SFB 649 Discussion Paper 2008-013

House Prices and Replacement Cost: A Micro-Level Analysis

Rainer Schulz*
Axel Werwatz**

* University of Aberdeen, United Kingdom
** Technische Universität Berlin, Germany

This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".

http://sfb649.wiwi.hu-berlin.de
ISSN 1860-5664

SFB 649, Humboldt-Universität zu Berlin
Spandauer Straße 1, D-10178 Berlin

SFB 649 ECONOMIC RISK BERLIN

House Prices and Replacement Cost: A Micro-Level Analysis

Rainer Schulz and Axel Werwatz*

December 2007

*Schulz, corresponding author: University of Aberdeen Business School, Edward Wright Building, Dunbar Street, Aberdeen, AB24 3QY, United Kingdom, r.schulz@abdn.ac.uk. Werwatz: Technische Universität Berlin, Institut für Volkswirtschaftslehre und Wirtschaftsrecht, Straße des 17. Juni 135, 10623 Berlin and SFB 649, Humboldt-Universität zu Berlin, Germany, axel.werwatz@tu-berlin.de. We have benefited from comments on earlier versions of this paper by Patric Hendershott, Karen M. Gibler, Euan Phimister, Nikolai Schmuklermann, Knut Berger, and from numerous seminar and conference session participants. We thank Martin Wersing for excellent research assistance. The usual disclaimer applies. Financial support from the Deutsche Forschungsgemeinschaft, SFB 373 *Quantification and Simulation of Economic Processes* and SFB 649 *Economic Risk*, is gratefully acknowledged.

Abstract

According to housing investment models, house prices and replacement cost should have an equilibrating relationship. Previous empirical work—mainly based on aggregate-level data—has found only little evidence of such a relationship. By using a unique data set, covering transactions of single-family houses over a 25 years period, we establish strong support for the relationship at the micro level. In the time series context, we find that new house prices and replacement cost align quickly after a shock. In the cross-sectional context, we find prices of old houses and replacement cost are closely related once building depreciation has been taken into account. As to be expected from these results, replacement cost information also proves to be useful for the prediction of future house prices.

Keywords: Tobin's Q, building depreciation, prediction accuracy
JEL classification: C52, C53, R31

1 Introduction

Housing investment models are built on the presumption that new construction is driven by deviations between prices of existing houses and replacement cost. High prices relative to replacement cost encourage construction while low prices relative to replacement cost have the opposite effect. New construction, or the lack thereof, changes the housing stock and thus affects existing house prices. Housing market adjustment occurs until, in steady state, prices of existing houses are equal to replacement cost.

Despite this straightforward economic reasoning, empirical support for the role of replacement cost in the housing market adjustment process is disappointing. While the prices of existing houses are commonly found to exert a significant positive influence on housing investment, proxies of replacement cost fail to have the expected significant negative impact (Lee, 1999; Mayer and Somerville, 2000; Topel and Rosen, 1988). Indeed, the estimated impact of commonly used measures of replacement cost has even been positive on several occasions (DiPasquale and Wheaton, 1994; Poterba, 1984).

In this paper, we approach the replacement cost puzzle without taking the detour via housing investment. In doing so, we greatly benefit from a unique data set that contains rich information for all transacted single-family houses in the city of Berlin, Germany, since 1980. For each house transaction, we observe the price, an estimate of the land cost derived from local sales of empty lots, and the estimated building cost derived from surveyed actual construction contracts. Thus, we have measures of both components of replacement cost: building cost and land cost. Unlike other studies, we do not have to rely on proxies of actual construction cost nor—for a lack of data—do we have to ignore land cost altogether.[1] By using data from a single metropolitan market we contribute to a literature that is mostly based on aggregated national data, even though it is well accepted that the behavior of house prices and cost might be best explored with data of individual metropolitan markets.

[1]Somerville (1999) has shown that cost indices commonly used in US studies are only a poor measure of actual construction cost. The study of DiPasquale and Wheaton (1994) is, to our knowledge, the only one that also considers the influence of (agricultural) land cost. However, in their sole investment specification where land cost has the expected significant negative coefficient, the proxy for construction cost has an implausible positive significant coefficient.

The unique data set allows us to improve on the existing empirical literature in two important ways.

First, we are able to examine the relationship between the prices of existing houses and their replacement cost both in a time series and a cross-sectional context. Time series characteristics of price and cost series have often been ignored in studies of the housing investment adjustment process (Mayer and Somerville, 2000). These characteristics are important because housing investment models predict that existing house prices and replacement cost have an equilibrating stochastic relationship. In the cross-sectional context, building depreciation is the core figure of interest. The deviation between the steady state prices of old houses and replacement cost defines the depreciation function of the building. This function can be directly estimated with transaction prices and the components of replacement cost. The explicit consideration of land and building costs in the estimation of the depreciation function avoids conceptual problems encountered by previous studies.

Second, we are able to explore if new and old houses are close substitutes by studying the ability of adjusted replacement cost to predict transaction prices. The adjustment considers depreciation and market-wide deviations of prices from cost. The outcome of the prediction experiment also has practical relevance: Real estate professionals often view replacement cost values as a last resort to be used only when sales comparison values cannot be computed because of insufficient data. Given the sound economic reasoning on the role of replacement cost, this view seems to underrate cost values.

Three main outcomes emerge from our analysis of house prices and replacement cost for different types of single-family houses. First, by estimating CES production functions and computing time series of replacement costs, we find that real prices and replacement cost are nonstationary time series. The ratios of house prices to replacement cost (Tobin's Q), however, are stationary, supporting the notion that prices and cost have an equilibrating relationship. It takes about two years from a shock to the housing market until prices and replacement cost are aligned again, which is comparable to the adjustment period for housing investment in the US established by Topel and Rosen (1988). The stationary relationship between prices and replacement cost is robust against structural changes in the price and cost series. The result is important because previous studies have provided mixed evidence. Using aggregate US data, Jud and Winkler (2003) find a nonstationary and strongly upward trending Q.[2] Berg and Berger (2006), using aggregate Swedish data, obtain a similar result for their period of analysis. Neither study explores land and construction cost separately. Only Rosenthal (1999), using data from the Vancouver metropolitan market, provides evidence of an equilibrating relationship between building prices and construction cost.[3] Our study strengthens this evidence for another metropolitan market over a longer sample period and for different types of single-family houses.

Second, the cross-sectional analysis provides several lessons about building depreciation. We introduce a flexible version of the depreciation function used by Cannaday and Sunderman (1986) that allows for a kink at some inflection age. This is consistent with a vintage quality effect: Once a building has reached the inflection age, its rate of depreciation begins to decrease. Allowing for a kink improves the empirical fit of the depreciation function substantially. Because we observe building and land cost separately, we are also able to assess the downward bias in the estimated depreciation function introduced by using the house prices as the dependent variable (Malpezzi et al., 1987). Subtracting land cost from house prices may alleviate this problem, but only if the market is in steady state. Our empirical results indicate that standard hedonic regression models, which have the price as dependent variable, underestimate building depreciation by about 50%.

Third, adjusted replacement cost perform well in the prediction experiment, confirming that new and old houses are close substitutes once building depreciation has been accounted for. Sales comparison values perform even better as predictors of transaction prices. Combinations of both values, however, produce the best predictions. Replacement cost thus provides information about the future price not already captured by current prices, which is in line with the role replacement cost plays in the housing market adjustment process.

In summary, our study reveals that the empirical relationship between prices and replacement cost is in-line with economic reasoning. Specifically, there is no evidence

[2]Their Q relates prices of existing new houses to prices of newly constructed houses. The upward trend is puzzling, because there is no reason why *prices* of existing new and newly constructed houses should deviate. Their nationally aggregated time series suffers, as Jud and Winkler point out, from differences in the types of houses and regions covered in the numerator and the denominator.

[3]Rosenthal infers land cost from house prices by using hedonic regression. The building price is then computed as house price minus inferred land cost. Building prices and construction cost are co-integrated and respond quickly to shocks.

at the micro-level of a replacement cost puzzle as often found with aggregate-level data. By providing this plausible result, our study highlights the importance of micro-level data for the analysis of the relationship between prices and cost (DiPasquale, 1999). In addition to providing this result for a specific metropolitan market, our study develops an empirical methodology that could be applied to other markets in the future.

The paper is organized as follows. Section 2 provides the economic motivation and explains the empirical methodology. Section 3 presents the data set. The time series behavior of prices, cost, and Qs of new houses is explored in Section 4. Section 5 estimates building depreciation and explores the accuracy of replacement cost as price predictor. The final Section 6 concludes.

