germany for the period 1984 to 2004. To this end, we use data from the German Socio Economic Panel Study (GSOEP). The GSOEP is a representative panel of German households that contains rich information on actual rents paid and a variety of dwelling characteristics. Exploiting the panel structure of the data, we consider the effect of unobserved dwelling characteristics, as well as time-varying regression parameters on the estimated index. Moreover, we provide constant-quality rent indexes for several German regions.

Our focus on rental price movements is motivated by two facts. First, the collection of rent data is not constrained by the low turn over of owner-occupied properties. Whereas, the construction of hedonic repeated measures price indexes is usually plagued by small sample sizes and selectivity issues (see e.g. Clapp and Giaccotto (1992), Hwang and Quigley (2004)), these data limitation are negligible in our case. Second, the – by international standards – low ownership rates in Germany make the rental sector a particular important part of the German housing market. The accurate measurement of rental price movements is thus an interesting task for itself (Hoffmann and Kurz 2002).

The empirical results of our study show that the problem of omitted dwelling characteristics in the traditional hedonic time dummy regression

biases the estimated constant-quality index. A more robust estimation procedure relies on a fixed effects specification of the hedonic regression equation. On the other hand, the presence of time-varying regression parameters – as chained hedonic time dummy indexes reveal – does not significantly affect the estimated indexes.

The remainder of this Chapter is organized as follows. In Section 4.2 we provide the methodological basis for our panel data approach to the construction of constant-quality rent indexes. The empirical application is presented in Section 4.3. We describe the rent data that is used to estimate the models, and provide a comparison of the estimated indexes. The final Section 4.4 concludes.

4.2 Methodology

The purpose of this section is to provide the methodological basis for our panel data approach to the construction of constant-quality rent indexes. We start by reviewing the traditional hedonic time dummy method, which provides a foundation for the applied hedonic repeated measures models. Both approaches employ hedonic regression techniques, the former using pooled cross-sectional data, while the latter uses (unbalanced) panel data.

To explore the effect of the unobserved quality characteristics on the constant-quality rent index, we consider, both, a random effects and fixed effects specification of the hedonic model. Furthermore, the issue of time-varying regression coefficients on variables not directly related to time is addressed. By confining the time dimension of the repeated measures model to pairs of adjacent years we allow for variation in the parameters; still being able to control for unobserved quality differences.

4.2.1 Hedonic time dummy method

Let y_{it} be the natural logarithm of the rental price of dwelling i ($i = 1, 2, \ldots, I$) in period t ($t = 0, 1, \ldots, T$). Let $\mathbf{x}_{it} = [x_{it1}, x_{it2}, \ldots, x_{itK}]$ be a row vector collecting structural and location characteristics of the correspondent dwelling, and D_{jit} ($j = 1, 2, \ldots, T$) a dummy variable marking the time period. In particular, D_{jit} takes the value one if the dwelling is observed in period j and zero otherwise. Then a standard form of the hedonic regression model is given by

$$y_{it} = \alpha_0 + \mathbf{x}_{it}\boldsymbol{\beta} + \mathbf{d}_{it}\boldsymbol{\gamma} + u_{it} \ , \tag{4.1}$$

where the row vector $\mathbf{d}_{it} = [D_{1it}, D_{2it}, \ldots, D_{Tit}]$ contains the time dummy variables. $\boldsymbol{\beta} = [\beta_1, \beta_2, \ldots, \beta_K]^\top$ is a column vector of regression coeffi-

cients, which reflect the implicit prices of the K measured attributes. Note, that these coefficients are assumed to be constant over time. The coefficients on the time dummy variables are collected in the column vector $\boldsymbol{\gamma} = [\gamma_1, \gamma_2, \ldots, \gamma_T]^\top$. These coefficients pick up period-specific intercepts, $\alpha_0 + \gamma_t$, which represent the portion of rent that is attributable to a temporal factor common to all dwellings in the population. Any unexplained influences on rental prices are captured by an error term, u_{it}, that has mean zero and variance σ_u^2. The error term is assumed to be mean independent conditional on $\mathbf{x}_{it}$ and $\mathbf{d}_{it}$, that is $E[u_{it}|\mathbf{x}_{it}, \mathbf{d}_{it}] = 0$ holds in every period $t = 0, 1, \ldots, T$.

In the present hedonic specification, logarithmic rent is a linear function in the implicit prices of the quality characteristics. From the standpoint of economic theory, however, the hedonic regression is a reduced-form equation reflecting, both, supply and demand. Thus, an explicit functional form cannot be established on theoretical grounds, and more appropriate specifications may rely on more flexible functional forms (see e.g. Halvorsen and Pollakowski (1981), Cropper et al. (1988)).[1] For reasons of convenience, we restrain to the log-linear functional form. Including continuous variables as functions of the underlying x_{it} in equation (4.1), will still allow us to capture potential non-linearities in the regression relationship.

To actually use equation (4.1) to construct a constant-quality rent index involves the estimation of the unknown regression coefficients. In practice, this requires the collection of pooled cross-sectional data – not necessarily panel data – on observed rents and the relevant set of dwelling characteristics. Consistent estimates of the regression coefficients can then be easily obtained by ordinary least squares regressions using the pooled data set (see e.g Wooldridge (2002, Chapter 7)).

If the same dwellings are repeatedly observed, more efficient estimators would recognize that the covariance between the error term at two different points in time may not be zero. Time-constant unobserved dwelling characteristics, for example, could induce serial correlated error terms. Therefore, it may be more efficient to use a generalized least square procedure when fitting equation (4.1) to panel data.

Given the estimated regression coefficients $\widehat{\alpha}_0$, $\widehat{\boldsymbol{\beta}}$, and $\widehat{\boldsymbol{\gamma}}$, index values for

[1] The theoretical foundation for the hedonic regression framework has been derived in Rosen (1974), in which a market for quality attributes of heterogenous goods is established (see also Lancaster (1966), Muellbauer (1974), Arguea et al. (1994)). Rosen's model, however, turns out to be extremely complex and provides only limited guidance to empirical work. Diewert (2003b) presents a more accessible version of the Rosen model, that reduces down to the hedonic time dummy regression presented here. However, even in Diewert's simplified model, an explicit functional form cannot be provided on theoretical grounds.

a reference dwelling with, say, characteristics $\mathbf{x}^0$ can then be calculated with

$$\widehat{I}_{0t} = \frac{\exp\left\{\widehat{\alpha}_0 + \widehat{\gamma}_t + \mathbf{x}^0\widehat{\boldsymbol{\beta}}\right\}}{\exp\left\{\widehat{\alpha}_0 + \mathbf{x}^0\widehat{\boldsymbol{\beta}}\right\}} = \exp\left\{\widehat{\gamma}_t\right\} \ . \tag{4.2}$$

Here, the base period is $t = 0$ for which the index is normalized to one. As the implicit prices on the quality characteristics are, by assumption, time-constant, the valued characteristics cancel out when calculating the index. Hence, the index values are constructed directly from the estimated time dummy coefficients and do not depend on the values of the quality attributes. The exponent of the estimated coefficient on the time dummy, $\widehat{\gamma}_t$, is, thus, an estimate of the quality-adjusted rate of growth in rental prices between period 0 and t. Note, that the simple retransformation via the exponential function leads to biased, yet consistent, estimates of $\widehat{I}_{0t}$. Kennedy (1981) provides a correction for this small sample bias.

Unobserved dwelling characteristics

A drawback with the hedonic time dummy regression (4.1) is that one can never be sure to include all relevant quality attributes in $\mathbf{x}_{it}$. In fact, the multitude of structural and location characteristics which affect the rental value of a dwelling make it very unlikely that the measurable attributes are satisfactory controls for all quality differences across and between the period under observation. Omitted variables in the pooled cross-sectional time dummy regression may bias the estimated time dummy coefficients for two reasons.

First, unobservable quality characteristics may not be constant through time. For example, local amenities, such as the quality of public services or infrastructures, are usually difficult to measure. If these location characteristics, say, improve over time and cannot be properly included in $\mathbf{x}_{it}$, the error term in the hedonic regression model will be positively correlated with time. Thus, the zero conditional mean assumption of the error term is violated and ordinary least squares estimates of the coefficients on the time dummies are biased. In this example, the estimated time dummy index overstates the increase in rental prices in later periods.

Second, even if the unobserved dwelling characteristics are time-constant their omission in the hedonic regression equation may bias the estimated time dummy coefficients. The source of this bias is due to a classical selection problem that results when the average values of the unobserved characteristics in the population change through time. For example, advances in technology

may improve unobserved quality attributes of newly built dwellings. If in later periods older, less attractive dwellings systematically drop out the sample, ordinary least squares estimates of the coefficients on the time dummies would exhibit an upward bias for these periods.

Unfortunately, the problem of time-changing unobserved quality characteristics cannot be dealt with within the hedonic regression framework. Moreover, one might argue that the changing mix of observed dwellings over time is only a problem when constructing real estate price indexes. Here, the infrequent sales of properties inevitable lead to unbalanced panel data sets. Rent data on the same dwellings, on the other hand, can be, at least in theory, collected consecutively period per period. Panel attrition and sample refreshments, however, may also require to control for time-constant omitted variables when constructing rent indexes.[2] We will next see how the hedonic repeated measures model addresses this issue.

4.2.2 Hedonic repeated measures indexes

The hedonic repeated measures model, developed by Shiller (1993a,b), is a variant of the traditional hedonic time dummy regression, that uses unbalanced panel data to approach the problem of omitted variables bias in real estate indexes. Therefore, the hedonic regression model (4.1) is extended to explicitly include an unobserved dwelling-specific effect. Formally, the hedonic repeated measures regression may be written as

$$y_{it} = \alpha_0 + \mathbf{x}_{it}\boldsymbol{\beta} + \mathbf{d}_{it}\boldsymbol{\gamma} + c_i + u_{it} \ . \tag{4.3}$$

Here, c_i denotes the dwelling-specific effect, which additively enters the regression equation.[3] This random variable accounts for whatever time-constant structural and location characteristics cannot be included in $\mathbf{x}_{it}$.

Generally, equation (4.3) can be used to construct constant-quality rent indexes in the same fashion as in the traditional hedonic time dummy method. The important improvement over the pooled cross-sectional approach indicated by equation (4.1) is that the estimated coefficients on the time dummies now serve as estimates of the change in rental prices conditional on, both, observed and unobserved dwelling characteristics. The actual influence of

[2] If there is no selection problem and the population mean of the unobserved quality characteristics stays constant over time, the presence of time-constant omitted variables would not bias the estimated hedonic time dummy, see e.g. Benkard and Bajari (2005).

[3] Shiller's (1993a,b) original formulation of the hedonic repeated measures model adds dummy variables for each cross-section observation to the hedonic regression model. The resultant regression can be considered as the classical fixed effects formulation of equation (4.3).

these unobserved variables on the time dummy coefficients, and thus consistent estimation of the index, however, depends on the stochastic properties of the dwelling-specific effect. The key issue is if the dwelling-specific effect is systematically related to the regressors in equation (4.3) or selection into the panel. In our empirical application, we consider two specifications of the hedonic repeated measures model: random effects and fixed effects.

Before we turn to these two basic panel data models, a note with respect to the error term u_{it} has to be made. Since the regression model (4.3) is fitted to unbalanced panel data, consistent estimation requires a stronger form of exogeneity than the conditional mean independence assumption stated above (Wooldridge 2002, Chapters 10 and 17). In particular, it must be assumed that u_{it} is strictly exogenous conditional on dwelling-specific effect, as well as selection into the panel. This implies that feedback effects on the expected level of rent from quality variables in other time periods are not allowed once the unobserved effect and selection into the panel have been controlled for.

Random effects specification

Under the random effects specification it is assumed that the dwelling-specific effect is stochastically independent from the regressors in equation (4.3), as well as selection into the panel. In this sense, c_i can be regarded as a time-constant component of a composite error term $\nu_{it} \stackrel{\text{def}}{=} u_{it} + c_i$. The resultant hedonic repeated measures model is then given by

$$y_{it} = \alpha_0 + \mathbf{x}_{it}\boldsymbol{\beta} + \mathbf{d}_{it}\boldsymbol{\gamma} + \nu_{it} \ . \tag{4.4}$$

Hence, equation (4.3) practically reduces down to the traditional hedonic time dummy regression. In fact, the random effects hedonic repeated measures model only differs from equation (4.1) with respect to the stochastic specification of the error term. More precisely, the presence of a time-constant unobserved effect c_i introduces serial correlation in the error term ν_{it}, whereas u_{it} is usually assumed to be uncorrelated over time.

By assumption, the dwelling-specific effect has thus no systematic influence on the expected level of rent. Therefore, equation (4.4) will not allow to overcome the omitted variable bias in the hedonic time dummy index that may be induced by the changing mix of dwellings observed in the data. However, the random effects specification is useful to assess the influence of unobserved dwelling characteristics on the estimated time dummy index when compared to the fixed effects specification discussed below.

To consistently estimate the coefficients in equation (4.4), one could still use pooled ordinary least squares. A more efficient estimator, however, accounts for the serial correlation in the composite error term. In our empirical

application, we therefore employ the random effects generalized least square estimator that exploits the specific structure of the covariance matrix of the composite error term, see e.g. Wooldridge (2002, Chapter 10).

Fixed effects specification

The fixed effects specification relaxes the assumption of the stochastic independence of the dwelling-specific effect. More precisely, c_i is allowed to be arbitrarily correlated with the regressors in equation (4.3), as well as selection into the panel. It is therefore the fixed effect specification of the hedonic repeated measure model which engages the potential omitted variables bias due to the changing mix of observed dwellings.

To consistently estimate the regression coefficients in equation (4.3) under the fixed effects specification two main methodologies exist: the first differencing estimator and the fixed effects estimator. The choice between these approaches mainly hinges on the assumptions on the idiosyncratic error term. While the former is efficient if u_{it} follows a random walk, the latter is efficient if u_{it} is i.i.d. (Wooldridge 2002, Chapter 10). Given the large number of observations in our data set, we abstain from efficiency issues and employ the fixed effects estimator.[4]

The key idea of the fixed effects estimator is to remove the dwelling-specific effect from the hedonic repeated measures model by time-demeaning all variables of the cross-section observations. Applying the fixed effects transformation – or within transformation – to equation (4.3), the estimation equation becomes

$$y_{it} - \bar{y}_i = (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)\boldsymbol{\beta} + (\mathbf{d}_{it} - \bar{\mathbf{d}}_i)\boldsymbol{\gamma} + (u_{it} - \bar{u}_i) \ . \tag{4.5}$$

where $\bar{y}_i$, $\bar{\mathbf{x}}_i$, and $\bar{\mathbf{d}}_i$ denote the time averages over the T observations of the respective variables for dwelling i. Without c_i in equation (4.5) the regression coefficients can then be consistently estimated by pooled ordinary least squares. Since the interpretation of these coefficients comes from the hedonic repeated measures model (4.3), the estimated coefficients on the transformed time dummies still serve as estimates of the quality-adjusted change in rental prices.

[4]Shiller (1993a,b) proposes to use a GLS variant of the first differencing estimator, that accounts for additional white noise in the error term at the time of observance. In our empirical application, we tested for several time-series specification of the error term structure. The test results, however, did not suggest one particular model. Moreover, additional heteroscedasticity make it difficult to employ a true GLS model that allows for arbitrary serial correlation.

It must be noted, that the within transformation not only removes the dwelling-specific effect, but also all time-constant dwelling characteristics in $\mathbf{x}_{it}$. As we are primarily interested in the coefficients on the time dummy variables, this does not pose any problems for our application.

Chained hedonic time dummy index

The hedonic repeated measures model (4.3) has maintained the assumption of time-constant regression coefficients embedded in the traditional hedonic time dummy method. If the implicit prices of the quality characteristics vary over the period of index construction, though, the time dummy coefficients will not generally reflect the quality-adjusted change in rental prices. In particular, the index values as defined in equation (4.2) depend on the common market trend, as well as the (re-)valued characteristics of the reference dwelling.

However, Silver and Heravi (2007) show that wrongly assumed constant implicit prices may not necessarily bias the estimated index obtained from the pooled (panel) regression. This is because the difference between the marginal valuation of a quality characteristics between two time periods can be interpreted as an omitted variable, which value is, at least in part, picked-up by the correspondent time dummy coefficient. In the particular case of a sample in which the mean value of the respective characteristic does not change over time, the size of this omitted variable bias exactly accords to the change in the implicit price.

To examine the potential bias in the estimated time dummy index, we construct a chained time dummy index by confining the time-dimension of the repeated measures model to pairs of adjacent years (Palmquist 1980, Munneke and Slade 2001). Thereby, we allow the regression parameters to vary over time, while directly using the time dummy coefficients as estimates of the rent index.[5] Moreover, this approach allows – unlike pure cross-sectional regressions – to explicitly control for unobserved quality characteristics.

We specifically divide the full period under observation into subintervals: The first interval contains periods 0 and 1, the second 1 and 2, and so on. The hedonic repeated measures regression (4.3) is then separately performed on these subintervals. Here, the respective regression equations contain only one time dummy variable, which takes the value one if the observation falls

[5] Alternative methods that, for example, allow for time-varying regression coefficients by interacting dwelling characteristics with the time dummies require to explicitly define the characteristics of the reference dwelling.

in the later half of the subinterval, and zero otherwise. These annual quality-adjusted rates of rental growth are multiplied into the chained index

$$\widehat{I}_{0t} = \prod_{i=1}^{t} \exp\{\widehat{\gamma}_i\} , \tag{4.6}$$

where $\widehat{\gamma}_i$ is the estimated time dummy coefficients from the regression covering the period from $t = i - 1$ to $t = i$.

4.3 Empirical application

This Section presents the empirical application of the hedonic repeated measures model to the construction of constant-quality rent indexes. We start by describing the data used to estimate all the models discussed above. In our comparison of the estimated indexes, we first concentrate on aggregate rent movements for West Germany. This is also the focus of a recent study by Hoffmann and Kurz (2002), who use the same data set to construct several benchmark indexes of rent inflation to cross-check the rental sub-index of the official German CPI. Among these is a hedonic index based on purely cross-sectional regressions. Panel data methods are not considered. Furthermore, we present estimates of constant-quality rent indexes for 30 West German regions.

