Improving Commercial Property Price Statistics

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TOC

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Improving commercial property price statistics

Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology
by the authority of the Rector Magnificus, prof.dr.ir. T.H.J.J. van der Hagen
chair of the Board for Doctorates
to be defended publicly on
Friday, 25 April 2025 at 15:00 o'clock

by

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Dr. J. de Haan	Delft University of Technology

Adapt what is useful,
reject what is useless,
and add what is specifically your own

Bruce Lee

Preface

I grew up hearing stories about the remarkable man my grandfather was. Every day, he would walk miles to the bus stop to travel to his job as a school principal, showing his deep commitment to education. In fact, a school was later named in his honor (yes, there's an Ishaak school in Surinam!). Sadly, he passed away a year before I was born, so we never had the chance to meet. I've never felt the need to prove myself to anyone in particular, yet here I am, paying a tribute to my grandfather, my 'dada', as I pursue my own educational journey. It's clear that his legacy has influenced me. As I approach the achievement of a PhD, the highest level in education, I hope he would have been proud.

Earning a PhD has been my dream ever since I graduated from Erasmus University 15 years ago. I didn't pursue it immediately because I believed that gaining work experience would make for a more meaningful PhD journey. While I now see many talented PhD candidates without work experience, I don't believe that this applies to everyone. However, I'm certain that the path I chose was the right one for me. My work has contributed to international official statistics, and the knowledge I gained over more than a decade in the field has made this possible.

A wonderful benefit of waiting was that my wife and kids could fully share this PhD journey with me. Rather than the stress often associated with a PhD, these past few years were quite joyful. It's been a time of growth and learning—about writing, methodology, storytelling, personal development and the academic world. I've met so many inspiring and wonderful people along the way, people I've learned from and enjoyed being around.

There are many people to thank for helping me reach this point, and I'll express my gratitude to them on the next pages.

Acknowledgements

Achieving a PhD is mainly seen as a personal achievement. The truth is that many people have contributed along the way. I will try to cover most people below in chronological order.

First, I would like to thank a few (ex) CBS colleagues.

- **Ilanah, Menno** and **Feron** for trusting me with the commercial real estate project 10 years ago. I bet you never imagined it would end up in a PhD study.
- **Thom** and **Jacobiene** for helping me set up the collaboration between CBS and the TU Delft. I really appreciate your effort in this crucial part of the PhD journey.
- **Thomas**, **Roeland** and **Kees** for their assistance in data-analyses. You guys helped me to stay sharp and avoid mistakes.
- **Ron**, **Pim** and **Egbert** for data-analyses, brainstorms and co-authoring articles. You really helped me taking the science to the next level!
- **Äron** for creating the right circumstances to finish the PhD. You prioritized my study, and I think this makes CBS look good as an employer.

Second, I want to express my appreciation to a few TU Delft colleagues.

- **Vincent** for his part in accepting my PhD study. Showing confidence in me in this early stage was obviously crucial for my PhD journey.
- **Ellen** for letting me gain teaching experience. Giving lectures and making exams really makes me feel useful and your guidance really helped.
- **Mohammad** and **Fatemeh** for their companionship during the entire 4 years. As buddies who started at the same time, I learned a lot from your experiences.
- **Rens** and **Jasmine** for letting me help in your Master theses. I hope you realize that I learned a lot from you as well.
- **Monique** for letting me steal time in her conference session. I enjoyed your energetic sessions, and unplanned, you kindly allowed me to present in one.
- **All REM management assistants** and in particular **Karin** and **Joke** for their assistance. Thanks to you, all aspects in completing my PhD went very smoothly.
- Although not a colleague at Delft, I'm thankful to **Peter Liu** from the Cornell University. You motivated me to gain more out of the portfolio sales study.

Third, I'm thankful to the **Tax Authorities**, the **Cadastre**, **W/E advisors** and **CBS** as these organizations allowed me to use their data. In particular I want to thank the following persons.

- **Pieter** for his help in interpreting the data from W/E advisors on sustainability.
- **Matthieu** for his expertise and mediation at the Cadastre.

Last, but certainly not least, I owe many thanks to a few who have been there for me along the entire journey.

- My supervisors, **Hilde**, **Jan** and **Peter**. From the very beginning, your belief in me was a tremendous boost to my confidence. **Peter**, your expertise in the field, as one of the leading authorities on the Dutch housing market, has been invaluable, and I feel truly fortunate to have been guided by you. **Jan**, long before I joined TU Delft, I shared my first thoughts about pursuing a PhD with you and our conversations fueled my enthusiasm. I'm grateful to have had you as a mentor all the way through. Even after your retirement, you continued to support me. **Hilde**, I really want to praise your excellent mentoring skills. Guiding someone who also has a full-time job is likely not easy, but you provided the perfect balance of freedom and support, allowing everything to run smoothly for me. You made my time at TU Delft not only enriching, but also enjoyable!
- My lovely wife **Fabiënne**, my enthusiastic daughter **Faye** and my goofy son **Ryu**. I needed the right circumstances to conduct a PhD study, and you did amazing by providing *excellent* circumstances.

Thanks everyone!

Contents

List of Tables

List of Figures

Abbreviations

ABR	Algemeen Bedrijven Register (General Business Register)
BAG	Basisregistratie Adressen en Gebouwen (Key Register Addresses and Buildings)
BPE	Bankruptcy Proof Entity
BRE	Bankruptcy Remote Entity
BREAAM	Building Research Establishment's Environmental Assessment Method
BRK	Basisregistratie Kadaster (Key Register Cadastre)
CBS	Centraal Bureau voor de Statistiek (Statistics Netherlands)
CPPI	Commercial Property Price Index
CRE	Commercial Real Estate
ECB	European Central Bank
ESRB	European Systemic Risk Board
EU	European Union
FSB	Financial Stability Board
G20	Collaboration of the world's twenty largest economies
GEKS	Gini, Eltetö, Köves and Szulc
HDI	Hedonic double imputation
HMTS	Hedonic Multilateral Time series Splice
HPI	House Price Index
ILO	International Labour Organization
IMF	International Monetary Fund
NSI	National Statistical Institute
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary Least Squares
PEEI	Principal European Economic Indicator
REIT	Real Estate Investment Trust
RTD	Rolling Time Dummy
SPE	Single Purpose Entity
U.S.	United States (of America)
UN	United Nations
VAT	Value Added Taxes
WCED	World Commission on Environment and Development
WOZ	Waardering Onroerende Zaken (Real Estate Valuation)

Summary

In 2008, Lehman Brothers' bankruptcy triggered a global financial crisis, revealing the dangers of real estate price bubbles driven by risky lending practices. Following this crisis, the International Monetary Fund (IMF) emphasized the need to prevent or contain real estate price bubbles and highlighted the necessity of indicators to monitor the real estate market (FSB & IMF, 2022). However, progress at National Statistical Institutes (NSIs) to develop indicators for commercial real estate (CRE) has been slow due to challenges like low observation numbers and high heterogeneity. This dissertation addresses these challenges by providing insights on data issues and improved methodologies. There is a focus on volume, value, and commercial property price indices (CPPIs) as these are essential for financial stability monitoring. Guided by the systems theory (Bertalanffy, 1950), this dissertation consists of five studies, examining the stages of data collection (input) and calculation methods (throughput), which ultimately lead to the construction of indicators (output).

The first study explores the presence of real estate share deals in the Netherlands (*chapter 2*). Share deals, legally viewed as company transfers, can involve Single Purpose Entities (SPEs) created solely to hold real estate. Trading SPEs, could be perceived as real estate transactions, but do not appear in conventional real estate trading registers. Using various Dutch registers, this study estimated the volume, value, and price trends of share deals. While share deals could be included in volume and value indicators, their impact on price indices is limited due to their low weight in the market. Share deal significance varies by country, influenced heavily by native legislation, making general recommendations for official statistics complex.

The second study examines portfolio sales, where groups of properties, like office spaces, retail areas, and industrial facilities, are sold together (*chapter 3*). Analyzing data from the Dutch Land Registry Office, this study investigates the market behavior of portfolio sales and its effect on transaction prices. In line with expectations based on the concepts of imperfect information and information asymmetry (Akerlof, 1970) and Prospect Theory (Kahneman and Tversky, 1979), the findings indicate that portfolio sales typically occur at a discount. Furthermore, the discount relates to the size of the portfolio. The findings also show high portfolio sale activity during price drops. This relationship aligns with the characteristics of a buyers' market. Understanding these dynamics can aid in assessing financial stability and market trends.

The third study demonstrates a processing method for including portfolio sales data in price indices (*chapter 4*). Using Dutch Land Registry data, the study proposes a distribution key to allocate portfolio prices across individual real estate units, creating price imputations. Two sources for imputations were tested: floor area and valuations. The method's effectiveness depends on data quality, which is assessed using model-predicted bootstrapping. This assessment method shows that in the Netherlands, valuations outperform floor area as a distribution key. The study also reveals that CPPIs for portfolio sales captures different price trends from CPPIs for single-property sales, indicating that including portfolio sales in total CPPIs improves market reflection and accuracy in CRE price indices.

The fourth study addresses methodological issues by developing a price index construction method that delivers stable, accurate for small domains like CRE (*chapter 5*). Common price index methods often result in volatile index series and attempts to reduce volatility often lead to frequent revisions of the entire index series, which can undermine user confidence. This study introduces a combination of hedonic imputation, multilateral calculations, time series analysis, and window splicing to achieve stable indices that limit the need for revision and has the ability to detect turning points in an early stage. The developed method was tested with office transactions from the Dutch Land Registry Office. Index performance on several methodological properties, such as identity, time reversibility and circularity were also measured. Findings show that the method balances between these methodological and practical needs. The resulting CPPIs effectively capture price trends and are robust enough for financial stability monitoring, supporting their suitability for official statistics where reliability is essential.

The fifth study explores the impact of sustainability on real estate transaction prices (*chapter 6*). Prior research shows that energy-efficient features can increase property values. This study examines broader sustainability aspects, analyzing data on 10,652 CRE transactions and sustainability scores in the Netherlands from 2012 to 2023. Using regression and hedonic imputation, the findings reveal that, unlike *energy* features, sustainability aspects regarding *environment*, *health*, *user quality* and *future prospects* negatively correlate with prices in lower segments of sustainable real estate but show positive correlations in higher segments. This indicates a nuanced relationship between sustainability and market value, highlighting areas for further exploration. A possible explanation is that green technologies can reduce user costs but can also increase user costs.

To conclude, the inclusion of share deals and portfolio sales were explored, recommending only the latter for CRE indicators in the Netherlands due to data challenges. Methodologically, a new method for price indices was developed. This method uses both index theory and time series analysis, and thereby contributes to the academic consideration on the combination of both. Furthermore, the role of sustainability was studied, which contributes to the academic debate on its relationship with real estate pricing. In practice, this dissertation contributes to the legislative framework that is currently being developed for EU NSIs to publish indicators for commercial real estate.

TOC

Samenvatting

In 2008 leidde het faillissement van de Lehman Brothers de wereldwijde financiële crisis in en maakte de risico's van vastgoedbubbels door risicovolle leningen zichtbaar. Na de crisis benadrukte het Internationaal Monetair Fonds (IMF) de noodzaak om vastgoedbubbels te voorkomen of onder controle te houden en wees op het belang van indicatoren om de vastgoedmarkt te monitoren (FSB & IMF, 2022). Het ontwikkelen van indicatoren voor commercieel vastgoed (CRE) verliep echter traag bij nationale statistische instituten (NSI's), vanwege uitdagingen zoals weinig waarnemingen en grote heterogeniteit. Dit proefschrift richt zich op deze uitdagingen en biedt inzichten in specifieke data-problemen en verbeterde methodologieën voor CRE-indicatoren. Er is een focus op volume-, waarde- en prijsindices voor commercieel vastgoed (CPPI's), omdat die essentieel zijn voor het bewaken van de financiële stabiliteit. Geleid door de systeemtheorie (Bertalanffy, 1950) bestaat dit proefschrift uit vijf studies waarin de stadia van dataverzameling (input) en berekeningsmethoden (verwerking) worden onderzocht.

