Bargain or Bust? Prices, Discounts, and Returns in the Market for Real Estate Foreclosures

Alexander Daminger Simon Wiersma

This draft: May 7, 2024

We examine foreclosure discounts and their subsequent impact on investor returns in Berlin's housing market from 1984 to 2022. Utilizing hedonic regression models and matching techniques on a data set of housing transactions, we determine that foreclosure discounts, ranging from 20% to 50%, are significant and persist over time. In a repeat sales approach, in which we explicitly account for the sequence of transactions, we show that initial investments in foreclosed properties yield average annualized returns surpassing matched non-distressed counterparts by 20.5 percentage points. However, when a foreclosure follows a regular sale, the average annualized returns are 9.6 percentage points lower than in matched non-distressed transaction pairs. Novel to the literature, we further show that this markdown is only associated with the foreclosure transaction, rather than putting a permanent stigma on the foreclosed apartment. Our ability to control for both observed and unobserved property characteristics suggests that this discount may be attributed to both a foreclosure stigma and the format used for foreclosure auctions in Germany. Consequently, our paper not only advances the foreclosure literature with new insights from a global city but also contributes to the discourse on auctions in a real estate context.

Keywords: Foreclosure Discounts, Real Estate Investments, Housing Market Dynamics
JEL Codes: R31, G12, D44

Alexander Daminger: Austrian Institute of Economic Research (WIFO), Arsenal Object 20, 1030 Vienna, Austria (e-mail: alexander.daminger@wifo.ac.at); Simon Wiersma: IRE|BS International Real Estate Business School, University of Regensburg, Universitaetsstrasse 31, 93040 Regensburg, Germany (e-mail: simon.wiersma@irebs.de). Much appreciated are the stimulating comments by Kristof Dascher, Tobias Just, and Hannah Salzberger. We are grateful to the Expert Committee for Property Values in Berlin (*Gutachterausschuss für Grundstueckswerte in Berlin*) for providing us with data on property transactions.

1. Introduction

Homeowners who experience residential foreclosure face severe financial and personal consequences. These include housing instability, reduced homeownership, financial distress (Diamond, Guren, and Tan 2020), and adverse health effects (Currie and Tekin 2015). They lose their property and, if they are owner-occupiers, have to relocate, but they also pay off their outstanding debts by liquidating their asset, and receive any surplus after satisfying the creditors. However, previous studies strongly suggest that foreclosed properties tend to sell at lower prices than similar, non-distressed properties in the same market. This phenomenon is known as the foreclosure discount.

The literature offers two main reasons for the existence of foreclosure discounts. One is that the discount reflects the actual lower quality of distressed properties compared to similar non-distressed properties, due to physical deterioration or neglect. This is called the "proxy effect". The other is that the discount is driven by a foreclosure stigma — the mere perception that distressed properties are in worse condition than comparable non-distressed ones, regardless of their actual condition. This is referred to as the "stigma effect" (Zhou et al. 2015). To separate the two effects, empirical models usually employ hedonic regressions that control for observable property attributes such as location, amenities, and condition when comparing foreclosure transactions to regular sales. This way, researchers try to eliminate the proxy effect arising from fundamental property characteristics, and isolate the foreclosure stigma effect.

The existence of foreclosure stigma discounts in the housing market suggests that buyers can exploit profit opportunities based on the property's type of sale. However, the magnitude and reality of these opportunities are contested in the literature. On one hand, several papers in different regions and market settings report large discounts for foreclosure transactions of more than 20% (e.g., Campbell, Giglio, and Pathak (2011); Donner, Song, and Wilhelmsson (2016); Just et al. (2019)). On the other hand, Harding, Rosenblatt, and Yao (2012) show, using a sample of repeat sales in US metropolitan areas, that, on average, the market discount for foreclosure transactions is less than typical transaction costs.

However, most of the studies in the foreclosure literature are not able to observe differences between distressed and non-distressed properties beyond what is recorded as property characteristics in the data. But these unobserved property characteristics (e.g., the condition or whether the property is vacant or not) are likely correlated with foreclosures and prices, thus the reported discounts are not causal but rather conditional correlations.

Recent work has tried to move in the direction of estimating the causal impact of foreclosures. Conklin, Coulson, and Diop (2023), for example, argue that the large discounts reported in other studies are likely due to omitted variable bias in the (mostly) hedonic estimates. Using a novel approach and a comprehensive data set for the entire United States, they find only a small – and thus economically negligible – foreclosure discount of 5%. In summary, although there is a vast amount of evidence on foreclosure discounts, the literature still seems to dispute whether these discounts actually exist, how large they are and what "caused" them.

Hence, this paper provides complementary evidence from a previously understudied real estate market with a distinct setting of foreclosure procedures. We analyze how foreclosure discounts in the housing market affect property appreciation rates, and how the appreciation rates of foreclosed properties compare to those on similar non-foreclosure properties. By estimating hedonic regressions and applying matching techniques to a comprehensive data set of housing transactions in Berlin since 1984, we, first, aim to identify the size of foreclosure discounts and evaluate their economic significance, ultimately advancing the understanding of the long-term dynamics of foreclosure discounts and their implications for investors and delinquent homeowners. Second, although one could think that with eliminating the "proxy effect" by controlling for property characteristics the "stigma effect" should best explain these discounts, we explicitly point to the transaction format, i.e., the auction procedure, that may also have a strong impact on the size of these discounts.

Our empirical strategy has two components: First, we use conventional cross-sectional hedonic analyses in line with the literature to estimate the magnitude of foreclosure discounts in the Berlin housing market. Second, we use matching techniques to create pairs of apartment repeat sales. Following a multi-arm trial design, we further disentangle foreclosure effects by the position of the distressed sale in the sequence of sales. Our first “treatment” arm involves a repeat sale with the foreclosure transaction first, followed by a regular sale later. Our second “treatment” arm is the transaction sequence most commonly referred to as a distressed repeat sale, characterized by a regular sale followed by a foreclosure transaction in subsequent years. Regardless of the “treatment” arm, the matched non-distressed repeat sale (the “control”) involves an apartment sold under regular circumstances on both occasions. Following the methodology of Harding, Rosenblatt, and Yao (2012), who show "implied market discounts" through comparisons of holding period returns proxied by appreciation rates, we compare the appreciation rates of distressed apartments in both "treatments" with that of non-distressed apartments.

Our results consistently point towards the presence of considerable discounts on foreclosed properties in the Berlin housing market. Firstly, in our analysis using hedonic dummy frameworks, we estimate foreclosure discounts of between 50% in the years before the onset of the financial crisis in 2008/2009 and around 20% in the most recent years of our sample. These discounts exceed the size of discounts usually reported in the foreclosure and distressed sale literature.

Secondly, we show that foreclosed properties appreciated more than comparable non-distressed properties throughout our entire observation period. Comparing appreciation rates using a matched control group, we show that for a repeat sale, where the first transaction is a foreclosure transaction followed by a regular sale, the average annualized appreciation rate surpasses that of a matched non-distressed property with similar housing and investment features (e.g., the holding period) by 20.5 percentage points. We interpret this estimate as the average excess profit over a comparable investment an investor obtains from the property being foreclosed. In the second treatment arm (regular sale followed by foreclosure transaction), our results suggest that the annualized appreciation rate is, on average, 9.6 percentage points lower than that of a matched non-distressed property. We interpret this estimate as the average markdown of a distressed homeowner's annualized asset appreciation, attributable to the property being foreclosed. However, we also show that this markdown in appreciation vanishes in following transactions, indicating that the foreclosure discount is temporary and associated with the *transaction*, rather than permanent and associated with the *property*.

Our paper aims to contribute to two distinct strands of the literature. First, we address the literature that studies the price differentials between distressed and non-distressed properties in the housing market. Using a comprehensive and verified administrative data set that covers four decades of housing transactions in Berlin, we estimate the foreclosure discounts in the urban context of a global city. This relates to both the traditional literature that uses hedonic frameworks to estimate foreclosure discounts (e.g., Shilling, Benjamin, and Sirmans 1990; Forgey, Rutherford, and VanBuskirk 1994; Hardin and Wolverton 1996; Springer 1996; Carroll, Clauretie, and Neill 1997) and the more recent papers that apply other methods or more representative data sets (e.g., Clauretie and Daneshvary 2009; Campbell, Giglio, and Pathak 2011; Donner, Song, and Wilhelmsson 2016; Donner 2017; Biswas, Fout, and Pennington-Cross 2023; Conklin, Coulson, and Diop 2023).

Building upon the empirical framework introduced by Harding, Rosenblatt, and Yao (2012), who studied investment returns by analyzing matched pairs of repeat housing sales, we scrutinize the price appreciation of distressed properties in comparison to their non-distressed counterparts within these transactions. However, we refine this approach through considerations of whether the foreclosure event occurred in the first or the second transaction of a repeat sale. This nuanced methodology enables us to examine a broader scope of cases, extending beyond the conventional focus on foreclosure "investments", and includes scenarios involving distressed homeowners who incur losses due to foreclosure. This distinction provides novel insights into not only the potential gains but also the potential losses in foreclosure transactions.

Both our empirical approaches document discounts for foreclosed properties in Berlin's context, consistent with most papers in this field. However, to explain the quantitative difference from other foreclosure discount estimates, we hypothesize that a potentially crucial mechanism lies in the way foreclosures are resolved in Germany. As distressed properties are transacted in public, open-bid English auctions, we argue that the distinct auction format that is characterized by the threat of collusion, entry deterrence and predation (Klemperer 2002a) might contribute to the discounts witnessed in Berlin. Consequently, our work also informs the literature interested in auctions in a real estate context as, e.g., Ashenfelter and Genesove (1992); Quan (1994); Mayer (1995); Lusht (1996); Dotzour, Moorhead, and Winkler (1998); Chow, Hafalir, and Yavas (2015); Gunnelin et al. (2023); Niedermayer, Shneyerov, and Xu (2023).

We proceed as follows: Section 2 introduces the institutional and legal framework for real estate foreclosures in Germany. Section 3 describes our transaction data. Sections 4 and 5 turn to the empirical analysis, which provides hedonic estimates of the foreclosure discounts, and identifies the difference in appreciation between distressed and similar non-distressed properties utilizing matched repeat sales. Section 6 provides a discussion of the results and the methodology. Section 7 concludes and provides some policy implications.

2. Background

The German foreclosure law, as outlined in the Act on Enforced Auction and Receivership (*Gesetz über die Zwangsversteigerung und die Zwangsverwaltung (ZVG)),* enables creditors to satisfy their outstanding claims through enforcement proceedings. Foreclosure procedures can only be initiated at the request of a qualified creditor when a debtor defaults on a mortgage contract. Upon the commencement of the procedure, the property of the defaulting owner is seized, limiting their ability to dispose of it freely. State-certified appraisers then prepare a market value assessment in compliance with statutory guidelines.

The period between the procedure's initiation and the auction can range from several months to years, depending on factors such as the proceeding's complexity and the county court's workload. The auction date is publicly announced in the official gazette and on the court's website. Recently, specialized real estate portals have been developed to aggregate and simplify access to information on foreclosure auctions nationwide.

There are a variety of formats for how auctions can be conducted, and most of them are also used in the real estate setting. The literature delineates four principal auction types, each characterized by unique mechanisms pertaining to the timing of bids and the payment obligations of the winning bidder: (i) first-price, sealed-bid auctions; (ii) second-price, sealed-bid auctions, also known as the Vickrey auction; (iii) Dutch auctions, involving descending bids; and (iv) English auctions, which feature ascending bids.

In first-price, sealed-bid auctions, bidders submit their bids simultaneously and without knowledge of the others' bids. The highest bidder is awarded the item and is required to pay the submitted bid amount. Conversely, in the second-price, sealed-bid auction, while bids are also made simultaneously and confidentially, the highest bidder wins but only pays an amount equivalent to the second-highest bid. The Dutch auction is distinguished by its descending-bid process wherein the auctioneer introduces the item with a high starting price and then progressively lowers it until a bidder accepts the current price. English auctions, on the other hand, commence either at an opening bid or a reservation price, with bidders sequentially increasing their bids. The auction concludes when no further bids are offered, the last and highest bidder winning at their bid price (Baye and Prince 2022).

In Germany, the foreclosure auction model is a variant of the English Auction, the open outcry auction, where bidders vocally announce their bids.[1] However, the auction's bidding amounts are governed by three restrictions. The minimum bid restriction requires that the auction proceeds can cover all rights taking precedence over the claims of the applicant creditors and the procedural costs. The 5/10 limit restriction mandates that the final highest bid must be at least half of the appraised market value.

[1]This is unlike alternative approaches, such as the Japanese auction, where the price is incrementally raised as bidders hold down buttons until deciding to opt out (Azasu 2006).

The 7/10 limit restriction generally grants a lower-ranking creditor the right to reject the highest bid if his claim is not or only partially covered, but would be covered by a bid of 7/10 of the appraised market value. These thresholds may lead to the highest bid being rejected and a new auction date being scheduled. The 5/10 and 7/10 limits apply only to the first auction date.

On any auction date, the highest-ranking creditor has the right to halt the proceedings by filing an application for discontinuation. If the bid limits have been met and the foreclosure application is still active, the highest bid is accepted at the end of the auction. From this date, all remaining encumbrances and usage rights are transferred to the highest bidder. However, the entry in the land register can only be made several months later, after asset distribution, the award decision becoming legally binding, and the property transfer tax being paid. Until this entry is made, a foreclosure investor is unable to resell the property.

In the United States, creditors often bid on defaulted properties, which, if successful, become part of their real estate owned (REO) inventory. The bank's resale of a REO constitutes a post-foreclosure auction transaction, potentially subject to the foreclosure stigma, as noted by several authors (e.g., Zhou et al. (2015)). In contrast, German creditors generally do not participate in foreclosure auctions, which prevents the inclusion of foreclosures in their REO inventory. This difference between the German and US systems results in any foreclosure discount measured in this paper – and thus maybe differing from papers examining US data – being a discount associated with the foreclosure *auction*, rather than a discount in a post-foreclosure transaction, like a REO sale.

3. Data

Our data set covers all residential property transactions in Berlin from 1984 to 2022.[2] These records are maintained by the city's appraiser committee, which is part of the Senate Administration for Urban Development, Building, and Housing. As notaries are legally obliged to submit every notarized property purchase contract to local appraisers, the database is guaranteed to contain all sales for the given period. The data set includes information such as transaction prices and types, property characteristics, and location details. In total, and before we clean the raw data from incomplete, inconsistent, or

[2] For East Berlin, which used to be the territory of the German Democratic Republic (GDR), we only have transaction data from 1993 onward.

irrelevant transactions as described below, we observe 539,179 property transactions.

Data cleaning. Our goal is to construct a data set consisting of "common" real estate transactions, specifically those involving the sale of a single residential property from a sole seller to a sole buyer. Therefore, we exclude any transactions classified as special sales cases, such as package sales involving multiple properties.[3] Moreover, we eliminate observations with missing information regarding property type (e.g., whether the property is a house or a condo) or other property characteristics (e.g., floor space or number of rooms). We also exclude properties that are not freely tradable in the market, such as active social or public housing units.

In addition, although our data includes transactions involving one- and two-family houses, we focus exclusively on transactions involving apartments in multifamily houses. This decision is motivated by two factors: firstly, in the urban context of Berlin, one- and two-family houses constitute a relatively small proportion of all housing transactions; secondly, real estate investors typically do not target one- and two-family houses as their main investment class.[4]

Furthermore, we restrict our analysis to observations where the contract type indicates either a regular sale or a foreclosure transaction, disregarding transactions labeled as expropriation, exchange, private auction, and similar categories. This filtering process results in a data set comprising a total of 394,842 transactions.