4.3.1 Data

Our data come from the German Socio Economic Panel (GSOEP) for the period 1984 to 2004. The GSOEP is yearly household panel that assembles rich information about living conditions in Germany. Among other data, the GSOEP contains longitudinal information on actual rents paid by households and major characteristics of their residence. Moreover, additional geo-code files are available, which allow to identify a household's place of residence on a variety of geographic aggregation levels (Spieß 2005). Consistent disaggregated information on East German households' place of residence, however, is only available from 1996 on. We thus restrict our analysis to West Germany.

The GSOEP started in 1984 with nearly 6,000 households. In 1990, the year of German unification, it was enlarged to include East German households. Due to further sample refreshments, the number of households reaches almost 12,000 in 2004. Of these about 8,900 households reside in West Germany. The focus of this Chapter, though, is the dwelling and not the household level. In the case of a move, the GSOEP follows a household to its

new residence and the old dwelling discards from the sample. Therefore, we cannot generate a true dwelling panel from the GSOEP household files. The composition of our dwelling sample rather depends on households' moving behavior, as well as successful follow-up by the GSOEP group.

For the period 1984 to 2004, we observe 9,852 individual dwellings that are located in West Germany. These observation comprise 7,383 individual households, where the greater number of dwellings reflects moves within the sample. Each of the dwellings appears at least twice in our sample, 50 percent of the observations appears less then four times, and less then one percent of dwellings is observed for the complete period under observation. Our data set is highly unbalanced. The total number of observations is 53,544. The minimum number of observations per year is 2,030, the maximum is 3,648, and the average is 2,550.

Table 4.1 presents means and standard deviations of rent and dwelling characteristics for the years 1984 and 2004. Reported rents are in nominal euros, and relate to the gross rent including operating cost net of heating cost. The operating cost include expenses on electricity, water supply, and waste disposal. Apart from information on rents, the GSOEP contains data on structural characteristics of the building, its location, as well as variables describing peculiarities in the tenancy agreement.[6]

Among the structural characteristics are the floor size of the dwelling, vintage of the building, building type, and numerous furnishing characteristics. As noted above, the location of a dwelling can be identified at different regional aggregation levels. In particular, these are the administrative regions according to the *Nomenclature des unités territoriales statistiques* (NUTS), as well as the planing regions defined by the Federal Building Office.[7]

Given the low number of observations on smaller geographical units, we choose the 30 West German Government Regions (NUTS2) to delineate the location of a dwelling. Figure 4.1 depicts these Government Regions and the Federal States of Germany. To further control for potential rent differences across lowly and highly populated areas within these regions, we gathered additional information on the type of conurbation the dwelling is located at. These data are provided by the Federal Building Office, and are linked to

[6]The GSOEP also contains some data on neighborhood characteristics. Among these are, for example, information on the type of area the household lives in. As the majority of dwellings are located in residential areas, opposed to commercial or mixed areas, these variables turned out to be insignificant in our analysis, and are not considered here.

[7]The delimitation of the planing regions (*Raumordnungsregionen*) mainly follows commuting patterns and socio-economic linkages, and may cross Federal State boundaries (Böltken et al. 1996).

Table 4.1: Summary statistics of rent and dwelling characteristics. GSOEP waves 1984 and 2004.

	1984		2004	
	Mean	S.D.	Mean	S.D.
Rent (*in Euro*)	216.45	102.92	467.66	200.53
Landlord-tenant relationship				
Occupancy duration (*in years*)	9.02	9.10	9.57	11.13
Socially subsidized	22.13%		12.78%	
Structural Characteristics				
Floor Size (*in sqm*)	71.13	24.77	77.59	27.24
Furnishing				
Kitchen	97.44%		98.66%	
Bathroom	88.23%		99.14%	
Central heating	68.78%		92.87%	
Balcony	51.61%		71.46%	
Garden	71.56%		63.50%	
Type of house				
Farm house	00.96%		01.16%	
1-2 Fam. House	11.61%		14.97%	
1-2 Fam. Rowhouse	09.83%		08.92%	
Apt. In 3-4 Unit Bldg.	19.10%		20.51%	
Apt. In 5-8 Unit Bldg.	36.52%		35.19%	
Apt. In 9+ Unit Bldg.	17.85%		17.72%	
High rise	02.40%		01.34%	
Other building	01.68%		00.14%	
Vintage				
built before 1918	16.26%		09.31%	
built between 1918 and 1948	23.85%		15.66%	
built between 1949 and 1971	45.11%		38.75%	
built between 1972 and 1990	14.76%		22.58%	
built after 1991	00.00%		13.68%	
Location Characteristics				
Conurbation Type				
Urban agglomeration (high density)	48.04%		47.02%	
Urban Agglomeration (low density)	19.01%		16.68%	
Urbanized area (high density)	13.92%		14.76%	
Urbanized area (medium density)	07.74%		09.25%	
Urbanized area (low density)	05.36%		05.92%	
Rural area	05.90%		06.34%	
Number of observations	2,488		2,792	

Notes: Table reports means and standard deviations of rent and dwelling characteristics. Occupancy duration is the time the household has spend in its current residence.

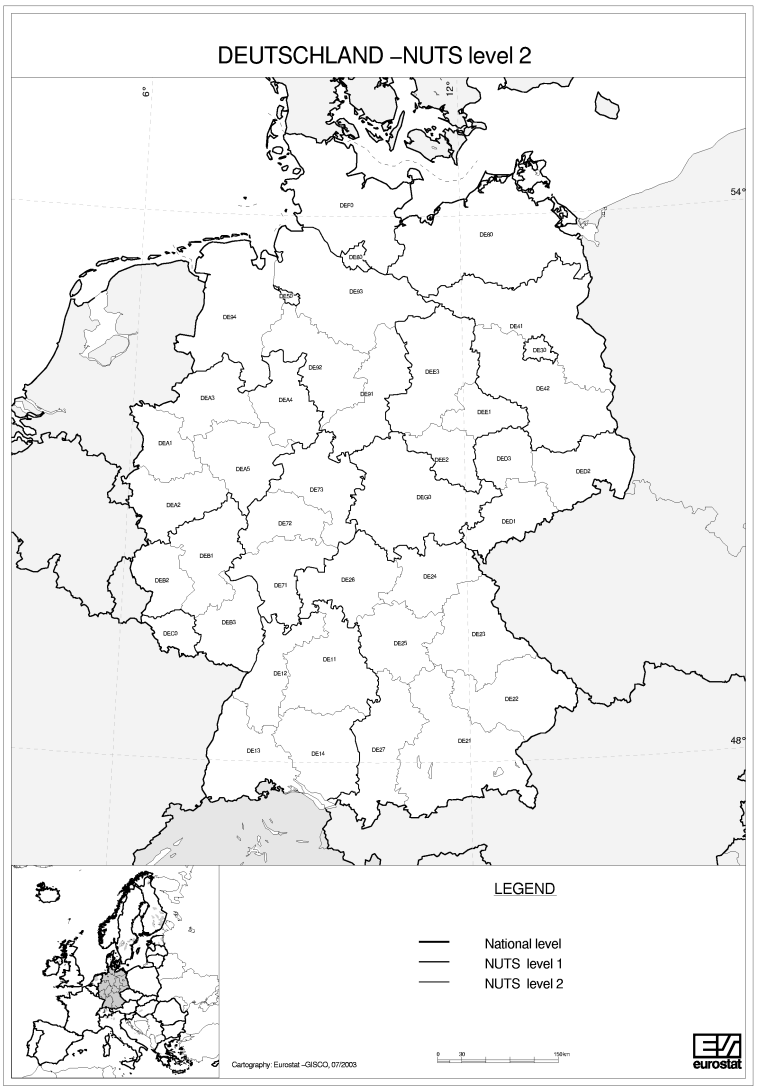

Figure 4.1: Germany's Federal States, NUTS1, and Government Regions, NUTS2, (Source: http://ec.europa.eu/eurostat/ramon/nuts/pngmaps/de2.png).

the GSOEP data according to the planing region the respective a dwelling is situated. For details on these data, see Janich et al. (2002).

The variables subsumed under the label landlord-tenant relationship in Table 4.1 intend to capture peculiarities in the tenancy agreement, as well as institutional factors of the German housing market. First, the GSOEP distinguishes between dwellings in the socially-subsidized and the private rental sector. As rent regulations mainly apply to subsidized dwellings, rent (growth) in this sector is likely to differ from those in the private sector. Second, the occupancy duration of sitting tenants accounts for potential length-of-stay discounts, that may be the result of legal restriction to rent increases.[8]

Comparing the observed dwellings in 1984 and 2004, it is striking that the average (nominal) rent in West Germany has more than doubled. Moreover, the dispersion of rental payments has significantly increased. Throughout the same period, the quality of the average dwelling, on the other hand, has only slightly changed. To some extent dwellings became larger, better equipped, and more modern. During the 20 years under observation the mean floor size, for example, has increased by approximately 9 percent. Furthermore, in 2004 dwellings are more likely to be equipped with central heating or balconies than in 1984. In both years, most dwellings are part of multi-family houses, and are located in highly populated urban areas. Naturally the share of dwellings built after 1984 has significantly increased over the period under observation. While the percentage of socially-subsidized dwellings has declined by about 40 percent, the average duration of occupancy of the sitting tenants has remained rather stable during the period under observation.

4.3.2 Empirical results

Model specification and estimates

As discussed in Section 4.2, we estimate, both, a random effects and a fixed effects specification of the hedonic repeated measures model (4.3). While the former serves as a benchmark model for the construction of a traditional hedonic time dummy index, the latter allows us to explore the potential bias in the estimated index due to omitted quality characteristics.

Table 4.2 reports estimates of the two models. In both cases, we have fitted the model using data on all dwellings located in West Germany. The estimation period covers the years from 1984 to 2004. The presented specification of the random effects model includes, both, time-varying and time-

[8] A further discussion of these issues can be found in Hoffmann and Kurz (2002).

constant dwelling characteristics. Our only continuous quality characteristic is the floor size of the dwelling. In order to capture potential non-linearities in the relationship between rent and size, we include this variable in a transformed way. In particular, we consider the Box-Cox type transformation function – and its square – introduced by Bunke et al. (1999) (see also Chapter 2). Here, the specific type of transformation function was chosen by maximizing the coefficient of determination of the correspondent regression. The optimal value of the transformation parameter λ is -1. Apart from the size variable, we include a variety of binary indicator variables. Among these are dummy variables for subsidized dwellings, different length of occupancy duration, furnishing characteristics, type and vintage of the building, and the conurbation type. As the result of various specification tests, we have summarized the original GSOEP variables for several of these characteristics into broader categories. To control for the location of a dwelling, we further include a full set of dummy variables for the NUTS2 regions. In our specification of the fixed effects model, on the other hand, we had to drop all time-constant dwelling-characteristics. Among these are the floor size of the dwelling, type and vintage of the building, as well as the conurbation type and region dummies. The presented model thus only includes variables describing furnishing characteristics and the indicators for socially-subsidized dwellings and the length of occupancy duration.

Table 4.2: Random effects and fixed effects hedonic repeated measures rent regressions for West Germany, 1984 – 2004.

	Dependent variable: log rent			
	Random Effects		Fixed Effects	
	Coef.	Std. Err.	Coef.	Std. Err.
T_{-1}(Floor size)	-1.699	1.389		
T_{-1}(Floor size)^2	4.232	0.901***		
No bathroom	-0.142	0.010***	-0.094	0.012***
No central heating	-0.115	0.006***	-0.061	0.007***
Single-family	-0.059	0.008***		
Apartment (3-4 unit)	-0.032	0.008***		
Apartment (high rise)	0.034	0.007***		
Other house type	-0.207	0.025***		
built $\leq$ 1918	-0.068	0.007***		
built $>$ 1918 and $\leq$ 1948	-0.035	0.005***		
built $\leq$ 1972 and $<$ 1990	0.064	0.005***		
built $\leq$ 1991	0.177	0.009***		
Subsidized Housing	-0.041	0.004***	-0.023	0.004***
1-5 Yrs. Occup.	-0.026	0.005***	-0.015	0.005***

Continued on next page

Table 4.2: *continued*

	Dependent variable: log rent			
	Random Effects		Fixed Effects	
	Coef.	Std. Err.	Coef.	Std. Err.
6-10 Yrs. Occup.	-0.057	0.006***	-0.020	0.006***
11-15 Yrs. Occup.	-0.078	0.007***	-0.015	0.008**
16-20 Yrs. Occup.	-0.092	0.007***	-0.011	0.010
21> Yrs. Occup.	-0.116	0.008***	-0.005	0.012
Urban Agglom. (low dens.)	0.036	0.012***		
Urbanized Area (high dens.)	-0.055	0.012***		
Urbanized Area (med. dens.)	-0.133	0.015***		
Urbanized Area (low dens.)	-0.108	0.016***		
Rural Area	-0.162	0.019***		
$\widehat{\sigma}_u$	0.161		0.162	
$\widehat{\sigma}_c$	0.250		0.418	
No of Observations		53544		53544
No of Dwellings		9852		9852
R^2 (overall)		0.674		0.339
Wald-Statistic		8045.81***		184.30***
DW		1.455		1.444
LBI		1.855		1.847

Notes: Table reports random effects and fixed effects estimates of equation (4.3). Coefficients for constant, time-dummies and region-dummies are not reported. Standard errors are calculated with Huber/White/sandwich estimator, which is robust to arbitrary heteroscedasticity and serial correlation. R^2 (overall) reports the squared correlations between y_{it} and the correspondent linear prediction $\widehat{y}_{it} = \mathbf{x}_{it}\widehat{\boldsymbol{\beta}} + \mathbf{d}_{it}\widehat{\boldsymbol{\gamma}}$. Wald-Statistic is for the null hypothesis that all coefficients reported in the table are jointly zero. DW reports the modified Bhargava et al. (1982) Durbin-Watson test statistic. LBI reports the Baltagi and Wu (1999) test statistic for zero first-order serial correlation. We can not reject the null hypothesis of no first-order serial correlation. *** significant at 1%-level ** significant at 5%-level * significant at 10%-level

By and large, the quality of the model fit is for, both, the random effects and fixed effects specification reasonably well. The squared correlations between the predicted and observed (log) rent ranges from 0.674 in the random effects estimates to 0.339 in the fixed estimates. Here, the significant decrease for the fixed effects model is attributable to the ignorance of the dwelling-specific effect – and the fewer number of explanatory variables – when calculating this measure of goodness-of-fit. As indicated by the modified Bhargava et al. (1982) Durbin-Watson test statistic and the Baltagi and Wu (1999) LBI test statistic, the regression residuals for both estimates exhibit substantial serial correlation, see Appendix 4.5.1. While we abstain

from efficiency issues of the employed estimators, the reported standard errors are robust to arbitrary heteroscedasticity and serial correlation in the error term.

The estimated coefficients are in most cases significant and show reasonable signs. In the random effects estimates the coefficients on the transformed floor size imply increasing rents, yet at diminishing rates, with increasing size of the dwelling. The rent for single-family houses and dwellings situated in small apartment buildings (3-4 units) lowers the rent compared to dwellings in larger apartment buildings (5–8 units). Dwellings in high rise buildings, on the other hand, are significantly more expensive. The vintage of the building has a negative effect on the rent level. Dwellings in older houses command lower rents than those in new buildings. Missing furnishing characteristics, like bathrooms and central heating, also reduce the rent. Note, that the estimated coefficients on these variables are significantly smaller in the fixed effects estimates. The type of conurbation also matters. Compared to dwellings located in highly dense urban agglomerations, rents are generally lower in less populated areas. Only dwellings in urban agglomerations with a low population density, that is suburbs of bigger cities, command a premium. As expected, we find that dwellings in the socially-subsidized sector have lower rents compared to those in the private sector. Moreover, the length of occupancy duration of the sitting tenant significantly reduces the rent. Again the coefficients on these variables are significantly lower in the fixed effects estimates. Overall, our estimates of the random effects specification are comparable to those found in the cross-sectional regression by Hoffmann and Kurz (2002).

The key distinction between the random effects and fixed effects specification of our hedonic repeated measures model, however, is the the treatment of the dwelling-specific effect. In both specifications, the estimated variance of the dwelling-specific effect is quite substantial. The fraction of the combined error variance, $\widehat{\rho} = \widehat{\sigma}_c^2/(\widehat{\sigma}_c^2 + \widehat{\sigma}_u^2)$, ranges from 70.65 percent (random effects) to 86.95 percent (fixed effects). A conducted Lagrange-multiplier test, as suggested by Baltagi and Li (1990), rejects the null hypothesis that σ_c^2 is equal to zero in the random effects specification. Furthermore, a F-test for the significance of the dwelling-specific effects indicates the presence of unobserved dwelling characteristics in the fixed effects specification.

However, the evidence on the presence of unobserved dwelling characteristics does not indicate which of the two model specification is more appropriate. To test the random effects assumption of zero correlation between the dwelling-specific effect and the regressors in equation (4.3), we conduct a variant of the Hausman (1978) specification test (see also Wooldridge (2002, pp. 286)). The testing procedure is based on the two-step representation of

the random effects estimator and inspects the difference between the random effects and fixed effects coefficient estimates of the time-varying variables. Unlike the conventional Hausman test, however, it is robust to arbitrary heteroscedasticity and/or serial correlation in the error term. For further details on the test, see Appendix 4.5.2.

Table 4.3: Hausman specification test.

Test equation: $\breve{y}_{it} = \breve{\mathbf{z}}_{it}\boldsymbol{\beta} + \ddot{\mathbf{w}}_{it}\boldsymbol{\theta}$			
	DF	χ^2-statistic	P-value
Global test	28	329.40	0.000
Test for subgroups			
Time dummies	20	30.76	0.058
Furnishing characteristics	2	154.17	0.000
Occupancy duration	5	72.22	0.000
Subsidized dwellings	1	54.50	0.000

Notes: Table reports robust version of Hausman test based on the OLS regression (4.8). For the global test the null hypothesis is $\boldsymbol{\theta} = 0$. P-value is for $\chi^2(28)$-distribution. The tests for subgroup of variables only restricts the correspondent coefficients in $\boldsymbol{\theta}$ to be zero under the null hypothesis. The correspondent P-values are for χ^2-distributions with degrees of freedom as indicated in the column DF.