2 Motivation and empirical methodology

The standard stock-flow housing investment model is built on the elementary economic reasoning that any deviations of the prices of existing houses from replacement cost will trigger an adjustment process until prices and cost are equalized. Underlying this reasoning are the assumptions that the housing construction industry is competitive and that houses can be constructed with a constant return to scale production function.[4]

The model assumes that all existing and newly constructed houses are of identical quality. Depreciation is of the 'light-bulb'-type, i.e., in every period there is a constant probability that a house deteriorates completely. Given the stock of houses, the (imputed) rent per house is determined by the demand for housing services. Investors can invest either in a house or another asset (bond). Bond's return rate is exogenously given. The asset stock market can only clear if investors are indifferent between both assets, i.e., if the return rate of a housing investment (rent plus capital

[4] This implies the equality of average cost, marginal cost, and price in steady state. Variants of the model are used in Kearl (1979); Poterba (1984); Sheffrin (1996); Summers (1981). The models of DiPasquale and Wheaton (1994) and Topel and Rosen (1988) are more elaborate, but give qualitative similar results. In the urban growth model used by Mayer and Somerville (2000) prices of new houses and replacement cost are always equalized because construction is instantaneous. In the empirical implementation, however, Mayer and Somerville model adjustment similar to the standard stock-flow model, see their discussion.

gains minus compensation for depreciation risk) equals the bond return rate. This determines the value V_t of an existing house in period t. The construction of new houses is the flow market. Construction is triggered by

$$Q_t = \frac{V_t}{C_t} \ ,$$

where C_t is the replacement cost, which depends on the building and land cost. Whenever $Q_t > 1$, the value of existing houses is larger than the cost of producing them and developers are inclined to construct and supply new houses. The new supply is, however, limited in the short-run because construction takes time, land might not be available in the short run, or other adjustment cost exist. The new supply increases the housing stock, driving rental income down, and reducing V_t. New supply is provided until $V_t = C_t$ ($Q_t = 1$), when developers only replace the depreciated stock. Whenever $Q_t < 1$, the value of existing houses is smaller than cost of producing them and developers are inclined to construct and supply new houses. Depreciation will cause the housing stock to shrink, this will drive up rents, and increase V_t. Once $V_t = C_t$ is reached, developers will construct just enough houses to replace the depreciated stock.[5]

Assuming that investors and developers have rational expectations, any shock to the housing market will lead to an immediate jump of Q_t, followed by a monotone adjustment path back to its steady state value of 1. Take as an example a positive demand shock to the rental market. Before the shock, the economy is in steady state and investors receive the same return rate on houses and bonds. The demand shock disturbs the steady state equilibrium. Given an unchanged housing stock, which cannot adjust instantaneously, the market clearing rent will increase immediately after the shock. This higher rental income makes a housing investment more attractive than a bond investment, driving V_t up immediately. With unchanged replacement cost, Q_t is greater than 1 and construction becomes attractive. The new construction—already anticipated by investors—increases the housing stock and reduces the rent and V_t. This continues until asset return rates are equalized and $Q_t = 1$.

When we investigate the time series characteristics of Q in Section 4, we construct series for different types of single-family houses as follows: Houses are constructed

[5]The model can allow for a growing economy: In steady state ($Q = 1$), developers provide enough new houses to keep the stock growing at the same rate as the whole economy. $Q \neq 1$ then triggers adjustment after non-persistent shocks back to the long-run growth trend.

with a constant returns to scale technology using the two inputs building and land; the technology is represented by the unit cost function $C(P_t^B, P_t^L)$. P_t^B is the cost per unit of building and P_t^L is the cost per unit of land. The quantity of building units times the cost per unit gives the building cost B_t and the quantity of land units times the cost per unit gives the land cost L_t. The replacement cost of a new house is then

$$C_t = C(P_t^B, P_t^L) = B_t + L_t \ .$$

The units of the prices are normalized to the quantities in the base period 0, so that $B_0 = P_0^B$ and $L_0 = P_0^L$. The replacement cost in the base period is C_0. Letting I_t denote a price index with base period 0, we can rewrite $P_t^B = I_t^B B_0$ and $P_t^L = I_t^L L_0$. The cost function is linear-homogeneous and it follows for a replacement cost index with base period 0

$$\begin{aligned} I_t^C &= \frac{C(P_t^B, P_t^L)}{C_0} \\ &= C\{w_0 I_t^B, (1 - w_0) I_t^L\} \ , \end{aligned} \tag{1}$$

where $w_0 = B_0/C_0$ is the weight of the building cost in the base period 0. With the constant-quality price index I_t^H for new existing houses and the Q ratio in the base period, the Q time series is

$$Q_t = \frac{I_t^H}{I_t^C} Q_0 \ . \tag{2}$$

When we investigate the cross-sectional characteristics of prices and replacement cost in Section 5, we also test the claim that age plays no role for house quality. However, while the claim is convenient for modeling purposes, we do not expect it to hold empirically. Age will lead to a decline in a building's value because of increased maintenance cost and decreased flow of housing services (Clapp and Giaccotto, 1998). The claim should be better understood as the assertion that old and new houses are substitutes once depreciation is accounted for (Leigh, 1980).

We estimate the depreciation function and test the relaxed claim using the following methodology: Replacement cost of a house adjusted for depreciation is

$$\begin{aligned} C_t(a) &= B_t\{1 - \delta(a)\} + L_t \\ &= C_t(0) - \delta(a) B_t \ . \end{aligned} \tag{3}$$

Here, a is building's age and $\delta(a)$ is the depreciation function with $0 \leqslant \delta(a) \leqslant 1$, $\delta(0) = 0$, and $\delta'(a) \geqslant 0$. In steady state, $V_t(a) = C_t(a)$ and it follows from (3) that the value of an old house is the value of a new house minus the depreciation of the building. Off steady state, values and replacement cost will deviate. Assuming that the relative deviation is the same for all building ages gives

$$\begin{aligned} V_t(a) &= Q_t[B_t\{1-\delta(a)\}+L_t] \\ &= Q_tC_t(0)\{1-w_t\delta(a)\}\ , \end{aligned} \tag{4}$$

where $w_t = B_t/C_t(0)$ is the building cost weight and Q_t is for a new house.

To estimate the unknown parameters of the assumed depreciation function, we replace the unobserved V with the transaction price P. We assume $P = VU$, where U is an unsystematic error term with $\mathcal{E}[U] = 1$, and obtain

$$\ln P_t(a) = \alpha_t + \ln C_t(0) + \ln\{1 - w_t\delta(a)\} + \varepsilon_t\ . \tag{5}$$

α_t is the regression constant and $\mathcal{E}[\varepsilon_t] = 0$. Fitting (5) with its explicit consideration of land's contribution prevents a downward bias of the estimated depreciation function. This bias plagues standard hedonic models commonly applied in depreciation studies.[6] It can happen, as is occasionally observed in cross-sectional studies, that the estimated depreciation function is decreasing in a. Equation (5) provides an explanation: If w is smaller for older vintages, then—even though buildings lose value with age—older houses may command higher prices simply because the building is less important.[7] Using the price minus land cost as dependent variable in the hedonic regression may avoid a bias, but only if the market is in steady state.[8]

By making use of the estimated building depreciation function, we then test the claim that accounting for depreciation is sufficient to make old and new houses

[6]Equation (5) reduces to a standard hedonic model when $C_t(0)$ is replaced with a function of observable house characteristics other than age and $w\delta(a)$ is replaced with $\tilde{\delta}(a)$ (a function not considering land's contribution).

[7]The house value increases with age and $\tilde{\delta}'(a) < 0$ if

$$\frac{\delta'(a)}{\delta(a)} < -\frac{w'(a)}{w(a)}\ ,$$

which could happen if vintage-related location preferences drive land cost for older buildings up and w, consequently, down. See Clapp and Giaccotto (1998) for a demand-driven interpretation of positive estimated age coefficients.

[8]A first order approximation, using (4), gives

$$\ln\{V(a) - L\} \approx \ln B + \ln\{1-\delta(a)\} + \frac{1 - w\delta(a)}{w\{1-\delta(a)\}}(Q-1)\ .$$

The third term on the right-hand side corresponds to the bias, which only disappears when $Q = 1$.

substitutes. The rationale of the test follows from equation (4): If this equation is valid, then the adjusted replacement cost (value of the substitute) should be able to predict the transaction price (value of the actual house) accurately. We use the accuracy of hedonic regression predictions as the benchmark to assess the predictive ability of replacement cost.

3 Data set

The main data set is provided by Berlin's local real estate surveyor commission (GAA, Gutachterausschuss für Grundstückswerte) out of its transactions data base (AKS, Automatisierte Kaufpreissammlung). The GAA conducts valuations needed for administrative and official purposes (public court, legal portioning, compulsory purchase) and provides information about the real estate market to professionals and the interested public. To provide these services the GAA is entitled to request and collect information on all real estate transactions occurring in Berlin.[9] Our data set contains information on all single-family house sales carried out between willing buyers and sellers in Berlin between 1980 to 2004. The information includes the transaction price, the size of the lot, the floor space, the age of the building, and the district. Transactions before 1990 are exclusively from the former Berlin West. Because building cost and a number of related variables are only reported from 1996 onwards, focus lies on the transactions between 1996 and 2004. Observations between 1980 and 1995 are used solely to estimate constant-quality house price and land cost indices.[10] After cleaning the database, the number of observations is reduced by roughly 2%, leaving us with 28460 transactions.

Between 1996 and 2004, we have 11342 observations, with at least 174, at most 497, and on average 315 transactions per quarter. Table 1 reports summary statistics for the age, price, cost, and type of the transacted houses.

[Table 1 about here.]

[9] For every real estate transaction, a copy of the deed must be sent to the GAA. Moreover, the commission can request additional information from buyers and sellers, such as characteristics of the building or rental income.

[10] Details on other observed house characteristics, the hedonic regression model, and the estimation results are provided in a supplement, which is available upon request.

The average age at the date of sale is about 40 years. 15.5% of the houses are either newly completed or still under construction. The observations include many quite old houses, about 25% are older than 66 years, which makes the data set suitable for the analysis of building depreciation. The unique feature of the data set is the separate information on the components of replacement cost, i.e., on land and building cost.