Finally, to eliminate outliers characterized by atypical sales prices or housing attributes, we retain only apartments with sale prices ranging from € 10,000 to € 1,000,000, recorded floor spaces ranging from $15\,\mathrm{m}^2$ to $300\,\mathrm{m}^2$, and a maximum of 10 rooms. Consequently, our final data set encompasses 391,420 observations.

Descriptive statistics. Table 1 shows the descriptive statistics of our sample of housing transactions, which consists of 11,137 foreclosure transactions and 380,283 regular sales. Foreclosed transactions account for 2.8 percent of the total sample and have significantly lower average transaction prices than regular sales. Furthermore, there are notable differences in most of the apartment and transaction characteristics between the two groups of sales. For instance, foreclosure transactions are more concentrated in the 2000s, with 24% and 29.6% of them occurring in the periods 2001–2005 and 2006–2010,

[3] It is important to note that our definition of "common" transactions encompasses foreclosure transactions as well.

[4] Only a small share of 3.3% of total transactions in the data were transactions of one- and two-family houses.

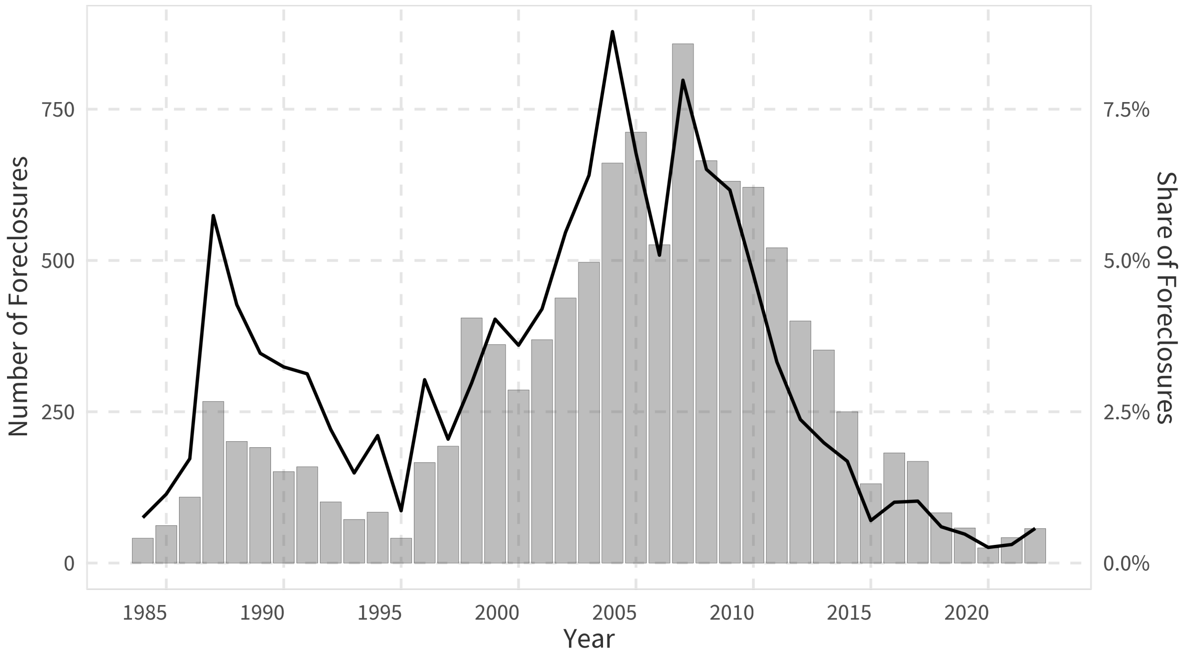


FIGURE 1. Foreclosure incidence over time

This figure plots the foreclosure incidence in in Berlin over time. The bars in grey display the (absolute) number of foreclosures in each year (left axis), while the solid line displays the share of foreclosure transactions in all apartment transactions in Berlin over time (right axis). Sources: Expert Commitee for Property Values in Berlin; authors' calculations.

respectively. In contrast, regular sales are more prevalent in the later years of the housing boom from 2011 to 2022. Figure 1 shows that the share of foreclosures in all apartment transactions in a given year is highest in 2004 (8.8 percent) and 2007 (7.9 percent). Between 2002 and 2009, the share of foreclosures in all apartment transactions was persistently above 5 percent. This distribution of foreclosures over time contrasts with the US experience, where foreclosures rose after the collapse of Lehman Brothers in 2008. It seems that in Berlin, distressed apartment transactions peaked already before this event. However, the two groups of sales do not differ much in terms of the location quality, the type of the apartment, and the floor level it is located on, as indicated by the similar proportions of transactions in each category.

Geography of Foreclosures. Figure 2 depicts the spatial distribution of foreclosures in Berlin's 194 zip codes, accumulated over the period from 1984 to 2022. Figure 2A displays the absolute number of foreclosures, while Figure 2B shows the share of foreclosures in all apartment transactions for each zip code. These maps reveal two main insights:

TABLE 1. Descriptive Statistics of Transactions

		Regular (N=380,283)		Foreclosure (N=11,137)			
		Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Transaction price (EUR)		171,693.05	150,099.38	65,253.28	62,187.13	-106,439.78	<0.001
Age of building (years)		59.86	40.40	68.24	35.29	8.37	<0.001
Number of rooms		2.48	1.03	2.33	0.99	-0.15	<0.001
Floor space (sqm)		71.36	30.62	66.42	27.53	-4.94	<0.001
Bathroom (dummy)		0.92	0.27	0.90	0.30	-0.02	<0.001
Separate WC (dummy)		0.14	0.35	0.12	0.32	-0.02	<0.001
Balcony (dummy)		0.48	0.50	0.41	0.49	-0.07	<0.001
Attic (dummy)		0.01	0.10	0.01	0.12	0.00	<0.001
Basement (dummy)		0.74	0.44	0.70	0.46	-0.04	<0.001
Atelier (dummy)		0.00	0.02	0.00	0.03	0.00	0.463
Hobby room (dummy)		0.01	0.10	0.01	0.11	0.00	0.101
Storage room (dummy)		0.57	0.49	0.57	0.50	0.00	0.432
Hallway (dummy)		0.19	0.39	0.16	0.36	-0.03	<0.001
Corridor (dummy)		0.84	0.36	0.88	0.33	0.03	<0.001
Elevator (dummy)		0.37	0.48	0.24	0.43	-0.13	<0.001
Private garage (dummy)		0.23	0.42	0.22	0.41	-0.01	0.177
Collective garage (dummy)		0.02	0.13	0.01	0.10	-0.01	<0.001
Parking lot (dummy)		0.06	0.23	0.05	0.23	0.00	0.106
		N	Pct.	N	Pct.		
Sale Period	1984-1990	36,751	9.7	1,022	9.2		
	1991–1995	23,233	6.1	457	4.1		
	1996–2000	45,433	11.9	1,411	12.7		
	2001–2005	42,595	11.2	2,677	24.0		
	2006–2010	54,586	14.4	3,301	29.6		
	2011–2015	83,773	22.0	1,654	14.9		
	2016–2022	93,912	24.7	615	5.5		
Location quality	Basic	151,967	40.0	5,163	46.4		
	Good	90,955	23.9	2,659	23.9		
	Intermediate	127,912	33.6	3,091	27.8		
	Very Good	9,449	2.5	224	2.0		
Type of Apartment	Attic Apartment	23,059	6.1	670	6.0		
	Duplex Apartment	9,188	2.4	227	2.0		
	Floor Apartment	346,025	91.0	10,184	91.4		
	Loft	592	0.2	4	0.0		
	Penthouse	658	0.2	3	0.0		
	Storefront Apartment	353	0.1	41	0.4		
	Terrace Apartment	408	0.1	8	0.1		
Floor level	Basement floor	1,331	0.4	58	0.5		
	First floor	66,242	17.4	2,431	21.8		
	Mezzanine floor	3,904	1.0	112	1.0		
	Upper floors	308,806	81.2	8,536	76.6		

The table reports descriptive statistics on the cleaned sample of housing transactions in Berlin from 1984 to 2022. Sources: Expert Commitee for Property Values in Berlin; authors' calculations.

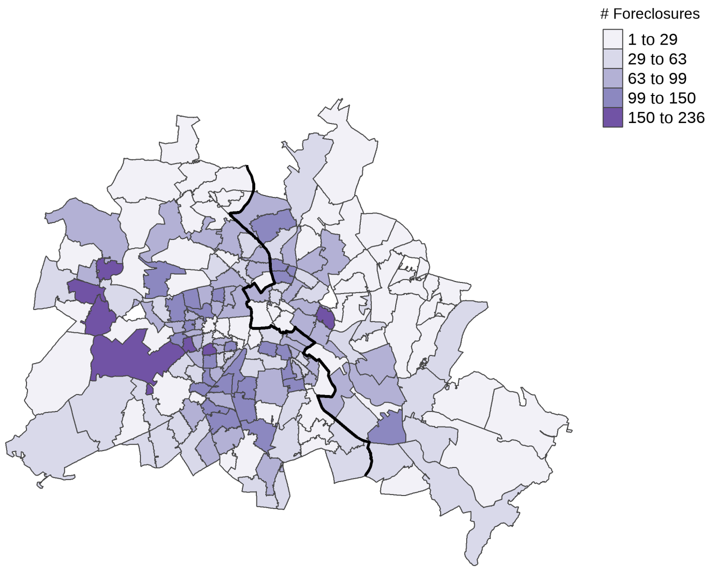
first, zip codes with more than 150 accumulated foreclosures are sparse and are mostly situated in the western part of the city. One might assume that this is because we only have transaction data for the eastern part of Berlin since 1993. However, we verified this potential issue and found that even when we restrict our analysis to transactions post-1992, the western zip codes still have more foreclosures than the eastern ones. We also provide a map that illustrates the share of foreclosure transactions in all apartment transactions (again accumulated from 1984 to 2022), as high numbers of foreclosures could simply reflect a higher transaction volume in these zip codes in general. Figure 2B demonstrates that the share of foreclosures in all apartment transactions is highest outside the central zip codes, but there is no clear pattern between East and West Berlin. We infer that foreclosure transactions are spatially dispersed over Berlin and there is no evident spatial clustering of foreclosure transactions in certain zip codes or parts of the city.

Market participants in foreclosures. We assume that the parties involved in the foreclosure process are distressed owners who auction their apartments and specialized real estate investors who buy these foreclosures, rather than other potential owners. We test this assumption with information about the legal entity of the participants in these transactions, i.e., whether they are private persons or corporations. The data show that more than 90% of sellers of foreclosed apartments are private persons, while the rest are corporations. Thus, most of those who foreclose their home are private homeowners.[5] On the buyer side, the data show that 2/3 of buyers of foreclosed apartments are private persons, and 1/3 are corporations. This may seem to contradict our assumption that specialized investors, who might naturally act as corporations, target foreclosures to buy. However, we note that these investors may not be necessarily incorporated, and that it is unlikely that 2/3 of buyers of foreclosed apartments are prospective owner-occupiers or landlords. It is more likely that a non-negligible share of these private persons are also “investors” who buy/sell speculatively, even if they do not act in the form of the legal entity of a corporation.

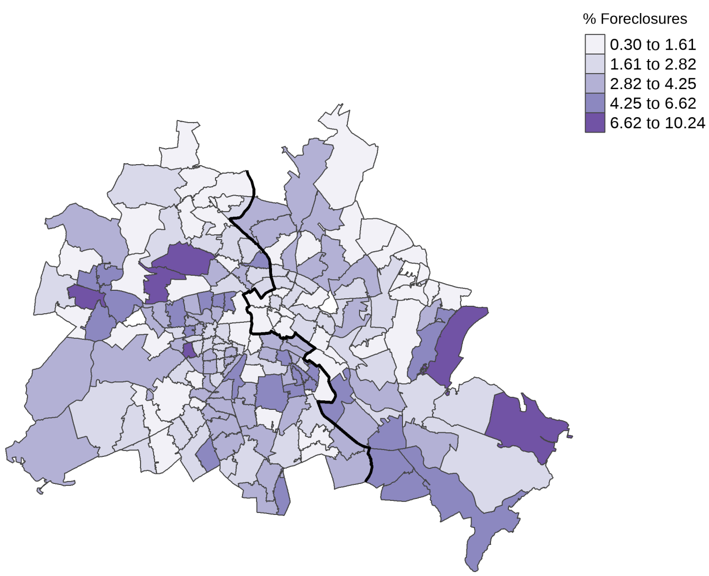
4. Empirical Strategy

To model the impact of the foreclosure status on prices and appreciation rates, we will apply two empirical approaches that complement each other by balancing their strengths

[5] However, we do not know whether they are owner-occupiers or landlords.



A. Number of foreclosures



B. Share of foreclosures

FIGURE 2. Number and share of foreclosures by zip code, 1984–2022

This figure shows the spatial distribution of foreclosures in Berlin by zip code, cumulated over the period from 1984 to 2022. It consists of two maps: Figure 2A displays the absolute number of foreclosures, and Figure 2B displays the share of foreclosures in all apartment transactions. We use the Jenks natural breaks classification method to determine the optimal arrangement of values into classes. This method minimizes the average deviation from the class mean within each class, while maximizing the deviation from the means of other classes. The maps use a color gradient where darker purple indicates a higher number of foreclosures/ a higher share of foreclosures. The black solid line approximates the course of the Wall between East and West Berlin before reunification. Sources: Expert Commitee for Property Values in Berlin; Berlin-Brandenburg Statistics Office; authors' calculations.

and weaknesses. First, we will use hedonic dummy models with cross-sectional data to estimate foreclosure discounts and document the price differential between foreclosed and non-foreclosed properties. The advantage of this approach is that it can draw on a comprehensive and representative sample of housing transactions, including both new and existing units. However, its limitation is that it cannot control for unobservable factors.

Second, we will use a sample of repeat sales to examine the price appreciation differential of foreclosed and non-foreclosed properties, and thus the differential in investment returns. This approach accounts for both observable and unobservable characteristics of housing units, but it is constrained by its dependence on a subset of transacting units, which may introduce a sample bias.

4.1. Identification of the foreclosure discount in prices

To estimate the difference in transaction prices between distressed and non-distressed properties – the foreclosure discount – in the Berlin housing market, we follow the literature on distressed housing sales and use hedonic models that include a foreclosure dummy in the regression. Our baseline model, adapted from Campbell, Giglio, and Pathak (2011), is:

$$y_{izt} = \alpha_{zt} + \beta F_i + \gamma X_i + \epsilon_{izt} \tag{1}$$

where y_{izt} is the log price of an apartment transaction i in zip code z in year t, F_i is a binary variable that equals one if the transaction i is a foreclosed sale and zero otherwise, X_i is a vector of apartment characteristics, and ϵ_{izt} is an error term that captures random shocks to apartment prices. We also include zip code-year fixed effects α_{zt} to control for time-varying differences in apartment prices across zip codes. In this model, the average time-invariant foreclosure discount can be read off the estimated coefficient $\hat{\beta}$.

Our data set allows us to control for a rich set of apartment characteristics. The vector X_i includes the log of the floor space in square meters, the number of rooms, and the age of the building and its quadratic term to capture a non-linear effect of age on the apartment price. Moreover, we include dummy variables that indicate whether the apartment has certain features or not.[6]

[6]These features are: a bathroom, a separate WC, a balcony, an attic, a basement, a hobby room, a

To examine how the foreclosure discount changes over time, we extend our baseline model by adding an interaction term between the foreclosure indicator F_i and a set of year fixed effects. This allows us to estimate a "dynamic", time-varying foreclosure discount. Our extended model is:

$$y_{izt} = \alpha_{zt} + \beta F_i + \sum_{t=1985}^{2022} \delta_t F_i \times Y_t + \gamma X_i + \epsilon_{izt} \tag{2}$$

where Y_t is a vector of year fixed effects with the first year of our data set (1984) omitted, and δ_t is a vector of coefficients that capture the variation in the foreclosure discount across different years. The remaining variables match those specified in Equation 1. We use OLS to estimate both our models and cluster the standard errors at the zip code level. We can calculate the foreclosure discount in percent by applying the following formulas to the estimated coefficients of Equations 1 and 2: the static foreclosure discount is $e^{\hat{\beta}} - 1$, while the dynamic foreclosure discounts are $e^{\hat{\beta}+\hat{\delta}_t} - 1$.