Table 4.3 reports the test results. The global test rejects the null hypothesis that all time-varying variables in equation (4.3) – including the time dummies – are uncorrelated with unobserved dwelling characteristics. As indicated by the tests for subgroups of the time-varying variables, especially the included furnishing characteristics and variables describing the landlord-tenant relationship are correlated with the dwelling-specific effect. Interestingly, the null hypothesis of zero correlation between unobserved quality characteristics and the time dummies can only be rejected at the 10 percent significance level. Altogether, Table 4.3 provides evidence that the random effects estimates of equation (4.3) are biased.

A potential caveat with both models presented in Table 4.2 is the presumed stability of the regression coefficients over time. To formally test the assumption of stable implicit prices of the dwelling characteristics, we conducted a Wald test of the null hypothesis of constant regression coefficients over the period from 1984 to 2004. We specifically compare the restricted version of the hedonic repeated measures model (4.3) with an unrestricted model that allows for separate slope coefficients for each year. See Appendix 4.5.3 for details.

Table 4.4: Wald test for equality of estimated coefficients on dwelling characteristics over time.

		RE		FE	
	DF	χ^2-statistic	P-value	χ^2-statistic	P-value
Global test	1040	2337.58	0.000	2072.43	0.000
Structural characteristics					
Floor size	40	37.06	0.603	180.78	0.000
No bathroom	20	16.64	0.677	17.68	0.608
No central heating	20	160.95	0.000	165.46	0.000
House type	80	109.34	0.016	125.43	0.001
Vintage	80	224.42	0.000	149.71	0.000
Landlord-tenant relationship					
Socially-subsidized	20	91.21	0.000	67.57	0.000
Occupancy Duration	100	153.88	0.000	118.39	0.089
Location characteristics					
Conurbation type	100	140.29	0.005	134.30	0.013
Region (NUTS2)	580	932.96	0.000	843.35	0.000

Notes: Table reports results of Wald test of the null hypothesis that the coefficients on the respective variable group are constant over the period from 1984 to 2004. P-value is for χ^2-distribution with corresponding degrees of freedom (DF).

Table 4.4 summarizes the test results. We conduct several Wald tests for, both, random effects and fixed effects estimates of the unconstrained regression model. A global test that the coefficients on all quality characteristics – including the region dummies – are time-constant rejects the null hypothesis at the usual confidence levels. However, for some of the considered subgroups of variables, such as the length of occupancy duration and specific furnishing characteristics, the null hypothesis of stable regression coefficients cannot be rejected. In sum, Table 4.4 provides evidence against the assumption of stable implicit prices in the hedonic repeated measures model.

We next turn to the estimated hedonic time dummy indexes that are implied by the hedonic repeated measures regression presented in Table 4.2. To asses the effect of time-varying regression coefficients, we further compare these indexes with a chained hedonic time dummy index.

Comparison of estimated rent indexes for West Germany

Figure 4.2 depicts the hedonic repeated measures rent indexes implied by the random effects and fixed effects estimates presented in Table 4.2. The index values are computed as

$$\widehat{I}_{0t} = \exp\{\widehat{\gamma}_t - 0.5\widehat{\sigma}^2_{\gamma_t}\} \times 100 \tag{4.7}$$

where $\widehat{\gamma}_t$ is the estimated time dummy coefficient from the respective hedonic repeated measures model. $\widehat{\sigma}^2_{\gamma_t}$ is the correspondent estimated robust variance of the coefficient estimator, which corrects for small-sample bias (Kennedy 1981). The indexes are normalized to 100 for the base period 1984. Asymptotic 95% confidence bands for the hedonic time dummy indexes are estimated with the delta method (see e.g. Davidson and MacKinnon (2004, pp. 202)).

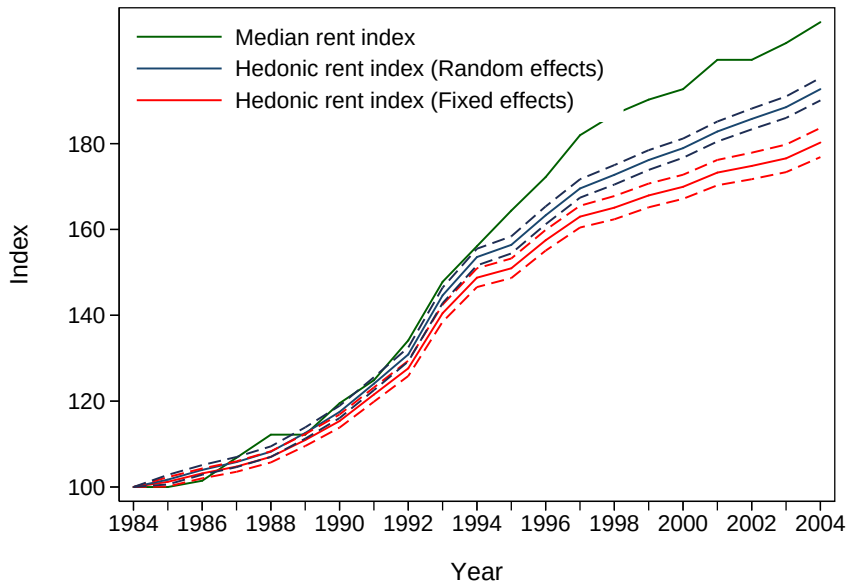

Figure 4.2: Figure shows median rent index and hedonic repeated measures rent indexes from random effects and fixed effects model for West Germany. The dashed lines around the hedonic repeat measures rent indexes are 95% pointwise confidence bands.

Figure 4.2 also shows a median rent index for West Germany. The correspondent index values are computed as the ratio of the median rent level in the respective year to the median rent level in the base period 1984. This elementary rent index does not control for any quality differences across and between periods, and serves as a means of comparison for the importance of quality-adjustment.

For the first 8 years of the period under observation, that is the period from 1984 to 1992, all three indexes show a very similar behavior. While the median rent index and the hedonic time dummy index derived from the

random effects specification of equation (4.3) exhibit slightly higher rates of rental growth, these differences are statistically indistinguishable from the fixed effect hedonic repeated measures index. This remarkable result can be rationalized by the rather slow changes in the observed dwelling characteristics in our data, as well as the stable composition of the sample during this period. Thus, we are mostly comparing matched observations on identical dwellings, and even the absence of any quality-adjustment will not induce much mismeasurement.

However, for the period from 1993 on, the estimated trends in rental prices clearly diverges for all three indexes. The median rent index produces the highest rate of rental growth. Changes in the composition of the sample suggest that the median rent index overstates true housing inflation. Both hedonic repeated measures indexes, that explicitly control for observed quality characteristics, exhibit significantly lower rates of rental growth. Here, the fixed effects estimates produce the lowest inflation rates. The statistically significant differences between the constant-quality indexes produced by the random effects and fixed effects specification of our hedonic model, show that ignoring unobserved dwelling characteristics indeed affects the estimated indexes. Given the support for the fixed effects specification, presented above, we conclude that the traditional hedonic time dummy method understates the true rate of quality-adjusted rental growth.

Next we asses how the presence of time-varying regression coefficients affects the estimated index. Figure 4.3 shows the chained hedonic time dummy index that is calculated according to equation (4.6). Here, the time dummy coefficients are estimated from fixed effects hedonic repeated measures regressions using data on pairs of adjacent years. The specification of the regression equation is equivalent to the fixed effects model presented in Table 4.2. For comparison the correspondent hedonic time dummy index is also plotted in Figure 4.3. Both indexes are corrected for small sample bias and asymptotic 95% confidence bands are estimated with the delta method.

Compared to the hedonic repeated measures index estimated from a single regression, the chained time dummy index is almost identical up to the year 1995. Only from this time, on the estimated rate of rental growth is slightly lower, when we allow for time-varying regression coefficients. As the 95 percent confidence bands reveal the differences to the restricted model, however, are statistically not significant. The divergence trends in the marginal contributions of the quality characteristics induce, thus, no severe mismeasurement in our hedonic repeated measures rent index. As discussed in Section 4.2, this remarkable result is attributable to the rather stable configuration of the average dwelling in our sample under the period of observation (see Table 4.1).

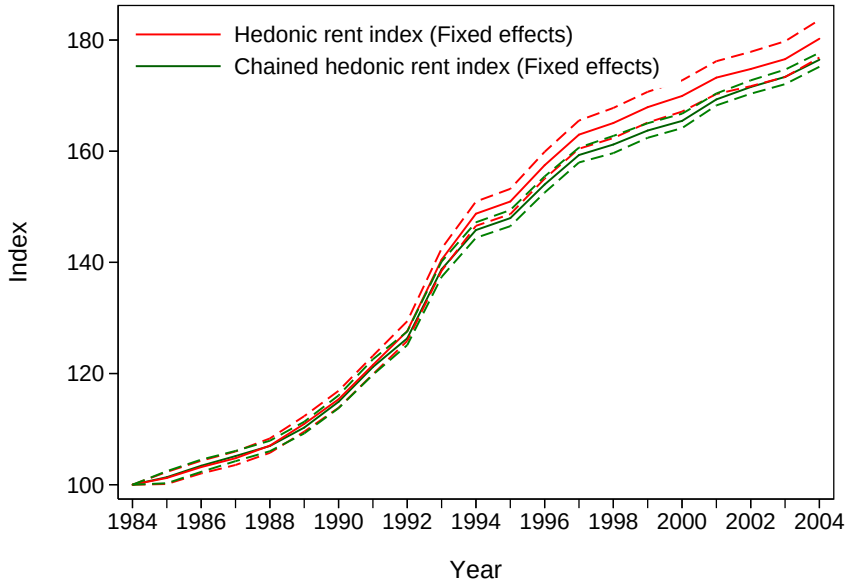

Figure 4.3: Figure shows chained hedonic time dummy index and fixed effects hedonic repeated measures rent index for West Germany. The dashed lines around the hedonic repeat measures rent indexes are 95% pointwise confidence bands..

Rent indexes for West German Government Regions

The previous results have shown that the hedonic repeated measures approach is suitable for the construction of aggregate rent indexes. However, residential housing markets are inherently regional. Therefore, it is of particular interest to also obtain disaggregated measures of rent inflation. We next present estimates of constant-quality rent indexes for the 30 West German Government regions for the period 1984 to 2004. These indexes will be used in the following Chapter 5 to measure households' exposure to regional rent risk.

In order to estimate the regional rent indexes we fit separate hedonic regressions for each of the 30 region under scrutiny. More precisely, we employ the fixed effects specification of the hedonic repeated measures model (4.3) as presented in Table 4.2. While using the same set of quality characteristics as in the aggregate estimates, the use of separate regressions allows for

varying regression coefficients across the regions. Overall, the model fit of these regressions is comparable to the results presented above. However, the number of observed dwellings in a few regions is quite low, and the correspondent estimates of the time dummy coefficients have large standard errors (see below).

Figure 4.4 shows the estimated hedonic repeated measures rent indexes for the 30 West German Government Regions. The index values are computed according to equation (4.7). As a means of comparison each graph in Figure 4.4 also shows the aggregate rent index for West Germany. This index is obtained from the fixed effects estimates presented in Table 4.2.

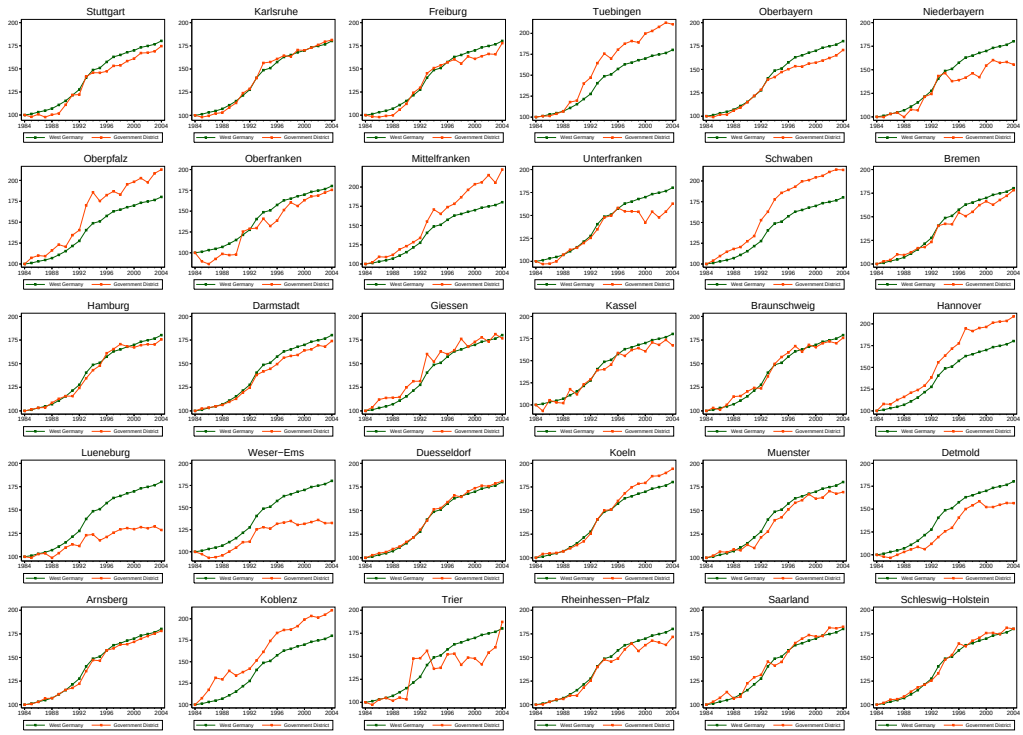

Figure 4.4: Red lines are the hedonic rent indexes for 30 West German government regions. Green line is the hedonic rent index for West Germany. All indexes are obtained from fixed effects panel regression for the period 1984 to 2004.

For the majority of the 30 Government Regions the estimated rent indexes closely resemble the aggregate trend of changes in rental levels. In particular, highly populated areas, like Hamburg and Düsseldorf, that account for a

large fraction of aggregate rent movements exhibit no substantial differences from the West German rent index. Across the regions, however, there are remarkable differences in the cumulative growth rates of rental prices. For example, rent inflation in more rural areas, such as Niederbayern, Lüneburg, and Weser-Ems, is substantially lower compared to the West German trend and some prosperous regions in the south of Germany.

Moreover, the volatility of rental growth rates differs across the regions. As noted above, however, some these differences are attributable to the low number of observations in some of the regions. Thus the estimation error is particular severe. Specifically, the three regions with the highest volatility of rental growth rates, that is Oberpfalz, Oberfranken, and Trier, are also the regions with lowest number of observed dwellings in our sample. Here, we have less than 500 individual dwellings for the complete period under observations.

4.4 Conclusion

In this Chapter, we have turned to the measurement of market-wide changes in the rental price of housing. Due to the heterogenous nature of real estate, the construction of rent indexes requires to control for quality differences of dwellings across and between any two periods of price measurement. Hedonic time dummy indexes attempt to keep the quality constant by disentangling the effect of dwelling characteristics on rent from pure temporal factors via multiple regression techniques. By utilizing panel data the hedonic repeated measures approach further allows to control for unobserved quality characteristics of the dwelling.

Our estimates of several hedonic repeated measures rent indexes for West Germany show that unobserved quality characteristics are likely to bias constant-quality real estate indexes obtained from pooled cross-sectional hedonic regressions. With the availability of panel data a more robust estimation procedures relies on a fixed effects specification of the underlying hedonic model. Furthermore, we have shown that the presence of time-varying regression coefficients on variables not directly related to time not necessarily affect the estimated hedonic time dummy index. Based on the results of our aggregate hedonic rent regressions, we have further estimated constant-quality rent indexes for 30 West German regions. The estimated regional rent indexes reveal that rent inflation vary across the country.

4.5 Appendix

4.5.1 Test for serial correlation

We conduct the following two tests for serial correlation in the error terms:

1. The Bhargava et al. (1982) modified Durbin-Watson test statistic is given by
$$d_p = \frac{\sum_{i=1}^{I}\sum_{t=2}^{T}(\widehat{u}_{it} - \widehat{u}_{it-1})^2}{\sum_{i=1} I \sum_{t=2} T\widehat{u}_{it}^2} ,$$
where $\widehat{u}_{it}$ denote the predicted residuals of the within-estimator. For the null hypotheses of serial independence against the alternative of serial correlation, the null is rejected for $d_p < d_{pl}$, the null can not be rejected for $d_p > d_{pu}$, and for $d_{pl} < d_p < d_{pu}$ the test is inclusive. Here, d_{pl} and d_{pu} denote the lower and upper bound, respectively. As exact critical values are are impractical to compute Bhargava et al. (1982) deliver tabulated values for different panel sizes and degrees of freedom. Moreover, they conclude that bounds are very tight even for moderate sample sizes. Therefore, they suggests to reject the null if $d_p < 2$ if testing against positive serial correlation or $(4 - d_p) < 2$ if testing against negative correlation. For a brief discussion of the modified Durbin Watson test see also Baltagi (2005, p. 98).

2. Baltagi and Wu (1999) suggest a locally best invariant test (LBI) for zero first-order serial correlation against positive or negative serial correlation. As the exact computation of critical values is computationally prohibitive Baltagi and Wu (1999) suggest to use a standardized test statistic. Let $d^\star$ denote the LBI test statistic, then the standardized test is given by
$$d_s = \frac{d^\star - E(d^\star)}{\sqrt{V(d^\star)}} ,$$
which can be compared against the critical values of a $N(0,1)$ distribution. Details are given in Baltagi and Wu (1999). Typically, a value of $d^\star$ far below 2 indicates rejection of the null. For a brief discussion of the LBI test see also Baltagi (2005, pp. 89).

4.5.2 Hausman specification test

For notational convenience, let the vector $\mathbf{z}_{it}$ collect all explanatory variables – including time dummies – in equation (4.3), and let the subset of time-varying variables be collected in the vector $\mathbf{w}_{it}$. The conventional Hausman

(1978) test is then asymptotically equivalent to a Wald test of the null hypothesis $\boldsymbol{\theta} = \mathbf{0}$ in the auxiliary OLS regression

$$\breve{y}_{it} = \breve{\mathbf{z}}_{it}\boldsymbol{\beta} + \ddot{\mathbf{w}}_{it}\boldsymbol{\theta} + \varepsilon_{it} \ , \tag{4.8}$$

where

$$\begin{aligned} \breve{y}_{it} &\stackrel{\text{def}}{=} y_{it} - \widehat{\lambda}\bar{y}_{it} \\ \breve{\mathbf{z}}_{it} &\stackrel{\text{def}}{=} \mathbf{z}_{it} - \widehat{\lambda}\bar{\mathbf{z}}_{it} \\ \ddot{\mathbf{w}}_{it} &\stackrel{\text{def}}{=} \mathbf{w}_{it} - \bar{\mathbf{w}}_{it} \\ \text{with} \quad \widehat{\lambda} &\stackrel{\text{def}}{=} 1 - \left\{ \widehat{\sigma}_u / \sqrt{\widehat{\sigma}_u^2 + \bar{T}\widehat{\sigma}_c^2} \right\}^{-1/2} \ . \end{aligned}$$

Here, the bars denote time-averages of the respective variables. $\widehat{\sigma}_u^2$ and $\widehat{\sigma}_c^2$ are the (estimated) variances of the idiosyncratic error term and the unobserved effect, respectively. $\bar{T}$ is the average number of time periods the individual dwellings are observed in the data set.