The land cost refer to the value of the land if the site of the subject house were undeveloped. GAA surveyors compute the land cost using two steps. In the first, initial land cost is computed by using transaction prices of undeveloped land in the respective area and by relying on expert knowledge (Senatsverwaltung für Stadtentwicklung, 2001). In the second step, the initial land cost is adjusted to consider special conditions of the subject site, such as rights of way or accessibility. Adjustment is frequent, but usually small. Specifically, 76.7% of all transactions after 1996 have land costs that differ from the unadjusted (initial) land cost, adjusted land costs on average are 3.2% lower than unadjusted land costs. Adjusted and unadjusted land costs are closely correlated (correlation coefficient of 0.98).

Building cost is for a new building. GAA surveyors compute the cost in two steps. They begin with cost figures reported in official tables by the German government to compute an initial cost estimate for a comparable *new* building. These reported 'usual construction cost' (NHK, Normalherstellungskosten) are based on a survey of the construction industry in a reference year (i.e., the survey year) and are reported per cubic meter of gross volume and per square meter of gross base area. NHK are available for three different types of single-family houses (detached, semi-detached and end-row, and mid-row) and many building specifications that consider, among other things, the type of the roof, type of cellar and the number of storeys. Most of the building costs in our data set are computed with NHK from the year 1995; a smaller part is computed with NHK from 2000. The surveyors then adjust the initial cost estimate for cost inflation with the regional construction cost index. The index is provided by the Statistical Office Berlin in its Statistical Report M I 4 and gives the cost for constructing a new single-family building based on observed contractual prices.[11] The result is the building cost at current prices for a comparable new

[11] About 430 construction firms in Berlin report on a quarterly basis on contractual prices of construction operations, such as shell, paint, or plumber works. These are about 10% of all active construction firms in Berlin (Salchow, 2001). The construction cost index is calculated as a

version of the building under consideration. In the raw data set, 1022 objects had initially no reported building cost and the cost of 3537 objects were out-dated. For 4550 of these objects we were able to compute building cost by using regression techniques.

4 Time series evidence

Constant-quality house price indices I_t^H are computed using the estimated time dummy coefficients of a hedonic regression fitted to the transaction data. The log price is the dependent variable and included characteristics are, among others, floor area, size of the lot, age of the building, and dummies for the condition and location of the house. We run a pooled regression—dummy variables account for the house types—and separate regressions for the three house types. Houses under construction are excluded. The separate constant-quality price indices show a behavior very similar to the house price index from the pooled regression, but—because less observations are used—are more volatile. The land cost index I_t^L is also computed with hedonic regression, where the land cost is the dependent variable and characteristics include lot size and location information.

Figure 1 shows the constant-quality house price and land cost indices together with the construction cost index I_t^B published by Berlin's Statistical Office.

[Figure 1 about here.]

For the computation of the replacement cost, we specify the construction technology with a CES function. The unit cost function is then

$$C(P_t^B, P_t^L) = \left\{\delta^\sigma (P_t^B)^{1-\sigma} + (1-\delta)^\sigma (P_t^L)^{1-\sigma}\right\}^{1/(1-\sigma)} .$$

σ is the elasticity of substitution between the two input factors building and land.

Laspeyres index, where the weights for the sub-costs are their relative shares in the respective base year. The shares are updated every five years.

The factor cost ratio is[12]

$$\ln\left(\frac{B_t}{L_t}\right) = c + (1-\sigma)\ln\left(\frac{I_t^B}{I_t^L}\right) \ . \tag{6}$$

Cross-sectional studies have found substitution elasticities in teh range between close to zero and up to one (McDonald, 1981; Thorsnes, 1997). As (6) shows, a one percent change in the relative factor price leads to a one percent change in the cost ratio if $\sigma = 0$ (fixed proportions or Leontief technology), i.e., if there is no substitution between the factors. The factor cost ratio remains unchanged if $\sigma = 1$ (Cobb-Douglas technology), because any change in the factor price is compensated with a proportional opposite change in the factor demand.

We estimate equation (6) by replacing the unobserved dependent variable with the average log factor cost ratio and by adding an error term, accounting for unsystematic deviations and possible measurement error of the dependent variable. Averages are computed with all houses that are new or under construction. The results of the factor cost ratio regressions are given in Panel A of Table 2.[13]

[Table 2 about here.]

Even at the upper 95% confidence level value, the estimated elasticities are small and only around 0.4. The Cobb-Douglas technology can always be reject at the 5% level. The fixed proportions technology, however, cannot be rejected for any of the three factor cost ratio regressions. A fixed proportions technology seems plausible in a time series context. While we expect much variation of the factor combinations in the cross-section, we expect much less variation for the *average* house over time. Further support for the fixed proportions technology is provided by the examination of average building cost weights; if houses are produced with a fixed proportion

[12] To derive (6), we apply Shephard's lemma to the unit cost function and obtain the factor demand functions, multiply them with their factor prices and obtain factor costs, divide building cost by land cost, take the log, and replace $P_t = I_t P_0$. The constant c depends on σ, δ, and the relative price of building to land cost in the base period.

[13] The average will be a more precise estimate of the dependent variable the more houses H_t that are used for its computation, and the variance of the regression error term will be proportional to $1/H_t$. We use weighted least squares regressions to take this into account. In 5 of the 36 quarters no transactions of new and under-construction houses are observed. The regression fit improves with the number of quarters that have observations, as can be seen from the values of R^2 in the last row

technology, then zero substitution means that the real building cost weight will be independent of the year in which the house was built in. Computing locally-smoothed average real weights with respect to the year of construction gives virtually constant averages for detached houses and slightly increasing averages for semi-detached and row houses.[14] Based on this evidence, we compute the replacement cost series for the different house types assuming a fixed proportions technology.

Having specified the unit cost function, the building cost weight w_0 is needed to implement (1). In accordance with the fixed proportions technology, we use all observations with base year building cost to estimate w_0. Table 2 gives the results in Panel B. Reasonably, the estimated w_0 is largest for mid-row houses, which have an average floor area ratio (FAR) of 0.58, second-largest for semi-detached and end-row houses (average FAR is 0.37), and smallest for detached houses (average FAR is 0.23). w_0 for the all house types is set to 0.522, which is the average of the three separate house type weights scaled by type's share in the data set (see Table 1, Panel B). The resulting replacement cost index series are, in effect, weighted averages of the building and land cost indices. The behavior of the series for different house types is very similar.

To explore the characteristics of the price and cost series, we use unit root tests that allow for a change in a series' deterministic component, see the Appendix for details. The data indicate that such a change was caused by the introduction of the European single market in 1993, which made it much easier for foreign construction firms and workers to enter the Berlin market. The increased competition slowed the growth of real construction cost and, consequentially, of real prices and land cost. The unit root tests provide evidence that real house prices, land, construction cost, and replacement cost are each integrated of order one, i.e., the series have nonstationary levels, but stationary growth rates. This is in accordance with results of Rosenthal (1999) and Mayer and Somerville (2000).

Using the price and replacement cost series, the Q_t series are computed according to formula (2). We use price replacement cost ratios of new houses sold during 2000-2003 to compute Q_0 for the different house types (see Table 2, Panel C) and

[14] It is also possible to explore the floor area ratios (FAR) as a proxy of factor quantities. Computing locally-smoothed average weights with respect to the year of construction produces again virtually constant averages for detached houses and slowly increasing averages for semi-detached and row houses.

normalize the Q_t series to have an average of Q_0 between 2000-2003. Q_0 for all single-family houses is again computed as a weighted average, which is 0.973. Table 3 presents summary statistics for the Q series in Panel A and Figure 2 shows the series.

[Figure 2 about here.]

The sample averages of the Q_t series are, as expected, close to 1. The higher volatilities of the price series for the separate house types result in Q_t series more volatile than the the series for all single-family houses, but otherwise the behavior is very similar. The series cross their respective averages many times during the 25 years period. Q_t for all single-family houses, for example, crosses its average 20 times. This indicates stationary and mean reverting processes. Table 3 presents results of unit root tests in Panel B, which support stationarity for all series.

[Table 3 about here.]

The ADF test has the null hypothesis of unit root, which can be rejected for all four Q series at least at the 10% significance level. The KPSS test has the null hypothesis of a stationary series, which cannot be rejected for any of the four series at the usual significance levels. Consistent with economic reasoning, all four series are stationary and prices and replacement cost follow an equilibrating relationship.

We analyze the reaction of Q_t to shocks by using fitted time series models. AR(2) models work well for three of the series, but the mid-row series requires the inclusion of a fourth lag to whiten the residuals. The fitted model for the pooled all single-family house series is

$$Q_t = \underset{(2.63)}{0.166} + \underset{(6.09)}{0.603}\, Q_{t-1} + \underset{(2.02)}{0.225}\, Q_{t-2} + \widehat{\varepsilon}_t \; .$$

t-values are reported in brackets and are computed with heteroskedasticity-robust standard errors. This model has an adjusted R^2 of 0.689 and uncorrelated residuals. Figure 3 shows the impulse-response function to a one-unit shock in period t.

[Figure 3 about here.]