To infer a causal effect of the foreclosure status on apartment prices, we would need to ensure that the foreclosure indicator F_i in our regressions is uncorrelated with unobserved hedonic characteristics. We do not have a way to rule out the existence of such confounding factors in our setting. Therefore, our results should be interpreted as correlations. We thus can answer the question whether foreclosed apartments sold at a lower price, but not whether the foreclosure status *caused* this price difference.

4.2. Identification of the foreclosure discount in appreciation rates

To calculate appreciation rates, we extract repeat sales from our data. To address the lack of a direct identifier indicating whether an apartment is sold twice or more, we adopt an approach that aims to identify repeat sales based on observable characteristics. More specifically, we use the combination of the exact geo-coordinates to identify the building in which the apartment is located and the individual ID of the apartment in the registered partition plan of the building, which allows apartments to be unambiguously identified within a building.

Additionally, we enforce a condition that ensures that apartment characteristics (e.g., the floor space, the number of rooms, whether there is a separate bathroom, a balcony, or parking lot) remain consistent across all identified repeat sales transactions.

storage room, a hallway, a corridor, an elevator, a private garage, a collective garage, or a private spot in a parking lot. We also control for the location quality of the apartment, the type of apartment, and the floor level it is located on. See Table 1 for an overview of these variables.

This criterion serves two essential purposes: firstly, it enhances the confidence that the transactions pertain to the same apartment, and secondly, it prevents us from including apartments that have undergone substantial renovations or modifications between transactions.

We derive our sample of repeat sales as follows: We start by observing an apartment, denoted as i, sold at time t with a recorded transaction price of p_{it}. If we subsequently observe apartment i for a second time at time $t+1$, with a recorded transaction price of p_{it+1}, these two observations constitute a repeat sale. As a result, we obtain two observed sales for the same apartment, which enables us to calculate the appreciation rates or (gross) returns over the holding period.[7] To standardize these appreciation rates relative to the holding period, we compute an annualized appreciation rate for each of our repeat sales.[8] For holding periods of less than one year, we round them up to one year.[9] Additionally, we exclude all repeat sales that consist of two foreclosures transactions. To exclude extreme annualized returns that are likely unrepresentative, we discard all repeat sales with an annualized appreciation rate exceeding the sample value at the 99th percentile.

"Treatments". Doerner and Leventis (2015) as well as Donner (2017) show that distressed price discounts in repeat sales, and thus also investment returns, crucially depend on whether the distressed sale is the first or second transaction in a repeat sale. We therefore create two "treatment" groups and one control group to assess the poten-

[7]The returns are gross returns, as they do not consider transaction costs. In the case of Berlin, regular sales and foreclosure transactions are subject to certain costs. For regular sales, a property transfer tax of 6% and registry costs of approximately 0.4% (based on § 3 Abs. 2 *Gerichts- und Notarkostengesetz*) need to be paid. Additionally, notary fees of approximately 1.0% (based on § 3 Abs. 2 *Gerichts- und Notarkostengesetz*) are applied. On the other hand, foreclosures incur surcharge fees of approximately 1.1% by the court (based on § 34 *Gerichtskostengesetz*). It is important to note that these costs are in addition to the purchase price. Ultimately, the total additional purchase costs for both transaction types are quite similar. For foreclosures, the total additional costs amount to 7.5% of the sales price, while for regular sales, the corresponding figure is 7.4% (based on an illustrative transaction price of € 100,000).

[8]More specifically, we calculate the annualized appreciation rate as $\left(\frac{p_{it+1}}{p_{it}}\right)^{\frac{1}{t}} - 1$. To determine the difference in years between dates t and $t+1$, we use weeks as the unit of measurement and divide the number of weeks between t and $t+1$ by 52.25.

[9]Note that annualized appreciation rates increase exponentially with shorter holding periods. For instance, an apartment purchased for € 100,000 and resold for € 150,000 after 90 days would yield an annualized appreciation rate or gross return of 418%, whereas the same apartment with a holding duration of one year would have an appreciation of only 50%. We argue that large returns generated due to very short holding periods are economically irrelevant, as high turnovers are difficult for real estate – subsequent to a property sale after 90 days, an investor is unlikely to find a similarly performing property the very next day. Therefore, we round up holding periods of less than one year to one full year in our calculations.

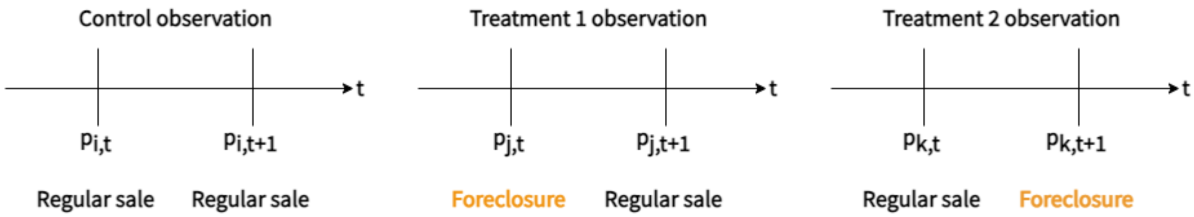


FIGURE 3. Repeat sales of different apartments and assignment to treatment arms

This graph visualizes the way we (i) derive repeat sales from our data set of individual sales and (ii) assign these repeat sales (that consist of two individual sales of the same apartment i, j, or k) to treatment arms. We also allow for $i = j = k$ if we observe apartment i in more than two transactions. The treatment and control groups defined in this way are the starting point for our matching approach. Sources: Authors' illustration.

tial returns and losses associated with foreclosure transactions.[10] Figure 3 illustrates the procedure. Treatment arm 1 includes apartments acquired through foreclosure auctions in the first transaction and subsequently sold on the open market as a regular sale in the second transaction, comprising a total of 4,745 observations. Our hypothesis is that foreclosure investors, leveraging their market knowledge, deliberately target distressed properties due to the availability of discounts. We presume these investors to resell the apartments quickly, aiming to generate capital returns rather than relying on the rental yields typically associated with long-term property holders. With our setup, we aim to investigate whether the returns derived from these transactions surpass the standard market returns observed in the control group.

Treatment arm 2, on the other hand, consists of a reverse sequence of sales, where apartments are initially purchased on the open market as a regular sale and subsequently transacted as foreclosure. We have a total of 5,459 repeat sales with this sequence of transactions. This scenario implies that a mortgage delinquency is resolved through a foreclosure auction. We hypothesize that individuals with delinquent mortgage debt may not achieve market prices for their properties and consequently incur losses, potentially due to foreclosure stigmatization and unfavorable auction processes. We therefore expect the returns over the holding periods for this group to be lower than those observed in the control group.

To summarize, we have 10,204 repeat sales in the two treatment arms. Since we allow each repeat sale to come from apartments that we observe more than twice during our observation period, our treatment observations in both arms can be linked

[10]Although we use the term "treatment", we note that our use of the term might deviate from uses in other context, e.g., we do not claim the foreclosure status to be exogenously or randomly assigned to apartment transactions.

to transactions involving 7,785 unique apartments. Of these, 71% generate only one repeat sale in one of the treatment arms, and the remainder generate two or more.

The pool of control observations comprises 100,472 repeat sales that consists of transactions involving two regular sales conducted on the open market. These observations serve as the counterfactual outcome, representing the returns that would have been realized if the transactions had not involved foreclosures in either the first or second transaction.

Matching. Apartment as well as transaction characteristics differ across repeat sales and groups, rendering results from naive comparisons of mean group outcomes untrustworthy. As we aim to estimate the effect of foreclosure on the appreciation rates of repeat sale transactions, we have to infer what the hypothetical appreciation rates of "the same" repeat sales without any foreclosure would have been. We therefore construct a counterfactual scenario, using a repeat sale from our pool of control transactions that matches the treated repeat sale as closely as possible. To do so, we employ nearest neighbor matching, a technique that identifies similar units based on covariates that are relevant for the treatment assignment, i.e., the presence of a foreclosure in either the first (Treatment 1) or the second (Treatment 2) transaction of a repeat sale. We compare two alternative distance metrics for matching: propensity score and Mahalanobis distance. The key difference between them is that the propensity score reduces the multidimensional covariate space to a single dimension, while the Mahalanobis distance preserves the original covariate space. This means that units matched by the propensity score may not have comparable values on each covariate, whereas units matched by the Mahalanobis distance will tend to have more balanced values on every covariate (Rosenbaum 2020).

However, achieving exact or near-exact matching on individual housing characteristics is crucial for ensuring the validity of our counterfactual scenario. We therefore opt for the Mahalanobis distance to ensure that our treatment and control repeat sales are highly similar regarding each of the matching variables that we introduce shortly.[11]

Our matching approach relies on a vector of six variables: We match on three housing attributes (apartment size; age; and the number of rooms), two temporal variables (the holding period of the apartment, i.e., the number of years between the two transactions of the repeat sale, and the date of the second transaction, i.e., when the profit is realized),

[11] There are also other arguments advising against the use of propensity scores for matching in observational studies, see, e.g., King and Nielsen (2019).

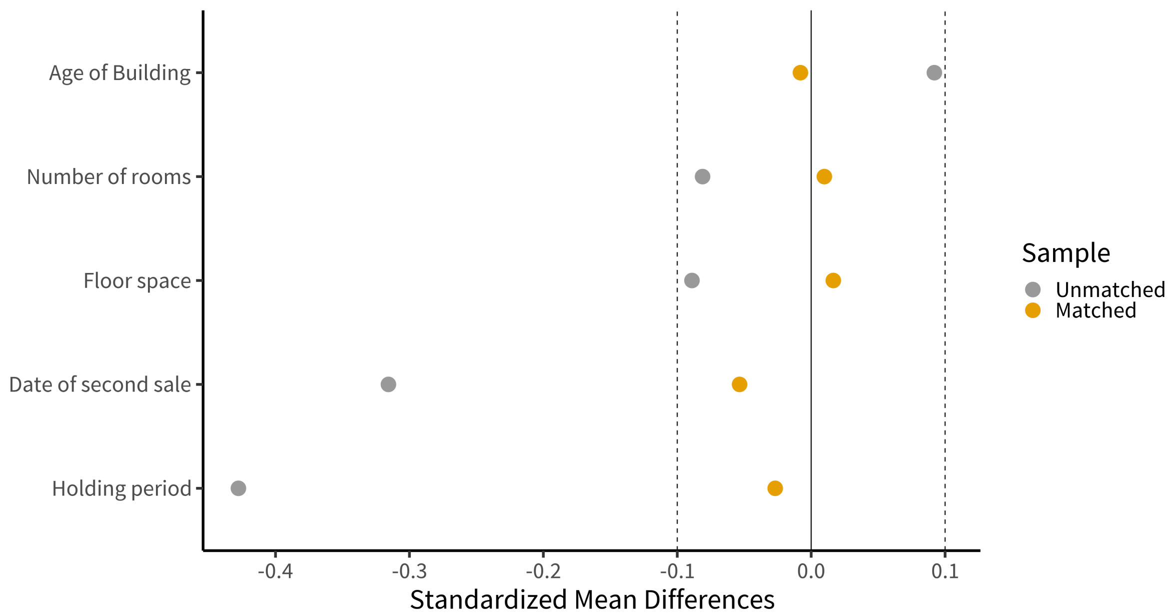


FIGURE 4. Covariate balance before and after matching

This plot indicates that balance, especially in the holding period and the date of the second sale, was quite low before matching. Nearest neighbor matching improved balance on all covariates, and all within a threshold of .1. For brevity reasons we do not report balance results on the zip code. Sources: Expert Commitee for Property Values in Berlin; authors' calculations.

and one spatial variable (the zip code of the apartment). Given the importance of location for apartment prices and appreciation rates, we enforce an exact match on the zip code of the apartment in our matching algorithm. We selected these six variables from our multitude of housing characteristics, as they appear best suited for satisfying the conditional independence assumption, i.e., that after matching on this set of observed covariates, the treatment assignment is independent of the potential outcomes (Rubin 1977). To each of our treated repeat sales, we match one control repeat sale. We exclude matching with replacement, which means that control repeat sales are not allowed to be matched to more than one treated repeat sale.[12]

Figure 4 graphically depicts the initial balance between the (unmatched) treated

[12]In k:1 matching, a treatment unit is matched with k control units. The most common is 1:1 matching, but this may result in a large loss of control units. Austin (2010) suggests that 1:1 or 2:1 matching (when matched with propensity scores) has the best performance in terms of minimizing the mean squared error. Rosenbaum (2020) demonstrates that the increase in precision with more control units (2:1, 3:1 matching etc.) diminishes sharply after the fourth control unit and therefore advises at most 4:1 matching. Our results are robust to different matching procedures, see Appendix B where we also report results for k:1 matching with up to five control units.

Table 2. Balance on Covariates after Matching

	Control (N=10,204)		Treated (N=10,204)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Age of building	71.8	34.5	71.5	34.7	-0.3	0.565
Number of rooms	2.3	1.0	2.3	1.0	0.0	0.477
Floor space	64.4	25.8	64.9	26.7	0.4	0.230
Date of second sale	8,866.4	2,985.5	8,710.3	2,919.6	-156.1	<0.001
Holding period	7.5	6.2	7.3	6.1	-0.2	0.057

The table reports distribution parameters for the matched data set. Age of building and holding period are measured in years, and living space is measured in square meters. The date of the second sale variable is measured as the day difference between the date of the second sale in a repeat sale and January, 1, 1984. Sources: Expert Commitee for Property Values in Berlin; authors' calculations.

and control repeat sales, and the balance for the matched data. Before matching, the pools of treatment and control repeat sales were significantly imbalanced. The control apartments were, on average, larger and newer, and had more rooms. , the average holding period of control apartments was about 2.5 years longer than that of the treatment units. All in all, this indicates substantial differences between the unmatched pools of repeat sales. However, with our approach of matching units on individual characteristics via the Mahalanobis distance, we were able to considerably improve this initial aggregate balance. As Table 2 shows, after matching, the pools of treatment and control apartments are, on average, equal in the age of the building the apartment is located in (diff. in means –0.3 years, p-value 0.565), in the number of rooms (diff. in means 0, p-value 0.477), and in the apartment size (diff. in means 0.4, p-value 0.230). We have also managed to reduce the average holding period difference and the difference in the date of the second sale: The mean difference in the date of the second sale in treated and control repeat sales in less than half a year (156 days) after matching, and the holding period difference is less than one quarter of a year. However, both the difference in the date of the second sale and the holding period remain statistically significant with p-values smaller than 0.05 and 0.1 respectively; in Appendix figure A1 we therefore provide evidence that although (small) differences in means persist, the distribution of treatment and control repeat sales is also in these two variables almost identical after matching.

Using this data set, we next aim to estimate the effect of foreclosure involvement on the annualized appreciation rate of apartments. We adopt two strategies: First, we use a multi-arm design to compare the average annualized appreciation rate of apartments transacted with and without foreclosure involvement. Second, we extend this design to allow for heterogeneous effects by holding periods. We do this by interacting treatment indicators with holding period dummies.

