Applying artificial intelligence and quantitative finance for a successful heat transition in the building sector

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The following sections are partly comprised of content taken from the research articles included in this thesis. To improve the readability of the text, I omit the standard labeling of these citations.

Abstract

Counteracting global warming requires intensifying decarbonization efforts across all sectors. To this end, the global residential building sector faces an urgent need to progress towards the climate goals, as it accounts for over a sixth of greenhouse gas emissions and over a quarter of energy consumption, most of which are caused by warm water and space heating and cooling. However, many economically and ecologically sensible retrofit measures are not conducted, among other reasons because of high perceived uncertainty regarding financial savings. Against this background, this doctoral thesis aims to contribute to successfully shaping the heat transition in the residential building sector by investigating three main aspects. The first aspect deals with reducing the perceived risk for energetic retrofitting by providing reliable data-driven decision support, as there is currently a research gap regarding long-term (i.e., annual) prediction for residential buildings and the resulting consequences of increased prediction accuracy. The findings in this thesis provide strong evidence that data-driven energy quantification methods reduce prediction errors by about 50% compared to the legally prescribed engineering methods. Assuming rational decision-making and setting up an agent-based building stock model, this increase in prediction accuracy translates into a substantial rise in energetic retrofitting from about 0.98% to 1.68%. Within the model setting, further prediction accuracy gains allow the retrofit rate to eventually exceed the envisaged 2% to successfully shape the heat transition in the residential building sector. The second aspect deals with understanding and managing the remaining risks connected to energetic retrofitting applying concepts from quantitative finance. To this end, this thesis follows literature and differentiates technological and operational risks (first aspect) from contextual and economic risks (second aspect). The findings indicate that risk perception is crucial for evaluating energetic retrofitting. Moreover, the findings provide the theoretical basis and highlight the potential of diversifying and hedging the remaining risk on the financial markets via risk transfer contracts. The third aspect deals with carefully tailored policy measures by constructing spatially and temporally differentiated incentive mechanisms to allocate scarce financial resources efficiently, maximizing the greenhouse gas emission reductions per monetary unit invested. The findings indicate significant influence from regionally differing socio-economic factors on energetic retrofitting. Moreover, time-dependent subsidy schemes incentivizing early retrofitting reduce greenhouse gas emissions substantially. Assuming rational decision-making, greenhouse gas emission reductions per monetary unit invested for time-dependent subsidy schemes exceed the reductions by static subsidy schemes by up to 675%. In summary, this cumulative doctoral thesis comprises seven research articles and aims to contribute to the heat transition in the residential building sector by applying artificial intelligence and concepts from quantitative finance and deriving managerial and policy implications for all focal aspects.

Keywords: *Data analytics, Machine learning algorithms, Risk management, Energy efficiency, Energetic retrofitting, Energy informatics, Final energy performance*

Table of Contents

I. Introduction

I.1. Motivation

Climate change is among the most compelling challenges of our time. A sharp increase in the extinction of flora and fauna, the rapid retreat of glaciers and arctic ice, and worsening extreme weather events worldwide leading to famine and migration are just some of the catastrophic consequences of global warming (Kling and Ackerly, 2020; Vargo et al., 2020). On this background, climate change shines a harsh spotlight on the fragile nature of our modern, globalized world, demonstrating how destructive disturbances to this system can be (Armitage and Nellums, 2020; Pan and Zhang, 2020; Thomas et al., 2020). This confronts us with the clear realization that climate change has become a colossal threat that we must urgently address.

Tackling this issue and collectively mitigating climate change unites the world's population more than any other goal in the past (Keller et al., 2019). This is reflected in the Paris Agreement concluded in 2015 at the international climate conference. Here, almost all the countries worldwide committed themselves to working together, shaping the climate transition, and creating a planet that can sustain human life (Beiser-McGrath and Bernaue, 2019; Falkner, 2016; McGrath and Bernauer, 2017). Limiting global warming to well below two degrees Celsius compared to pre-industrial levels is the central goal of the ambitious Paris Agreement (Glanemann et al., 2020). This, consequently, requires intensifying decarbonization efforts to curb greenhouse gas emissions concomitantly (Forster et al., 2020). However, despite these ambitious international climate goals, the current state of the low-carbon transition paths lacks significantly behind the set goals, requiring higher activities across all sectors (Da Graça Carvalho, 2012; Häckel et al., 2017; Michelsen and Madlener, 2016; Roelfsema et al., 2020).

The global residential building sector accounts for 17% of greenhouse gas emissions and 27% of energy consumption and, therefore, faces an urgent need to progress towards decarbonization (Nejat et al., 2015; Robert and Kummert, 2012). Here, warm water and space heating and cooling stand out as predominant energy consumers, highlighting the paramount relevance of energy efficiency in the residential building sector (Ürge-Vorsatz et al., 2015). To this end, most of the current national building stocks were constructed before thermal standards and more stringent building codes came into place (e.g., European Commission (2014), Jennings et al. (2011)). Considering low demolition and reconstruction rates, a sharp increase in energetic retrofitting is essential for achieving climate goals. However, many economically and ecologically sensible retrofit measures are not conducted because, among other reasons, high upfront investments, coupled with uncertain energy savings and risk aversion on the side of the homeowner, form substantial investment barriers (Amecke, 2012). This phenomenon has coined the term energy efficiency gap (Jaffe and Stavins, 1994). In fact, most major markets exhibit annual retrofit rates of about 1% (International Energy Agency, 2020), albeit retrofit rates of about 2% are required to successfully shape the heat transition (Deutsche Energie-Agentur GmbH, 2021).

Against this background, it becomes apparent that further measures must be taken. Promising options are, among others, reducing the perceived risk for energetic retrofitting by providing reliable decision support, conducting further risk mitigation measures by applying concepts from quantitative finance such as risk transfer contracts, and incorporating carefully tailored policy measures (Achtnicht and Madlener, 2014; Csutora and Zsóka, 2011).

I.2. Research aim

In 2002, the European parliament and council passed a directive declaring mandatory energy performance certificates (EPC). This directive should contribute to increasing energetic retrofitting by informing about possible retrofit measures and the buildings' final energy performance (FEP) – the annual amount of energy required for space and water heating, cooling, and ventilation per square meter effective building area under the climatic conditions of a test reference year and location (Arcipowska et al., 2014; European Parliament and the Council, 2002; Poel et al., 2007). EU member states have incorporated the details regarding EPCs into their national legislation in different ways (although there is overlap in most cases), which is why we focus on Germany as an example. Here, EPCs are issued by qualified auditors conducting on-site inspections and using by-law prescribed energy quantification methods (EQM) to ensure high quality in the results. These by-law prescribed engineering EQMs are based on physical laws to calculate thermal dynamics and energy behavior (Zhao and Magoulès, 2012), thus requiring detailed information on building components (Arcipowska et al., 2014). If the input data quality is low, e.g., because the insulation materials are unknown and cannot be determined with reasonable effort, the result will also be erroneous. To this end, EPCs are subject to criticism for failing to meaningfully impact retrofit activity due to low FEP prediction accuracy (Hardy and Glew, 2019).

Data-driven EQMs were introduced in research to overcome the shortcomings of engineering EQMs, obtaining promising results (Sutherland, 2020). Data-driven EQMs learn underlying dependency structures from available data without relying on expert knowledge of building physics or precise information on building components (Amasyali and El-Gohary, 2018). In turn, this allows enhancing FEP prediction accuracy while simultaneously simplifying data collection. However, there is a lack of studies on data-driven EQMs in residential buildings with a focus on long-term (annual) energy prediction, as required for EPCs (Amasyali and El-Gohary, 2018; Wei et al., 2018). Thus, the first research aim of this doctoral thesis is to investigate whether data-driven EQMs based on machine learning algorithms (MLA) as an alternative to engineering EQMs can increase the FEP prediction accuracy.

Following the first research aim, two subsequent considerations are important for data-driven FEP predictions: (1) to which degree will homeowners subjectively perceive the results as trustworthy, and (2) how do differing prediction accuracies translate to in- or decreased retrofit activity. Regarding the former, MLAs are often considered black-box models, bearing the disadvantage of highly complex inner structures and calculation mechanics (Foucquier et al., 2013). Understanding how MLAs derive their predictions is essential to reduce perceived uncertainty and contribute bridging the energy efficiency gap (Mohseni et al., 2018). Otherwise, the opposite effect of reduced retrofit activity may arise despite higher prediction accuracy, in case the decrease in trust from increased computational complexity outweighs the accuracy gains. In this regard, the field of explainable artificial intelligence (XAI) enables understanding the predictions of the applied MLA. More precisely, XAI allows generating more explainable models, enabling homeowners to understand and trust their predictions while maintaining high prediction accuracy (Barredo Arrieta et al., 2020). Regarding consideration (2), robust statements on the effect of higher prediction accuracy on the retrofit rate are not available at present. Despite a large volume of research (particularly in the engineering disciplines) on the evaluation and refinement of FEP prediction accuracy, no study has addressed this research gap. Thus, the second research aim is to investigate these challenges and opportunities of data-driven FEP prediction. On the one hand, this includes the evaluation of data-driven EQMs' explainability and, on the other hand, the impact prediction accuracy has on the retrofit rate within an agent-based building stock model (BSM) and under the assumption of rational decision-making.

In summary, the first two research aims provide the foundation for data-driven EQMs, examining the potential in terms of prediction accuracy and explainability and linking this potential to the retrofit rate under the limitations of the specific model setup and assumptions. However, this is a narrow focus on one source of risk because the FEP does not yet consider, for instance, energy prices and differing climatic conditions. To this end, Mills et al. (2006) differentiate risks in energy savings projects into five categories: economic, contextual, technology, operational, and measurement and verification risks. For instance, economic risks cover uncertain future price paths for the underlying energy carrier, and contextual risks include uncertain weather and climate developments. Obviously, increasing FEP prediction accuracy can, by definition, not mitigate all these risks. Therefore, the resulting investment decision is stochastic and subject to risk even under perfect FEP prediction accuracy because, for instance, energy prices and weather developments still constitute stochastic influences. Here, applying risk transfer contracts may further mitigate the underlying risk. Hence, the third research aim of this thesis is understanding and managing the risks connected to energetic retrofitting from both the perspective of the homeowners willing to enter risk transfer contracts and the respective issuer by applying methods from quantitative finance. More precisely, homeowners may either perceive energetic retrofitting as a risky investment with uncertain financial savings or as insurance against energy price exposure, leading to different retrofitting behavior. The remaining risk can be further mitigated through risk transfer contracts, diversification, and hedging on the financial markets on the side of the issuer of the risk transfer contracts.

The previous research aims focused on individual energetic retrofit decisions and their immediate impact. However, decarbonizing the residential building sector also requires intensifying efforts on the policy level through well-designed policy measures. Nonetheless, the mechanisms currently in place often follow a scattergun approach, not differentiating spatial or temporal circumstances to increase efficiency. Taking these circumstances into account allows for allocating scarce financial resources efficiently. Thus, the fourth research aim of this thesis is to examine spatially and temporally differentiated policy measures. This includes investigating the effect of socio-economic differences on energy efficiency to design locally tailored policy measures and the effects of financial subsidy schemes incentivizing either early or late retrofitting.

Concluding, this doctoral thesis aims to contribute to successfully shaping the heat transition by overcoming the current barriers hindering widespread energetic retrofitting. More precisely, the scope of this thesis is threefold: (1) Increasing the FEP prediction accuracy by applying data-driven EQMs and investigating the impact thereof on the retrofit rate in an agent-based BSM assuming rational decision-making while accounting for explainability. (2) Understanding and managing the risks connected to energetic retrofitting. (3) Analyzing how to allocate scarce financial resources by differentiating spatial and temporal circumstances to maximize greenhouse gas emission reductions per monetary unit invested. This way, the thesis opens with a highly specific topic, focusing on a single source of risk and individual decision-making as the basis for the following sections. Thereafter, the perspective is broadened, and further risk factors are integrated. Finally, the perspective is shifted from individual decision-making to a societal perspective.

I.3. Structure of the thesis and embedding of the research articles

This doctoral thesis disposes of a composite structure consisting of seven research articles that contribute to the stated research aims. Figure 1 illustrates the overarching structure and how each research article is embedded in the doctoral thesis.

The remainder of this doctoral thesis is structured as follows: Following this introduction, Section II investigates the potential of data-driven EQMs for FEP prediction accuracy. Here, Research Article #1 elaborates on benchmarking both engineering and data-driven EQM based on real-world data on the example of the German residential building stock. This section provides the basis for the remainder of the doctoral thesis (Research Articles #2 through #7) by establishing the competitive advantage of data-driven EQMs compared to their engineering and legally prescribed counterpart.