The shock could correspond to a positive housing demand shift as described in Section 2. The initial jump of Q induces new construction, which then leads to an adjustment of the housing stock and house prices. Using the point estimates, about 60% of a shock to Q is gone after four quarters, and more than 75% is gone after eight quarters. Taking the confidence intervals into account, prices and replacement cost might be realigned after about two years. Given that obtaining building permits plus construction time usually takes four quarters, this seems reasonable. The monotone adjustment of the impulse-response function indicates rational market participants. There is no passing through the steady state during adjustment and thus no indication of 'overbuilding' (Wheaton, 1999, Proposition 4). Compared to the finding of Rosenthal (1999) for Vancouver, adjustment seems to take longer in Berlin. This could be caused by a higher adjustment cost or a longer construction process. The finding could also be spuriously caused by the introduction of the European single market. To investigate this, we test the Q series for structural breaks. The tests provide no evidence for a structural change, see the Appendix for details. We conclude that while the single market slowed the growth of real prices and replacement cost, it left the Q adjustment process unaffected.

5 Cross-sectional evidence

Having established an equilibrating relationship between prices of new houses and replacement cost, we now investigate the relationship between prices for old houses and replacement cost. We specify the depreciation function as

$$\delta(a) = 1 - \left(1 - \frac{a}{l}\right)^{\beta} \quad \text{with} \quad l = \begin{cases} \underline{l} & \text{if } a \leqslant a_K \\ \underline{l} + (a - a_K) & \text{if } a > a_K \ , \end{cases} \tag{7}$$

where $\underline{l}$ is the unconditional life span of a new house measured in years. The free parameters β, $\underline{l}$, and a_K make the above depreciation function very flexible. For $a \leqslant a_K$, the depreciation accelerates with age if $0 < \beta < 1$, remains constant if $\beta = 1$, and declines if $\beta > 1$. The rate of depreciation slows once a building has reached the age of a_K. A building of age a_K or above is either of excellent quality or worthy of being kept in good condition (unique design). 'Light-bulb'-type depreciation is nested with $\beta = 0$, in which case the building value is independent of age. Cannaday and Sunderman (1986) were the first to use (7) for detached houses, but they did not consider a slowing depreciation for very old buildings. This is reasonable given the oldest house in their data set was just 26 years. The GAA surveyors use the depreciation function

$$\delta_{GAA}(a) = \frac{a}{2l}\left(1 + \frac{a}{l}\right) \quad \text{with} \quad l = \begin{cases} 80 & \text{if } a < 65 \\ a + 15 & \text{if } a \geqslant 65 \,, \end{cases} \tag{8}$$

which allows for a slowing depreciation for buildings older than 64 years, but is otherwise less flexible than (7).

We use the hedonic regression model (5) to estimate the parameters in (7) with nonlinear least squares over a grid of $\underline{l}$ and a_K values. Two specifications of the depreciation function are used: the original specification of Cannaday and Sunderman (CS function) and the specification that allows for a kink at a_K (CSK function). Table 4 gives the results of the specifications with the highest R^2. The flexible CSK depreciation function always has the best fit. The fit of the GAA function (8) is also reported: the fit is poor and in two cases produces more variation than is present in the dependent variable. As expected, 'light-bulb'-type depreciation can always be rejected for both the CS and the CSK function at the usual significance levels.

[Table 4 about here.]

Figure 4 plots the estimated depreciation function for all single-family houses. Because the CSK function has the best fit, it serves as the benchmark. The poor performance of the GAA function is caused by the buildings losing less value in the first 65 years than is assumed. The kink of the function, on the other hand, seems to be reasonable. The CS function copes well with relatively young buildings, but has problems with older buildings. Not allowing for a vintage effect reduces the fit by about 10%.

[Figure 4 about here.]

The magnitude of the CSK depreciation for the value of a detached house, $w_0\delta(a)$, is strikingly similar to the results of Cannaday and Sunderman (1986, Table 4). Moreover, the unconditional life span $\underline{l}$ is in the range used in their study. The CSK function tells us that a detached house has lost 2.8% of its value after 5 years, 16.4%

after 30 years, and 26.7% after 50 years. The reduction of the building value is, however, much larger and amounts to 6.2% after 5 years, 36.1% after 30 years, and 58.8% after 50 years. This indicates the magnitude of underestimation for building depreciation in standard hedonic regression depreciation models.

The prediction experiment tests if new and old houses are indeed substitutes once building depreciation has been taken into account. The experiment covers the 20 quarters between 2000-2004. 85% of the houses transacted during this period were not new, with an average building age of 41 years. The adjusted replacement cost values are computed according to (4), using the CSK depreciation function. The sales comparison values, which serve as the benchmark, are computed using rolling-window hedonic regressions fitted with observations from the respective 16 quarters preceding the transaction period. Sales comparison values constitute a demanding benchmark, because prices of existing houses are determined in the asset stock market and sales comparison values make direct use of (past) price information. One could reason that sales comparison values will automatically be more accurate if, on average, more existing houses are being transacted than new houses are being constructed, leading to less information on the flow market. However, such an informational differential does not seem to exist in Berlin, where the activity of stock and flow markets over the period 1986-2004 was of comparable magnitude. Take 2004 as example: out of the total stock of about 142000 single-family houses, 2710 houses changed hands and 2233 were newly completed, which are 1.9% and 1.6% of the stock, respectively. In the land market, 1569 sites for single-family houses were sold, which is 1.1% of the stock of single-family houses. Although there were fewer transactions of undeveloped land, land is more homogeneous than houses and it is plausible to assume that land cost can be measured more easily.

Table 5 presents summary statistics for the log prediction errors.[15] Panel A presents statistics for errors when no adjustment is made for the trend between the valuation period t and the prediction period $t+1$. This understates the true prediction potential, because time series models could be used for trend forecasting. Panel B presents statistics for errors when the trend adjustment is made with the realizations of I^H_{t+1}, I^B_{t+1}, I^L_{t+1}, and Q_{t+1}. This overstates the true prediction potential

[15] Log errors treat under- and overvaluations symmetrically and are preferred to percentage errors, which create a preference for undervaluations (Dittman and Maug, 2006). The qualitative results are unaltered if percent prediction errors are used.

because the realizations are not known with certainty in t. Predictions with estimated trend adjustments will always have a performance in-between. The predictive performance of simple average prices is also given in Table 5. Sales comparison and replacement cost values should perform better than average price values, because the latter ignore house-specific characteristics.

[Table 5 about here.]

In Panel A, sales comparison values perform best, having a mean error (ME) of -4.4%, a mean squared error (MSE) of 6.0%, a mean absolute error (MAE) of 18.3%, and the highest probability of having a prediction error no greater than 25%. The adjusted replacement cost values come second, with a higher ME, MSE, MAE, and a smaller probability of prediction errors at most as large as 25%. The relative ranking is the same in Panel B. According to the MSE and the MAE, valuations with trend adjustment perform better for (relatively homogeneous) row and semi-detached houses than for (heterogeneous) detached houses; results for predictions without trend adjustment are similar and not reported. The difference between the performance of sales comparison and replacement cost values is the smallest for detached buildings. Unadjusted replacement cost values perform nearly as bad as average price values and overstate prices substantially. This is in accordance with the rejection of the 'light-bulb'-type depreciation function and highlights the importance of depreciation.

Panel A of Table 6 provides evidence of the significance of the predictive performance. The statistics for the pairwise MSE, MAE, and Signed-Rank tests are all asymptotically standard-normal distributed. The 5% critical value for the one-sided hypothesis that the value mentioned first performs at least as good as the value mentioned second in Panel A is 1.645. This hypothesis cannot be rejected when the replacement cost and sales comparison values are compared to the average price values. According to the statistics of the Sign test, the replacement cost values perform better than the average price for 64.6% of the predictions and the sales comparison values for 71.0%. These outcomes are to unlikely to have been the result of equally-accurate valuations and we reject the hypothesis in both instances. Both cost and sales comparison values thus perform significantly better than the average price values.

[Table 6 about here.]

The result that sales comparison values perform better than average price values is not surprising. Like the average price values, sales comparison values use transaction data, but take house-specific characteristics explicitly into account. If these characteristics were to play no role for prices, then the sales comparison values would correspond to the average price; if the characteristics play a role, then sales comparison values will be more accurate. The result that replacement cost values perform significantly better than the average price gives credibility to the notion that accounting for building depreciation makes old and new houses comparable. When comparing the replacement cost and sales comparison values, however, we reject the null that cost values perform at least as well as sales comparison values for all tests. 57.5% of the sales comparison values are closer to the transaction prices than the cost values, allowing us to reject the hypothesis that both values have the same degree of accuracy. Because replacement cost are less accurate than sales comparison values, the relationship between new and old houses must be more complex than is assumed in (4). This does not mean, however, that (4) is irrelevant. If it were, then replacement cost would not contain any information not already considered in sales comparison values. Panel B of Table 6 presents a test on the incremental prediction contribution of adjusted replacement cost: if the difference between both values is uncorrelated with the prediction errors of the sales comparison values then replacement cost do not contribute. The hypothesis of no contribution can be rejected for all house types and each separate house type at the usual significance levels. This rejection is in accordance with economic reasoning: prices of existing houses are established in the stock market, making sales comparison values the first choice for price predictions; deviations between prices and replacement cost trigger an adjustment process of the housing stock, making (adjusted) replacement cost of at least incremental value for price predictions.

[Table 7 about here.]

To assess the contribution of replacement cost values to prediction accuracy, we investigate the optimal weighting. Panel A of Table 7 presents fitted regressions of transaction prices on the cost and the sales comparison values. The individual slope coefficients for both values are significant in all regressions, which emphasizes that both past asset stock and flow market information is relevant for future house prices. Panel B presents the performance of the weighted average valuations. Even 'naive' geometric averages perform better than the sales comparison values with respect to the MSE for the three house types, but marginally fail to do so for the pooled all house types. Optimal averaging puts more weight on sales comparison (65% on average) than on cost values (35%). The contribution of replacement cost values is, however, substantial and reduces the MSE by 11% on average.