4.2.1. The general effect on housing returns

Next, we will present the basic empirical model that we will use to determine if the involvement of a foreclosure transaction in a repeat sale results in either an increased or decreased appreciation rate, when compared to a non-foreclosure control repeat sale. Specifically, we estimate the equation:

$$y_i = \alpha + \beta_1 \, T1_i + \beta_2 \, T2_i + \epsilon_i. \tag{3}$$

Equation 3 defines y_i as the annualized appreciation rate of repeat sale i. $T1_i$ (Treatment 1) is a dummy variable denoting a repeat sale that consists of a foreclosure transaction followed by a regular sale, while $T2_i$ (Treatment 2) denotes the opposite sequence, i.e., a regular sale followed by a foreclosure transaction.[13]

The coefficient α represents the "baseline" annualized appreciation rate of the control group, while β_1 measures the deviation from this baseline for the Foreclosure:Regular sale sequence (Treatment 1), and β_2 for the Regular:Foreclosure transaction sequence (Treatment 2). If buying a foreclosure apartment yields a profit premium for buyers, we expect $\hat{\beta}_1$ to be positive and statistically significant, indicating a stronger appreciation than the control group. Conversely, if transacting an apartment in a foreclosure process entails a markdown (for the seller), we expect $\hat{\beta}_2$ to be negative and statistically significant.

4.2.2. The conditional effect on housing returns

We next explore more nuanced effects on housing appreciation rates that are conditional on the holding period of apartment i. We specify the following empirical model:

[13] We briefly point out that the "contamination bias" of treatment effects that could arise in this type of multi-treatment linear regression (Goldsmith-Pinkham, Hull, and Kolesár 2022; Imbens and Wooldridge 2009) is not an issue here, as we do not condition on additional controls.

$$
\begin{aligned}
(4) \qquad y_{ip} = \alpha + \sum_{b=2}^{11} \beta_0^b \,\mathrm{Hold}_{ip} &+ \sum_{b=1}^{11} \beta_1^b \,\mathrm{Hold}_{ip} \times T1_i \\
&+ \sum_{b=1}^{11} \beta_2^b \,\mathrm{Hold}_{ip} \times T2_i + \epsilon_{ip}\,.
\end{aligned}
$$

The outcome variable y is the annualized appreciation rate of repeat sale i with holding period p. Hold is an indicator for holding period bins, varying from up to one year (b = 1), more than one year up to two years (b = 2), . . ., to more than ten years (b = 11). To circumvent the dummy variable trap, we omit the dummy for the holding period bin "up to one year" (b = 1). We use OLS to estimate this model for our matched repeat sale sample.

4.2.3. The persistence of foreclosure effects

We are interested in whether foreclosure effects are transient, associated with the *transaction*, or enduring, and thus linked to the *apartment* itself. A permanent stigma from foreclosure would likely result in reduced sale prices and appreciation rates for apartments in subsequent non-distressed transactions.

To empirically investigate this, we leverage the extensive duration of our data set, which captures multiple transactions of the same apartments. Following Chang and Li (2014), we identify the two sales of an apartment preceding and following a foreclosure event. We then compute the appreciation rate across these sales, deliberately excluding the foreclosure transaction in the middle. Using our matching algorithm detailed in section 4.2, we identify a comparable apartment's repeat sale that did not undergo foreclosure. Figure 5 visualizes our approach; ultimately, we are interested in the difference between appreciation rates of treatment and control observations. We estimate a treatment effect using a basic regression with a single treatment dummy:

$$
(5) \qquad y_i = \alpha + \beta_1 \, T_i + \epsilon_i.
$$

In Equation 5, y_i is defined as the annualized appreciation rate of repeat sale i. The variable T_i represents a treatment dummy for a "triple" sale sequence, where the intervening foreclosure sale is omitted. The coefficient α provides the baseline average

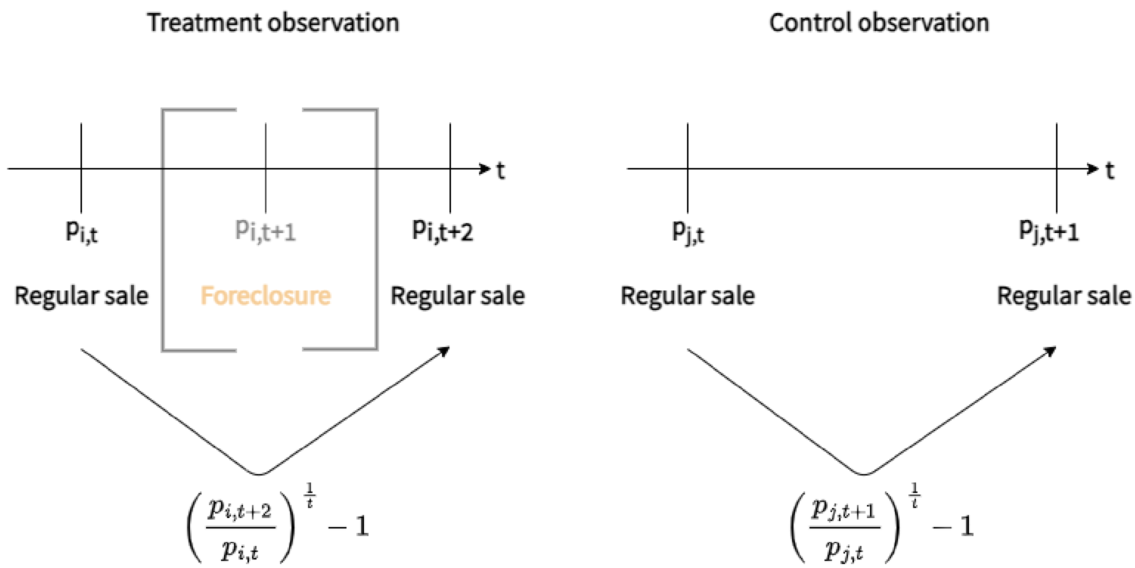


FIGURE 5. Appreciation rates of treatment and control apartments

This graph visualizes the way we derive our sample for the analysis of the persistence of foreclosure effects. For the treatment group, we derive "triple" repeat sales from individual sales of the same apartment i, where the middle transaction is a foreclosure. For the control group, we derive standard ("double") repeat sales from two individual sales of the same apartment j. We then calculate appreciation rates between the first and last individual sale in both groups. Sources: Authors' illustration.

annualized appreciation rate for control repeat sales unaffected by foreclosure, while β_1 measures the deviation from this baseline for apartments that were foreclosed between two regular sales.

Should the impact of foreclosure be merely temporal, we expect no difference in the annualized appreciation rate between "treated" and "untreated" repeat sales, rendering $\hat{\beta}_1$ statistically non-significant. Conversely, if the foreclosure puts a permanent stigma on the property, resulting in persistently lower appreciation rates, we expect $\hat{\beta}_1$ to be negative and statistically significant.

5. Results

We will next present our results on the foreclosure discount in prices by estimation of Equations 1 and 2, and the results on the foreclosure effects in appreciation rates by estimating Equations 3, 4, and 5. However, since both approaches focus on different outcomes, namely the price differential and the price appreciation differential, it is challenging to reconcile the results and draw meaningful conclusions. Therefore, as a third step, we will attempt to synthesize the results from both approaches to ensure the validity and reliability of our findings.

5.1. Foreclosure effects in transaction prices

Figure 6 illustrates the static (dashed line) and dynamic (solid line) foreclosure discount over time, based on our empirical models 1 and 2 with use of our full data set of 391,420 housing transactions. Table 3 provides the exact numbers underlying the dynamic discount in Figure 6. Furthermore, full regression results are reported in the Appendix table A1.

We find that foreclosure discounts in Berlin are substantial and vary significantly over time. The static foreclosure discount suggests a remarkable price discount of 39 percent for foreclosed properties. However, when we allow the discount to change over time, we observe "boom" and "bust" cycles of foreclosure discounts: Immediately after reunification in 1989, we see declining foreclosure discounts, which is consistent with the narrative of investors' prevailing expectation that Berlin's economic and political importance will rapidly increase and thus fuel the housing market (Holtemöller and Schulz 2010). However, after this expectation failed to materialize, the housing market declined sharply, which is also reflected in our analysis by an increase in the foreclosure discount by 19.1 percentage points between 1996 and 2004.[14] Since 2010, the foreclosure discount decreased over time, in parallel with the housing boom in Germany, and especially in Berlin, after the financial crisis. Moreover, the number of foreclosures declined significantly since 2010 and plateaued after 2015 (recall Figure 1).

A possible explanation for this could be that defaulting borrowers are more inclined (and it is easier) to sell the property on the open market during phases of a real estate boom. If the sale price exceeds the amount owed to the lender, they receive the surplus.[15] However, most recently, the foreclosure discount again increased, reaching 19 percent in 2022.

[14] In addition, between 1991 and 1998, East Germany and the entire city of Berlin were eligible for high special depreciation allowances for residential property. These short-term tax incentives led to a build-up of overcapacity in the housing market, which had a severe impact on the price structure (Michelsen and Weiß 2010).

[15] According to anecdotal evidence, the properties that are still foreclosed during these phases are often those where there are legal disputes, such as divorces or inheritance disputes.

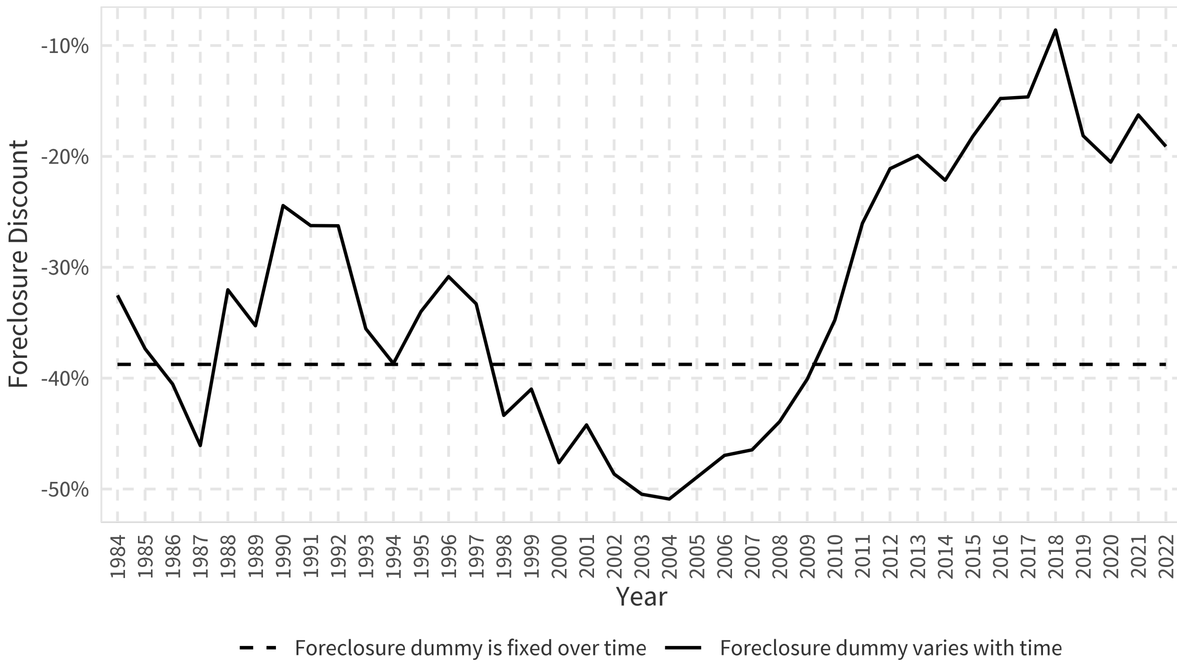


FIGURE 6. Foreclosure discounts from hedonic estimates

Figure 6 shows the discount for foreclosed apartments from hedonic dummy models. The dashed line shows the discount from a model including a single foreclosure dummy which is fixed over time while the solid line shows the discount calculated from a model which additionally includes interactions of the foreclosure dummy with year fixed effects. Sources: Expert Commitee for Property Values in Berlin; authors' calculations.

5.2. Foreclosure effects in appreciation rates

Although these results indicate that foreclosure transactions have lower transaction prices than regular sales (after controlling for observable apartment characteristics), the question whether these discounts translate into different appreciation rates – and thus housing returns – for distressed and non-distressed properties remains unanswered. We will therefore next present results how these price differentials translate into appreciation rates, which may be crucially dependent on the holding period.

General Effect. The results for our nearest neighbor matched sample of repeat sales, presented in Table 4, bear out both our expectations that (i) apartment that were foreclosed and later transacted on the open market have significantly higher appreciation rates, and (ii) apartments that were transacted on the open market and later foreclosed have significantly lower appreciation rates than the matched control apartments.

The annualized gross return for the control group equals $\hat{\alpha}$ and is 8.4%, as shown in

TABLE 3. Dynamic Foreclosure Discount from Hedonic Estimates

Year	Discount (%)	Year	Discount (%)	Year	Discount (%)	Year	Discount (%)
1984	–32.5	1994	–38.7	2004	–50.9	2014	–22.2
1985	–37.3	1995	–34.0	2005	–48.9	2015	–18.2
1986	–40.5	1996	–30.8	2006	–47.0	2016	–14.8
1987	–46.1	1997	–33.3	2007	–46.5	2017	–14.6
1988	–32.0	1998	–43.4	2008	–43.9	2018	–8.6
1989	–35.3	1999	–41.0	2009	–40.1	2019	–18.1
1990	–24.4	2000	–47.6	2010	–34.8	2020	–20.5
1991	–26.2	2001	–44.2	2011	–26.0	2021	–16.3
1992	–26.3	2002	–48.6	2012	–21.1	2022	–19.1
1993	–35.5	2003	–50.5	2013	–19.9		

This table shows the dynamic discounts calculated from estimated coefficients of Equation 2. They are also graphically shown in Figure 6. Sources: Expert Commitee for Property Values in Berlin; authors' calculations.

column 1. Treatment-1-transactions, which involve a foreclosure as the first transaction, generate an average markup of 22.6 percentage points ($\hat{\beta_1}$), leading to an annualized return of 31.0% ($\hat{\alpha} + \hat{\beta_1}$). Treatment-2-transactions, which involve a foreclosure as the second transaction, suffer an average markdown of 17.0 percentage points ($\hat{\beta_2}$) compared to the average return of control transactions, resulting in a negative annualized return of –8.6%.

We control for various fixed effects to account for the heterogeneity in apartment prices across zip codes, years, and market phases. In column 2, we include zip code fixed effects for apartment i, and year fixed effects for *i*'s first and second transaction, while column 3 additionally includes the interaction of these transaction year fixed effects. The zip code fixed effects capture time-invariant differences in apartment prices across Berlin's 194 small-scale areas, while the year fixed effects and their interactions adjust for differences in apartment returns due to the timing of the individual transactions (and the combination of these). In column 4, we add a three-way interaction of the fixed effects to account for the effect of market phases on the local level of zip codes. This is important because the probability of an apartment being foreclosed might be higher in economic downturns, and they might also cluster in certain neighborhoods in these cases.