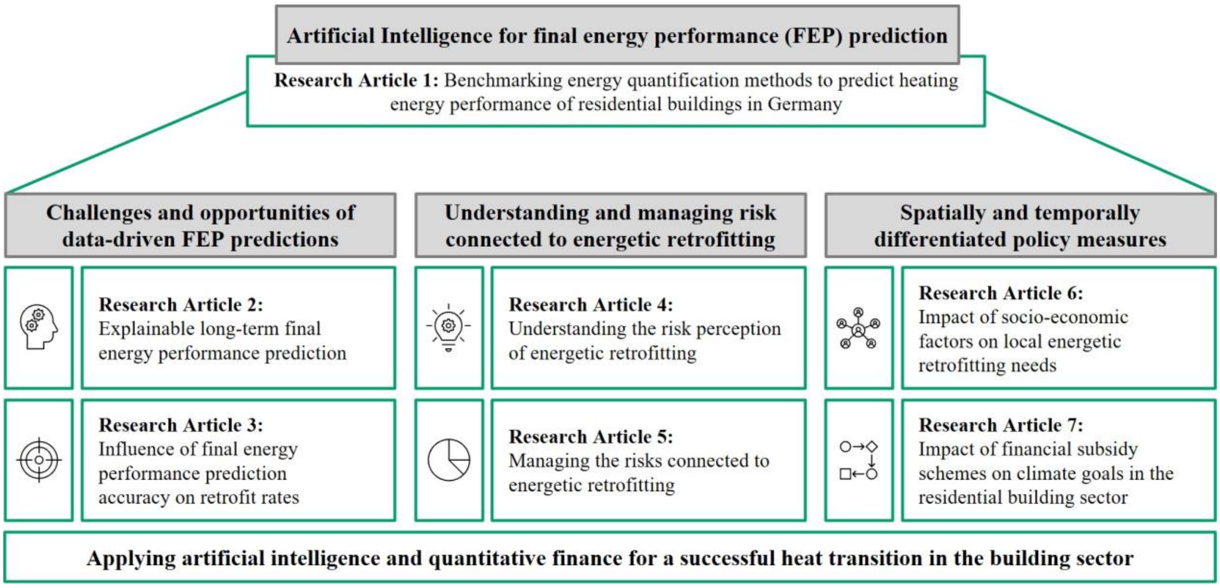

Figure 1: Structure of the doctoral thesis and classification of the research articles.

Section III deals with the challenges and opportunities of data-driven FEP prediction. Taking advantage of increased FEP prediction accuracy requires a high degree of explanatory power in the data-driven EQMs used. Else, missing trust and perceived uncertainty may compromise the prediction accuracy increments. Therefore, Subsection III.1 investigates how XAI can be applied to increase trust in the predictions of data-driven EQMs to overcome this often-claimed drawback of data-driven EQMs. Here, Research Article #2 substantiates the previous findings from Research Article #1 by further investigating and comparing the explainability of several EQMs. In a rigorous case study based on real-world data for the German residential building stock, Research Article #2 explores aspects of explainability by applying post-hoc explainability methods to different EQMs.

Subsection III.2 then provides the missing link between FEP prediction accuracy and retrofit activity. So far, it is unclear which impact higher prediction accuracies have on the retrofit activity. Research Article #3 fills that research gap by applying an agent-based BSM to simulate retrofit activity for differing degrees of uncertainty in the underlying EQMs assuming rational decision-making. This enables quantifying the impact of FEP prediction accuracy gains on retrofit rates under the given model constraints.

As mentioned, some types of risk, such as economic and contextual risk, will continue to impact retrofit decisions independent of the previous findings as the FEP does not consider these influences. Therefore, Section IV deals with understanding and managing the risks connected to energetic retrofitting, drawing on topics of quantitative finance to answer the stated research aims. In Subsection IV.1, Research Article #4 first investigates the risk from the homeowner's perspective. Here, the theoretical basis regarding risk perception when facing energetic retrofit decisions is covered. To this end, Research Article #4 identifies two perspectives on risk, formulates a mathematical model regarding similarities and differences, and analyzes their influence on energetic retrofitting in a case study.

Subsection IV.2 subsequently covers further risk mitigation potential through risk transfer contracts, diversification, and hedging with financial derivatives on the financial markets. To this end, two different types of energy savings insurances with negatively correlated claim structures are investigated. In contrast to Subsection IV.1, Research Article #5 thereby takes the perspective of an energy savings insurance company and not the homeowner's perspective.

Against the background of governments operating under monetary constraints, an efficient allocation of tax money is essential to maximize greenhouse gas emission reductions per monetary unit invested. However, most policy measures do not differentiate neither spatially nor temporally, leading to inefficient allocations. Therefore, Section V deals with carefully tailored policy measures. More precisely, Subsection V.1 covers the influence of socio-economic factors on building energy efficiency. Here, Research Article #6 investigates the UK building stock and performs several regression analyses to derive regional differences in the building stock. Subsequently, the article discusses exemplary locally tailored policy mechanisms. The focus on the UK is due to an abundance of publicly available EPC data necessary for this large-scale analysis. Several open data sources jointly containing 158 socio-economic factors enrich the EPC dataset.

Subsection V.2 continues from the preceding research article. However, it considers the allocation problem from a temporal rather than a spatial perspective. To this end, Research Article #7 examines time-dependent subsidy schemes as financial policy mechanisms, analyzing the impacts of early and late subsidizing on achieving the climate goals. More precisely, financial subsidy schemes incentivizing early retrofitting may lead to lock-in effects, which in turn leads to not realizing energy savings potential from technological advancements in the long run. However, at the same time, incentivizing early retrofitting results in longer periods in which the greenhouse gas emissions are realized, potentially minimizing the combined total emissions. The research article analyzes and discusses the discrepancy between the two opposing goals of minimizing annual emissions in 2050 and minimizing total greenhouse gas emissions until 2050.

Section VI concludes this doctoral thesis by summarizing the major findings throughout the research articles in Subsection VI.1, stating relevant limitations and prospects for further research in Subsection VI.2, and acknowledging previous work inspiring this doctoral thesis in Subsection VI.3.

Finally, Section VII lists the references, and Section VIII entails the appendix. The appendix provides additional information on the research articles included in this thesis in Subsection VIII.1, details the author's contributions in Subsection VIII.2, and reproduces the (extended) abstracts in Subsection VIII.3. The supplementary material is not intended for publication and contains the full texts of all research articles.

II. Artificial Intelligence for final energy performance prediction

As mentioned, achieving the ambitious climate goals requires intensifying decarbonization efforts over all sectors, including increasing the rate of purposeful retrofit measures in the building sector. To overcome investment barriers arising from uncertainty in energy savings, EPCs have been designed as important evaluation and rating criteria (Amecke, 2012; Arcipowska et al., 2014; European Parliament and the Council, 2002). However, because the legally prescribed engineering EQMs exhibit low prediction accuracy, the added value from EPCs is low, and research turned to more promising data-driven EQMs as alternatives (Hardy and Glew, 2019; Sutherland, 2020). Nonetheless, there is still a research gap regarding data-driven EQMs in residential buildings, focusing on long-term (annual) energy prediction, as required for EPCs (Amasyali and El-Gohary, 2018; Wei et al., 2018). Thus, it remains unclear whether and which data-driven EQMs can increase FEP prediction accuracy compared to engineering EQMs. Research Article #1, therefore, benchmarks several data-driven EQMs against their engineering counterpart to fill this research gap.

More precisely, Research Article #1 addresses the research gap by implementing and tuning several MLAs on an extensive real-world dataset containing 25,000 German single and two-family buildings. Figure 2 provides descriptive statistics regarding the regional distribution and histograms for central variables. To this end, the representativeness of the dataset is ensured by applying post-stratification on the performance evaluation measures. Subsequently, the error in FEP prediction is compared between the MLAs and the engineering EQM based on another dataset of 345 additional buildings gathered by qualified energy auditors. This second dataset encompasses both the calculated FEP from the prescribed engineering EQM and the actual metered energy consumption. The article further benchmarks the MLAs against each other in-depth based on nested cross-validation on both building datasets to ensure robust results and comply with state-of-the-art machine learning practices. Moreover, the article examines several performance evaluation measures and analyzes two variables – the building age and the living space – in more detail to account for potential systematic biases.

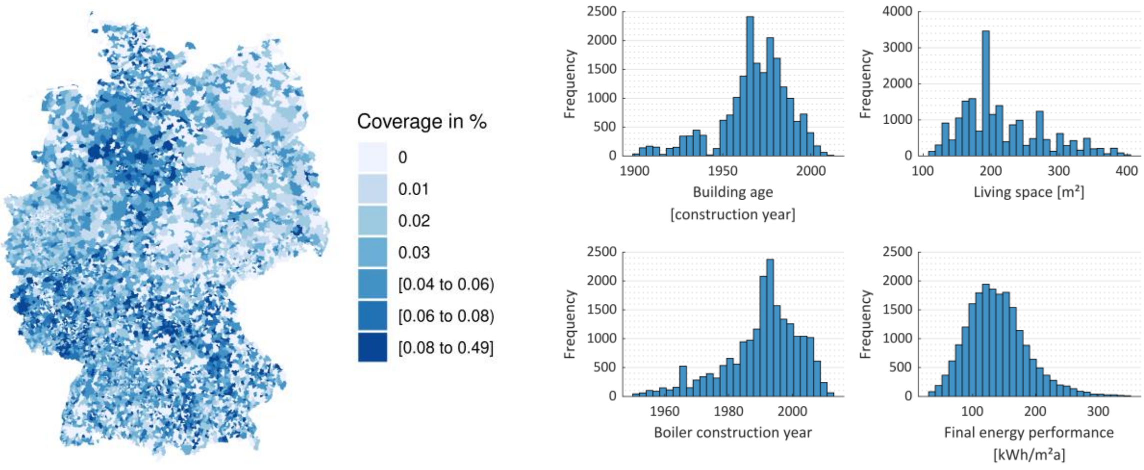

Figure 2: Descriptive statistics for the pre-processed dataset on 25,000 German real-world single- and two-family buildings.

The results provide strong evidence that the data-driven EQMs outperform the engineering EQM by a large margin, each reducing the prediction error by almost 50%. However, the results do not support findings from literature that artificial neural networks and support vector regressions are particularly suited for FEP prediction (Amasyali and El-Gohary, 2018). Instead, extreme gradient boosting exhibits the highest prediction accuracy for most cases. Nonetheless, the differences are slight and general statements require statistical hypothesis tests. Despite minor variations for aggregations in the variables “building age” and “living space”, the general tendency holds, indicating robust results. This is further substantiated by the additional error measures yielding similar results. Thus, data-driven EQMs are, in general, more suitable for residential building FEP prediction. Figure 3 visualizes the accuracies for the error measure coefficient of variation (CV), which is given as the root-mean-square error (instead of the standard deviation) divided by the mean. This adaptation of the CV is the most commonly used error measure in this domain, increasing comparability with related studies (Amasyali and El-Gohary, 2018).

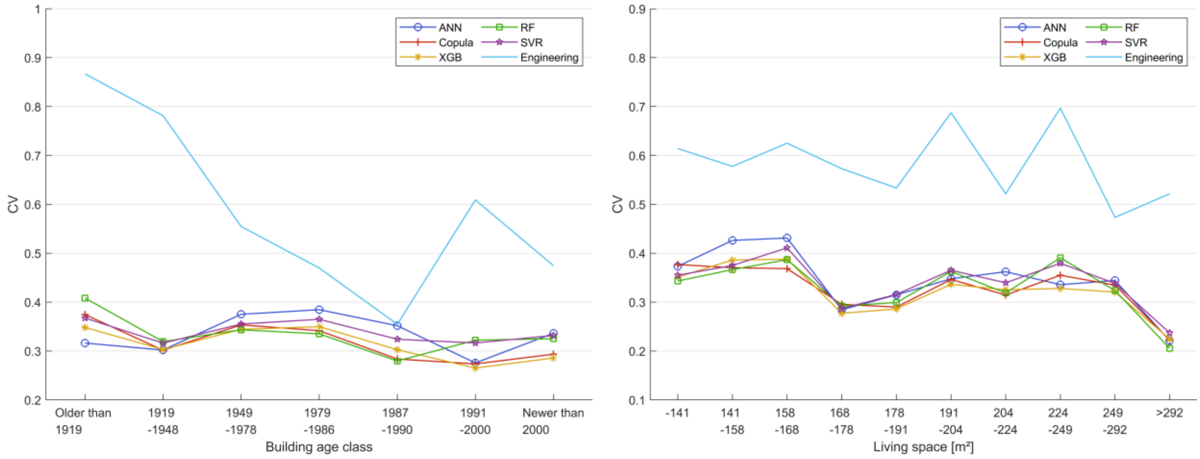

Figure 3: Coefficient of variation error measure for the different energy quantification methods for aggregations of the variables “building age” on the left-hand side and “living space” on the right-hand side.