6 Conclusion

Researchers and real estate professionals alike have been pessimistic about the existence of an equilibrating relationship between prices of existing single-family houses and replacement cost, and, therefore, the usefulness of replacement cost to predict transaction prices. The findings of our paper are more optimistic: Using a unique micro-level data set from a single metropolitan market, we find evidence of a close relationship between prices and cost both in the times series and the cross-sectional context.

The empirical methodology of our paper is flexible and can be applied in future to similar data sets as they become available. For instance, while the fixed proportions technology was appropriate for our application, other applications may favor different constant return to scale technologies. With respect to the flexible depreciation function, we conjecture that the kink at the inflection age—leading to a near 'light-bulb'-type depreciation—might be more important for European countries than for many metropolitan areas in the USA or Japan, which have fewer vintage houses. While our motivation of the kink as a vintage effect is intuitive, further research is needed to fully understand this effect.

Appendix

Unit root tests

We apply the unit root testing procedure of Perron (1989, 1990), which first removes deterministic trend changes from the time series and then performs an ADF-type test with the trend-removed residuals. Ignoring such deterministic changes in a time series biases standard unit root tests towards non-rejection of the unit root null hypothesis. We apply the tests to real house price and cost. Real series are generated by deflating with Berlin's consumer price index, which is provided by the Statistical Office Berlin in its Statistical Report M I 2.

Tables 8 and 9 present the results of the Perron unit root tests. For the log levels, the null hypothesis of a unit root cannot be reject at the usual significance levels, see the last column of Table 8. For the growth rates, the null hypothesis of a unit root can be rejected at least at the 10% significance level for all but the construction cost series, see the last column of Table 9.

[Table 8 about here.]

[Table 9 about here.]

In addition to 'additive outlier' (AO) models, results of which are reported in Tables 8 and 9, we also fit 'innovational outlier' (IO) models, which assume a gradual instead of an immediate change. The IO model results (not reported) are qualitatively identical to the AO model results, except for the growth of real replacement cost of mid-row houses, where the null hypothesis of a unit root can no longer be rejected at the 10% level (t-Statistic is -2.81). The AO models seem to be more appropriate in the present context: First, as Perron (1989, p. 1381) explains in detail, the IO model for levels does not permit for a drift change under the null, making it incompatible with the IO model for growth rates, where such a change is allowed. Second, European construction firms were well prepared for the single market, which makes an immediate change more plausible.

The non-rejection of the unit root hypothesis for the real construction cost growth rate could be caused by the series' seasonal component, which may reduce the power of the second step ADF-type test. To investigate further, we fit the seasonal model $y_t = \mu + \alpha y_{t-4} + \varepsilon_t$ to the series, which provides residuals behaving like white noise. To test for a seasonal unit root, we apply the test proposed by Dickey et al. (1984, Table 5) and reject the null of a unit root at the usual significance levels (t-Statistic is -5.66 and the 1% critical value is -3.09). The seasonal model ignores, however, the possible change of the expected growth rate. Running the regression with a split constant term and conducting a ADF test for the residuals from this regression gives a unit root test statistic of -9.29. Under usual circumstances, this indicates a clear rejection of the null (1% critical value is -2.59).[16] Based on this evidence, we treat the real construction cost—like the other price and cost series—as difference stationary.

All series are thus well captured by Perron's (1989) Model B $y_t = \mu_0 + y_{t-1} + (\mu_1 - \mu_0)DU_t + e_t$, where $DU_t = 0$ before the introduction of the single market and $DU_t = 1$ afterwards, and e_t is a stationary and invertible ARMA process. The corresponding real growth rate $\Delta y_t = \mu_0 + (\mu_1 - \mu_0)DU_t + e_t$ is a stationary process with a changing mean. The negative and mostly significant β_1 estimates in Table 9 indicate a slow down of real price and cost growth after the introduction of the single market. Because e_t might be not white noise, the growth rate regressions of the Perron procedure are not necessarily the best way to estimate β_1. Because of this, we also fit more general ARMA models to the real growth series, which leads to similar and significant β_1 estimates.

Structural change tests

Given the structural breaks in the price and cost series, we test if the process of the Q series is stable. Table 10 presents results of tests for structural change of the time series model coefficients following the introduction of the single market. The first is the standard Chow test; this test will be invalid if there is heteroskedasticity.[17] The other two tests in Table 10 take the possibility of heteroskedasticity into account. In both tests, the covariance matrix of the coefficient estimators is estimated

[16] This is only indicative, because we apply the test to estimated residuals.

[17] There is some evidence for heteroskedasticity: White's test rejects the null of homoskedasticity for detached house, semi-detached and end-row house, and all single-family house Q series at the 5% significance level.

with a sandwich estimator, where the Wald version uses the residuals from a regression assuming structural change, whereas the LM version uses the residuals from a restricted regression assuming no change. Although both tests are asymptotically equivalent, in finite samples the performance of the LM test is better than the Wald test, because the latter tends to reject the correct null too frequently (Davidson and MacKinnnon, 1985).

[Table 10 about here.]

The test results in Table 10 are robust in all but one instance and do not allow rejection of the null of no structural change at the 5% significance level. The Wald test rejects the null for the all house types series at the 5% level, but the LM test does not. Because of better performance of the LM test in finite samples, we base our decision on the LM-Statistic and conclude for all series that they were not affected by the introduction of the single market in 1993.

References

Berg, L., Berger, T., 2006. The Q theory and the Swedish housing market—an empirical test. Journal of Real Estate Finance and Economics 33, 329–344.

Cannaday, R. E., Sunderman, M. A., 1986. Estimation of depreciation for single-family appraisals. AREUEA Journal 14, 255–273.

Clapp, J. M., Giaccotto, C., 1998. Residential hedonic models: A rational expectations approach to age effects. Journal of Urban Economics 44, 415–437.

Davidson, R., MacKinnnon, J. G., 1985. Heteroskedasticity-robust tests in regressions directions. Annales de l'INSEE 59/60, 183–218.

Dickey, D. A., Hasza, D. P., Fuller, W. A., 1984. Testing for unit roots in seasonal time series. Journal of the American Statistical Association 79, 355–367.

Diebold, F. X., Mariano, R. S., 1995. Comparing predictive accuracy. Journal of Business & Economic Statistics 13, 253–263.

DiPasquale, D., 1999. Why don't we know more about housing supply? Journal of Real Estate Finance and Economics 18, 9–23.

DiPasquale, D., Wheaton, W. C., 1994. Housing market dynamics and the future of housing prices. Journal of Urban Economics 35, 1–27.

Dittman, I., Maug, E., 2006. Biases and error measures: How to compare valuation methods. Finance Working Paper 2006-07, Universität Mannheim.

Harvey, D. I., Leybourne, S. J., Newbold, P., 1998. Tests for forecast encompassing. Journal of Business & Economic Statistics 16, 254–259.

Jud, G. D., Winkler, D. T., 2003. The Q theory of housing investment. Journal of Real Estate Finance and Economics 27, 379–392.

Kearl, J. R., 1979. Inflation, mortgages, and housing. Journal of Political Economy 87, 1115–1138.

Lee, G. S., 1999. Housing investment dynamics, period of production, and adjustment costs. Journal of Housing Economics 8, 1–25.

Leigh, W. A., 1980. Economic depreciation of the residential housing stock of the United States, 1950-1970. Review of Economics and Statistics 62, 200–206.

MacKinnon, J. G., 1989. Heteroskedasticity-robust tests for structural change. Empirical Economics 14, 77–92.

Malpezzi, S., Ozanne, L., Thibodeau, T. G., 1987. Microeconomic estimates of housing depreciation. Land Economics 63, 372–385.

Mayer, C. J., Somerville, C. T., 2000. Residential construction: Using the urban growth model to estimate housing supply. Journal of Urban Economics 48, 85–109.

McDonald, J. F., 1981. Capital-land substitution in urban housing: A survey of empirical estimates. Journal of Urban Economics 9, 190–211.

Perron, P., 1989. The great crash, the oil price shock, and the unit root hypothesis. Econometrica 57, 1361–1401.

Perron, P., 1990. Testing for a unit root in a time series with a changing mean. Journal of Business & Economic Statistics 8, 153–162.

Perron, P., Vogelsang, T., 1993. Erratum. Econometrica 61, 248–249.

Perron, P., Vogelsang, T. J., 1992. Testing for a unit root in a time series with a changing mean: Corrections and extensions. Journal of Business & Economic Statistics 10, 467–470.

Poterba, J. M., 1984. Tax subsidies to owner-occupied housing: An asset-market approach. Quarterly Journal of Economics 99, 729–752.

Rosenthal, S. S., 1999. Residential buildings and the cost of construction: New evidence on the efficiency of the housing market. Review of Economics and Statistics 81, 288–302.

Salchow, J., 2001. Das Baugewerbe in Berlin 1999. Statistische Monatsschrift Berliner Statistik 2001 (5), 206–212.

Senatsverwaltung für Stadtentwicklung, 2001. Bodenrichtwertatlas Stand 01.01.2001. Berlin, CD-ROM.

Sheffrin, S. M., 1996. Rational Expectations, 2nd Edition. Cambridge Surveys of Economic Literature. Cambridge University Press, Cambridge.

Somerville, C. T., 1999. Residential construction cost and the supply of new housing: Endogeneity and bias in construction cost indexes. Journal of Real Estate Finance and Economics 18, 43–62.