The coefficients of our treatment dummies are highly significant across all specifications. In our most stringent specification, in column 4, we find that Treatment-1-

TABLE 4. Results for Matched Sample

	Dep. Var.: Annualized appreciation rate			
	(1)	(2)	(3)	(4)
Constant	0.084***			
	(0.003)			
Treatment 1 (Foreclosure:Regular)	0.226***	0.199***	0.171***	0.205***
	(0.010)	(0.009)	(0.010)	(0.017)
Treatment 2 (Regular:Foreclosure)	−0.170***	−0.144***	−0.086***	−0.096***
	(0.005)	(0.005)	(0.004)	(0.007)
ZIP code FE		✓	✓	✓
Y first sale FE		✓	✓	✓
Y second sale FE		✓	✓	✓
Y first sale × Y first second FE			✓	✓
ZIP code × Y first sale FE			✓	✓
ZIP code × Y second sale FE			✓	✓
ZIP code × Y first sale × Y second sale FE				✓
Num. obs.	20,408	20,408	20,408	20,408
R^2	0.210	0.308	0.661	0.816

OLS regressions with the annualized holding period return as response variable. Standard errors are clustered at the ZIP code level. Sources: Expert Commitee for Property Values in Berlin; authors' calculations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

apartments have an excess annualized return of 20.5 percentage points over the control apartments, while Treatment-2-apartments have a markdown of 9.6 percentage points, relative to the average annualized return of the control apartments.

To ensure that the relatively small sample size resulting from our application of a 1:1 matching protocol does not drive our results, we conducted additional analyses employing alternative matching strategies that retain a greater number of control observations. The alternative matching approach outcomes, displayed in Table A3 in the Appendix, confirm the robustness of our most stringent specification from column 4.

Conditional effect. The appendix contains Table A2, which shows the complete regression results of Equation 4 and variants in which various fixed effects are introduced additively. To simplify the presentation, we re-estimate Equation 4 omitting the constant α and letting the sum of $\beta_0^b \text{Hold}_{ip}$ run from $b = 1$. We can then directly read off the annualized returns by group from the estimated coefficients without the need of adding up interaction effects and recalculating standard errors.

Figure 7 and Table 5 illustrate the returns of investing in foreclosed apartments and reselling them in regular sales for different holding periods. We find that these investments have significantly higher returns than the control group for all holding periods, but the returns decrease as the holding period increases, partly due to the technical effect of annualization.[16] However, the average compound gross returns are very similar across holding periods.[17]

"Flipping" a distressed apartment, i.e., reselling it within one year from the foreclosure, yields an average return of 62.1 percent. This is more than twice the return of similar, non-distressed apartments with the same holding period (30.5 percent). Since we control for apartments not changing observable characteristics, and it is unlikely that there are (changes in) unobserved characteristics, such as locational amenities, within one year from the first sale, our finding suggests that there is a large discount for foreclosed properties in Berlin that is not related to housing quality.[18]

We also examine the annualized returns of Treatment-2-apartments, i.e., the "classic" foreclosure repeat sale, where a regular sale is followed by a foreclosure transaction. We find that these apartments have (i) considerably lower returns than the control group for all holding periods and (ii) in absolute terms face negative returns for all holding periods. This means that delinquent owners both fall short compared to the return benchmark and make losses in absolute terms.

Temporary vs. permanent effect. We have seen that repeat sales in the Treatment-2-setting appreciate between 9.6 and 17 percentage points *less* than comparable repeat sales, in which the second transaction was a regular transaction. However, we yet do not know whether this foreclosure discount is associated only with the foreclosure transaction and is thus temporary or whether the foreclosure puts a permanent stigma on foreclosed apartments, which would result in permanently lower appreciation rates even in subsequent non-distressed transactions.

To assess the persistence of the foreclosure discounts, our approach is as follows: We extract all apartments from our data set that have been transacted multiple times and have experienced foreclosure at least once. We identify the regular transactions that

[16]Recall that for comparing investment returns for different holding periods, we rely on the annualization of the return.

[17]The mean holding period in each holding period bin except ">10" is around the middle of the respective interval. The mean holding period for apartments in the ">10" bin is 15 years.

[18]This is consistent with LaCour-Little and Yang (2023) who find that (i) flip sales outperform non-flip sales in terms of returns and (ii) this over-performance (i.e., excess returns for flips over non-flips) is highest for distressed property sales.

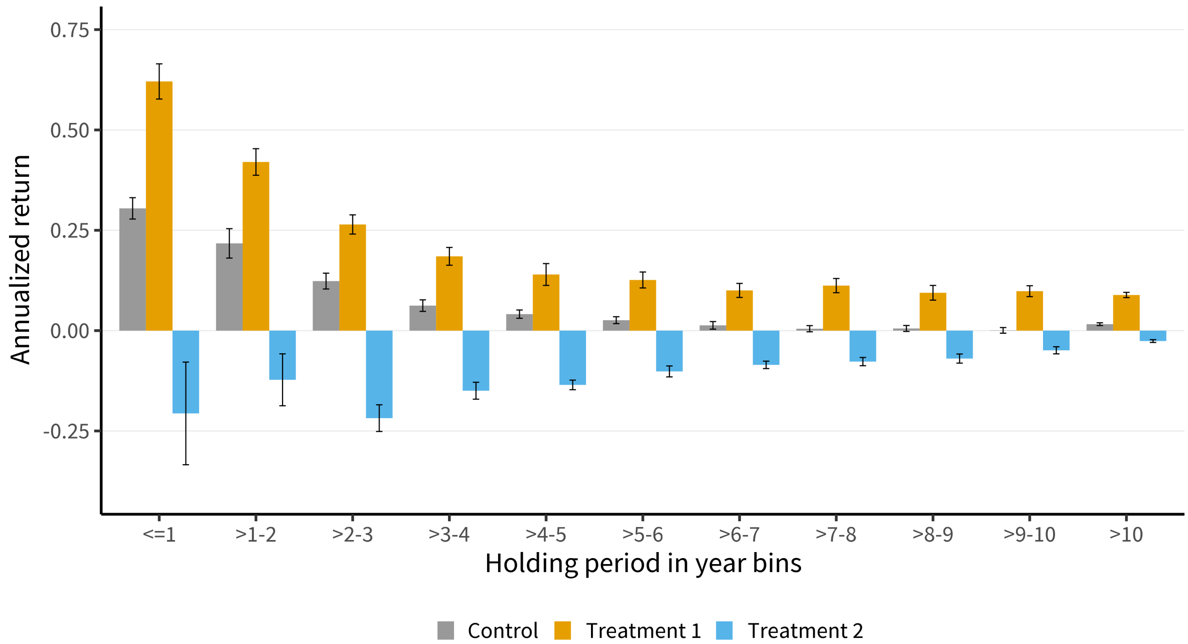


FIGURE 7. Results by holding period

This figure shows the annualized returns for the Control, Treatment 1, and Treatment 2 group along with 95% confidence intervals of the estimated coefficients. Sources: Expert Commitee for Property Values in Berlin; authors' calculations.

occurred immediately before and after the foreclosure event (as depicted in Figure 5). From our data, we isolate 2,239 apartments with such a transaction sequence. We then compute the (annualized) appreciation rates for these apartments, considering only the sales before and after the foreclosure, while disregarding the foreclosure sale itself. Employing the matching algorithm described in Section 4.2, we match each of those "treated" repeat sales to a comparable, non-distressed repeat sale based on location (exact zip code match), transaction timing (holding period and date of the second sale), and key property characteristics (size, age, and number of rooms). This process yields a sample of 4,478 repeat sales for analysis. Additionally, we verify the balance of our matched sample; post-matching, the mean differences of all our matching variables between the treated and control groups are statistically non-significant, with p-values exceeding 0.1.

The results presented in Table 6, derived from the matched sample of 4,478 repeat sales observations, offer insights into the persistence of foreclosure discounts. Column (1) reveals that the average annual appreciation rate for non-distressed repeat sales stands at 1.9 percent. In contrast, repeat sales of apartments that experienced a fore-

TABLE 5. Annualized appreciation rate by group and holding period

	Holding period in years										
	≦1	>1-2	>2-3	>3-4	>4-5	>5-6	>6-7	>7-8	>8-9	>9-10	>10
Control	**30.5**	**21.7**	**12.3**	**6.2**	**4.1**	**2.6**	**1.3**	**0.5***	**0.5***	**0.1***	**1.6**
SE	1.3	1.9	1.0	0.7	0.5	0.4	0.5	0.4	0.4	0.4	0.2
n	1,499	736	683	668	711	697	622	525	478	379	3,206
Treatment 1	**62.1**	**42.0**	**26.4**	**18.5**	**14.0**	**12.6**	**10.0**	**11.2**	**9.4**	**9.8**	**8.9**
SE	2.2	1.7	1.2	1.1	1.4	1.0	0.9	0.9	0.9	0.7	0.3
Δ Control (PP)	31.6	20.3	14.1	12.3	9.9	10.0	8.7	10.7	8.9	9.8	7.3
n	1,415	551	344	272	231	199	151	141	102	100	1,239
Treatment 2	**–20.6**	**–12.3**	**–21.8**	**–15.0**	**–13.5**	**–10.2**	**–8.5**	**–7.7**	**–7.0**	**–4.9**	**–2.6**
SE	6.5	3.3	1.7	1.1	0.6	0.7	0.5	0.5	0.6	0.4	0.2
Δ Control (PP)	–51.1	–34.0	–34.1	–21.2	–17.6	–12.8	–9.8	–8.2	–7.5	–5.0	–4.2
n	71	117	324	459	612	579	531	428	356	312	1,670

This table shows the annualized holding period returns in year bins by group, obtained from a variant of Equation 4. Numbers in bold are annualized returns in percent, non-bold numbers in rows denoted with "n" indicate the number of observations (i.e. number of repeat sales) in the respective group-category combination while rows denoted with "SE" indicate the standard error of the estimated coefficient. "Δ Control (PP)" indicates the "excess profit" of the treatment annualized returns over the control group with the same holding period in percentage points. * estimated coefficient with p-value > 0.1. Sources: Expert Commitee for Property Values in Berlin; authors' calculations.

closure in between exhibit a 2 percentage point reduction compared to the control group of non-distressed repeat sales. At first glance, this suggests that foreclosures may put a lasting stigma on the apartment rather than merely affecting the foreclosure transaction.

Even after introducing fixed effects for the zip code, and for the year of the first and second transaction, treated repeat sales experience 1.8 percentage points less annualized appreciation than control repeat sales (column (2)). However, the introduction of fixed effects interactions to account for time-variant heterogeneity in appreciation rates across zip codes (columns (3) and (4)) results in the estimated coefficient of β becoming statistically insignificant. This finding implies that when adequately controlling for unobserved temporal and spatial variations in appreciation rates, apartments that have been foreclosed once do not exhibit lower appreciation than comparable never foreclosed apartments. Consequently, we infer that the foreclosure discount is likely restricted to the transaction itself and does not impose a lasting stigma on the property.

TABLE 6. Results for permanence of effects

	Dep. Var.: Annualized appreciation rate			
	(1)	(2)	(3)	(4)
Constant	0.019***			
	(0.003)			
Treatment (foreclosed in between)	−0.020***	−0.018***	0.001	0.000
	(0.003)	(0.003)	(0.004)	(0.004)
ZIP code FE		✓	✓	✓
Y first sale FE		✓	✓	✓
Y second sale FE		✓	✓	✓
Y first sale × Y first second FE			✓	✓
ZIP code × Y first sale FE			✓	✓
ZIP code × Y second sale FE			✓	✓
ZIP code × Y first sale × Y second sale FE				✓
Num. obs.	4,478	4,478	4,478	4,478
R^2	0.007	0.247	0.963	0.974

OLS regressions with the annualized appreciation rate as response variable. Standard errors are clustered at the ZIP code level. Sources: Expert Commitee for Property Values in Berlin; authors' calculations. $^{***} p < 0.01$; $^{**} p < 0.05$; $^{*} p < 0.1$

5.3. Synthesis, robustness and situating in the literature

Alignment. In this section, we synthesize the results of our two empirical approaches to facilitate a meaningful comparison between the two estimates. A summary conclusion is challenging because our two approaches measure different outcomes, with the hedonic estimates measuring the price difference between distressed and non-distressed properties, and the repeat sales estimates measuring the price appreciation between both types of properties. Additionally, both approaches use different samples: Our hedonic approach uses the full data set of over 390,000 transactions, while our repeat sales approach uses only about 20,000 transaction pairs.

However, in our view, the challenge that both approaches measure different outcomes (price difference vs. price appreciation) is no drawback but rather an asset of our empirical strategy. Both approaches lead to the same qualitative conclusion: After controlling for the difference in property characteristics, foreclosed properties are sold at a discount to non-foreclosed properties and have – while controlling for the holding periods – different price appreciations and annualized return. This means that foreclosed properties offer profits for buyers/investors and losses for distressed homeowners that are very different from those of comparable but non-foreclosed properties.

The second challenge, the different samples, is easier to overcome. To align both approaches, we re-estimate our hedonic price equations 1 and 2 using only the 36,808 transactions that form our 20,408 transaction pairs in the repeat sales sample.[19] We present results in Appendix table A1. We find that the static foreclosure discount in the matched repeat sales sample is 37%, i.e., only two percentage points lower than in the full sample estimate. The dynamic discount shows a similar trend, with small deviations in amplitude in some years. The spearman ranked correlation coefficient, measuring the correlation between our dynamic foreclosure discounts from the matched repeat sales estimate and the full sample estimate is 0.97, suggesting a high similarity between both time series. In summary, both samples yield highly similar results underpinning the validity of our analysis.

Contrast. We compare our results for Berlin with four studies that are most similar to ours, as it is impossible to contrast our results with the vast literature on estimates of foreclosure discounts from different samples, time periods, and data sources.

First, we compare our estimated foreclosure discount with that of Just et al. (2019), as this is the only other study that analyzes foreclosure discounts in Germany, to the best of our knowledge. The authors combine data on all foreclosures in Germany between 2008 and 2011 and a data set on asking prices from a platform for real estate advertisements to infer market values of residential properties. They estimate a foreclosure discount of 19–25.5 percent (depending on their hedonic model specification). Although their use of asking data as counterfactual transaction prices and their specific sample time period may question the external validity of their discount estimates, we conclude that their finding of substantial foreclosure discounts in the same institutional setting supports our results.

Second, Pennington-Cross (2006) uses a repeat sales approach to test the difference in house price appreciation rates between pairs of regular transactions (the "control transactions" in this paper) and repeat sales that involve a foreclosure as the second transaction (the "Treatment-2-transactions" in this paper). He finds that Treatment-2-apartments appreciate 22% less than the area appreciation rate, which is calculated

[19]The repeat sales sample comprises not 40,816 unique transactions but rather 36,808, due to some transactions being involved in both Treatment-1 and Treatment-2 observations. For instance, consider an apartment i that undergoes three transactions on dates r_1, f, and r_2, where sales at r are regular sales and at f are foreclosures and $r_2 > f > r_1$. In this scenario, the pair (r_1, f) constitutes a Treatment-2-observation, while (f, r_2) forms a Treatment-1-observation within our analysis. Consequently, what appears as two separate repeat sales actually involves merely three distinct transactions.

from the price differential of the control apartments. Although Pennington-Cross (2006) was unable to control for individual property or neighborhood characteristics, and the estimates may be biased due to selection issues, his estimates are close to our results of 8.2 and 15.6 percentage points *less* appreciation for Treatment-2-apartments using a matched repeat sales sample that should be more robust to selection bias.