De eerste studie onderzoekt vastgoedaandelentransacties in Nederland (*hoofdstuk 2*). Aandelentransacties zijn juridisch gezien bedrijfsoverdrachten en kunnen entiteiten bevatten, die enkel het bezit van vastgoed als doel hebben (SPE's). Dit zijn bedrijven die uitsluitend onroerend goed bezitten. De handel in deze SPE's kan als vastgoedhandel worden gezien, maar deze overdrachten verschijnen niet in gangbare vastgoedregisters. Met behulp van diverse Nederlandse registers schat deze studie het volume, de waarde en de prijsontwikkeling van aandelentransacties. Hoewel aandelentransacties in volume- en waarde-indicatoren kunnen worden opgenomen, is hun impact op prijsindices beperkt vanwege het lage marktaandeel. De omvang van aandelentransacties zal variëren per land, omdat het sterk wordt beïnvloed door nationale wetgeving.

De tweede studie onderzoekt portefeuilleverkopen, waarbij groepen panden, zoals kantoren en winkels, samen worden verkocht (*hoofdstuk 3*). Door data van het Kadaster te analyseren, onderzoekt deze studie het marktgedrag van portefeuilleverkopen en de invloed op transactieprijzen. In lijn met concepten als *imperfecte informatie* en *informatieasymmetrie* (Akerlof, 1970) en *prospecttheorie* (Kahneman en Tversky, 1979), laten de resultaten zien dat op portefeuilleverkopen vaak een korting zit. Uit de resultaten blijkt ook een hoge activiteit in portefeuilleverkopen tijdens een neerwaartse prijstrend, wat wijst op een kopersmarkt. Inzicht in deze dynamiek draagt bij aan het beoordelen van de financiële stabiliteit en markttrends.

De derde studie onderzoekt methoden voor het opnemen van portefeuilleverkopen in prijsindices (*hoofdstuk 4*). Met gegevens van het Kadaster is een distributiesleutel ontwikkeld om portefeuilleverkoopprijzen toe te wijzen aan afzonderlijke vastgoedobjecten, waardoor prijsimputaties ontstaan. Twee bronnen voor imputaties zijn getest: vloeroppervlak en taxaties. De datakwaliteit wordt beoordeeld door 'model-predicted bootstrapping'. Deze methode toont aan dat in Nederland taxaties beter presteren dan vloeroppervlak als distributiesleutel. De studie laat ook zien dat CPPI's met portefeuilleverkopen andere prijstrends heeft dan CPPI's met enkele verkopen, wat aantoont dat het opnemen van portefeuilleverkopen in totale CPPI's de marktweergave verbetert.

De vierde studie onderzoekt een prijsindexmethode die stabiele, nauwkeurige indices voor kleine domeinen zoals CRE oplevert (*hoofdstuk 5*). Gangbare prijsindexmethoden resulteren vaak in volatiele reeksen en pogingen om volatiliteit te verminderen leiden vaak tot veelvuldige bijstellingen, wat het vertrouwen van gebruikers kan ondermijnen. Deze studie introduceert een combinatie van hedonische imputatie, multilaterale berekeningen, tijdreeksanalyse en 'window-splicing' om stabiele indices te berekenen met beperkte bijstellingen en vroegtijdig inzicht in kantelpunten. De methode is getest met kantoortransacties van het Kadaster. De prestaties van de index op diverse methodologische eigenschappen, zoals identiteit, tijdomkeerbaarheid en transitiviteit, zijn ook gemeten. Uit de bevindingen blijkt dat de methode een balans vindt tussen methodologische en praktische behoeften. De resulterende CPPI's geven effectief prijstrends weer en zijn robuust genoeg om de financiële stabiliteit mee te monitoren, waardoor ze geschikt zijn voor gebruik in officiële statistieken.

De vijfde studie onderzoekt het effect van duurzaamheid op vastgoedprijzen (*hoofdstuk 6*). Uit eerder onderzoek blijkt dat energie-efficiency de vastgoedwaarde verhoogt. Deze studie onderzoekt bredere duurzaamheidsaspecten door data van 10.652 CRE-transacties en duurzaamheidscores in Nederland tussen 2012 en 2023 te analyseren. Met behulp van regressie en hedonische imputatie laten de resultaten zien dat, in tegenstelling tot *energie-efficiency*, duurzaamheidsaspecten met betrekking tot *milieu*, *gezondheid*, *gebruikerskwaliteit* en *toekomstperspectieven* een negatief effect hebben op prijzen in lagere segmenten en een positief effect hebben in hogere segmenten van duurzaam vastgoed. Duurzaamheid en marktwaarde hebben dus een genuanceerde relatie. Een mogelijke verklaring is dat duurzame technologieën gebruikskosten zowel kunnen verlagen als verhogen.

Concluderend zijn aandelentransacties en portefeuilleverkopen onderzocht, maar wordt alleen de laatste aanbevolen voor opname in CRE-indicatoren vanwege dataproblemen. Daarnaast is een nieuwe methode voor prijsindices ontwikkeld die zowel indextheorie als tijdreeksanalyse gebruikt en daarmee bijdraagt aan de academische discussie over de combinatie van beide. Verder is duurzaamheid bestudeerd, wat bijdraagt aan het academische debat over de relatie met vastgoedprijzen. In de praktijk draagt dit proefschrift bij aan de wetgeving die momenteel wordt ontwikkeld voor NSI's om indicatoren voor CRE te publiceren.

1 Introduction

In September 2008, the United States was shocked when Lehman Brothers filed for bankruptcy. This was the largest bankruptcy in U.S. history at the time and was triggered, among other factors, by the provision of loans to borrowers with poor credit. This easy access to credit caused real estate prices to rise to unsustainable levels, fueling a *real estate price bubble*. In other words, people bought homes and investors bought property they could not actually afford. The fall of Lehman Brothers triggered a domino effect, revealing that real estate price bubbles were globally present. Thus, the real estate market played a crucial role in the emergence of the global financial crisis that followed (Baily et al., 2008; Acharya & Richardson, 2009).

In the following months, most countries witnessed a steep drop in *house prices,* and this was accompanied by substantial financial losses. These losses extended beyond the financial realm, causing significant social and human impacts, including an increase in bankruptcies and job losses. In response to these developments, the International Monetary Fund (IMF) emphasized the need to prevent or contain real estate price bubbles. While the form of such policy is still widely debated, there is consensus on the necessity of indicators to monitor the real estate market. For instance, *price indices* are crucial in detecting real estate price bubbles and are, therefore, considered important indicators (FSB & IMF, 2022).

By 2009, policymakers worldwide recognized that the need for house price indicators was largely met, as most *National Statistical Institutes (NSIs)* published house price indices. However, they also noted that the need for price indicators for other types of real estate, such as offices and retail buildings, was far from being fulfilled. In response, the G20—the collaboration of the world's twenty largest economies—identified the lack of *commercial real estate (CRE) statistics* as a significant data gap (FSB & IMF, 2009). Consequently, NSIs around the world began developing CRE statistics.

Today, in 2024, fifteen years later, few NSIs have succeeded in developing CRE statistics. Having worked as a statistician in this field for over a decade and observed this scarcity of success stories, I was motivated to pursue a PhD. *This dissertation, therefore, aims to address the challenges and explore solutions for the development of CRE statistics.* Ultimately, the goal is to assist statisticians in enhancing CRE price statistics and to accelerate their development at NSIs. This introductory chapter outlines the key challenges and potential solutions.

1.1 Background: challenges in CRE price statistics

The scope of this dissertation is commercial real estate (CRE). When considering CRE, the focus is typically on office and retail buildings, rather than residential real estate. However, CRE can be interpreted in various ways. Therefore, before discussing the challenges encountered in developing CRE price statistics, it is important to define CRE. The definition used in this dissertation is based on Eurostat's (2017) definition for the collection of CRE price statistics.

Commercial real estate means income-producing real estate, including rental housing. Income-producing means income generated by rents or profits from sales. This study focusses on four categories: rental housing, industrial buildings, retail buildings and office buildings.

Within the broad scope of CRE statistics, there is a particular need for on *volume indicators*, *value indicators*, and *price indices*. Volume corresponds to sales or transaction numbers, value to the total value of the volume, and price indices to price fluctuations compared to other periods. These statistics provide policymakers with a solid overview to monitor the *financial stability* of the market.

However, developing such statistics proves to be difficult for two main reasons:

1. Low transaction numbers
2. High degree of heterogeneity

The first reason is illustrated in Figure 1.1, which shows low transaction numbers (and thus few observations) for CRE compared to owner-occupied housing[1]. The comparison to owner-occupied housing is relevant because official statistics are already well-established for this category. The methodology is well-developed and, given the large number of observations, these methods produce reliable results. In the case of CRE, however, the smaller number of observations typically leads to less accurate estimates. Since price indices are inherently estimates, having fewer observations presents a significant challenge. Although volume and value indicators

1 Owner-occupied housing refers to residential properties owned by the individuals who live in them, as opposed to rental housing, where the occupants do not own the property. Commercial real estate includes rental housing but excludes owner-occupied housing.

could be interpreted as ‘simple’ summations and might seem less affected by low transaction numbers, the CRE market has some complexities that make even simple summations challenging. For example, many CRE properties have mixed uses, such as being both office and warehouse spaces. In these cases, straightforward classification is not possible, making simple summation unfeasible. While classifying these properties separately as mixed-use might seem like a solution, it increases the problem of few observations for constructing price indices. Therefore, low transaction numbers remain a challenge in creating accurate CRE price statistics.

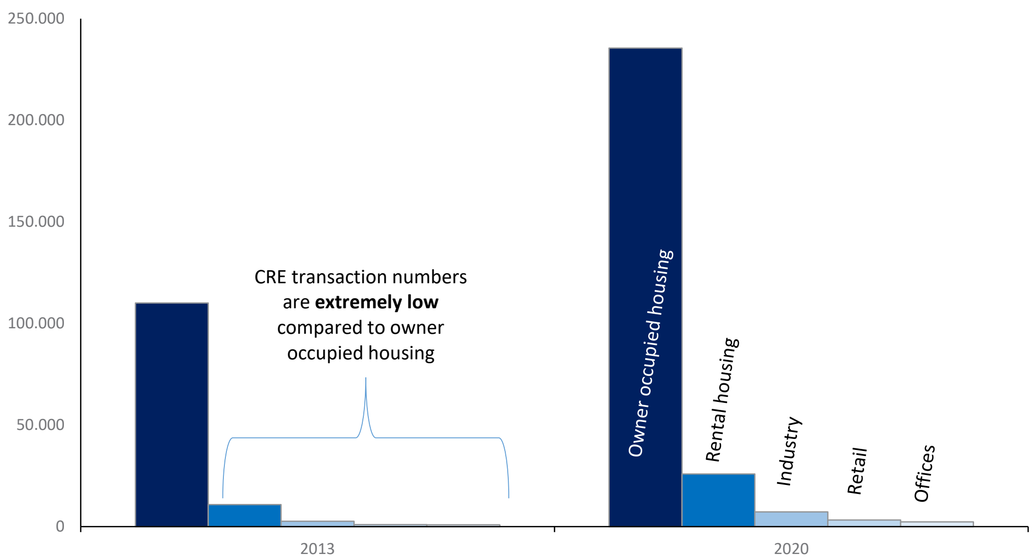

FIG. 1.1 Real estate transaction numbers in the Netherlands. Source: Author’s own creation based on data from CBS and the Land Registry Office (2024).

