Market Timing, Machine Learning Methods and their Interpretability in Real Estate

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1 Introduction

1.1 General Motivation and Theoretical Background

Classical finance theory suggest that investors consider all information available within their investment decision and trade assets rationally (Case & Shiller, 1990). This notion is based on the efficient market hypothesis as proposed by Fama (1970). Consequently, market efficiency would imply asset pricing based on economic fundamentals and eliminate disequilibria in a timely manner. However, efficient markets are often only a theoretical framework. The reality looks different, since inefficiency in markets can occur due to several reasons. Behavioral finance demonstrates that investors are subject to irrational behavior, resulting in deviations from fundamental values and asset mispricing.[1]

In the real estate sector, research shows that participants in real estate markets base their investment decisions on observable fundamental characteristics (Scott, 1990). A broad range of research states macro- and microeconomic conditions to play an important role in determining real estate markets, although behavioral aspects of market participants have shown to result in deviations from economic fundamentals (Clayton, 1998). Farlow (2004) argues that over-optimism is a major aspect of real estate markets and highly affects decision-making. Special characteristics of the underlying asset intensify mispricing in the real estate sector. Real estate markets have shown to be informationally inefficient and highly non-transparent. Furthermore, deviations from fundamental values are even more pronounced as real estate as an asset class is segmented and short selling is limited (Beracha & Skiba, 2011). As Hayunga and Lung (2011) state, real estate markets are therefore a well suited research subject for mispricing behavior.

Asset mispricing is often associated with market timing, as the link between pricing deviations and trading is intuitive. Market participants possess different beliefs of the fundamental value. As information changes over time, the deviation between different estimates of the intrinsic value generates trade since an owner would sell at the time when an overconfident buyer possesses higher expectation of future cash flows (Scheinkman & Xiong, 2003; Cao & Ou-Yang, 2008). Hence, the timing of investment decisions becomes an essential factor in real estate markets (Ooi et al., 2010; Hochberg & Muhlhofer, 2011).[2]

[1] See e.g. Sharma and Kumar (2019) for an extensive review on market efficiency and behavioural finance. See e.g. Palan (2013) for an overview of factors that influence mispricing behavior.

[2] Several explanations have been proposed to explain asset mispricing in real estate markets. See e.g. Hayunga and Lung (2011) for an investigation on inflation-illusion hypothesis and overconfidence theory.

Market timing per se is a well-studied phenomenon in capital markets, since the market's perception of the firm's value is available on a daily basis due to global stock trading. Summers (1986, p. 600) early states that market values can show high deviations from rational expectations of future cash flows and consequently form their intrinsic valuation. He argues that "it does suggest caution in treating stock prices or their changes as rational reflection of fundamental values". In the real estate sector, Barkham and Ward (1999) e.g. found persisting discounts of market prices to net asset values (NAV). An outperformance from investments in real estate corporations is found to be the result of specific investors' abilities and private beliefs rather than rational investment strategies (Cici et al., 2011). Timing behavior is also present for financing decisions (Graham & Harvey, 2001). Baker and Wurgler (2002) state that the capital structure of a company is the cumulative outcome of past attempts to time the equity market. Especially real estate investment trusts (REITs), which regularly rely on the access to capital markets, are taking advantage of overoptimistic expectations by timing the market (Boudry et al., 2010). Consequently, deviations from economic fundamentals question on the one hand the efficiency of financial markets including real estate securities, and on the other hand enable market participants to exploit market disequilibria by optimally timing investment or financing activities in capital markets.

As in indirect markets, literature shows that the link to market fundamentals is as pronounced in direct real estate markets (Zhou, 2010; Yunus, 2012). Although economic fundamentals are of high importance in the determination of real estate prices and rents, they are, however, only able to explain their changes over time in a limited way (Quigley, 1999; Farlow, 2013). More than this, Clayton (1998, p. 41) applies measures for mispricing and deviations from intrinsic values to "provides strong evidence against market efficiency [in direct real estate markets]". The inelasticity of supply (Glaeser et al., 2008), financing aspects (Hunter et al., 2005) as well as the heterogeneous and local nature of real estate properties and the effect of bargaining power (Harding et al., 2003) further contribute to disequilibria in direct real estate markets. The limited short-selling ability in periods of over- and undervaluation as well as the fact that market fundamentals affect different types of real estate investors to varying extents likely result in persisting mispricing in real estate asset markets (Ling et al., 2014; Ke & Sieracki, 2019).

In contrast to stock markets, the markets estimation of the commodities' value is not directly observable on a frequent or even daily basis. Hence, the value of a property is derived from formal and informal appraisals (Redding, 2006). Appraisal-based estimations typically contain time lags (Fisher et al., 1999) and are only an imprecise measure for true market values (Cannon & Cole, 2011). Because "precise, timely estimations of property values are critical for real estate investors" (Kok et al., 2017, p. 203), property markets face difficulties to assess asset mispricing and consequently identify opportunities for market-timing behavior.

Technological advances seek to remedy these shortcomings. On the one side, new sources of information, based e.g. on Multiple Listing Systems (MLS), provide an innovative data environment to identify mispricing in a timely manner (Kok et al., 2017; Pérez-Rave et al., 2019). On the other side, ongoing improvements in computational power led the way to the development of Artificial Intelligence (AI) and Machine Learning (ML) to contribute to a methodological framework that enables further mispricing analysis in real estate (Zurada et al., 2011). ML thereby provides a far-reaching toolset in research and practice (Hastie et al., 2009). Given the high predictive performance of ML models and the fact that "one of the main approaches to face [new data sources] is machine learning" (Pérez-Rave et al., 2019, p. 5), modern regression techniques provide a suitable framework to precisely identify mispricing in property markets.

Nevertheless, letting the machine 'understand' the relationships within the data impedes the acceptance of modern approaches. Because the internal logic and consequently the rationale behind the individual predictions is rather hidden (Mullainathan & Spiess, 2017), the use of ML often lacks transparency and is criticized for its 'black box' character (Carvalho et al., 2019). Because sole measures like predictive accuracy are an incomplete description of most real-world tasks (Doshi-Velez & Kim, 2017), explaining the inner working of a ML model is crucial to understand and validate how a certain decision is achieved (Adadi & Berrada, 2018). It is, therefore, not surprising that these issues on the interpretability of algorithmic decision-making are finding its way into international legislation, with the European Union including a "right to explanation" in their General Data Protection Regulation (Guidotti et al., 2018; Carvalho et al., 2019).

In this context, the thesis attempts to extend the literature on market timing in direct as well as indirect real estate markets and aims to provide a practical framework for market participants to identify asset mispricing in the real estate sector. Because both precise and timely estimations as well as the rationale behind the modelling approach are of crucial importance to assess mispricing and derive investment strategies, the dissertation furthermore sheds light on emerging data sources and Machine Learning methods as well as their interpretability.

1.2 Course of Analysis and Research Questions

The following section provides an overview over the course of analysis. Although all three main chapters, each representing one research paper, address the topic of mispricing and market timing in real estate, they highlight distinct aspects of the area under investigation.

Paper 1 | Underpricing and Market Timing in SEOs of European REITs and REOCs

The central objective of Paper 1 is to set the theoretical framework of market timing based on findings in the indirect real estate market. Due to the importance of raising capital, it examines how managers time the equity market by offering equity when market values are high and investors are overconfident. While a large strand of literature examine timing behavior as such, the study goes even further in examining how market timing affects the pricing of equity offerings. Its findings complement the literature on offer price discounts in European markets and further shed light on the particularities of REITs.

Research Questions

- Do European property companies show price discounts at seasoned equity offerings (SEOs) and therefore accept additional cost of raising capital? How do real estate specific particularities affect the cost of raising capital?
- How do asset mispricing and market timing affect capital increases in real estate? Do managers time the market and exploit favorable market conditions?
- How do property company managers benefit from lower cost of raising capital within their market timing behavior? Do high market valuations and optimistic investors result in lower offer price discounts at SEOs?

Paper 2 | Rental Pricing of Residential Market and Portfolio Data – A Hedonic Machine Learning Approach

The second Paper transfers the theoretical framework and findings on timing behavior to direct real estate markets. Using algorithmic modelling techniques and data from MLS, it does not only highlight the predictive performance of several algorithm-driven hedonic models but furthermore identifies mispricing in residential portfolios and enables a conceptual framework to derive market timing strategies in terms of investment or disinvestment decisions. The findings show that ML leads to more accurate predictions than traditional models. In addition, they indicate that algorithmic models are able to reveal a higher degree of mispricing in institutional portfolios. The application of ML therefore can be a valuable extent to current analysis to identify investment opportunities more precisely and in a timely manner.

Research Questions

- Does the growing data availability from MLS provide a suitable framework for the analysis of direct real estate in mainly opaque property markets?
- Are ML algorithms more accurate in predicting residential rents than traditional models due its ability to capture complex pattern and deal with large datasets?
- Can the applications of ML models to a portfolio of institutionally managed apartments reveal new insights on asset pricing and provide well-founded investment strategies?

Paper 3 | Peeking inside the Black Box: Interpretable Machine Learning and Hedonic Rental Estimation

Paper 3 complements the previous findings in property markets and sheds light on the interpretability of ML-based results. Because the inner working of ML models is rather hidden, their predictive framework is often criticized as a black box. Using Interpretable Machine Learning (IML) methods enables to peek inside the predictive behavior of algorithmic models and improve trust in ML-based estimates. The findings reveal the rationale behind the final prediction of complex models. Consequently, IML methods can e.g. reveal the rationale behind the estimation of asset mispricing and consequently highlight its reliability. The study provides valuable inferential insights in ML-based results in residential markets while maintaining the remarkable predictive performance of ML that was and still is a major driver for the widespread application of algorithmic models.

Research Questions

- How do algorithmic hedonic models come to its final rental prediction? Is the rationale behind the decision-making behavior of ML models based on the economic context of residential property markets?
- Do model-agnostic interpretation methods identify which property characteristics are important for the ML model and how these characteristics contribute to the final prediction?
- Can IML methods provide inferential insights on the dependencies the algorithm has learned from the underlying data? Do model-agnostic reveal possibly hidden relationships in residential real estate markets?

1.3 Submissions and Conference Presentations

This section complements the previous descriptions with details regarding submission to journals, publication status and conference presentations.

Paper 1 | Underpricing and Market Timing in SEOs of European REITs and REOCs

Authors:	Felix Lorenz
Submission to Journal:	Journal of Property Investment & Finance
Current status:	Accepted for publication (04.11.2019) and published in Vol. 38 No. 3 (16.12.2019)

Conference Presentation:

This paper was presented at the 35th Annual Conference of the American Real Estate Society (ARES) in Paradise Valley, US (2019) and the 26th Annual Conference of the European Real Estate Society (ERES) in Cergy-Pontoise, France (2019).

Paper 2 | Rental Pricing of Residential Market and Portfolio Data – A Hedonic Machine Learning Approach

Authors:	Marcelo Cajias, Jonas Willwersch, Felix Lorenz, Wolfgang Schaefers
Submission to Journal:	Real Estate Finance
Current status:	Accepted for publication (27.04.2021)

Conference Presentation:

This paper was presented at the 26th Annual Conference of the European Real Estate Society (ERES) in Cergy-Pontoise, France (2019), the 2nd Workshop on "Artificial Intelligence and Finance" of the Center of Finance of the University of Regensburg held online (2020), and the 37th Annual Conference of the American Real Estate Society (ARES) held online (2021).

Furthermore, the paper is submitted to be presented at the 27th Annual Conference of the European Real Estate Society (ERES) in Kaiserslautern, Germany (2021) and the Annual Meeting of the "Verein fuer Socialpolitik" (VfS) in Regensburg, Germany (2021).

Paper 3 | Peeking inside the Black Box: Interpretable Machine Learning and Hedonic Rental Estimation

Authors:	Felix Lorenz, Jonas Willwersch, Marcelo Cajias, Franz Fuerst
Submission to Journal:	Real Estate Economics
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Conference Presentation:

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2 Underpricing and Market Timing in SEOs of European REITs and REOCs

2.1 Abstract

This paper contributes to the literature on seasoned equity offerings (SEOs) by examining underpricing of European real estate corporations and identifying determinants explaining the phenomenon of setting the offer price at a discount at SEOs. With a sample of 470 SEOs of European real estate investment trust (REITs) and real estate operating companies (REOCs) from 2004-2018, multivariate regression models are applied to test for theories on the pricing of SEOs. This paper furthermore tests for differences in underpricing for REITs and REOCs as well as specialized and diversified property companies.

Significant underpricing of 3.06% is found, with REITs (1.90%) being statistically less underpriced than REOCs (5.08%). The findings support the market timing theory by showing that managers trying to time the equity market gain from lower underpricing. Furthermore, underwritten offerings are more underpriced to reduce the risk of the arranging bank, but top-tier underwriters are able to reduce offer price discounts by being more successful at attracting investors. The results cannot support the value uncertainty hypothesis, but are in line with placement cost stories. In addition, specialized property companies are subject to lower underpricing.

An optimal issuance strategy taking into account timing, relative offer size and the choice of the underwriter can minimize the amount of "money left on the table" and therefore contribute to lower cost of raising capital. This is the first study to investigate SEO underpricing for European real estate corporations, pricing differences of REITs and REOCs and the effect of market timing on the pricing of SEOs.

Keywords: Underpricing, Offer price discount, SEO, Equity offering, Europe, Market timing, REIT, Property company

2.2 Introduction

As Ghosh et al. (2000) states, SEOs are major events in the lifetime of a listed property company and essential to ensure profitable growth and sustainable development. Especially REITs need to regularly raise money through capital increases and therefore access the capital market more often than industrial firms due to their limited funding possibilities with restriction on debt ratio and retained earnings (Boudry et al., 2011). Although SEOs play an important role for listed companies, issued shares are regularly offered at an offer price significantly lower than the price the shares are traded on the offer day – defined as underpricing – or the day before the offering – defined as discounting. Besides direct cost of raising capital the issuing firm is consequently accepting additional expenses as "money left on the table" at equity offerings. Because the extent of underpricing represents potential equity capital the issuer decided to forego convincing arguments must exist to justify such losses.

As Goodwin (2013) states, equity offerings of property companies, in particular REITs, are an interesting research topic due to their unique characteristics. Besides restrictions on the equity ratio and income requirements, REITs are mainly characterized by their high profit distribution (80-95% of net profit). Although REITs are an internationally well-known investment vehicle, country specific differences in limitations of their business activity exist. In addition, the valuation of property companies is complex not only due to valuation variation of real estate as the underlying assets. Relatively low transparency in the real estate sector and the added stock market risk also contribute to valuation uncertainty of real estate corporations.

There is existing literature to explain the phenomenon of setting the offer price at a discount at SEOs. Being mainly focused on industrial firms, far less is known about the pricing of equity offerings in the real estate sector, especially in Europe. But with more and more countries establishing the REIT regime, this listed real estate investment vehicle gain increasing importance in European real estate markets (Ascherl & Schaefers, 2018). This is to our best knowledge the first study to (1) investigate underpricing of equity offerings in the European real estate sector, (2) examine pricing differences for REITs and REOCs at SEOs and (3) analyze the impact of market timing behavior on the pricing of seasoned offerings.

2.3 Listed Real Estate Markets in Europe

REITs have shown to be an attractive investment alternative in the capital market in the past decades (Laopodis, 2009) and gain increasing significance especially in Europe (Newell & Marzuki, 2018). While several countries in Europe adopted the REIT regime in the late 2000th, emerging real estate markets in southern and eastern Europe are still into extending their spectrum of real estate investment vehicles, with Poland and Portugal being the most recent to establish the REIT regime in 2019. While in 1999, only one REIT existed in Europe, the value of listed real estate in the European Union reached $ 387.6Bn with 226 REITs accounting for $ 186.9Bn in market capitalization (EPRA, 2019b).

Table 2.1 provides an overview of listed real estate markets in Europe. Regarding total market capitalization of property companies by country, Germany (€ 92.1Bn), the United Kingdom (€ 77.0Bn) and France (€ 55.5Bn) have shown to be the largest listed markets in Europe. While Germany is characterized by REOCs (e.g. Vonovia with € 22.8Bn and Deutsche Wohnen with 11.5Bn) and further investment vehicles like open and closed end funds with only a small proportion being invested in REITs, the UK REIT market is highly matured comprising more than 80% of UKs total market capitalization of listed real estate companies. The same appears for France, where REITs account for € 51.0Bn out of € 55.5Bn. While developed listed real estate markets like Sweden and Switzerland (€ 53.7Bn and € 46.0Bn) have not adopted the REIT status yet, REITs play an important role in Belgium, the Netherlands and Spain with high proportions being invested in the tax-exempt investment vehicle.

Italy (3 REITs comprising € 1.0Bn) and Spain (71 REITs with € 22.9Bn) show on average the lowest REIT size within Europe, with the two largest Spanish REITs (MERLIN Properties with € 5.7Bn and Inmobiliaria Colonial with € 5.0Bn) account for almost half of the Spanish REIT market size. In contrast, France is characterized by large average REIT size with Gecina being valued at € 9.8Bn and Klepierre at € 8.6Bn. WFD Unibail-Rodamco represents the largest European REIT with a market capitalization of € 18.2Bn (EPRA, 2019a).

Table 2.1. Overview of listed real estate markets in Europe

	REIT status since	No. REOCs	Market cap REOCs (€Bn)	No. REITs	Market cap REITs (€Bn)	Biggest REIT
Austria	-	6	7.45	-	-	-
Belgium	1995/ 2014	11	5.30	17	16.32	Warehouse DePauw
Bulgaria	2004	3	0.47	29	0.43	-*
Croatia	-	1	0.08	-	-	-
Cyprus	-	12	1.05	-	-	-
Czech Rep.	-	1	0.50	-	-	-
Denmark	-	11	1.90	-	-	-
Estonia	-	3	0.09	-	-	-
Finland	2010	5	5.19	-	-	-
France	2003	17	4.47	30	51.01	Gecina
Germany	2007	54	87.89	5	4.24	alstria Office REIT
Greece	1999	7	0.88	4	1.52	-*
Hungary	-	2	0.40	-	-	-
Ireland	2013	-	-	4	3.14	Green Rent PLC
Italy	2007	7	0.24	3	0.96	igd
Latvia	-	1	0.00	-	-	-
Lithuania	2008/ 2013	2	0.04	-	-	-
Luxembourg*	2007/ 2016	-	-	-	-	-
Malta	-	5	0.30	-	-	-
Netherlands	1969/ 2003	3	0.09	5	21.52	Unibail-Rodamco
Norway	-	8	5.24	-	-	-
Poland	2019	40	5.65	3	0.72	-*
Portugal	2019	2	0.03	-	-	-
Rumania	-	3	6.42	-	-	-
Spain	2009	14	5.69	71	22.95	MERLIN Properties
Sweden	-	48	53.67	-	-	-
Switzerland	-	40	45.98	-	-	-
UK	2007	37	12.90	55	64.06	Segro

Notes: Market capitalization reported as of June 2019; *No further information provided by EPRA. *Source:* EPRA (2019a) and EPRA (2019b).

2.4 Theoretical Background

Different theories evolved to understand the phenomenon of setting the offer price at a discount at equity offerings.

Asymmetric information and value uncertainty theory

Rock (1986) was one of the first to explain underpricing using informational disparities between the parties involved at equity issuances. As investors with informational advantages create a negative externality for uninformed investors by only subscribing when the offer price is below the expected true value, uninformed investors are permanently faced with negative returns. Underpricing is suggested to be necessary to keep uninformed investors in the market and recompense for the adverse selection. Beatty and Ritter (1986) extend the model by adding ex-ante value uncertainty around the offering. They assume higher ex-ante uncertainty about the true value of the firm to be linked to a more cost-intensive information gathering process with investors being therefore compensated by higher underpricing.

Placement cost theory

To attract investors and compensate for higher illiquidity and lower fungibility of the shares, Altınkılıç and Hansen (2003) suggest that shares being hard to place in the market are subject to higher underpricing. They conclude that keeping total firm size (total proceeds) constant, placement cost increase (decrease) with greater total proceeds (firm size). Further research corroborate the results, suggesting that larger offerings (higher proceeds or number of shares) are more likely to be absorbed by uninformed investors (Corwin, 2003; Goodwin, 2013).

Underwriter reputation and investment banking power

Intermediary institutions between investors and the issuing firm are suggested to play an important role at capital increases. Early research showed that the pricing of equity offerings has an impact on the stock market valuation of the lead underwriter (Nanda & Yun, 1997) and high deviation from "fair pricing" at IPOs is linked to a loss in the underwriter's market share (Dunbar, 2000). The literature therefore assumes the reputation of the lead underwriter to affect the amount of "money left on the table" (Bowen et al., 2008). Since higher ranked underwriters are supposed to be more successful in attracting investors they are associated with lower underpricing (Altınkılıç & Hansen, 2003).

The investment banking power is adding some insights into the role of intermediaries at SEOs. Underpricing represents – besides underwriter spreads as direct cost of raising capital – another way to maximize the investment banks earnings. Mola and Loughran (2004) and Corwin (2003) show that investment banks use mechanisms in offer price settings to gain from higher discounts by setting the offer price at a lower integer or even-eighths fraction. They suggest that issuing firms focus more on underwriter services in terms of being able to take up the shares offered rather than minimizing the offer price discount. Armitage et al. (2014) suggest underwritten offerings to be more underpriced to reduce the reputational risk for the underwriting bank. Consequently, two opposing effects are supposed to occur. While underwritten SEOs are expected to show higher underpricing because investment banks try to maximize their earnings and minimize the risk of SEO failure, higher reputation of the underwriting intermediary is suggested to be linked to lower offer price discounts.

Market timing theory

The market timing theory, proposed to understand managers financing decisions, can also help to explain the extent of underpricing. Baker and Wurgler (2002) conclude that the capital structure is the cumulative outcome of past attempts to time the equity market. Consequently, firms prefer to offer equity rather than debt when investors are over-optimistic about the value of the firm. Market timing is therefore referred to as offering shares when market values are high. Using a survey of CFOs, Graham and Harvey (2001) were one of the first to find evidence that the valuation of the stock is an important determinant in issuing equity. Especially REITs take advantage of capital market conditions (Ooi et al., 2010). Using investor sentiment to explain the extent of underpricing in SEOs, Deng et al. (2014) assume two possible effects to occur considering the timing of equity markets. On the one side manager could gain from over-optimism in the market by setting the offer price higher to reduce offer price discounts and increase offer proceeds. On the other hand, managers could also be supposed to place their shares with closely connected investors and therefore set the offer price lower than necessary to protect them from possible price declines in the future. Market timing could consequently also be linked to higher underpricing at SEOs.

The "REIT effect"

High distribution of earnings and limited accessibility to loan capital are important reasons for REITs to access the equity market more frequently compared to industrial corporations (Goodwin, 2013). As Deng et al. (2014) suggest frequent access to the capital market results in higher information disclosure. Furthermore, REITs have to meet high regulatory requirements to benefit from the tax-exempt status, resulting in higher transparency. Consequently, REITs do not only show on average lower underpricing at IPOs than industrial firms (Dolvin & Pyles, 2009). They are also less underpriced than REOCs at initial public offerings (Ascherl & Schaefers, 2018; Dimovski, 2016). The REIT status is therefore assumed to be negatively linked to offer price discounts.

2.5 Literature Review

Underpricing in SEOs

The academic interest on SEO pricing remained low until the early 2000th when SEO underpricing was investigated in detail, finding evidence for average discounting and underpricing of around 2-3% for industrial firms in the US. Altınkılıç and Hansen (2003) corroborate with the value uncertainty and placement cost hypothesis. Corwin (2003) focusses on variation in discounting over different timeframes. Including underwriter reputation and analyst coverage, Mola and Loughran (2004) suggest an increase in investment banking power over time. Chemmanur et al. (2009) are regarding the role of institutional investors at SEOs.

In a European background, Armitage et al. (2014) examine seasoned equity issues of industrial firms listed in the UK to conclude for market reaction and the choice of issuance methods. Andrikopoulos et al. (2017) are also focusing on UK SEOs, regarding institutional ownership and the linkage to offer price discounts. As Bairagi and Dimovski (2012) or Gokkaya et al. (2013) show, underpricing and discounting of SEOs is often used as control variable for direct cost of raising capital.