Summers, L. H., 1981. Inflation, the stock market, and owner-occupied housing. American Economic Review (Papers and Proceedings) 71, 429–434.

Thorsnes, P., 1997. Consistent estimates of the elasticity of substitution between land and non-land inputs in the production of housing. Journal of Urban Economics 42, 98–108.

Topel, R., Rosen, S., 1988. Housing investment in the United States. Journal of Political Economy 96, 718–740.

Wheaton, W. C., 1999. Real estate "cycles": Some fundamentals. Real Estate Economics 27, 209–230.

List of Figures

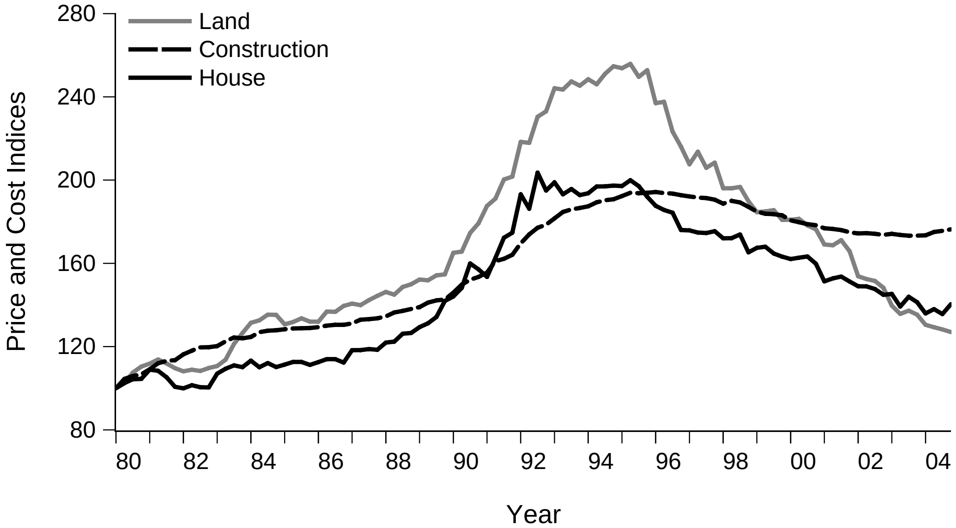

Figure 1: Quarterly indices of Berlin single-family house prices I_t^H, land cost I_t^L, and construction cost I_t^B, 1980:1 to 2004:4. Normalization period is 1980:1, where index values are set to 100.

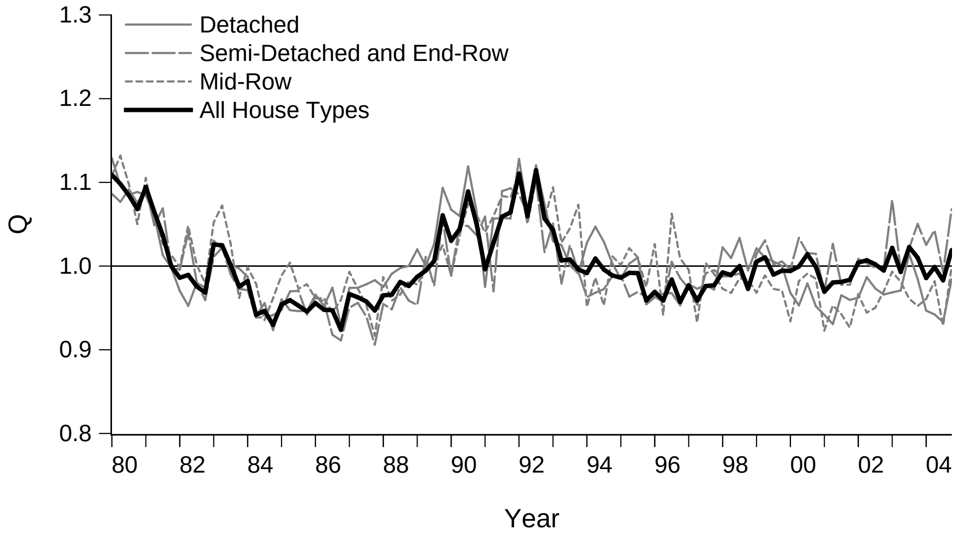

Figure 2: Quarterly Q indices for new houses 1980:1 to 2004:4, different single-family house types. In the graph, all indices are normalized to have a mean of 1.

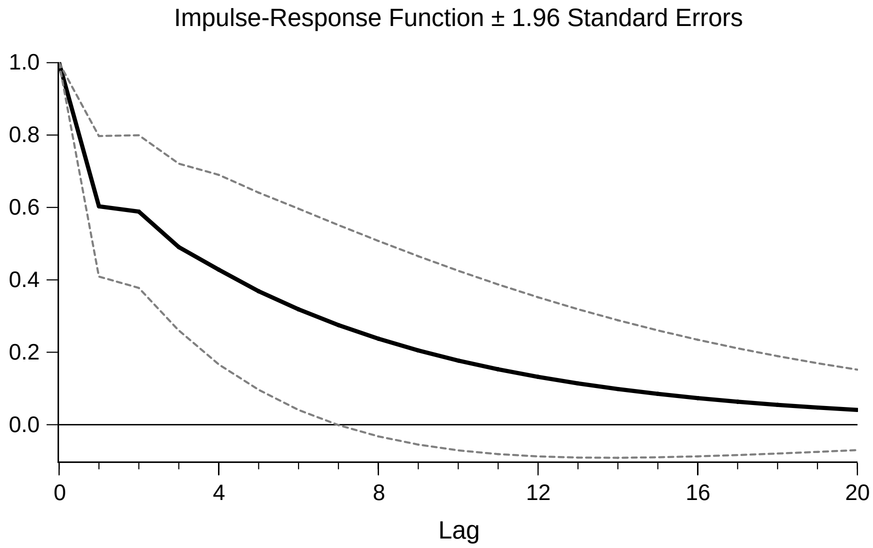

Figure 3: Estimated impulse-response function for Q series, all house types. Graph shows the response to shock of one unit in period 0. Function is based on estimated AR(2) process. Standard errors are based on asymptotic confidence intervals at the 95% level computed with the Delta method.

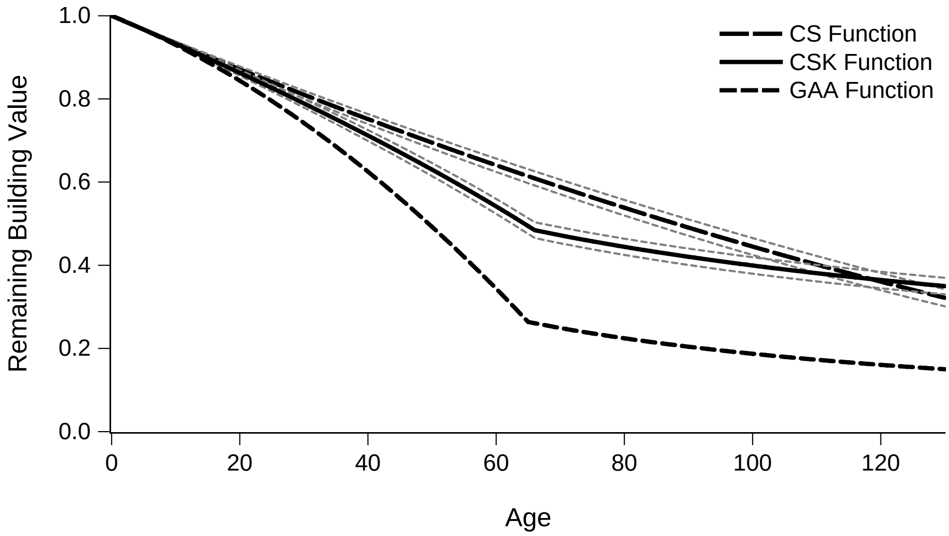

Figure 4: Figure shows the remaing building value as a function of age $1 - \delta(a)$ for three different depreciation functions $\delta(a)$. Upper and middle functions are estimated, dash lines around the solid lines are confidence bands at the 95% level. Lower function is the depreciation function applied by GAA valuers.

List of Tables

Table 1: Summary statistics for age, price, cost, and type of transacted single-family house in Berlin between 1996:1 to 2004:4.

Panel A: Age, Price, and Cost				
	Mean	Median	Std. Dev.	Units
Age	39.8	39.0	28.0	Years
Price	255.3	219.4	162.5	(000)
Building cost	185.5	172.2	81.1	(000)
Land cost	146.1	114.7	134.2	(000)
Replacement cost	331.4	284.8	187.1	(000)
Panel B: House Type				
Detached	51.3%	Semi-detached		23.2%
End-row	9.1%	Mid-row		16.4%

Notes: 11342 observations. Age refers to the age at the date of transaction. Prices and cost are in year 2000 Euros. Building cost are cost of constructing a new building. Replacement cost is the sum of building and land cost. 9 objects have no building cost and therefore no replacement cost.

Table 2: CES unit cost regressions for new houses, building cost weights for all houses, and Q ratios for new houses.