The second reason for the challenge of constructing CRE price statistics is the high level of heterogeneity in commercial real estate. Real estate already varies significantly in location, height and construction year, but in CRE this heterogeneity, or diversity, is even more pronounced in terms of size and price. For example, some properties may sell for €100,000, while others reach €50 million – a range far broader than that of residential real estate. A similar wide range exists for square meters in CRE. These wide ranges especially cause problems when combined and become diffuse. For instance, in housing, there is a clear relationship between prices and square meters. This relationship exists in CRE as well, but it is less straightforward than in housing. Other factors, such as accessibility via a highway location, maintenance condition, and often intangible aspects, are needed to explain prices more accurately. This heterogeneity is visualized in Figure 1.2 with stylized data, showing that CRE data is more scattered and, therefore, more heterogeneous. This heterogeneity causes price predictions to be less accurate, forming another obstacle in constructing CRE price statistics.

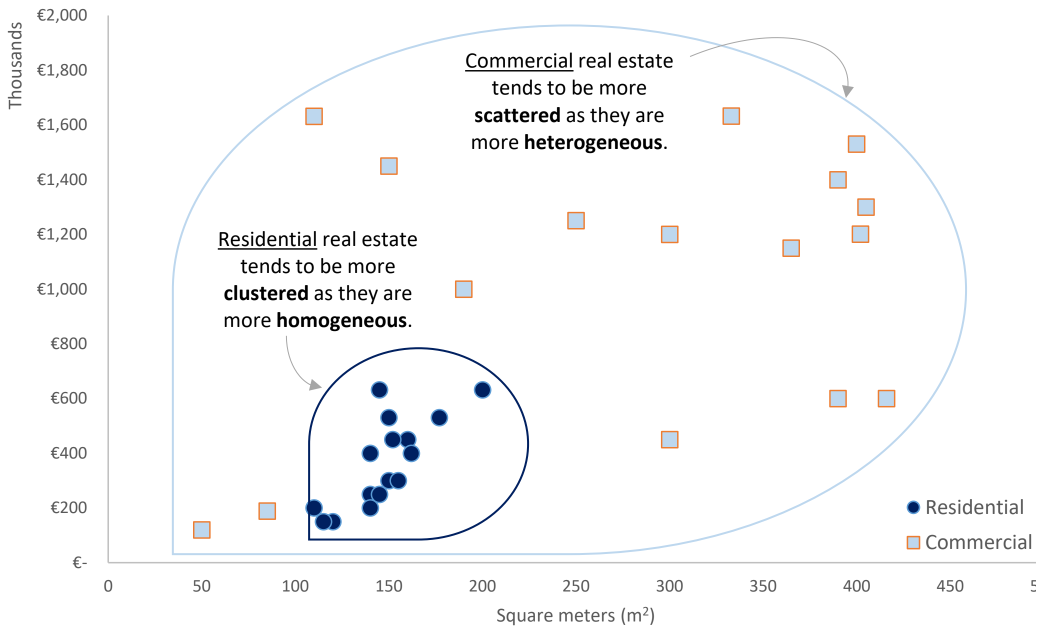

FIG. 1.2 Heterogeneity in real estate. Source: Author’s own creation based on fictional data.

1.2 Research aim: improving CRE price statistics

Constructing accurate CRE price statistics is challenging due to the obstacles discussed in the previous section. A few studies in the literature attempt to address these obstacles, primarily focusing on index methodology (Beekmans & Beckers, 2013; Diewert & Shimizu, 2015; Deschermeier, Voigtländer, & Seipelt, 2014). While this study also examines index methods, it differs by targeting (1) the compilation of indicators in a broader context and (2) the specific requirements for official statistics.

As for the broader perspective, compiling indicators involves not only methodological choices but also handling data issues. As the saying goes: *garage in, garbage out.* The message here is that poor quality input will always lead to poor quality output, regardless of methodological soundness. Therefore, this study also covers data issues in the compilation of statistics.

As for the compilation specifically for official statistics, these figures are typically constructed by fundamental principles (UN, 2014) and refer to independent, published indicators from National Statistical Institutes (NSIs). Ideally, CRE price statistics produced by NSIs should adequately reflect market developments by tracking price changes while controlling for property quality. Additionally, NSIs are required to follow established standards and codes of practice (for EU countries, this is Eurostat, 2017). Meeting these standards presents unique scientific challenges, as price indices must demonstrate stable results, be minimally subject to revisions and enable early detection of market shifts. Solutions from academic literature are only applicable if they address all of these standards simultaneously, but most existing studies focus on addressing just one of these criteria at a time.

So far, academic literature has generally not taken this comprehensive approach: simultaneously addressing both data and methodological issues, nor has it focused on solutions designed specifically for official statistics. This study seeks to fill this knowledge gap by addressing the overarching research question: *what opportunities are there to construct accurate commercial property price indicators for official statistics?* The next paragraph elaborates on this question.

1.3 Research approach: official statistics as a general system

Despite all efforts to remain objective, a researcher's beliefs inevitably influence the outcome of their research. These beliefs form a research paradigm, which is a comprehensive framework guiding the study. A research paradigm typically includes assumptions about the nature of reality (ontology), the nature of knowledge (epistemology), and methods for acquiring knowledge (methodology) (Tubey et al., 2015). In this study, the ontological and epistemological assumptions are overarching, while the methodology varies per chapter or sub-study.

In ontology, there are two contrasting positions: objectivism and constructionism (Antwi & Hamza, 2015). Objectivism assumes an independent reality, while constructionism posits that reality is the product of social processes. This study aligns more with the constructionist view, as commercial real estate statistics are shaped by societal needs. Thus, the challenges in constructing these statistics are seen as constructs rather than independent truths.

Epistemology questions the relationship between the knower and what is known (Krauss, 2005). It presents two contrasting positions: positivism and interpretivism (Antwi & Hamza, 2015). Positivism employs deductive logic and empirical observations, while interpretivism uses inductive logic and focuses more on interpreting observations. This study leans towards positivism due to its data-driven nature. It focuses on official statistics and aims to identify large patterns based on empirical data.

The approach to ultimately answer the overarching research question becomes clear by examining its elements.

1. **Opportunities** for constructing accurate statistics are explored by specifically targeting the main obstacles: low transaction numbers and a high degree of heterogeneity. Understanding these obstacles should also reveal potential opportunities.

2. Within the scope of **commercial property price indicators**, the study focuses on volume, value, and price indices, thus defining the scope of the research.

3 The emphasis is entirely on **official statistics**. The study employs the general systems theory (Bertalanffy, 1950) to model the statistical process, which is divided into three stages: input, throughput, and output. The first step is to retrieve data (input), followed by performing specific calculations on the data (throughput), which eventually leads to the desired indicators (output).

This delineation of the research question is visualized in Figure 1.3.

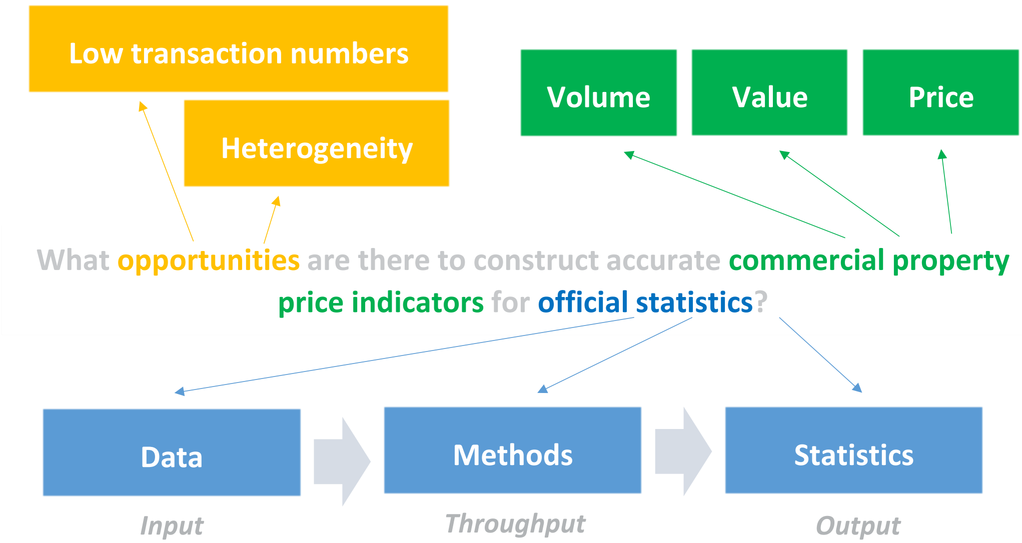

FIG. 1.3 Delineation of the research question. Source: Author's own creation.

1.4 Dissertation outline

Given the delineation presented in the previous section, opportunities for constructing accurate CPPIs (output) can be found in either the data (input) or method (throughput) phase. Furthermore, an opportunity either address the issue of low numbers or heterogeneity or both. This provides the structure of this dissertation and is visualized in Figure 1.4.

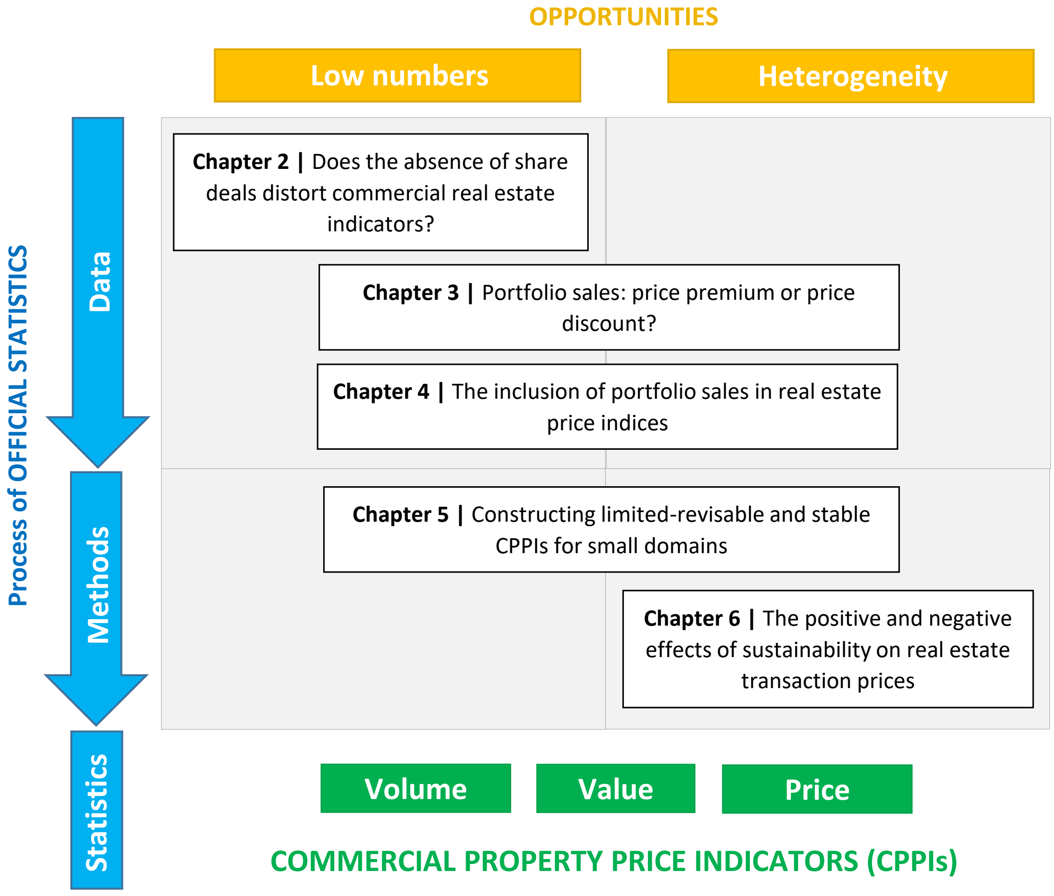

FIG. 1.4 Research framework. Source: Author's own creation.