Third, we compare our results with Harding, Rosenblatt, and Yao (2012), who examine the appreciation rates of repeat sales with transaction pairs that involve foreclosures as the first, and regular sales as the second transaction ("Treatment 1") using data from 13 MSAs in the United States. In general, this paper concludes that there are no excess returns of distressed properties over matched non-distressed properties; in an analysis similar to ours in section 4.2.2, their paper, in line with our results, finds excess annualized returns of 33.2% for distressed properties with a holding period of less than one year. However, only "flipping" a distressed property significantly outperforms the return rates of regular apartments, as excess returns for other holding periods are negligible, unlike our findings.[20]

Finally, we compare our results with Donner (2017), who uses data from Stockholm, Sweden and an empirical approach similar to ours in section 4.2.1. He finds that distressed repeat sales with the foreclosure as the first transaction ("Treatment 1") have an annualized holding period return that is 37.8 to 48.6 percentage points higher than a matched control repeat sales pair. For the reversed sequence of transactions ("Treatment 2"), he finds a 7.6 to 10.7 percentage points lower annualized return. Our results with an appreciation markup of between 18.7 and 25.4 percent for Treatment-1-transactions, and –8.2 and –15.6 for Treatment-2-transactions are qualitatively consistent with his estimates. However, his findings suggest an even larger markup for Treatment-1-transactions than ours. This may be due to the different mean holding periods for the different groups of repeat sales: We observe 5.8 years for Treatment-1-apartments and 8.4 years for Treatment-2-apartments. In contrast, Donner (2017) reports 4.3 years for Treatment-1-transactions and 1.2 years for Treatment-2-transactions. Since the holding period affects the annualized return, the quantitative differences from our estimates are less surprising.

[20] In comparison, these results are based on a much smaller sample than ours. We base our results in Table 5 on 4,745 distressed repeat sales, while Harding, Rosenblatt, and Yao (2012) uses 868 pairs of repeat sales. They also show that these excess returns for holding periods of less than one year are associated with (much) higher risks, which we cannot confirm in our data.

6. Discussion and Limitations

Having established that Berlin experienced significant foreclosure discounts and excess returns for buyers of foreclosed apartments, in this section we turn to a discussion of the possible mechanism behind and explanations for this price differential, and discuss the limitations of our analysis.

Auction format. The literature identifies mainly two reasons for foreclosure discounts: The "proxy effect", the lower quality of distressed properties, and the "stigma effect", the negative perception of distressed properties, regardless of their actual condition. After controlling for apartment characteristics, and thus minimizing the proxy effect, we might attribute all of the effects we find to the foreclosure status, and thus the stigma effect. However, we propose that the format of foreclosures transactions in Germany also contributes to the foreclosure discount.[21] We hypothesize that it offers both: too little transparency from an outside view and too much transparency from an inside view.

The foreclosure auction process has some barriers that may discourage potential buyers, such as the weekday timing, the physical presence requirement, and the lack of prior inspection, which may complicate financing. Therefore, one possible explanation for the foreclosure discount related to the auction is the limited pool of bidders, who are mostly specialized investors. The literature on auction theory (e.g., Bulow and Klemperer 1996) and the empirical evidence from (non-distressed) real estate auctions support the idea that a higher number of bidders increases the likelihood of a higher maximum bid (Ong, Lusht, and Mak 2005; Ooi, Sirmans, and Turnbull 2006; Levin and Pryce 2007; Hungria-Gunnelin 2013; Stevenson and Young 2015; Chow, Hafalir, and Yavas 2015). Focusing on foreclosure auctions, Mazzola (2022) shows that introducing an electronic bidding system eliminates a previously existing foreclosure discount by increasing the number of bidders.

A second concern in the ascending auction format used in foreclosure auctions in Germany is the possibility of collusion among participants to avoid bidding up prices (Klemperer 2002a). We hypothesize that specialized buyers of foreclosed properties, who frequently interact with each other at different foreclosures, form bidding rings (or “bidding cartels”) (see, e.g., Pagnozzi 2011; Marshall, Marx, and Meurer 2014; Lorentziadis

[21] For the United States, Mian, Sufi, and Trebbi (2015) and Cordell and Lambie-Hanson (2016) show that foreclosure discounts in states with a *judicial* foreclosure process, i.e., the requirement to auction foreclosures at court, are significantly larger than in states without a judicial foreclosure process.

2016) and coordinate their (low) winning bids at different foreclosure auctions, avoiding competition.[22]

Moreover, ascending auctions enable bidders to signal to each other or intimidate opponents through bidding strategies, such as high opening bids, high bid increases ("jump bids"), short response times to others' bids, or "code bidding" (Avery 1998; Isaac, Salmon, and Zillante 2007; Ettinger and Michelucci 2016; Hungria-Gunnelin 2018; Cramton and Schwartz 2000; Khazal et al. 2020; Sommervoll 2020; Dalland et al. 2021; Gunnelin et al. 2023).

Unfortunately, we do not have data on the foreclosure auctions themselves like, e.g., the number of bidders, or the sequence and amount of bids. In principal, however, these data should be available as paper records of the auction process at the respective district courts archives. Compiling and analyzing these data to better understand the role of the auction format in the foreclosure discount might thus be a promising, although labor-intensive, avenue for further research.

Transaction costs. We base our returns in repeat sales on the transaction prices of the property, without considering the various costs that are involved in real estate transactions. Therefore, in the context of transaction costs, our estimates of (annualized) returns should be viewed as upper bounds of the true (annualized) returns. However, we note that most transaction costs, except for the court fees generated by the foreclosure, are common to any type of sale. Our reported (annualized) returns of foreclosed apartments are compared to the return of non-distressed control apartments. The excess returns of foreclosed apartments are so large that even after accounting for the court fees, apartments in the Treatment-1-setting would still generate returns that are much higher than those of the non-distressed control apartments.

Debt financing. Another point related to the previous one is that in our interpretations of the estimated returns, we implicitly assume that properties are financed entirely with equity and without debt. This implies that the returns shown for Treatment-1-apartments are unleveraged property returns. Moreover, the distressed owner of a Treatment-2-apartment only suffers the full amount of the loss shown if there is no outstanding mortgage that limits the downside. Otherwise, the lender would share part of the loss. However, especially high-leverage mortgages seem to be closely associated

[22] We have anecdotal evidence from market participants that this behavior occurs among "foreclosure investors" in Berlin.

with foreclosures (Corbae and Quintin 2015). Therefore, in the context of financing, our return estimates for Treatment-1-apartments should be viewed as the lower bound of actual returns, while those for Treatment-2-apartments should be viewed as the upper bound – at least from the perspective of the distressed seller.

Risk premium. We acknowledge that we do not account for the different risk profiles associated with foreclosed and non-foreclosed apartments. In some cases, the return premium on Treatment-1-apartments might reflect the higher ex-ante risk associated with foreclosure apartments, such as the limited or absent opportunity to inspect the apartment before the auction. Therefore, the higher ex-post returns of apartments in the Treatment-1-regime might only compensate for the higher risks; the risk-adjusted returns between treated and control apartments might be more similar than those we report in this paper. We also speculate that at least some of the 1,415 apartments in the Treatment-1-setting that involved foreclosed apartments and were resold in a regular sale within one year from the auction date are likely apartments in which these ex-ante risks did not materialize. That is, the fear of a poor apartment condition before foreclosure, which might have driven down the auction price, did not turn out to be true.

"Fire sales". We find negative annualized returns for Treatment-2-transactions for all holding periods. It is tempting to attribute all of this effect to the foreclosure status. However, previous studies have shown that distressed sales tend to be shorter on the market and have higher selling pressure than non-distressed sales (Clauretie and Daneshvary 2009, 2011; Shilling, Benjamin, and Sirmans 1990; Springer 1996; Aroul and Hansz 2014; Goodwin and Johnson 2017).[23] This could lead distressed sellers to sacrifice price for speed and sell at lower prices. The discount would then be more of an indirect, rather than a direct, effect of the foreclosure status. However, this argument does not apply to our institutional setting, where the transaction/foreclosure of the property is done directly by the court. The court also sets the minimum bid according to legal instructions. Therefore, the marketing time and selling pressure of foreclosure apartments are no relevant factors driving the price or foreclosure discount.

[23] However, recently Allen et al. (2024) found time-on-market to be *longer* for foreclosures, compared to regular transactions. They explain their contradicting evidence with a better measure of time-on-market than previous studies used.

Unobserved changes and omitted variable bias. We check the apartment characteristics in our repeat sales data to make sure that apartments have not changed between transactions. However, we cannot exclude the possibility that there have been (minor) renovations that improve the appearance and value of the apartment but are not recorded. We also cannot measure, beyond the information in our data, whether and how amenities around the apartment have changed. These changes in amenities, which are more likely for longer holding periods, could also affect our results. We do control for such time-varying and invariant factors at the zip code level in our regressions using fixed effects, but we cannot control for factors that occur at a more small-area level around the apartment, such as a change in the view from the apartment due to a new building nearby. If there are changes in the home or neighborhood that we do not account for, this could create an omitted variable bias in our estimates.

Spillover effects and SUTVA. One distinct strand of the foreclosure literature is interested in the spatial spillover effects of foreclosed properties on neighboring, non-distressed properties (e.g., Immergluck and Smith 2006; Lin, Rosenblatt, and Yao 2009; Harding, Rosenblatt, and Yao 2009; Hartley 2014; Anenberg and Kung 2014; Fisher, Lambie-Hanson, and Willen 2015; Lambie-Hanson 2015; Bak and Hewings 2019; Biswas, Fout, and Pennington-Cross 2023).[24] They find that foreclosed properties can lower the neighborhood house prices, and thus the prices of non-distressed properties, for two reasons. First, foreclosed properties may be a "dis-amenity" in the neighborhood due to physical neglect or vacancy. Second, foreclosed properties may increase the supply of housing units on the market without a corresponding increase in demand, which would lower the equilibrium price in a standard market model. These spillover effects could potentially bias our results because they could affect the prices and returns of our control group of non-distressed apartments. If this is the case, the control group's prices and returns would not be independent of the "treatment effect" of foreclosure, violating the Stable Unit Treatment Value Assumption (SUTVA).

However, we argue that dis-amenity spillover effects are less likely in our analysis because they are more relevant for single- or two-family houses, whose physical characteristics are more visible "from the street". Apartments in multifamily houses are less exposed to this effect.[25] However, we cannot rule out that the additional supply of

[24] Yet another strand of the foreclosure literature is interested in the "contagion effect" of foreclosures, i.e., the spillover effect in terms of the probability of neighboring properties being foreclosed as well (see, e.g., Towe and Lawley 2013; Chan et al. 2013).

[25] We acknowledge that spillover effects on other apartments in the same building are still possible (for

housing units through foreclosures (recall Figure 1) might have had some price effects on non-distressed properties. If these spillovers occurred, they would bias the price and returns of transactions in our control group downwards, which would mean that we underestimated the return and price differences between foreclosed and non-foreclosed apartments.

7. Conclusion

This paper provides evidence that Berlin's housing market has experienced significant and persisting inefficiencies related to real estate foreclosures. The estimated foreclosure discounts of 20–50% represent major "excess" profit opportunities that have not been eliminated over almost four decades of observations. At the same time, the analysis documents that distressed sellers must accept substantial losses when resolving mortgage delinquencies through foreclosure.

These findings suggest several policy implications. First, the results indicate issues with the efficiency and transparency of Germany's foreclosure auction process. Large discounts persisting for so long likely point to barriers deterring wider auction participation, such as inconvenient timing or the lack of possibilities for property inspection before the transaction. One the one hand, reforms to facilitate more bidders – bringing greater transparency to the auction – could help reduce discounts; electronic auctions, might be one way to achieve wider participation, as suggested by recent evidence. Regarding the auction format, the ascending auction could be made robust by forcing bidders to bid "round" numbers or making bids anonymous – bringing less transparency to the auction – to make it harder to use bids to signal other bidders (Klemperer 2002b). A transition to a sealed-bid auction with simultaneous bids would especially make tacit collusion much harder than in an ascending auction, while being more attractive to entrants[26].

Second, the considerable losses for distressed sellers underline the high personal costs of mortgage defaults. The results suggest that policies should aim to prevent delinquencies and facilitate alternatives to foreclosure. Expanding mortgage assistance

instance through non-visible factors such as smell) and – as, e.g., Fisher, Lambie-Hanson, and Willen (2015) argue – may be a relevant factor for price discounts.

[26]As an alternative auction format, Klemperer (1998) proposed kind of a hybrid model of the ascending and descending auction, the "Anglo-Dutch" auction. The first part of the auction is held like an ascending clock auction, in which the price is raised continously until all but two bidders have dropped out. The two remaining bidders, as a second part of the auction, make a final sealed-bid offer that is not lower than the current asking price, and the winner pays the winning bid.

programs and promoting short sales could help owners avert foreclosures. Where foreclosure is unavoidable, further research is needed to understand how the process could be made less punitive for distressed sellers.

Overall, the findings point to foreclosures representing a significant housing policy challenge, especially in times of interest rate turnarounds, when the number of foreclosures is likely to rise. Ongoing reforms should focus on enhancing efficiency and fairness by facilitating broader auction participation, improving transparency, avoiding unnecessary foreclosures, and supporting distressed homeowners. Tackling these issues could help mitigate the currently severe consequences of mortgage distress evident in the results.

References

Allen, Marcus T., Justin D. Benefield, Christopher L. Cain, and Norman Maynard. 2024. "Distressed Property Sales: Differences and Similarities Across Types of Distress." *The Journal of Real Estate Finance and Economics* 68 (2): 318–353.

Anenberg, Elliot, and Edward Kung. 2014. "Estimates of the Size and Source of Price Declines Due to Nearby Foreclosures." *American Economic Review* 104 (8): 2527–2551.

Aroul, Ramya Rajajagadeesan, and J. Andrew Hansz. 2014. "The Valuation Impact on Distressed Residential Transactions: Anatomy of a Housing Price Bubble." *The Journal of Real Estate Finance and Economics* 49 (2): 277–302.

Ashenfelter, Orley, and David Genesove. 1992. "Testing for Price Anomalies in Real-Estate Auctions." *The American Economic Review* 82 (2): 501–505.

Austin, Peter C. 2010. "Statistical Criteria for Selecting the Optimal Number of Untreated Subjects Matched to Each Treated Subject When Using Many-to-One Matching on the Propensity Score." *American Journal of Epidemiology* 172 (9): 1092–1097.

Avery, Christopher. 1998. "Strategic Jump Bidding in English Auctions." *The Review of Economic Studies* 65 (2): 185–210.

Azasu, Samuel. 2006. "Auctions in the Real Estate Market – a Review."

Bak, Xian F., and Geoffrey J. D. Hewings. 2019. "The Heterogeneous Spatial Impact of Foreclosures on Nearby Property Values." *The Annals of Regional Science* 62 (3): 439–466.

Baye, Michael R., and Jeff Prince. 2022. *Managerial Economics and Business Strategy*. 10th ed. The McGraw-Hill Series Economics. New York: McGraw Hill.

Biswas, Arnab, Hamilton Fout, and Anthony Pennington-Cross. 2023. "Mortgage Losses under Alternative Property Disposition Approaches: Deed-in-Lieu, Short Sales, and Foreclosure Sales." *The Journal of Real Estate Finance and Economics* 66 (3): 603–635.

Bulow, Jeremy, and Paul Klemperer. 1996. "Auctions Versus Negotiations." *The American Economic Review* 86 (1): 180–194.

Campbell, John Y, Stefano Giglio, and Parag Pathak. 2011. "Forced Sales and House Prices." *American Economic Review* 101 (5): 2108–2131.

Carroll, Thomas, Terrence Clauretie, and Helen Neill. 1997. “Effect of Foreclosure Status on Residential Selling Price: Comment.” *Journal of Real Estate Research* 13 (1): 95–102.

Chan, Sewin, Michael Gedal, Vicki Been, and Andrew Haughwout. 2013. “The Role of Neighborhood Characteristics in Mortgage Default Risk: Evidence from New York City.” *Journal of Housing Economics* 22 (2): 100–118.

Chang, Yan, and Xiaoming Li. 2014. “Distressed Home Sales: Temporary Discount or Permanent Devaluation.”

Chow, Yuen Leng, Isa E. Hafalir, and Abdullah Yavas. 2015. “Auction versus Negotiated Sale: Evidence from Real Estate Sales.” *Real Estate Economics* 43 (2): 432–470.