Research Article #1 leads to several managerial and policy implications. First, the results suggest policymakers should revise the current legislation and establish data-driven EQMs either as stand-alone EQMs or alongside their engineering counterparts. The higher FEP prediction accuracies may contribute to overcoming investment barriers by mitigating uncertainties connected to energetic retrofitting. This, in turn, contributes to achieving the climate goals, as the current state of the low-carbon transition paths requires higher retrofitting rates. Second, the results suggest that data-driven EQMs may be beneficially applied in other fields, e.g., asset management, urban planning, and insurance, because correctly evaluating buildings’ energy efficiency is often essential to the economic success of companies (Bozorgi, 2015). For instance, to collect cost-efficient information is particularly relevant for the initial energy evaluation of real estate, as energy-efficient buildings yield higher rents than energy-inefficient buildings (Cajias and Piazolo, 2013). Third, benchmarking MLAs should be focused on because most studies only evaluate individual algorithms and disregard comparisons, limiting the generalizability of their results.

III. Challenges and opportunities of data-driven final energy performance predictions

III.1. Explainable long-term final energy performance prediction

Facilitating data-driven EQMs to positively impact national retrofit rates requires that the generated results reduce the uncertainty that formed the investment barrier. This, in turn, necessitates both increasing prediction accuracies and allowing homeowners to understand and trust the predictions. Because data-driven EQMs often exhibit complex structures and calculation methods, establishing trust requires explainability approaches from the field of XAI (Burkart and Huber, 2021; Mohseni et al., 2018). Otherwise, perceived uncertainty resulting from the complex structures and black-box characteristics may compromise the prediction accuracy gains, potentially even reducing the willingness to energetic retrofitting (Golizadeh Akhlaghi et al., 2021).

While research agrees that XAI generally enables understanding complex MLAs (Barredo Arrieta et al., 2020), there is no consensus in the research community on specific definitions regarding the scope and measurement of XAI (Das and Rad, 2020). Likewise, application areas range from basic understanding and variable importance to capturing how MLAs work as a whole (Barredo Arrieta et al., 2020; Burkart and Huber, 2021; Doran et al., 2017). However, the literature generally differentiates transparent models interpretable by design and post-hoc explainability models (Moradi and Samwald, 2021). In both cases, quantifying the degree of explainability is difficult because explainability is often perceived subjectively (Burkart and Huber, 2021; Hoffman et al., 2018; Mohseni et al., 2018; Zhou et al., 2021). Additionally, increasing explainability usually decreases the prediction accuracy by restricting the solution space in the process. Thus, these two opposing goals form a trade-off (Shmueli and Koppius, 2011).

The novel QLattice algorithm, inspired by Richard Feynman’s path integrals, is supposed to reach desirable outcomes in the trade-off between prediction accuracy and explainability (Broløs et al., 2021; Wilstup and Cave, 2021). It applies symbolic regression to explain the dependent variable by independent variables using a set of mathematical expressions (Wilstup and Cave, 2021). It models and evaluates these mathematical expressions as a superposition of an infinite set of spatial paths in a multidimensional lattice space using repeated reinforcement to avoid high computation times (Broløs et al., 2021). The QLattice is supposedly less susceptible to overfitting and enables interpreting the regression as an explainable mathematical formula. Thus, the QLattice is also suitable for generating insights and relationships between variables on top of predicting dependent variables (Broløs et al., 2021).

Literature finds that more research on XAI for data-driven FEP prediction is required to leverage its full potential (Arjunan et al., 2020; Miller, 2019). Therefore, Research Article #2 sets out to examine the potential of the novel QLattice algorithm in terms of FEP prediction accuracy and explainability. To this end, it substantiates the finding of Research Article #1 by additionally considering computational performance and explainability, building upon the same extensive real-world dataset.

The results indicate that the QLattice indeed compromises between explainability and FEP prediction accuracy. To this end, the novel algorithm exhibits the worst prediction accuracy on the training data and the second to worst on the test data among the investigated MLAs. However, the differences are slight, and general statements regarding superiority require statistical hypothesis tests. At the same time, the QLattice as a transparent model presents an interpretable and understandable formula for how the variables interact for knowledgeable but non-expert applicants, fulfilling the requirements regarding trust. All models were additionally evaluated using post-hoc explainability approaches, yielding results that are approximately in line with each other.

Despite multiple linear regression performing better in the specific case study of Research Article #2 in terms of computational performance, prediction accuracy, and explainability, the QLattice still provided more insight than the remaining EQMs in terms of explainability without major drawbacks in the remaining evaluation criteria. Considering the drawback of multiple linear regression not being able to handle non-linearities, the QLattice might establish itself as viable option for prediction tasks, as it does not focus solely on one individual evaluation criterion.

The article bears several implications for research and practice. First, the QLattice may bridge the gap between data science and engineering disciplines in the context of FEP prediction by providing relevant insights to both disciplines about important variables and their complex interactions. Second, for this specific case study, the QLattice was dominated by multiple linear regression for all three evaluation criteria: prediction accuracy, computational performance, and explainability. However, for use cases exhibiting more non-linearities in the relationship between dependent and independent variables, we expect the QLattice to eventually exceed the prediction performance of multiple linear regression. Thus, the QLattice may emerge as a viable option for FEP prediction when more complex building characteristics are included in the dataset. Additionally, the QLattice performs several data pre-processing tasks internally, making its application less error-prone for non-experts in the field of data science. Third, due to its transparent design, the QLattice might increase retrofit activity by reducing uncertainty and distrust as investment barriers for knowledgeable applicants (Golizadeh Akhlaghi et al., 2021). Fourth, because the QLattice depends on only a few and easily accessible input variables, its calculation scheme enables a simple self-service for homeowners to derive an initial assessment of their FEP before and after energetic retrofitting, potentially sparking interest in gathering further retrofitting information. Fifth, the results suggest that future research should consider multiple evaluation criteria in an integrated manner to avoid omitting important sub-aspects such as explainability.

III.2. Influence of final energy performance prediction accuracy on retrofit rates

The previous articles established the increased FEP prediction accuracy when switching from the legally prescribed engineering EQM to data-driven alternatives while simultaneously allowing for a certain degree of explainability. However, the implications and consequences arising from increased FEP prediction accuracies are not yet discussed. Even though the relationship between increasing FEP prediction accuracy and an increased retrofit rate is intuitively plausible because of mitigated perceived uncertainty, no study has so far quantified the impact strength of FEP prediction accuracy on retrofit rates. However, this is a crucial characteristic because if the retrofit rate would, for instance, only marginally be impacted by increased FEP prediction accuracy, effortful refinements in the underlying EQMs to increase the FEP prediction accuracy would have an equally limited effect.

To contribute to filling this research gap, Research Article #3 quantitatively investigates to which extent FEP prediction accuracy affects retrofit rates and the resulting CO_2 emissions released in the residential building sector. To this end, the article builds on an agent-based building stock model (BSM) to derive this relationship, assuming rational decision-making. The retrofitting decision process of individual homeowners as agents is simulated for a stratified subsample of the previously introduced dataset on German residential buildings using the established risk preference function. By artificially varying the degree of uncertainty, i.e., the standard deviation in FEP prediction, the agents evaluate retrofit options differently and draw differing conclusions. This, in turn, allows deriving the impact of uncertainty in FEP prediction accuracy on the retrofit rate. The article then quantifies the comparative advantage in terms of increased retrofit rate and CO_2 emission reduction potential of data-driven EQMs by inserting values from the literature.

The results show a pronounced relationship between the FEP prediction accuracy and the retrofit rate as well as the CO_2 emission reductions (c.f. Figure 4). The uncertainty values or standard deviation in FEP prediction for the currently applied engineering EQM result in an approximately 0.98% annual retrofit rate. Inserting the uncertainty derived for the MLA XGBoost in Research Article #1 increases the retrofit rate from 0.98% to 1.68% by about 70% or 0.7 percentage points, which is equivalent to a comparative advantage over the engineering EQM of almost 45 Mt by 2050 in CO_2 emission reductions.

The increase in economically sensible retrofit activity also yields higher social welfare and turnover. To this end, the estimated increase in social welfare scaled to the entire German residential building sector equals 310.19 mn € for the first year when revising current law and applying the data-driven EQM instead of the engineering EQM. This value equals the reduced annual heating expenses (assuming long-term average climatic conditions and no behavioral changes) less the retrofit investments and excludes foregone profits of energy companies. The additionally conducted retrofits also yield an increase in turnover of 1.195 bn €, fed into the economy.

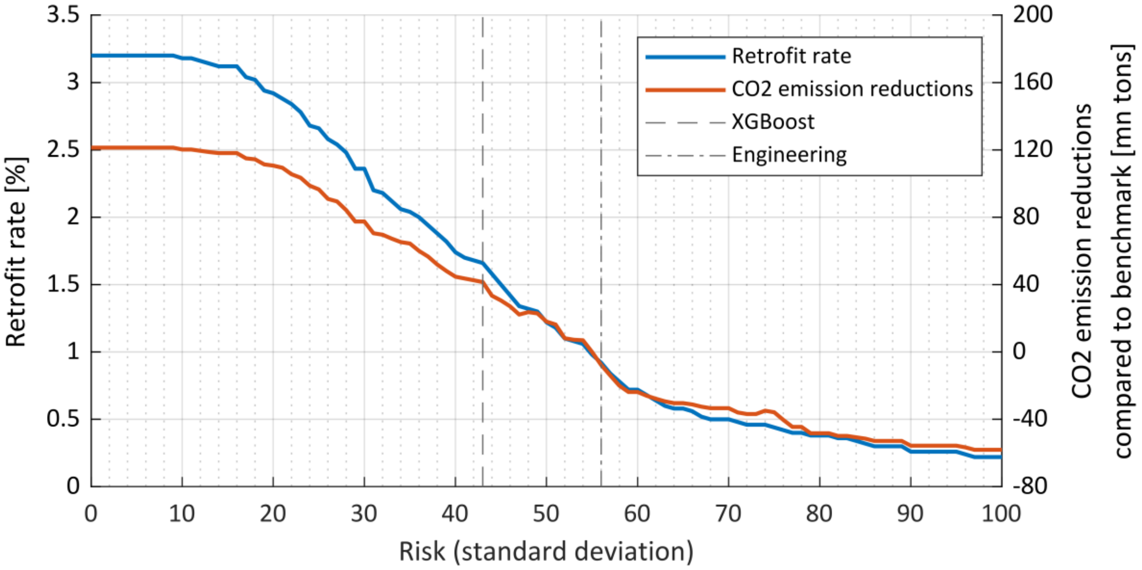

Figure 4: Risk of final energy performance misprediction negatively influences the retrofit rate and CO_2 emission reductions.

In addition to the quantitative results, the article discusses further potential benefits. The higher investment volume potentially enables upcoming companies to establish themselves on the market, strengthening Germany as an export and business location and creating new jobs. Moreover, the government may benefit from increased FEP prediction accuracy via tax payments. Additionally, considering ambitious climate goals, increasing FEP prediction accuracy by switching the underlying EQM may come at smaller opportunity costs than, for instance, financial subsidy programs to reach the same retrofit rate. However, these advantages face some restrictions as well, for instance, the shortage of skilled workforce.

The results have several managerial and policy implications. First, FEP prediction accuracy is (among other impacting factors) a crucial element for boosting retrofit activity. As high FEP prediction accuracy supports the implementation and the market penetration of economically and ecologically sensible energetic retrofit measures, policymakers may benefit from progressing towards the climate goals, energetic retrofit companies can increase sales and revenue, and homeowners are subject to lower energy expenditures. Revising the current legislation regarding data-driven EQMs is therefore highly advised. Second, the results within the specific model setting indicate the retrofit rate to eventually exceed the envisaged 2% to successfully shape the heat transition in the German residential building sector. Thus, there is further CO_2 emission reduction potential for more accurate EQMs; hence, improving existing EQMs or introducing novel and more accurate EQMs appears fruitful. However, exact numbers may differ due to the assumptions made. Third, the results only cover FEP misprediction risk yet leave out other risk sources. Risk mitigation measures, such as risk transfer contracts (Research Article #5), tokenization of energy investments (c.f. “efforce”), or well-designed subsidy programs (Ahlrichs et al., 2020; Mills, 2003), may further leverage the effect shown.