The three studies in chapters 2-4 focus on the **data phase**.

- **Chapter 2** addresses one issue of low transaction numbers by examining share deals, a type of transaction where a company's main objective is to own real estate. This chapter is published in the *Journal of European Real Estate Research* (Ishaak et al., 2023).

- **Chapter 3** investigates portfolio sales, transactions involving the sale of multiple properties together, which can also lead to low transaction numbers. The importance of portfolio sales is studied here. This chapter is submitted at a peer reviewed journal.

- **Chapter 4** explores multiple opportunities to include portfolio sales in CRE price indicators, which can help reduce heterogeneity. Potential methods are assessed on its usability by discussing the advantages and disadvantages. This chapter is submitted at a peer reviewed journal.

The two studies in chapters 5-6 focus on the **method phase**.

- **Chapter 5** presents a price index method that meets the needs of official statistics. The method, called HMTS, utilizes hedonic modelling, a multilateral approach, time series analyses, and window splicing, addressing both low transaction numbers and heterogeneity. This chapter is published in the *Journal of Official Statistics* (Ishaak et al., 2024).

- **Chapter 6** explores the relationship between sustainability and transaction prices. Sustainability has become a significant aspect of real estate, as it potentially adds value to a building. If this hypothesis holds true, sustainability could be incorporated into hedonic models to manage heterogeneity. This chapter is published in the *Journal of Sustainable Real Estate* (Ishaak & Remøy, 2024).

- **Chapter 7** summarizes the conclusions of the main chapters, discusses issues raised by these conclusions, and reflects on their implications.

2 Share deals and commercial property price statistics

The previous chapter introduced the need for official commercial property price statistics. This need is not yet met, because commercial real estate faces specific challenges of low observations numbers and heterogeneity in real estate. These challenges can be addressed in either the data (input) or method (throughput) phase of making official statistics.

This chapter addresses the issue of low observation numbers in the data phase. A specific real estate trade construction is studied, namely share deals. Share deals are actually, in legal terms, company transfers. These trades are typically omitted in commercial property price statistics. In this study, the effect of omitting share deals in commercial real estate statistics is estimated.

2.1 Introduction

In 2009 the G20 identified the lack of commercial real estate (CRE) indicators, such as volume, value and price developments, as a data gap, which led to global actions at statistical agencies to address this gap (FSB & IMF, 2009). In particular, the banking sector is highly interested in using these indicators as a tool to monitor and facilitate financial stability and macroeconomic developments (Eurostat, 2017; BIS, 2020). Compiling CRE indicators, however, appears to be difficult and much more complex than compiling similar indicators for residential property. One of the most commonly mentioned reasons that complicate the realization of CRE indicators is a small number of observations (Eurostat, 2017). There could be several reasons for this. An obvious one is that there is less commercial real estate to transact than there is residential real estate (for which small numbers are usually not an issue).[2] However, there could be another cause as well: real estate can be traded in a way that prevents the transaction to enter official real estate transaction registrations (such as the Land Registry Office). This can be achieved by accommodating real estate into a separate company that is specifically established to legally own the real estate. After that, shares of the company can be traded instead of the real estate itself (Ter Braak & Bol, 2007; Alickovic & Brauweiler, 2020).

In official real estate price statistics, it is common to consider only actual asset deals as real estate transactions (Statistics Denmark, 2021; CBS, 2024b). These are, for instance, transfers of real estate ownership as recorded by Land Registry Offices or documented real estate sales in purchase agreements by real estate agents. In case of asset deals, transfers refer to a reallocation of legal ownership of a real estate property. While an asset deal is one way to trade real estate, trading shares of a company that solely owns real estate can be perceived as an alternative method. The latter is referred to as a share deal and the company that owns the real estate is referred to as a Single Purpose Entity (SPE). In case of a share deal of an SPE, there is no shift of legal ownership of the property. The SPE legally owns the property, both before and after a transfer of shares. The economic ownership, however, is transferred from one shareholder to another.

2 Over 87% of the real estate stock in the Netherlands is residential property (CBS, 2021a) and 57% of all residential property in the Netherlands is owner occupied (CBS, 2021b). This fact, combined with research findings that the moving of households (and thus sales of residential property) strongly relates to a family life cycle (McAuley & Nutty, 1982), supports the belief that owner occupied residential property is transacted more than commercial property (as a family life cycle is absent or at least very different for companies).

Given that asset deals and share deals seem interchangeable, there is a surprising lack of research focusing on the contribution of share deals to commercial property price indicators.

The aim of this research is to provide more insight in share deals and their importance. Previous research has mainly focused on the legal aspects of real estate SPEs. Motives for establishing SPEs are a well discussed topic (Kurtz & Kopp, 1969; Bertane, 1975; Stogel & Jones, 1976; Sewell, 2006) as well as how to use it in a transaction (Seligman, 2005; Alickovic & Brauweiler, 2020). However, it is not yet clear what the effect is of real estate share deals on CRE indicators. The concern here is that the absence of share deals may cause sample selection bias in CRE indicators, resulting in statistics that do not accurately reflect market developments.

This research addresses the following question: To what extent does the absence of share deals distort commercial real estate statistics? Three indicators for share deals are constructed and compared with the asset deal counterparts to assess its impact on CRE statistics. These indicators are: (1) transactions volumes (numbers of share deals and transacted real estate properties), (2) transaction values (total value of share deals and transacted real estate) and (3) price developments (changes in real estate prices).

This research contributes to the discussion on defining and further demarcating real estate share deals. What may be considered as real estate share deals in statistics, is discussed in Section 2.2. The data and methodology description (Section 2.3) may be beneficial to statisticians who aim to create similar indicators for share deals in other countries than the Netherlands. The findings (Section 2.4) will contribute to the assessment on the importance of including share deals in real estate statistics or not. A discussion is presented in Section 2.5 on how we could perceive and handle share deals, which leads to the conclusions in Section 2.6.

2.2 Background

2.2.1 Defining share deals in commercial real estate SPEs

Decomposing 'share deals in SPEs that hold commercial real estate' leads to a search for definitions regarding 'share deals', 'SPEs' and 'commercial real estate'. The most relevant literature findings are summarized below.

In the literature, various definitions of an SPE can be found. All of these definitions share the essence that an SPE refers to a legal entity that is specifically created to satisfy a specific purpose. In the case of this study, the purpose is owning real estate. The terms that accompany the definition above come in a variety. Commonly used terms are 'Single Purpose Entity', 'Special Purpose Entity', 'Single Asset Entity' and 'Special Purpose Vehicle' (Seligman & Stein, 2004). These terms are interchangeable in the context of the definition above. Terms that are also used to describe similar constructions are 'Straw corporations' and 'Nominee corporations' (Tanenbaum, 1963; Kurtz & Kopp, 1969; Bertane, 1975; Stogel & Jones, 1976). Both these terms refer to entities that legally own property and by itself are beneficially owned by a parent company. Straw or nominee corporations could be SPEs, but do not necessarily have to be. The terms are typically used in the context of a way to circumvent property transfer tax, it is likely that straw corporations may also hold a second purpose to conceal the first purpose (and thus do not have to be SPEs).

Terms that are also common are 'Bankruptcy Remote Entity (BRE)' or the more extreme 'Bankruptcy Proof Entity (BPE)' (Seligman & Stein, 2004; Sewell, 2006). These terms refer to specific forms of an SPE. BREs or BPEs are always SPEs, but added legal specifications make them more resistant to bankruptcy. In this research, an SPE (Single Purpose Entity) is defined as a legal entity that is specifically created to own real estate.

Alickovic and Brauweiler (2020, p. 233) provide a clear definition for a share deal: "A share contains the purchase of all company shares or the purchase of a certain rate of shares which empowers the buyer to exercise control over the company. Thereby all rights and obligations and with that, all assets and liabilities were transmitted to the buyer." Combining this definition with the above-mentioned SPE definition implies that a share deal is an indirect way of transferring real estate (or 'assets' as referred to in the share deal definition).

Other terms that require further explanation are 'commercial property' and 'commercial real estate'. First of all, these two are used interchangeably from now on. Second, the term is interpretable in multiple ways. In this research, the definition provided by the ESRB (2019) is used, which states that every type of real estate that is not owner occupied for residential purposes is considered as CRE. Coarsely, commercial real estate refers to property that is owned by companies (and therefore includes rental housing). The focus in this research is on SPEs as owners of real estate. As SPEs are organizations and not private households, the real estate owned by SPEs is by definition 'commercial' real estate. Furthermore, in this research the main focus is on offices, industrial buildings, rental dwellings and retail buildings, since these are the most common categories for commercial property (Eurostat, 2017; CBS, 2024b). Indicators are also made for all other non-residential real estate in Section 2.4 (in a bundled category 'other buildings').

Combining these definitions provides the following definition: a share deal in a real estate SPE refers to a transaction of company shares in a legal entity that is specifically created to own real estate. This definition is used in this study.

2.2.2 Motives for choosing share or asset deals

There are many arguments for an investor that could be decisive in choosing an asset deal or a share deal to transfer the economic ownership of real estate. The choice of a suitable construction depends on the specific circumstances like the applicable regulations, the value of the real estate (portfolio), the number of buyers/sellers and the current organization structure. The most decisive reasons in choosing a transfer construction are most likely legally and financially driven.

From a legal perspective, there are clear advantages for companies to put the ownership of real estate at distance in a separate entity. In the management of real estate (not in transferring) SPEs are formed to reallocate liabilities (Bridson & Flammier, 2013). The reason is that declining performances of one of the organization entities does not harm the other(s) and therefore SPE structures create obstacles in the path towards bankruptcy. This also causes real estate investments to be more attractive to commercial lenders (Sewell, 2006). Accommodating real estate in an SPE is a very common structure in asset management. In transacting real estate however, selling shares instead of assets may have some negative aspects. Ter Braak and Bol (2007, p. 180) point out that purchasing an SPE implies for instance purchasing liabilities that are not related to the real estate, such as employment contracts, levies and fines. In this regard, all documentation that is required for the transaction will be more complex, especially when a due diligence is conducted (Alickovic & Brauweiler, 2020).[3] They, however, add that in case of large real estate portfolio transfers, the documentation could actually be simpler. This is also supported by Alickovic and Brauweiler (2020, p. 233) who state that the advantage of a share deal is that "the assets don't have to transferred one by one, but rather in one transaction."

From a financial perspective, buying an SPE could be very beneficial (Tanenbaum, 1963; Ter Braak & Bol, 2007). This, however, depends on the specific tax regulations and other legislations regarding real estate investment activities (Seligman & Stein, 2004). A transfer of legal ownership of real estate is typically accompanied with property transfer tax. When the ownership of a company changes (share deal) instead of the asset itself (asset deal), other rules regarding the application of property transfer tax and other taxes may apply. Corporation tax, sales tax and income tax are examples of other possible applicable taxes (Ter Braak & Bol, 2007). In case of share deals, it is not always clear if the intention of both parties was to economically transfer real estate. Whether transfer tax applies in situations depends on the applicable legislation and the specifics of the deal. In the Netherlands for instance, transfer tax does apply to SPE transactions once a couple of conditions are met (Staatsblad van het Koninkrijk der Nederlanden, 1995). One of the conditions is a minimum percentage of the value of the SPE that should relate to real estate. Given the strong dependence on applicable legislation, and differences in legislation between countries, this is likely to cause incoherence between the frequencies of share-based deals among countries. A relaxation of tax regulations on share deals may cause investors to choose an SPE transaction more frequently. The Polish example illustrates this. Asset deals are in Poland subject to Value Added Tax (VAT). The payed VAT (by the buyer) is recoverable once a few conditions are met. In 2016, the recoverability was limited due to an upgrade of the conditions (Accace, 2017). Since the VAT only applies to asset deals, this caused – according to Toczyska (Budai & Toczyska, 2022) – a drop in asset deals and a rise in share deals. This shows that in case of changes in regulations, a decline in transaction numbers of asset deals does not necessarily reflect market developments as it could be compensated by an increase in share deals.