Under the null hypothesis the OLS regression (4.8) is asymptotically equivalent to the GLS random effects estimator, see e.g. Wooldridge (2002, pp. 286). As a result, the null hypothesis states that there are no differences between the random effects and fixed effects estimates. In this case the random effects specification is appropriate.

Notably, equation (4.8) can be readily used to test, if the coefficients on a subset of variables included in $\mathbf{w}_{it}$ differ between the random effects and fixed effects specification. Therefore, the correspondent null hypothesis of the Wald test only restricts the coefficients of the respective variables to be jointly zero.

To implement the test we proceed in two steps. We first obtain estimates of $\widehat{\sigma}_u^2$ and $\widehat{\sigma}_c^2$ from a first step random effects GLS regression of equation (4.3). Given these estimates we calculate the dependent and explanatory variables of equation (4.8) according to the definitions given above. In the second step, we perform the OLS regression and conduct the Wald test. In order to ensure valid inference in the presence of heteroscedastic and/or serial correlated errors, we use panel robust standard errors (Wooldridge 2002, pp. 286).

4.5.3 Test for time-varying parameters

The test for the presence of time-varying coefficients in the hedonic repeated measures model is based on the following unrestricted version of the equation

(4.3):

$$y_{it} = \alpha_0 + \sum_{k=1}^{K} \{\beta_{k0} x_{ki0} + \beta_{kt} x_{kit} D_{jit}\} + \mathbf{d}_{it}\boldsymbol{\gamma} + c_i + u_{it} \ . \tag{4.9}$$

Here, the D_{jit} $(j = 1, 2, \ldots, T)$ is a dummy variable that takes the value one if the dwelling is observed in period j and zero otherwise. For each year, but the base period $t = 0$, these time dummies are interacted with each of the K explanatory variables. The correspondent coefficients are denoted with β_{kt}. These coefficients capture the differences between the marginal valuation of the respective variable in the base period, β_{k0}, compared to period t. Note, that the interacted time-constant variables can also be included in the in the fixed effects specification of equation (4.9).

The null hypothesis of time-constant coefficients for the k-th characteristics in equation (4.9) is then

$$H_0 : \quad \beta_{k1} = \beta_{k2} = \ldots = \beta_{kT} = 0$$

To test this simple composite linear hypothesis, we perform standard Wald tests that use panel robust standard errors. Correspondingly, the global test of the null hypothesis of time-constant coefficients for all K variables restricts all coefficients on the interacted variables to be jointly zero.

Chapter 5

Renting versus owning and the role of labor income risk

5.1 Introduction

For most households, choosing whether to rent or buy a home is a difficult, multifaceted problem. Not only do households have to grapple with the uncertainties of future movements of housing prices and the substantial cost of changing residence. Households' tenure mode choice is further complicated by the presence of uninsurable background risks. Background risk may stem from other decisions with multi-period implications for households' wealth. These decisions, like the tenure mode decision, may be costly to withdraw from or even irreversible. Of these, professional career decisions, like choosing an industry and occupation, are among the most important. This is because human capital, the most important source of household wealth, has been shown to have sizeable industry- and occupation-specific components (Neal 1995, Cunha and Heckman 2007). Furthermore, incomplete markets do not allow households to fully insure against the income risk associated with a professional career.

In this study we empirically investigate the impact of professional career decisions on households' tenure mode choice. Several arguments have been proposed recently in the literature that imply a relationship between profession-specific income risk and a household's tenure mode (Ortalo-Magné and Rady 2002, Sinai and Souleles 2005, Davidoff 2006). First, renting might be desirable for households in professions where job mobility is important. Renting will lead to lower transaction cost in the likely event of a job change and will shield the household from the resale price risk faced by homeowners. Second, renting may be preferred by members of professions whose labor

income is positively correlated with regional housing cost. Then renting allows to diversify some of the systematic income risk. However, renting also exposes the household to rent risk and if this is large it may outweigh the diversification benefit.

We test the above hypotheses regarding the impact of these risk considerations on the tenure mode choice of German households. To identify the effect of the relative net income risk if renting, we exploit variation in rent and labor income movements across 30 West German regions and 14 professions. These professions are found by clustering industry and occupation categories. Profession specific mobility needs are predicted from a survival analysis of households' residence duration. These key explanatory variables, as well as the main analysis, are estimated from data drawn from the German Socio Economic Panel Study (GSOEP). The GSOEP is a representative panel of German households with rich information on household's housing choices and mobility histories, as well as the labor market careers of their adult members. Germany is a particular interesting terrain for studying the rent or buy decision because of it's well-developed private rental sector that allows market-based choice between owner-occupied and rental dwellings.[1]

We present evidence on the impact of profession-specific income risk on households' tenure mode choice at both the regional level and the household level. At the regional level, we find that the relative riskiness of renting has a significant influence on rental shares. A decrease of the net income variance if renting, relative to the profession-specific income variance, by 10 percent increases profession-region rental shares by about 1.0 percentage points. On average, households exploit diversification benefits of renting when these are present. Rent risk, however, makes renting less attractive. Furthermore, the share of renters of different professions in different regions is significantly smaller if households within these cells have on average a longer remaining length of residence spells.

At the household level, we find further support for the proposed impact of income risk and mobility needs on households' tenure mode choice. Using data on both recent movers and the general population, we find that

[1] In Germany, dwellings in the owner-occupied sector and in the rental sector are generally available at market prices without further conditions. Rent regulations mainly apply to the socially-rented sector. In the private rental sector initial rents are freely negotiable. Subsequent rent increases, however, have an upper limit of 30% within three years and must be in line with the rent a comparable dwelling in the same neighborhood commands. The duration of a rental lease is indefinite and landlords cannot give notice without justification. Households are thus well protected from eviction risk. A thorough discussion of the institutional and legal setting in Germany can be found in Tomann (1990) and Hubert (1998).

a household's probability to rent it's home increases by about 1.2 percentage points for a 10 percent decrease of the net income variance if renting. This result holds even after controlling for the substantial state dependence of households' current housing choices and unobserved heterogeneity. Still the length of remaining residence spells significantly decreases a household's probability to rent it's home. A one year increase in the expected residence duration reduces the probability to rent by about 1.4 percentage points.

The remainder of this Chapter is organized as follows. We sketch out the theoretical background in Section 5.2. Section 5.3 outlines our empirical approach and describes the data. Furthermore, we explain the construction of our key explanatory variables, that is the relative net income risk if renting and the expected remaining residence duration. The estimation methodology for our empirical models is discussed in Section 5.4. Section 5.5 presents the results and the final Section 5.6 concludes.

5.2 Theoretical background

The risk aspects of households' tenure mode choice have been widely acknowledged in the economic literature. It is well documented that buying a single-family home is the single most important investment in the life of many households, tilting household portfolios heavily in the direction of real estate (see e.g. Guiso et al., 2001). In a world with complete markets, the decision to become a renter or owner-occupier has no influence on the household's portfolio, because tenure mode and investment decisions are separable. If markets are not complete, however, tenure mode choice will affect the risk of the household's portfolio.[2] Moreover, the illiquidity of real estate creates substantial cost for homeowners when adjusting their housing consumption in response to economic shocks.

The presence of real estate price risk may therefore affect tenure mode choice and financial risk taking by households. With regard to tenure mode choice, the theoretical work by Henderson and Ioannides (1983) and Fu (1991, 1995) suggests that higher house price risk and/or a low degree of risk tolerance discourages households from owning their home.[3] Berkovec and Fuller-

[2]From this perspective homeownership presents an uninsurable (background) risk that may distort financial asset allocation – or even asset market participation – away from the predictions of standard portfolio theory. A comprehensive review of the literature on household portfolio choice in the presence of background risk can be found in Curcuru et al. (2006).

[3]Building on the theoretical work by Henderson and Ioannides (1983), Rosen et al. (1984) find that the share of homeowners in the U.S. is indeed significantly smaller in periods when the difference of the variance forecast between the cost of owning and the

ton (1992) explore tenure mode and financial asset choice in a general equilibrium framework. In their model homeownership is positively related to a household's potential of holding a well-diversified portfolio of financial assets – thus their level of wealth – as well as the taxation of housing returns which pools the risk of real estate investments.[4]

From a risk perspective, however, owner-occupation may also be beneficial. Whereas renting does not commit households to tilt their portfolios towards a single asset, it does expose renter households to rental price risk. Homeownership, on the other hand, provides households with a durable asset that delivers a constant stream of housing services for a known up-front price. Owner-occupation can therefore be used to hedge changes in the relative prices of housing and non-housing consumption (Sinai and Souleles 2005, Pelizzon and Weber 2007). The focus on rent and house price risk, however, ignores the riskiness of the largest component of a household's wealth: human capital.

Usually most of this human capital is acquired early in life and the professional career decisions leading to specific human capital endowments are difficult to reverse. Furthermore, the future returns to this capital are risky and cannot be fully insured against. However, a strong comovement between income streams and regional housing cost may allow members of some professions to diversify part of their systematic income risk by choice of housing tenure. Ortalo-Magné and Rady (2002) emphasize this idea in their theoretical work. They provide a dynamic model in the context of risky housing and uninsurable labor income that highlights the risk trade-offs inherent in tenure mode choice. For the sake of brevity we refrain from stating a formal model in their tradition, but rather outline a household's decision problem to motivate the empirical analysis to follow.[5]

In a discrete-time dynamic utility maximization framework a household has to decide to rent or buy it's home. The household derives utility from housing and a nondurable consumption good. Dwellings available for rent and to buy provide the same use value. The household's objective is then to

cost of renting is high.

[4]Taxation under uncertainty does not only reduce the expected return of an asset, but also – at least when losses can be fully offset – the variance of the returns. These two effects counteract and taxation under uncertainty might even lead to an increase of the demand for the taxed asset (Gordon 1985). Berkovec and Fullerton (1992) consider both effects in a simulation study for the US and find that abolishing the tax exemption of owner-occupied housing would increase the number of owner-occupiers.

[5]The focus on risk aspects abstracts from several well-established determinants of tenure mode choice. Among these are potential wealth constraints and the different tax-treatment of owner-occupied and rental housing that may distort a household's rent or buy decisions. We will control for these factors in our empirical analysis.

find the tenure mode which yields the highest expected utility of non-housing consumption. Renter household have to pay rents that may fluctuate from period to period. Renters per period net income, available for non-housing consumption, is thus the difference between their risky labor income and the rental payment. A household buying the dwelling has to pay the house price up-front. At the end of the stay the household will sell the home. If the purchase is financed with a fixed-rate mortgage, the household's net income equals it's labor income net of fixed mortgage payments during the time of stay.[6] In the moving period the household's net income further depends on the uncertain resale price of it's home.

Dwellings are supplied by risk neutral agents, who are prepared to act as landlords or to sell the dwellings. House prices then equal the discounted stream of future expected rents and homeowners lock-in their future housing cost at the expected level of future rents. This in turn implies that a household's expected consumption of non-housing goods is the same regardless of the tenure mode. A risk averse household will therefore choose the tenure mode that yields the lowest variance of non-housing consumption, that is it's labor income net of housing cost. Obviously this net income risk might be quite different for either form of accommodation. In particular, two predictions on the influence of professional career decisions on tenure mode choice emerge from this framework.[7]

First, all other things equal, a household is more likely to rent if there is a strong comovement between regional rents and profession-specific labor income. In this case, renting allows to diversify part of the systematic income risk. A high regional rent volatility, however, may outweigh this diversification benefit. Second, all other things equal, a household is less likely to rent it's home the longer the expected time in the dwelling. This is because owning isolates the household from rental price risk for the time of the stay. An alternative, yet complementary rationalization, for the proposed negative relationship between expected length of stay and the preference for renting

[6]The choice of a fixed-rate loan is crucial for a household's ability to lock-in future housing cost. In the presence of uninsurable labor income risk the availability of adjustable-rate mortgages would widen households' risk management opportunities (Campbell and Cocco 2003). In Germany, fixed interest loans are the dominant type of residential mortgages (ECB 2003).

[7]Ortalo-Magné and Rady (2002) further show that, all other things equal, a household is more likely to rent the less house prices are comoving between regions. A low price covariance exposes owner-occupiers to the risk of selling their house at a price that is low compared to prices in the region they are moving to. As this effect only occurs in the moving period it is doubtful that it plays an important role. In some specifications of our empirical models we have indeed found a negative, yet statistically insignificant, effect of this variable on the propensity to rent.

are the lower moving cost for renter households.[8] In both cases, the necessity for residential moves should increase the probability to rent.

Our paper is not the first that empirically investigates the role of these considerations on tenure mode choice. For the U.S., Sinai and Souleles (2005) find that high rent volatility and lower mobility needs make owning more attractive both at the MSA and household level. However, they do not consider income risk and the diversification potential from rent risk. To our knowledge the study by Davidoff (2006) is the only one that tests for the diversification benefit of renting.[9] Using U.S. household data he shows that the covariance between industry-specific income growth and regional house price growth decreases the size of a household's position in owner-occupied housing. His study, however, provides only mixed evidence on the impact of the income rent covariance on the rent or buy decision itself.

5.3 Empirical implementation

Does rental price risk and it's potential to diversify profession-specific income risk influence a household's rent or buy decision? Does the need to be mobile influence a household's rent or buy decision? To answer these questions our empirical analysis proceeds in two steps:

1. We first construct a measure of the profession-specific income risk under both tenure modes and a measure of households' (expected) mobility needs.

2. We then estimate the relationship between a household's probability to rent it's home and our risk and mobility measures.

While the details of Step 1 are described in Section 5.4 below, the purpose of this Section is to outline our empirical strategy and describe the construction of our key explanatory variables.

[8]Henderson and Ioannides (1989) outline a dynamic optimization problem in which a short expected length of stay may households not allow enough time to enjoy the consumption benefits of owning – for instance substituting different uses of space over the life cycle – to outweigh the differential in moving cost between renters and owners. Empirically they find that the expected length of stay is indeed shorter for renter households.

[9] Other papers study the influence of income certainty on tenure mode choice, however, focussing on transitory – not systematic – income risk. For instance, Diaz-Serrano (2005) finds that greater income uncertainty increases a household's propensity to rent. He interprets this result as evidence for restrictions in accessing the mortgage market faced by households exposed to greater income risk.

To model the relationship between income risk, mobility needs and a household's probability to rent it's home, we employ probit models of the following form:

$$P\left(\text{RENTER}|\rho,\mu,\mathbf{x}\right)=\Phi\left(\beta_0+\beta_1\rho+\beta_2\mu+\mathbf{x}\boldsymbol{\delta}\right)\ . \tag{5.1}$$

Our first key explanatory variable is ρ, which we define as the relative net income risk of owning compared to renting. Here, we measure income risk with the variance of the growth rate of profession-specific income streams net of regional housing cost under the respective tenure mode. In this sense, ρ relates the systematic risk of homeowners' income (labor income net of locked-in rent) to the systematic risk of renters' income (labor income net of rent). We thus expect a positive sign on the coefficient β_1. Our second key explanatory variable is μ, which we define as the expected (remaining) length of a household's current residence spell. The sign on the coefficient β_2 is therefore expected to be negative. Socio-economic control variables are collected in the row vector $\mathbf{x}$.

We estimate equation (5.1) using data at both the aggregate level and the household level. At the aggregate level, we consider average tenure mode decisions of households sharing a profession and a region. While an analysis of rental shares ignores lagged effects of past choices, as well as the heterogeneity among households within each profession-region cell, it is still worthwhile, because exposure to rent and labor income risk is shared within each cell. In order to control for the dynamic nature of households' housing choices and (unobserved) heterogeneity, we then turn to the rent or buy decision of individual households.

At the household level, we start by analyzing the rent or buy decision of recent movers. Restricting our analysis to recent movers has the advantage to investigate households who have made an active tenure mode decision. The estimates of a recent mover's probability to rent should therefore avoid the impact of lagged effects on current housing choices and more closely reflect equilibrium conditions then rental shares (Ihlanfeldt 1981, Boehm et al. 1991). Using a sample of recent movers, however, poses the problem of selection on unobservables. We hope to avoid this problem, by secondly estimating dynamic panel probit models of tenure mode choice within the general population.

5.3.1 Data and key variables

The data for analysis come from the German Socio Economic Panel Study (GSOEP) for the period 1984 to 2004. The GSOEP is a yearly panel of

German households and all adult members of a surveyed household. At the household level the GSOEP data contains rich longitudinal information on households' tenure mode, housing cost, mobility histories, and socio-economic characteristics, such as household size, composition and wealth. Furthermore, the GSOEP covers information on the occupational and employment histories of household members, as well as their received labor income.

We use the GSOEP, both, for our main analysis of households' rent or buy decision and to construct our two key explanatory variables. To avoid the transition process after German re-unification, we restrict our analysis to West German households. Our geographical units of investigation are the 30 West German government regions (NUTS2).[10]

Defining groupings of professions

The GSOEP reports both the industry (NACE Rev.1) and occupation (ISCO-88) of all employed household members. The administratively defined industry and occupation categories, however, do not necessarily reflect individual careers. As people are likely to change jobs during their life, possibly moving to new industries or occupations, measures of income risk based on these categories are likely to differ from the systematic income risk individuals are truly exposed to (Shiller and Schneider 1998).

Following Shiller and Schneider, we therefore use a cluster analysis to find professions whose members define relatively stable groups. To build these groups our cluster algorithm uses the transition matrix between 126 initially observed industry-occupation categories defined by 14 main NACE industries and 9 major ISCO-88 occupations. We estimate the transition probabilities from all household heads and spouses who have been in the GSOEP for at least two years during the period 1984 to 2004. The cluster algorithm groups the initial categories in such a way that individuals are unlikely to move between clusters. Further details on the cluster analysis are given in Appendix 5.7.1.