IV. Understanding and managing risk connected to energetic retrofitting

IV.1. Understanding the risk perception of energetic retrofitting

Promoting energetic retrofitting constitutes an important part of environmentally friendly energy policy. In this context, holistically understanding the investment decision-making of homeowners is essential to develop and implement effective policy instruments. However, the previous research articles focused on the technical aspect of FEP prediction accuracy for data-driven EQMs and the resulting consequences, not covering the homeowners' holistic decision-making process. Thus, Research Article #4 investigates how homeowners perceive risk connected to energetic retrofitting to further broaden the scope of this doctoral thesis.

In general, energetic retrofitting requires an upfront investment intended to enhance the energetic state of the building and resulting in reduced energy demand. This, assuming a volumetric tariff, reduces energy bill costs over time. Here, two different perspectives emerged in the literature.

One stream of literature argues that the energy bill savings from reduced energy bill costs can be interpreted as uncertain cash flows following an initial investment (Häckel et al., 2017). These energy bill savings are impacted by, for instance, weather and commodity price developments, leading to a fluctuation in the energy bill savings commonly perceived as risk (Mills, 2003). Hence, the higher the investment volume and the corresponding energy bill savings, the higher the risk. Assuming risk-aversion, homeowners invest less in energetic retrofitting, as larger investments correspond to larger fluctuations in the energy bill savings. Research Article #4 defines this perspective as the *investment perspective*.

The other stream of literature does not focus on the energy bill savings, i.e., the reduction in energy bill costs, but on the remaining energy bill costs themselves. Naturally, energy bill costs are impacted by weather and price developments even if no energetic retrofitting is conducted (Thompson, 1997). Thus, in contrast to the investment perspective, the corresponding risk is not the fluctuation in the energy bill savings but the fluctuation in the remaining energy bill costs. Hence, higher investment volumes result in less fluctuating future cost streams due to reduced energy price exposure (Naumoff and Shipley, 2007). Again assuming risk-aversion, homeowners invest more in energetic retrofitting, as larger investments simultaneously reduce the fluctuations of the remaining energy bill costs (Buhl et al., 2018). Research Article #4 defines this perspective as the *energy bill perspective*.

Despite two perspectives, the underlying sources of risk remain the same because the perspectives are only different perceptions of the same objective risk (Slovic and Weber, 2002). Figure 5 illustrates both perspectives, showing energy bill costs over time with and without energetic retrofitting. The white-colored area illustrates the savings achievable with energetic retrofitting, while the green area illustrates the remaining energy bill costs.

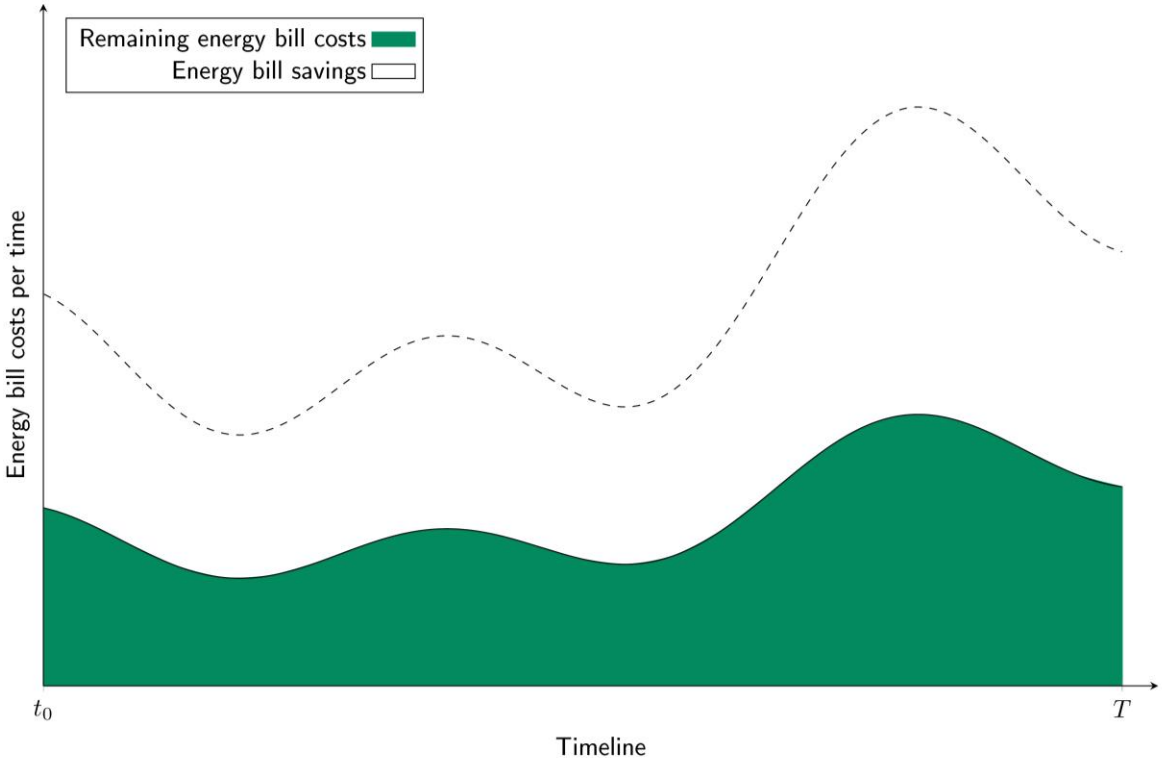

Figure 5: The investment perspective (white area) and energy bill perspective (green area) for an exemplary retrofit option. The grey dashed line represents the energy bill costs without energetic retrofitting and the solid line with energetic retrofitting.

Research Article #4 formulates a mathematical decision model based on expected utility theory (Bernoulli, 1954) and constant absolute risk aversion utility functions to investigate the influence of the two perspectives on energetic retrofitting. The theoretical findings are further substantiated by conducting a Monte Carlo simulation based on a real-world example in a case study. The theoretical and empirical results are in line with each other and provide strong evidence that there are significant differences in the investment volume depending on the risk perception. To this end, homeowners evaluating energetic retrofitting from the energy bill perspective invest about 175% more compared to homeowners evaluating energetic retrofitting from the investment perspective.

The results have three main implications. First, the article establishes risk perception as an influencing factor on energetic retrofitting. Understanding and correctly applying this factor is essential for deriving effective policy measures. For instance, the effect of carbon taxes depends on the homeowner’s risk perception. Higher energy bill costs due to carbon taxes also increase the savings after retrofitting, and consequently, the fluctuations in the savings. Hence, when evaluating from the investment perspective, carbon taxes make energetic retrofitting less attractive ceteris paribus. Second, understanding the two perspectives allows for nudging homeowners towards more sustainable investment behavior, as highlighted by the 175% investment increase in the case study. Thus, the theoretical considerations can enhance information campaigns and raise awareness of the risk-reduction potential of energetic retrofitting. Third, the results partially explain contradictions in previous studies, as some results potentially only emerged due to the specific adopted perspective.

IV.2. Managing the risks connected to energetic retrofitting

Research Article #4 addressed reducing perceived risk to increase energetic retrofitting. However, as already mentioned in the introduction, risk-averse homeowners will still not necessarily conduct economically and ecologically sensible retrofit measures because the remaining perceived risk may still outweigh the benefits. Here, risk transfer contracts issued by a governmental organization or private companies may play an important role (Shogren and Taylor, 2008; Stern, 2011).

In general, risk transfer contracts guarantee a certain project performance in return for a predefined premium and reimburse any shortfalls that breach a contractually defined threshold (Tol, 1998). On the example of energetic retrofitting, risk transfer contracts can take the form of energy efficiency insurances (EEI) already prevalent in the business sector (Mills et al., 2006; Mills, 2003). Here, the risk event refers to higher energy demand during operation than initially predicted, also known as the performance gap (Calì et al., 2016). Thus, the insurer bears the project risks. In this way, risk transfer contracts may contribute to overcoming investment barriers arising from homeowners overrating the corresponding risk (Häckel et al., 2017; Töppel and Tränkler, 2019).

Following the results in Research Article #3, risk mitigation connected to energetic retrofitting and the concomitant increase in the retrofit rate yields substantial economic benefits. Hence, issuing EEIs may be a viable business model if the transferred risk can be diversified accordingly. To this end, financial service providers may charge risk premia higher than the actuarially derived fair premium, as, in imperfect markets, the price of bearing risk within the firm is not necessarily equal to the price of passing it outside by capital markets. I.e., it may still be beneficial to acquire insurance at actuarially unfair rates, for instance, due to tax liabilities or inelastic supply of external financing (Froot et al., 1993; Hoyt and Liebenberg, 2011; Smithson and Simkins, 2005). Alternatively, issuing risk transfer contracts could be set up as a governmental self-sustaining funding model to spur retrofits, given the government's revenue increase through tax payments. Therefore, Research Article #5 sets out to evaluate the diversification and hedging potential of EEIs from an insurer's perspective.

To this end, Research Article #5 stepwise evaluates portfolio risk mitigation on three levels based on the Solvency II regulatory framework: The first step investigates portfolios consisting of different contractual types of EEIs, applying collective risk diversification. The two types considered are EEIs that guarantee maximum expenses and EEIs that guarantee minimum savings (c.f. Figure 6). The second step examines adding existing insurance portfolios such as property insurances applying cross-product line diversification. The third step analyzes the risk reduction when additionally hedging with financial derivatives on the capital market.

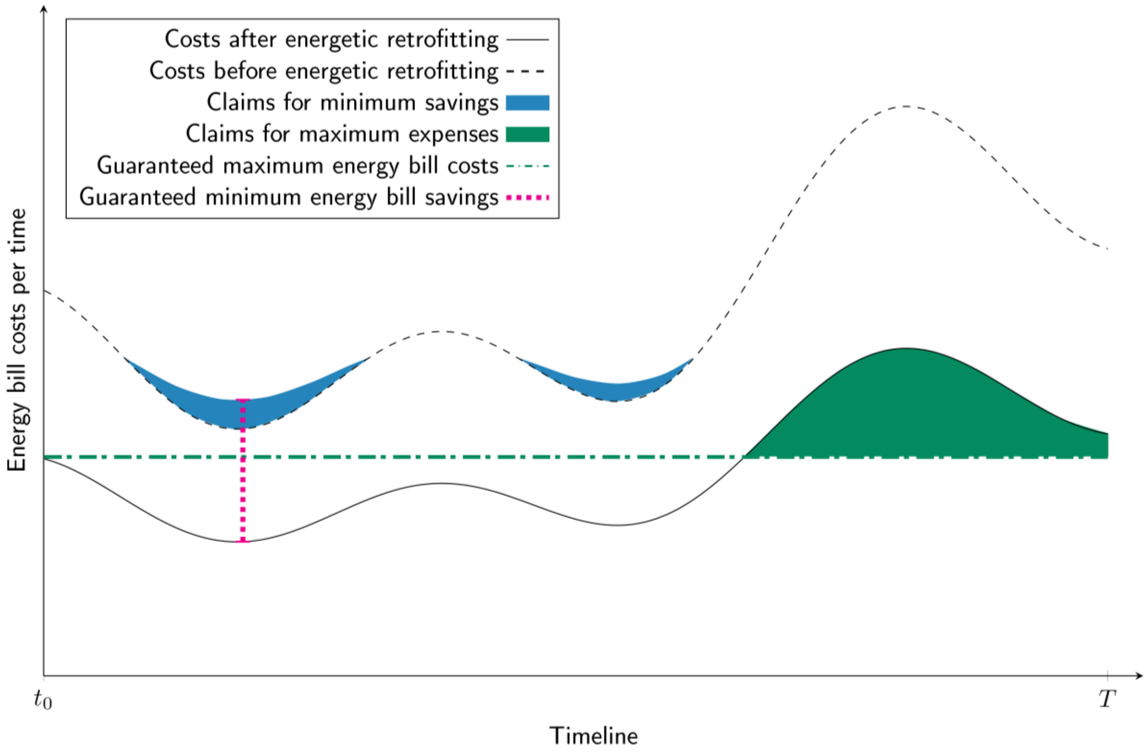

Figure 6: Visualization of the energy efficiency insurances and claim structures.