The literature on SEOs in the real estate sector is well established on announcement effects (Myers & Majluf, 1984) and the operating performance around equity issuances (Ghosh et al., 2013). In contrary, less is known about the pricing of REIT SEOs. Ghosh et al. (2000) are the first to investigate underpricing in the real estate sector. Regarding US REIT SEOs, Goodwin (2013) shows that difficulties in the placement of shares as well as greater uncertainty in the valuation both imply higher discounting. Regarding direct cost of raising capital for REIT SEOs, Gokkaya et al. (2013) are using discounting as control, stating that SEOs in hot market phases are subject to lower discounts. Using a sample of US REIT equity offerings from 1986 to 2009, Deng et al. (2014) use investor sentiment to explain SEO pricing, stating that in high sentiment periods higher discounting and underpricing is observed.

Market timing at SEOs

With an anonymous survey of CFOs admitting to market timing in SEOs, Graham and Harvey (2001) were amongst the first to find evidence that the valuation of a firm is an important determinant for issuing equity. Firms prefer to offer equity rather than debt when investors are over-optimistic about the market value of the firm and shares are highly valued. Baker and Wurgler (2002) therefore state, that the capital structure is the cumulative outcome of past attempts to time the equity market. Feng et al. (2007) are applying the financing decision model to a REIT framework. Ooi et al. (2010) are stating that REITs tend to time the equity market by offering equity when stock values are high. Further studies found strong evidence supporting the market timing hypothesis by analyzing share repurchase decisions of REITs (Brau & Holmes, 2006), suggesting that REITs tend to undertake repurchases when stocks are undervalued.

Analyzing managers' financing decisions, Baker and Wurgler (2002), Feng et al. (2007) and DeAngelo et al. (2010) use market-to-book ratio (M/B) to identify the manager's perception of mispricing in the capital market. With high M/B being linked to optimistic expectation of investors, managers attempt to exploit the firm's overvaluation by issuing equity. Ooi et al. (2010) and Gibilaro and Mattarocci (2018) are using price-to-earnings ratio (P/E) as indicators for market timing. Boudry et al. (2010) are applying price-to-NAV ratio (P/NAV) as an indicator for REITs to gain from favorable market conditions in financing decisions. Because these indicators are linked to stock market mispricing as well as growth options (Fama & French, 2002), it is necessary to control for growth factors when interpreting valuation estimates (Dai, 2012). Boudry et al. (2010) are using average returns to control for growth in order to extract the effect of mispricing. Deng and Ong (2018) include REIT growth, defined as the change in total assets from last period, as control.

The literature on market timing is mainly focused on capital structure and issuance choice. There is to our best knowledge only little research regarding the effect of market timing on the pricing of SEOs. For industrial firms, Armitage et al. (2014) are using M/B as a measure for information asymmetry, suggesting that lower M/B indicates proportional higher tangible assets. Andrikopoulos et al. (2017) use M/B, return on equity and leverage to explain underpricing in SEOs. They assume high values to represent young growth companies and to be therefore associated with higher offer price discount to ensure a successful equity issuance. According to Baker and Wurgler (2002), M/B is suggested to be an indicator for investment opportunities and risk in trade-off stories, while market timing theories suggest M/B values to reflect mispricing in the equity market. We would therefore suggest Andrikopoulos et al. (2017) to be in line with trade-off theories rather than market timing. As Boudry et al. (2010) state, trade-off theories are limited in their explanatory power for REITs due to their regulatory requirements. Investigating the linkage between IPO and SEOs for industrial firms in China, Gounopoulos et al. (2013) follow Kim and Weisbach (2008) to use M/B as proxy for market timing. They find evidence that high M/B is significantly and negative linked to initial return at SEOs.

2.6 Data and Summary Statistics

Sample design and variables

We use a sample of REIT SEOs collected from S&P Market Intelligence, former known as SNL Financial. We excluded Adjustable Rates, Forward Sale Agreements, De Novo Bank Offerings and Flow Through from the sample. Exchange offers, offerings made as part of the consideration in a merger or acquisition and offerings made as part of Employee Stock Ownership Plans or Dividend Reinvestment Plans are removed as well due to different pricing characteristics. We follow Corwin (2003) by removing secondary offers and Altınkılıç and Hansen (2003) by removing penny stocks. This results in a final sample of 470 SEOs of REITs and REOCs from 1st of January 2004 until 31st of December 2018 from 18 European countries.

To control for outliers and mistakes in the provided data, Corwin (2003) and Bowen et al. (2008) exclude offerings with over- and underpricing of more than 60% respectively 50%. As various authors state, the offer dates can contain errors, since offers can be conducted after the close of trading. Consequently, the offer day has to be corrected by taking the day after as appropriate, if the trading volume the day after the official offer date is more than two times the volume on the offer day or more than two times the average trading volume of the last 250 trading days.

Underpricing and discounting are used as dependent variables to identify significant determinants on the pricing of SEOs. Also referred to as offer-to-close return or offer price discount at SEOs, we follow Ghosh et al. (2000) to calculated underpricing as

$$\text{underpricing} = \frac{\text{offer day closing price} - \text{offer price}}{\text{offer price}} \text{ or underpr} = \frac{p_t}{p_o} - 1$$

Following Altınkılıç and Hansen (2003) and Goodwin (2013), discounting is calculated as

$$\text{discounting} = \frac{\text{day before closing price} - \text{offer price}}{\text{offer price}} \text{ or disc} = \frac{p_{t-1}}{p_o} - 1$$

Table 2.2. Independent variables with expected sign and previous research

Variable		Definition and previous studies
REIT	-	Equals 1, if corporation obtained the REIT status *(Dolvin & Pyles, 2009; Dimovski, 2016)*
PROP_TYPE	-	Equals 1, if firm is specialized on a property type *(Goodwin, 2013; Ascherl & Schaefers, 2018)*
Measures of market timing		
M/B	-	Market capitalization divided by book value *(Gounopoulos et al., 2013; Deng & Ong, 2018)*
P/NAV	-	Price divided by net asset value *(Boudry et al., 2010)*
P/E	-	Price divided by earnings *(Ooi et al., 2010; Gibilaro & Mattarocci, 2018)*
Controls for growth		
ASSETGROWTH	-	Change in total assets in the last 12 months *(Dai, 2012; Deng & Ong, 2018)*
ROA	-	Net income divided by average total assets *(Andrikopoulos et al., 2017)*
Measures of placement cost		
REL_PROCEEDS	+	Total proceeds divided by market capitalization *(Corwin, 2003; Goodwin, 2013)*
Measures of value uncertainty		
MARKETCAP (€Mn)	-	Natural logarithm of market capitalization *(Altınkılıç & Hansen, 2003; Dimovski, 2016)*
ALREADY_SEO	-	Equals 1, if firm has already conducted a SEO before *(Ghosh et al., 2000)*
VOLATILITY	+	Price volatility 30 to 2 days prior to the offering *(Altınkılıç & Hansen, 2003; Chemmanur et al., 2009)*
CASH_ASSETS	-	Cash and cash equivalents divided by total assets *(DeAngelo et al., 2010; Deng & Ong, 2018)*
Measures of underwriter reputation and investment banking power		
URANK	-	Reputation of the lead underwriter as of the ranking of Migliorati and Vismara (2014) *(Mola & Loughran, 2004)*
UNDERWRITTEN	+	Equals 1, if the offering is underwritten *(Armitage et al., 2014)*
INTEGER_0.25	+	Equals 1, if the offer price is set at even-eighths *(Chemmanur et al., 2009; Mola & Loughran, 2004)*
Further control variables		
PROCEED_3M (€Mn)	+	Natural logarithm of proceeds raised in the last three months *(Gokkaya et al., 2013)*
STOCKLIQUIDITY	-	Average trading volume divided by shares outstanding *(Ghosh et al., 2000; Armitage et al., 2014)*
LEVERAGE	+	Total debt divided by total assets *(Gibilaro & Mattarocci, 2018; Andrikopoulos et al., 2017)*

To test for the aforementioned theories, we use measures for value uncertainty, placement cost, market timing as well as underwriter reputation and investment banking power as shown in Table 2.2. *MARKETCAP*, *ALREADY_SEO*, *VOLATILITY* and *CASH_ASSETS* are included as proxies for value uncertainty at the offering. The proceeds relative to the market capitalization (*REL_PROCEEDS*) are used to test for placement cost. To get further insights on underwriter reputation and investment banking power in European listed real estate markets, we include the reputation of the lead underwriter (*URANK*), a measure for price setting mechanism (*INTEGER_0.25*) and a dummy variable for underwritten offers (*UNDERWRITTEN*). In the literature, underwriter reputation is measured using the Carter-Manaster ranking. As Migliorati and Vismara (2014) state, the ranking covers only 67.5% of all underwriters participating in European SEOs. While the US investment banking market is tightly oligopoly with few player dominating the market, the European market is suggested to be more competitive (Krakstad & Molnár, 2014). Because differences in the performance of investment banks are supposed to be hard to determine in Europe, earlier research suggested that underwriter reputation is hardly possible to be derived in the European equity market (Armitage et al., 2014). Using the European-based ranking of Migliorati and Vismara (2014) for IPOs we are able to be one of the first to test for underwriter reputation in Europe.

Following Baker and Wurgler (2002) and Feng et al. (2007) we use *M/B* to analyze the effect of market timing behavior. In addition, we follow Boudry et al. (2010) and Gibilaro and Mattarocci (2018) by furthermore including *P/NAV* and *P/E* as further measures of market timing. To control for growth, we include *ASSETGROWTH* and the return on asset (*ROA*) in our model. We control for hot and cold equity markets by including overall proceeds raised by the market within the last three months (*PROCEEDS_3M*). A proxy for the liquidity of the stock (*STOCKLIQUIDITY*) and the debt ratio (*LEVERAGE*) are included as further control variables. We use year and country dummies to control for time and country fixed effects (Corwin, 2003; Deng et al., 2014). In the literature, overall market conditions are also used as controls but heteroscedasticity with year and country variables impede the integration in our model specifications. The same appears for the maturity of the REIT market in terms of months since the REIT regime was introduced in the respective country. We suggest both effects to be captured by the fixed effect controls. We use natural logarithm transformation for selected variables in order to minimize the influence of outliers and reduce asymmetry.

Summary statistics

As reported in Table 2.3, the sample consists of 470 SEOs of European property companies from 2004 to 2018 in 18 countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Monaco, Netherlands, Norway, Poland, Spain, Sweden, Switzerland and United Kingdom. We find more equity offerings being placed by REITs (299) than by REOCs (171) due to restrictions on debt and retained earnings and therefore frequent access to the capital market. Within the sample, the UK accounts for 201 SEOs. We suggest the UK to play a predominant role in raising equity in Europe due to the fact that the UK represents the largest REIT market, comprises the highest number of property companies and is characterized by enhanced transparency and a highly mature capital market. While Austria and the Netherlands show on average overpricing of 0.66% and 3.01%, we find high underpricing for Greece and Italy (39.74% and 12.71%), which could be traced back to challenges within the financial market of both countries over the last decade.

Table 2.4 shows the descriptive statistics of the variables in the sample, divided into subsamples REITs and REOCs. We find statistically significant underpricing of 3.06% in the whole sample, with REITs being on average less underpriced (1.90%) than REOCs (5.08%). REITs also show lower discounting (3.08%) compared to REOCs (6.20%). The results are below comparable studies of IPO underpricing for European REITs and REOCs (Ascherl & Schaefers, 2018: 4.63%), but higher than studies of SEO underpricing of US REITs (Goodwin, 2013: 1.21%; Deng et al., 2014: 1.64%). We suggest IPOs to be more underpriced than SEOs due to higher uncertainty about the true value of the firm at its initial offering. Lower offer price discounts in the US could be traced back to higher transparency, a matured REIT market and high market acceptance of REIT equity issuances. Regarding only the average underpricing in the sup-sample REIT, our results are in line with the findings on REIT SEO underpricing in the US.

Table 2.3. Number of SEOs by REITs and REOCs from 2004 to 2018 in the sample

Country	Number of SEOs			Mean underpricing (%)	Mean proceeds (€Mn)
	Total	REIT	REOC		
Austria	7	0	7	-0.66	247.49
Belgium	46	46	0	4.66	77.11
Denmark	5	0	5	6.46	31.62
Finland	23	2	21	4.74	118.58
France	54	54	0	3.60	133.50
Germany	70	23	47	3.55	59.71
Greece	2	1	1	39.74	171.62
Ireland	3	3	0	1.80	71.67
Italy	5	2	3	12.71	96.94
Luxembourg	4	1	3	10.79	184.05
Monaco	1	0	1	23.60	0.09
Netherlands	7	5	2	-3.01	216.52
Norway	8	0	8	8.54	101.63
Poland	2	0	2	3.66	97.49
Spain	1	1	0	2.69	93.44
Sweden	20	0	20	5.18	152.93
Switzerland	11	0	11	8.64	191.93
UK	201	161	40	1.02	65.43

Table 2.4. Descriptive statistics of European REITs and REOCs from 2004 to 2018

	Full Sample					Mean	
	Mean	Median	St. Dev.	q25	q75	REOC	REIT
UNDERPR (%)	3.06***	2.08***	17.965	-0.03	6.38	5.08***	1.90***
DISC (%)	4.22***	3.21***	18.635	-0.05	8.52	6.20***	3.08***

	Mean	Median	St. Dev.	q25	q75
Panel A: REITs					
M/B	1.08	1.06	0.24	0.99	1.15
P/NAV	1.12	1.10	0.24	1.00	1.21
P/E	23.65	12.70	114.84	7.83	22.22
ASSETGROWTH	0.26	0.13	0.42	0.02	0.37
ROA	0.04	0.05	0.09	0.02	0.07
REL_PROCEEDS	0.16	0.10	0.23	0.04	0.20
MARKETCAP (€Mn)	648.65	339.95	827.75	200.66	815.81
ALREADY_SEO	0.95	1.00	0.21	1.00	1.00
CASH_ASSETS	0.05	0.03	0.06	0.01	0.07
VOLATILITY	0.30	0.03	0.81	0.02	0.17
URANK	0.06	0.00	0.12	0.00	0.09
INTEGER_0.25	0.16	0.00	0.36	0.00	1.00
UNDERWRITTEN	0.45	0.00	0.50	0.00	1.00
PROCEED_3M (€Mn)	3,053.93	2,307.84	2,006.17	1,740.36	3,956.43
STOCKLIQUIDITY	0.00	0.00	0.01	0.00	0.01
LEVERAGE	0.43	0.46	0.17	0.31	0.56
PROP_TYPE	0.60	1.00	0.49	0.00	1.00
Panel B: REOCs					
M/B	1.00	1.03	0.42	0.70	1.23
P/NAV	1.04	1.04	0.40	0.83	1.18
P/E	11.60	13.70	44.63	-0.13	26.14
ASSETGROWTH	0.18	0.05	0.53	-0.03	0.25
ROA	0.02	0.04	0.08	0.00	0.06
REL_PROCEEDS	0.31	0.13	0.55	0.06	0.31
MARKETCAP (€Mn)	736.51	448.37	957.78	138.08	912.36
ALREADY_SEO	0.92	1.00	0.27	1.00	1.00
CASH_ASSETS	0.06	0.03	0.12	0.02	0.07
VOLATILITY	0.21	0.08	0.48	0.03	0.20
URANK	0.05	0.00	0.11	0.00	0.03
INTEGER_0.25	0.09	0.00	0.29	0.00	1.00
UNDERWRITTEN	0.50	1.00	0.50	0.00	1.00
PROCEED_3M (€Mn)	2,832.27	2,157.57	2,241.79	1,173.84	3,550.66
STOCKLIQUIDITY	0.00	0.00	0.00	0.00	0.25
LEVERAGE	0.50	0.53	0.22	0.29	0.65
PROP_TYPE	0.41	0.00	0.49	0.00	1.00

Notes: Coefficients of statistical significance at *10%, **5% and ***1% by testing if the mean (median) is different from zero.

Underpricing over time

The sample comprises 15 years from 2004 to 2018 with the global financial crisis (GFC) as extraordinary market event. Following Ascherl and Schaefers (2018) and Dimovski et al. (2017) we use different timeframes as reported in Table 2.5 to analyze the pricing of SEOs over time. Optimistic investors and "fair priced" or even overpriced equity offerings with high mean proceeds mainly characterize pre-crisis years. With the beginning of the GFC in mid-2008, plummeting proceeds and high offer price discounts reflect property companies being faced on the one side with pressure on firm's profits and on the other side with high liquidity problems due to a global credit crunch (Krakstad & Molnár, 2014). High underpricing was required to attract investors, with a peak in median underpricing of 6.07% in 2009. In years of market recovery from 2012 to 2015 underpricing regained stability with median underpricing of 1.87%, although the average amount of money raised remained low. Peaking mean proceeds with REOCs offering € 147.40Mn on average from 2016 to 2018 reflect regained confidence in the listed real estate market.

Table 2.5. Underpricing of European REITs and REOCs from 2004 to 2018 over time

Time period	No. of observations	Underpricing (%)		Proceeds (€Mn)
		Mean	Median	Mean
Panel A: REITs				
2004-2007 (pre-crisis)	14	-12.39	-1.82	119.74
2008-2011 (crisis)	61	2.58	1.75	96.84
2012-2015 (recovery)	132	1.50	1.96	57.41
2016-2018	92	4.40	2.63	82.58
2004-2018	299	1.90	2.01	73.74
Panel B: REOCs				
2004-2007 (pre-crisis)	25	-0.70	0.07	114.56
2008-2011 (crisis)	48	5.77	5.29	56.02
2012-2015 (recovery)	65	4.27	1.83	80.95
2016-2018	33	10.51	3.92	147.40
2004-2018	171	5.08	2.43	93.15
Panel C: All property companies				
2004-2007 (pre-crisis)	39	-4.89	-0.46	116.42
2008-2011 (crisis)	109	4.08	3.09	77.69
2012-2015 (recovery)	197	2.42	1.87	65.25
2016-2018	125	6.01	2.74	99.70
2004-2018	470	3.06	2.08	80.80

Nevertheless, with median underpricing of 2.74%, overpricing as in pre-crisis years cannot be observed. Instead, remaining mistrust in the stability of the financial sector, fear of rising interest rates and potential exaggerations in the commercial investment market in major European cities could be an explanation for relatively high offer price discounts in recent years.[3] Our findings are in line with Andrikopoulos et al. (2017), stating that the GFC had a major impact on the capital market with significant effects on property companies equity offerings. Regarding the two subsamples, REITs are less underpricing in all timeframes and seem to be less affected by the GFC with relatively lower median underpricing and higher average proceeds. We could assume higher transparency and the easier valuation process of REITs to result in lower value uncertainty than REOCs especially in crisis years and therefore less "money left on the table".

2.7 Empirical Results

Methodology, model specifications and regression results

To test for the aforementioned theories on underpricing in equity offerings, we follow Goodwin (2013), Dimovski et al. (2017) and Ascherl and Schaefers (2018) by applying multiple linear regression models using OLS with

$$\begin{aligned} Underpr = \beta_0 + \ & \beta_i \ (measures\ of\ market\ timing) \\ & + \gamma_j \ (controls\ for\ growth) \\ & + \delta_k \ (measures\ of\ placement\ cost\ and\ value\ uncertainty) \\ & + \lambda_l \ (underwriter\ reputation\ and\ investment\ banking\ power) \\ & + \mu_m (control\ variables) + \ \varepsilon \end{aligned}$$

We assume the error term $\varepsilon \sim \mathrm{N}(0, \sigma^2)$.

Regarding Table 2.6, we are in line with Altınkılıç and Hansen (2003) to support the placement cost theory. With REL_PROCEEDS being significant and positive over all model specifications, we can state that shares being harder to place in the market are subject to higher underpricing. Keeping total firm size (total proceeds) constant, placement costs increase (decrease) with greater total proceeds (firm size).

[3] Table 2.5 reports higher average underpricing in recent years (2016 to 2018) than in 2008 to 2011 comprising the GFC. This is because SEOs until mid-2008 prior to the GFC showed low underpricing or even overpricing and only few highly underpriced equity offerings took place within the second half of 2008.

Table 2.6. Multiple regression results on SEO underpricing of European REITs and REOCs from 2004 to 2018

	Model 1 & 2: M/B				**Model 3 & 4: P/NAV**				**Model 5 & 6: P/E**			
M/B	-0.1192	(-3.57) ***	-0.1050	(-3.34) ***								
P/NAV					-0.1052	(-2.90) ***	-0.0869	(-2.62) ***				
P/E									-0.0002	(-2.34) **	-0.0002	(-2.34) **
ASSETGROWTH	-0.0495	(-2.48) **	-0.0426	(-2.24) **	-0.0498	(-2.48) **	-0.0439	(-2.30) **	-0.0510	(-2.54) **	-0.0466	(-2.44) **
REL_PROCEEDS	0.0770	(3.00) ***	0.0807	(3.27) ***	0.0752	(2.91) ***	0.0801	(3.23) ***	0.0817	(3.16) ***	0.0844	(3.40) ***
MARKETCAP	0.0254	(2.55) **	0.0267	(2.92) ***	0.0238	(2.35) **	0.0255	(2.76) ***	0.0132	(1.39)	0.0180	(2.03) **
ALREADY_SEO	-0.0080	(-0.21)			-0.0070	(-0.18)			-0.0090	(-0.23)		
CASH_ASSETS	0.1281	(1.14)			0.1154	(1.02)			0.0227	(0.21)		
VOLATILITY	0.0211	(1.22)			0.0272	(1.55) **			0.0193	(1.10)		
URANK	-0.2879	(-3.05) ***	-0.2901	(-3.11) ***	-0.2625	(-2.78) *	-0.2651	(-2.85) ***	-0.2399	(-2.54) **	-0.2415	(-2.60) ***
INTEGER_0.25	0.0452	(1.21)			0.0361	(0.97)			0.0369	(0.99)		
UNDERWRITTEN	0.0535	(2.59) **	0.0547	(2.68) ***	0.0545	(2.62) ***	0.0553	(2.70) ***	0.0546	(2.62) ***	0.0538	(2.62) ***
PROCEEDS_3M	0.0009	(0.05)			-0.0007	(-0.04)			0.0017	(0.10)		
STOCKLIQUIDITY	-0.8120	(-0.49)			-0.7536	(-0.45)			0.2271	(0.14)		
LEVERAGE	-0.0320	(-0.53)			-0.0247	(-0.40)			-0.0778	(-1.30)		
PROP_TYPE	-0.0339	(-1.87) *	-0.0422	(-2.47) **	-0.0316	(-1.73) *	-0.0401	(-2.33) **	-0.0287	(-1.56)	-0.0380	(-2.20) **
REIT	-0.0192	(-0.87)			-0.0219	(-0.99)			-0.0171	(-0.77)		
Intercept	Yes		Yes		Yes		Yes		Yes		Yes	
Country effects	Yes		Yes		Yes		Yes		Yes		Yes	
Time effects	Yes		Yes		Yes		Yes		Yes		Yes	
N	470		470		470		470		470		470	
R^2	0.2181		0.2047		0.2103		0.1969		0.2049		0.1944	
Adjusted R^2	0.1351		0.1366		0.1265		0.1281		0.1205		0.1254	
AIC	-0.6579		-0.6749		-0.6479		-0.6651		-0.6412		-0.6621	
Max. VIF	1.93		1.53		1.92		1.54		1.67		1.49	
White-Test	1.22	(0.21)	1.11	(0.33)	1.27	(0.17)	1.14	(0.29)	1.23	(0.21)	1.07	(0.39)

Notes: Coefficients of statistical significance at *10%; **5% and ***1%; t-statistic is reported in brackets; White test is applied following H_0: Var $(\varepsilon \mid x) = \sigma^2$ (homoscedasticity).

To attract investors and compensate for lower fungibility of the shares, high relative proceeds are faced with larger offer price discounts. In contrast to placement cost stories, we cannot find evidence regarding the value uncertainty theory. It is assumed that higher uncertainty about the true value of the firm is linked to higher underpricing of the offering. Large and well-known firms with high maturity in the market are suggested to show lower uncertainty and could therefore gain from "less money left on the table" at equity offerings.