Panel A: CES Cost Function Regressions					
House type	N	$\widehat{\beta}$	t-Stat.($\widehat{\beta}$)	t-Stat.($\widehat{\sigma}$)	R^2
Detached	28	1.332	4.38	-1.09	0.425
Semi-detached and end-row	31	0.957	4.75	0.21	0.438
Mid-row	25	1.650	3.40	-1.34	0.335
Panel B: Real Building Cost Weights					
House type		N	Mean	Median	Std. Dev.
Detached		5260	0.454	0.456	0.119
Semi-detached and end-row		3319	0.566	0.566	0.146
Mid-row		1747	0.650	0.639	0.130
Panel C: Quarterly Average Qs of New Houses, 2000-2003					
House type		N	Mean	Median	Std. Dev.
Detached		73	0.983	1.005	0.056
Semi-detached and end-row		539	0.972	0.945	0.041
Mid-row		221	0.941	0.909	0.057

Notes: All observations have building cost with base year 1995. N is the number of observations. Panel A reports results of the regression $(\overline{\ln B - \ln L})_t = \alpha + \beta(\ln I_t^B - \ln I_t^L) + \varepsilon_t$, where the dependent variable is the average log ratio of building to land cost in quarter t. Averages are computed with all H_t new houses (newly constructed or still under construction). I_t^B and I_t^L are the construction and the land cost indices. Observations in the regression are weighted with $\sqrt{H_t}$. There are 137 detached, 1002 semi-detached and end-row, and 482 mid-row new houses. $\sigma = 1 - \beta$ is the elasticity of substitution. Coefficients for regression constants are not reported. Panel B reports summary statistics of the building cost weights, i.e., ratios of building cost to replacement cost (building plus land cost). Real weights for the year 1995 are computed by deflating the land cost with the land cost index I_t^L and by using the NHK1995 building cost. Panel C reports summary statistics for quarterly average Q ratios of new houses sold in the years 2000 to 2003. The number of observations N is the total number of new house sold during the period. These observations are used to compute average Qs in the respective quarter of transaction. No new detached house was transacted in the first quarter of 2000, and we use only 15 instead of 16 quarterly Q averages for this house type.

Table 3: Summary statistics and unit root tests for Q time series of different house types.

Panel A: Descriptive Statistics for Q Time Series			
	Mean	Std. Dev.	CV
All house types	0.974	0.041	4.16
Detached house	1.017	0.049	4.83
Semi-detached and end-row house	0.962	0.044	4.55
Mid-row house	0.981	0.048	4.91
Panel B: Unit Root Tests			
ADF	Lags K	t-Statistic	P-Value
All house types	1	-3.05	0.033
Detached house	0	-3.12	0.029
Semi-detached and end-row house	1	-2.79	0.063
Mid-row house	4	-2.62	0.092
KPSS			LM-Statistic
All house types			0.087
Detached house			0.219
Semi-detached and end-row house			0.097
Mid-row house			0.343

Notes: Each time series has 100 observations. In Panel A, CV is the coefficient of variation in percent. In Panel B, the ADF regression $\Delta Q_t = \mu + \rho Q_{t-1} + \sum_{k=1}^{K} \phi_k \Delta Q_{t-k} + \varepsilon_t$ is fitted. t-Statistic is for $\rho = 0$, P-Value for the null of a unit root is computed using MacKinnon's critical values. Regressions all have uncorrelated residuals. The critical values for the KPSS test of the null of a stationary series are 0.739 (1%), 0.463 (5%), 0.347 (10%). LM-Statistic is computed using the Bartlett kernel, where the bandwidth is selected with the Newey-West method.

Table 4: Nonlinear least squares model fit for depreciation function.

	N	$\underline{l}$	a_K	$\widehat{\beta}$	t-Stat.($\widehat{\beta}$)	R^2
All house types	10712					
GAA		80	65	.	.	-0.064
CS		300	.	1.997	34.84	0.139
CSK		98	66	0.648	36.26	0.153
Detached house	5766					
GAA		80	65	.	.	0.004
CS		300	.	2.531	25.40	0.147
CSK		93	54	1.149	26.04	0.163
Semi-detached and end-row house	3300					
GAA		80	65	.	.	0.106
CS		300	.	2.512	25.09	0.243
CSK		89	65	0.718	25.84	0.257
Mid-row house	1646					
GAA		80	65	.	.	-0.351
CS		300	.	1.306	12.90	0.140
CSK		76	68	0.281	14.74	0.170

Notes: Dependent variable is the log price replacement cost ratio. Regression function is $\ln P_t - \ln C_t(0) = \alpha_t + \ln\{1 - w_t\delta(a)\} + \varepsilon_t$, depreciation function is either (7) (CS and CSK) or (8) (GAA). N is the number of observations. The estimated time dummy coefficients α_t are not reported. Because the GAA function is already completely specified, only the time dummy coefficients had to be estimated. For the CS function, the coefficient β was estimated 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 detached, 116 for semi-detached and end-row, and 107 for mid-row houses. For the CSK function, the coefficient β was estimated separately for all possible combinations of $\underline{l} \in \{70, \ldots, 110\}$ and $a_K \in \{50, \ldots, 70\}$. Coefficients reported in the table are from the models that produced the highest R^2.

Table 5: Predictive performance of replacement cost and sales comparison values. Summary statistics of one-quarter log prediction errors for transactions between 2000:1 to 2004:4.

Panel A: Valuations without Trend Adjustment						
	N	ME	MDE	MSE	MAE	PE25
All house types	6229					
Cost value		-7.2	-6.6	8.5	22.0	66.9
Sales comparison value		-4.4	-3.6	6.0	18.3	74.2
Average price value		-1.7	-3.5	22.6	35.3	48.2
Panel B: Valuations with Trend Adjustment						
	N	ME	MDE	MSE	MAE	PE25
All house types	6229					
Cost value		-6.3	-5.8	8.3	21.7	67.2
Sales comparison value		-3.6	-2.7	5.9	18.2	74.2
Average price value		0.0	-1.9	22.3	35.1	48.2
Cost value new building		-26.1	-22.3	16.2	30.8	51.0
Detached house	3140					
Cost value		-3.1	-3.2	7.8	21.5	67.2
Sales comparison value		-3.4	-2.7	7.0	20.4	68.9
Average price value		0.0	-4.1	24.8	37.5	45.7
Cost value new building		-34.4	-32.9	20.5	37.0	38.4
Semi-detached and end-row house	1988					
Cost value		-1.2	-1.9	6.8	18.8	73.9
Sales comparison value		-2.7	-2.6	5.6	16.9	78.1
Average price value		0.0	0.7	16.2	29.8	55.1
Cost value new building		-20.3	-14.9	13.5	26.5	61.1
Mid-row house	1088					
Cost value		7.0	5.0	7.6	20.4	70.8
Sales comparison value		-0.8	0.4	5.4	16.1	80.1
Average price value		0.0	2.6	14.8	29.7	51.9
Cost value new building		-12.4	-8.1	9.5	21.6	69.1

Notes: All measures are reported in percent. Cost values are computed according to (4), where the estimated CSK function is used; sales comparison values are computed with estimated hedonic regression models. Valuations with trend adjustment take price and cost changes between the valuation period t and the transaction period $t+1$ into account. Average price value is the geometric average houses price of either the valuation period t (Panel A) or the transaction period $t+1$ (Panel B). Prediction errors are computed as $e = \ln P - \ln V$, where P is the transaction price and V is the respective valuation. N is the number of predictions made. 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 errors no larger than 25% in absolute value.

Table 6: Tests on the predictive performance of replacement cost, sales comparison, and average price values for all house types. Tests on forecasts encompassing of replacement cost by sales comparison values for different house types.

Panel A: Test Statistics for Relative Prediction Performance				
	MSE	MAE	Sign	Rank
Cost vs. average price	-26.43	-31.95	2208	-28.86
Sales comparison vs. average price	-32.78	-44.38	1808	-40.28
Cost vs. sales comparison	15.81	16.83	3581	15.50

Panel B: Forecast Encompassing of Cost by Sales Comparison Values			
House type	N	Test-Stat.	P-Value
All	6229	11.52	0.000
Detached	3140	11.27	0.000
Semi-detached and end-row	1988	7.01	0.000
Mid-row	1088	4.96	0.000

Notes: Test statistics are computed based on functions $d(e_1, e_2)$ of the 6229 prediction errors $e_i = \ln P - \ln V_i$. P is the transaction price and V_i is either the replacement cost, sales comparison, or the average price value. In Panel A, the value mentioned first in table's rows corresponds to $i = 1$. The test statistic for the MSE is computed with $d(e_1, e_2) = e_1^2 - e_2^2$. The statistic is a standard t-Statistic for the average d, which is asymptotically standard-normal distributed. The test for the MAE is similar and uses $d(e_1, e_2) = |e_1| - |e_2|$. The Sign and the Signed-Rank tests also use $d(e_1, e_2) = |e_1| - |e_2|$. The statistic of the Sign test is the number of predictions with $d(e_1, e_2) > 0$. The statistic 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. In the test in Panel B, $d(e_1, e_2) = (e_1 - e_2)e_1$, where 1 stands for sales comparison values and 2 for cost values. The null hypothesis is $\mathcal{E}[d] = 0$ and the statistic is a standard t-Statistic for the average d, which is asymptotically standard-normal distributed. For details on the tests see Diebold and Mariano (1995); Harvey et al. (1998).

Table 7: Performance of weighted replacement cost and sales comparison values. Summary statistics of one-quarter log prediction errors for transactions between 2000:1 to 2004:4.