3 A due diligence is a form of document research aimed to assist the management in justifying an acquisition by verifying and analysing data (Spedding, 2009).

2.2.3 Constructions of SPE share deals

In an asset deal (top of Figure 2.1), the ownership of a property is not only economically transferred, but also legally. Asset deals are usually processed by a notary and subsequently by a Land Registry Office. Asset deals are typically input in the construction of Commercial Property Price Indices (CPPIs) (e.g. CPPIs of the Bank of Portugal (Raposo & Evangelista, 2016) and Statistics Netherlands (CBS, 2024b)).

A share deal in its simplest form (Figure 2.1, part 2) is one where the SPE (company X) is the legal owner of (a portfolio of) real estate. In this situation, company X has the role of a subsidiary of company A. Company A is, as a parent company, the legal owner of company X and therefore the beneficial owner of the property. In the transfer scenario, where A intends to sell real estate to B, it will not (and is legally not able to) sell the legal ownership of the real estate, but it will transfer the legal ownership of company X to company B. Since this concerns a company transfer, the transfer applies to the shares of company X.

Another example is a construction where there are multiple layers of entities between parent company A and child company X (Figure 2.1, part 3). Here, again, company A has the intention to economically transfer the property to company B. This is realized by transferring the shares of company Z, which is still three layers away of legally owning the property itself. Even though the provided example is hypothetical, the sketched organizational structure seems to be common throughout the world and is often referred to as a pyramid construction or a business group (Claessens et al., 2000; Khanna & Yafeh, 2007, Fan et al., 2013). Business groups are formed for a variety of reasons. These are, among which, exploiting scale benefits and taking advantage of established brands. Regarding the latter reason, groups can enter new businesses by expanding the pyramid while relying on the reputation of the group (Khanna & Palepu, 1997).

Another more complex SPE transaction is a so-called Real Estate Investment Trust (REIT). A REIT is a company that owns, operates or finances income-producing real estate. It’s “a pass-through entity that distributes most of its earnings and capital gains” (Geltner et al., 2007, p. 586). The REIT allows multiple investors to buy and sell shares in the company and earn from profits due to value increases of the owned real estate. A simplified construction is illustrated in the bottom of Figure 2.1. The main takeaway is that there are no longer only two beneficial companies. In fact, there could be dozens of shareholders, each owning a part of the shares and therefore able to sell only a part of the SPE and underlying property.

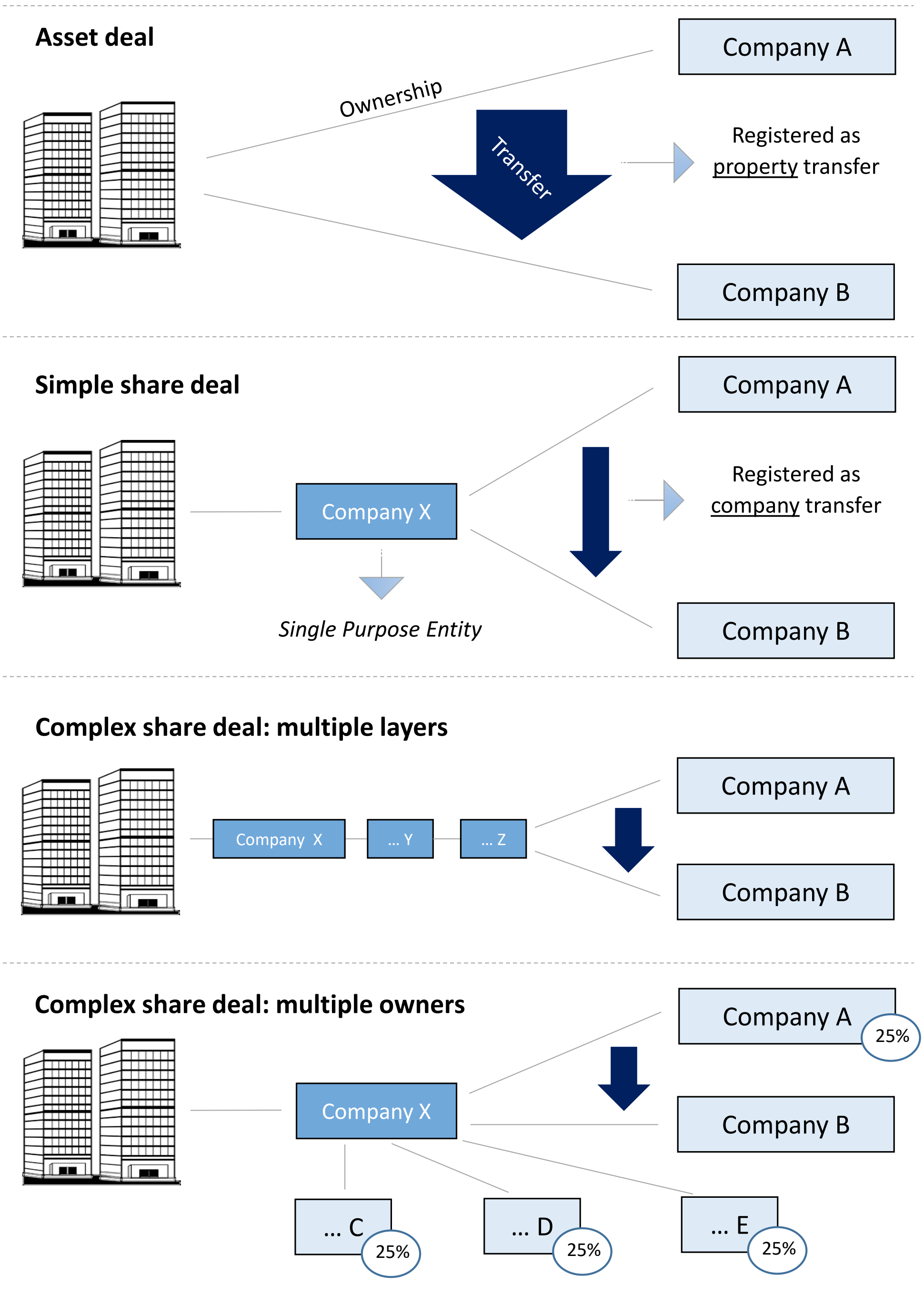

FIG. 2.1 Illustrations of asset and share deals. Source: Author's own creation.

Figure 2.1 shows the many forms in which share deals exist, from simple to very complex. The complexity level affects the data collection: the simpler an SPE construction is, the more likely it is that it is properly registered. The more complex an SPE construction is, the more likely it is that a registration is ambiguous, scattered among multiple registrations or not registered at all. Some studies have specifically focused on these complex SPE forms and gathered REIT information from private data sources (Horrigan et al., 2009; Morri & Jostov, 2018; Çelik & Arslanli, 2021. In this study, the focus is on official real estate indicators and therefore only official data sources were used. A consequence is that complex SPE constructions are excluded. This is further elucidated in Section 2.3.

2.3 Data and methodology

To gain more insight into the market of real estate SPE share deals, extensive data research was conducted in the Netherlands. The process contains collecting, cleaning and filtering data in such a way that it results in usable data to create the three indicators: transaction numbers (volume), total transactions values and price developments. Indicators for asset and share deals are constructed by using the same methods and data sources.

2.3.1 Data collection

The research is conducted with data on share deals by Dutch investors and real estate that is located in the Netherlands. Multiple datasets of official authorities were collected to identify SPE share deals.[4] An overview of these sources and its key information for this study is provided in Table 2.1.

4 In the Netherlands, there are a few key registers or base registers. The government has officially instated these registers as mandatory data registration sources for public institutions (Digital Government, 2021).

TABLE 2.1 Overview of used data sources. Source: Author's own creation.

Source owner	Dataset	Key information	
		Share deals	Asset deals
Statistics Netherlands	General Business Register (ABR)	Company share transfers Number of employees Percentage of real estate on balance sheet	
Tax authorities	Property Transfer Tax	Tax paying companies	
Land Registry Office	Key Register Cadastre (BRK)	Real estate owned by companies	Real estate transactions
Municipalities	Key Register Addresses and Buildings (BAG)	Property types	Property types
Municipalities	Key Register 'Waardebepaling Onroerende Zaken' (WOZ)	Official valuations (WOZ)	Official valuations (WOZ)

After linking and filtering of above data sources, a dataset was created that includes a selection of real estate share deal and asset deal transactions. An overview of the resulting coverage is provided in Table 2.2.

TABLE 2.2 Coverage of resulting dataset. Source: Author's own creation.

Included	Excluded
Transactions between 2016-2020	
Transactions involving only Dutch investors	Transactions involving at least 1 international investor
More simple share deals (Figure 2.1, part 2)	More complex share deals (Figure 2.1, parts 3-4)
All real estate in the Netherlands	
All property types as registered in the BAG	
Property sold within portfolio sales	
Existing real estate	Newly built real estate
Valuations	Transaction prices

Transaction prices of real estate in share deals are not available (in official registers). Therefore, as shown in table 2.1, valuations by the Dutch municipalities were used to value the real estate in share deals. Moreover, if transaction price data would be available, using it would be troublesome as share deal prices may not only apply to real estate, but to other aspects of a company transfer as well. In case of share deals, therefore, transaction prices seem unreliable beforehand. To bypass this, official valuation data is used to estimate the value of objects. These official valuations (WOZ) cover 100% of real estate in the Netherlands and are annually updated. It is known that valuations in general and WOZ valuations in particular are not always accurate representations of transaction prices. Lubberink, Van der Post & Veuger (2018) for instance, concluded that WOZ values are not always reliable market value indicators. Yet, they see consistent patterns in market valuations biases. For instance, offices in less promising locations are generally valued higher than the realized transaction price. Furthermore, WOZ valuations are not 100% market valuations, but market value approximations under special assumptions. Unlike an actual transaction price, the WOZ value is not the result of price negotiations and is, therefore, merely an approximation. To hold these biases in prices constant between asset and share deals, WOZ valuations are in the current study used as price estimations for both asset and share deals. If there is a bias, it will occur on both sides of the comparison, and this will limit the effect on the outcomes.

2.3.2 Data strategy

The aim is to assess the effect of share deals by compiling three indicators: sales numbers, total sales values and price developments. Compiling these indicators requires a process of linking data and applying filters. This is visualized in Figure 2.2.