Table 5.1 presents the allocation of industries and occupations to professions, along with broad categories we have assigned to the groups. We find 14 professions that are characterized by high transition probabilities within and low transition probabilities between groups (see Table 5.7 in Appendix 5.7.1). The allocation of industries and occupations to the 14 professions largely follows intuition. For instance, professions in the health or financial

[10] A government region (*Regierungsbezirk*) is an administrative subdivision of a certain federal state (*Bundesland*). Government regions correspond to the Nomenclature of Territorial Units for Statistics level 2 (NUTS2) defined by Eurostat.

Table 5.1: Allocation of industries and occupations to 14 profession groups.

Profession group (Occupation/Sector)	
1: Management/Production, trade	8: All occupations/Health, social work
2: Management/Public, private	9: Manual/Production, service
3: Management/Public	10: Elementary/Public, private
4: All occupations/Natural resources	11: Service work/Service
5: All occupations/Energy, utilities	12: Service work/Production
6: All occupations/Hotel,restaurants	13: All occupations/Agricultural
7: All occupations/Transport, commun.	14: All occupations/Financial

	ISCO-88								
	1	2	3	4	5	6	7	8	9
NACE A	13	2	2	2	13	13	9	13	13
NACE C	4	4	4	4	12	-	4	4	4
NACE D	1	1	1	1	12	13	9	9	9
NACE E	5	5	5	5	12	-	5	5	5
NACE F	1	2	1	1	12	13	9	9	9
NACE G	1	1	1	1	12	13	9	9	10
NACE H	6	6	6	6	6	6	9	9	6
NACE I	7	7	7	7	7	13	7	7	7
NACE J	14	14	14	14	11	14	14	14	10
NACE K	1	3	1	1	11	13	9	10	10
NACE L	2	2	2	2	11	13	9	10	10
NACE M	3	3	3	3	11	13	9	10	10
NACE N	8	3	8	8	8	8	9	8	10
NACE O	3	3	3	3	11	13	9	9	10

Notes: Table presents 14 profession clusters. Occupation categories are the 9 main occupations according to ISCO-88 classification. ISCO-88 comprises the following occupations: *ISCO 1* Legislators, senior officials and managers, *ISCO 2* Professionals, *ISCO 3* Technicians and associate professionals, *ISCO 4* Clerks, *ISCO 5* Service workers and shop and market sales workers, *ISCO 6* Skilled agricultural and fishery worker, *ISCO 7* Craft and related trades workers, *ISCO 8* Plant and machine operators and assemblers, *ISCO 9* Elementary occupations. Industry categories are the 14 main sectors according to NACE, Rev. 1.1 classification. NACE comprises the following sectors: *NACE A* Agriculture, hunting and forestry, *NACE B* Fishing, *NACE C* Mining and quarrying, *NACE D* Manufacturing, *NACE E* Electricity, gas and water supply, *NACE F* Construction, *NACE G* Wholesale and retail trade, *NACE H* Hotels and restaurants, *NACE I* Transport, storage and communication, *NACE J* Financial intermediation, *NACE K* Real estate, renting and business activities, *NACE L* Public administration and defence, *NACE M* Education, *NACE N* Health and social work, *NACE O* Other community, social and personal service activities, *NACE P* Activities of households, *NACE Q* Extra-territorial organizations and bodies.

sector comprise almost all occupations (Group 8 and Group 14). Craftsman and the like, on the other hand, form their own professional group regardless of the industry (Group 9).

Relative riskiness of renting

To measure the relative riskiness of renting we proceed as follows. We first estimate a annual series of real percentage changes in the net income level if renting, that is the level of labor income net of rents, for each of the 14 professions. These series are estimated separately for each of the 30 government regions and cover the period 1984 to 2004. We then measure the riskiness of renting with the variance of the growth rate of income net of average rents relative to the variance of the net income growth rate if renting. For our analysis of rental shares the relative riskiness of renting is attributed to all households in a given profession-region cell. At the household level we further account for the profession specific income movements of spouses if necessary.

Formally, the real growth rate of net income if renting and the real growth rate of income net of average rents are calculated as

$$\Delta Y_{prt}^{(Rent)} = \frac{(Y_{prt} - D_{rt}) - (Y_{prt-1} - D_{rt-1})}{(Y_{prt-1} - D_{rt-1})} \tag{5.2}$$

and

$$\Delta Y_{prt}^{(\overline{Rent})} = \frac{(Y_{prt} - \overline{D}_r) - (Y_{prt-1} - \overline{D}_r)}{(Y_{prt-1} - \overline{D}_r)} \ . \tag{5.3}$$

Here, Y_{prt} is the real labor income level for profession p in region r and year t. The real rent level in region r and year t is denoted with D_{rt}. $\overline{D}_r = 21^{-1} \sum_{t=1984}^{2004} D_{rt}$ is the corresponding within-region time average of rents. We estimate the income level for each profession-region cell by deflating the median labor income level in each region for the year 1995 with a constant-quality income index for the respective profession.[11] The rent level in each region is estimated by deflating the median rent level in the year 1995 with a constant-quality rent index for the respective region. To obtain real values we deflate all series with the German CPI excluding housing services.

Both the profession-specific income indexes and the regional rent indexes are estimated from hedonic regressions. We specifically run fixed-effects panel regressions using GSOEP data on labor income and apartment rents for the period 1984 to 2004. The constant-quality indexes are computed from time-dummy coefficients included in the regressions. The final labor income

[11]The income movement of a certain professions may also depend on region-specific factors. Thus, one would ideally like to compute constant-quality income indexes for each profession-region cell. Due to the lack of sufficient observations on the profession-region level in the GSOEP, we are however not able to estimate precise enough income indexes for each profession-region cell.

indexes are computed as weighted averages of the income received if employed and the benefit received if unemployed. Unemployment replacement rates are provided by the OECD.[12] The weights are based on the actual unemployment rates of panel members within a given profession and year. Further details on the estimation of the income indexes can be found in Appendix 5.7.2. For information on the rent indexes, we refer to Chapter 4.

Given these income series we measure the relative riskiness of renting for each of the 420 profession-region cells with the ratio of the variance of income growth net of average rents to the variance of income growth net of rents:

$$\begin{aligned} \rho_{pr} &= \frac{V\left(\Delta Y_{prt}^{(\overline{Rent})}\right)}{V\left(\Delta Y_{prt}^{(Rent)}\right)} \\ &= \frac{\sum_{t=1985}^{2004}\left(\Delta Y_{prt}^{(\overline{Rent})} - \Delta \overline{Y}_{pr}^{(\overline{Rent})}\right)^2}{\sum_{t=1985}^{2004}\left(\Delta Y_{prt}^{(Rent)} - \Delta \overline{Y}_{pr}^{(Rent)}\right)^2} . \end{aligned} \tag{5.4}$$

Clearly the denominator in equation (5.4) increases with the variance of regional rents and decreases with the covariance of profession-specific labor income growth and regional rent growth. The nominator, on the other hand, is only affected by the profession-specific income volatility. If $\rho_{pr} = 1$, the net income risk if renting risk is exactly the same as the riskiness of income net of constant rental payments. The co-movement between labor income growth rates and rent growth rates will allow household to exploit diversification benefits if $\rho_{pr} > 1$. If $\rho_{pr} < 1$, negative correlation between profession-specific income growth and regional rent growth and/or the regional rent volatility itself does not allow to diversify income risk by renting.

At the household level we further adjust our measure of the relative riskiness of renting for the profession-specific income movements of spouses who are members of the labor force. This is necessary because households with a secondary source of labor income may benefit from intra-household risk sharing. We therefore replace the real income levels Y_{prt} in equations (5.2) and (5.3) with

$$Y_{ht} = \begin{cases} Y_{p(H)rt} & \text{if} \quad \text{single-earner household} \\ \frac{1}{2}\left(Y_{p(H)rt} + Y_{p(S)rt}\right) & \text{if} \quad \text{dual-earner household} \end{cases}$$

where the subscripts $p(H)$ and $p(S)$ denote the profession of the household head and the spouse, respectively. Thus, the resulting series of net income

[12]The OECD summary measure of replacement rates is defined as the average of the gross unemployment benefit replacement rates for two earnings levels, three family situations and three durations of unemployment. For further details, see Martin (1996).

growth rates will depend not only on the household head's profession but possibly the spouse's profession as well. The household specific measure of the relative riskiness of renting is calculated along the lines of equation (5.4).

Expected remaining residence duration

To measure households' degree of mobility we estimate a parametric survival model of households' residence spells. The model is estimated using information on households' mobility histories in the GSOEP. From the fitted model we then predict the expected remaining residence duration of each household, that is the expected length of a residence spell after the household has spent time τ in it's current residence. The expected remaining residence duration is further allowed to depend on the profession of the household head and the composition of the household.

Let $T \geq 0$ be a continuous random variable which represents the duration of household tenure, that is the elapsed time since a household has last moved. T is characterized by a (parametric) distribution function $F(\tau) = P(T \leq \tau)$. The expected remaining duration (also known as the mean residual time) is formally defined by $\mu(\tau) = E[T - \tau | T > \tau]$ which can be given as

$$\mu(\tau) = \frac{1}{S(\tau)} \int_{\tau}^{\infty} (u - \tau) f(u) du \,. \tag{5.5}$$

Here, $S(\tau) = 1 - F(\tau)$ denotes the survival function and $f(\tau)$ is the density. It is obvious that the mean residual time at the beginning of a residence spell, that is $\tau = 0$, is the expected value of T. Closed-form solutions for the integral on the right hand side of equation (5.5) exist for a number of well-known life time distributions (see e.g. Lai and Xie, 2006).

We specifically assume that residence spells have a lognormal distribution given possibly time-varying household characteristics $\mathbf{x}(\tau)$.[13] This implies that $\ln(\tau)$ has a conditional normal distribution $N(\mathbf{x}(\tau)\boldsymbol{\beta}, \sigma^2)$. Under the lognormal assumption the mean residual time function is given by

$$\mu(\tau) = \begin{cases} \exp\{\mathbf{x}(\tau)\boldsymbol{\beta} + 0.5\sigma^2\} & \text{if } \tau = 0 \\ \frac{1-\Phi\left(\frac{\ln(\tau)-\mathbf{x}(\tau)\boldsymbol{\beta}-\sigma^2}{\sigma}\right)}{1-\Phi\left(\frac{\ln(t\tau)-\mathbf{x}(\tau)\boldsymbol{\beta}}{\sigma}\right)} \exp\{\mathbf{x}(\tau)\boldsymbol{\beta} + 0.5\sigma^2\} - \tau & \text{if } \tau > 0 \end{cases} \tag{5.6}$$

where $\Phi(\bullet)$ denotes the standard normal c.d.f.. Note, that $\mu(\tau)$ initially decreases and then monotonically increases with the elapsed residence duration.

[13] We have discriminated between a number of parametric distributions, including the exponential, lognormal, log-logistic, and weibull distribution. Notably the lognormal distributions allows for general duration dependence. As the residence spell increases, the probability that a household instantaneously moves (hazard rate) first rises and then falls.

Given estimates of the unknown parameters $\boldsymbol{\beta}$ and σ, we can easily impute the expected remaining residence duration for each household by plugging in the elapsed duration τ and household characteristics at time τ in equation (5.6).

In order to obtain estimates of $\boldsymbol{\beta}$ and σ, we run tobit-type regressions using a flow sample of households' residence spells extracted from the GSOEP. In particular, we regress the log of households' observed residence duration on a vector of dummy variables representing household head's profession and other household characteristics. Among these are the age of the household head at the beginning of the spell, household size, marital status, and gender. Notably the profession of household heads significantly influences households' expected residence duration. Further details on the survival analysis are given in Appendix 5.7.3.

5.3.2 Samples and descriptives

Descriptives of key variables

In order to illustrate households' exposure to background risk, Table 5.2 presents summary statistics of our key variables across the 14 professions and 30 government regions. Both rent risk and income risk are quite substantial. Between 1984 and 2004 the average (across and within government regions) standard deviation of real rent growth was about 3.9 percent per year. For the same time period the average (across and within professions) standard deviation of real income growth rates was about 3.4 percent. In 1995, 56 percent of West German households rented their home. On average they spent approximately 15 percent of their gross labor income for rental payments. There is, however, substantial variation in rental shares, rent levels, and income levels across the regions.

In 1995, the median of our measure for the relative riskiness of renting was 0.98. As evidenced by the means of the relative riskiness of renting for the bottom and top halves of it's distribution, the diversification potentials from renting vary substantially across professions and regions. Members of profession-region cells with a relative riskiness of renting below it's median value have on average a 9.53 percent higher net income variance if renting. Households living in profession-region cells with a relative riskiness of renting above it's median value, on the other hand, reduces their net income variance on average by about 4.49 percent if renting their home.

Households' residential mobility is rather small. The average (across professions) expected remaining residence duration (mean residual time) was

Table 5.2: Summary statistics of key variables at Profession and NUTS2 level. Mean of variables.

	Profession level		NUTS2 level	
	1984–2004	1995	1984–2004	1995
Real income growth	0.012			
	[0.036]			
S.d. of real income growth	0.034			
	[0.013]			
Median of ρ_{pr}		0.988		
		[0.034]		
S.d. of ρ_{pr}		0.086		
		[0.037]		
Mean of ρ_{pr} if below median		0.913		
		[0.032]		
Mean of ρ_{pr} if above median		1.047		
		[0.024]		
Real rent growth			0.014	
			[0.041]	
S.d. of real rent growth			0.039	
			[0.017]	
Mean residual time		13.268		
		[1.862]		
Real median income				2223.42
				[245.80]
Real median rent				331.70
				[39.212]
Proportion of renters				0.564
				[0.125]
Number of observations	280	14	600	30

Notes: Standard deviations of the variables are in square brackets. Rent growth and income growth, and the standard deviations of rent and income growth are computed from constant-quality rent and income indexes. Relative riskiness of renting, ρ_{pr}, is calculated according to equation (5.4). Mean residual time is calculated according to equation (5.6). Median rent level, median income level, and the proportion of renters are estimated from GSOEP wave 1995. All euro values are in real (2000) euros, deflated by the German CPI excluding housing services.

about 13.3 years in 1995. On the profession-region cell level, the average standard deviation of this variable is only 1.86 years. It must be noted, however, that the expected remaining residence duration not only depends on a household's profession, but also it's composition. Thus averaging across households of the same profession considerably reduces the variation of this variable.

Samples and socio-economic controls

For our analysis of households' tenure mode choice, we draw three different samples from the GSOEP. In all cases, we restrain the analysis to households residing in one of the 30 West German NUTS2 regions. We further focus on households whose head is between 18 and 65 years of age. Households who live in residential homes and the like are excluded. As the GSOEP only reports the industry and occupation of household members who are employed at the date of the survey, we carry forward the last observed profession if necessary. Thus our measure of the relative riskiness of renting is assigned to unemployed household members according to their last job.

The first sample is a pooled cross-section of 3935 profession-region cells for the period 1984 to 2004. The second sample is a pooled cross-section of recently moved households. We define recent movers as those households who have moved into their current residence within the previous year. Since the GSOEP does not provide information on a change of residence in 1984, we restrict this sample to the period 1985 to 2004. We observe 5820 recent movers comprising, due to multiple moves, 3364 individual households. The third sample is an unbalanced panel of households regardless of their residence duration. Here, we have 36625 observations on 3476 individual household.

Besides our two key explanatory variables, the relative riskiness of renting and the expected remaining residence duration, we consider a number of socio-economic control variables. Among these are demographic characteristics, like the age of the household head, household size, number of children, and years of education of the household head. To capture economic factors, such as credit constraints, and tax effects, we include an indicator for households who do not report financial asset holdings, the ratio of average regional house prices to yearly household income, and yearly (real) labor income. Information on regional house prices are provided by the Ring Deutscher Makler (RDM).[14]

Table 5.3 presents summary statistics of all variables used in the empirical analysis by the three samples. Between 1984 and 2004 the average rental share across profession-region cells was about 54 percent. There is, however,

[14]The RDM is an association of real estate agents that publishes annual surveys on house price developments in German cities. This information is not based on systematic statistics but inquiry among members. Nevertheless it should provide a reasonable good picture of regional price levels. To obtain house price levels for the NUTS2 regions, we aggregate the city level data by weighting each observation with the city's population. Population figures are taken from the *Gemeindeverzeichnis* published by the Federal Statistical Office.

Table 5.3: Summary statistics by household sample. Mean of variables.

	Profession-region cells 1984–2004	Recent movers 1985–2004	Unbalanced household panel 1984–2004
Renter	0.536	0.782	0.531
	[0.174]		
Relative riskiness	0.984	0.978	0.976
	[0.104]	[0.101]	[0.102]
Mean residual time	13.791	9.787	16.589
	[2.609]	[4.893]	[4.602]
Age	41.474	34.492	47.867
	[4.946]	[10.415]	[9.943]
Education	11.892	11.676	11.285
	[1.935]	[2.766]	[2.687]
Household Size	2.816	2.367	3.035
	[0.648]	[1.259]	[1.409]
Yearly labor income	29.120	22.811	26.015
	[9.541]	[17.265]	[19.951]
House price/Hh. inc.	9.966	14.375	11.508
	[4.218]	[10.773]	[9.055]
Female	0.285	0.384	0.161
	[0.264]		
Kids	0.500	0.339	0.569
	[0.234]		
Married	0.654	0.451	0.771
	[0.227]		
No assets	0.079	0.143	0.097
	[0.129]		
Foreigner	0.149	0.132	0.157
	[0.234]		
Number of obs.	3925	5820	36625

Notes: Standard deviations of the variables are in square brackets. Relative riskiness of renting is calculated according to equation (5.4). In column 2 and column 2 this variable is allowed to depend on both the household heads' and spouses' profession. Mean residual time is calculated according to equation (5.6). Yearly labor income is income of household head in (2000) Euros, deflated by the German CPI excluding housing services. Price-income ratio is the ratio of the mean price of a single-family dwelling of average quality and yearly household income. Data for regional house prices are provided by the Ring Deutscher Makler (RDM).

substantial variation in rental shares which is largely attributable to cross-sectional differences across professions and regions. At the household level the average probability of renting within the general population exhibits a similar magnitude of 53 percent. As expected the average probability to rent is considerably larger in our sample of recent movers. In fact 78 percent of

recently moved households rent their new home.