Panel A: Optimal Combination of Cost and Sales Comparison Values					
House type	N	$\widehat{\beta}_0$	$\widehat{\beta}_1$	$\widehat{\beta}_2$	R^2
All	6229	0.055	0.248	0.744	0.757
		(0.54)	(13.98)	(37.13)	
Detached	3140	0.128	0.393	0.594	0.750
		(0.88)	(19.51)	(13.67)	
Semi-detached and end-row	1988	0.071	0.357	0.635	0.696
		(0.32)	(9.43)	(15.78)	
Mid-row	1088	0.589	0.336	0.617	0.709
		(1.66)	(8.61)	(10.61)	

Panel B: Performance of Combined Values						
House type	N	ME	MDE	MSE	MAE	PE25
All	6229					
Equal weights		-5.0	-4.0	6.0	18.4	73.8
Optimal weights		0.0	1.1	5.5	17.6	75.5
Detached	3140					
Equal weights		-3.2	-2.9	6.5	19.8	70.2
Optimal weights		0.0	0.3	6.3	19.6	71.1
Semi-detached and end-row	1988					
Equal weights		-1.9	-2.2	5.1	16.3	79.6
Optimal weights		0.0	-0.2	5.0	16.0	79.5
Mid-row	1088					
Equal weights		3.1	2.4	4.8	15.7	78.7
Optimal weights		0.0	-0.3	4.6	15.1	80.7

Notes: Panel A reports the results of the fitted regression $\ln P = \beta_0 + \beta_1 \ln C + \beta_2 \ln S + \varepsilon$. P is the transaction price, C the cost and S the sales comparison value. Valuations are trend-adjusted. N is the number of observations. t-Statistics are reported in parentheses and are calculated with heteroskedasticity-robust standard errors. The performance measures in Panel B are reported in percent. Valuation errors are computed as $e = \ln P - \ln V$, where V is either the geometric average of C and S or the weighted geometric average computed with the optimal combination weights. 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 prediction errors no larger than 25% in absolute value.

Table 8: Unit root tests for log levels of real price and cost index series. Test allows for a trend change following the introduction of the European single market in 1993.

		First step				Second step	
		$\widehat{\beta}_1$	t-Stat.$(\widehat{\beta}_1)$	$\widehat{\beta}_2$	t-Stat.$(\widehat{\beta}_2)$	Lags K	t-Stat.$(\widehat{\rho})$
Real house price	Detached house	0.008	13.68	-0.019	-16.98	0	-3.06
	Semi-detached and end-row house	0.007	11.45	-0.014	-13.13	1	-2.30
	Mid-row house	0.006	11.08	-0.015	-14.08	5	-2.65
	All house types	0.007	12.64	-0.016	-15.04	0	-2.66
Real land cost		0.011	17.80	-0.025	-21.89	4	-2.97
Real construction cost		0.004	14.21	-0.007	-14.75	4	-2.34
Real replacement cost	Detached house	0.008	17.48	-0.017	-20.62	8	-1.38
	Semi-detached and end-row house	0.007	17.23	-0.015	-20.02	8	-1.50
	Mid-row house	0.006	16.95	-0.014	-19.45	8	-1.63
	All house types	0.007	17.34	-0.016	-20.27	8	-1.44

Notes: Dependent variable is the log of the respective series. Each series has 100 observations; 1993Q1 corresponds to observation 53. The first step regression of the Perron (1989) test procedure is $y_t = \beta_0 + \beta_1 t + \beta_2 DT_t + \tilde{y}_t$, where $DT_t = t - T_B$ if $t > T_B = 53$. The coefficient for the constant in the first step regression is not reported. The second step regression uses the residuals $\tilde{y}_t$ and fits $\Delta\tilde{y}_t = \rho\tilde{y}_{t-1} + \sum_{k=1}^{K} \phi_k \Delta\tilde{y}_{t-k} + \varepsilon_t$. Number of lags K is selected so that residuals behave like white noise. The critical values for the unit root test t-statistic are -4.49 (1%), -3.93 (5%), -3.65 (10%), see Perron and Vogelsang (1993, Table 1) with $\lambda = 0.5 \approx 53/100$.

Table 9: Unit tests for growth rates of real price and cost index series. Test allows for a mean change following the introduction of the European single market in 1993.

		First step				Second step	
		$\widehat{\beta}_0$	t-Stat.($\widehat{\beta}_0$)	$\widehat{\beta}_1$	t-Stat.($\widehat{\beta}_1$)	Lags K	t-Stat.($\widehat{\rho}$)
Real house price	All house types	0.005	1.30	-0.015	-2.87	0	-12.04***
	Detached house	0.005	0.99	-0.017	-2.45	0	-11.89***
	Semi-detached and end-row house	0.005	0.97	-0.014	-1.87	0	-16.26***
	Mid-row house	0.005	0.91	-0.015	-1.92	3	-7.40***
Real land cost		0.009	2.52	-0.026	-5.14	4	-3.61**
Real construction cost		0.003	2.77	-0.007	-4.30	3	-2.78
Real replacement cost	All house types	0.006	3.03	-0.016	-5.61	7	-3.67**
	Detached house	0.006	2.95	-0.017	-5.54	7	-3.89**
	Semi-detached and end-row house	0.006	3.08	-0.015	-5.66	7	-3.51**
	Mid-row house	0.005	3.19	-0.014	-5.72	7	-3.16*

Notes: Dependent variable is the first log difference of the respective series. Each series has 99 observations; 1993Q1 corresponds to observation 52. The first step regression of the Perron (1990) test procedure is $y_t = \beta_0 + \beta_1 DU_t + \tilde{y}_t$, where DU_t is 1 if $t > T_B = 52$ and 0 else. The second step regression uses the residuals $\tilde{y}_t$ and fits $\Delta\tilde{y}_t = \rho\tilde{y}_{t-1} + \sum_{j=0}^{K} \omega_j DTB_t + \sum_{k=1}^{K} \phi_k \Delta\tilde{y}_{t-k} + \varepsilon_t$, where DTB_t is 1 if $t = T_B + 1$ and 0 else, see Perron and Vogelsang (1992). Number of lags K is selected so that residuals behave like white noise. The critical values for the unit root test t-statistic are -4.04 (1%,***), -3.38 (5%,**), -3.08 (10%,*), see Perron (1990, Table 4) with $T = 100$ and $\lambda = 0.5 \approx 52/99$.

Table 10: Tests for structural change of Q time series processes following the introduction of the European single market in 1993.

		Tests for Structural Change					
	Model	Chow-Stat.	P-Value	Wald-Stat.	P-Value	LM-Stat.	P-Value
All house types	AR(2)	4.38	0.223	10.44	0.015	7.20	0.066
Detached house	AR(2)	2.14	0.544	2.38	0.498	2.36	0.501
Semi-detached and end-row house	AR(2)	2.11	0.550	3.82	0.281	3.36	0.339
Mid-row house	AR(4)	8.83	0.066	5.91	0.206	5.15	0.272

Notes: All time series models include a constant. The null hypothesis is that the coefficients of the time series models are the same before and after 1993:1. For all but the mid-row house series, this leads to $r = 3$ coefficient restrictions. The model for the mid-row house series has one additional coefficient and $r = 4$ coefficient restrictions. The Chow-Statistics are computed as $r \times F$-Statistic, where the F-Statistic is for a test on the r coefficient restrictions, the Wald-Statistics are computed with heteroskedasticity-robust covariance matrices, and the LM-Statistics are computed with artificial regressions as proposed by MacKinnon (1989). All three statistic are asymptotically $\chi^2(r)$ distributed, reported P-Values for the test statistics are from the asymptotic distributions.

SFB 649 Discussion Paper Series 2008

For a complete list of Discussion Papers published by the SFB 649, please visit http://sfb649.wiwi.hu-berlin.de.

001 "Testing Monotonicity of Pricing Kernels" by Yuri Golubev, Wolfgang Härdle and Roman Timonfeev, January 2008.
002 "Adaptive pointwise estimation in time-inhomogeneous time-series models" by Pavel Cizek, Wolfgang Härdle and Vladimir Spokoiny, January 2008.
003 "The Bayesian Additive Classification Tree Applied to Credit Risk Modelling" by Junni L. Zhang and Wolfgang Härdle, January 2008.
004 "Independent Component Analysis Via Copula Techniques" by Ray-Bing Chen, Meihui Guo, Wolfgang Härdle and Shih-Feng Huang, January 2008.
005 "The Default Risk of Firms Examined with Smooth Support Vector Machines" by Wolfgang Härdle, Yuh-Jye Lee, Dorothea Schäfer and Yi-Ren Yeh, January 2008.
006 "Value-at-Risk and Expected Shortfall when there is long range dependence" by Wolfgang Härdle and Julius Mungo, Januray 2008.
007 "A Consistent Nonparametric Test for Causality in Quantile" by Kiho Jeong and Wolfgang Härdle, January 2008.
008 "Do Legal Standards Affect Ethical Concerns of Consumers?" by Dirk Engelmann and Dorothea Kübler, January 2008.
009 "Recursive Portfolio Selection with Decision Trees" by Anton Andriyashin, Wolfgang Härdle and Roman Timofeev, January 2008.
010 "Do Public Banks have a Competitive Advantage?" by Astrid Matthey, January 2008.
011 "Don't aim too high: the potential costs of high aspirations" by Astrid Matthey and Nadja Dwenger, January 2008.
012 "Visualizing exploratory factor analysis models" by Sigbert Klinke and Cornelia Wagner, January 2008.
013 "House Prices and Replacement Cost: A Micro-Level Analysis" by Rainer Schulz and Axel Werwatz, January 2008.

SFB 649, Spandauer Straße 1, D-10178 Berlin
http://sfb649.wiwi.hu-berlin.de

This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".