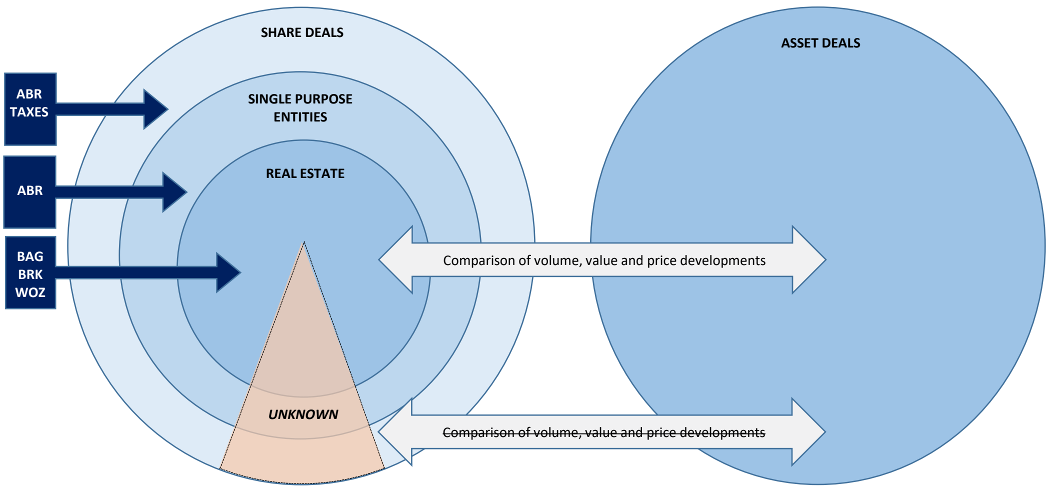

FIG. 2.2 Demarcation of CRE share deals in SPEs. Source: Author's own creation.

First, the selection of share deals in companies is made in the General Business Register (ABR) and the property transfer tax data. In the ABR, the shares of companies in other companies were compared between consecutive periods to detect a transfer of shares (indicating a share deal). Complementary, companies that paid tax were derived from the property transfer tax data. In the latter source, the assumption was made that the share deal refers to all companies that the taxpayer owns (due to data deficiencies). However, the share may be only applicable to a selection of companies. The possible consequence of this is an overestimation of selected share deals. This potential overestimation is further elucidated and visualized in Section 4.1.

Second, an indication was made whether the deals can be seen as an economic transfer of only real estate. After all, many share deals occur without the intention to trade real estate (company takeovers, merges, intracompany reallocations and so on). In other words, it was determined whether the company, whose shares were traded, functions as a single purpose entity for owning real estate. From the ABR, three filters were applied to indicate SPEs: (1) an SPE has a maximum of two employees in the organization, (2) an SPE has a minimum of 30% of real estate on the balance sheet and (3) the owning company has a minimum of 33% of shares in the SPE. Multiple filter parameters - very strict to very loose versions - were tested, but the alternative results did not lead to different research conclusions. The last two filters were chosen in accordance with the law on property transfer taxes, in which the same limits are applied (Staatsblad van het Koninkrijk der Nederlanden, 1995).

Third, it was retrieved for SPEs whether and which real estate it legally owns (as registered in the BRK: Key Register Cadastre). In legal transfers is it very common to see multiple real estate properties to be part of a single transfer (Seymour & Akers, 2019; CBS, 2024b). A company can own multiple real estate properties and therefore a single share deal can involve more than one real estate property (presented in Section 4.4). Given this one-to-many relationship between transactions and sold properties, a comparison between numbers of sold properties is more useful than a comparison between numbers of transactions. In this step, there is therefore a switch in unit of measurement from transactions to transacted real estate properties. Furthermore, in this step, the property type of real estate is retrieved from the Key Register Addresses and Buildings (BAG) and the valuations are added from the WOZ data. A drawback of valuation prices is that they typically lag market prices (Shimizu et al., 2012), which is also the case in the Netherlands (Waarderingskamer, 2020). In this study, valuations are used to assign a value to property in both types of deals. As such, indicators for asset and share deals are comparable.

The part in Figure 2.2 containing ‘unknown’ is a visualization of the data limitations. These cases are omitted from the comparison and most likely lead to an underestimation of the counted real estate in share deals.

2.3.3 Calculating price developments

Once the selection of share deals has been made and the appraisal values have been assigned, the price indices – or actually, valuation indices – were calculated. The downside of working with appraisals as approximation for prices in pricing developments is that the appraisals could be influenced by transaction prices of comparable buildings. Asset deal transactions could, therefore, influence share deal appraisals and the other way around. The use of appraisals is therefore unlikely to provide insight in the contribution of share deals on price indices. Yet, appraisal-based price indices may provide insight in the differences between share and asset deals. If share deals and asset deals are primarily found in different market segments, their (appraisal-based) price developments may also differ.

The upside of working with official valuation data is that for most real estate properties there are appraisals for every year throughout a longer period. An index can, therefore, simply be constructed by calculating ratios of paired appraisals. In this research, the ratios are aggregated by calculating the arithmetic mean as shown in equation (2.1). This equation resembles a Carli index as described by Van der Grient and De Haan (2008). For a price index, a geometric mean (Jevons index) is actually preferred. In the analyses, however, comparisons are made the require arithmetic averages (T-tests). Therefore, the Carli index is used in this study.

$$I^{t+1,t-1} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{A_i^{t+1}}{A_i^{t-1}}\right) \qquad (2.1)$$

In this formula, I denotes the price change between period $t+1$ and $t-1$. A denotes the appraisal value of property i and n equals the number of observations.

Besides the index method, data choices regarding the reference moment of the appraisals are also essential. Appraisals are assumed to be estimates of actual selling prices. One difference between the two is the moment of activity. The transaction date could be anytime during a year. The valuations are always set at the beginning of the year (1st of January). By definition, the appraisal is from before or after, but never on the actual transaction date.[5] Where this may be a downside in considering appraisals as an estimate, in this case it is an advantage. In pairing appraisals of period $t-1$ and $t+1$, the periods adjacent to the transaction date (period t) are chosen. This is illustrated in Figure 2.3. By doing this, the price development of the selling price compared to the previous year is estimated. This is possible because the valuations are updated every year by municipalities (Waarderingskamer, 2022).

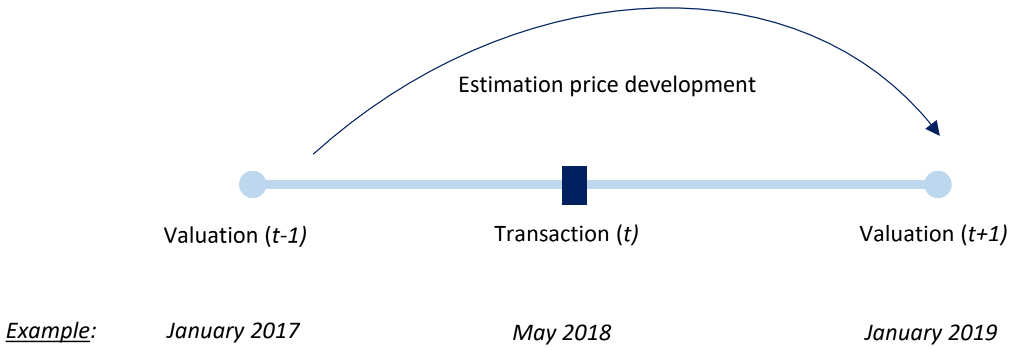

FIG. 2.3 Time span for choosing valuation pairs. Source: Author's own creation.

The final step is to repeat the process for asset deals. The process for asset deals is, however, more straightforward. The selection of asset deals, prepared by the Land Registry Office and Statistics Netherlands, is used as a starting point. The BAG is linked to obtain more real estate information (classification into property types), and the WOZ is linked to obtain comparable values. After that, equation (2.1) is used to construct similar indicators (based on appraisals) for asset deals.

5 An exception would be if a transaction occurred on January 1st. In the Netherlands, this is impossible since January 1st is a national holiday. Notaries do not record transactions on this day.

2.4 Findings

2.4.1 Investors, SPEs and involved real estate

In the data, there are 493 distinctive buyers of SPEs (many buyers purchased SPEs more than once). These buyers are categorized by number of employees (indicating the size of the company) in Table 2.3. The results show that SPEs are not only utilized by larger companies. In fact, there are many owners of SPEs with zero employees. This is an indication of an SPE-construction illustrated in Figure 2.1 (part 4), where there are multiple layers of SPEs. At the end of the chain of ownership, there might be larger companies, but this cannot be derived from the data. A closer analysis, however, does show that companies with zero employees generally own larger SPEs. In the data, there are 1,566 distinctive SPEs (many SPEs were sold more than once). On the right side of table 2.3 these SPEs are categorized by number of properties owned (indicating the size of the SPE). The results show that while most SPEs hold a limited number of properties (ten or less), there are also very large SPEs containing more than 1,000 properties.

TABLE 2.3 Size of SPE investors and size of SPEs in the Netherlands. Source: Author's own creation.

Number of employees (categorized)	Number of SPE investors	Number of properties (categorized)	Number of SPEs
0	245	1	542
1-10	178	1-10	669
11-100	27	11-100	279
101-1,000	14	101-1,000	69
>1,000	29	>1,000	7
Total	**493**	**Total**	**1,566**

Within the data there is a certain degree of uncertainty. When the buyer of an SPE already possesses other SPEs, the data does not allow us to determine whether the acquisition applies to all of these SPEs, or to a few or just one. Figure 2.4 illustrates the degree of uncertainty caused by this data limitation. Around 12% meets the minimum value of SPEs. This percentage refers to the very minimum where only one SPE is transacted in all transactions, which is also the least valuable SPE within the owner's portfolio. The minimum has a deliberate strict setting to show the potential uncertainty in data regarding share deals opposed to the straightforward registration of asset deals. This illustrates the ambiguity in share deal registrations. Around 88% meets the maximum value of SPEs. In this scenario, the transactions include all possible SPEs within owner's portfolios.[6] A part of these SPEs were not part of the share deal transactions. This part could not be determined and creates uncertainty in the output. In the remainder of the findings, the uncertain observations are included in the indicators for share deals, because manual inspection of multiple random cases indicates that the minimum is too strict (but could not be determined with certainty). Besides, a larger issue is an anticipated underestimation due to data loss (after linking multiple data sources) and limitations of the data sources (described in Section 2.3.1).

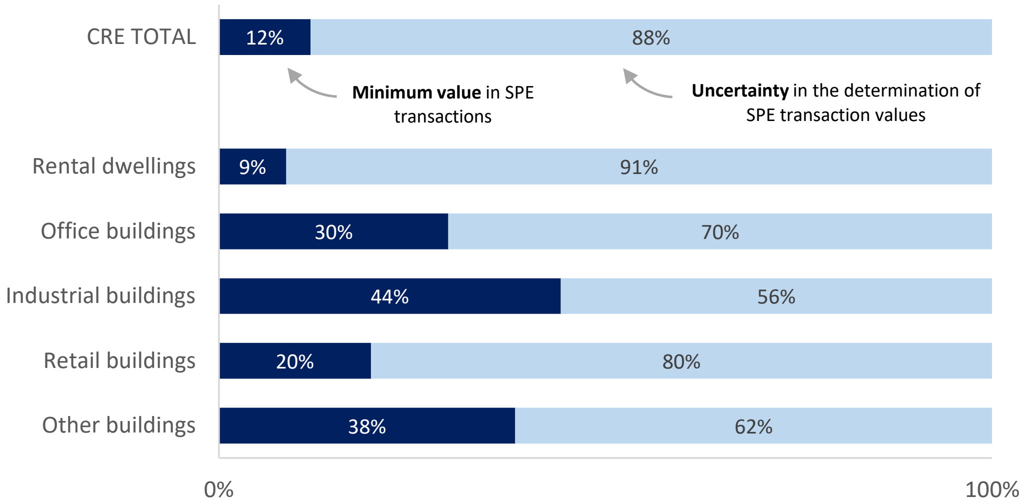

FIG. 2.4 Uncertainty in determining the real estate value in share deal transactions in the Netherlands. Source: Author's own creation.

6 Other buildings refer to all unmentioned property types. This includes the following usage types that are typified within the BAG: *Meeting*, *Healthcare*, *Cell*, *Accommodation*, *Sports*, *Education* and *Other*.