The average of our measure of the relative riskiness if renting ranges from 0.976 to 0.984. In all three samples the dispersion of this variable is of similar magnitude and in fact quite substantial. The standard deviation of this variable is roughly 0.100 in all three samples. This magnitude implies that the net income variance if renting (holding the profession-specific income variance constant) decreases by approximately 10 percent for a one standard deviation increase of the relative riskiness of renting from it's mean value.

The average of households' expected remaining residence duration (mean residual time), on the other hand, differs considerably by sample. It is particulary striking that recent movers are more mobile than households in our samples of the general population. While the average mean residual time is only 9 years for recent movers, it goes up to approximately 16 years in the unbalanced household panel. Across profession-region cells the mean of this variable is about 14 years.

The socio-economic characteristics further suggest that households in our sample of recent movers are in the early stage of their life-cycle. Compared to the average household across profession-region cells and the general population, recent movers earn less income and have accumulated less assets. They are on average also younger, of smaller size, and comprise less families (with less children). Taken together, the summary statistics indicate that our sample of recent movers is not representative of the general population in West Germany.

5.4 Econometric models

5.4.1 Rental share regressions

Let $\overline{y}_{prt}$ denote the observed proportion of renter households within profession-region cell (pr) and year t. Here, p indexes the profession of the household head and r the region the household lives in. We specify the corresponding population quantity as a probit model of the following form:

$$\overline{y}_{prt} = \Phi\left(\beta_0 + \beta_1 \rho_{pr} + \beta_2 \overline{\mu}(\tau)_{prt} + \overline{\mathbf{x}}_{prt}\boldsymbol{\delta}\right) + \varepsilon_{prt} \ , \tag{5.7}$$

where $\Phi(\bullet)$ denotes the standard normal c.d.f., and the idiosyncratic error ε_{prt} has mean zero. The profession-region specific relative net income risk if renting is captured by our time-constant measure ρ_{pr}. The mean residual time, $\overline{\mu}(\tau)_{prt}$, is computed as the arithmetic mean of the expected remaining residence duration of all households belonging to the respective cell in year

t. $\overline{\mathbf{x}}_{prt}$ is a vector collecting cell means of socio-economic controls. We futher include a full set of profession dummies and time dummies in $\overline{\mathbf{x}}_{prt}$.

Instead of directly estimating equation (5.7) by nonlinear least squares, we use a linear approximation. A Taylor series expansion to the inverse of the standard normal c.d.f. around the observed rental share yields the linear regression model:

$$\Phi^{-1}\left(\overline{y}_{prt}\right) = \beta_0 + \beta_1 \rho_{pr} + \beta_2 \overline{\mu}(\tau)_{prt} + \overline{\mathbf{x}}_{prt}\boldsymbol{\delta} + u_{prt} \ , \tag{5.8}$$

where the error term u_{prt} has mean zero and heteroscedastic variance.[15] Thus, estimates of the coefficients can be easily obtained by standard (weighted) least squares methods. In order to assess the magnitude of the effect of the explanatory variable on rental shares, we compute partial effects of the variables under scrutiny. For instance, the estimated partial effect of ρ_{pr} on rental shares is given by $\phi(\widehat{\beta}_0 + \widehat{\beta}_1\rho + \widehat{\beta}_2\overline{\mu}(\tau) + \overline{\mathbf{x}}\widehat{\boldsymbol{\delta}})\widehat{\beta}_1$. Here $\phi(\bullet)$ denotes the standard normal p.d.f. and the explanatory variables are set to fixed values of interest.

There are three econometric issues associated with the regression given by equation (5.8). First, the heteroscedastic error term suggests that weighted least squares regressions produce efficient parameter estimates. Households within the same profession-region cell, however, may share unobserved characteristics, which in turn can lead to substantial reduction of heteroscedasticity (Dickens 1990). Furthermore, pooling cross-sections of profession-region cells over time is likely to introduce serial correlated error terms. To avoid these potential misspecifications of the weighted least squares estimator, we run ordinary least squares regressions. OLS delivers consistent (yet inefficient) parameter estimates.

Second, the regression given by equation (5.8) involves generated regressors, namely the relative riskiness of renting ρ_{pr} and the mean residual time $\overline{\mu}(\tau)_{prt}$. We thus need to adjust standard errors accordingly. As we are primarily interested in the partial effects of the explanatory variables on rental shares, we use bootstrap standard errors (Efron and Tibshirani 1993). We

[15] Let y_i denote the observed proportion of renters and n_i the number of observed households in profession-region cell i. The corresponding population quantity is $\pi_i = \Phi(x_i\beta)$. We then have $y_i = \pi_i + \varepsilon_i$, and the error ε_i is binomial distributed with mean zero and variance $V(\varepsilon_i) = \pi_i(1-\pi_i)/n_i$. A Taylor series approximation to $\Phi^{-1}(\bullet)$ around the point $\varepsilon_i = 0$, that is around $\pi_i = y_i$, yields

$$\Phi^{-1}(y_i) = \mathbf{x}_i\boldsymbol{\beta} + \varepsilon_i/\phi(\pi_i) \ .$$

The error $u_i \stackrel{\text{def}}{=} \varepsilon_i/\phi(\pi_i)$ has $E[u_i|\mathbf{x}_i] = 0$ and variance $V(u_i|\mathbf{x}_i) = \pi_i(1-\pi_i)/n_i\phi(\pi_i)^2$. A detailed discussion of this model class can be found, e.g. in Amemiya (1981).

consider 200 replications from the set of profession-regions cells, and based on the resulting bootstrap sample estimate partial effects. The standard deviations across the replications serve as the bootstrap standard errors.

Third, the share of renters of different professions in different regions largely reflects the cumulative attainment of either tenure mode among cell members. Given the substantial transaction cost associated with adjustments to housing tenure, a static analysis likely attributes historical choices to today's conditions. To capture the dynamic nature of households' tenure mode choice, we next turn to the rent or buy decision of individual households. This further allows us to explicitly control for (unobserved) heterogeneity across households within the same profession-region cell.

5.4.2 Probit models

Probit model for recent movers

At the household level, we start by estimating the relationship between a recent mover's probability to rent it's home and our two key explanatory variables. We specifically estimate pooled probit models of the following form:

$$P\left(y_{ht} = 1 | \rho_{ht}, \mu(\tau)_{ht}, \mathbf{x}_{ht}\right) = \Phi\left(\beta_0 + \beta_1 \rho_{ht} + \beta_2 \mu(\tau)_{ht} + \boldsymbol{\delta}\mathbf{x}_{ht}\right) \ , \qquad (5.9)$$

where h indexes the household and t the year of it's most recent move. y_{ht} is an indicator variable that takes the value one if the households rents it's home and zero otherwise. The net income risk if renting is captured by our measure for the relative riskiness of renting ρ_{ht}, that may depend on both the household head's and the spouse's profession. The households' expected (remaining) residence duration is denoted $\mu(\tau)_{ht}$, where τ is almost always equal to zero. The vector $\mathbf{x}_{ht}$ collects socio-economic controls, including a full set of profession dummies and time dummies.

Parameter estimates of the probit model in equation (5.9) are easily obtained by the method of maximum likelihood. In order to assess the magnitude of the influence of our key explanatory variables on a household's probability to rent it's home, we compute partial effects. The estimated partial effect of $\mu(\tau)_{ht}$ on the probability to rent, for instance, is given by $\phi(\widehat{\beta}_0 + \widehat{\beta}_1\rho + \widehat{\beta}_2\overline{\mu}(\tau) + \mathbf{x}\widehat{\boldsymbol{\delta}})\widehat{\beta}_2$. Here $\phi(\bullet)$ denotes the standard normal p.d.f. and the explanatory variables are set to fixed values of interest.

There are three econometric issues associated with the probit model given by equation (5.9). First, the usual standard errors are invalid because: i.

unobserved shocks may be serial correlated if the same household moves more than once during the period under observation, and ii. the use of generated regressors. We therefore use bootstrap standard errors (Efron and Tibshirani 1993). Based on 200 bootstrap samples from the set of households, we estimate partial effects. The standard deviations across the replications serve as the bootstrap standard errors.

Second, using a sample of recent movers poses the problem of selection on unobservables. Our estimates can be inconsistent, if households' moving decisions are systematically related to unobserved factors that also affect tenure mode choice (van de Ven and van Praag 1981). For instance, households with inherent preferences to rent are presumably more likely to move despite a large value of $\mu(\tau)_{ht}$. This is because the substantially lower moving cost if renting allow them to adjust their housing consumption more easily in response to economic shocks. Hence, the estimated coefficient β_2 may be biased towards zero, and away from the prediction of a negative effect. In order to avoid these problems of sample selection, we next analyze the tenure mode choice within the general population.[16]

This will thirdly allows us to explicitly control for unobserved heterogeneity. While the probit analysis of recent movers allows us to control for some of the heterogeneity across households who share a profession and a region, there may be unobserved factors, such as households' risk tolerance, that influence tenure mode choice. If these factors are independent of the observed explanatory variables, the estimated partial effects can be interpreted as partial effects averaged over the distribution of the unobserved factor.[17] However, we can not consistently estimate (average) partial effects, if the unobserved factor stochastically depends on observed explanatory variables.

[16]Van de Ven and van Praag (1981) propose a Heckman-type (1979) correction for sample selection. While their estimation procedure is formally identified if both the selection equation (modelling the decision to move) and the outcome equation (modelling the decision to rent or buy) include the same set of explanatory variables, the sole source of identification is the nonlinearity of the probit model. A more convenient analysis hinges on appropriate exclusion restrictions. Given the joint nature of moving and tenure mode decisions these are hard to come by in our case.

[17]To see this, let c be a household-specific unobserved effect. The model of interest is $P(y = 1|\mathbf{x}, c) = \Phi(\mathbf{x}\boldsymbol{\beta} + c)$. If the unobserved effect is assumed to be independent of the explanatory variables and normal distributed $c \sim N(0, \sigma_c^2)$, the average partial effect of x_j is given by $\beta_{jc}\phi(\mathbf{x}\boldsymbol{\beta}_c)$. Here β_{jc} denotes the population averaged parameter $\beta_{jc} \stackrel{\text{def}}{=} \beta/(1 + \sigma_c^2)^{1/2}$, which can be consistently estimated by probit of y on $\mathbf{x}$ (see e.g. Wooldridge, 2002).

Dynamic Probit model for general population

When estimating the relationship between our key explanatory variables and the probability to rent within the general population, we need to take the (usually) sluggish adjustment of housing choices into account. Our approach to modelling the dynamics of households' tenure mode choice is a dynamic random effects probit model of the following form:

$$\begin{aligned} P\left(y_{ht}=1|y_{ht-1},\ldots,y_{h0},\boldsymbol{\rho}_h,\boldsymbol{\mu}(\tau)_h,\mathbf{x}_h,c_h\right) &= \Phi\big(\beta_0+\beta_1\rho_{ht}+\beta_2\mu(\tau)_{ht} \\ &\quad +\gamma y_{ht-1}+\mathbf{x}_{ht}\boldsymbol{\delta}+c_h\big) \quad (5.10) \end{aligned}$$

where h indexes the household and t the year. y_{ht} is an indicator variable that takes the value one if the households rents it's home and zero otherwise. The potential state dependence of households' current tenure mode decisions are captured by the tenure mode status in the previous period y_{ht-1}. The household specific term c_h stands for all unobserved determinants of tenure mode choice that are time-invariant for a given household. Among these might be factors such as households' risk tolerance or general preferences for either tenure mode. The vectors $\boldsymbol{\rho}_h$, $\boldsymbol{\mu}(\tau)_h$, and $\mathbf{x}_h$ collect the entire path of the explanatory variables, which are defined as above. These variables are assumed to be strictly exogenous once c_h is controlled for.

The presence of unobserved heterogeneity in equation (5.10) leads to two methodological problems (Heckman 1981, Wooldridge 2005). First, household specific factors, such as the ones mentioned above, are likely to be correlated with observed characteristics. The degree of risk aversion, for instance, may vary across demographic characteristics.[18] Second, the household specific factor causes serial dependence in the underlying process of households' tenure mode states. Therefore, the first observed tenure mode status is stochastically dependent on c_h. Presumably this is also true when we observe a household at the beginning of it's life. This is because the initial rent or buy decision is most likely related to unobserved (risk) preferences as well.

Both of these issues can be addressed by parameterizing the household specific effect conditional on the initial observation and the entire path of all non-redundant exogenous variables (Mundlak 1978, Chamberlain 1980, Wooldridge 2005). Modelling the distribution of c_h leads to a conditional maximum likelihood approach based on the joint distribution of tenure mode

[18]For instance, Barsky et al. (1997) find that risk preferences are related to demographics such as age, sex, and religion. A recent study by Sahm (2007) shows that there are few sources of systematic change in risk preference, like age, but substantial and large persistent differences in preferences across individuals that can be explained by demographics.

states conditional on the initial observation and the exogenous variables.[19] We implement this approach by parameterizing the distribution of the household specific effect as:

$$c_h = \alpha_0 + \alpha_1 y_{h0} + \alpha_2 \overline{\rho}_h + \alpha_3 \overline{\mu}(\tau)_h + \overline{\mathbf{x}}_h \boldsymbol{\alpha}_4 + a_h \ , \tag{5.11}$$

where y_{h0} is the first observed tenure mode status. The bars denote time averages of the observations on the exogenous variables, for instance, $\overline{\rho}_h = T^{-1} \sum_{t=1}^{T} \rho_{ht}$ is the average of the relative riskiness of renting for each household over the sample period. a_h is assumed to be independent of the exogenous variables and the initial tenure mode state, and distributed normal $a_h | (y_{h0}, \boldsymbol{\rho}_h, \boldsymbol{\mu}(\tau)_h, \mathbf{x}_h) \sim N(0, \sigma_a^2)$.

Under the assumptions made the probability to rent, given $(y_{ht-1}, \ldots, y_{h0}, \boldsymbol{\rho}_h, \boldsymbol{\mu}(\tau)_h, \mathbf{x}_h, a_i)$, follows a probit model with outcome probability:

$$\Phi\big(\beta_0 + \beta_1 \rho_{ht} + \beta_2 \mu(\tau)_{ht} + \gamma y_{ht-1} + \mathbf{x}_{ht} \boldsymbol{\delta} + \alpha_1 y_{h0} + \alpha_2 \overline{\rho}_h + \alpha_3 \overline{\mu}(\tau)_h + \overline{\mathbf{x}}_h \boldsymbol{\alpha}_4 + a_h\big) \ ,$$

which joint density, integrated against the Normal$(0, \sigma_a^2)$, has exactly the same structure as the conditional likelihood of the random effects probit model. Parameter estimates are therefore easily obtained by standard conditional maximum-likelihood methods (see e.g. Wooldridge, 2002). However, it should be noted that we can only include the averages of time-varying variables in equation (5.11). This is because correlation of time-constant variables with c_h and their impact on the probability to rent can not be discriminated.

In order to assess the effect of our key explanatory variables on the probability to rent, we compute average partial effects. Average partial effects evaluate the impact of a change in an explanatory variable on the outcome probability averaged over the distribution of the unobserved effect. Wooldridge (2005) shows that the expected outcome probability with respect to the distribution of c_h can be consistently estimated by:

$$N^{-1} \sum_{h=1}^{N} \Phi\big(\widehat{\beta}_{a0} + \widehat{\beta}_{a1} \rho + \widehat{\beta}_{a2} \mu(\tau) + \mathbf{x} \widehat{\boldsymbol{\delta}}_a + \widehat{\gamma}_a y_{t-1} + \widehat{\alpha}_{a1} y_{h0} + \widehat{\alpha}_{a2} \overline{\rho}_h + \widehat{\alpha}_{a3} \overline{\mu}(\tau)_h + \widehat{\boldsymbol{\alpha}}_{a4}^{\top} \overline{\mathbf{x}}_h\big) \ , \tag{5.12}$$

[19] The usual way to account for the initial condition's problem in dynamic nonlinear panel models is to model the distribution of the initial observation conditional on the unobserved effect and the exogenous variables, see e.g. Heckman (1981). The approach followed here serves the same purpose, but leads to a much simpler estimator of the parameters and average partial effects. A detailed discussion can be found Wooldridge (2005).

where the subscript a denotes the population averaged parameters, that is the original parameter estimate multiplied by $(1+\sigma_a^2)^{-1/2}$. N is the number of all observations in all time periods. The explanatory variables ρ, $\mu(\tau)$, $\mathbf{x}$, and y_{t-1} are set to fixed values of interest. We then obtain average partial effects by computing changes or derivatives of expression (5.12) with respect to the variable under scrutiny.

Standard errors for the average partial effects are estimated from a panel (or block) bootstrap, where we resample the individual household panels as a whole (Efron and Tibshirani 1993). Furthermore, we resample the same number of households from each observed panel size. This procedure preserves the sample size, as well as, the pattern of unbalancedness in our data. We consider 200 replications from the set of household panels and based on the resulting bootstrap sample estimate average partial effects. The standard deviations across the replications serve as our bootstrap standard errors.

There are two econometric issues associated with the dynamic correlated random effects probit model given by equations (5.10) and (5.11). First, identification of the impact of variables with limited variation within households on the probability to rent may be hard to establish. In particular, the relative riskiness of renting is almost always time constant inducing severe multicollinearity between ρ_{ht} and $\overline{\rho}_h$. Hence, the average of this variable may turn out to be significant, while the direct effect is insignificant. We therefore estimate two specifications of the correlated random effects model: i. a model that includes $\overline{\rho}_h$, and ii. a model without $\overline{\rho}_h$. In addition we report pooled probit estimates of equation (5.10) that ignore any correlation between c_h and the explanatory variables. Further details on the specification of the unobserved effect are presented in the next section.

Second, the maximum likelihood estimator for the dynamic correlated random effects model hinges on the strict exogeneity assumption of the explanatory variables. This assumption implies that future values of any explanatory variables can not be related to households' current tenure mode. However, in our case, misspecification may arise from feedback effects of home-ownership to a household's expected remaining residence duration. We tested for exogeneity of this variable, by including future values of $\mu(\tau)_{ht}$ into the model. If the current mean residual time is strictly exogenous, we should find the future values to be insignificant (see e.g. Wooldridge, 2002). We indeed found that the coefficient on the lead of the mean residual time is not distinguishable from zero. Thus, providing justification for the strict exogeneity assumption.