Neither the fact that firms have already conducted an SEO (*ALREADY_SEO*) with relevant information on the offering process being already disclosed, nor the pre-offering volatility as proxy for value uncertainty indicate significant influence. The same appears for the relation of cash and cash equivalents to total assets (*CASH_ASSETS*), with high cash portions representing firms that are easier to value. Only the size of the offering firm (*MARKETCAP*) show significance. While value uncertainty stories would suggest larger firm to be less underpriced, we find evidence for a positive relation between market capitalization and underpricing. Our results therefore rather support the placement cost theory. We suggest larger firms to raise more capital resulting in higher relative proceeds and more "money left on the table". While uncertainty about the true value of the firm plays an important role at IPOs in the European listed real estate market (Ascherl & Schaefers, 2018), the disclosure of information at initial offerings and the market estimation of the firm value in the secondary market could diminish the effect of value uncertainty at seasoned offerings.

Although we cannot find statistical evidence regarding the price rounding at integer or even-eighths (*INTEGER_0.25*), we can support the theories regarding underwriter reputation and investment banking power. Our results show that if an intermediary ensures the sale of the shares by underwriting the offering (*UNDERWRITTEN*), he is able to reduce the risk of SEO failure and maximize his profit by setting the offer price at a higher discount. The results are in line with the suggestions of Mola and Loughran (2004) and Armitage et al. (2014). Corroborating with Altınkılıç and Hansen (2003) and Bowen et al. (2008), the decision which underwriter to choose is therefore of high importance. We find evidence that the reputation of the lead underwriter can outdo the losses of being underwritten. Higher ranked underwriter are more successful in attracting investors and placing the shares within the market. Higher reputation therefore results in lower underpricing.

To test for market timing within the pricing of seasoned offerings, *M/B*, *P/NAV* and *P/E* are included separately within different model specifications. With all three measures of market timing being statistically significant and negative over all models we can state that firms trying to time the equity market also gains from lower underpricing and therefore less "money left on the table". Consequently, manager's timing the equity market by issuing equity when valuation estimates are high are able to not only sell their shares at favorable market prices but also gain from lower offer price discounts. We find high valuation estimates to be subject to lower underpricing and can therefore support the theory that managers take advantage of favorable conditions in the equity market.

As Ro and Ziobrowski (2011) suppose, REITs limit their investment focus to a specific property type to profit from superior expertise of the specialized investment management. However, they find no evidence for specialized REITs to outperform diversified ones. Ling and Ryngaert (1997) show that focusing on different property types implies variation in the transparency, being partly due to different lease structures. Analyzing announcement effects in European property companies, Brounen and Eichholtz (2001) stated that specialized property portfolios are subject to lower price reaction at SEOs. Freybote et al. (2008) are in line with their findings, stating that difficulties for investors to assess the firm's value at the IPO because of a diversified business strategy could still affect the pricing of SEOs. We therefore include the specialization on a specific property type (*PROP_TYPE*) in our model specifications. Following Ascherl and Schaefers (2018) we furthermore apply propensity score matching using probit regression to verify our results. To estimate the effect of specialization on a specific property type the average treatment effect on the treated (ATT) is used. Our regression results shown in Table 2.6 and the ATT shown in Table 2.7 both show that a focus on a specific property type can enhance benefits in terms of being subject to lower offer price discounts. We suggest both superior expertise for a specific property type and easier assessment of the true firm value within a specialized investment focus result in lower underpricing at the offering.

Table 2.7. ATT results using propensity score matching

Treatment variable	No. of observations	ATT	St. error	*t*-statistics
PROP_TYPE	470	-0.0498**	0.0197	-2.52
REIT	470	-0.0517**	0.0231	-2.24

Notes: Coefficients of statistical significance at *10%, **5% and ***1%.

Ascherl and Schaefers (2018) and Dimovski (2016) both find a positive "REIT effect" in the pricing of initial offerings. REITs are suggested to provide higher transparency due to their regulatory requirements and restrictions on the business activities. In addition, an easier estimation process of the firm's value with more information being disclosed is supposed to result in lower underpricing. While the summary statistics would indicate an impact of the REIT status with REITs being on average less underpriced than REOCs, we cannot find evidence regarding the "REIT effect" within the different model specifications over the whole sample. However, regarding Table 2.9, tobit regression of positive underpricing following Altınkılıç and Hansen (2003) show significance of the "REIT effect" (Model 13).

We can therefore conclude that the REIT regime can help to reduce offer price discounts when offerings are positively underpriced. Furthermore, the REIT status lead to lower underpricing especially in post-GFC periods (Model 14). Propensity score matching verifies the results. We can support our findings from the summary statistics that a "REIT effect" exists in term of higher transparency and therefore lower offer price discounts. A lack of statistical significance in the overall data can possibly be traced back to different company and offering specific characteristics for REITs and REOCs diminishing the "REIT effect" in the whole sample.

Table 2.8. Multiple regression results on market adjusted underpricing and discounting

	Model 7: ROA		**Model 8: Market adjusted**		**Model 9: Discounting**		**Model 10: Disc. market adj.**	
M/B	-0.115	(-3.68) ***	-0.110	(-3.50) ***	-0.109	(-3.33) ***	-0.109	(-3.34) ***
ROA	-0.342	(-2.56) **						
ASSETGR.			-0.042	(-2.22) **	-0.046	(-2.37) **	-0.047	(-2.42) **
REIT	-0.029	(-1.36)	-0.023	(-1.07)	-0.025	(-1.13)	-0.022	(-1.01)
REL_PROC.	0.067	(2.69) ***	0.078	(3.11) ***	0.081	(3.15) ***	0.084	(3.23) ***
MARKETC.	0.029	(3.17) ***	0.026	(2.94) ***	0.028	(2.97) ***	0.029	(3.06) ***
URANK	-0.282	(-3.03) ***	-0.283	(-3.03) ***	-0.294	(-3.02) ***	-0.294	(-3.03) ***
INTEG._.25	0.049	(1.36)	0.053	(1.46)	0.045	(1.20)	0.049	(1.30)
UNDERWR.	0.050	(2.48) **	0.051	(2.52) **	0.062	(2.95) ***	0.062	(2.93) ***
PROP_TYPE	-0.039	(-2.23) **	-0.036	(-2.07) **	-0.027	(-1.48)	-0.026	(-1.47)
Intercept	Yes		Yes		Yes		Yes	
Time effects	Yes		Yes		Yes		Yes	
Country eff.	Yes		Yes		Yes		Yes	
N	470		470		470		470	
R^2	0.2137		0.2097		0.2158		0.2157	
Adjusted R^2	0.1424		0.1381		0.1447		0.1445	
AIC	-0.6779		-0.6741		-0.5990		-0.5980	

Notes: Coefficients of statistical significance at *10%, **5% and ***1%; variables of statistical significance are shown.

Robustness of results

In order to verify reliable und robust results, additional model specifications are used. Regarding Table 2.8, we construct a model including *ROA* as another proxy for growth opportunities (Model 7). We use market adjusted underpricing (Model 8) as dependent variable to control for market movements at the offer day (Ghosh et al., 2000; Dimovski et al., 2017). Discounting and market adjusted discounting (Model 9 and 10) are further verifications.

As shown in Table 2.9, we also use winsorizing on the 99% and 95% level (Model 11 and 12) following Chemmanur et al. (2009) to check for the robustness of the results with respect to extreme values. In accordance with Altınkılıç and Hansen (2003), we furthermore only include positive underpricing and conduct tobit regression to verify our results (Model 13). Our results are robust over all model specifications. Both Ascherl and Schaefers (2018) and Dimovski et al. (2017) find significant influence of the GFC on the pricing of initial offerings. To control for the extraordinary event, we not only include time dummy variable in our model specifications but also run regression on the post-crises period (Model 14). The results are in line with the overall results.

Table 2.9. Multiple regression results on variations in the dependent variable

	Model 11: Win. 95%		**Model 12: Win. 99%**		**Model 13: Tobit**		**Model 14: 2012-2018**	
M/B	-0.039	(-2.48) **	-0.107	(-3.48) ***	-0.064	(-1.93) *	-0.138	(-4.46) ***
ASSETGR.	-0.022	(-2.39) **	-0.040	(-2.17) **	-0.088	(-4.31) ***	-0.049	(-2.40) **
REIT	-0.012	(-1.10)	-0.024	(-1.15)	-0.089	(-3.87) ***	-0.048	(-2.14) **
REL_PROC.	0.039	(3.13) ***	0.074	(3.03) ***	0.036	(1.10)	0.051	(1.79) *
MARKETC.	0.008	(1.88) *	0.025	(2.79) ***	0.025	(2.43) **	0.020	(2.08) **
URANK	-0.091	(-1.94) *	-0.273	(-2.98) ***	-0.079	(-0.82)	-0.286	(-3.13) ***
INTEG_.25	0.036	(1.98) **	0.048	(1.35)	0.052	(1.25)	0.036	(0.73)
UNDERWR.	0.032	(3.13) ***	0.050	(2.53) **	0.042	(-2.06) **	0.004	(1.99) **
PROP_TYPE	-0.014	(-1.64)	-0.034	(-2.02) **	-0.033	(-1.76) *	-0.006	(1.96) *
Intercept	Yes		Yes		Yes		Yes	
Time effects	Yes		Yes		Yes		Yes	
Country eff.	Yes		Yes		Yes		Yes	
N	470		470		347		322	
R^2	0.2689		0.2114				0.2698	
Adjusted R^2	0.2026		0.1398				0.2028	
AIC	-2.0483		-0.7112		-0.8480		-1.1557	

Notes: Coefficients of statistical significance at *10%, **5% and ***1%; variables of statistical significance are shown.

2.8 Conclusion

As Ghosh et al. (2000) state, SEOs are major events in the lifetime of a property company and essential to ensure profitable growth and sustainable development. Although especially REITs need to regularly raise money through capital increases and therefore access the capital market more often, the issuing firms decides to forego potential equity capital by setting the offer price significantly lower than the price the shares are traded on the offer day – defined as underpricing. With a sample of 470 SEOs of European REITs and REOCs from 2004 to 2018, this study contributes to the literature on SEO pricing in several ways.

We can document significant underpricing of 3.06%, with REITs (1.90%) being significantly less underpriced than REOCs (5.08%). With our results being below comparable studies on IPO underpricing in Europe (Ascherl & Schaefers, 2018: 4.63%), we suggest lower underpricing at SEOs due to disclosed information and matured business structures after the initial offerings. While value uncertainty plays an important role at IPOs, we cannot find statistical significance at seasoned offerings. In contrast, we can support placement cost stories. Keeping firm size constant, higher proceeds are subject to higher offer price discount. Following Goodwin (2013), we suggest that shares being hard to place in the market require higher underpricing.

Intermediary institutions are essential in the pricing mechanism of SEOs. In line with of Mola and Loughran (2004) and Armitage et al. (2014), we find underwritten offers to be more underpriced and can therefore conclude that underwriting institutions are able so set the offer price lower to reduce the risk of SEO failure. Managers focus more on the ability of underwriters to take up the shares rather than reducing offer price discounts. The indirect cost associated with the offering being underwritten can be balanced out by choosing a top-tier underwriter. We find higher ranked underwriter to be linked to lower underpricing and suggest them to be more successful in attracting investors – resulting in less “money left on the table”.

As Baker and Wurgler (2002) and Boudry et al. (2010) show, managers try to time the equity market by issuing equity when market values are high and investors are over-optimistic. We can contribute to the literature on market timing by showing that managers trying to time the equity market also gain from lower indirect cost of raising capital. In addition, we find a “REIT effect” suggesting that REITs show higher transparency and are easier to value due to their regulatory restrictions, resulting in lower offer price discounts. Furthermore, our results show that a specialization on a specific property type results in “less money left on the table” due to managerial expertise and specialized business strategy being easier to value.

Goodwin (2013) suggests frequent and smaller capital increases for the offering firm to be preferred to reduce placement cost and gain from lower underpricing. We can add to their findings that an optimal issuance strategy taking into account timing, the relative offer size and the choice of the underwriter in combination with a specialized investment focus can minimize the amount of “money left on the table” and therefore contribute to lower cost of raising capital for the offering firm.

Consequently, investors chasing returns in SEOs of REITs and REOCs need to consider the intermediary party involved in the offering as well as managers attempt to time the equity market. Highly valued firms do not only show lower underpricing and therefore lower initial returns for investors at SEOs. They are also subject to declining operating performance following the offering (Ghosh et al., 2013). Managers try to exploit favorable market conditions by offering shares when market values are high. Seasoned offerings of highly valued property companies therefore need to be analyzed carefully to maximize returns in SEO investments. Furthermore, our results show that investors are compensated by higher initial returns not only for lower liquidity of the shares due to higher relative proceeds. Value estimation being harder for non-REITs and non-specialized property companies due to lower restrictions on the business activity and varying investment strategies also requires higher first day returns for investors.

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3 Rental Pricing of Residential Market and Portfolio Data – A Hedonic Machine Learning Approach

3.1 Abstract

Artificial intelligence (AI) and especially machine learning (ML) methods increasingly offer valuable alternatives to answer questions in real estate research and practice. This study comprises two components: First, we investigate whether ML methods are suitable of estimating residential rents by comparing a conventional hedonic model with four ML algorithms, namely Support Vector Regression (SVR), Random Forest Regression (RFR), Gradient Tree Boosting (GTB) and eXtreme Gradient Boosting (XGB).

We find ML methods to model rental values more precisely than traditional linear regression. While RFR shows the highest predictive performance, GTB appears to be most robust to overfitting. Second, we use these findings to estimate rental values for an institutionally managed portfolio and match them with their corresponding contract rents. On average, we find the apartments to be underrented, with ML models indicating higher deviation of estimated and contract rents than linear Ordinary Least Squares (OLS) models. Thus, our findings indicate that investors rather rely on traditional methods to derive contract rent levels within their portfolio. With that, this study reveals potential benefits when applying ML hedonic models in the area of residential markets and portfolios.

Keywords: Machine learning, hedonic models, residential real estate, rent prediction, multiple listing systems

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3.2 Introduction

The role of residential rents is of central importance in the real estate industry for both tenants and landlords. Considering the former, rents often account for the largest portion of their monthly spending. For the latter, they mark the fundamental determinant of the value of housing (Gallin, 2008; Genesove, 2003). Consequently, literature has long concentrated on the question of how rental prices develop within a market. Today, more than ever, this is of great importance given urbanization and demographic changes leading to thriving residential markets especially in metropolitan areas (IMF, 2018; ULI, 2020).

In the case of a common house or apartment itself, its rent is "a single-dimensional summary of the market's valuation of all the physical, service and locational attributes […]" (J. Goodman, 2004; Verbrugge et al., 2017). In other words, every single characteristic of a residential property should be priced in and thus, ultimately contributes to the rent that the market will accept. However, prices for individual attributes are not fixed. Researchers have long tried to fathom the connections between the characteristics of a property and its associated rent. While rather conventional statistical methods such as Ordinary Least Squares (OLS) still represent the preferred statistical tool, new possibilities arise from the field of artificial intelligence (AI).

While those methods are increasingly used in several areas of real estate research and practice, they have only been applied in the derivation and analysis of residential rents in a limited way yet. Given the above, this paper investigates whether hedonic machine learning (ML) methods are capable of providing new insights and applications in residential rental markets. Recent research in the field of real estate applying ML methods focuses predominantly on valuation aspects. Authors such as Lindenthal (2020), Hamilton and Johnson (2018) and Lindenthal and Johnson (2019) apply such techniques to investigate whether aesthetics and architectural styles affect real estate prices. Using ML, Chin et al. (2020) estimate the benefit of infrastructural investments on property values while Pérez-Rave et al. (2019) apply ML to big data for predictive and inferential purposes. The subject of rents and how market participants can use AI to assess and verify investment decisions has, however, not yet been investigated in depth.

Consequently, literature on this topic is scarce even though new tools seem to have capabilities that may outperform conventional hedonic methods. From a practical point of view, next to its relevance for the institutional sector, our findings may be useful to governments, for whom such methods can serve as additional instruments to engage in housing markets. Consequently, we attempt to shed light on which ML methods are best suitable for capturing and processing price formations in rental markets. ML methods differentiate from traditional regression methods in their underlying predefined assumptions. The former presuppose a linear or non-linear relationship between rental values and the hedonic characteristics whereas artificial intelligent learning methods 'think' differently. More precisely, there is no such predetermined prerequisite, but an algorithm. Hence, an econometrician takes advantage of letting the machine decide the steps necessary to model the relationship between the response and the explanatory variables in several training steps.

The aim of this study is to shed light on the application of algorithm-driven methods in rental markets. In addition, we aim to assess the value that market participants might obtain when managing a residential real estate portfolio based on ML methods as opposed to fundamental OLS analysis. Consequently, we

(1) assess how accurate linear and algorithm-driven hedonic models predict rents based on a large data set from multiple listing systems (MLS). For this purpose, a variety of performance metrics (error measures) is used.
(2) transfer the findings from (1) to a dataset of an institutionally managed residential portfolio. Using the previous model specifications, we estimate rental values an investor could expect for the portfolio apartments in re-lettings scenarios. Further, we compare them to their corresponding contract rents to find out whether the different models would estimate a potential (or need) for rental adjustments.

The paper is structured as follows. Section 2 contains an overview of the literature in the field of real estate and ML. Section 3 explains the composition of the two data sets. In section 4, the ML methods used for rent analysis throughout the paper are introduced. The results are presented in section 5. The sixth and final section summarizes the conclusions.

3.3 Hedonic Modelling in the Real Estate Literature

The aim of hedonic modelling is to better understand the fundamental factors affecting property rents and prices. By expressing the rent or price of an apartment as the sum of its estimated individual characteristics, hedonic modelling can be used for inferential and predictive purposes. Traditionally, a hedonic model employs multiple linear regression to establish the relationship between the response and the corresponding hedonic characteristics (Rosen, 1974, A. C. Goodman, 1978). Depending on the spatial characteristics of the market under investigation and the data structure, a hedonic model needs to fulfil a minimum number of assumptions (see e.g. Sirmans et al., 2005 and Bourassa et al., 2007).[4] However, several authors such as Lai et al. (2008), Bourassa et al. (2010) and Cajias (2018) have demonstrated the limited explanatory power of traditional hedonic models and shown that statistical developments such as the inclusion of spatial and non-linear effects lead to significant enhancements in model accuracy (see more: Fik et al., 2003; Lin et al., 2009; Banzhaf & Farooque, 2013).

Over the last decade, advances in computational power and ML algorithms have enabled the development of modern regression techniques. By abandoning the previously mandatory functional form of the relationship between the response and the covariates, a variety of ML algorithms emerged – such as Gradient Boosting Trees (GTB) (Friedman, 2001), Random Forest Regression (RFR) (Breiman, 2001) and Support Vector Regression (SVR) (Smola & Schölkopf, 2004). Given the goal of ML methods is to maximize explanatory power and prediction accuracy, real estate literature has identified these to be well suited for predictive questions.[5]

Hedonic Analysis of Property Prices – Mass Appraisal and Automated Valuation

Aside from traditional valuation models, automated valuation methods (AVM) based on ML algorithms are becoming even more popular (Kontrimas & Verikas, 2011). Commonly, authors focus on a specific ML method and look at its predictive power on real estate prices to draw conclusions on the stand-alone improvements. In this context, Yoo et al. (2012) use transaction data on 4,469 houses in Onondaga County, NY (USA) to demonstrate the superior model accuracy of RFR, compared to traditional regression techniques due to the ability of modelling non-linear relationships. The findings are in line with Antipov and Pokryshevskaya (2012), who investigate a dataset of 2,848 transactions relating to apartments in St. Petersburg (Russia). Both call for a more frequent application of ML methods in predicting property prices. Moreover, Yao et al. (2018) use RFR to map fine-scale housing prices in Shenzhen (China). By analyzing residential property transactions in Hong Kong and Nanjing (China), Lam et al. (2009) apply SVR to predict property prices. Moreover, the investigation of 100 house transactions in Lithuania by Kontrimas and Verikas (2011) shows that SVR is well suited due to its ability to capture non-linear relationships. Regarding boosting methods, van Wezel et al. (2005), for

[4] The assumptions are intended to correspond to the variables to be included in the model, controlling for spatial characteristics and nearby amenities. The data structure is generally either cross-sectional, time serial, panel or pooled cross-sectional and determines the normality assumptions of the residuals.

[5] The black box character of ML methods is often perceived as a disadvantage that prevents the econometrician from understanding and interpreting the influence of certain variables. However, if the goal of ML methods is prediction, this disadvantage is not very harmful, since the focus is not recognizing relationships between variables, but rather optimizing the predictive performance.

example, deploy gradient boosting to predict automobiles as well as real estate sales prices in Boston (USA), Windsor and Essex (Canada), and the Netherlands. Moreover, Kok et al. (2017) demonstrate the performance of boosting as well as RF and OLS on property prices with a dataset containing 54,000 US multi-family houses.

Furthermore, recent literature in the field of modelling property prices compares several ML techniques. Zurada et al. (2011) apply OLS, further linear regression techniques, regression trees (RT) and SVR, using a sample of 16,366 transaction prices in Louisville, Kentucky (USA). Baldominos et al. (2018) show the performance of RFR and SVR on house prices in Spain, using online listings. Moreover, Mayer et al. (2019) analyze the accuracy of different hedonic valuations models – including RFR, GTB and OLS as well as further linear models – and propose the application of different data updating techniques for property price valuations. Pace and Hayunga (2020) compare the performance of spatial models to ML techniques using tree-based algorithms. Ho et al. (2020) apply different ML methods for a dataset of housing transactions in Hong Kong. Bogin and Shui (2020) find RFR to perform best in accurately estimating rural property prices. The authors conclude that ML is more appropriate in modelling property prices due to its ability to allow for non-linear effects, whereas traditional models might suffer from misspecification.

Hedonic Analysis of Residential Rents

Especially for ML methods, most studies within the hedonic modelling literature focus on real estate prices. Far less is known about explaining and modelling rental values by applying ML approaches. Early research estimated the determinates of rental values (Sirmans et al., 1989; Kee & Walt, 1996). Recent studies on the rental housing market, including Thomschke (2015), Zhang and Yi (2017) and Cajias and Ertl (2018), show that traditional methods are still able to estimate property rents properly. While, for example, V. James et al. (2005) use spatial models to predict apartment rents, Cajias (2018) shows that semi-parametric models are capable of improving model accuracy by accounting for non-linear relationships in rental markets. Although traditional models are limited in their ability to reveal and model non-normal complex relationships, a lack of research exists regarding the application of ML methods for modelling property rents, as Hu et al. (2019) state.

Given the relevance of rental estimation for tenants, investors and governmental bodies together, with the "potential of AI-based methods" (Zurada et al., 2011, p. 350), it is important to also accurately model the underlying rental market. Even though there is a growing body of literature on the topic, further investigation is needed due to various reasons: First, literature is rather silent when it comes to a holistic comparison of various

ML approaches for evaluating the varying performance measurements of different algorithms. Second, to the best of our knowledge, property rents have not been analyzed in depth so far in an ML context. Third, the emerging velocity and volume of real estate data through MLS enables new insights to real estate markets and provides a promising field of research, since "one of the main approaches to face [such data sources] is machine learning" (Pérez-Rave et al., 2019, p. 5). And finally, the potential of ML applications for market participants to derive well-founded decisions in real estate markets has not yet been fully explored nor used.

3.4 Data

This study encompasses the residential real estate market in Munich, Germany. The country is home to one of the largest and most active real estate markets in Europe. As it is well-known as a safe haven for national and international investors, it attracts both domestic and cross-border capital allocation. As of 2019, Germany consisted of 42 million occupied apartments while having one of the lowest owner-occupancy rates in Europe with 47%. With that, Germany is considered one of the most important hubs for capital allocation in residential real estate on the continent, and thus, offers an interesting market for an in-depth investigation. With approximately 1.5 million residents and an annual growth rate of about 0.75%, Munich is the third largest city in Germany. The city and its metropolitan areas have one of the most prospering economies in Germany, accommodating several globally active companies in sectors such as automotive, environmental techniques, information and communication, insurance, life sciences and medicine. Stable economic growth and good employment conditions have yielded a positive development of the residential market throughout the last decade.