The results indicate great diversification potential for EEIs. Constructing a minimum variance portfolio of different EEI types reduces the standard deviation compared to the stand-alone standard deviations by 89.14% and 48.97%, respectively, due to the opposing risk events for insurance claims. The second step, adding property insurances, further reduces the standard deviation by 10.63%. However, using weather derivatives, hedging on the financial markets did not bear substantial diversification potential, reducing the standard deviation by merely 1.6%. These results are in line with the Value at Risk and the negative semi-variance and were tested for robustness in a sensitivity analysis. The final minimum variance portfolio consists of 76% EEIs, indicating their potential as a viable hedging alternative for other insurance portfolios.

The results have several managerial implications. First, the results provide the foundation for further analyses fostering the market introduction of EEIs. Moreover, the results offer insights into how EEIs may affect existing insurance portfolios by reducing actuarial risks, entailing lower risk margins and regulatory equity capital. Second, insurers should proceed with both contractual types of EEI. The diversification potential arising from the opposing risk events is particularly interesting for insurers acting under Solvency II constraints, as it frees up regulatory equity capital, improving the respective return measures. Third, EEIs may replace financial derivatives based on risk events influencing the FEP as they exhibit similar risk characteristics. For instance, energy price derivatives or weather derivatives are acquired through third parties at market prices. As EEIs generate profit margins, they release funds leveraging business opportunities, allowing insurers to retain more financial resources at equal risk. This is in line with previous studies elaborating on the desirable risk characteristics of EEIs (Mills, 2003).

V. Spatially and temporally differentiated policy measures

V.1. Impact of socio-economic factors on local energetic retrofitting needs

In addition to understanding and managing risks, policy measures, such as financial subsidy schemes, can be established to further encourage homeowners to conduct energetic retrofitting (Filippini et al., 2014; Weiss et al., 2012). However, current efforts in policy measures often fall short of the envisaged greenhouse gas emission reductions (Bergman and Foxon, 2020; Hall and Caldecott, 2016; Marchand et al., 2015). One reason might be that they are often designed as scattergun approaches without considering local circumstances (Jones et al., 2009; Kastner and Stern, 2015), albeit these circumstances influence the effectiveness of energetic retrofitting (Jones et al., 2009). Moreover, Morton et al. (2018) highlight the necessity of locally tailored policies considering socio-economic and contextual factors instead of national policies.

Nonetheless, despite several studies on the effect of socio-economic and contextual factors in general (Achtnicht and Madlener, 2014; Kastner and Stern, 2015; Palmer and Cooper, 2013; Wilson et al., 2015), there is still a research gap regarding local differences in the buildings' characteristics and energy efficiency as well as how socio-economic factors influence them. Understanding these differences and interdependencies is a prerequisite for an efficient resource allocation in the form of locally tailored policy measures (Fylan et al., 2016; Gerarden et al., 2017; Rosenow and Eyre, 2016). Especially when considering the current public health and economic crisis, it is essential to maximize emission reductions per monetary unit invested (Sengupta, 2020). Thus, Research Article #6 sets out to fill this research gap, investigating local differences in the residential building stock and allowing for deriving locally tailored policy measures. In this vein, Research Article #6 continues with broadening the scope from FEP prediction uncertainty as a central yet highly specific influencing factor for energetic retrofitting, over risk perception and management in general, to taking a national perspective in policy measures. Due to data availability, the article focuses on England, Scotland, and Wales instead of Germany.

The article first applies χ^2-independence tests to derive local differences in the residential building stock's energy efficiency. This first step is a prerequisite for the subsequent analyses. Second, the individual buildings were clustered using a k-means cluster analysis based on the feature selection resulting from a random forest classifier. For each archetypical cluster, the article derived the respective energetic retrofitting needs. Based on the distribution of the archetypes' prevalence, local policymakers can easily determine the most prominent local retrofitting needs and formulate appropriate countermeasures accordingly in the form of policy mechanisms. Last, the article identified socio-economic factors influencing energy efficiency by applying random forest regressions on different energy efficiency quantiles for each local authority.

The results confirm local differences in the building stock's energy efficiency and archetype distributions. To this end, seven archetypes were identified, each standing out with one pronounced energetic retrofitting need except for one archetype exhibiting overall good building conditions. Both results were significant at the 5% significance level; despite a modest effect strength, the efficacy is expected to increase with more granular data. The results further show that the present energy efficiency level moderates the effect of socio-economic factors on building energy efficiency. Nevertheless, some factors appear generally more important. For instance, the share of agriculture, forestry, and fishing in employment and the share of vacant houses are generally considered important. Figure 7 illustrates for all superordinate domains their respective weighted importance depending on the energy efficiency quantile.[1] The figure indicates pronounced trends when omitting the extreme 1% and 99% quantiles. For instance, "Economic" and "Socio-economic" become gradually more important in contrast to "Employment" and "Housing". Here, "Socio-economic" refers to one superordinate domain instead of summarizing all socio-economic factors; the naming originates from the census 2011. Moreover, the results present two exemplary local tailored policy measures, considering the previous findings.

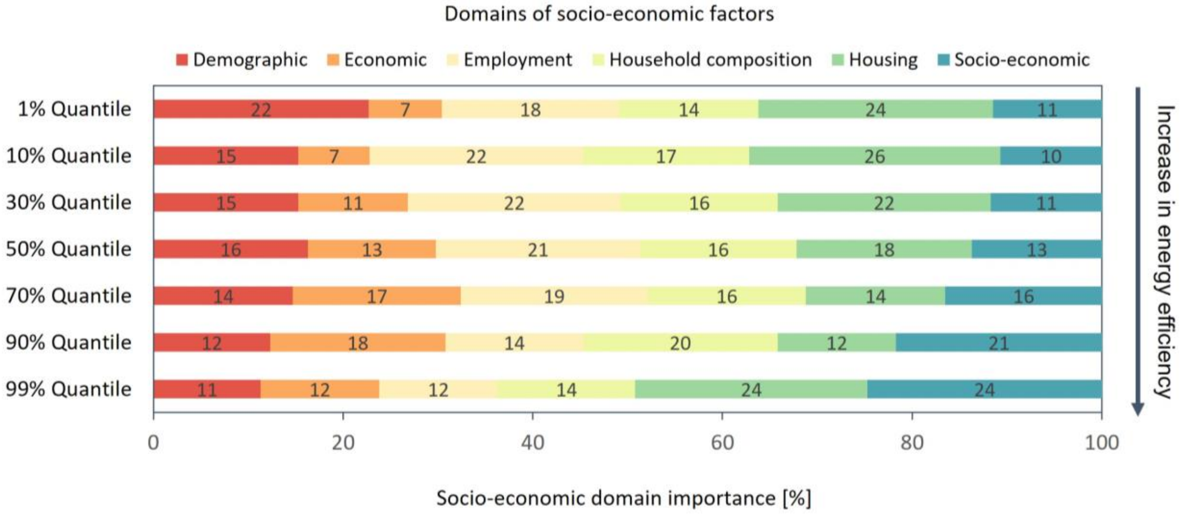

Figure 7: Overview of weighted importance of domains explaining energy efficiency in the residential building sector.

The results have several policy implications: First, policy measures should reflect local circumstances in building characteristics to be most effective. Building upon fine-granular data is advised during the design and monitoring stages. Second, it is essential to account for local circumstances regarding prevalent socio-economic factors. Even for two buildings from the same archetype, i.e., with the same retrofitting need, differing socio-economic influences may necessitate differing policy measures. To this end, policymakers should further mind the moderating effect of energy efficiency on the influence of socio-economic factors to allocate scarce financial resources efficiently. Third, individual policy measures can be ranked and prioritized considering the archetype distribution of the residential building stock within a local authority. This provides an easy and fast tool for initial assessments.

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[1] Each domain includes a different number of factors.

V.2. Impact of financial subsidy schemes on climate goals in the residential building sector

Liu et al. (2020) differentiate policy measures into six subtypes, whereby financial support policies appear to be the most effective for energetic retrofitting (Filippini et al., 2014; Weiss et al., 2012). However, incentivizing early retrofitting might induce lock-in effects (Dubois and Allacker, 2015; Lee et al., 2014; Leinartas and Stephens, 2015; Polly et al., 2011). For instance, as wall insulations often dispose of service lives of 50 years upwards, they are unlikely to be replaced again by the end of the climate goals in 2050.[2] However, technological progress regarding heating system efficiency and thermal insulation capacities provides increasingly energy-conserving solutions. Thus, even when adhering to strict thermal insulation standards, it is reasonable that many lock-in effects will arise when incentivizing early retrofitting, losing out on emission reduction potential.

On the other hand, early retrofitting saves greenhouse gas emissions over longer periods, making even small improvements in the energetic state of buildings accrue to large volumes and contributing to counteracting climate change (Nägeli et al., 2019; Streicher et al., 2021). Financial subsidy schemes can be tailored to either incentivize early or late retrofitting. Thus, as governments impact the retrofitting behavior through financial subsidy schemes and regulations (Dolšak et al., 2020), understanding the impact of either retrofitting behavior is essential to provide sensible incentives. Therefore, Research Article #7 complements the spatial perspective for policy mechanisms by a temporal perspective, investigating time-dependent subsidy schemes to maximize emission reductions per monetary unit invested.

To this end, Research Article #7 initializes a bottom-up agent-based BSM for the German residential building stock, simulating the years 2020 to 2050 and assuming several instances of time-dependent and static subsidy schemes, as well as rational decision-making. The investigated schemes are no subsidies (Zero Subsidies), the current subsidies (Business as Usual),[3] no subsidies over the first 15 years and doubled subsidies afterward (Late Subsidies), and doubled subsidies over the first 15 years and no subsidies afterward (Early Subsidies). For each subsidy scheme, the years until 2050 are simulated in which the homeowners (agents) decide for each year between several retrofit options based on their utility. Not retrofitting is also possible. Annual greenhouse gas emissions are calculated via an artificial neural network and scaled to the German residential building sector. Thereby, the article connects back to Research Article #1 (FEP prediction via MLA) and Research Articles #4 and #5 by additionally calculating the savings potential assuming risk-neutral agents (next to risk-averse agents), which is achievable by applying risk transfer contracts.

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[2] The climate goals for Germany are formulated for 2045 but Research Article #7 considers the years until 2050 to enable comparisons with related studies.

[3] The Business as Usual case corresponds to the subsidy scheme from the German governmentally owned bank for reconstruction and development (Bankengruppe 2021) that was discontinued in January 2022.

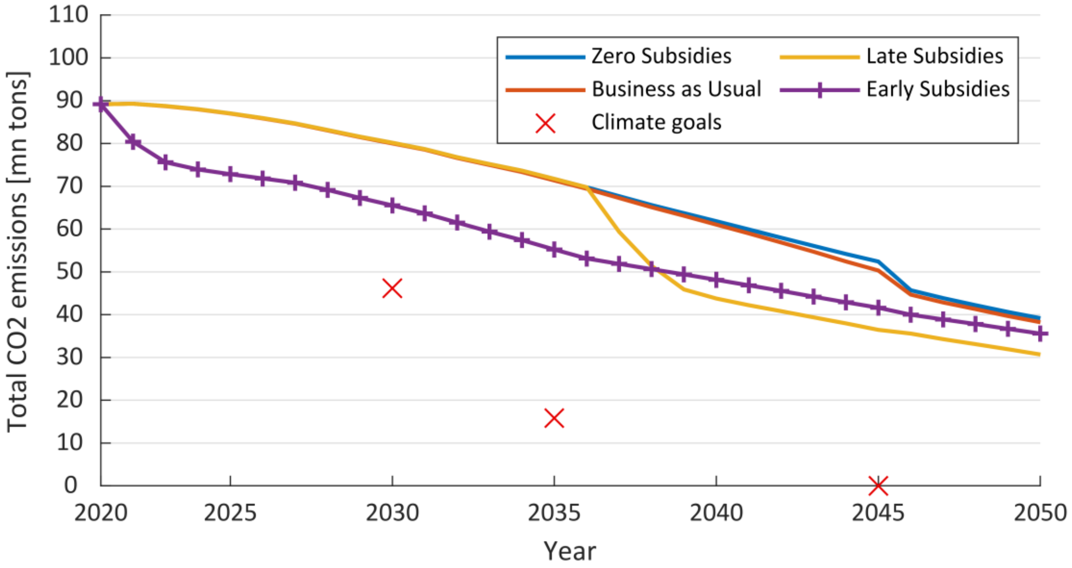

Figure 8: CO_2 emissions for the German residential building sector until 2050 under different subsidy schemes.