Clauretie, Terrence M., and Nasser Daneshvary. 2009. “Estimating the House Foreclosure Discount Corrected for Spatial Price Interdependence and Endogeneity of Marketing Time.” *Real Estate Economics* 37 (1): 43–67.

Clauretie, Terrence M., and Nasser Daneshvary. 2011. “The Optimal Choice for Lenders Facing Defaults: Short Sale, Foreclose, or REO.” *The Journal of Real Estate Finance and Economics* 42 (4): 504–521.

Conklin, James N., N. Edward Coulson, and Moussa Diop. 2023. “Distressed Comps.” *Real Estate Economics* 51 (1): 170–195.

Corbae, Dean, and Erwan Quintin. 2015. “Leverage and the Foreclosure Crisis.” *Journal of Political Economy* 123 (1): 1–65.

Cordell, Larry, and Lauren Lambie-Hanson. 2016. “A Cost-Benefit Analysis of Judicial Foreclosure Delay and a Preliminary Look at New Mortgage Servicing Rules.” *Journal of Economics and Business* 84: 30–49.

Cramton, Peter, and Jesse A. Schwartz. 2000. “Collusive Bidding: Lessons from the FCC Spectrum Auctions.” *Journal of Regulatory Economics* 17 (3): 229–252.

Currie, Janet, and Erdal Tekin. 2015. “Is There a Link between Foreclosure and Health?” *American Economic Journal: Economic Policy* 7 (1): 63–94.

Dalland, Simen, Randi Hammervold, Henrik Tangen Karlsen, Are Oust, and Ole Jakob Sønstebø. 2021. “Aggressive Bidding Strategies in Real Estate Auctions – a Structural Equation Modelling (SEM) Approach.” *Journal of European Real Estate Research* 14 (2): 229–245.

Diamond, Rebecca, Adam Guren, and Rose Tan. 2020. “The Effect of Foreclosures on Homeowners, Tenants, and Landlords.”

Doerner, William M., and Andrew V. Leventis. 2015. “Distressed Sales and the FHFA House Price Index.” *Journal of Housing Research* 24 (2): 127–146.

Donner, Herman. 2017. “Foreclosures, Returns, and Buyer Intentions.” *Journal of Real Estate Research* 39 (2): 189–214.

Donner, Herman, Han-Suck Song, and Mats Wilhelmsson. 2016. “Forced Sales and Their Impact on Real Estate Prices.” *Journal of Housing Economics* 34: 60–68.

Dotzour, Mark, Everard Moorhead, and Daniel Winkler. 1998. “The Impact of Auctions on Residential Sales Prices in New Zealand.” *Journal of Real Estate Research* 16 (1): 57–72.

Ettinger, David, and Fabio Michelucci. 2016. “Hiding Information in Open Auctions with Jump Bids.” *The Economic Journal* 126 (594): 1484–1502.

Fisher, Lynn M., Lauren Lambie-Hanson, and Paul Willen. 2015. “The Role of Proximity in Foreclosure Externalities: Evidence from Condominiums." *American Economic Journal: Economic Policy* 7 (1): 119–140.

Forgey, Fred A., Ronald C. Rutherford, and Michael L. VanBuskirk. 1994. "Effect of Foreclosure Status on Residential Selling Price." *The Journal of Real Estate Research* 9 (3): 313–318.

Goldsmith-Pinkham, Paul, Peter Hull, and Michal Kolesár. 2022. "Contamination Bias in Linear Regressions."

Goodwin, Kimberly R., and Ken H. Johnson. 2017. "The Short Sale Stigma." *The Journal of Real Estate Finance and Economics* 55 (4): 416–434.

Gunnelin, Ake, Rosane Hungria-Gunnelin, Bryan MacGregor, and Martin Wersing. 2023. "Empirical Insights from Swedish Real Estate Auctions."

Hardin, William, and Marvin Wolverton. 1996. "The Relationship between Foreclosure Status and Apartment Price." *Journal of Real Estate Research* 12 (1): 101–109.

Harding, John P., Eric Rosenblatt, and Vincent W. Yao. 2009. "The Contagion Effect of Foreclosed Properties." *Journal of Urban Economics* 66 (3): 164–178.

Harding, John P., Eric Rosenblatt, and Vincent W. Yao. 2012. "The Foreclosure Discount: Myth or Reality?" *Journal of Urban Economics* 71 (2): 204–218.

Hartley, Daniel. 2014. "The Effect of Foreclosures on Nearby Housing Prices: Supply or Dis-Amenity?" *Regional Science and Urban Economics* 49: 108–117.

Holtemöller, Oliver, and Rainer Schulz. 2010. "Investor Rationality and House Price Bubbles: Berlin and the German Reunification." *German Economic Review* 11 (4): 465–486.

Hungria-Gunnelin, Rosane. 2013. "Impact of Number of Bidders on Sale Price of Auctioned Condominium Apartments in Stockholm." *International Real Estate Review* 16 (3): 274–295.

Hungria-Gunnelin, Rosane. 2018. "An Analysis of Auction Strategies in Apartment Sales." *Journal of European Real Estate Research* 11 (2): 202–223.

Imbens, Guido W., and Jeffrey M. Wooldridge. 2009. "Recent Developments in the Econometrics of Program Evaluation." *Journal of Economic Literature* 47 (1): 5–86.

Immergluck, Dan, and Geoff Smith. 2006. "The External Costs of Foreclosure: The Impact of Single-family Mortgage Foreclosures on Property Values." *Housing Policy Debate* 17 (1): 57–79.

Isaac, R. Mark, Timothy C. Salmon, and Arthur Zillante. 2007. "A Theory of Jump Bidding in Ascending Auctions." *Journal of Economic Behavior & Organization* 62 (1): 144–164.

Just, Tobias, Michael Heinrich, Mark Andreas Maurin, and Thomas Schreck. 2019. "Foreclosure Discounts for German Housing Markets." *International Journal of Housing Markets and Analysis* 13 (2): 143–163.

Khazal, Aras, Ole Jakob Sønstebø, Jon Olaf Olaussen, and Are Oust. 2020. "The Impact of Strategic Jump Bidding in Residential English Auctions." *Journal of Property Research* 37 (3): 195–218.

King, Gary, and Richard Nielsen. 2019. "Why Propensity Scores Should Not Be Used for Matching." *Political Analysis* 27 (4): 435–454.

Klemperer, Paul. 1998. "Auctions with Almost Common Values: The 'Wallet Game' and Its Applications." *European Economic Review* 42 (3): 757–769.

Klemperer, Paul. 2002a. "What Really Matters in Auction Design." *Journal of Economic Perspectives* 16 (1): 169–189.

Klemperer, Paul. 2002b. "How (Not) to Run Auctions: The European 3G Telecom Auctions."

European Economic Review 46 (4): 829–845.
LaCour-Little, Michael, and Jing Yang. 2023. "Seeking Alpha in the Housing Market." *The Journal of Real Estate Finance and Economics* 67 (3): 319–374.
Lambie-Hanson, Lauren. 2015. "When Does Delinquency Result in Neglect? Mortgage Distress and Property Maintenance." *Journal of Urban Economics* 90: 1–16.
Levin, Eric J., and Gwilym B. J. Pryce. 2007. "A Statistical Explanation for Extreme Bids in the House Market." *Urban Studies* 44 (12): 2339–2355.
Lin, Zhenguo, Eric Rosenblatt, and Vincent W. Yao. 2009. "Spillover Effects of Foreclosures on Neighborhood Property Values." *The Journal of Real Estate Finance and Economics* 38 (4): 387–407.
Lorentziadis, Panos L. 2016. "Optimal Bidding in Auctions from a Game Theory Perspective." *European Journal of Operational Research* 248 (2): 347–371.
Lusht, Kenneth M. 1996. "A Comparison of Prices Brought by English Auctions and Private Negotiations." *Real Estate Economics* 24 (4): 517–530.
Marshall, Robert C., Leslie M. Marx, and Michael J. Meurer. 2014. "The Economics of Bidder Collusion." In *Game Theory and Business Applications,* edited by Kalyan Chatterjee and William Samuelson, 367–397. Boston, MA: Springer US.
Mayer, Christopher J. 1995. "A Model of Negotiated Sales Applied to Real Estate Auctions." *Journal of Urban Economics* 38 (1): 1–22.
Mazzola, Francesco. 2022. "Electronic Foreclosures."
Mian, Atif, Amir Sufi, and Francesco Trebbi. 2015. "Foreclosures, House Prices, and the Real Economy: Foreclosures, House Prices, and the Real Economy." *The Journal of Finance* 70 (6): 2587–2634.
Michelsen, Claus, and Dominik Weiß. 2010. "What Happened to the East German Housing Market? A Historical Perspective on the Role of Public Funding." *Post-Communist Economies* 22 (3): 387–409.
Niedermayer, Andras, Artyom Shneyerov, and Pai Xu. 2023. "Foreclosure Auctions."
Ong, Seow, Kenneth Lusht, and Chee Mak. 2005. "Factors Influencing Auction Outcomes: Bidder Turnout, Auction Houses and Market Conditions." *Journal of Real Estate Research* 27 (2): 177–192.
Ooi, Joseph T.L., C.f. Sirmans, and Geoffrey K. Turnbull. 2006. "Price Formation Under Small Numbers Competition: Evidence from Land Auctions in Singapore." *Real Estate Economics* 34 (1): 51–76.
Pagnozzi, Marco. 2011. "Bids as a Vehicle of (Mis)Information: Collusion in English Auctions with Affiliated Values." *Journal of Economics & Management Strategy* 20 (4): 1171–1196.
Pennington-Cross, Anthony. 2006. "The Value of Foreclosed Property." *Journal of Real Estate Research* 28 (2): 193–214.
Quan, Daniel C. 1994. "Real Estate Auctions: A Survey of Theory and Practice." *The Journal of Real Estate Finance and Economics* 9 (1): 23–49.
Rosenbaum, Paul R. 2020. "Modern Algorithms for Matching in Observational Studies." *Annual Review of Statistics and Its Application* 7 (1): 143–176.
Rubin, Donald B. 1977. "Assignment to Treatment Group on the Basis of a Covariate." *Journal of*

Educational Statistics 2 (1): 1–26.

Shilling, James D., John D. Benjamin, and C. F. Sirmans. 1990. "Estimating Net Realizable Value for Distressed Real Estate." *The Journal of Real Estate Research* 5 (1): 129–140.

Sommervoll, Dag Einar. 2020. "Jump Bids in Real Estate Auctions." *Journal of Housing Economics* 49: 101713.

Springer, Thomas M. 1996. "Single-Family Housing Transactions: Seller Motivations, Price, and Marketing Time." *The Journal of Real Estate Finance and Economics* 13 (3): 237–254.

Stevenson, Simon, and James Young. 2015. "The Role of Undisclosed Reserves in English Open Outcry Auctions." *Real Estate Economics* 43 (2): 375–402.

Towe, Charles, and Chad Lawley. 2013. "The Contagion Effect of Neighboring Foreclosures." *American Economic Journal: Economic Policy* 5 (2): 313–335.

Zhou, Hanqing, Yuan Yuan, Christopher Lako, Michael Sklarz, and Charles McKinney. 2015. "Foreclosure Discount: Definition and Dynamic Patterns." *Real Estate Economics* 43 (3): 683–718.

Appendix A. Full regression results

TABLE A1. Hedonic regressions for static and dynamic foreclosure discounts

	Full sample		Matched repeat sales sample	
	Static	Dynamic	Static	Dynamic
	Dep. Var.: Ln(Transaction price)			
Ln(Floor space)	1.082***	1.082***	1.002***	1.005***
	(0.008)	(0.008)	(0.016)	(0.015)
Number of rooms	0.004	0.003	0.021***	0.020***
	(0.003)	(0.003)	(0.005)	(0.005)
Age of building	–0.001***	–0.001***	–0.001***	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Age of building squared	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Bathroom	0.015***	0.014***	0.054***	0.051***
	(0.005)	(0.005)	(0.011)	(0.011)
Separate WC	0.026***	0.025***	0.015	0.015
	(0.003)	(0.003)	(0.010)	(0.010)
Balcony	0.029***	0.028***	0.029***	0.028***
	(0.002)	(0.002)	(0.005)	(0.005)
Attic	0.025**	0.025**	0.094***	0.091***
	(0.010)	(0.010)	(0.025)	(0.024)
Basement	–0.007**	–0.007**	–0.011	–0.011
	(0.003)	(0.003)	(0.007)	(0.007)
Atelier	–0.055	–0.054	0.059	0.086
	(0.036)	(0.036)	(0.121)	(0.119)
Hobby room	0.127***	0.127***	0.156***	0.162***
	(0.008)	(0.008)	(0.030)	(0.030)
Storage room	–0.021***	–0.021***	–0.002	–0.003
	(0.003)	(0.003)	(0.006)	(0.006)
Hallway	–0.005	–0.005	0.007	0.011
	(0.004)	(0.004)	(0.011)	(0.011)
Corridor	–0.027***	–0.028***	0.018	0.020
	(0.005)	(0.005)	(0.013)	(0.013)
Elevator	0.060***	0.060***	0.015*	0.014*
	(0.004)	(0.004)	(0.008)	(0.008)
Private garage	–0.011***	–0.011***	–0.007	–0.006
	(0.002)	(0.002)	(0.005)	(0.005)
Collective garage	0.023***	0.023***	0.071***	0.069***
	(0.006)	(0.006)	(0.021)	(0.021)
Parking lot	0.028***	0.028***	0.040***	0.038***
	(0.004)	(0.004)	(0.010)	(0.010)
Type of Apartment, reference = Floor Apartment				

	Full sample		Matched repeat sales sample	
	Static	Dynamic	Static	Dynamic
Attic Apartment	0.131***	0.131***	0.125***	0.125***
	(0.004)	(0.004)	(0.011)	(0.011)
Duplex Apartment	0.064***	0.063***	0.052***	0.050**
	(0.005)	(0.005)	(0.020)	(0.020)
Loft	–0.011	–0.014	0.253**	0.268**
	(0.030)	(0.029)	(0.112)	(0.131)
Penthouse	0.223***	0.223***	0.024	0.031
	(0.014)	(0.014)	(0.101)	(0.108)
Storefront Apartment	–0.129***	–0.127***	–0.042	–0.026
	(0.023)	(0.023)	(0.055)	(0.055)
Terrace Apartment	0.162***	0.164***	0.194***	0.216***
	(0.019)	(0.020)	(0.058)	(0.063)
Location quality, reference = Intermediate				
Basic	–0.016***	–0.016***	–0.038***	–0.040***
	(0.005)	(0.005)	(0.013)	(0.012)
Good	0.087***	0.087***	0.079***	0.077***
	(0.006)	(0.006)	(0.014)	(0.014)
Very good	0.298***	0.294***	0.475***	0.470***
	(0.024)	(0.023)	(0.060)	(0.060)
Floor level, reference = Upper floors				
Basement floor	–0.202***	–0.204***	–0.289***	–0.300***
	(0.014)	(0.015)	(0.044)	(0.044)
First floor	–0.052***	–0.053***	–0.070***	–0.072***
	(0.002)	(0.002)	(0.006)	(0.006)
Mezzanine floor	0.007	0.007	–0.034	–0.032
	(0.008)	(0.008)	(0.023)	(0.021)
Type of transaction, reference = Regular sale				
Foreclosure	–0.490***	–0.393***	–0.463***	–0.332***
	(0.008)	(0.084)	(0.008)	(0.094)
Foreclosure × Year 1985		–0.074		–0.105
		(0.104)		(0.116)
Foreclosure × Year 1986		–0.126		–0.239**
		(0.098)		(0.119)
Foreclosure × Year 1987		–0.224**		–0.167
		(0.105)		(0.102)
Foreclosure × Year 1988		0.007		–0.012
		(0.090)		(0.105)
Foreclosure × Year 1989		–0.042		–0.050
		(0.089)		(0.101)
Foreclosure × Year 1990		0.113		0.043
		(0.096)		(0.105)
Foreclosure × Year 1991		0.089		0.026