To analyze the rental market in Munich, we use two different data sets: First, asking data from MLS enables us to estimate and compare the predictive performance of the applied hedonic models. Based on the derived values, we then estimate rental values for a residential portfolio of institutionally managed apartments and compare the estimates to the observed contract rents.

MLS Data

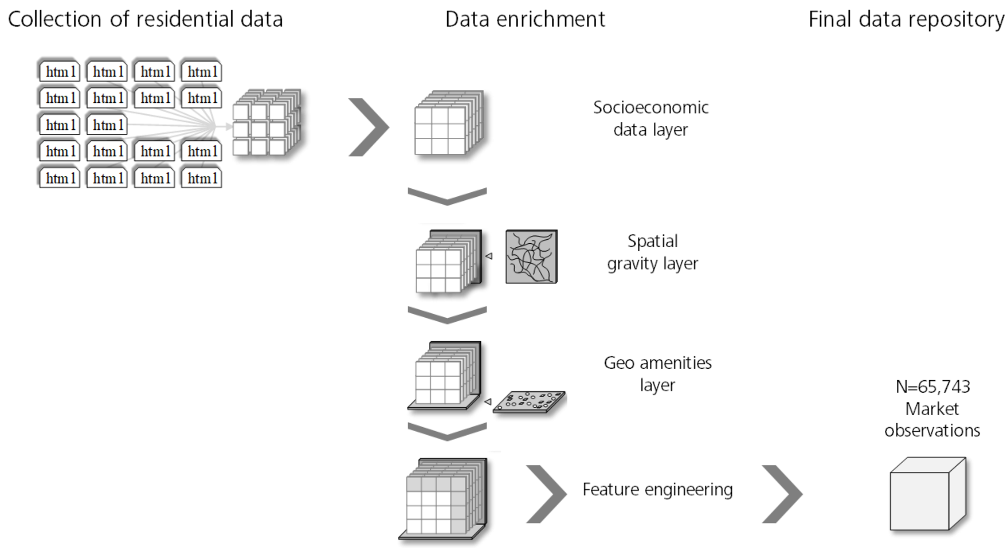
In contrast to comparable international real estate markets, Germany does not require either private or institutional landlords to publish rental information. Therefore, no general database of contract rents exists. Consequently, asking rents from MLS serve as the main source of pricing information and are used to estimate the current rental level in the German residential market (see well-established applications, such as F+B Residential Index, Empirica Real Estate Index, etc.). The use of asking data can be advantageous as it offers the possibility to capture and rapidly reveal market movements. Y. Chen et al. (2016) and Baldominos et al. (2018) argue that it is more appropriate for modelling timely dynamics of housing markets on a fine-scale level.

When it comes to real estate sales, early research has documented that differences between listing and transaction prices exist and that these are highly associated with market liquidity, measured by time on market (TOM). Jud and Winkler (1994) and Jud et al. (1996) found that both the degree of above market pricing and changes in the listing price affect TOM. Yavas and Yang (1995) state that overpricing increases the marketing time. Analyzing the German residential market, Cajias and Freudenreich (2018) show that Munich is subject to high market liquidity, with the degree of overpricing being comparably low. Since the German residential market is a renter's rather than a buyer's market, their findings indicate diminishing deviations between asking and market rents. Cajias (2018, p. 216) suggests that "the deviation [of asking and market rents] is not expected to lead to error bias, especially after controlling for […] hedonic characteristics". As Gröbel (2019, p. 8) suggests, asking data in Germany "reflects the currently prevailing overall market situation" since the price formation in the housing market is perceived to be determined by the offering party.

Moreover, MLS asking data can overcome the challenges raised by the general lack of European housing contract data which is mentioned, for instance, by Rondinelli and Veronese (2011). It is actively used for empirical research by several authors such as Hanson and Hawley (2011), Rae (2014), Gröbel and Thomschke (2018), Pérez-Rave et al. (2019) and Gröbel (2019) for studies in Germany, the US and the UK. As Pérez-Rave et al. (2019) state, MLS data shows important characteristics of big data in terms of volume, variety and value. This enables researchers and market participants to overcome temporal delays and limited analyses on market developments that are associated with, for example, official statistics. In this context, MLS are perceived as "one of the most significant feature of today's real estate industry" (Li & Yavas, 2015, p. 471). Due to the characteristics of the Munich residential real estate market, we expect the asking rents to be a good approximation for market-conform rental values. Although asking data plays a significant role in housing markets (see e.g. Shimizu et al., 2016, Han & Strange, 2016), differences to transaction data can occur that need to be kept in mind.

To assess the performance of hedonic models, our study comprises a dataset of 65,743 residential apartments in Munich, including hedonic characteristics, socio-economic information and distance variables, from January 2013 to June 2019. To avoid sample bias for the investigation of Munich's residential market that is mainly dominated by apartments, we exclude single houses as well as semi-detached and terraced houses. Furthermore, highly specialized market segments like student apartments, senior living accommodations, furnished co-living spaces, and short-stay apartments are not considered.

Figure 3.1. Extraction-Load-Tranform (ELT) process for hedonic models



Source: Own depiction.

We access Empirica Systeme, one of the largest providers of real estate data in the German residential market. It uses web-scraping techniques for collecting, preparing and integrating real estate listings from more than 120 different MLS with full hedonic characteristics.[6] Furthermore, we include socio-economic data from Growth from Knowledge (GfK), Germany's largest market research institute. We also add a gravity layer using data from Eurostat and the German statistical office to implicitly enable the models to account for spatial information. Finally, we complement each georeferenced residential data point by an amenities layer measuring the Euclidean proximity to important amenities. This information is gathered from Open Street Map (OSM) and Google via an API in R (R

[6] The Empirica Systeme GmbH is an established partner in data analytics solutions for the residential market in Germany and a data provider for brokers such as CBRE, Colliers, Engel&Voelkers, JLL, Savills as well as for banks, institutional real estate managers, cities and others.

Core Team, 2016). Data preparation and processing is displayed in Figure 3.1. This results in a dataset comprising eight structural characteristics (living area, age and whether the apartment has a bathtub, built-in kitchen, parking lot, terrace, balcony and an elevator), two socio-economic (number of households and households purchasing power in ZIP code area), and seven distance variables (proximity to bus station, park, school, subway, supermarket, neighborhood center and city center). Rent, living area, distances as well as both socio-economic characteristics are incorporated using their log-transformation to account for the distribution. Quarter and year dummies are used to control for time effects. Earlier studies found additional contract and market information to affect price formation in housing markets (see e.g. competition and listing density in Turnbull and Dombrow (2006)). However, since we do not have access to further information, our analysis is limited to structural, neighboring and locational characteristics.

Table 3.1. Descriptive statistics of the MLS data

Variable name	Unit	Spat. Ref.	Source	Mean	Median	SD	Min	Max
Living Area	sqm	Apartment	Empirica	76.49	71.00	36.49	10.00	435.00
Age	Integer	Apartment	Empirica	42.36	41.00	33.84	-2.00	118.00
Centroid ZIP	km	Distances	OSM	0.60	0.53	0.38	0.00	2.43
Centroid NUTS	km	Distances	OSM	4.62	4.57	2.08	0.22	12.33
Rent	EUR/p.m.	Apartment	Empirica	1,238.00	1,079.34	721.82	123.97	10,764
No. households (HH)	HH/ZIP	ZIP	GfK	11,423	11,768	3,305	1,860	16,978
HH purchase power	EUR/HH/ZIP	ZIP	GfK	59,855	58,849	5,501	46,170	71,765
Bus	km	Distances	OSM	1.14	0.75	1.10	0.00	6.20
Park	km	Distances	OSM	0.79	0.44	0.92	0.00	4.75
School	km	Distances	OSM	0.56	0.24	0.85	0.00	4.89
Subway	km	Distances	OSM	1.44	0.75	1.67	0.00	11.76
Supermarket	km	Distances	OSM	0.76	0.35	1.03	0.00	5.16
Bathtub	Binary	Apartment	Empirica	0.54	1	0.5	0	1
Built-in kitchen	Binary	Apartment	Empirica	0.68	1	0.47	0	1
Parking lot	Binary	Apartment	Empirica	0.62	1	0.49	0	1
Terrace	Binary	Apartment	Empirica	0.18	0	0.38	0	1
Balcony	Binary	Apartment	Empirica	0.63	1	0.48	0	1
Elevator	Binary	Apartment	Empirica	0.56	1	0.5	0	1

Notes: This table reports the summary statistics comprising data from January 2013 to June 2019. Age is calculated as the difference from building age to the year 2017. All distance variables are calculated as the distance to the specific apartment in kilometers. Binary variables report whether the apartment includes a certain characteristic (1) or not (0). Rent is presented as euro per month. Information on households is reported on ZIP level. SD: standard deviation, Min: minimum value, Max: maximum value.

Table 3.1 shows the descriptive statistics. We find a mean asking rent of 1,238 EUR/p.m. (euros per month), with rental values ranging from 123.97 EUR/p.m. up to 10,764 EUR/p.m. An average apartment is 76.49 sqm (square meters), comprises approximately three rooms, and was built in 1975. Each apartment is on average 1.44 km distant from the subway, 0.76 km from a supermarket and 0.56 km from the next school. Moreover, the city center is on average 4.62 km away, the center of the corresponding ZIP code is in 0.60 km distance. The mean number of households in a ZIP area accounts for 11,423 with a mean purchasing power of 59,855 EUR each.

Portfolio Data

In addition to the obtained data through MLS, a German asset manager granted access to portfolio data from institutionally managed residential real estate that is publicly not available. The portfolio consists of 716 apartments located in Munich, comprising contract rents and the same explanatory variables as presented in the previous section.

Table 3.2. Descriptive statistics of the portfolio

Variable name	Unit	Spat. Ref.	Source	Mean	Median	SD	Min	Max
Living Area	sqm	Apartment	Portfolio	71.99	75.56	30.59	20.92	179.79
Age	Integer	Apartment	Portfolio	37.91	46.00	29.64	1.00	90.00
Centroid ZIP	km	Distances	OSM	0.50	0.50	0.28	0.20	1.00
Centroid NUTS	km	Distances	OSM	6.77	6.00	5.24	1.70	19.00
Rent	EUR/p.m.	Apartment	Portfolio	1,009.37	938.61	469.33	204.52	3,179
No. households (HH)	HH/ZIP	ZIP	GfK	13,200	13,662	2,321	9,720	16,256
HH purchase power	EUR/HH/ZIP	ZIP	GfK	55,441	54,496	3,309	52,045	63,720
Bus	km	Distances	OSM	0.92	0.64	0.83	0.13	2.77
Park	km	Distances	OSM	0.65	0.68	0.26	0.29	1.14
School	km	Distances	OSM	0.57	0.43	0.23	0.26	0.92
Subway	km	Distances	OSM	0.60	0.53	0.26	0.13	1.01
Supermarket	km	Distances	OSM	0.58	0.66	0.23	0.01	0.87
Bathtub	Binary	Apartment	Portfolio	0.50	1	0.10	0	1
Built-in kitchen	Binary	Apartment	Portfolio	0.21	0	0.41	0	1
Parking lot	Binary	Apartment	Portfolio	0.50	1	0.10	0	1
Terrace	Binary	Apartment	Portfolio	0.06	0	0.25	0	1
Balcony	Binary	Apartment	Portfolio	0.94	1	0.23	0	1
Elevator	Binary	Apartment	Portfolio	0.63	1	0.48	0	1

Notes: This table reports the summary statistics comprising data from June 2019. Age is calculated as the difference of the building age to the year 2017. All distance variables are calculated as the distance to the specific apartment in kilometers. Binary variables report whether the apartment includes a certain characteristic (1) or not (0). Rent is presented as euro per month. Information on households is reported on ZIP level. SD: standard deviation, Min: minimum value, Max: maximum value.

Table 3.2 summarizes the descriptive statistics of the residential portfolio. An average apartment contains 71.99 sqm and yields a rental income of 1,009.37 EUR/p.m. The distance to the city center of 6.77 km is about 2 km further than the distance of an average apartment, but the distance to the center of the related ZIP code is with 0.50 km 200 m shorter. Moreover, the distances to all important infrastructure facilities is on average closer compared to the apartments in the previous dataset. Purchasing power and number of households are about the same. We again consider additional hedonic characteristics and time controls as dummy variables.

3.5 Methodology

Our analysis comprises two components. In the first part, we apply five hedonic models and estimate rental values based on the MLS data presented in section 3.1. Several error measures are used to compare the results to determine the model's predictive performance. The methods and error measures are presented throughout this section. In the second part, we transfer the findings and model specifications to the portfolio dataset discussed in 3.2. Comparing the estimated rents to their contract rents enables us to identify to what extent a possible potential (or need) for rental adjustments exists as well as to highlight which new insights investors can get when applying ML methods in their rental estimation.

Hedonic Modelling with Traditional and Machine Learning Methods

The analysis encompasses one linear and four ML models. We follow Zurada et al. (2011) and Chin et al. (2020) by choosing OLS as the base case for the comparison of several algorithm-driven hedonic models. OLS is a widespread variant for hedonic modelling and consequently a well-known and easy interpretable benchmark for performance analysis. SVR, RFR, GTB and eXtreme Gradient Boosting (XGB) represent the modern approaches that will be applied in our analysis. Except for XGB, all methods have been used for real estate related questions in areas such as valuation. XGB is a method developed in the last few years that shows computational advantages especially in large data sets. In the following, we discuss the basic structure of each hedonic method under investigation:

Ordinary Least Squares Regression (OLS) is the most common approach for traditional regression. The rent y of property i is described as the sum of the predicted values of its j characteristics x_{ij}. By making use of OLS as a parametric optimization procedure, the estimated parameters β_j are achieved by minimizing the sum of the squared residuals as a loss function. The linear relationships between rents and the hedonic characteristics are valid for the entire population whenever the Gauss-Markov theorem is valid, that is, the estimators are the best linear unbiased estimators of the observed market values. Several statistical instruments can be further employed to increase the explanatory power, such as interaction terms, polynomial effects, and spatial effects.

Machine Learning Methods

ML techniques can identify complex structures and patterns. They provide high flexibility by avoiding the assumption of a specific functional form between the response and independent variables and are at the same time able to learn from the underlying data and optimize the predictive model. By dividing the dataset into a training and test set, overfitting within the training set (in-sample) is penalized by poor out-of-sample accuracy within the test set. Removing the test set during the learning process could mean that important patterns within the data remain unnoticed. Hence, z-fold cross validation is necessary. The resampling approach within this study makes use of a 5-fold cross-validation technique with a 75:25 ratio between the train and the test sets based on random sampling.[7]

Support Vector Regression (SVR) is a modification of the Support Vector Machine, to categorize observations by finding a dividing hyperplane within an a-priori defined gap between the categories (Cortes & Vapnik, 1995). Instead of dividing the feature space by a certain gap, SVR attempts to fit observations within this specific threshold area to estimate a hyperplane – representing the regression line – that is able to capture the observed values. The threshold area is characterized by the soft margin ε. It defines the form of the hyperplane and is determined by choosing support vectors (SV) with respect to a specific loss function that allows an error margin tolerance. While error terms less than ε (and consequently within the threshold area) stay unconsidered, the part of the error exceeding the margin (ξ) is subject to a linear penalization. Consequently, SVs are chosen in a way that the threshold area includes as many observed values as possible while still accepting values exceeding the boundary through penalization. The model consequently tries to fit a hyperplane that on the one hand stays as flat as possible and on the other hand, accounts for exceeding values within its functional form by estimating the amount up to which deviations larger than ε are tolerated.

Random Forest Regression (RFR) is mainly characterized by Breiman et al. (1984) and is a bagging method based on the concept of regression trees (RT). The idea of a RT is to

[7] An in-depth description of cross validation is provided by Ho et al. (2020) with a discussion of possible advantages and disadvantages of selected ML methods. See Hastie et al. (2009) and G. James et al. (2015) for a more detailed description of the applied ML methods.

divide the regression space into sub-intervals and provide a predicted value for each final interval, called leaf R_p. Starting with a specific input variable x_j, observations are binary partitioned at the node t_n into values being higher or lower than the chosen splitting value. The process of binary partitioning is iteratively applied at each resulting node, first choosing an independent variable x_j and the value s at which the splitting will take place. s is chosen in such a way that the sum of squared errors of the two inferior nodes is minimized. At each individual terminal node R_p, the predicted value $\hat{y}|t_n$ is a constant term that is equal to the average of the observed values with respect to the partition.

Partitioning can be applied any number of times to grow the tree and improve the approximation to the data. However, deep trees can be subject to noise as fewer observations in each terminal partition are available to estimate the predicted value. To avoid overfitting, penalty terms are used to identify, for example, the optimal number of nodes and to prune the tree. Since single pruned trees perform poorly in predicting observed values, a forest of trees is built by using several different trees simultaneously. The difference between the trees is ensured by using bootstrap aggregation. The overall predicted values are calculated by averaging the individual prediction rules.

Gradient Tree Boosting (GTB) is, aside from bagging techniques such as the abovementioned RFR, a boosting method and a representative of ensemble learners that combine the results of multiple models. The idea is to consolidate many so-called weak learners (standalone prediction rules that lead to imprecise results) into a meaningful and powerful so-called committee of predictions (Hastie et al., 2009). The GTB, proposed by Friedman (2001), is a boosting concept with an ensemble of RTs as weak learners. In contrast to RFR, GTB does not consider the average prediction rule of the underlying trees but an ensemble of independent trees as the final predicted value. It uses the prediction rule of subsequent trees and an ensemble of trees that depend on the prediction of the preceding decision rule. Based on an initial decision rule, GTB proceeds with the prediction error of the initial (or preceding) rule as the target variable and iteratively builds a subsequent RT on the prediction error in order to incrementally enhance the final prediction rule.

Extreme Gradient Boosting (XGB) is a scalable ML method for tree boosting. Moreover, it is an extension of the GTB algorithm. Developed by T. Chen and Guestrin (2016), it is a rather new approach to classification as well as regression, as it contains specific features that won several Kaggle[8] competitions in the recent past. The Gradient Boosting

[8] Kaggle is one of the leading online platforms for the data science community and regularly hosts data competitions.

framework provides the foundation for the XGB algorithm, which offers several advancements.

The first involves a so-called regularized objective $\mathcal{L}(\phi)$ that penalizes complex models and therefore counteracts overfitting. Second XGB also contains a shrinkage parameter as a learning rate that rescales the predictions of individual trees to ensure further model improvements by following trees. A further addition of the method enables column subsampling that performs better in preventing overfitting than the traditional row subsampling. Split finding is one of the major challenges associated with tree learning. To find optimal split points, XGB offers the exact greedy algorithm and the approximate algorithm, both of which can be situationally applied. Since conventional approximate splitting algorithms may face difficulties in dividing data when the data points are not of equal weight, XGB adds the weighted quantile sketch algorithm. The latter ensures optimal splitting even when data is weighted. However, this method not only improves the computational procedures, it also increases the machine's system design via various features.

Error-based Comparison of Model Performance

Following Zurada et al. (2011), Schulz et al. (2014) and Mayer et al. (2019), we use mean absolute error (MAE), mean absolute percentage error (MAPE), root mean squared error (RMSE) and coefficient of determination R^2 to conclude on the accuracy of the applied methods. We furthermore investigate the precision regarding over- or underestimation by applying the mean percentage error (MPE). While similar research give little attention to the dispersion of the errors within the prediction, we discuss error buckets (PE10 and PE20), coefficient of dispersion (COD) and inter-quartile-range (IQR) to assess the magnitude of the estimation errors. By looking at the accuracy, precision and dispersion, we aim to derive further insights on the differences between the applied ML methods. Detailed descriptions of the error metrics can be found in Table 3.6 in the appendix.

3.6 Econometric Results

In the first part of our analysis, we aim to investigate the predictive performance in terms of accuracy (how well models perform on average), precision (if models over- or underestimate observed values) and dispersion (the distribution and variance of estimation errors).

Predictive Performance of Hedonic Models

All results were obtained with the following model specifications. We used repeated cross-validation with five folds and five repetitions running on 72 central processing units (CPUs) simultaneously. GTB worked best with a tree depth of 6, a shrinkage rate of 0.07 and the number of trees being 438. SVR ran on the following specifications: $C = 0.9$, $\varepsilon = 0.0451$, $\sigma = 0.00679$. While the number of trees where 498 for RFR, XGB was trained with $\alpha = 0.112$, $\gamma = 0.601$ and $\eta = 0.216$.

Table 3.3. Error-based comparison of model performance at market level

Measure	Unit	OLS	SVR	GTB	XGB	RFR
MAE	EUR/p.m.	179.31	135.71	130.73	136.02	116.16
	EUR/sqm/p.m.	2.34	1.77	1.71	1.78	1.52
RMSE	EUR/p.m.	269.81	216.83	203.62	217.63	185.82
MAPE	%	15.60	11.63	11.36	11.72	10.16
R^2	%	81.65	87.79	89.32	87.87	91.35
ME	EUR/p.m.	18.81	13.07	21.16	22.7	22.91
MPE	%	1.65	1.40	2.01	2.05	1.56
PE10	%	40.65	56.02	56.92	55.50	62.62
PE20	%	71.67	84.82	86.11	84.97	88.49
IQR	EUR/p.m.	257.14	176.34	171.47	180.13	153.84
COD	%	-24.23	27.52	11.47	12.52	18.02

Notes: This table reports the error-based measurements on the predictive performance through MAE, RMSE, MAPE and R^2. ME and MPE indicate over- or underestimation. PE10, PE20, IQR and COD show the dispersion. All measures are out-of-sample (test set) and are based on the calculations presented in Table 3.6 in the appendix. Absolute values are reported in euro per month. Relative values are reported in percent.

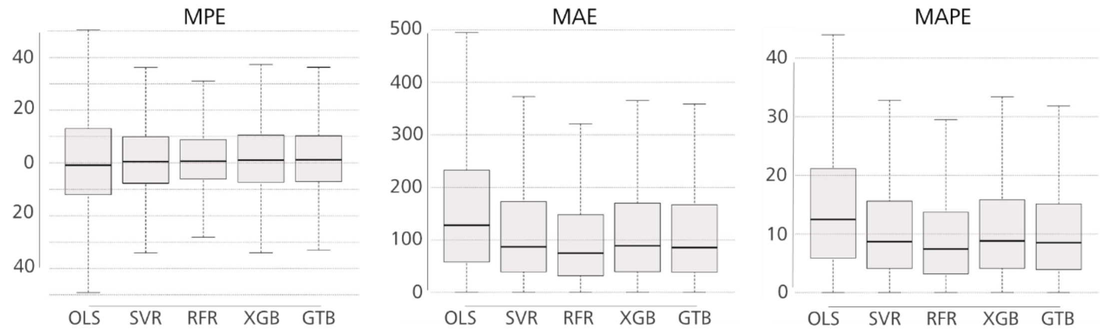
With respect to the results displayed in Table 3.3, we find all ML methods to be more accurate in modelling rents than traditional OLS regression.[9] While OLS provides on average highest absolute rental estimation errors (MAE), we find all ML methods to considerably increase the model accuracy, with RFR being most accurate. Figure 3.2 shows

[9] The complete results of the OLS estimation are displayed in the appendix in Table 3.7.

the boxplots of the error distribution. The graphical analysis regarding median and quantiles underpin the findings. To illustrate these results, we convert the MAE to EUR/sqm, dividing it by the size of an average apartment of 76.49 sqm. The estimation error decreases from 2.34 EUR/sqm (OLS) to 1.52 EUR/sqm (RFR). Regarding the RMSE, which differs from the MAE by penalizing extreme deviations, the results show a similar picture. Compared to OLS, all ML methods are more robust to extreme deviations. These findings complement the results of Bogin and Shui (2020) and Pace and Hayunga (2020) for property prices estimations, who likewise determine the highest prediction accuracy for RFR.