Figure 8 illustrates the emission development for risk-averse agents with overall reductions approximately in line with the literature (Diefenbach et al., 2016; Nägeli et al., 2020a; Streicher et al., 2020).[4] Nonetheless, reductions fall short of the envisaged intermediary and final reduction goals for 2030, 2035, and 2045. The results provide strong evidence that Early Subsidies result in higher annual emissions in 2050 than Late Subsidies, reducing the probability of achieving percentual emission reduction goals while simultaneously minimizing total greenhouse gas emissions. In this vein, total emission reductions per monetary unit invested differ by almost 100%, i.e., subsidizing early retrofitting is almost twice as efficient as subsidizing late retrofitting and almost seven times as efficient as the current static subsidy schemes because the savings accrue over longer periods. More precisely, emission reductions per Euro invested equal 57.76 g/€ for Business as Usual, 231.93 g/€ for Late Subsidies, and 390.43 g/€ for Early Subsidies. Hence, despite evading lock-in effects, Late Subsidies are inefficient.

The results have several policy implications. First, emission reduction levels for specific years (e.g., 80% CO_2 emission reduction until 2035) and total greenhouse gas emission goals do not follow the same objective; in fact, they are best supported by the opposite financial subsidy schemes. Due to the large impact on retrofitting exerted by governments through financial subsidy schemes and regulations, correctly incentivizing retrofitting is crucial for counteracting climate change. Second, the results partially explain contradictions in previous studies regarding lock-in effects. Third, risk-neutral evaluation increased emission reductions per monetary unit invested by almost 250% compared to the risk-averse evaluation, not including operation and transaction costs as well as strategic behavior. This result highlights the potential of risk mitigation measures in connection to energetic retrofitting.

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[4] The risk-neutral evaluation yielded higher yet similar reductions and is thus omitted to avoid redundancy.

VI. Conclusion

VI.1. Summary

Counteracting global warming requires intensifying decarbonization efforts across all sectors (Forster et al., 2020). To this end, the global residential building sector faces an urgent need to progress towards decarbonization, as it accounts for 17% of greenhouse gas emissions and 27% of energy consumption, most of which are caused by warm water and space heating and cooling (Nejat et al., 2015; Robert and Kummert, 2012; Ürge-Vorsatz et al., 2015). However, many economically and ecologically sensible retrofit measures are not conducted because of high perceived uncertainty regarding the financial savings (Amecke, 2012), which has coined the term energy efficiency gap (Jaffe and Stavins, 1994). Against this background, this doctoral thesis aims to contribute to successfully shaping the heat transition in the residential building sector by investigating three main aspects: First, this work aims to reduce the perceived risk for energetic retrofitting resulting from FEP misprediction by providing reliable data-driven decision support. Second, following the differentiation of risk connected to energetic retrofitting by Mills et al. (2006), the remaining risk (mainly economic and contextual risk arising from uncertain energy prices and weather developments) is analyzed and managed to further increase energetic retrofitting by applying concepts from quantitative finance. Third, carefully tailored policy measures are examined to efficiently allocate scarce financial resources and maximize emission reductions per monetary unit invested. All three focal points allow deriving managerial and policy implications.

On the first aspect, Section II lays the foundation for the following analyses by offering insights into data-driven FEP prediction as an alternative to the legally prescribed engineering EQM. Here, the results in Research Article #1 provide strong evidence that the data-driven EQMs outperform the engineering EQM by a large margin, reducing the prediction error by almost 50%. This finding, tested for robustness and systematic bias, suggests revising the current legislation and establishing data-driven EQMs for FEP prediction to overcome investment barriers by mitigating uncertainties connected to energetic retrofitting. Section III complements these findings by elaborating on the challenges and opportunities of data-driven FEP prediction. Here, Research Article #2 is concerned with explainability as an often-claimed drawback of data-driven EQMs. The results indicate that both transparent models and post-hoc explainability approaches applied to untransparent models yielded high levels of explainability and prediction accuracy. A special focus is on the novel QLattice algorithm that is specifically designed for explainability. Research Article #3 subsequently provides the missing link between FEP prediction accuracy and the retrofit rate, under the assumption of rational decision-makers. The results indicate that currently available data-driven EQMs may already increase the retrofit rate from 0.98% to 1.68% by about 70% or 0.7 percentage points, which is equivalent to a comparative advantage over the engineering EQM of almost 45 Mt by 2050 in CO_2 emission reductions. The article further elaborates on the substantial increase in social welfare and turnover resulting from the increased retrofit activity. Albeit there are many more influencing factors impacting the retrofit rate, further FEP prediction accuracy potential already allows the retrofit rate to eventually exceed the envisaged 2% to successfully shape the heat transition in the German residential building sector within the model setting.

On the second aspect, Section IV deals with understanding and managing the risks connected to energetic retrofitting. This broadens the scope from one important yet highly specific risk factor (FEP misprediction) to risk in general impacting energetic retrofitting. Research Article #4 provides the theoretical basis regarding risk perception when facing energetic retrofit decisions from the homeowner’s perspective and validates the derived formulas in a case study. The theoretical model indicates higher investments in energetic retrofits when homeowners evaluate from the energy bill perspective. The case study substantiates these findings, quantifying an investment surplus of 175% for homeowners evaluating energetic retrofitting from the energy bill perspective compared to homeowners evaluating energetic retrofitting from the investment perspective. This knowledge allows enhancing information campaigns and deriving adequate policy measures, as well as nudging homeowners towards more sustainable investment behavior. Subsequently, Research Article #5 aims to diversify and hedge the remaining risks from energetic retrofitting via risk transfer contracts on the financial markets applying collective risk diversification, cross-product line diversification, and hedging with financial derivatives. The results indicate the great diversification potential of EEIs in a portfolio context, implying substantial market potential of risk transfer contracts for energetic retrofitting, which may, in turn, further reduce investment barriers. Moreover, EEIs may also replace existing hedging alternatives such as weather derivatives based on the same risk factors. As EEIs generate profit margins, they release funds leveraging business opportunities, allowing insurers to retain more financial resources at equal risk.

On the third aspect, Section V investigates both spatially and temporally differentiated policy measures to foster their full potential and maximize greenhouse gas emission reductions per monetary unit invested. Research Article #6 investigates the local differences in the residential building stock as well as the impact of socio-economic factors on energy efficiency to allow for deriving locally tailored policy measures. The results provide strong evidence for regional differences and significant impact from socio-economic factors, whereby the energetic state of the buildings exerts a moderating effect on these factors. The article concludes that policy measures should reflect local circumstances in building characteristics to be most effective. Research Article #7 complements this spatial perspective with a temporal perspective. The article examines time-dependent financial subsidy schemes to weigh early emission reduction potential from incentivizing early retrofitting against potential lock-in effects and not realizing higher savings from technological progress later on. The results indicate that, despite accepting lock-in effects and potentially missing annual emission reduction goals, incentivizing early retrofitting indeed minimized total greenhouse gas emissions for the considered period until 2050. To this end, the emission reductions per monetary unit invested are up to 675% higher for early subsidy schemes compared to static subsidy schemes.

From an overarching perspective, the results of the individual articles show coherent and sequential approaches to relevant and contemporary issues, revealing various synergies between the individual findings. From the specific decision support of individual homeowners solely based on the FEP prediction accuracy as a decision criterion, over the inclusion of further risk factors, to an overall societal perspective, solution approaches are presented for the respectively identified research gaps. In this way, this doctoral thesis considers the complete spectrum, from the decision of individuals to policy measures, and gives relevant policy and managerial implications regarding the respective research questions. Thereby, the individual articles build on each other so that the results of the more specific research articles are incorporated into the more general articles. For instance, the high FEP prediction accuracy of data-driven EQMs not only improves the issuance of EPCs – and, therefore, the decision support for energetic retrofitting – but may also be applied in the subsequent articles' analyses to improve their result quality.

In summary, the analyses in this doctoral thesis have revealed the great potential of data-driven methods and concepts from quantitative finance to support counteracting climate change. Although further research is required, promising approaches may soon mature into more advanced solutions. Ultimately, policymakers will have to incorporate these solutions into (multi-) national legislation.

With this thesis, I hope to encourage researchers, practitioners, and policymakers to elaborate on these concepts to contribute a small but important step towards achieving the climate goals.

VI.2. Limitations and future research

As any research endeavor, the articles within this doctoral thesis are subject to limitations and likewise give rise to prospects for further research. The following paragraphs provide a non-conclusive overview; detailed limitations and prospects for further research are listed in the individual research articles.

First and foremost, the results of this doctoral thesis largely depend on the underlying data quality. The individual articles relied on several extensive real-world datasets, each with its individual benefits and shortcomings. More precisely, five of the presented research articles rely on a dataset comprising 25,000 German single- and two-family houses, one article draws from EPC data of 20 million English, Scottish and Welsh buildings, and the last articles initializes a case study based on average buildings characteristics of German commercial buildings. Hence, all articles' findings are limited by the quality of the underlying datasets. To this end, relevant information was missing, particularly regarding occupant behavior and important building characteristics, which necessitated making assumptions. This first limitation is particularly relevant for Research Article #6 because the socio-economic factors were only available on an aggregated basis for each local authority. In general, publicly available data for this domain is scarce (Carpino et al., 2019). Thus, future research might increase the findings' validity by gathering further and more complete data. It is reasonable to assume that more extensive documentation on building materials, insulation, and energetic retrofitting will be recorded for the future building stock. For the existing building stock, on the other hand, expensive and complex test drilling is sometimes necessary to derive insulation material and thickness, whereby the efforts often outweigh the benefits of additional data points. An expansion of smart home appliances can also ensure access to occupants' presence and behavior data. If this data is enriched with socio-economic factors - in compliance with strict data protection guidelines - this provides an excellent basis for validating the presented results and further research.

Second, all research articles within this doctoral thesis may be subject to model risks. Models are supposed to simplify reality to such a degree that underlying interdependencies are understandable and analytically tractable. Thus, although results were tested for robustness and systematic bias where applicable, relying upon a model always bears the risk of over-simplifying the underlying causalities and leaving out relevant elements, yielding incorrect results. For instance, Research Article #1 and Research Article #2 benchmarked several MLAs. The results are limited to the well-selected yet restricted choice of algorithms and the pre-processing and tuning steps conducted despite thorough training and hyperparameter tuning. In addition, Research Article #3 and Research Article #7 applied (agent-based) BSMs, while Research Article #5 built upon Markowitz's portfolio theory (Markowitz, 1952). Thus, these articles are also subject to the respective model assumptions and limitations. This restriction particularly holds for the assumption of rational decision-making made in Research Articles #3 and #7. Future research might substantiate the findings by lifting some of these limitations. In particular, the stepwise relaxation of assumptions may provide a good starting point for successively generalizing the results. In addition, future research might investigate further algorithms in the benchmarking process or validate findings by reproducing the results with alternative models and methodologies.

Third, despite continuously broadening the scope and including further external influences, this doctoral thesis cannot provide a holistic picture of the heat transition on its own. The highly interconnected nature of the globalized world and the energy system, in particular, requires the heat transition to be addressed in an integrated perspective along with related endeavors such as the energy transition and the mobility transition. Naturally, a holistic depiction of all these challenges is beyond the scope of this doctoral thesis. Nonetheless, future research might complement and refine the results by considering related topics. A key concept that has not been addressed in this doctoral thesis is the rebound effect, which states that anticipated savings resulting from investments in more efficient appliances are frequently not realized due to changes in consumer behavior (Berkhout et al., 2000; Sorrell and Dimitropoulos, 2008). For instance, in the example of energetic retrofitting, this translates to adjusting thermostat settings and raising the indoor temperature after acquiring a more efficient heating system since the price for thermal comfort is reduced. Further restrictions in the scope of this doctoral thesis are the focus on residential buildings, one climatic region, and excluding self-generation. Therefore, compelling research directions include transferring the analyses to other climatic areas, investigating non-residential buildings, and integratively considering, for instance, the heat transition and the energy transition.

This doctoral thesis is subject to many more minor limitations listed in the individual research articles. Therefore, the reader is referred to the supplementary material to avoid a too fine-grained enumeration.

VI.3. Acknowledgment of previous and related work

All research projects were either co-authored in close collaboration or benefited from fruitful discussions and inspirations by colleagues from the Branch Business & Information Systems Engineering of the Fraunhofer Institute for Applied Information Technology (FIT) and the Research Center Finance & Information Management (FIM) in Augsburg and Bayreuth. Thus, the following paragraph presents where this doctoral thesis builds on previous and related works.