5.5 Empirical results

5.5.1 Aggregate level

Table 5.4 reports estimated partial effects obtained from ordinary least squares regressions of equation (5.8). The partial effects are evaluated at sample averages of mean household characteristics (see column 1 of Table 5.3). Column 1 of Table 5.4 summarizes the estimation results from a regression that does not control for differences in the composition of households across profession-region cells. Column 2 adds the socio-economic control variables. Both specifications include a full set of time dummies and profession dummies.

As expected the impact of the profession-region specific relative riskiness of renting, ρ_{pr}, on rental shares is positive. The share of renters of professions living in regions with a lower net income risk if renting are larger compared to regions where renting does not allow to diversify some of the profession-specific income risk. This effect is statistically significant in both specifications. To gauge the magnitude of the income risk effect, we multiply the estimated partial effects by a one standard deviation of ρ_{pr}. Such an increase in the relative riskiness of renting implies that the average household's net income variance if renting (holding the profession-specific income variance constant) decreases by approximately 10 percent. In column 1 this reduction in net income risk yields an increase of rental shares by 1.4 percentage points. The magnitude of the effect, however, decreases considerably after including the socio-economic controls. The same increase of ρ_{pr} is accompanied by an increase in rental shares of 1.0 percentage points in column 2.

Turning to the impact of mobility needs on rental shares, we find that the estimated partial effect of the mean residual time, $\overline{\mu}(\tau)_{prt}$, has the expected negative sign in both specifications. The share of renters is significantly smaller in profession-region cells that are characterized by on average longer expected length of remaining residence spells. This result, of course, not only reflects home-owners' exposure to resale price risk, but also the substantially lower transaction cost of changing residence if renting. Increasing the mean residual time by one year, implies a decrease of rental shares by 2.7 percentage points. Given the positive correlation between demographics, such as household size (see Table 5.9 in Appendix 5.7.2), and the mean residual time it is not surprising that the mobility effect is smaller in column 2. Here the same increase in $\overline{\mu}(\tau)_{prt}$ yields a decrease of rental shares by 1.6 percentage points.

The signs of the estimated partial effects of the socio-economic characteristics in column 2 of Table 5.4 are throughout reasonable. The average

yearly labor income has a negative, yet statistically insignificant, effect on rental shares. The ratio of regional house prices to yearly household income and the proportions of households with no financial assets, on the other hand, have a positive and significant effect on rental shares. These effects are consistent with the presence credit constraints that prevent households from buying a home.

Table 5.4: Partial effects from ordinary least squares regression of profession-region rental shares. Pooled cross-section for the period from 1984 to 2004.

Dependent variable: Φ^{-1} (profession-region rental share)				
	(1)		(2)	
ρ_{pr}	0.138	(0.026)***	0.093	(0.023)***
$\overline{\mu}(\tau)_{prt}$	-0.027	(0.001)***	-0.016	(0.003)***
Income			-0.001	(0.000)
No assets			0.055	(0.025)**
Price/Hh.inc			0.004	(0.001)***
Age			-0.001	(0.001)
Education			0.011	(0.003)***
Female			0.021	(0.014)
Hh. size			-0.020	(0.008)***
Kids			-0.074	(0.021)***
Married			-0.039	(0.026)*
Foreigner			0.344	(0.018)***
Observations		3935		3935
$\bar{R}^2$		0.250		0.356

Notes: Table reports partial effects from ordinary least squares regression of equation (5.8). Partial effects are calculated at sample means of explanatory variables. Constant, profession-dummies, and time-dummies are not reported. Bootstrap standard errors are reported in parenthesis. Number of replications is 200. $\bar{R}^2$ is the adjusted R^2. *** significant at 1%-level ** significant at 5%-level * significant at 10%-level

Demographic characteristics, like household size, number of children, and marital status, have the expected negative impact on the proportion of renters. Notably the proportion of households with a foreign head decreases rental shares, as well. These effects are statistically significant and exhibit reasonable magnitudes. The impact of household heads' gender and age on rental shares, on the other hand, are indistinguishable from zero. While

economic theory does not suggest any particular influence of the former variable, identification of the latter is aggravated by the rather small variation of household heads' mean age across profession-region cells.

Surprisingly the estimated effect of household heads' education is positive. If formal education is a proxy for households' earning potential, the propensity to rent should decline with this variable. While this line of reasoning especially holds at the beginning of household (adult) lives (Gyourko and Linneman 1997), the static nature of the rental share regressions may distort our estimation results. Below we find the expected negative impact of household heads' education on the probability to rent for individual households.

We conclude that the results in Table 5.4 provide evidence for the proposed effect of income risk and mobility needs of different professions on households' tenure mode choice. Households within profession-region cells, however, are heterogenous with regard to observed and unobserved characteristics that may influence tenure mode choice. Furthermore, the static nature of the rental share regressions relates past housing choices to current household decisions. However, below we confirm the key results when analyzing individual households' tenure mode choice in a dynamic context.

5.5.2 Household level

Results for recent movers

Table 5.5 reports estimated partial effects from the pooled probit model for recent movers given in equation (5.9). The partial effects are evaluated at sample averages of household characteristics (see column 2 of Table 5.3). Column 1 of Table 5.5 summarizes the estimation results of a specification that only includes our two key explanatory variables, time dummies, and profession dummies. The socio-economic control variables are added in column 2.

We find for both specifications that the estimated partial effect of the household specific relative riskiness of renting, ρ_{ht}, is again positive and statistically significant. Thus, the average recent mover's probability to rather rent then buy a home decreases with the household's net income risk if renting. Notably the magnitude of the income risk effect is of a similar size as in the rental share regressions. Multiplying the estimated partial effect of 0.117 in column 2 (and 0.131 in column 1) with a one standard deviation increase of ρ_{it} – implying a decrease of the net income variance if renting (holding the

profession-specific income variance constant) by roughly 10 percent – yields an increase in the probability to rent by 1.2 (1.3) percentage points.

Table 5.5: Partial effects from probit model for recent movers. Pooled cross-section for the period from 1985 to 2004.

Dependent variable: one if household is renter, zero otherwise				
	(1)		(2)	
ρ_{ht}	0.131	(0.056)**	0.117	(0.053)**
$\mu(\tau)_{ht}$	-0.028	(0.001)***	-0.006	(0.003)**
Income			-0.001	(0.000)***
No assets			0.095	(0.014)***
Price/Hh.inc			0.006	(0.001)***
Age			-0.003	(0.001)***
Education			-0.004	(0.002)*
Female			0.003	(0.014)
Hh. size			-0.013	(0.008)*
Kids			-0.052	(0.020)**
Married			-0.141	(0.019)***
Foreigner			0.137	(0.010)***
Observations		5820		5820
Log likelihood		-2635.34		-2397.53
Pseudo R^2		0.136		0.214

Notes: Table reports partial effects from probit regression of equation (5.9). Partial effects are calculated at sample means of explanatory variables. Constant, profession-dummies, and time-dummies are not reported. Bootstrap standard standard are reported in parenthesis. Number of replications is 200. The pseudo R^2 is computed as $1 - \mathcal{L}_{ur}/\mathcal{L}_o$, where $\mathcal{L}_{ur}$ is the log likelihood value of the unrestricted model and $\mathcal{L}_o$ the log likelihood value of a constant only model. *** significant at 1%-level ** significant at 5%-level * significant at 10%-level

Still the impact of household's expected (remaining) residence duration, $\mu(\tau)_{ht}$, on the probability to rent is negative and statistically significant. Considering the estimated partial effect in column 1, an increase of the mean residual time by one year yields a decrease of the probability to rent by 2.8 percentage points. While the magnitude of this effect is of similar size compared to the results of the rental share regressions, the estimated mobility effect decreases even more dramatically after controlling for some of the heterogeneity across households. In column 2 the same increase of $\mu(\tau)_{ht}$

decreases the probability to rent by only 0.6 percentage points. Given the discussion in the previous section, this results is most likely attributable to the selection of the sample on the basis of active moving decisions.

The estimated partial effects of the socio-economic control variables are reasonable and of similar magnitude as at the aggregate level (see Table 5.4). A household's probability to rent increases significantly with the ratio of average house prices to household income, as well as the absence of financial asset holdings. Unlike in the rental shares the influence of yearly labor income is now statistically significant. As expected the greater sample variation in this variable allows us to identify the expected negative impact of this variable on the probability to rent.

The demographic control variables, like household size, marital status, number of children, and foreign household heads, have a statistically significant influence on the probability to rent. Compared to their effect on rental shares, the magnitude of these effects are only slightly lower. Notably the age and the education of household heads have the expected negative influence on households' probability to rent. It is, however, not clear if the significant age effect mirrors true life cycle effects like wealth accumulation. This is because there may be indirect age effects due to correlation between this variable and unobserved factors, such as risk tolerance.

Results for general population

Table 5.6 reports average partial effects (APE) from pooled probit and correlated random effects estimates of equation (5.10). In the case of the pooled probit model we ignore the unobserved effect c_h. We interpret the estimated coefficients as population averaged parameters, from which we directly compute the APEs (see e.g. Wooldridge, 2002). The correlated random effects model parameterizes the unobserved effect as a function of the within-household averages of the time-varying explanatory variables and a vector of dummy variables to represent the first observed tenure mode state. We compute the APEs based on expression (5.12). Both the APEs of the pooled probit and correlated random effects model are evaluated at sample average of household characteristics (see column 3 of Table 5.3).

Column 1 and 2 summarize the estimation results from two specifications of the pooled probit model. In column 1 we only include our two key explanatory variables, the initial and lagged tenure mode state, time dummies, and profession dummies.[20] Column 2 adds the the socio-economic control

[20]The first observed tenure mode state, y_{h0}, is included, because y_{h0} must be correlated with the unobserved factor c_h if present (see e.g. Heckman, 1981).

Table 5.6: Average partial effects from dynamic panel probit model. Unbalanced household panel for the period from 1984 to 2004.

	Dependent variable: one if household is renter, zero otherwise					
	Pooled Probit		Correlated Random Effects (A)		Correlated Random Effects (B)	
	(1)	(2)	(3)	(4)	(5)	(6)
y_{ht-1}	0.946	0.944	0.579	0.584	0.579	0.585
	(0.003)***	(0.003)***	(0.039)***	(0.035)***	(0.039)***	(0.036)***
ρ_{ht}	0.117	0.137	0.061	0.062	0.102	0.121
	(0.059)**	(0.061)**	(0.148)	(0.150)	(0.066)	(0.067)*
$\mu(\tau)_{ht}$	-0.013	-0.017	-0.019	-0.014	-0.019	-0.014
	(0.002)***	(0.004)***	(0.003)***	(0.004)***	(0.003)***	(0.004)***
Income		-0.001		-0.001		-0.001
		(0.000)***		(0.000)*		(0.000)*
No assets		0.100		0.030		0.030
		(0.025)***		(0.020)		(0.020)
Price/Hh.inc		0.005		0.003		0.003
		(0.001)***		(0.001)**		(0.001)**
Age		0.006		0.002		0.002
		(0.001)***		(0.003)		(0.003)
Education		-0.008		-0.006		-0.006
		(0.003)***		(0.007)		(0.007)
Female		-0.028		-0.029		-0.030
		(0.021)		(0.022)		(0.023)
Hh. size		-0.011		-0.025		-0.025
		(0.007)		(0.009)***		(0.009)***
Kids		-0.007		0.009		0.008
		(0.019)		(0.023)		(0.023)
Married		-0.051		-0.035		-0.034
		(0.026)*		(0.030)		(0.030)
Foreigner		0.172		0.168		0.167
		(0.016)***		(0.020)***		(0.020)***
$\widehat{\sigma}_a$			1.073	0.977	1.073	0.976
$\bar{\chi}^2$-Statistic			176.01***	166.16***	176.08***	166.14***
Observations	36625	36625	36625	36625	36625	36625
Log likelihood	-4147.35	-3942.43	-3971.98	-3764.40	-3972.10	-3764.63
Pseudo R^2	0.836	0.844	0.843	0.851	0.843	0.851

Notes: Table reports average partial effects (APE) from pooled probit and correlated random effects estimates of equation (5.10). APEs are calculated at sample means of explanatory variables. y_{h0}, constant, profession-dummies, time-dummies, and missing-dummies are not reported. Correlated random effects specification (A) also includes $\overline{\rho}_h$, $\overline{\mu}(\tau)_h$, and $\overline{\mathbf{x}}_h$. Specification (B) leaves $\overline{\rho}_h$ out. Bootstrap standard errors are reported in parenthesis. Number of replications is 200. $\bar{\chi}^2$-Statistic is for likelihood ratio test of the null hypothesis that $\theta = \sigma_a^2/(\sigma_a^2 + 1)$ is zero. The pseudo R^2 for the pooled probit model is computed as $1 - \mathcal{L}_{ur}/\mathcal{L}_o$. The pseudo R^2 for the correlated random effects model is computed as $(\mathcal{L}_o - \mathcal{L}_{ur})/\mathcal{L}_o$. $\mathcal{L}_{ur}$ is the log likelihood value of the unrestricted model and $\mathcal{L}_o$ the log likelihood value of a constant only model. *** significant at 1%-level ** significant at 5%-level * significant at 10%-level

variables. Column 3 through 6 summarize the results for four specifications of the correlated random effects model: The correlated random effects specification (A) allows for correlation between the time-average of the relative riskiness of renting, $\overline{\rho}_h$, and the unobserved effect. Specification (B) leaves $\overline{\rho}_h$ out. In the reported results, we further drop the time-averages of gender and nationality of household heads. These variables are almost always time-constant. In order to allow panel attrition to be correlated with the unobserved effect, we also include a full set of dummy variables representing the years a household is not observed.

In all four specifications of the correlated random effects model the estimated variance of the unobserved effect is substantial. A likelihood ratio test of the null hypothesis that $\theta \stackrel{\text{def}}{=} \sigma_a^2/(\sigma_a^2+1)$ is zero is always rejected.[21] Furthermore, controlling for unobserved effects improves the fit of the model, as evidenced by the change in the log likelihood and Pseudo R^2. Notably there is still much unobserved heterogeneity even after explicitly considering socio-economic differences across households. Without controls a_h accounts for approximately 53 percent of the unexplained error variance (column 3 and 5), compared to 48 percent after including demographics (column 4 and 6). There is thus strong evidence that unobserved factors influence households' tenure mode choice.

Before we turn to the estimated effects of our key explanatory variables, it is of it's own interest to discuss how past tenure mode decisions influence current choices. In column 1 through 6 the impact of the lagged tenure mode state, y_{ht-1}, is positive and significant. Occupancy of either tenure mode highly affects current housing choices. It is striking that, comparing the correlated random effects estimates to the pooled probit estimates, the magnitude of the APEs are substantially smaller. This result suggests that the coefficient on y_{ht-1} in the pooled probit estimates has picked up the effect of unobserved household characteristics. However, even after controlling for unobserved effects, the degree of state dependence is substantial. Changing the tenure mode from owner to renter increases a household's probability to rent it's home in the following year by approximately 58 percentage points in column 3 through 6.

Even after controlling for the strong state dependence of households' housing choices (and unobserved heterogeneity) the estimated effect of the household specific relative riskiness of renting, ρ_{ht}, has a positive sign. The probability to rather rent then buy a home decreases with the net income risk

[21] Since the variance of the idiosyncratic error in the underlying latent variable model is unity, θ measures the relative importance of σ_a^2. If θ equals zero the unobserved effect is unimportant and random effects estimates are not different from pooled probit estimates. For further details, see e.g Wooldridge (2002).

if renting in column 1 through column 6. The income risk effect, however, is indistinguishable from zero in the correlated random effects specifications (A). This result can be explained by the severe collinearity between ρ_{ht} and it's within household time average $\overline{\rho}_{ht}$. As expected identification of the true effect of ρ_{ht} on the probability to rent and it's correlation with the unobserved effect is aggravated, because ρ_{ht} only varies over time when household members change their profession or the household moves to a new region.

While the presence of uninsurable income risk may influence unobserved household characteristics such as their risk tolerance (Guiso and Paiella 2008), our use of a relative measure should eliminate these dependencies. In this case we can largely confirm the results from the rental share and probit regressions of recent movers. While the estimated APE of ρ_{ht} on the probability to rent is only weakly significant (with a p-value of 0.125) in column 5, the income risk effect is statistically significant after controlling for socio-economic differences across households. Multiplying the estimated APE of 0.121 in column 6 with a one standard deviation increase of ρ_{ht}, which implies a decrease of the net income variance if renting by roughly 10 percent, increases the probability to rent by 1.2 percentage points.

Turning to the impact of mobility needs, we find that the estimated APEs of households' expected remaining residence duration, $\mu(\tau)_{ht}$, have the expected negative sign in column 1 through 6. The mobility effect is throughout statistically significant. In our preferred model specification, the correlated random effects specification (B) with socio-economic controls (column 6), a one year increase in $\mu(\tau)_{ht}$ decreases the probability to rent by about 1.4 percentage points. Notably the magnitude of the estimated APEs only slightly vary across estimation methods and model specifications. Moreover, the size of the mobility effect is throughout comparable to the magnitude of partial effects which we have found in the rental share regressions (see column 2 of Table 5.4).

The estimated impact of the socio-economic controls on the probability to rent have reasonable directions in column 2, 4, and 6. After allowing for correlation between these variables and the unobserved effect, however, the APEs of most controls are indistinguishable from zero. Exceptions are labor income, the ratio of average house prices to household income, household size, and foreign household heads, which all have the expected influence on the probability to rent. The insignificant APEs are likely to be due to two reasons: First, some of the variables, such as the age, affect tenure mode choice indirectly through their correlation with unobserved factors. Second, in some cases the rather time-consistent nature of variables, like education and marital status, severely aggravates identification.

5.5.3 Robustness tests

We checked the sensitivity of our results with a number of robustness tests. First, we investigated whether the inclusion of potentially constrained households distort the estimated effects of our key explanatory variables. Households who are credit constraint, in the sense that their lifetime resources are sufficient to buy a home, but current wealth does not suffice the down-payment requirement to obtain bank financing, are renters by default. Under the presumption that these households purchase their housing services in public housing sector, we re-estimated the three empirical models using only households operating in the private sector. The key results in Tables 5.4, 5.5, and 5.6 remained unchanged.