	Full sample		Matched repeat sales sample	
	Static	Dynamic	Static	Dynamic
		(0.089)		(0.100)
Foreclosure × Year 1992		0.089		–0.029
		(0.094)		(0.109)
Foreclosure × Year 1993		–0.046		–0.055
		(0.104)		(0.110)
Foreclosure × Year 1994		–0.096		–0.070
		(0.108)		(0.114)
Foreclosure × Year 1995		–0.022		–0.114
		(0.096)		(0.107)
Foreclosure × Year 1996		0.025		–0.111
		(0.090)		(0.107)
Foreclosure × Year 1997		–0.011		–0.075
		(0.089)		(0.101)
Foreclosure × Year 1998		–0.175*		–0.248**
		(0.094)		(0.105)
Foreclosure × Year 1999		–0.134		–0.163
		(0.093)		(0.101)
Foreclosure × Year 2000		–0.253***		–0.300***
		(0.092)		(0.101)
Foreclosure × Year 2001		–0.190**		–0.259**
		(0.093)		(0.103)
Foreclosure × Year 2002		–0.273***		–0.310***
		(0.090)		(0.101)
Foreclosure × Year 2003		–0.309***		–0.371***
		(0.090)		(0.100)
Foreclosure × Year 2004		–0.318***		–0.368***
		(0.089)		(0.100)
Foreclosure × Year 2005		–0.279***		–0.330***
		(0.089)		(0.098)
Foreclosure × Year 2006		–0.241***		–0.319***
		(0.090)		(0.100)
Foreclosure × Year 2007		–0.231***		–0.313***
		(0.089)		(0.099)
Foreclosure × Year 2008		–0.185**		–0.248**
		(0.089)		(0.099)
Foreclosure × Year 2009		–0.119		–0.191*
		(0.088)		(0.099)
Foreclosure × Year 2010		–0.034		–0.014
		(0.087)		(0.096)
Foreclosure × Year 2011		0.092		0.076
		(0.088)		(0.097)
Foreclosure × Year 2012		0.156*		0.172*
		(0.088)		(0.097)
Foreclosure × Year 2013		0.171**		0.176*
		(0.087)		(0.097)
Foreclosure × Year 2014		0.143		0.166*

	Full sample		Matched repeat sales sample	
	Static	Dynamic	Static	Dynamic
		(0.088)		(0.097)
Foreclosure × Year 2015		0.193**		0.215**
		(0.090)		(0.100)
Foreclosure × Year 2016		0.234***		0.240**
		(0.089)		(0.100)
Foreclosure × Year 2017		0.235***		0.201**
		(0.088)		(0.098)
Foreclosure × Year 2018		0.304***		0.247**
		(0.093)		(0.106)
Foreclosure × Year 2019		0.193**		0.185
		(0.098)		(0.117)
Foreclosure × Year 2020		0.164		0.090
		(0.109)		(0.125)
Foreclosure × Year 2021		0.216**		0.123
		(0.101)		(0.121)
Foreclosure × Year 2022		0.182*		0.176
		(0.094)		(0.110)
ZIP code × Year FE	✓	✓	✓	✓
Num. obs.	391,420	391,420	36,808	36,808
R^2	0.856	0.857	0.790	0.799

OLS regressions with the log of the transaction price as response variable. The variable "Age of building" is the actual age of the building multiplied by 10. Standard errors are clustered at the ZIP code level. Sources: Expert Commitee for Property Values in Berlin; authors' calculations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

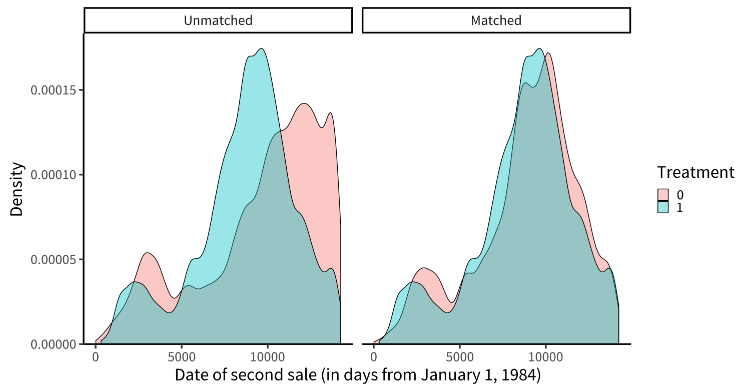
Table A2. Matched sample effect by holding period

	Dep. Var.: Annualized appreciation rate			
	(1)	(2)	(3)	(4)
Constant	0.305***			
	(0.013)			
< 1 year × Treatment 1	0.316***	0.324***	0.331***	0.360***
	(0.025)	(0.022)	(0.029)	(0.038)
< 1 year × Treatment 2	–0.511***	–0.499***	–0.525***	–0.567***
	(0.066)	(0.067)	(0.069)	(0.114)
1–2 years	–0.087***	–0.094***	–0.027	0.011
	(0.022)	(0.022)	(0.030)	(0.040)
1–2 years × Treatment 1	0.203***	0.197***	0.203***	0.157***
	(0.024)	(0.023)	(0.024)	(0.040)
1–2 years × Treatment 2	–0.340***	–0.336***	–0.384***	–0.432***
	(0.034)	(0.033)	(0.047)	(0.070)
2–3 years	–0.181***	–0.196***	–0.076**	–0.066
	(0.016)	(0.016)	(0.033)	(0.044)
2–3 years × Treatment 1	0.141***	0.147***	0.150***	0.126***
	(0.013)	(0.012)	(0.016)	(0.031)
2–3 years × Treatment 2	–0.341***	–0.317***	–0.296***	–0.307***
	(0.019)	(0.016)	(0.024)	(0.034)
3–4 years	–0.242***	–0.251***	–0.126***	–0.099**
	(0.016)	(0.015)	(0.035)	(0.047)
3–4 years × Treatment 1	0.123***	0.127***	0.128***	0.146***
	(0.014)	(0.013)	(0.016)	(0.023)
3–4 years × Treatment 2	–0.212***	–0.192***	–0.163***	–0.161***
	(0.012)	(0.011)	(0.015)	(0.016)
4–5 years	–0.263***	–0.267***	–0.134***	–0.107**
	(0.015)	(0.015)	(0.039)	(0.052)
4–5 years × Treatment 1	0.099***	0.096***	0.090***	0.121***
	(0.014)	(0.010)	(0.017)	(0.020)
4–5 years × Treatment 2	–0.176***	–0.146***	–0.129***	–0.130***
	(0.008)	(0.006)	(0.010)	(0.010)
5–6 years	–0.279***	–0.281***	–0.132***	–0.109**
	(0.015)	(0.014)	(0.041)	(0.054)
5–6 years × Treatment 1	0.100***	0.101***	0.117***	0.103***
	(0.011)	(0.009)	(0.014)	(0.013)
5–6 years × Treatment 2	–0.128***	–0.103***	–0.091***	–0.086***
	(0.007)	(0.007)	(0.009)	(0.007)
6–7 years	–0.292***	–0.287***	–0.129***	–0.109**
	(0.015)	(0.015)	(0.042)	(0.054)
6–7 years × Treatment 1	0.087***	0.084***	0.072***	0.061**
	(0.010)	(0.010)	(0.015)	(0.027)
6–7 years × Treatment 2	–0.098***	–0.072***	–0.059***	–0.057***
	(0.006)	(0.005)	(0.011)	(0.008)
7–8 years	–0.300***	–0.282***	–0.115**	–0.103*
	(0.014)	(0.014)	(0.045)	(0.055)

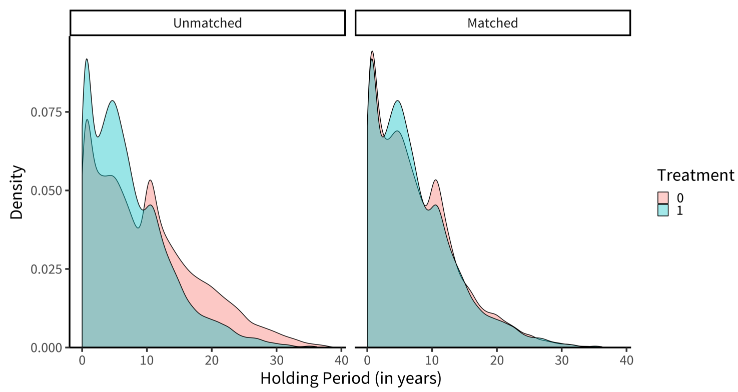
	(1)	(2)	(3)	(4)
7–8 years × Treatment 1	0.107***	0.092***	0.101***	0.096***
	(0.010)	(0.011)	(0.019)	(0.013)
7–8 years × Treatment 2	−0.082***	−0.059***	−0.037***	−0.050***
	(0.006)	(0.005)	(0.010)	(0.008)
8–9 years	−0.299***	−0.272***	−0.079*	−0.101*
	(0.014)	(0.014)	(0.045)	(0.057)
8–9 years × Treatment 1	0.089***	0.067***	0.061***	0.094***
	(0.010)	(0.007)	(0.021)	(0.015)
8–9 years × Treatment 2	−0.075***	−0.059***	−0.045***	−0.034***
	(0.006)	(0.005)	(0.011)	(0.009)
9–10 years	−0.304***	−0.271***	−0.070	−0.098*
	(0.014)	(0.015)	(0.045)	(0.056)
9–10 years × Treatment 1	0.098***	0.054***	0.064***	0.046***
	(0.008)	(0.008)	(0.017)	(0.014)
9–10 years × Treatment 2	−0.050***	−0.037***	−0.036***	−0.030***
	(0.005)	(0.004)	(0.011)	(0.007)
> 10 years	−0.289***	−0.254***	−0.079*	−0.092
	(0.014)	(0.014)	(0.047)	(0.057)
> 10 years × Treatment 1	0.073***	0.045***	0.047***	0.051***
	(0.003)	(0.002)	(0.006)	(0.005)
> 10 years × Treatment 2	−0.042***	−0.028***	−0.015***	−0.019***
	(0.002)	(0.002)	(0.005)	(0.002)
ZIP code FE		✓	✓	✓
Y first sale FE		✓	✓	✓
Y second sale FE		✓	✓	✓
Y first sale × Y first second FE			✓	✓
ZIP code × Y first sale FE			✓	✓
ZIP code × Y second sale FE			✓	✓
ZIP code × Y first sale × Y second sale FE				✓
Num. obs.	20,408	20,408	20,408	20,408
R^2	0.408	0.448	0.687	0.829

OLS regressions with the annualized appreciation rate as response variable. Standard errors are clustered at the ZIP code level. Sources: Expert Commitee for Property Values in Berlin; authors' calculations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Appendix B. Robustness



A. Variable "Date of second sale"



B. Variable "Holding period"

FIGURE A1. Distributional balance for “Date of second sale” and "Holding Period"

These figures document the distribution of variables "Date of second sale" (Figure A1A) and "Holding period" (Figure A1B) in the unmatched and the matched sample. After matching, although small differences in means persist, the distributions in these variables are fairly identical between foreclosed and non-foreclosed repeat sales. Sources: Expert Commitee for Property Values in Berlin; authors’ calculations.

TABLE A3. Robust results with k:1-matching

	Dep. Var.: Annualized appreciation rate			
	2:1-match	3:1-match	4:1-match	5:1-match
Treatment 1 (Foreclosure:Regular)	0.204***	0.197***	0.193***	0.187***
	(0.016)	(0.014)	(0.013)	(0.013)
Treatment 2 (Regular:Foreclosure)	−0.094***	−0.092***	−0.089***	−0.090***
	(0.005)	(0.005)	(0.004)	(0.004)
ZIP code FE	✓	✓	✓	✓
Y first sale FE	✓	✓	✓	✓
Y second sale FE	✓	✓	✓	✓
Y first sale × Y first second FE	✓	✓	✓	✓
ZIP code × Y first sale FE	✓	✓	✓	✓
ZIP code × Y second sale FE	✓	✓	✓	✓
ZIP code × Y first sale × Y second sale FE	✓	✓	✓	✓
No. obs.	30,597	40,735	50,761	60,220
# Treated | # Matched Control	10,204 | 20,393	10,204 | 30,531	10,204 | 40,557	10,204 | 50,016
R^2	0.756	0.723	0.705	0.691

OLS regressions with the annualized holding period return as response variable. The regression model is constant across columns but used samples vary depending on the matching procedure indicated in the column header. Note that the matching algorithm could not always assign k control units to each treated unit. Standard errors are clustered at the ZIP code level. Sources: Expert Commitee for Property Values in Berlin; authors' calculations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

TABLE A4. Descriptive statistics on Treatment-1 and Treatment-2-apartments

		Treatment 1 (N=4,745)		Treatment 2 (N=5,459)			
		Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Sales price of second sale (EUR)		120,115.41	108,701.80	65,676.85	65,905.49	-54,438.56	<0.001
Age of building (years)		71.03	35.91	71.88	33.69	0.85	0.220
Number of rooms		2.30	0.99	2.26	0.96	-0.04	0.039
Floor space (sqm)		65.89	27.31	63.96	26.13	-1.93	<0.001
Bathroom (dummy)		0.90	0.30	0.90	0.30	0.00	0.886
Separate WC (dummy)		0.12	0.32	0.11	0.31	-0.01	0.030
Balcony (dummy)		0.42	0.49	0.41	0.49	-0.01	0.346
Attic (dummy)		0.01	0.11	0.02	0.12	0.00	0.246
Basement (dummy)		0.71	0.45	0.71	0.45	0.00	0.964
Atelier (dummy)		0.00	0.03	0.00	0.03	0.00	0.605
Hobby room (dummy)		0.01	0.10	0.01	0.09	0.00	0.629
Storage room (dummy)		0.58	0.49	0.55	0.50	-0.02	0.020
Hallway (dummy)		0.17	0.37	0.14	0.35	-0.02	0.003
Corridor (dummy)		0.87	0.34	0.88	0.32	0.01	0.026
Elevator (dummy)		0.26	0.44	0.20	0.40	-0.06	<0.001
Private garage (dummy)		0.22	0.41	0.22	0.41	0.00	0.832
Collective garage (dummy)		0.01	0.09	0.01	0.10	0.00	0.328
Parking lot (dummy)		0.06	0.24	0.06	0.23	0.00	0.321
		N	Pct.	N	Pct.		
Location quality	Basic	1,976	41.6	2,699	49.4		
	Good	1,208	25.5	1,110	20.3		
	Intermediate	1,472	31.0	1,546	28.3		
	Very Good	89	1.9	104	1.9		
Type of Apartment	Attic Apartment	309	6.5	279	5.1		
	Duplex Apartment	92	1.9	97	1.8		
	Floor Apartment	4,325	91.1	5,059	92.7		
	Loft	0	0.0	2	0.0		
	Penthouse	3	0.1	2	0.0		
	Storefront Apartment	12	0.3	16	0.3		
	Terrace Apartment	4	0.1	4	0.1		
Floor level	Basement floor	25	0.5	27	0.5		
	First floor	999	21.1	1275	23.4		
	Mezzanine floor	39	0.8	58	1.1		
	Upper floors	3,682	77.6	4,099	75.1		

The table reports descriptive statistics on Treatment-1 and Treatment-2-transactions. In general, it seems that the hedonic characteristics of apartments in the two "treatment regimes" do not differ. Sources: Expert Commitee for Property Values in Berlin; authors' calculations.