Kratsch et al. (2021), Niemierko et al. (2019), and Amasyali and El-Gohary (2018) inspired and influenced Research Article #1, Research Article #2, and Research Article #3 by addressing related MLA benchmarking and data-driven FEP prediction issues as well as singling out the research gap on data-driven FEP prediction. The works by Buhl et al. (2018), Häckel et al. (2017), Mills (2003), and Töppel and Tränkler (2019) provided a sound basis for Research Article #4 and Research Article #5 by discussing risk and risk management connected to energetic retrofitting, investigating the different perceptions of risk, and establishing energy efficiency insurances. Pasichnyi et al. (2019), Tziogas et al. (2021), Magnani et al. (2020), and Gómez-Navarro et al. (2021) laid the foundation for Research Article #6 by suggesting EPC data to derive energy policy instruments and investigating local differences and circumstances in national building stocks. Finally, Research Article #7 was inspired by fruitful discussions on an earlier version of Töppel (2019) as well as by the works of Dubois and Allacker (2015), Lee et al. (2014), and Nägeli et al. (2020b), who provided a sound methodological approach and investigated lock-in effects arising from early retrofitting.

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VIII. Appendix

VIII.1. Research articles relevant to this doctoral thesis

Research Article #1: Benchmarking energy quantification methods to predict heating energy performance of residential buildings in Germany

Wenninger, S.; Wiethe, C. (2021). “Benchmarking Energy Quantification Methods to Predict Heating Energy Performance of Residential Buildings in Germany”. In: *Business & Information Systems Engineering*. DOI: 10.1007/s12599-021-00691-2
(VHB-JQ3 Category: B)

Research Article #2: Explainable long-term building energy consumption prediction using QLattice

Wenninger, S.; Kaymakci, C.; Wiethe, C. (2022). “Explainable Long-Term Building Energy Consumption Prediction Using QLattice”. In: *Applied Energy*. DOI: 10.1016/j.apenergy.2021.118300
(VHB-JQ3 Category: n.a., Impact Factor: 9.746)

Research Article #3: The influence of building energy performance prediction accuracy on retrofit rates

Wiethe, C.; Wenninger, S. (2021). „ The influence of building energy performance prediction accuracy on retrofit rates”. Submitted

Research Article #4: Understanding the risk perception of energy efficiency investments: investment perspective vs. energy bill perspective

Rockstuhl, S.; Wenninger, S.; Wiethe, C.; Häckel, B. (2021). “Understanding the Risk Perception of Energy Efficiency Investments: Investment Perspective vs. Energy Bill Perspective”. In: *Energy Policy*. DOI: 10.1016/j.enpol.2021.112616
(VHB-JQ3 Category: B)

Research Article #5: Managing the risks of energy efficiency insurances in a portfolio context: an actuarial diversification approach

Baltuttis, D.; Töppel, J.; Tränkler, T.; Wiethe, C. (2020). “Managing the risks of energy efficiency measures: An actuarial portfolio diversification approach”. In: *International Review of Financial Analysis*. DOI: 10.1016/j.irfa.2019.01.007
(VHB-JQ3 Category: n.a., Impact Factor: 5.373)

Research Article #6: Impact of socio-economic factors on local energetic retrofitting needs - a data analytics approach

Ahlrichs, J.; Wenninger, S.; Wiethe, C.; Häckel, B. (2022). “Impact of Socio-Economic Factors on Local Energetic Retrofitting Needs - A Data Analytics Approach”. In: *Energy Policy*. DOI: 10.1016/j.enpol.2021.112646.
(VHB-JQ3 Category: B)

Research Article #7: Impact of financial subsidy schemes on climate goals in the residential building sector

Wiethe, C. (2022). “Impact of Financial Subsidy Schemes on Climate Goals in the Residential Building Sector”. In: *Journal of Cleaner Production*. DOI: 10.1016/j.jclepro.2022.131040.
(VHB-JQ3 Category: B)

I also co-authored further research papers throughout the dissertation, which are not part of this doctoral thesis. An excerpt of the articles can be found in the following:

- Rockstuhl, S., Wenninger, S., Wiethe, C., Ahlrichs, J. (2022). “The influence of risk perception on energy efficiency investments: Evidence from a German survey”. In: *Energy Policy*
- Töppel, J.; Tränkler, T.; Wiethe, C. (2019). „The impact of energy economical behavior on long-term energetic retrofitting roadmaps: a vine copula quantile regression approach”. In: *Proceedings of 11th International Conference on Applied Energy*, Västerås, Sweden.
- Wenninger, S.; Kaymakci, C.; Wiethe, C.; Römmelt, J.; Baur, L.; Häckel, B.; Sauer, A. (2022). „How Sustainable is Machine Learning in Energy Applications? – The Sustainable Machine Learning Balance Sheet”. In: *17. Internationale Tagung Wirtschaftsinformatik*, Nürnberg, Germany.
- Wenninger, S.; Wiethe, C. (2022). “The human’s comfort mystery – supporting energy transition with light-color dimmable room lighting and IS?”. In: *Sustainability*
- Wederhake, L.; Wenninger, S., Wiethe, C., Stirnweiß, D., Fridgen, G. (2022). “The influence of risk perception on energy efficiency investments: Evidence from a German survey”. Submitted
- Buhl, H. U., Graf-Drasch, V., Wiethe, C. (2022). „What to Say and What to Do: How Communication of Sustainability Targets determines Customer Satisfaction”. Submitted
- Ritter, C., Wiethe, C. Häckel, B., Federmann, F. (2022). “Evaluating Methods for Automated Revenue Forecasting: A Case Study in the Semiconductor Industry”. Submitted
- Bjørndal, E., Bjørndal, M., Schott, P., Weibelzahl, M., Wiethe, C. (2022). „Long-Term Transmission and Generation Investments in Hybrid Electricity Markets”. Submitted
- Konhäuser, K., Wenninger, S., Werner, T., Wiethe, C. (2022). „Leveraging advanced ensemble models to increase building energy performance prediction accuracy in the residential building sector“. Submitted

VIII.2. Individual contribution to the research articles

This doctoral thesis is cumulative and consists of seven research articles that comprise the main body of work. Six of the seven research articles were developed in teams with multiple co-authors. This section provides details on the respective research settings and highlights my contributions to each article.

Research Article #1, titled “Benchmarking Energy Quantification Methods to Predict Heating Energy Performance of Residential Buildings in Germany,” was co-authored by a team of two. Both co-authors were jointly responsible for writing the text of the originally submitted version and the revised versions of the article. All co-authors collaborated to develop a methodological approach for benchmarking different methods for quantifying the energy performance of buildings, which allows for comparing the predictive performance of approaches from engineering and data science. Further, all co-authors contributed equally to the evaluation and analysis of the results and the derivation of managerial and policy implications to enhance the final energy performance prediction accuracy. In the research project, I was specifically responsible for setting up the technical environment, writing the underlying programming code, and performing quantitative analyses.

Research Article #2, titled “Explainable Long-Term Building Energy Consumption Prediction Using QLattice,” was co-authored by a team of three. All co-authors were to differing parts responsible for writing the text of the originally submitted version and the revised versions of the article. Further, all co-authors contributed to the analysis and discussion of the results. As a subordinate author of this article, I was responsible for writing and revising parts of the article covering the computational performance and the QLattice algorithm, analyzing the results, and discussing the evaluations.

Research Article #3, titled “The influence of building energy performance prediction accuracy on retrofit rates,” was co-authored by a team of two. As the leading author of this article, I developed the basic idea and created its content to a large extent. Specifically, I determined the research methodology, analyzed and structured literature, wrote the underlying code, graphically visualized the results, and was largely responsible for evaluating and discussing the results and deriving implications for practice and research. Although I am the leading author of this project, the co-author was involved in analyzing the results, writing and revising the text, and discussing the results throughout the project.

Research Article #4, titled “Understanding the Risk Perception of Energy Efficiency Investments: Investment Perspective vs. Energy Bill Perspective,” was co-authored by a team of four. Three authors, including myself, were jointly responsible for writing the text of the originally submitted version and the revised versions of the article. As a team, we agreed that two co-authors and I should assume the roles of leading authors of the research article. The other co-author contributed as a subordinate author, mainly in the form of feedback during the submission and review process and in his role as a scientific supervisor and mentor. All leading authors jointly elaborated on the methodological approach to analyze how the investment and energy perspective influence decision-making with a theoretical model and a case study based on real-world data of the German retrofitting market. Further, all leading authors contributed equally to the evaluation and analysis of the results and the derivation of policy measures promoting the energy bill perspective for higher investments in energetic retrofitting. In the case study conducted, I was particularly responsible for the rigorous mathematical setup to allow for correct energy savings calculations.

Research Article #5, titled “Managing the risks of energy efficiency insurances in a portfolio context: an actuarial diversification approach,” was co-authored by a team of four. All co-authors were jointly responsible for writing the text of the originally submitted version and the revised versions of the article. All co-authors collaborated to develop a methodological approach for setting up the energy efficiency insurance designs and diversifying the portfolio. Further, all co-authors contributed equally to the evaluation and analysis of the results and the derivation of managerial and policy implications to enhance the final energy performance prediction accuracy. In the research project, I was specifically responsible for setting up the technical environment, writing the underlying programming code, and evaluating, analyzing, and graphically visualizing the results.

Research Article #6, titled “Impact of Socio-Economic Factors on Local Energetic Retrofitting Needs - A Data Analytics Approach,” was co-authored by a team of four. Three authors, including myself, were jointly responsible for writing the text of the originally submitted version and the revised versions of the article. As a team, we agreed that two co-authors and I should assume the roles of leading authors of the research article. The other co-author contributed as a subordinate author, mainly in the form of feedback during the submission and review process and in his role as a scientific supervisor and mentor. All leading authors jointly elaborated on the methodological approach to combine and analyze the different data sources so that the impact of socio-economic factors on local energetic retrofitting needs could be identified. Further, all leading authors contributed equally to evaluating and analyzing the results and deriving locally tailored policy measures considering retrofitting needs and socio-economic factors. I was particularly responsible for ensuring a sound methodological approach regarding the data analysis methods applied.

Research Article #7, titled “Impact of Financial Subsidy Schemes on Climate Goals in the Residential Building Sector,” was not co-authored by another author. In this project, I developed the basic idea and created its content. Specifically, I determined the research methodology, analyzed and structured literature, wrote the underlying programming code, graphically visualized the results, and was responsible for evaluating and discussing the results and deriving implications for practice and research.

VIII.3. Research Article #1: Benchmarking energy quantification methods to predict heating energy performance of residential buildings in Germany

Authors:	Simon Wenninger, Christian Wiethe
Published in:	Business & Information Systems Engineering (2021)
Abstract:	To achieve ambitious climate goals, it is necessary to increase the rate of purposeful retrofit measures in the building sector. As a result, Energy Performance Certificates have been designed as important evaluation and rating criterion to increase the retrofit rate in the EU and Germany. Yet, today’s most frequently used and legally required methods to quantify building energy performance show low prediction accuracy, as recent research reveals. To enhance prediction accuracy, the research community introduced data-driven methods which obtained promising results. However, there are no insights in how far Energy Quantification Methods are particularly suited for energy performance prediction. In this research article the data-driven methods Artificial Neural Network, D-vine copula quantile regression, Extreme Gradient Boosting, Random Forest, and Support Vector Regression are compared with and validated by real-world Energy Performance Certificates of German residential buildings issued by qualified auditors using the engineering method required by law. The results, tested for robustness and systematic bias, show that all data-driven methods exceed the engineering method by almost 50% in terms of prediction accuracy. In contrast to existing literature favoring Artificial Neural Networks and Support Vector Regression, all tested methods show similar prediction accuracy with marginal advantages for Extreme Gradient Boosting and Support Vector Regression in terms of prediction accuracy. Given the higher prediction accuracy of data-driven methods, it seems appropriate to revise the current legislation prescribing engineering methods. In addition, data-driven methods could support different organizations, e.g., asset management, in decision-making in order to reduce financial risk and to cut expenses.
Keywords:	Energy informatics; Energy quantification methods; Energy performance certificates; Benchmarking; Data-driven methods; Machine learning algorithms; Building energy; Data analytics

VIII.4. Research Article #2: Explainable long-term building energy consumption prediction using QLattice