2.4.2 Volume and value indicators

To assess whether share deals form a significant part of the real estate trading market, volume and value indicators were calculated. These figures are added to the asset deal volumes and values. The resulting contribution of share deals in the market (in %) is presented in Figure 2.5. Volume figures are distinguished in number of deals and number of real estate properties. In number of deals, numbers of SPE transfers were counted (regardless of the size of the SPEs). In number of real estate properties, the total number of real estate properties in SPEs transfers were counted.[7] The total value of all deals is equal to the total value of all SPE transfers as well as the total value of all real estate properties.

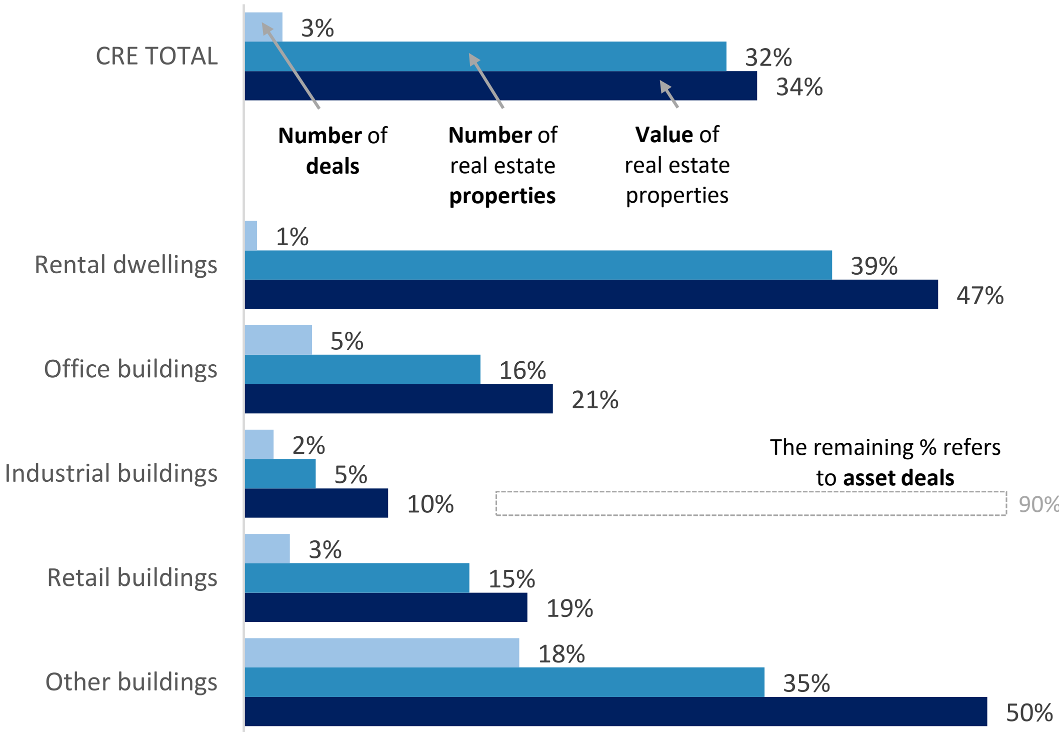

FIG. 2.5 Contribution of share deals in the total Dutch market, period 2016-2020. Source: Author's own creation.

7 The unit of measurement of real estate, for both asset and share deals, is a single occupational unit as defined in the BAG.

Figure 2.5 shows that overall, the value of SPE share deals accounts for 34%. From Figure 2.5, it also becomes clear that buildings, other than rental dwellings, industrial, office and retail buildings, are most popular in share deal trading. This high percentage of 50% is caused by a specific group within the category, namely for those buildings with an accommodation function. The official definition for this accommodation function is 'providing accommodation or temporarily shelter to persons' (Staatsblad van het Koninkrijk der Nederlanden, 2021). In practice, this category involves hotels and resorts. While share deals in rental dwellings appear to be less common, in traded properties and in total value these are quite common too. The contribution of SPE share deals in the market are lower in number of properties than in values. This finding is consistent over all property types and indicates a higher average property value for share deals than for asset deals. After checking all average prices per year and per property type, this turns out to be consistently the case: real estate properties that are sold through SPE share deals are on average more valuable than real estate property that are sold through asset deals. Figure 2.6 shows that real estate in share deals is on average valued higher than real estate in asset deals.

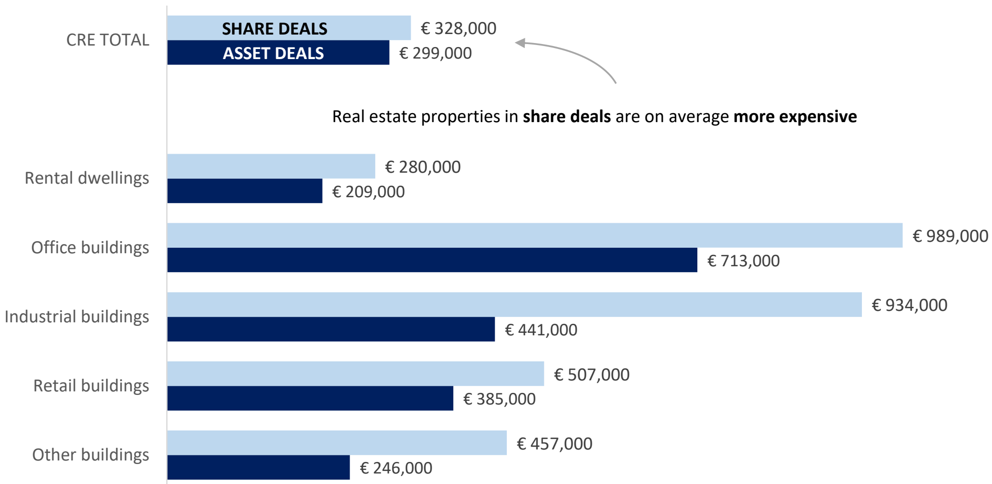

FIG. 2.6 Average value of share deal properties vs. asset deal properties in the Netherlands, period 2016-2020. Source: Author's own creation.

This image does not change when the average values are broken down into more periods.[8] Based on this finding, one might say that share deals tend to be focused on properties that are more expensive. This suspicion is confirmed as the lower and higher quartiles of share deal prices is consistently higher compared to the same quartiles of asset deals. A possible explanation is that share deal investors tend to lean more towards low risk and more secure investments, which is more often found in the higher segment of the market. A clarification may also be found by looking at different investment strategies. Geltner et al. (2007, p. 125) distinguish the ‘growth objective’ and the ‘income objective’. Others also refer to these strategies as the buy-and-hold strategy (Hui et al., 2014) and the buy-and-sell strategy (Brown, 1996). The growth objective or the buy-and-hold strategy implies holding real estate for a longer period. The investment does generate income (while holding), but there is no fixation on making profit in the short term. It aims at a long-term value increase and a direct return on investment over a long period. The income objective or buy-and-sell strategy, on the other hand, is aimed at making profit in the short term through buying, adapting and selling real estate for a higher price. A link between above strategies and another research provides a possible explanation for the higher valued properties in share deals. The research of Lim, Berry and Sieraki (2013) shows that the lower segment of the CRE market displays greater volatility compared to the higher segment when it comes to investment returns. Ergo, an explanation that is in line with the figures is that share deal investors lean more towards the growth objective and asset deal investors lean more towards the income objective. This is also plausible since share deals involve more administrative hassle (such as due diligence) and are less attractive for a quick buy and sell.

2.4.3 Analysis of price developments

To assess whether the absence of share deals distorts price indices, price developments were estimated for share and asset deals. The aim is to investigate whether share and asset deals represent different groups in the population of real estate transactions. If share deals are primarily found in a different segment from asset deals, the price developments may also differ. The absence of share deals in commercial property price indices may, therefore, distort commercial real estate indicators. Figure 2.7 shows estimations of price developments for rental dwellings, industrial buildings, offices and retail buildings for the years 2016, 2017 and 2018.

8 An independent samples T-test confirms that the average value of share deal properties is significantly different (and higher) from the asset deal counterpart.

The estimated price developments are valuation developments for specific selections of real estate sold as share deal or asset deal. Figure 2.7 also contains robustness indicators. For each development, 95% confidence intervals are presented. These intervals are calculated according to the bootstrap method as described by Efron and Tibshirani (1994). In essence, the intervals are obtained by simulating variations, using the variability in the data. The developments are calculated 500 times, and, in each calculation, the original input is altered by sampling with replacement until the original sample size is reached. Furthermore, T-tests were performed on each comparison between share deal and asset deal developments to assess whether the differences are significant.

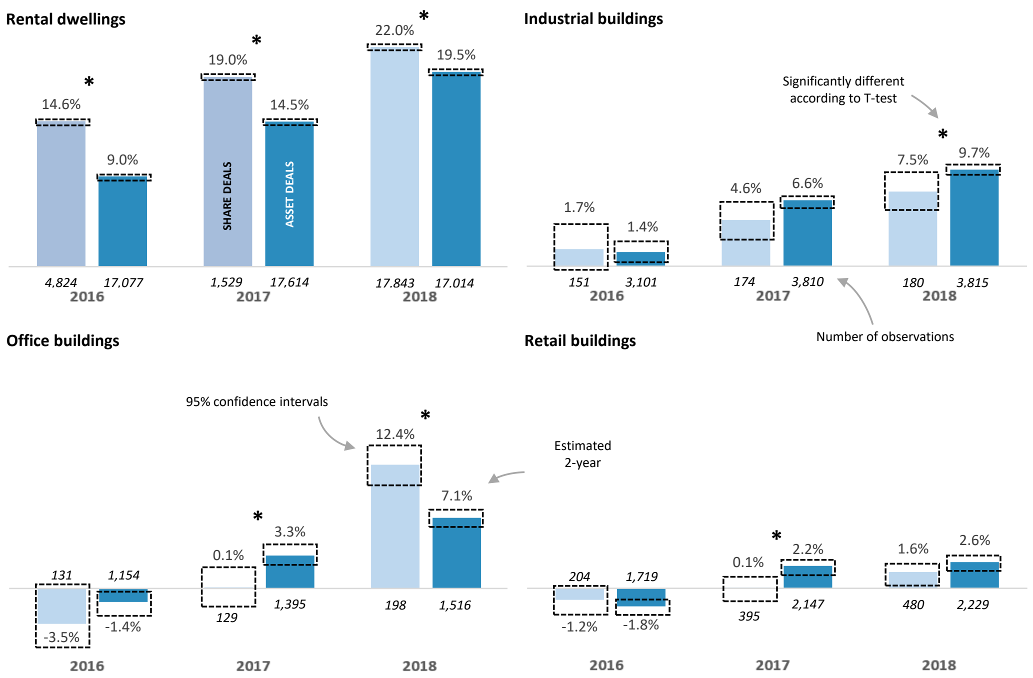

FIG. 2.7 2-year price developments per property type in the Netherlands. Source: Author's own creation.

The results in Figure 2.7 show significant differences in price developments for rental dwellings. Both share deals and asset deals display price increases, but the price increases of share deals appear to be consistently higher. For offices, the last two years show significant differences, but share deals price developments are not consistently higher or lower. Industrial and retail buildings, on the other hand, show no significant difference in price developments in most periods. Apart from rental dwellings, the exclusion of share deals is not likely to distort price indices based on asset deals as they will have a minimum weight in CPPIs.