While OLS shows an R^2 of 81.65%, GTB and RFR are able to explain approximately 90% of the deviation. Ho et al. (2020) find similar results for housing transactions. Wu et al. (2008) and Y. Chen et al. (2016) show SVR to be robust and also accurate in modelling property prices and rents. It is therefore not surprising that SVR works well in our setting (R^2 of 87.79%) and is similar to ensemble learners such as XGB and GTB.

Figure 3.2. Graphical comparison of model performance at market level



Notes: The box represents 50% of the data within the quantiles 25 and 75%. The line measures the median, that is, the quantile 50%. The antennas cover the 5% and 95% range of the data.

A look at the MAPE shows that traditional OLS misestimates the observed rents by 15.60% on average, while RFR improves model accuracy with an average misspecification of about 10%. These findings corroborate the results of Hu et al. (2019), who also show the tree-based bagging algorithm RFR to be most suitable for modelling property rents. Regarding transactions prices, Baldominos et al. (2018) likewise highlight ensembles of regression trees to perform best.

As Fik et al. (2003) state, Freddie Mac early suggested that at least 50% of the predicted sale prices of residential properties should be within 10% of the true value. In common real estate valuation practice, the estimated value of a property is allowed to vary 10% to 20% from its market value. Transferring this to rents, all our models yield satisfactory results. As Figure 3.2 shows, the median percentage deviation of all ML methods, as displayed in the boxplots, is below 10%. Therefore, we conclude ML algorithms to be capable of precisely modelling rents.

Aside from the previously analyzed accuracy, the quality of an estimation is additionally influenced by its precision, which indicates whether hedonic models predict values that are on average above or below observed rents. In the field of property valuations, Bogin and Shui (2020) find real estate prices often to be overestimated, resulting in problems for mortgage lending. In the case of residential rents, we propose overestimated rental values to be less problematic for market participants, given that tenants are expected to react to landlords' high rental expectations with contract negotiations. In contrast, underestimations would lead to rental values that are below market level and mean landlords miss income. In Table 3.3, the positive MPEs indicate that all methods underestimate the observed rental value on average.

In addition, the dispersion of the estimation adds another possibility for investigation. The boxplots of MPE in Figure 3.2 show a symmetric distribution of all methods, indicating no general bias for traditional as well as ML variants. PE10 calculates the percentage of observations with a deviation of less than 10%. This metric can also be referred to as 'hit rate'. While OLS can estimate 40.65% of all observations within this range, algorithm-driven RFR models estimate 62.62% correctly. Within a deviation of +/-20%, we find all ML methods exceed 84%. The IQR draws a similar picture. While OLS estimates 50% of all observed values within a range of 1.68 EUR/sqm above or below the median, the ML models significantly decrease the range of deviations (+/-1.00 EUR/sqm).[10] The COD also confirms these results. Thus, ML methods are not only more accurate on average, but the error dispersion is also lower leading to a better predictive performance.

To verify the robustness of our results especially in terms of general applicability, we run all methods on an additional sample of rents from July 2019 to September 2019. The model specifications are the same as in the previous analysis (January 2013 to June 2019). The results are presented in Table 3.8 and in

Figure 3.4 in the appendix. They consequently provide error-based measurements for a one-period-ahead out-of-sample forecast. Our findings are equivalent to the findings in the original dataset. An upward shift in all error-based measurements can be traced back to thriving residential real estate markets in German metropolitan areas – especially in Munich. Bogin and Shui (2020) find RFR to be prone to overfitting. We can corroborate their results. While RFR performs best when it comes to the original dataset, we now find

[10] The range as EUR/sqm is calculated by dividing the IQR by the average size of an apartment as reported in the descriptive statistics. Because the IQR displays the distance between the q25 and q75, we can therefore show the interval that comprises 50% of all estimations.

all other ML methods to be more accurate in forecasting future rents. Regarding RMSE as well as PE10 and PE20, the results indicate that RFR seems to show some misspecification for high deviations. We suggest RFR fits extreme values generally well (lowest RMSE in Table 3.3) but fails to explain them within new sample of future rents (as it shows the highest RMSE besides OLS, but good results for PE10 and PE20 in Table 3.8 in the appendix).

To summarize, the key facts in the first part of our analysis are:

- In terms of accuracy, all ML methods are more accurate in modelling rents than OLS with RFR performing best.
- All methods underestimate observed values on average although the extent of underestimation is low.
- ML methods bear less risk than OLS due to a lower amount of misspecification.
- SVR shows similar results to the tree-based ML methods (RFR, GTB and XGB).
- RFR appears to be prone to overfitting whereas boosting methods (GTB and XGB) are more robust.

Altogether, a reasonable explanation for the better performance of ML methods can be given by the fact that they are able to capture non-linear and non-normal relationships (Pace & Hayunga, 2020; Bogin & Shui, 2020). Because non-linearity is an important characteristic of real estate markets, the application of ML techniques provides more accurate estimates of residential rents.

Rental Prediction at Portfolio Level

The previous results demonstrate that both traditional and ML methods can mimic the price formation in residential rental markets. By means of the previous model specifications, the models can estimate a rental value an investor could expect in a re-letting scenario. We transfer this knowledge to the portfolio data described in section 3.2 to estimate a rent for every apartment based on their hedonic, socio-economic and spatial characteristics. A comparison of the estimated rent with the actual contract rent provides information on the feasibility of rental adjustments when re-letting apartments from the portfolio. In a first step, we use MAE, RMSE and MAPE to analyze the accuracy.

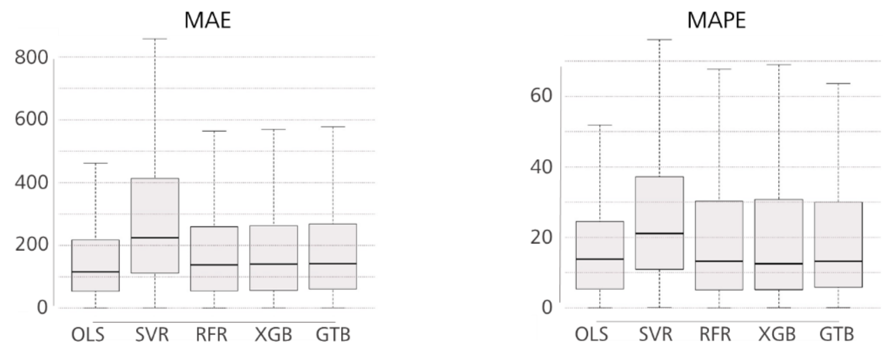
Table 3.4. Error-based comparison of model performance at portfolio level

Measure	Unit	OLS	SVR	GTB	XGB	RFR
MAE	EUR/p.m.	158.64	268.51	197.79	195.59	168.44
	EUR/sqm/p.m.	2.20	3.73	2.75	2.72	2.34
RMSE	EUR/p.m.	211.29	323.94	256.58	261.39	222.84
MAPE	%	15.70	25.83	17.74	17.64	16.24
PE20	%	68.44	45.39	62.43	62.43	63.39

Notes: This table reports the model accuracy through MAE, RMSE and MAPE. PE20 shows the dispersion. All measures are based on the calculations presented in Table 3.6. Absolute values are reported in euro per month. Relative values are reported in percent.

In Table 3.4, OLS displays the lowest absolute error. All ML methods show a considerably higher deviation within their estimation. While OLS only allows for an average estimation error of 2.20 EUR/sqm, tree-based methods RFR, GTB and XGB result in an average deviation of 2.34 to 2.75 EUR/sqm. RMSE and MAPE underpin these findings. Interestingly, this is contrary to the previous findings in section 5.1. Hence, a look at the models' 'hit rate' reveals the following: While tree-based methods can estimate about 63% of all observed rents within a deviation of +/-20%, OLS is able to model 68.44% accurately. For the portfolio data, we can consequently conclude that linear OLS leads to more accurate estimates. The graphical illustration is shown in Figure 3.3.

Figure 3.3. Graphical comparison of model performance at portfolio level



Notes: The box represents 50% of the data within the quantiles 25% and 75%. The line measures the median, that is, the quantile 50%. The antennas cover the 5% and 95% range of the data.

Furthermore, it is noticeable that SVR shows the highest deviation of portfolio rents from estimated rents, with an MAE of 3.73 EUR/sqm, which requires a deeper discussion. SVR is very sensitive to the choice of support vectors and tends to neglect the informational content of observations within the threshold area that defines the hyperplane. Because investors usually follow predefined investment goals when acquiring their portfolio apartments, specifications in the portfolio dataset can result in biased estimations of rental values for the portfolio observations when applying SVR. We assume its poor performance to be attributed to the difficulties encountered in correctly modelling the portfolio data and therefore exclude SVR in the following comparison.

Regarding the interpretation of the results in this section, however, one must keep the following in mind: A low error measurement (and therefore a low average deviation) indicates that estimated rents are to a large extent in line with observed contract rents. Because estimated rents represent a rental value a landlord could expect in re-lettings, OLS (with the lowest error measures) would indicate a low potential (or need) for rental adjustments. In contrast, ML models show considerably higher deviations. Because these models have confirmed a higher predictive performance in 5.1 on the MLS dataset, we would assume that estimates from ML models more accurately reflect the potential rental value in re-letting. An investor who bases the rental estimation on OLS would consequently underestimate possible rental changes in upcoming re-letting negotiations. Given the estimated rents from OLS are in line with contract rents to a higher degree, we assume investors to 'think linear'. The results indicate that investors use linear models within their rental estimation, although ML methods can identify higher rental potentials.

Table 3.5. Average potential for rental increases

	As % of contract rents (MPE)			**As rent in EUR/sqm (ME/sqm)**		
Method	All	q5 & q95	q10 & q90	All	q5 & q95	q10 & q90
OLS	-4.95% *	-4.85%*	-4.75%*	-0.87*	-1.02*	-1.09*
GTB	-14.81% *,**	-14.13%*,**	-13.64%*,**	-2.29*,**	-2.32*,**	-2.34*,**
XGB	-14.56%*,**	-13.99%*,**	-13.59%*,**	-2.21*,**	-2.30*,**	-2.36*,**
RFR	-12.54%*,**	-12.10%*,**	-11.91%*,**	-1.67*,**	-1.82*,**	-1.92*,**

Notes: This table reports the average rental lift potential. Relative values are calculated as the difference between contract rent and estimated rent as % of contract rent. Absolute values are calculated as the same difference divided by the rental area. The column 'All' includes results for the whole sample, while q5 & q95 excludes observations of the highest and lowest 5% quantile and q10 & q90 of the highest and lowest 10% quantile, respectively.
*denotes whether the mean is significantly different from the observed mean on a significance level of 1%.
** denotes whether the mean is significantly different from the OLS mean on a significance level of 1%.

To assess to which extent this rental potential exists and consequently whether portfolio apartments are under- or overrented, we calculate the relative difference of estimated rents to contract rents. According to the results in Table 3.5, all models indicate that contract rents are below estimated rents. While OLS indicates portfolio apartments to be underrented by 4.95% (0.87 EUR/sqm) on average, algorithm-driven hedonic models signal contract rents to be 12.54% (1.67 EUR/sqm) (RFR) to 14.81% (2.29 EUR/sqm) (GTB) below estimated rents. Our results are robust even if we exclude the highest and lowest 5%-quantile and 10%-quantile, respectively. The fact that all models show underrent situations is intuitive, especially in metropolitan areas in Germany, since rental growth in the residential real estate market exceeds inflation and hence, contract rents lag behind.

However, the difference between the methods is of special interest. An investor using OLS underestimates the rental-lift potential in his portfolio. By 'thinking linear' when researching the market, he assumes that contract rents are in line with estimated rents to a high extent. In contrast, our study reveals that ML methods show the potential for rental increases to be two to three times higher. In fact, we assume the potential to be at the level of the results of GTB and XGB, since boosting methods have shown to be more robust than RFR.

However, given current market practice, the following must be considered additionally: Contractual arrangements on lease term and rental adjustments, specific regulations in rental markets and further legal peculiarities between landlords and tenants impede the realization of the full rental potential. Nevertheless, the sole identification in this case provides investors with valuable possibilities to derive investment decisions. Aside from the linearity perception of an investor, another possible reason contributing to OLS' high performance is the rather homogenous composition of the portfolio, whose data structure can be well captured by linear models. Moreover, considering the general economics of property management, another possible explanation becomes apparent: A residential manager is contractually not incentivized to achieve the highest rents but rather to focus on minimizing costs, again, favoring OLS, which does not capture high rental deviations. These complementary explanations should be examined in more detail if the ML methods are to be used in real case scenarios.

3.7 Conclusion

In this study, we investigate the predictive performance of traditional and algorithm-driven hedonic models and the added value an application of those methods can provide for market participants in the residential real estate market. In the first part of our analysis, both traditional linear and ML methods perform well in explaining residential rents. However, algorithm-driven models are more accurate: While OLS on average misestimates observed market rents by 15.60% (2.34 EUR/sqm), tree-based RFR shows the highest accuracy by reducing the absolute estimation error to 10.16% (1.52 EUR/sqm), followed by boosting methods. Hence, ML methods provide a valuable alternative for modelling market rents. However, it is important to bear in mind that these techniques tend to underestimate, resulting in below-market rental expectations in contract negotiations. Moreover, we find the bagging approach of RFR to be prone to overfitting. We suggest the use of boosting methods GTB and XGB to lead to more robust rental estimations.

Transferring these findings to an institutionally managed portfolio, we obtain the following insights: OLS indicates that contract rents are only 4.95% below estimated rents. In contrast, ML methods – which have shown to be more accurate in modelling rents – identify potential for rental increases that is two to three times higher. Given these contrasting results, we assume investors 'think linear' and make use of OLS findings when determining rental values; for example in contract negotiations. That being said, the application of ML methods can provide added value in residential portfolios by revealing considerable potential for rental adjustments that have not been identified by more traditional approaches. Nevertheless, complementary explanations for findings of this kind should be considered when applying ML to day-to-day operations.

Practical implications of our study are manifold. Whereas investment managers gain insights to rethink and structure their portfolios, governmental bodies and policy makers can evaluate housing policies in a timely manner by showing the impact on residential markets. Possible applications of artificial intelligence are consequently not limited to the private sector. Since almost every investigation is confronted with limitations, a thorough reflection is appropriate when comparing or applying findings in other scenarios. The first part of our analysis uses asking data, which is considered a valuable proxy for timely rents. However, deviations to transaction data can occur. Moreover, since our study covers a period with stable economic conditions, it would be interesting to see how the models react to stagnating or downturn markets. Also, our analysis solely focuses on the residential market, which further limits the general applicability since we assume that algorithms may behave differently when learning from office or retail data.

While traditional models remain an important and valid tool in hedonic modelling, ML models provide beneficial insights into rental markets and portfolios. Overall, we assume an increasing number of AI applications to lead to additional ideas and added value in research and practice. Future research in this area may further expand this knowledge since new algorithms and methods are constantly being developed. Expanding data sets by investigating other markets will strengthen the use of ML methods in the area of real estate in the future.

3.8 Appendix

Table 3.6. Error-based measurements on the predictive performance

Accuracy		
Mean Absolute Error (MAE)	$MAE(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$	Average of all absolute errors. Lower MAE signals higher precision in units.
Root Mean Squared Error (RMSE)	$RMSE(y,\hat{y}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	Average of squared residuals. In contrast to MAE, RMSE penalizes high deviations.
Mean Absolute Percentage Error (MAPE)	$MAPE(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert$	Average of all absolute percentage errors. Lower MAPE signals higher accuracy in percent.
R^2	$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$	Goodness of fit of the model.
Precision		
Mean Error (ME)	$ME(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$	Average of difference between observed and predicted value.
Mean Percentage Error (MPE)	$MPE(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)$	Positive and negative errors cancel out due to the lacking absolute value operation. Positive (negative) MPE signals (over-) underestimation.
Dispersion		
Error buckets (PE(x))	$PE(x) = 100\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert < x$	Percentage of predictions where the percentage error is less than x%, with x being set to 10 and 20.
Coefficient of Dispersion (COD)	$COD = \frac{100}{n}\frac{\sum_{i=1}^{n}(\frac{\hat{y}_i}{y_i} - Median\left(\frac{\hat{y}_i}{y_i}\right))}{Median(\frac{\hat{y}_i}{y_i})}$	Ratio of the mean deviation from prediction errors to the median prediction error, divided by the median.
Inter-Quartile Range (IQR)	$IQR = (y_i - \hat{y}_i)_{75} - (y_i - \hat{y}_i)_{25}$	Range in terms of the difference between the 75th and 25th percentile of the distribution of the prediction error.

Table 3.7. Results of the OLS estimation

Variable	**Estimate**	**Std. Error**	**t value**	**sign. level**
log Living Area	0.918	0.002	422.377	***
Age relative to 2017	-0.001	0.000	-16.385	***
log Centroid ZIP	-0.014	0.001	-9.572	***
log Centroid NUTS	-0.036	0.002	-18.420	***
log Number of households (HH)	-0.730	0.035	-23.916	***
log Household purchasing power	3.400	0.151	22.569	***
log Bus	-0.028	0.001	-19.727	***
log Park	-0.017	0.001	-12.122	***
log School	0.002	0.001	1.181	
log Subway	-0.020	0.001	-13.561	***
log Supermarket	0.001	0.001	0.806	
Bathtub	-0.012	0.002	-6.616	***
Built-in kitchen	0.052	0.002	25.868	***
Parking lot	0.019	0.002	8.126	***
Terrace	0.023	0.003	8.734	***
Balcony	-0.012	0.002	-5.811	***
Elevator	0.070	0.002	34.014	***
Intercept	-3.451	0.401	-8.601	***
Time dummies	Yes			

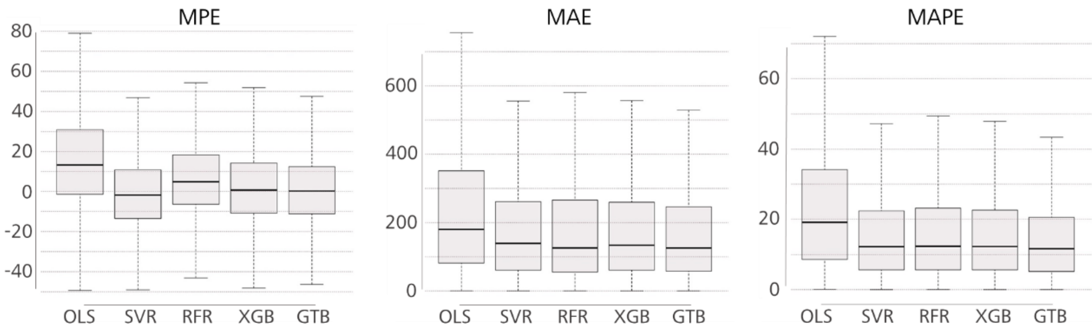
Notes: The dependent variable is log rent per month per apartment. The OLS model delivers an adjusted R^2 of 80.42% calculated in-sample (training set). ***, ** and * represent statistical significance at 0.01, 0.05 and 0.10 levels, respectively.

Table 3.8. Error-based comparison of model forecasting at market level

Measure	Unit	OLS	SVR	GTB	XGB	RFR
MAE	EUR/p.m.	271.14	201.84	189.52	203.61	212.35
	EUR/sqm/p.m.	3.54	2.64	2.48	2.66	2.78
RMSE	EUR	418.86	303.76	292.20	320.88	366.93
MAPE	%	24.00	15.69	15.02	16.08	16.77
R^2	%	80.12%	84.39%	86.39%	84.60%	83.93%
ME	EUR	177.59	10.54	26.13	42.26	108.20
MPE	%	15.47	1.16	1.13	1.94	6.61
PE10	%	29.54%	42.12%	44.38%	41.42%	43.21%
PE20	%	57.22%	70.46%	74.22%	70.89%	72.75%
IQR	EUR	322.61	275.89	258.27	274.44	273.39
COD	%	1.94	-9.73	79.99	25.80	4.09

Notes: This table reports the error-based measurements on the predictive performance through MAE, RMSE, MAPE and R^2. ME and MPE indicate over- or underestimation. PE10, PE20, IQR and COD show the dispersion. All measures are out-of-sample (test set) and are based on the calculations presented in Table 3.6. Absolute values are reported in euro per month. Relative values are reported in percent.

Figure 3.4. Graphical comparison of model forecasting at market level



Notes: The box represents 50% of the data within the quantiles 25% and 75%. The line measures the median, that is, the quantile 50%. The antennas cover the 5% and 95% range of the data.

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4 Peeking inside the Black Box: Interpretable Machine Learning and Hedonic Rental Estimation

4.1 Abstract

While Machine Learning (ML) excels at predictive tasks, its inferential capacity is limited due to the complex non-parametric structure. This paper aims to elucidate the analytical behavior of ML in real estate through Interpretable Machine Learning (IML). After estimating residential rents for Frankfurt am Main (Germany) with a hedonic ML approach, we apply a set of model-agnostic interpretation methods. Our results suggest that IML methods permit a peek into the 'black box' of algorithmic decision-making by illustrating the relative importance of hedonic variables and their relationship with rental prices.

Keywords: Hedonic modelling, residential real estate, rental estimation, interpretable machine learning, black box

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4.2 Introduction

Possible applications of Artificial Intelligence (AI) and Machine Learning (ML) are manifold and are rapidly gaining importance across a number of domains. While most members of the general public interact with ML algorithms on a daily basis (e.g. personalized web ads, mail spam filter, etc.), there is also a growing number of discoveries and implementations in research. Recently, Deepmind and its interdisciplinary research team solved one of the biggest challenges in biology with their AI-based system AlphaFold to predict how proteins fold – a problem that has been investigated for nearly 50 years (Senior et al., 2020). Further high stake domains include arrival planning in emergency department and cancer diagnosis in healthcare (Ahmad et al., 2018) or recidivism forecasting in criminal justice (Berk & Bleich, 2013).

But how is it that these methods are only gradually coming to the fore? The high predictive performance marks ML as a promising extension for existing regression as well as classification tasks due to their ability to incorporate complex patterns and deal with large datasets. However, because the methods are often perceived as opaque, their so-called 'black box' character is repeatedly criticized. Certain use cases such as an AI-based decision support of credit applications may improve and accelerate business operations of banks, however the sole decision of whether a credit may be granted or denied lacks accountability and does not represent a satisfactory outcome for neither the applicant nor the creditor. Consequently, explaining the inner working of an ML model is important to justify and validate how a certain decision is made as well as to discover new insights (Adadi & Berrada, 2018).

A similar picture can be seen for the application of AI in the real estate industry. Because real estate represents one of the largest asset classes worldwide (Kok et al., 2017), an adequate estimation of real estate prices and rents are of crucial importance for investors, landlords and tenants. By treating the property as the sum of its individual characteristics, the hedonic price regression has established itself as the main approach for price and rent estimation. ML models have proven to be helpful in real estate hedonic modelling especially for predictive purposes. Nevertheless, their inferential capabilities are limited, since the aforementioned missing transparency hides the inner logic and decision making process (Mullainathan & Spiess, 2017). But how to overcome this obvious weakness? One possibility is to design models in such a way that their complexity is kept low from the beginning to ensure interpretability. An example comes from Lechner et al. (2020), who have created a deep learning algorithm that manages to control a car based on only a few artificial neurons. As a result, the decisions made by the algorithm are easy to understand while maintaining robustness and functionality. Another possibility is to examine existing ML algorithms and their results with special analysis tools in order to establish interpretability. This is where this study picks up. The ML algorithm eXtreme Gradient Boosting (XGB) is used for a hedonic estimation of rents in the city Frankfurt am Main, Germany, and forms the basis for the application of Interpretable Machine Learning (IML) methods. Different model-agnostic tools such as feature importance and feature effects are applied to illustrate how hedonic characteristics contribute to the final prediction of the applied ML model. To the best of the authors' knowledge, this is the first real estate related study to use ex-post IML methods to justify machine-based decision-making on the one hand, and on the other hand, to gain further insights into the individual value of certain hedonic characteristics of an apartment.

4.3 Literature Review

For decades, hedonic models have formed the basis for empirically assessing prices and rents of properties based on their characteristics, such as amenities or location. A hedonic model estimates the effects of these characteristics by bundling them into a function and can thus determine the price of a property. The approach is commonly used because the concept offers many possible applications for a wide variety of problems.