Authors:	Simon Wenninger, Can Kaymakci, Christian Wiethe
Published in:	Applied Energy (2022)
Abstract:	The global building sector is responsible for nearly 40% of total carbon emissions, offering great potential to move closer to set climate goals. Energy performance certificates designed to increase the energy efficiency of buildings require accurate predictions of building energy performance. With significant advances in information and communication technology, data-driven methods have been introduced into building energy performance research demonstrating high computational efficiency and prediction performance. However, most studies focus on prediction performance without considering the potential of explainable artificial intelligence. To bridge this gap, the novel QLattice algorithm, designed to satisfy both aspects, is applied to a dataset of over 25,000 German residential buildings for predicting annual building energy performance. The prediction performance, computation time, and explainability of the QLattice is compared to the established machine learning algorithms artificial neural network, support vector regression, extreme gradient boosting, and multiple-linear regression in a case study, variable importance analyzed, and appropriate applications proposed. The results show quite strongly that the QLattice should be further considered in the research of energy performance certificates and may be a potential alternative to established machine learning algorithms for other prediction tasks in energy research.
Keywords:	Building energy performance; Energy quantification methods; Energy performance certificates; Explainable AI; Machine learning algorithms; QLattice

VIII.5. Research Article #3: The influence of building energy performance prediction accuracy on retrofit rates

Authors:	Christian Wiethe, Simon Wenninger
Extended Abstract[5]:	Studies estimate the financial burdens of climate change to increase with each year of inaction by 0.6 trillion US dollars (Sanderson and O'Neill, 2020). To curb the progress of climate change requires significant CO_2 emission reductions across all sectors and industries. To this end, the residential building sector faces an urgent need to reduce CO_2 emissions, as it accounts for 20% of the final energy demand and causes over 22% of CO_2 emissions worldwide. Hence, it constitutes a good option for decarbonization through widespread energetic retrofitting (International Energy Agency, 2019). However, conducting energetic retrofits is mainly a financial investment decision, with homeowners evaluating upfront costs and financial savings from lower energy expenditures over time (Sutherland, 1991). To this end, risk aversion on the homeowner's side and uncertainty connected to the financial benefits of energetic retrofits (stemming largely from inaccurate FEP predictions) form a significant investment barrier (Amecke, 2012). This leads to many economically and ecologically sensible retrofitting measures that are not performed, which coined the term energy efficiency gap (Jaffe and Stavins, 1994). Even though there is plenty of literature on FEP prediction accuracy of different methods, the resulting impact of accuracy gains, i.e., the relationship to the retrofit rate and CO_2 emission reduction potential, are not yet determined. Thus, the question arises to what extent does FEP prediction accuracy affect retrofit rates and the resulting CO_2 emissions released in the residential building sector? The article designs an agent-based building stock model (BSM) to derive the relationship between FEP prediction accuracy and retrofit rate, assuming rational decision-making, to contribute to filling this research gap. The retrofitting decision process of individual homeowners as agents is simulated for a stratified subsample of an extensive real-world dataset of 25,000 German residential buildings using the established risk preference function. By varying the degree of uncertainty, the article derives the impact of uncertainty

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[5] At the time of writing, this research article is under review for publication in a scientific journal. Therefore, an extended abstract, taken from the research article, is provided here.

	in FEP prediction accuracy on the retrofit rate, given the limitations from the chosen model setting. To this end, inserting FEP prediction accuracy values from literature allows determining the CO_2 emission reduction potential resulting from available and more accurate EQMs, i.e., the CO_2 emission reduction potential of changing regulatory frameworks and altering the legally prescribed EQMs. Results indicate that higher prediction accuracies positively affect the retrofit rate. Using data-driven prediction methods from research significantly increases the retrofit rate by over 70% from around 0.98% to 1.68% compared to the legally prescribed engineering method. This equals CO_2 emission reductions of almost 45 Mt by 2050 for Germany and leads to a surplus in consumer rent of 310.19 mn €, while investments in retrofits increase about 1.195 bn €, and the government benefits from tax payments and saved opportunity costs. The results have several managerial and policy implications. First, accuracy in the FEP prediction is, among other impacting factors, crucial for high retrofit rates. This is relevant both for policymakers and – where legally possible – independent energetic retrofit companies providing FEP predictions. A reputation for high FEP prediction accuracy supports the implementation and market penetration of economically and ecologically sensible energetic retrofit measures (however, other constraints such as a shortage of skilled workforce still apply). For companies, this means a direct increase in sales and revenue, while for policymakers, this supports the heat transition to meet climate goals. Additionally, homeowners benefit from lower energy expenditures over time. Therefore, a change to more accurate available EQMs is advised. Second, the results show that there is still high potential for CO_2 emission reductions when further increasing FEP prediction accuracy, particularly when considering the over-proportional increase in potential retrofits for increasing FEP prediction accuracy. To this end, improving existing EQMs or introducing novel and more accurate EQMs appears fruitful. Engineering EQMs could benefit from more occupant data to calibrate their models accordingly. Other constraining variables for engineering EQMs are the available time and qualification of the respective auditor. For data-driven EQMs, the widespread implementation of smart home appliances and smart meters can help to increase FEP prediction accuracy through enhanced data availability and quality. In addition, approaches of explainable artificial

	intelligence could further reduce uncertainty and increase trust in data-driven models, which are often referred to as "black boxes" (Barredo Arrieta et al., 2020). Third, the results argue for further risk mitigation measures. Considerable approaches include, for instance, risk transfer contracts in the form of energy savings insurances, tokenization of energy investments (c.f. “efforce”), or well-designed subsidy programs (Ahlrichs et al., 2020; Mills, 2003). The additional reduction of perceived risk during the investment process will again over-proportionally increase the retrofit rate. On the part of, e.g., financial service providers or retrofit companies, this may even provide a lucrative business model through risk premia while applying diversification and hedging (Baltuttis et al., 2019). On the part of policymakers, this could be set up as a governmental self-sustaining support model to boost retrofits. Fourth, the implemented status-quo bias affected the results, as almost all agents considered installing double-glazed windows, while far fewer agents considered more advanced alternatives. It may be beneficial to raise awareness for new and potentially superior insulation or heating system technologies. Moreover, this holds for customers and energy consultants, as status-quo bias has also been reported on the side of installation companies. Thus, next to FEP prediction accuracy, the awareness of retrofit options may significantly benefit the retrofit rate.
Keywords:	Building stock model; Climate goals; Energy quantification methods; Data-driven methods; Machine learning algorithms; Data analytics; Decision-making; Risk
References:	Ahlrichs, Jakob; Rockstuhl, Sebastian; Tränkler, Timm; Wenninger, Simon (2020): The impact of political instruments on building energy retrofits: A risk-integrated thermal Energy Hub approach. In: Energy Policy 147, S. 111851. DOI: 10.1016/j.enpol.2020.111851. Amecke, Hermann (2012): The impact of energy performance certificates: A survey of German home owners. In: Energy Policy 46, S. 4–14. DOI: 68: 101313. 10.1016/j.irfa.2019.01.007. Baltuttis, Dennik; Töppel, Jannick; Tränkler, Timm; Wiethe, Christian (2019): Managing the risks of energy efficiency insurances in a portfolio context: An actuarial diversification approach. In: International

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VIII.6. Research Article #4: Understanding the risk perception of energy efficiency investments: investment perspective vs. energy bill perspective

Authors:	Sebastian Rockstuhl; Simon Wenninger; Christian Wiethe, Björn Häckel
Published in:	Energy Policy (2021)
Abstract:	Promoting energy efficiency is an important element of environmentally friendly energy policy and necessary to avert climate change. In this context, understanding the investment decision-making of individuals is important to develop and implement effective policy instruments. Literature analyzing decision-making of energy efficiency investments and especially the influence of connected risk finishes with two different conclusions, i.e., analyzes risk from two different perspectives. First, studies within the investment perspective describe investment risk, caused by volatile future energy bill savings, as a key barrier for energy efficiency investments. Second, studies within the energy bill perspective argue that energy efficiency is reducing energy price exposure and the resulting decrease of overall risk is described as investment promoting. This dichotomy in risk perception is the focus of our study. With the help of a theoretical model as well as a case study based on real-world data of the German retrofitting market, we analyze how the contrary perspectives influence expected utility, i.e., decision-making. Thereby, we find that decision-makers invest more in energy efficiency when evaluating from the energy bill perspective and derive important implications for environmentally friendly energy policymaking.
Keywords:	Energy efficiency; Risk evaluation; Expected utility theory; Case study

VIII.7. Research Article #5: Managing the risks of energy efficiency insurances in a portfolio context: an actuarial diversification approach

Authors:	Dennik Baltuttis, Jannik Töppel, Timm Tränkler, Christian Wiethe
Published in:	International Review of Financial Analysis (2020)
Abstract:	To achieve ambitious international climate goals, an increase of energy efficiency investments is necessary and, thus, a growing market potential arises. Concomitantly, the relevance of managing the risk of financing and insuring energy efficiency measures increases continuously. Energy Efficiency Insurances encourage investors by guaranteeing a predefined energy efficiency performance. However, literature on quantitative analysis of pricing and diversification effects of such novel insurance solutions is scarce. This paper provides a first approach for the analysis of diversification potential on three levels: collective risk diversification, cross product line diversification, and financial hedging. Based on an extensive real-world data set for German residential buildings, the analysis reveals that underwriting different Energy Efficiency Insurance types and constructing Markowitz Minimum Variance Portfolios halves overall risk in terms of standard deviation. We evince that Energy Efficiency Insurances can diversify property insurance portfolios and reduce regulatory capital for insurers under Solvency II constraints. Moreover, we show that Energy Efficiency Insurances potentially supersede financial market instruments such as weather derivatives in diversifying property insurance portfolios. In summary, these three levels of diversification effects constitute an additional benefit for the introduction of Energy Efficiency Insurances and may positively impact their market development.
Keywords:	Energy efficiency investment; Energy efficiency insurance; Energy portfolio risk management; Energy portfolio optimization; Risk diversification

VIII.8. Research Article #6: Impact of socio-economic factors on local energetic retrofitting needs - a data analytics approach

Authors:	Jakob Ahlrichs; Simon Wenninger; Christian Wiethe, Björn Häckel
Published in:	Energy Policy (2022)
Abstract:	Despite great efforts to increase energetic retrofitting rates in the residential building stock, greenhouse gas emissions are still too high to counteract climate change. One barrier is that policy measures are mostly national and do not address local differences. Even though there is plenty of research on instruments to overcome general barriers of energetic retrofitting, literature does not consider differences in local peculiarities. Thus, this paper aims to provide guidance for policy-makers by deriving evidence from over 19 million Energy Performance Certificates and socio-economic data from England, Scotland, and Wales. We find that building archetypes with their respective energetic retrofitting needs differ locally and that socio-economic factors show a strong correlation to the buildings' energy efficiency, with the correlation varying depending on different degrees of this condition. For example, factors associated to employment mainly affect buildings with lower energy efficiency whereas the impact on more efficient buildings is limited. The findings of this paper allow for tailoring local policy instruments to fit the local peculiarities. We obtain a list of the most important socio-economic factors influencing the regional energy efficiency. Further, for two exemplary factors, we illustrate how local policy instruments should consider local retrofitting needs and socio-economic factors.
Keywords:	Energy efficiency; Local environmental policy; Residential building stock; Socio-economic effects; Data mining; Environment; England; Scotland; Wales; Energy performance certificates; Socio-economic

VIII.9. Research Article #7: Impact of financial subsidy schemes on climate goals in the residential building sector

Authors:	Christian Wiethe
Published in:	Journal of Cleaner Production (2022)
Abstract:	The international Paris agreement climate goals regarding the residential building sector were mainly incorporated into national legislation as CO_2 emission reduction levels for specific years (e.g., 80% CO_2 emission reduction until 2035). Financial subsidy schemes incentivizing early retrofitting can lead to lock-in effects, not realizing energy savings potential from technological advancements in the long run and potentially failing emission reduction goals. However, early retrofitting leads to CO_2 emission reductions over longer periods, minimizing the combined total CO_2 emissions. Depending on which of these two conflicting goals is pursued, differing subsidy schemes are suitable to incentivize respective retrofits. Knowledge about the effects of these subsidy schemes is relevant to setting correct incentives. We, therefore, investigate the difference in CO_2 emission reductions of time-dependent subsidy schemes per monetary unit invested. We apply an agent-based building stock model for a case study to the German residential building stock using an extensive real-world dataset. Results indicate that prioritizing early retrofits reduces the probability of achieving emission reduction goals while simultaneously minimizing total CO_2 emissions. Total CO_2 emission reductions per monetary unit invested differ up to 675% compared to static subsidy schemes. We conclude that political incentive mechanisms should not be designed to meet the climate goals but instead minimize total CO_2 emissions.
Keywords:	Building stock model; Energetic retrofitting; Energy policy; Machine learning algorithms; Agent-based; Risk