It must be noted, however, that the GSOEP does not provide information if initially subsidized houses have been turned into privately rented dwellings during the course of time. The exclusion of renters who reportedly live in socially subsidized houses thus not always display the true status of their home. Therefore, we secondly restricted the analysis to households who report at least some resources that may be utilized as a down-payment for an owner-occupied home. In particular, we excluded households with no financial asset holdings (besides saving accounts). Again the key results in Tables 5.4, 5.5, and 5.6 remained unchanged.

Finally, we restricted the analysis to households whose head is of German origin. As households with foreign heads might have quite different planning horizons, their inclusion could also distort our results. In particular, foreign households may expect to re-emigrate to the country of their origin after retirement, and thus do not invest in owner-occupied housing regardless of the risk aspects under consideration. The key results in Tables 5.4, 5.5, and 5.6, however, remained unchanged when re-estimating the three empirical models using only German household.

5.6 Conclusion

In this study we have empirically investigated the impact of professional career decisions and their associated income risk and mobility needs on the tenure mode choice of German households. Economic theory suggests that members of professions whose income comoves with regional housing cost should prefer to rent their home. Then periods of declining labor income are accompanied by decreasing rents allowing to smooth consumption of non-housing goods. Renting, however, exposes households to the future volatility of rents, which may more than offset the protection against income shocks.

Given homeowners exposure to the resale price risk of their house and the substantially larger transaction cost of changing residence, members of professions requiring high mobility should also prefer to rent.

We find empirical support for these two impacts of professional career decisions on households' tenure mode choice. First, we find that a 10 percent decrease of the net income variance if renting relative to the profession specific income variance increases the share of renters of different professions in different regions by roughly 1.0 percentage points. Second, rental shares are smaller in profession-region cells that are characterized by on average longer expected residence duration of their members. Using data on both recent movers and the general population, we confirm these key results at the household level. Even after controlling for the substantial state dependence of households' current housing choices and unobserved heterogeneity, we find that income risk and mobility needs affect the propensity to rent as expected.

The empirical findings of our study are particulary interesting with respect to households' risk management opportunities. Starting with Shiller's (1993) initial contribution, a vast amount of literature has focussed on new financial instruments that allow homeowners to insure against house price fluctuations. However, a well-functioning rental market as in Germany does not only allow households to separate their consumption and investments demand for housing, but can also provide further diversification benefits. The results of our study indicate that households exploit these benefits of renting if present. In future research it would be worthwhile to study the impact of renting versus owning on the optimal risk sharing in the context of risky housing and uninsurable labor income. While the general equilibrium welfare consequences of different tenure systems are by no means obvious, it is natural to expect that any governmental preference for one type of tenure mode should be avoided.

5.7 Appendix

5.7.1 Cluster analysis

To delineate profession groups, our cluster analysis uses the observed transitions between industry-occupation categories in the GSOEP. Let i denote a occupation-industry group and p_{ij} the probability of a person to belong to this group conditional on being a member of group j in the previous period.

Table 5.7: Transition matrix for the 14 profession groups found by cluster analysis.

		To:													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
	1	90.73	0.61	1.10	0.14	0.18	0.23	0.81	0.70	3.02	0.04	0.08	1.61	0.06	0.69
	2	2.78	90.26	2.47	0.26	0.17	0.07	0.38	1.10	0.15	0.45	0.63	0.07	0.29	0.93
	3	2.87	2.18	90.24	0.27	0.07	0.24	0.29	2.52	0.29	0.04	0.50	0.20	0.04	0.25
	4	2.69	1.24	1.65	83.06	0.72	0.10	0.83	5.48	3.62	0.21	0.00	0.41	0.00	0.00
	5	3.64	1.46	0.31	0.42	87.93	0.42	1.04	0.21	3.43	0.42	0.10	0.31	0.00	0.31
	6	2.96	0.25	0.54	0.14	0.07	84.06	1.59	2.81	3.86	0.18	0.61	2.70	0.04	0.18
	7	3.34	0.53	0.44	0.04	0.21	0.53	88.49	1.10	3.43	0.80	0.21	0.34	0.06	0.47
From:	8	1.82	0.55	2.06	0.61	0.07	0.62	0.64	88.62	2.63	0.54	0.90	0.65	0.08	0.21
	9	3.27	0.10	0.18	0.08	0.11	0.34	0.78	0.93	92.98	0.31	0.13	0.55	0.13	0.12
	10	0.50	2.13	0.63	0.06	0.50	0.19	2.57	3.88	6.26	81.72	0.56	0.56	0.25	0.19
	11	1.07	3.36	1.47	0.04	0.00	0.90	0.33	3.56	1.56	0.49	83.82	1.39	1.84	0.16
	12	10.77	0.20	0.65	0.13	0.15	1.50	0.48	1.83	4.38	0.13	0.65	78.78	0.03	0.33
	13	1.11	1.03	0.16	0.00	0.00	0.63	0.39	1.42	1.42	0.79	3.24	0.32	89.34	0.16
	14	3.02	0.87	0.63	0.02	0.02	0.05	0.39	0.41	0.48	0.02	0.14	0.19	0.02	93.72

Notes: Table reports the estimated transition probabilities between 14 profession groups. Each element gives the probability that an individual moves from the profession indicated by the row to the profession indicated by the column.

These initial transition probability are estimated by

$$p_{ij} = \frac{\sum_{t \in T} N_{i,t|j,t-1}}{\sum_{t \in T} N_{i,t}} \ ,$$

where $N_{i,t|j,t-1}$ is the number of persons employed in group i in period t conditional on being employed in group j in period $t-1$. $N_{i,t}$ denotes the total number of persons employed in group i in period t.

In order to estimate the elements of the initial transition matrix we use observations on 122,978 employed individuals (household heads and spouses) who live in West-Germany, are of age 18-65, and have been in the panel for at least two years. The initial occupation-industry groups are assigned to each individual according to the ISCO-88 1-digit classification of occupations and the NACE Rev.1 1-digit classification of industries. ISCO-88 covers 9 main occupations. NACE 16 covers main industries of which two industries are not observed in our sample.

The transition matrix between the 124 ($= 9 \times 14$) initially observed industry-occupation groups is the data matrix from which we build the profession groups. We therefore employ a weighted-average linkage cluster algorithm that begins with each initial group being regarded as its own profession. Then the two closest groups are combined, and the process continues until all groups belong to the same cluster (see e.g. Rencher, 2002).

As a proximity measure between groups i and j we use the Q-correlation coefficient

$$d_{ij} = \frac{\sum_{k=1}^{K}(p_{ik} - \bar{p}_i)(p_{jk} - \bar{p}_j)}{\left(\sum_{k=1}^{K}(p_{ik} - \bar{p}_i)^2 \sum_{k=1}^{K}(p_{jk} - \bar{p}_j)^2\right)^{1/2}} \ .$$

where $\bar{p}_i$ denotes the mean over the variables $(p_{i1}, \ldots, p_{iK})$ and p_{ik} is the value of the k-th variable of group i, i. e. the transition probability from group i to group k. The proximity between group k and a new group $k(ij)$, which is constructed by combining group i and j is given by

$$d_{k(ij)} = \frac{n_i}{n_i + n_j} d_{ki} + \frac{n_j}{n_i + n_j} d_{kj} \ ,$$

where d_{ki} (d_{kj}) denotes the proximity between group k and group i (j), and n_i, n_j, n_k are the number of initial groups in the respective group.

To determine the final number of group, we both inspected dendrograms and the allocation of industries and occupations to professions. Table 5.7 reports the estimated transition probabilities between the chosen 14 profession groups. The cluster analysis was quite successful in assigning industry and occupation categories to stable professions. The diagonal elements of the matrix, that is the transition probabilities within professions, are almost always

above 80 percent. The lowest within transition probability is 79 percent, the highest within transition probability is 94 percent. The off-diagonal elements, that is the transition probabilities between clusters is almost always lower than 3 percent. The lowest between transition probability is virtually 0 percent, the highest between transition probability is about 10 percent.

5.7.2 Income indexes

To estimate constant-quality income indexes for each profession, we employ the following hedonic panel regression:

$$y_{it} = \beta_0 + \sum_{c=1}^{C} \beta_c x_{cit} + \sum_{p=2}^{P} \gamma_{p0} d_{pi0} + \sum_{p=1}^{P} \sum_{t=1}^{T} \gamma_{pt} d_{pit} + c_i + u_{it} \ , \qquad (5.13)$$

where y_{it} is the log gross labor income of person i in period t. x_{cit} are person characteristics. Here, we consider age (in years), education (in years), labor force experience (in years), work hours, and tenure with the current firm (in years). To capture region specific income level effects, we further include a full set of region dummies in x_{cit}. The profession-specific time-trend of labor income is captured by the time-dummies d_{pit}. In particular, the dummy variables d_{pit} takes the value one, if person i is occupied in profession p in period t and is zero otherwise. To account for differences in the income level between professions in the base period, we also include a full set of profession dummies d_{pi0}. Note, that individual who switch professions break the collinearity (see Shiller and Schneider (1998)). c_i is a person specific fixed effect and u_{it} is an error term.

We fit equation (5.13) by fixed effects using an unbalanced panel of employed persons. The sample is extracted from the GSOEP for the period 1984 to 2004. It contains 107,073 observations. Table 5.8 reports the estimation results for our preferred model specification. Here, we transform education levels and labor force experience according to theoretical foundations provided in the Mincer wage regression literature (see e.g. Heckman et al. (2003)). Age and work hours are transformed with a Box-Cox like transformation function $T(\cdot)$, see Bunke et al. (1999).

The index values are computed as

$$I_{pt} = \frac{\exp\{\widehat{\gamma}_{pt} - 0.5\widehat{\sigma}^2_{\gamma_{pt}}\}}{\exp\{\widehat{\gamma}_{p0} - 0.5\widehat{\sigma}^2_{\gamma_{p0}}\}} \times 100 \qquad (5.14)$$

which corrects for small-sample bias (Kennedy 1998, p. 37). $\widehat{\gamma}_{pt}$ is the estimated time-dummy coefficient for profession p and $\widehat{\sigma}^2_{\gamma_{pt}}$ is the correspondent

Table 5.8: Fixed effects income regression for 14 professions.

Dependent variable: log labor income			
	Coef.	Std. Err.	P-Value
T(Age)	16.699	0.384	0.000
T(Age)^2	-22.381	0.691	0.000
Education in Yrs.	0.060	0.002	0.000
Experience	0.048	0.002	0.000
Experience^2	-0.001	0.000	0.000
T(Workhours)	-114.697	7.866	0.000
T(Workhours)^2	142.569	8.597	0.000
Tenure	0.003	0.000	0.000
Regression diagnostics			
Observations	107073	Groups	15701
R^2_{Within}	0.486	$R^2_{Between}$	0.664
$R^2_{Overall}$	0.614	Corr(u_i, X)	0.234
Wald-Statistic	12786.72	P-Value	0.000
$\widehat{\sigma}_u$	0.286	$\widehat{\sigma}_c$	0.429
Joint significance of region dummies			
Wald-Statistic	104.69	P-Value	0.000
Regression based Hausman test			
Wald-Statistic	1494.74	P-Value	0.000
Test for first-order serial correlation			
Durbin-Watson	1.220	LBI	1.755

Notes: Table reports FE estimates of equation (5.13). Coefficients for constant, time-dummies, and region dummies are not reported. Standard errors are calculated with the robust Huber/White/sandwich estimator. Wald-Statistic is for the null hypothesis that all coefficients reported in the table are jointly zero. P-Value is for a $\chi^2(8)$ distribution. P-Value for the Wald-Test of the joint significance of the region dummies is for a $\chi^2(29)$ distribution. Regression based Hausman test is for the null hypothesis that unobserved heterogeneity is uncorrelated with exogenous variables. Corresponding Wald-Statistics is calculated using heteroscedasticity-robust standard errors. P-Value is for a $\chi^2(37)$ distribution. For details on the test see Wooldridge (2002, Chapter 10). Durbin-Watson reports the modified Bhargava et al. (1982) Durbin-Watson test statistic. LBI reports the Baltagi and Wu (1999) test statistic for zero first-order serial correlation. In both cases, we reject the null hypothesis of zero first-order serial correlation against the alternative of positive serial correlation.

estimated robust variance of the coefficient estimator. The index values are normalized to 100 for the base period $t = 0$. Note that the denominator in (5.14) is set to 1 for the reference profession. The weighted index values are computed as

$$I_{pt}^{W} = I_{gt} \cdot (1 - u_{pt}) + I_{pt} B_t \cdot u_{pt} \tag{5.15}$$

where I_{pt} is the income index calculated from (5.14), u_{pt} is the observed unemployment rate for profession p in period $t'$and B_t is the *OECD*-Summary measure of unemployment benefits.

5.7.3 Survival analysis

To estimate the unknown parameters in equation (5.6), we employ the following linear regression for censored data:

$$\ln(\tau_i) = \mathbf{x}_i(\tau)\boldsymbol{\beta} + \varepsilon_i \ . \tag{5.16}$$

Here, we define τ_i to be the duration of the i-th households' residence spell, that is the elapsed duration since the household has moved into it's current residence. A Spell is completed if the household moves to a new residence or dissolves. Dissolving household are the result of emigration, death, or disbandment for other reasons. Otherwise spells are defined to be right-censored. The row vector $\mathbf{x}_i(\tau)$ collects (possibly) time-varying household characteristics at time τ. To capture profession specific impacts on households' mobility, we further include dummy variables representing the household head's profession. The reference category are household heads' who are not in the labor force. The error term ε_i is assumed to be standard normal distributed $\varepsilon_i \sim N(0, \sigma^2)$.

We fit equation (5.16) by the method of maximum-likelihood using a flow sample of households' residence spells. For details on the estimation method, see e.g. Lancaster (1990). The sample is extracted from the GSOEP for the period 1985 to 2003. A new observation on a residence spell enters our sample when a household moves to a new residence or is newly formed in the year under consideration. The 1984 and 2004 waves are excluded for the following reasons: (i) The GSOEP does not identify a households moving status in 1984, (ii) spells entering our sample in 2004 are right censored by definition. Note, that we allow for multiple spells of the same household. In total we have 8052 residence spells. Of these 4438 are completed. The remaining spells are right-censored.

Table 5.9 reports maximum likelihood estimates of equation (5.16). In our preferred model specification we include age, age squared of the household head at the beginning of the spell and dummy variables for three different

Table 5.9: Maximum likelihood estimates of lognormal regression of residence spells.

Dependent variable: log residence duration			
	Coef.	Std. Err.	P-Value
Age	0.058	0.009	0.000
Age^2	-0.001	0.000	0.001
Dualearner	0.166	0.034	0.000
Household size=2	0.203	0.037	0.000
Household size=3	0.165	0.047	0.000
Household size≥4	0.374	0.053	0.000
Foreigner	-0.090	0.033	0.006
Married	0.374	0.038	0.000
Female	-0.063	0.030	0.034
Profession1	0.094	0.044	0.036
Profession2	0.041	0.071	0.569
Profession3	0.046	0.058	0.433
Profession4	-0.218	0.190	0.250
Profession5	-0.102	0.138	0.461
Profession6	-0.300	0.073	0.000
Profession7	0.103	0.070	0.141
Profession8	0.026	0.060	0.668
Profession9	0.082	0.046	0.072
Profession10	-0.059	0.088	0.504
Profession11	0.075	0.106	0.481
Profession12	0.121	0.087	0.164
Profession13	0.156	0.135	0.250
Profession14	0.104	0.075	0.167
σ	1.026	0.010	
Regression diagnostics			
Number of observations	38343	Spells	8052
Log likelihood	-8513.23	AIC	17112.46
Wald statistics	42.241	P-Value	0.000

Notes: Table reports maximum likelihood estimates of equation (5.16). Constant and time dummies are not reported. Reported standard errors are robust to serial correlated errors. Wald statistic is for the null hypothesis that reported coefficients on profession dummies are jointly zero. P-Value is for $\chi^2(14)$ distribution.

household sizes, dual-earner households, household heads' marital status, and household heads' gender as demographic control variables. The coefficients on these variables are statistically significant and have reasonable

signs. The age of household heads, for instance, has a hump-shaped profile: The expected length of residence spells increases up to an age of 35 years and subsequently decreases. The coefficients on the profession dummies, on the other hand, are mostly insignificant at the usual confidence levels. The null hypotheses that the coefficients on the profession dummies are jointly zero is, however, rejected by a simple Wald test. Thus, providing some evidence that the profession of the household head affects residential mobility.

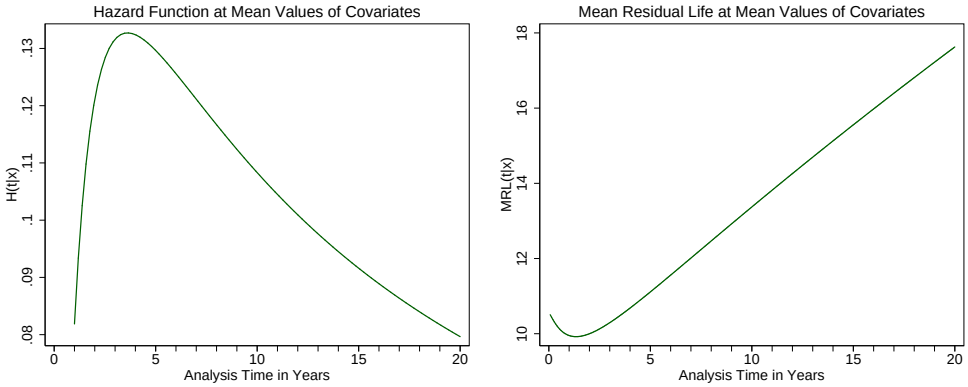

Figure 5.1: Hazard function and mean residual life function from log normal regression of residence spells. Both functions are evaluated at sample means of explanatory variables.

Figure 5.1 depicts the hazard function and the mean residual life function (expected remaining residence duration) implied by our estimates. Both functions are evaluated at sample means of the explanatory variables. The hazard rate, that is the probability of moving conditional on being in the current residence for τ years, increases up to 5 years, and then decreases monotonically. Accordingly, the mean residual life function first decreases and then increases monotonically. Note, that the shape of both functions is determined by our distributional assumptions.

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Selbständigkeitserklärung

Hiermit erkläre ich an Eides statt, dass ich die Dissertation selbständig verfasst habe; die von mir benutzten Hilfsmittel und Quellen sind aufgeführt.

Martin Wersing
Berlin, den 7. Januar 2010