According to Sirmans et al. (2005), origins of the hedonic model do not go back to just one founding father. Whereas Court (1939) first used a hedonic procedure to determine automobile prices, Lancaster (1966) and Rosen (1974) paved the way for the application in real estate. Since then, a large body of literature has emerged dealing with issues surrounding the relationship between the price or rent of a property and its characteristics. Essays by Sheppard (1999), Malpezzi (2002) and Sirmans et al. (2005) provide an overview of the diversity, but also the complexity of the questions that arise within hedonic research. However, the starting point is, as so often, the underlying data set or the available features of a property. Dubin (1988) argues that building characteristics that usually determine prices in a hedonic model can be grouped into three categories: Structural, location and neighborhood variables. Can (1992) and Stamou et al. (2017) define them as follows: Structural variables describe the nature of an apartment, such as its size, the number of rooms or the age of the property. Location variables, on the other hand, such as distance to the central business district (CBD), define the geographic location. Neighborhood variables tie in here and illustrate the socio-economic environment such as household income or the physical make-up of the closer environment. Often, the location and neighborhood variables are considered together, as sometimes the distinction is not evident (Can, 1992, Haider & Miller, 2000, Des Rosiers et al., 2011, Stamou et al., 2017). In the recent past, much of the focus of studies has been on the effect of these locational or neighborhood characteristics. Within this group, variables of interest come mainly from the environmental, infrastructure and social domains. With respect to features in the immediate environment of a property, Dumm et al. (2016), Rouwendal et al. (2017) and Jauregui et al. (2019) analyze the effect of proximity to water on price. Studies by Below et al. (2015) and Dumm et al. (2018) show the price impact of nearby subsurface conditions such as sinkholes or land erosion. Other issues such as the influence of distance to urban green spaces (Conway et al., 2010) or the presence of air pollution (Fernández-Avilés et al., 2012) also receive attention. Considering the group of neighboring infrastructural facilities and their impact on properties, different studies emerged. Hoen et al. (2015), Hoen and Atkinson-Palombo (2016) and Wyman and Mothorpe (2018) study the effects of nearby electric facilities on property prices, such as wind turbines and power lines. Availability of transportation facilities such as of a highway and rail transit are investigated by Chernobai et al. (2011), Li (2020) and Chin et al. (2020). According to Theisen and Emblem (2018) and Zheng et al. (2016), the possibility of an easy access to early childhood education and training in the form of nearby kindergarten or schools is also a price-determining factor of residential properties. There are even more exotic themes such as the influence of strip clubs (Brooks et al., 2020) or the proximity to food trucks (Freybote et al., 2017). Nevertheless, factors in the immediate social environment can also play a role. For example, Goodwin et al. (2020) find that the presence of home ownership associations has price-determining effects. Seo (2018) shows that the neighborhood condition is similarly price determining.

When it comes to the model design, the usual hedonic approach involves a parametric, semi- or non-parametric multiple regression analysis, which uses a pooled data set of properties and their individual features. Interestingly, the development of improved computational capabilities has recently allowed other methods such as ML to complement this estimation process. While the parametric hedonic price regression approach is largely applied for inferential purposes, its potential for predictive tasks is rather limited (Pérez-Rave et al., 2019). The scope of ML methods, however, is the other way around. While inference has hardly played a role so far due to the mostly opaque algorithms, the predictive qualities of these methods are much more pronounced. ML algorithms, like gradient tree boosting (GTB) (Friedman, 2001), random forest regression (RFR) (Breiman, 2001a) and support vector regression (SVR) (Smola & Schölkopf, 2004), are capable of artificially learning from the underlying data and continuously improving their predictive performance. Hence, these algorithms have shown remarkable accuracy. In the real estate literature, various studies demonstrate the performance of ML algorithms and parametric hedonic models, including Lam et al. (2009) and Kontrimas and Verikas (2011) for SVR, Yoo et al. (2012), Antipov and Pokryshevskaya (2012) and Yao et al. (2018) for RFR and van Wezel et al. (2005) and Kok et al. (2017) for boosting methods such as GTB. Furthermore, Zurada et al. (2011), Mayer et al. (2019) and Ho et al. (2020) document the performance of different ML methods.

However, these methods are viewed critically due to their black box character (McCluskey et al., 2013), since the final result often delivers the raw prediction without letting one know how it came to the respective conclusion. As Mayer et al. (2019) state, the predictive accuracy is only achieved by reduced comprehensibility of the ML models due to its ability to artificially capture highly complex pattern within the underlying data. In consequence, researchers are mostly faced with the trade-off between what is predicted (prediction) and why the prediction took place (inference).

In general, many ML methods, such as SVR, RFR and GTB, provide model transparency since there is an understanding of how the underlying algorithm works and the algorithm can be described mathematically without further knowledge of the data – although the structure of ML methods is increasingly complex. Nevertheless, model interpretability in terms of identifying and understanding what factors impact the final predictions seems to be the bottleneck for an overall acceptance and implementation of ML methods, because sole measures like predictive accuracy are "an incomplete description of most real-world tasks" (Doshi-Velez & Kim, 2017).

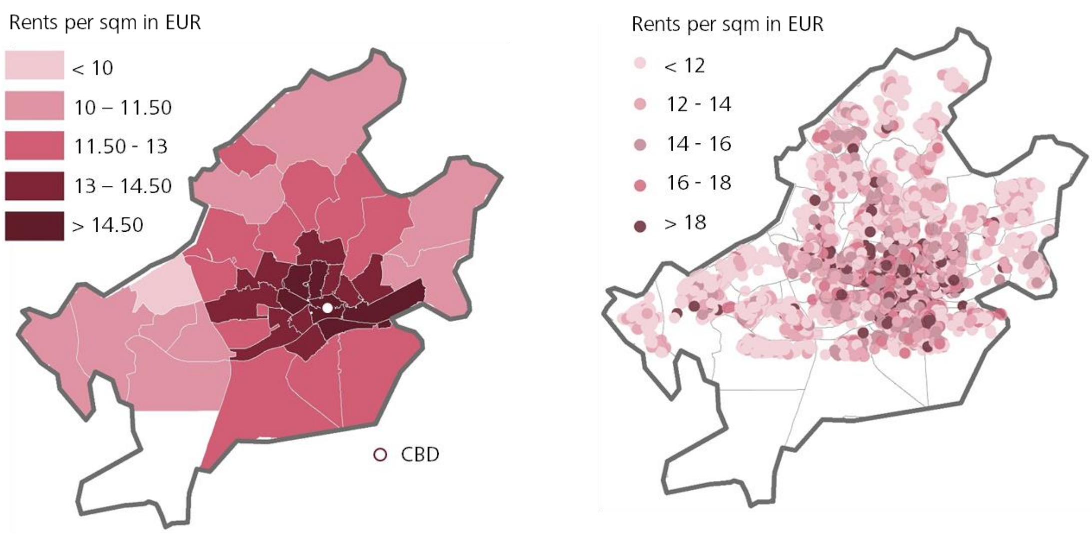
In the real estate literature, first approaches have been made to combine predictive and inferential purposes within a ML context. Pérez-Rave et al. (2019) propose a variable selection approach called "incremental sample with resampling" tested on two data sets of property prices. They apply random forests to varying subsamples to predict the final property prices. Variables are identified as important, if the feature is used in the final prediction rule of the RFRs for 95% of the subsamples. The final inferential interpretation is based on a parametric hedonic model using only the ML-selected variables. Moreover, Pace and Hayunga (2020) analyze the informational content of residuals from linear, spatial hedonic regression and ML models. After applying regression trees, they find that spatial information is still present in the residuals of ML models. Although single trees are easy to understand and their decision rule can be illustrated graphically, they show limited predictive performance and tend to be unstable due to high sensitivity to changes in the data or tuning parameter.

To conclude this section, this rather young field of research opens up the possibility to further engage with the interpretability of ML models and the impact of hedonic characteristics. In the following, we present the data set of our analysis and describe the methods we use to enable the interpretability of ML-based predictions. After that, we discuss the results and summarize our findings in the conclusion.

4.4 Data

The sample for our analysis comprises 52,966 observations of residential rents in Frankfurt am Main, Germany. The country is the fourth largest economy worldwide and known as a safe haven for both domestic and cross-border real estate investments. With one of the lowest home ownership ratios of 51% being well below the European average, Germany is seen as a rental market rather than a homeowner market. Frankfurt represents the leading financial hub in continental Europe and is hosting the European Central Bank and the Frankfurt Stock Exchange amongst many important financial institutions. Its metropolitan region is home to more than 5.8 million inhabitants.

Figure 4.1. Distribution of rents and observations of the Frankfurt data sample



Notes: The left map shows average rents per sqm for each ZIP code. The right map depicts all observations. Both cover the Frankfurt city area from 2013 to 2019. The thin grey lines display the ZIP codes.

Rental data stems from Empirica Systeme, one of the largest German provider of real estate data, which comprises, amongst others, real estate listings of leading German Multiple Listing Systems (MLS). Data preparation and cleaning is performed to account for duplicates and erroneous data points. As the study focuses on the urban rental market in Frankfurt that is mainly determined by apartment rentals, we exclude single, semi-detached and terraced houses. We furthermore leave out student apartments, senior living accommodations, furnished co-living spaces, and short-stay apartments to control for highly specialized sub-markets that are expected to bias the overall rental market. Figure 4.1 provides two maps of the rental distribution in the data sample for Frankfurt. It highlights the average rent per sqm in every ZIP Code (left) and displays all observations gathered (right). Both maps indicate that the highest rents are found in the center, while lower rents tend to occur in the outskirts. There are no rental observations in the most southern part of Frankfurt due to highly forested areas and the airport of Frankfurt.

Besides the rent as target variable, the data contain information on structural characteristics in terms of living area, building age, floor and whether a kitchen, parking spot, balcony, terrace, bathtub and elevator is present or whether an apartment is refurbished. We add socio-economic data from Growth from Knowledge, Germany's largest market research institute. Since all rental data points are georeferenced, we are able to add a spatial gravity layer based on data from Eurostat, the German statistical office and Open Street Map to account for spatial information and therefore add several location variables. We include the distance to the CBD as well as to numerous important amenities. Proximity to bus and railway station account for public transport and accessibility. Bakery, supermarket, convenience and department store distances comprise the local supply. Bar, beergarden and café represent the access to hospitality. While distances to school and park allow insights on public amenities, proximity to car wash and traffic signal incorporate adverse effects mainly due to noise emissions.

MLS are frequently used in German rental markets from professional as well as from private landlords. Moreover, since neither landlords nor tenants are obliged to disclose contract information in Germany, listing data is the main source of information for both researchers and practitioners.[11] In addition, it should be noted that rental price formation in major German cities is generally dominated by the offering party since residential vacancy rates in metropolitan areas are remarkably low.[12] A look at individual renting scenarios reveals that a landlord regularly receives inquiries in the double-digit range for an apartment that has been advertised. In consequence, the rental decision is not based on auction procedures but rather on timely application and best (personal and solvent) fit for the landlord. In the literature, Cajias and Freudenreich (2018) demonstrate that German residential markets are subject to low Time-on-Market and diminishing degrees of overpricing. As Gröbel (2019, p. 8) suggests, asking data in Germany "reflect the currently

[11] See e.g. Gröbel and Thomschke (2018) using German rental listing prices in research as well as well-established applications of listing data e.g. F+B Residential Index or Empirica Real Estate Index in practice.

[12] According to CBRE, the vacancy rate for residential real estate in the city of Frankfurt am Main marks 0.4% of the stock. Moreover, Immobilienscout 24, the leading online listing platform for real estate in Germany, reports 198 clicks on average for an online apartment advertisement.

prevailing overall market situation". Although we do not claim that rental listing precisely reflect the agreed contract rent, we expect the listing rents to be a useful framework for the ongoing analysis.

Table 4.1. Descriptive Statistics of the dataset for Frankfurt am Main

Variable name	Unit	Mean	Median	Std.Dev
Rent	EUR/month	1,036.123	884	638.175
Living area	sqm	78.175	72	36.688
Floors	Integer	2.396	2	2.328
Age (relative to 2017)	Integer	49.377	48	39.701
Bathtub	Binary	0.564	1	0.496
Refurbished	Binary	0.242	0	0.428
Built-in kitchen	Binary	0.688	1	0.463
Balcony	Binary	0.633	1	0.482
Parking	Binary	0.487	0	0.500
Elevator	Binary	0.449	0	0.497
Terrace	Binary	0.136	0	0.342
Purchasing Power	EUR/HH/ZIP	50,390	49,993	5,798
CBD_distance	Km.	3.616	3.604	1.896
Bar_distance	Km.	0.722	0.511	0.636
Beergarden_distance	Km.	1.135	0.937	0.759
Cafe_distance	Km.	0.346	0.240	0.325
Bakery_distance	Km.	0.370	0.245	0.403
Convenience store_distance	Km.	0.849	0.589	0.748
Department store_distance	Km.	1.550	1.306	0.997
Supermarket_distance	Km.	0.252	0.223	0.167
Bus station_distance	Km.	3.062	2.667	1.566
Railway station_distance	Km.	0.835	0.581	0.685
Traffic signals_distance	Km.	0.186	0.157	0.135
Car wash_distance	Km.	1.266	1.234	0.584
Park_distance	Km.	0.266	0.236	0.158
School_distance	Km.	0.302	0.278	0.167

Notes: The table reports the summary statistics comprising data as of January 2013 to December 2019. Age is calculated as the difference of the building age to the year 2017. All distance variables are calculated as the distance to the specific dwelling in kilometers. Binary variables report whether the dwelling includes a certain characteristic (1) or not (0). Rent is presented as euro per month. Information on households (HH) is reported on ZIP level. SD: standard deviation, Min: minimum value, Max: maximum value.

Table 4.1 shows the descriptive statistics. We find a mean asking rent of 1,036.12 EUR p.m. (euros per month). An average apartment is 78.175 sqm located on the 2nd floor in a property that was built in 1968. The apartment contains a bathtub, a built-in-kitchen, a balcony, but neither a parking slot nor an elevator. On average, it is 3.62 km away from the CBD, 350 meters to the next café and 250 meters to the closest supermarket. The bus and railways station are 3 km and 0.84 km away, whereas the next school is located 300 meters nearby. The mean household purchasing power amounts to 50,390 EUR p.m.[13]

4.5 Methodology

ML has proven its predictive power in the literature and is commonly used by real estate professionals to inform their decision making (RICS, 2017). We apply a tree-based approach to build the foundation for further analysis. As Pace and Hayunga (2020) state, a regression tree (RT) is easy-to-understand while still being capable of identifying complex pattern. That is because trees can capture non-linear relationships as well as interactions. In its core, a RT can be understood as nested if-else conditions. Tree-based models divide the data in distinct subsets and make a prediction for every subset (which usually is the average outcome of all observations in the specific subset). The division is made by several splitting steps, in which iteratively a feature variable is chosen and its feature space is split in a way that a certain criterion is affected most (e.g. the prediction error is reduced most) until a stopping point is reached.

Since single trees are prone to misspecification, ensembles are used to aggregate and combine the prediction rule of multiple trees. We choose XGB as an ensemble boosting method, which has shown to be capable of accurately predicting property prices and rents and at the same time yield robust estimation results.[14] Developed by Chen and Guestrin (2016), it is a promising approach for regression, as well as for classification, as it contains specific features that won it several Kaggle[15] competitions in the recent past. In its basic concept, boosting fits an initial tree, calculates the residuals of the initial prediction, and fits another tree on the residuals to stepwise reduce the prediction error and incrementally enhance the final prediction rule. To prevent overfitting cross-validation is applied.

[13] In Table 4.3 in the appendix, we provide a full set of correlation coefficients for all variables.

[14] In general, tree-based ensemble algorithms are based on two different approaches, namely boosting and bagging. See e.g. Hastie et al. (2009) for a more detailed introduction to the fundamentals of ML models.

[15] Kaggle is one of the leading online platforms for the data science community and regularly hosts data competitions.

Because the internal logic and consequently the rationale behind the individual predictions is rather hidden, the use of ML often lacks transparency. In consequence, a growing body of literature on IML[16] has evolved in recent years to further 'improve trust' in algorithmic decisions (See e.g. Adadi & Berrada, 2018; Carvalho et al., 2019; Arrieta et al., 2020 or Linardatos et al., 2021). In general, tree-based ML methods show some sort of algorithmic transparency, since their underlying concept and theory is comprehensible and mathematically described (James et al., 2015). Nevertheless, it is not evident, which feature[17] and to what extent it contributes to the prediction.

One possibility to understand how predictions are achieved in this context is to use **interpretable ML models.**[18] Like in parametric models, specific restrictions limit the complexity of the model and therefore allow inferential insights. RTs are a well-known example of interpretable ML models if e.g. the depth of the tree is limited. As Molnar (2020) states, short trees with a depth up to three splits are interpretable in a comprehensive way, since a maximum combination of three if-else-conditions as the decision rule is enough to explain how the model yield a certain prediction.

Limiting the models complexity often results in depriving ML much of its effect, since their flexible structure enables a strong predictive performance (Breiman, 2001b)[19]. Consequently, (post-hoc) model-agnostic **interpretation methods** have been developed, which separate the explanatory framework and the ML model, thus preserving its predictive capabilities. In contrast to interpretable models, the ML model remains a black box, with the separated interpretation methods aiming at extracting interpretable information post-hoc. Model-agnostic tools benefit from their flexibility because they do not depend on a specific ML method and can be applied to various learners (Ribeiro et al., 2016).

Interpretation methods differ on whether their focus is on feature importance or feature effects. The first one aims at evaluating which feature contributes the most to the prediction, whereas the second one sheds light on how a single feature contributes to the prediction. The methods are perceived as typical and useful tools to show the impact of features in ML models and explain the inner working on a global level (Hastie et al., 2009).

[16] In the context of IML, the term Explainable Artificial Intelligence (XAI) is often used synonymously.

[17] To describe the covariates, hedonic literature mainly refers to them as variables or characteristics, while research on IML generally uses the term features.

[18] Interpretable ML models are also referred to as transparent models, since they are considered to be understandable by itself.

[19] See e.g. Shmueli (2010) for further discussion on the trade-off between model accuracy and interpretability.

We use the FeatureEffect and FeatureImp functions both implemented in the iml package in R (R Core Team, 2016).

Feature importance (FI) measures the relevance of a single feature for the prediction. The importance of a feature is calculated by permutation of the observed feature values and its effect on the prediction error, keeping all other features constant. Based on the concept of Breiman (2001a) for random forests, Fisher et al. (2019) provides a model-agnostic framework for measuring the covariates contribution to the accuracy of an ML model called 'model reliance'.

Let X be the feature matrix, Y the dependent variable and f the ML model, with the prediction error e being measured by a loss function $L(Y, f(X))$. The feature importance is defined as the ratio of the model error after permutation to the original model error before switching features.

$$FI(f) = \frac{e_{perm}(f)}{e_{orig}(f)} \tag{1}$$

The permutated error is thereby calculated as the expected error of the ML model based on the permuted feature matrix X_{perm}.

$$e_{perm}(f) = \mathrm{E}L(Y, f(X_{perm})) \tag{2}$$

To visualize the most important features, every variable is ranked and plotted according to their FI. Alternatively, the FI score can also be calculated as the difference of both errors, although the ratio provides the advantage of higher comparability. We use the Mean Absolute Error (MAE) as loss function. By switching the feature values of all observations (e.g. an observation with 1 for a kitchen being present is switched to 0), FI calculates how much this change leads to an observable decrease in prediction accuracy. It can consequently identify whether the specific feature contributes to the overall prediction or whether its change does not perceptibly affect the outcome. Lastly, we average the importance measures over 100 repeated permutations. As Fisher et al. (2019) states, FI is a helpful tool to identify influential features and increase the transparency of black box models.

In addition to the individual importance, **feature effects** show how a single feature influences the predicted outcome of an ML model. After the training process, a ML model has learned a specific relationship between the covariates and the target variable that can be analyzed. Partial Dependence (PD) plots visualize the marginal effects of features on the model's prediction (Friedman, 2001). The plots are based on partial dependence functions which highlight the effect of one feature on the target variable when the average effects of all other features are accounted for. PD plots reveal useful information e.g. whether the relationship can be explained linearly or in a more complex manner.

Let once again X_j be the vector of the *j* variables and n be the number of observations. The PD is the effect of features of a subset X_S by marginalizing over all other features in the complement subset X_C (Zhao & Hastie, 2021). Given the ML model f, the partial function f_{x_S} is defined as:

$$f_{x_S}(x_S) = E_{x_C}[f(x_S, x_C)] = \int f(x_S, x_C)\, d\mathbb{P}(x_C) \tag{3}$$

With $d\mathbb{P}(x)$ being the marginal distribution of X_C. Marginalizing over all other features leads to a function that is solely dependent on the features X_S to be analyzed. The partial function f_{x_S} is estimated using the Monte Carlo method to average over actual features values $x_C^{(i)}$ while keeping X_S constant:

$$f_{x_S}(x_S) = \frac{1}{n}\sum_{i=1}^{n} f\left(x_S, x_C^{(i)}\right) \tag{4}$$

As shown in Greenwell (2017), all values of feature x_S (e.g. living area) are in a first step replaced with the particular feature value (e.g. of the first observations). The ML model predicts expected output values for the newly created dataset (where all observations have the same constant feature value x_S). Averaging over these predictions calculates the marginal effect at the particular feature value. This step is repeated *n* times to obtain a marginal effect for all observed feature values. Finally, the single feature values are plotted against the resulting f_{x_S}. For a linear hedonic model, e.g. based on ordinary least squares (OLS), a PD plot would show a straight line representing the specific estimated coefficient. As Zhao and Hastie (2021) state, PD plots are a valuable visualization tool to interpret how the prediction of ML models depend on specific features.

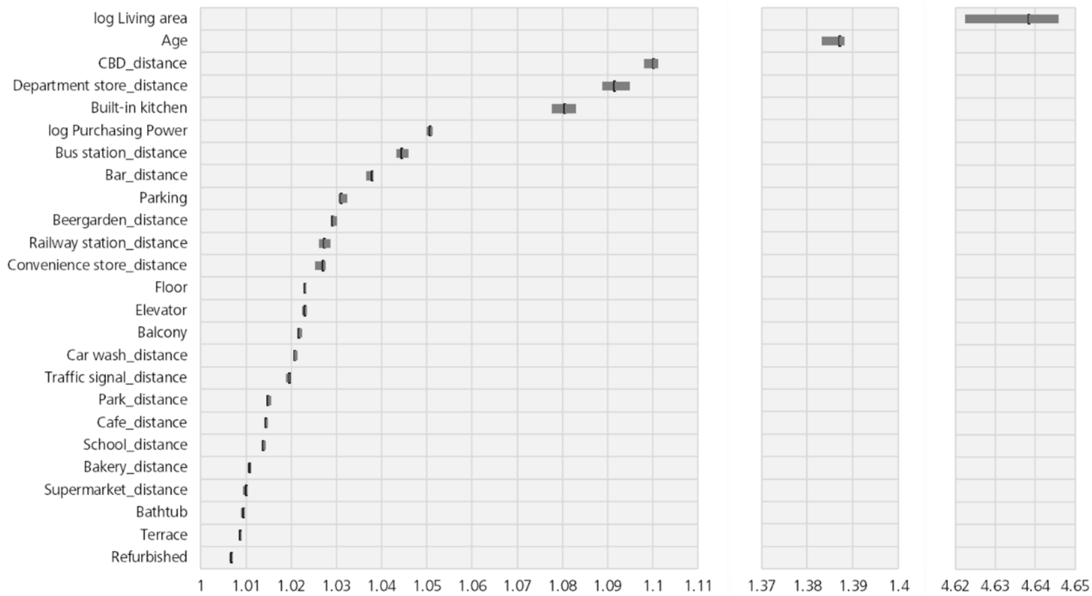
4.6 Econometric Results

To set up a functional ML framework, we first train the XGB algorithm on our dataset of rental prices described in the data section. We apply random cross-validation with five folds and five repetitions. The tuning process takes 16 hours with 72 central processing units (CPUs) running simultaneously. The final XGB model is trained with $\eta = 0.243$, $\gamma = 0.0431$, $\lambda = 28.99$ and $\alpha = 22.64$. The out of sample rental prediction with XGB yields to a R^2 of 92.50%. The mean absolute percentage error marks 11.13%. Moreover, 57.96% of all predictions deviate less than 10% from the observed values. The tuned XGB algorithm subsequently allows a post-hoc analysis with a set of model-agnostic interpretation tools to identify feature importance and feature effects.[20]

Feature importance of the hedonic characteristics

Figure 4.2 provides the relevance of all characteristics for the ML prediction based on FI. The features are individually ranked on the y-axis from most important at the top to least important at the bottom. The x-axis provides information of how much prediction accuracy changes when the feature values are permutated. Median values are plotted with the bar denoting the 5% and 95% quantiles. Feature importance ratios exceeding 1 indicate an observable impact on the overall prediction. Ratios that tend towards 1 imply a rather negligible influence of the features.

Figure 4.2. Feature importance of the hedonic characteristics



Notes: The figure displays the median values of the relative feature importance obtained with XGB. MAE is chosen as loss function. Variables are ranked based on their FI score. The bar denotes the 5% and 95% quantiles of the distribution of FI scores after 100 repetitions. A break in the horizontal axis is conducted to ease readability.

It is not surprising, that living area and age are seen to have by far the biggest impact on rental prediction. Their median values highlight that randomly permuting living area and age individually 100 times, increases the model error by a factor of 4.64 and 1.39, while keeping all other variables constant. Furthermore, distance to the CBD and to a department store are of high importance and associated with an increase in MAE of 1.10 and 1.09. We expect both variables to be a suitable proxy for a good location.[21] Moreover,

[20] To ensure basic hedonic functionality of a hedonic rent estimation, we apply linear, spatial and non-linear methods in advance. The corresponding methodology is discussed in the appendix and the results are presented in Table 4.2. All variables show expected signs and do not contradict findings from related literature.

[21] In major German cities, department stores are usually located either close to the city center or in highly frequented and therefore good shopping locations.

the presence of a built in kitchen is also heavy influential. The purchasing power per household is followed by the distances to the bus station and the next bar and beergarden.[22] The existence of a parking spot complements the ten most influential variables. We will not discuss the remaining variables in detail since their contribution seems rather marginal. The small distribution of FI for all variables demonstrated by the 5% and 95% quantile indicates that the results are stable over all repetitions. To summarize, feature importance ranks how relevant a variable is for the predictive task as it provides which variables are more or less influential for an ML model. One can thus obtain a first impression whether an algorithmic hedonic model delivers reliable results that are based on a plausible understanding of the economic context. However, FI does not provide any information about the sign. To clarify e.g. whether a small or large distance is decisive, we investigate feature effects in a next step.

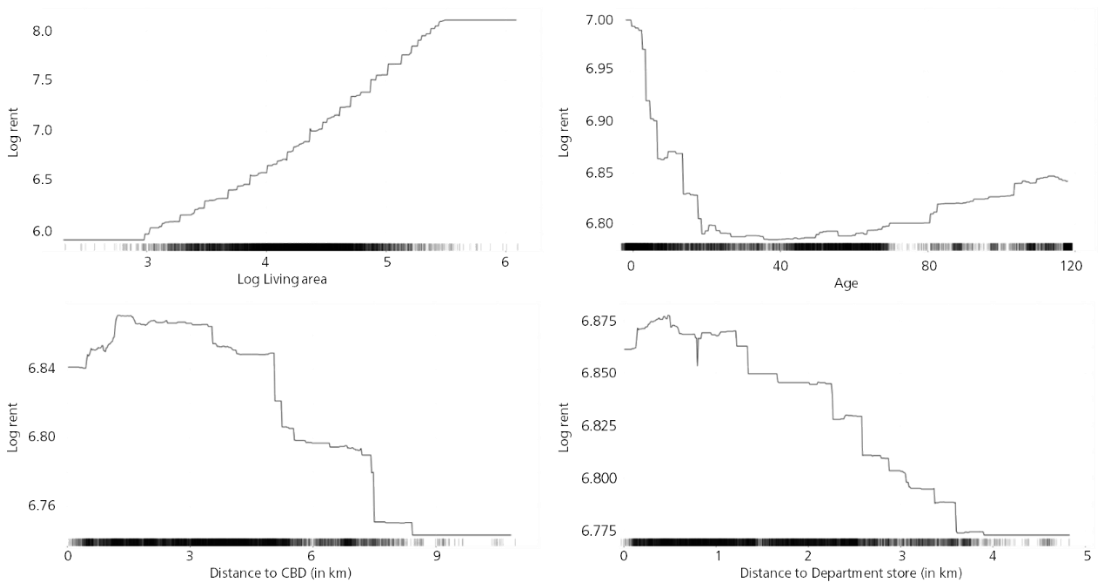
Feature effects of the hedonic characteristics

PD plots enable an analysis of how a certain feature influences the rental prediction and which relationships between residential rents and property characteristics has been traced by the algorithm. While the X-Axis provides information on the independent variable with the stacked black lines indicating the amount of observations, the Y-Axis shows the respective rent level. Since marginal effects are calculated and averaged for every feature value, PD plots require high computational power. Thus, we plot the partial dependence for the year 2019, whose generation took eight hours of computing time.

Figure 4.3 demonstrates how rental prices are associated with the four most influential characteristics living area, age and distance to CBD and department store. We start with the most important feature living area, which is incorporated as the natural logarithm. Since the PD plot highlights a linear relationship, the commonly applied log-log transformation can be confirmed as a good approximation of the positive relationship between living area and rent. Recent hedonic literature on property prices provides similar findings for the positive relationship (e.g. Dumm et al., 2016, Dumm et al., 2018 or Stamou et al., 2017).

[22] Beergardens are perceived as important hospitality institutions in Germany and thus the result is not surprising.

Figure 4.3. PD plots for living area, age, distances to CBD and department store



Notes: The figure displays the partial dependence of the most important feature regarding two structural characteristics and distance to CBD and department store. The vertical axis denotes the feature values of log rent level while the horizontal axis represents the covariates feature values. Stacked black lines display the number of observations.

Age is perceived to be more complex, though intuitive. We find rental values to decrease with greater age until a building year of 1990-2000. While newly build apartments obtain highest rents, depreciation, changes in living preference as well as increasing requirements on energy-efficient construction most likely result in a steep decline in rental values. This is followed by an indifference of rental values up to 1940th. Frankfurt was heavily bombed in World War II, with emergence constructions of social housing provided by the government in the following decades. Therefore, historical pre-war buildings face higher rents. Consequently, building age displays a u-shaped relationship, as e.g. incorporated in Mayer et al. (2019).

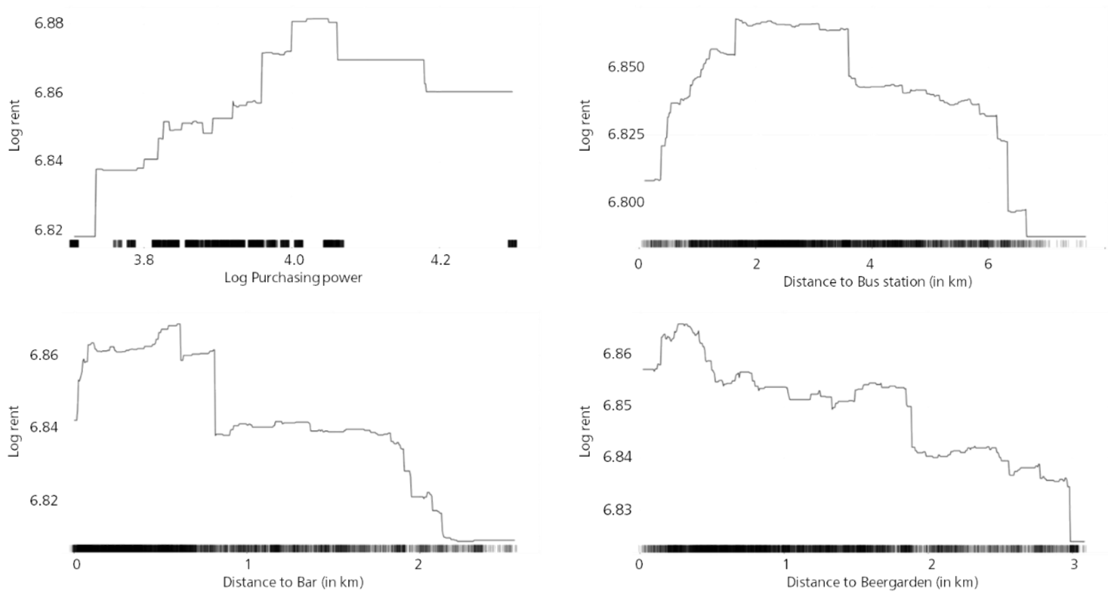
Distance to CBD is perceived to be highly influential. In general, we find rental prices to decline with greater distance to the city center. Hedonic literature suggests similar conclusions since authors such as Osland (2010) or Zheng et al. (2016) also find a negative relationship between property prices and distance to the city center. However, the opposite effect is visible for close proximity. We expect tenants to appreciate separation from very urban areas. A graphical turning point can be found at about 1.5 km, followed by moderate decline in rental prices. Interestingly, apartments close to the CBD face comparable rental values than the ones in 5 km distance. A steep decrease in rent levels can be seen beyond 5 and 7.5 km.

Regarding local supply, department stores are rather linearly and negatively associated with rental values. The proximity to shopping facilities results in increasing rents. We do not find an equivalent distance variable in the hedonic literature, however, Dubé and

Legros (2016) show a positive price effect for properties not more than 1 km away from a shopping center. Interesting to note, the distance to department store drops sharply at about 1.5 and 2.5 km. This could indicate a critical distance for consumer goods. However, FI identifies supermarket as the least important distance variable. We assume that a high density of supermarkets in urban areas ensure local supply for everyday goods and therefore result in a negligible influence on rental values. In contrast, we assume different circumstances in rural communities. With minor influence due to the limited appearance of department stores, we expect the importance of supermarket to be more pronounced in non-metropolitan areas.

Furthermore, FI ranks the presence of a built-in kitchen as important. Gröbel and Thomschke (2018) find a significant positive relationship between built-in kitchens and rents in Berlin (Germany). However, due to its binary nature, the visualization with PD plots is limited.

Figure 4.4. PD plots for purchasing power, distance to bus, bar and beergarden



Notes: The figure displays the partial dependence of the most important feature regarding two structural characteristics and distance to CBD and department store. The vertical axis denotes the feature values of log rent level while the horizontal axis represents the covariates feature values. Stacked black lines display the number of observations.

The next most important characteristics displayed in Figure 4.4 are, according to FI, purchasing power and distance to bus station, bar and beergarden. We find socio-demographic information to show a rather linear relationship. Neighborhoods with high purchasing power are associated with more expensive apartments and thus the variable is perceived as a characteristic of a good residential area. A steep increase in rental values for high wealth districts could reflect the segment of high-rise apartments in residential towers. While the construction of high-rise buildings is restricted in most German cities, Frankfurt has early incorporated tower buildings in urban planning. These do not only represent the highest price segment in the residential market of Frankfurt but have shown to be driver of residential prices and rents in the last years.

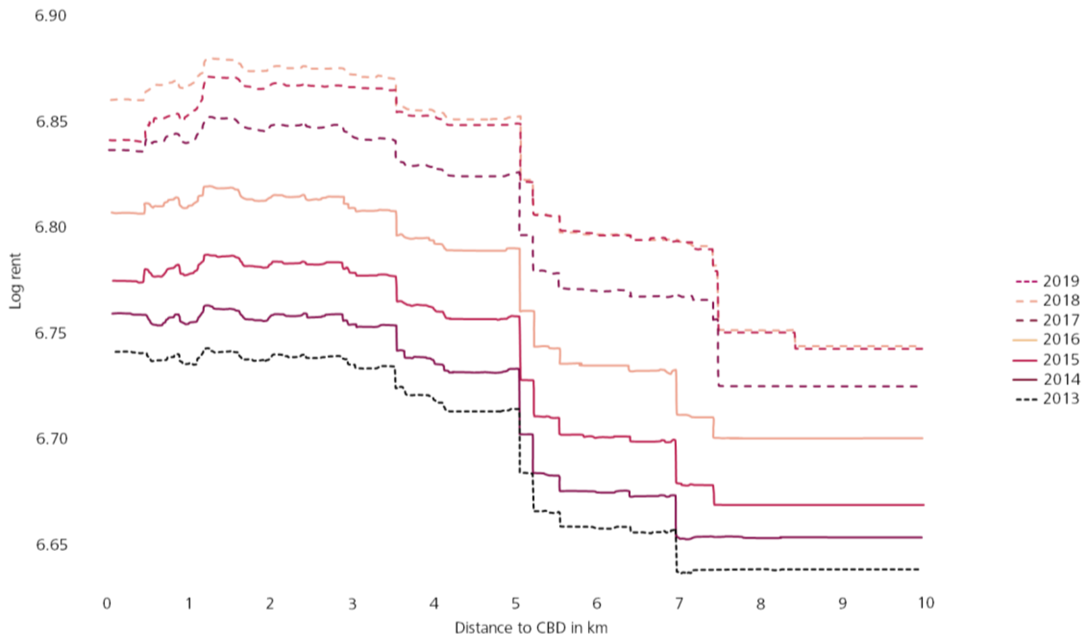
Interesting to note, the distance to bar, beergarden and bus station have shown to affect the overall prediction the most out of all hospitality and public transport features. All three variables show a non-linear relationship with residential rents. We find the distance to a bar to be positively associated with rental values up to approx. 700 meters. While a bar in close proximity would result in lower rents, the access to hospitality leads to an increase in rental values only from a certain distance. We expect tenants to face a trade-off between accessibility and negative externalities such as noise.

The same relationship holds for the variable bus station. A location further away from a central bus hub is linked to higher rental values up to approx. 1.7 km. Since central hubs are related to mostly high urban density and traffic, we assume that tenants appreciate locational separation. The plot reveals the relationship to be quite constant until 3.5 km, followed by declining rental prices. The accessibility to central hubs through different means of transport seems to overlay negative effect of a larger distance. However, after 3.5 km, we find this effect to become visible and apartments that are poorly located in terms of transport face discounts for low accessibility. The presence of a parking spot complements the ten most influential variables, yet as a binary variable, it is not displayed as a PD plot.

Adding a temporal dimension to our analysis by displaying feature effects on a yearly basis enables us in a last step to illustrate temporal dynamics of the effects of hedonic characteristics. We demonstrate the latter by analyzing the distance to the CBD (Figure 4.5) and the distance to a department store (Figure 4.6).

At first, Figure 4.5 shows a negative relationship between rents and the distance to CBD across time. A continuous upwards shift for all feature values indicates increasing rent levels during the observed period. Only the graph of the year 2019 behaves differently, since it moves below 2018 for closer proximity and analogous from 5 km distance onwards. This development could be attributed to a declining preference for downtown locations in combination with overall stable rent levels in recent years.

Figure 4.5. PD plots for distance to CBD for the years 2013 to 2019

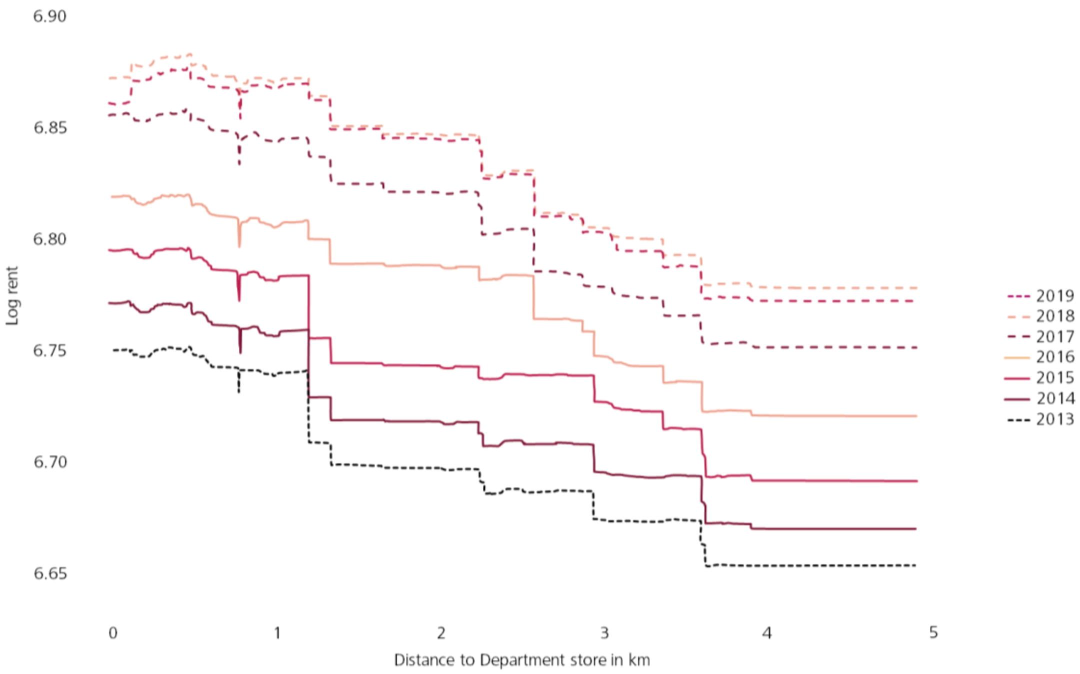


Notes: The figure displays the partial dependence of important variables over different periods. The vertical axis denotes the feature values of the log rent level while the horizontal axis denotes the covariates feature values.

Although the course of all lines is quite similar, we find some differences. First, a drop in rental prices at a distance of 5 km is less pronounced for 2017, 2018 and 2019 than for previous years. This possibly indicates that residential locations further away from the center experienced rent increases due to a growing preference for sub-urban areas during the last years. Second, another major decline can be recognized at 7 km for 2013 to 2016. In the following years 2017 to 2019, however, this is only noticeable at a distance of approx. 7.5 km, but the downturn is considerably stronger. Both changes indicate that residential locations in medium distance to the center (5 to 7.5 km) experienced stronger rent increases compared to central as well as periphery location. We would assume that high demand in central locations results in a preference shift towards apartments further away from the CBD.

In Figure 4.6, a negative relationship between rents and the distance to a department store is displayed, yet a similar pattern for the graphs can be seen in terms of comparable upwards shift of rents throughout all periods and 2019 being slightly below 2018. A first major decline is visible at approximately 1.2 km, with the years 2013, 2014 and 2015 experiencing a stronger decrease. From 2.6 km distance, the picture is the other way around. Whereas rents fell rapidly from 2016 to 2019, the downturn was not as strong as in previous years.

Figure 4.6. PD plots for distance to department store for the years 2013 to 2019



Notes: The figure displays the partial dependence of important variables over different periods. The vertical axis denotes the feature values of the log rent level while the horizontal axis denotes the covariates feature values.

The findings indicate that while locations between 1.2 km and 2.8 km gained popularity, locations in close proximity as well as further away remained more or less stable. Figure 4.7 in the appendix provides additional and centered PD plots for the features Distance to department store. Centered PD plots aid and underpin the interpretation of the differences in PDs throughout the years.

Ultimately, the feature effects technique yields greater transparency of how the different inputs contribute to the final estimation of the ML model. By visualizing the individual relations between the variables and the rent to be estimated, this method demonstrates which (economic) rational the algorithm has learned from the data and accordingly integrated into its internal calculations.

4.7 Conclusion

This paper sheds light on how Machine Learning (ML) based decision making in hedonic modelling can be made more transparent. We visualize and investigate the relationship between residential rents and a set of hedonic variables, which was learned by a ML model. Based on a residential dataset of more than 52k apartments in Frankfurt am Main, Germany, we apply the eXtreme Gradient Boosting algorithm (XGB) for rental prediction. Model-agnostic Interpretable Machine Learning (IML) methods are subsequently used to examine feature importance and feature effects. Feature importance (FI) reveals that living area, age and the distance to CBD and a department store influence the overall rental prediction the most. In contrast, the least important features are several structural dummy variables and the distance to a supermarket and a bakery.

We plot the partial dependences (PD) for the influential variables that were detected in the preceding analysis to highlight feature effects. Although the relationship of rental values and the distance to CBD and department store is mainly linear, major declines at specific proximity values indicate that critical distances to the center as well as to local supply exist. Furthermore, there seems to be a difference in rent level to the wealthiest neighborhoods. Interestingly, we find that close proximity to hospitality and public transport is associated with rental discounts. In addition, the inspection of PD plots on a yearly basis reveals that especially apartments in a medium distance to the city center face considerable higher rent increases over the years. We assume both an increasing preference for less urban areas as well as peaking rent in the center to be possible reasons.

To conclude, interpretation methods can reveal the rationale behind the ML models estimation by demonstrating what relationship the algorithm detects in the underlying data. Peeking inside the black box enables researchers to reenact how a ML model arrived at its prediction and will help to gain new insights, ease practical applications and enhance reliability in algorithmic decisions.

The insights gained by these methods are relevant not only for research but also for practice in the private as well as public sector. Since real estate professionals commonly use ML to inform their decision making (RICS, 2017), model-agnostic methods provide a useful framework to effectively handle AI-based results. Whereas the advantages of these methods have already been discussed in detail, difficulties and limitations must also be pointed out. First of all, there are challenges in terms of computing power. Whereas parametric or semi-parametric methods are usually able to estimate hedonic models within seconds, ML-based methods such as XGB take considerably longer. This also applies to the application of IML. Furthermore, it should be noted that data availability is of course essential for hedonic models. Even with ML-based models, an omitted variable bias can drastically reduce the informative value and thus the applicability. Admittedly, the data set of this study is quite extensive, but there are of course other additional apartment features imaginable that could influence the meaning of the results.

IML is a rapidly evolving field with new methods and applications being continuously proposed. Although this research area has achieved a degree of stability (Molnar et al., 2020), it is still in its infancy and faces several challenges to overcome. On the one hand, there is a need to define what interpretability means to then evaluate how black box models can be made more interpretable. On the other hand, the sensitivity of interpretation methods is of high importance, since not only these methods, but also the ML techniques are dynamically developing. To further improve 'trust' in algorithmic decisions ongoing research is necessary. We expect IML methods to be a valuable addition to the hedonic practice, both because it contributes to the transparency of ML models and because it provides insights on potentially unknown relationships in real estate hedonic modelling.

4.8 Appendix

We apply different hedonic methods that have been used regularly in the literature. First, we deploy a hedonic OLS modelling approach to estimate the effects of property characteristics on rental prices. Linear hedonic regression represents the standard approach in modelling real estate prices and rents and is frequently used in housing studies (Mayer et al., 2019). The hedonic regression describes the rent Y as the sum of the predicted values of its characteristics X_j:

$$Y = \beta_0 + \sum_{j=1}^{J} X_j \beta_j + \varepsilon \tag{5}$$

In accordance to the real estate literature, a semi-log functional form with log-transformation of the dependent variable is conducted. Property characteristics include structural, socio-economic neighborhood and locational features. Proximity variables account for the spatial distance to public amenities and transport. Further spatial effects are modelled via spatial expansion by incorporating the coordinates in terms of longitude and latitude (Bitter et al., 2007, Chrostek & Kopczewska, 2013, Pace & Hayunga, 2020). Furthermore, temporal dummies are included for the specific month and year.

Many authors argue that property prices and rents may contain two key figures, namely spatial autocorrelation and spatial heterogeneity, that can require the spatial extension of hedonic models (LeSage, 1999). Since the occurrence of spatial effects can lead to misspecifications and biased results in the OLS framework (Anselin, 1988), we additionally apply a spatial autoregressive regression (SAR) with the following functional form:

$$Y = X\beta + \rho W Y + \varepsilon \tag{6}$$

ρWY denotes a spatial lag of the target variable Y, with W being the spatial weight matrix that specifies the spatial structure, and ρ representing the spatial lag parameter.

However, linear models are subject to various restrictions due to their functional parametric form that can yield to misspecifications (Mason & Quigley, 1996; Pace, 1998). Because relationships in housing markets appear often to be non-linear, hedonic modelling can require the incorporation of more flexible functional forms to account for nonlinearity (Bontemps et al., 2008; Brunauer et al., 2013). Hence, a semi-parametric generalized additive model (GAM) is further considered.

$$Y = \beta_o + \sum_{j=1}^{J} X_j \beta_j + \sum_{p=1}^{P} f_p(X_p) + \varepsilon \tag{7}$$

GAM relaxes the linearity assumption by replacing the parametric linear relationship with non-parametric smoothers (e.g. splines, near neighbor and kernel smoothers). The linear equation is expanded by p smooth functions f_p in order to identify latent non-linear effects. The results of the aforementioned methods are presented in Table 4.2. The coefficients provide expected signs and confirm a good model fit by showing acceptable R^2.

Table 4.2. Results of the OLS, SAR and GAM estimation

Variable name	OLS			GAM			SAR		
log Living area	0.939	***	(0.002)	0.900	***		0.928	***	(0,008)
Floors	0.002	***	(0.0004)	0.003	***	(0.0003)	0.003	***	(0,002)
Age (relative to 2017)	-0.0002	***	(0.00003)	s 8.000	***		-0.000	***	(0,0001)
Bathtub	-0.032	***	(0.002)	-0.016	***	(0.001)	-0.032	***	(0,006)
Refurbished	-0.015	***	(0.002)	0.005	***	(0.002)	-0.013	***	(0,007)
Built-in kitchen	0.084	***	(0.002)	0.077	***	(0.002)	0.077	***	(0,007)
Balcony	0.011	***	(0.002)	0.025	***	(0.002)	0.012	***	(0,007)
Parking	0.053	***	(0.002)	0.032	***	(0.002)	0.048	***	(0,008)
Elevator	0.053	***	(0.002)	0.020	***	(0.002)	0.048	***	(0,009)
Terrace	0.041	***	(0.002)	0.020	***	(0.002)	0.041	***	(0,009)
log Purchasing Power	0.406	***	(0.011)	0.069	***	(0.002)	0.313	***	(0,040)
CBD_distance	-0.019	***	(0.001)	s 8.692	***		-0.014	***	(0,002)
Bar_distance	-0.031	***	(0.002)	s 8.579	***		-0.024	***	(0,008)
Beergarden_distance	-0.020	***	(0.002)	s 8.631	***		-0.015	***	(0,005)
Cafe_distance	-0.014	***	(0.003)	s 8.700	***		-0.011	***	(0,010)
Bakery_distance	-0.011	***	(0.003)	s 8.842	***		-0.016	***	(0,009)
Convenience store_distance	-0.036	***	(0.002)	s 8.144	***		-0.035	***	(0,007)
Department store_distance	-0.006	***	(0.001)	s 8.580	***		-0.008	***	(0,005)
Supermarket_distance	-0.018	***	(0.006)	s 6.487	***		-0.029	***	(0,020)
Bus station_distance	-0.028	***	(0.001)	s 8.794	***		-0.017	***	(0,004)
Railway station_distance	-0.020	***	(0.002)	s 8.757	***		-0.020	***	(0,007)
Traffic signals_distance	0.086	***	(0.007)	s 8.243	***		0.075	***	(0,024)
Car wash_distance	0.012	***	(0.002)	s 8.763	***		0.007	***	(0.006)
Park_distance	-0.024	***	(0.006)	s 8.343	***		-0.019	***	(0.020)
School_distance	-0.003	***	(0.005)	s 8.412	***		0.008	***	(0,006)
Constant	-34.043	***	(3.087)	2.405	***	(0.100)	-22.860	***	(11,359)
rho							0.131	***	
time controls	Yes			Yes			Yes		
locational controls	Yes			Yes			Yes		
observations	52,966			52,966			52,966		
R^2	0.880						0.885		
adjusted R^2	0.880			0.898					
UBRE				0.028					

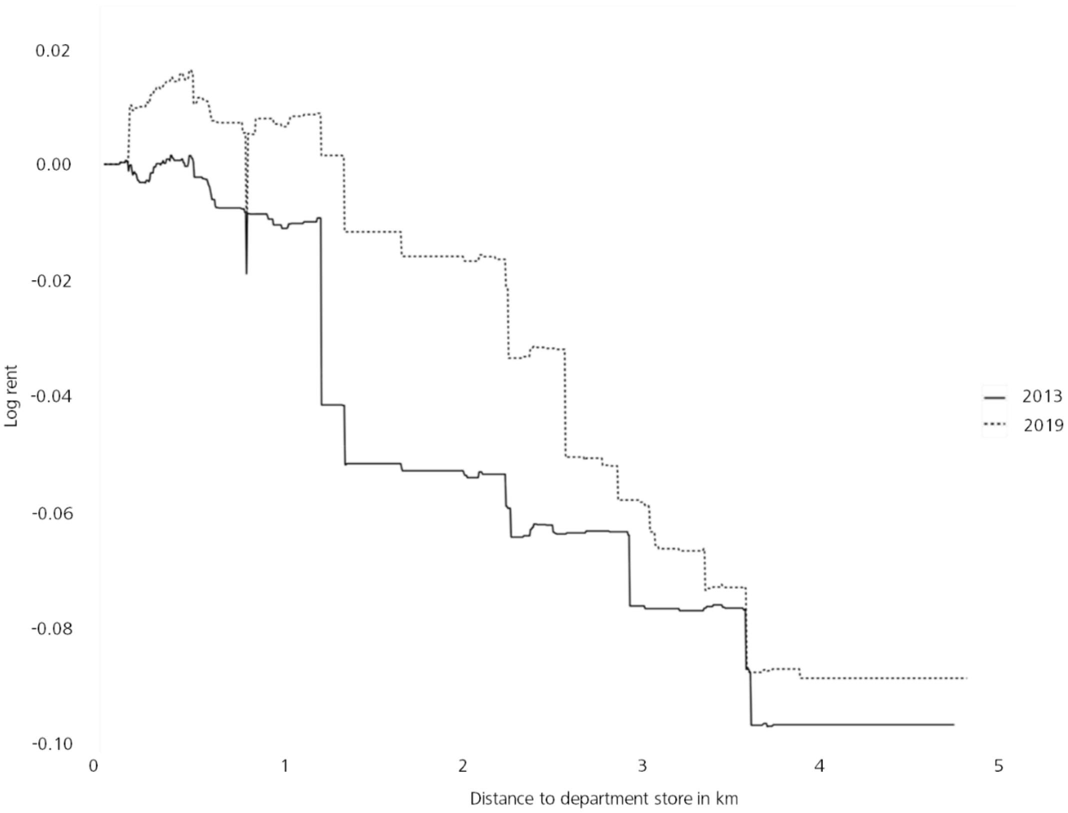
Notes: *p<0.1; **p<0.05; ***p<0.01, standard errors are displayed in parentheses. The GAM column reports the estimated degrees of freedom of the smooth terms (s) as well as their joint significance. Time controls (year and month) as well as location controls (apartment coordinates) are included in all models.

Table 4.3. Correlation matrix

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.
1.	Log rent p.m.	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2.	Log living area	0,89	1	0	0	0	0	0	0	0	0	0	0	0	0	0,01	0	0,90	0	0	0	0	0,21	0,92	0	0	0
3.	Floor	0,07	0,02	1	0	0,05	0	0	0	0	0	0	0	0	0	0,23	0	0	0	0	0	0	0	0	0	0	0
4.	Age	-0,14	-0,10	-0,09	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5.	Bathtub	0,12	0,18	-0,01	-0,06	1	0,74	0	0	0	0	0	0,22	0	0,02	0	0	0,77	0	0	0,01	0,51	0	0,01	0,62	0	0,05
6.	Refurbished	-0,09	-0,08	-0,04	0,23	0,00	1	1,00	0	0	0	0	0	0	0,91	0	0	0	0	0	0	0	0	0	0	0,46	0
7.	Bulit-in-kitchen	0,32	0,21	0,05	-0,13	0,02	0,00	1	0	0	0	0	0,01	0	0	0,01	0	0	0	0	0	0	0	0	0	0	0
8.	Balcony	0,19	0,19	0,10	-0,27	0,12	-0,06	0,06	1	0	0	0	0,85	0	0	0	0	0	0	0	0	0,09	0	0,02	0	0	0
9.	Parking	0,37	0,33	0,05	-0,57	0,08	-0,12	0,24	0,21	1	0	0	0	0	0,24	0	0	0	0	0	0	0,04	0	0	0	0	0
10.	Elevator	0,24	0,12	0,28	-0,56	0,03	-0,17	0,18	0,23	0,45	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11.	Terrace	0,21	0,21	-0,17	-0,20	0,05	-0,06	0,09	-0,09	0,21	0,11	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0,07	0
12.	Purchasing power	0,10	0,11	-0,10	0,04	0,01	0,05	0,01	0,00	0,01	-0,06	0,05	1	0	0	0	0	0	0	0	0	0	0	0	0	0,01	0
13.	CBD_distance	-0,22	-0,07	-0,11	-0,04	0,01	0,02	-0,12	-0,03	-0,02	-0,18	0,03	0,42	1	0	0	0	0	0	0	0	0	0	0	0	0	0
14.	Bar_distance	-0,20	-0,04	-0,13	-0,08	0,01	0,00	-0,16	0,02	-0,01	-0,19	0,04	0,19	0,42	1	0	0	0	0	0	0	0	0	0	0	0	0
15.	Beergarden_distance	-0,06	0,01	-0,01	-0,28	0,03	-0,11	-0,01	0,09	0,18	0,13	0,06	-0,06	0,07	0,05	1	0	0	0	0	0	0	0	0	0	0	0
16.	Cafe_distance	-0,15	-0,03	-0,10	-0,14	0,03	-0,03	-0,15	0,07	0,04	-0,10	0,06	0,18	0,35	0,53	0,20	1	0	0	0	0	0	0	0	0	0	0
17.	Bakery_distance	-0,09	0,00	-0,07	-0,12	0,00	-0,02	-0,08	0,04	0,06	-0,06	0,06	0,22	0,33	0,37	0,11	0,31	1	0	0	0	0	0	0	0	0	0
18.	Convenience store_distance	-0,11	0,03	-0,11	-0,22	0,02	-0,05	-0,07	0,06	0,13	-0,02	0,09	0,45	0,54	0,48	0,38	0,42	0,42	1	0	0	0	0	0	0	0	0
19.	Department store_distance	-0,18	-0,02	-0,09	-0,21	0,05	-0,05	-0,11	0,07	0,11	-0,07	0,06	0,17	0,43	0,47	0,46	0,43	0,22	0,58	1	0	0	0	0	0	0	0
20.	Supermarket_distance	-0,05	0,03	-0,10	-0,08	0,01	-0,03	-0,07	0,03	0,03	-0,11	0,06	0,27	0,28	0,37	0,16	0,39	0,31	0,34	0,22	1	0	0	0	0	0	0
21.	Bus station_distance	-0,25	-0,09	-0,15	-0,08	0,00	0,02	-0,15	0,01	-0,01	-0,18	0,03	0,29	0,62	0,57	0,07	0,40	0,48	0,59	0,48	0,29	1	0	0	0	0	0
22.	Railway station_distance	-0,14	0,01	-0,12	-0,21	0,03	-0,05	-0,09	0,07	0,11	-0,06	0,07	0,41	0,59	0,40	0,45	0,43	0,35	0,65	0,64	0,34	0,52	1	0	0	0	0
23.	Traffic signals_distance	-0,08	0,00	-0,09	-0,03	0,01	0,02	-0,08	0,01	-0,01	-0,14	0,04	0,20	0,38	0,45	0,10	0,37	0,26	0,42	0,30	0,37	0,33	0,35	1	0	0	0
24.	Car wash_distance	0,08	0,08	-0,01	-0,05	0,00	-0,02	0,03	0,03	0,04	0,06	0,03	0,16	-0,13	0,31	0,16	0,09	0,03	0,13	-0,08	-0,03	-0,05	0,02	0,09	1	0	0
25.	Park_distance	-0,11	-0,03	-0,04	-0,06	0,03	0,00	-0,08	0,03	0,01	-0,08	0,01	0,01	0,24	0,32	-0,02	0,23	0,35	0,25	0,23	0,14	0,30	0,18	0,24	-0,08	1	0
26.	School_distance	-0,06	-0,02	0,03	-0,11	0,01	-0,03	-0,04	0,05	0,04	0,02	0,02	-0,08	0,05	0,19	0,16	0,24	0,17	0,20	0,24	0,30	0,10	0,16	0,25	0,01	0,15	1

Notes: Pearson correlation coefficients are displayed below the diagonal and p-values above.

Figure 4.7. Centered PD plots for distance to department store



Notes: The figure displays the partial dependence centered at lowest feature value. The vertical axis denotes the feature values of the log rent level while the horizontal axis denotes the covariates feature values.

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5 Conclusion

5.1 Executive Summary

Market efficiency, price formation in competitive markets and timing behavior are economic frameworks that are topics for academic studies and ongoing debates since decades. In this context, the dissertation provides valuable insights in several ways. First, building up a comprehensive data framework in mainly opaque property markets enables in-depth analysis and contributes to well-founded decision-making in the real estate sector. As data in real estate markets is limited or only available in unstructured form, the emergence of new sources of information can form a basis to overcome the shortcomings that come with the limited availability of housing data especially in Europe (Rondinelli & Veronese, 2011).

Second, advances in computational power and the development of Machine Learning algorithms enable modern regression techniques that are able to identify new insights in asset mispricing. Given the "high potential of AI-based methods" (Zurada et al., 2011) together with the limited reliability of current statistical models when facing large datasets, "new approaches should be introduced to analyze the big datasets that are quickly becoming the new standard in [real estate] econometrics" (Arbia et al., 2019). AI-based results can not only model residential markets more accurately, but also reveal considerable pricing differences in residential portfolios.

Despite the high predictive performance of Machine Learning methods, their inner working and how these models derive a final prediction is rather hidden. These issues raise the question on the reliability of ML-based results and the economic context their prediction is based on, which is a "crucial feature for the practical deployment of AI models" (Arrieta et al., 2020). Peeking inside the black box allows understanding how an artificial model comes to its final result and reveals the economic rationale behind its decision-making process.

Last, and most important, the findings add further evidence on asset mispricing and market timing in direct and indirect real estate markets. Both that stock prices or their changes are rational reflection of fundamental values only to a certain extent (Summers, 1986) and that "fundamentals do not provide a sufficient determinant for real estate" (Farlow, 2013) build the basis for real estate markets to be a well-suited research subject for mispricing behavior. More than this, it enables possibilities for market participants to exploit disequilibria and generate excess returns. Regarding listed real estate, market timing is, in addition to daily trading behavior (Barkham & Ward, 1999; Cici et al., 2011), highly present in equity offerings. Not only the capital structure is suggested to be the result of attempts to time the capital market (Baker & Wurgler, 2002). The findings of this thesis highlights that, furthermore, the pricing of such events is determined by deviations of market prices from fundamental values and consequently market timing.

As asset mispricing is even more pronounced in direct real estate markets due to the illiquid and heterogeneous nature of properties and the issues associated with appraisal estimations, timing is an important factor for property investment activities. The findings of this thesis indicate that mispricing is not only a persistent aspect in residential portfolios, but can be identified more precisely and in a timely manner with algorithmic-based methods. This does on the one hand support a more frequent application of modern approaches in the real estate sector and on the other hand provides investment strategies for market participants in property markets.

To provide a comprehensive overview of all research findings throughout this thesis, the following sections provide a brief summary of each individual research paper. Final remarks and an outlook complement the work.

Summary - Paper 1

Underpricing and Market Timing in SEOs of European REITs and REOCs

Analyzing the market timing behavior in indirect real estate markets, the paper contributes to the phenomenon of discounts in capital increases. Building a linkage between market valuation and underpricing in seasoned equity offerings, the findings highlight investors that time the equity market benefit from lower cost of raising capital. By offering shares when market values are high, real estate companies are subject to lower underpricing. Furthermore, the REITs status as well as property specific investment strategies face lower discounts. This indicates that capital markets reward higher information disclosure and transparency.

The study comprises a dataset of 470 SEOs of REITs and REOCs from January 2004 to December 2018. Data is collected from S&P Market Intelligence, former known as SNL Financial. Multivariate regression models are applied to identifying determinants explaining the phenomenon of setting the offer price at a discount at SEOs and investigate market timing in real estate capital markets. Following Baker and Wurgler (2002) and Feng et al. (2007), market-to-book values form the basis to analyze the effect of timing behavior. Information on stock price to net asset value and to earnings complement the methodological approach (Boudry et al., 2010; Gibilaro & Mattarocci, 2018). The results are robust to different controls for growth, market-adjusted offer discounts, timely and winsorized sub-samples and tobit regression.

As and Boudry et al. (2010) show, managers try to time the equity market by issuing equity when market values are high and investors are over-optimistic. Baker and Wurgler (2002) stated that that the capital structure is the cumulative outcome of past attempts to time the equity market. As Ooi et al. (2010) shows, real estate companies tend to time the equity market by offering equity when stock values are high. The paper adds to the literature by demonstrating that market-timing behavior in SEOs is rewarded with lower offer price discounts. Highly valued firms do not only show lower underpricing and therefore lower initial returns for investors at SEOs. They are also subject to declining operating performance following the offering (Ghosh et al., 2013). Consequently, managers try to exploit favorable market conditions within their financing decision.

Summary - Paper 2

Rental Pricing of Residential Market and Portfolio Data – A Hedonic Machine Learning Approach

Transferring the theoretical framework and findings on timing behavior to direct real estate markets, the aim of this paper is to identify mispricing in residential portfolios and enables a conceptual framework to derive market-timing strategies in terms of investment or disinvestment decisions. It furthermore attempts to shed light on how listing systems as new data source and Machine Learning can form the foundation for a suitable investigation of property markets.

The study investigates the German residential market in Munich, comprising 65,743 apartments from January 2013 to June 2019. Since Germany does not require neither private nor institutional landlords to disclose rental information, we use Multiple Listing Systems as emerging source of information to overcome the challenges raised by the general lack of European housing data. Socio-economic, spatial gravity and geo amenity layers complement the dataset.

By expressing the rental price of an apartment as the sum of its estimated individual characteristics, the study uses traditional hedonic modelling approaches for rental prediction. Since the potential of parametric hedonic price regressions for predictive tasks is rather limited (Pérez-Rave et al., 2019), several Machine Learning methods, namely Support Vector Regression, Random Forest Regression, Gradient Tree Boosting and eXtreme Gradient Boosting are applied. Given the relevance of rental estimation for tenants, investors and governmental bodies, together with the “potential of AI-based methods” (Zurada et al., 2011), the paper evaluates the performance of different algorithmic hedonic models. Since these models estimate a market willingness to pay for an apartment based on its hedonic, neighboring and locational characteristics, previous findings and model specifications are applied to a residential portfolio of 716 institutionally managed apartments to identify mispricing in terms of deviations from contract rent to their corresponding market willingness to pay.

The study demonstrates that, on average, institutionally managed apartments show a considerable potential for rental adjustments in re-letting scenarios. Furthermore, Machine Learning models indicating higher deviation of estimated and contract rents than linear models. Thus, the findings indicate that investors rather rely on traditional methods to derive contract rent levels within their portfolio, whereas AI-based regression approaches would identify higher rental potential. With that, this study reveals potential benefits when applying Machine Learning models in the area of residential markets and portfolio to identify asset mispricing.

Summary - Paper 3

Peeking inside the Black Box: Interpretable Machine Learning and Hedonic Rental Estimation

Machine Learning can detect complex relationships to solve problems in various research areas and excels at predictive tasks. Although it represents a promising extension to the hedonic literature since it is able to increase predictive accuracy and is more flexible than standard regression-based approaches, specific characteristics impede its widespread application. This is mainly due to its limited inferential capabilities (Mullainathan & Spiess, 2017).Because the internal logic and consequently the rationale behind the individual predictions is rather hidden, the use of Machine Learning often lacks transparency (Carvalho et al., 2019). It comes without saying that this circumstance impairs trust in AI-based results. The study applies Interpretable Machine Learning to identify how the algorithm comes to its final prediction and reveals insights on the economic rationale behind ML-based rental prediction.

Using a dataset of 52,966 apartment in Frankfurt am Main (Germany), we estimate rent levels with the eXtreme Gradient Boosting Algorithm. Model-agnostic interpretation methods, namely feature importance and feature effects, are applied to reveal which hedonic characteristics are most influential and how they contribute to the overall algorithmic prediction.

The paper sheds light on how ML-based decision making in hedonic modelling can be made more transparent. By visualizing and investigating the relationship between residential rents and hedonic characteristics the model has traced and learned, the findings enable the interpretability of ML-based prediction to improve trust in algorithmic decision-making in real estate. While e.g. living area, age and distance to city center is most influential, the distance to supermarket and bakery shows minor importance. Furthermore, interpretation methods reveal, amongst others, that close proximity to hospitality and public transport face rental discount and preference shifts toward medium central locations over time exist. Not only are ML models able to identify mispricing in institutional portfolios more precisely, as e.g. shown in paper 2. Interpretable ML methods can furthermore reveal the rationale behind the estimation of asset mispricing and consequently highlight their reliability, which has long been seen as the bottleneck for AI applications.

5.2 Final Remarks and Outlook

Presuming that the market price is the best estimate of the fundamental or intrinsic value, theories on efficient markets have come a long way. Despite, or even because of its simplicity, there is still no consensus in the literature on their validity. As Țițan (2015) states, "even if many tried to find the truth behind the efficient market hypothesis, no ultimate conclusion exists". Whether asset mispricing is therefore the exception to the rule of market efficiency, or rather puts the final nail in the coffin of the theoretical framework will be a fascinating topic for future studies in research and practice. It therefore comes without saying that this dissertation does not claim to provide a holistic picture to this puzzling topic.

As John Bogle, founder of The Vanguard Group and index fund pioneer, stated, "inefficiency doesn't make it easier for *all* investors to beat the market." Or in other word: If one would expect markets to be inefficient, they would still be hard to outperform. In an attempt to shed light on timing behavior and opportunities, the thesis aims to add another piece to the puzzle on asset mispricing and market timing, especially in real estate markets. It therefore should not only build a comprehensive framework for market participants in the real estate sector, but furthermore encourage current and future scholars to further this research.

With one of the most severe pandemic crisis in recent history in mind, uncertainties and the divergence to fundamental values may lead to a reinvigoration of the discussion on market efficiency. Extending this strand of research to recent downturn markets that have been strongly sentiment-driven can add further insights on timing behavior. Further research could also include both the ongoing progress in data availability and methodological advancements. While new data sources can provide a suitable data environment fur detailed and timely analysis, their contribution to in-depth analyses especially in mainly opaque real estate markets need to be treated carefully. Although e.g. listing data is seen to play a significant role in housing markets (see e.g. Shimizu et al., 2016, Han & Strange, 2016), differences to transaction data can occur that need to be kept in mind (Kolbe et al., 2021).

In addition, Machine Learning and algorithmic decision-making is a rapidly evolving field with new technical and methodological enhancements continuously evolving. This does not only provide novel areas of applications, but also impedes consistency and comparability and therefore hinder a comprehensive understanding. The same applies to the field of Interpretable Machine Learning. Further research is necessary to increase trust in AI-based results and ease their application. As mispricing is often linked to behavioral finance and market sentiment, it would be promising to apply interpretation methods to further research areas, such as image recognition or textual analysis. Being e.g. able to explain which words drive sentiment in textual analysis and analyze how sentence structure influence the informational context of news or company reports could reveal further insights on the understanding of market sentiment.

As Adadi and Berrada (2018) state for mortgage lending, AI-based decision support of credit applications may improve and accelerate business operations of banks, however the sole decision of whether a credit may be granted or denied lacks accountability and does not represent a satisfactory outcome for neither the applicant nor the creditor. Especially when it comes to high-stake domains like wealth management, financial services or real estate, the rationale behind the algorithmic decision is crucial. Especially since regulatory authorities are the key enables to path the way to a comprehensive adoption of AI to inform human decision-making, the interpretability of AI-based results will play a decisive role in further research and practice as well as legislation. In an attempt to provide new insights on market efficiency, timing behavior and the potential of AI in this context, this thesis aims to contribute to scientific progress, encourage further research and offer starting points for future studies.

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