2.5 Discussion

2.5.1 Defining precedes measurement

There will probably not be a lot of discussion whether a simple share deal (Figure 2.1, part 2) should be included in CRE indicators. There is a clear intention of selling real estate and to quote Lynn (1962, p. 73): “it would only seem logical that entities engaging in essentially the same activities should be taxed essentially the same – that the choice of business form should not affect taxation and, in reverse, taxation should not affect the choice of business form”. In this statement, the emphasis is on tax treatment, but there is a strong similarity in compiling real estate statistics. The more complex SPE constructions (Figure 2.1, part 3-4) become, however, the more a grey area emerges between two extremes. On one side, there is ‘transacting legal ownership’ and on the other side, there is ‘transacting economic ownership’. Transacting legal ownership excludes SPEs by definition and transacting economic ownership includes everything up until very complex forms of share deals. The optimal choice for CPPI input selection lies most likely somewhere in the middle. Furthermore, as far as harmonization is desired, these thresholds should be aligned between countries to increase comparability.

2.5.2 Comparison of CRE indicators

The analysis in Section 2.2 shows that financial arguments are the most decisive in choosing between a share or asset deal. The differences in tax regulations among countries affects investors’ strategies. Simplified: a country without tax restrictions regarding share deals will probably show a larger portion of share deals than a country with tax restrictions. Comparing volume and value figures of commercial real estate between countries may therefore be distorted depending on the differences in tax regulations.

Changing tax regulations may also affect the use of SPEs (compared to asset deals) within a country. In the Netherlands for example, share deals are only taxed since the year 1995 by the adoption of new legislation (Staatsblad van het Koninkrijk der Nederlanden, 1995). Time series of commercial real estate indicators that would cover the years before and after 1995, are thus likely to suffer from a structural break. An observed change would not be due to a change in market activity, but due to a shift in favored transaction constructions.

2.5.3 Feasibility to enrich commercial property price indicators.

The construction of CRE indicators for share deals proves to be very difficult. Regarding the construction of transaction volumes, a clear-cut selection of real estate share deals is not available. Many datasets have to be linked, which introduces data loss and many assumptions have to be made to approach the pre-set definition. The potential uncertainty is visualized in Section 2.4.1. Regarding value indicators and price developments, the use of valuations seems inevitable. Using actual prices seems problematic for two reasons. First, retrieving share deal prices is very difficult since price information is not always registered. This especially accounts for smaller share deals, transacting less than 100% of the shares. Second, even when retrieving the data would be successful, interpreting the price would be an obstacle. A share deal remains, after all, a transfer of a company's share and the price does not merely have to reflect the transfer of real estate. Price indicators for share deals seem, therefore, only feasible when valuations are used instead of real prices. Even then, the construction would be very costly and time-consuming. Scanning the market every now and then (as conducted in this study) to ensure that share deals do not distort commercial property price indicators, may be a more pragmatic way to go.

2.6 Conclusions

2.6.1 Main conclusions

This study increases our understanding of share deal transactions in the domain of commercial real estate. In particular, this study investigates to what extent the absence of share deals leads to CRE indicators that do not accurately reflect the market. Comparisons of the total monetary values show that real estate share deals in the Netherlands cover up to approximately 34% of the CRE trading market. The popularity varies per property type. The measured number and total value were the highest for rental dwellings and other buildings (other than industry, office and retail). The role of other property appears to be limited. This is likely due to the Dutch legislation regarding property transfer tax, which does not safeguard share deals from paying tax. This tax applies to both asset deals and share deals (under a few conditions) and, hence, does not benefit share deals. Nevertheless, the results indicate that adding share deals would increase volume and value indicators. In terms of financial stability, the calculated risks would be larger and thus would volume and value indicators for commercial property transactions benefit from an addition of share deals.

As for price indices, some estimations show different developments for various property types. In this regard, CPPIs should include share deals. Given that reliable and valid actual prices are hard to get and the contribution of share deals in a CPPI aggregate would be minimal (due to low weighting), including share deals in price indices is less obvious than including them in volume and value indicators.

2.6.2 Limitations and directions for future research

Legislation has a lot of influence on the choice between share and asset deals. Legislation differs among countries and the significance of share deals is therefore expected to vary in each country's real estate market. Performing similar research in other countries will provide useful insights, because it will not only enable a comparison of the magnitude of share deals, but also a comparison of the legislation. This consequently enables investigating the effect of legislation on the magnitude of share deals.

This study shows that using administrative data sources to capture the complete market of share deals has its limitations, at least for the Netherlands. Especially complex share deals, for instance where there is an involvement of foreign entities, are hard to grasp in figures. The findings show that real estate traded in share deals are overall more expensive. A few possible explanations were provided, but giving an actual explanation requires additional research.

TOC

3 Portfolios sales and commercial property price statistics

The previous chapter addressed the issue of low observation numbers in the data phase by focusing on a specific construction of real estate trading: share deals. The study showed that omitting share deals from CPPIs could lead to an incomplete image of the market. The incompleteness depends heavily on a country's legislation as this primarily influences the size of share deals in a market. In the Netherlands, share deals are primarily a valuable addition in the trading of rental dwellings and specifically in volume and value indicators.

This chapter also addresses the issue of low observation numbers in the data phase. In addition, the issue of heterogeneity is addressed. This is done by focusing on another trading construction that is common in commercial real estate: portfolio sales. Portfolio sales are transfers where multiple properties, including office buildings, retail spaces, and industrial facilities, are sold together. This study examines how portfolio sales differ from regular sales in terms of pricing.

3.1 Introduction

Since the global financial crisis began in 2008, there has been a growing awareness of the crucial role that commercial real estate markets play in financial system stability. In 2009, the G20—the collaboration of the world's twenty largest economies—initiated the Data Gaps Initiative (DGI) to develop commercial real estate indicators that aid in monitoring financial stability. The most used indicators are transaction volume, value, and price indices (Eurostat, 2017).

For the residential market, these indicators are mostly available as house price indicators, and methods for residential price indices have been widely studied (Eurostat, 2013b). However, while methods for these indicators seem to be available, price indicators for the commercial market are largely absent because they are difficult to construct. This difficulty arises because the commercial market has characteristics very different from the residential market. One key difference is the existence of real estate portfolios, where multiple properties are bundled into one portfolio. Studies have shown that the commercial market is characterized by portfolios (Brown & Mathyslak, 1995; Geltner, 1997). Trading entire portfolios instead of single properties appears to be common: Eurostat (2017) reports that portfolio sales account for over 20% by value in the United States. Figures of Statistics Netherlands show that in some segments, the share of portfolio sales can be as high as 75% in certain periods (CBS, 2024b).

Despite the recognition of portfolio sales as a global phenomenon in the commercial market, studies rarely consider their impact on the market. Patterns in portfolio sales are understudied. Consequently, it is unknown how the share of portfolio sales fluctuates over time, how this share correlates with the economic business cycle, and what impact portfolio sales have on the price of individual real estate objects and on volume, value, and price indices. This study addresses these issues, focusing on whether there is a price premium or discount in portfolio sales.

To pursue our aim, we performed hedonic regression analyses on transaction data. We used official data from the Netherlands, including commercial real estate transactions from the Land Registry Office, additional building characteristics from the Key Register Addresses and Buildings (BAG), and official valuations (WOZ) from municipalities. These data allowed us to identify portfolios in notary deeds, which contain information on all involved real estate objects and the corresponding transaction price.

Section 3.2 elucidates the phenomenon of portfolios in commercial real estate. In Section 3.3, the data and methodology are further explained, and Section 3.4 presents our findings on the price effects of portfolio sales. Section 3.5 concludes and provides a discussion of the results.

3.2 Background

3.2.1 Definition of a portfolio sale

Before elucidating the phenomenon of portfolio sales, it is necessary to define a portfolio sale. In our study, a portfolio sale is defined as a single legal transaction that includes the transfer of multiple real estate properties. While this may seem straightforward, it heavily depends on the demarcation of a real estate property, i.e., the unit of measurement. The following example illustrates potential issues and their effects.

Building A contains five office units with different renters and is owned by a single owner. Each office unit has its own entrance bordering a public space, meaning they could theoretically be sold separately. If building A, including all offices, is transferred to another owner, the choice on whether to perceive all units as separate real estate properties, determines if this is a portfolio sale or not.

In this example, three units of measurement can be distinguished: the transaction level, the building level, and the unit level. In our study, the unit of measurement for a real estate property sale is at the building level. Thus, the sale would not be marked as a portfolio sale since all units are within the same building and transferred in a single transaction. If the units were transferred in two separate sales, this would still not constitute a portfolio sale but rather two single property sales.

There are two main reasons for choosing the entire building as the unit of measurement. First, from a market perspective, the transfer of a building, even one containing multiple units, is not perceived as a portfolio sale. It is marketed as a single large building that can host multiple renters rather than a bundle of multiple properties. Second, measuring at the unit level would unnecessarily inflate the number of portfolios. Our study aims to explore the phenomenon of portfolio sales, focusing on the diversification of portfolios rather than units within buildings. Choosing the unit of measurement is crucial, as it can drastically alter the number of perceived portfolios.

3.2.2 Hypothesis from theory

Building on the concepts of imperfect information and information asymmetry (Akerlof, 1970) and prospect theory (Kahneman and Tversky, 1979), we argue that transferring real estate within a portfolio is likely to result in a price discount for buyers.

Several theories, such as portfolio theory (Markowitz, 1991), assume that investors have access to sufficient information to estimate risk and return. With this information, investors can optimize their portfolio composition, either by maximizing returns for a given level of risk or minimizing risk for a chosen level of return (Geltner et al., 2007). However, in practice, reliable and comprehensive information is not always available. Mangram (2013) highlights the assumption of perfect information as a limitation of modern portfolio theory, emphasizing that, in reality, information is often untimely, incomplete, or inaccurate. Moreover, information asymmetry exists, meaning that the timeliness, completeness, and accuracy of information differ between parties, typically favoring the seller over the buyer. Akerlof (1970) explains how information asymmetry leads to price discounts: buyers are generally aware that they have less information about a property's quality and liquidity than the seller. To mitigate this uncertainty, buyers are often more successful in negotiating lower prices, effectively securing a discount on the property. These concepts of imperfect information and information asymmetry form the foundation of our first hypothesis: portfolio sales involve a price discount.

The concepts of diversification and imperfect information form the basis for the first hypothesis in our study: portfolio sales involve a price discount. Buyers of portfolios benefit from an already diversified portfolio, which immediately (at the moment of sale) reduces risk. Reduced risk usually involves more stable (and not maximized) returns, leading sellers to accept a lower lower price per property. Additionally, given information asymmetry, buyers likely know they have less information about the quality and liquidity of properties than the current owner. To compensate for this, buyers more often succeed in bargaining for a lower price per property, i.e., ask for a ‘discount’. Akerlof (1970) was one of the first to describe this mechanism between information asymmetry and discounts.

TOC

Prospect theory describes how people (in our case, investors) make choices in uncertain situations. Contrary to classical economic theory, prospect theory states that decisions are based not on utility maximization but on potential profit and loss, with potential losses weighing more heavily than potential gains. This concept is known as loss aversion. The presence of loss aversion in commercial real estate pricing has been demonstrated by Bokhari and Geltner (2011). The prospect theory also proposes that people favor certainty over probability: certainty (100%) of a gain or loss weighs more heavy than potential gain or loss. This is known as the certainty effect. Both loss aversion and the certainty effect suggest that larger portfolios should involve higher discounts. For loss aversion, larger portfolios increase the perception of potential loss (Kahneman and Tversky, 1979; Novemsky & Kahneman, 2005). For the certainty effect, the consequences of a bad purchase are greater with larger amounts (Stewart & Stewart, 2001), justifying a buyer's pursuit of a greater discount. Based on these arguments, our second hypothesis is that larger portfolio sales involve relatively larger price discounts.

In the following sections, we will test the following hypotheses:

1. Portfolio sales involve a price discount
2. Larger portfolio sales involve relatively larger price discounts.

3.3 Data & methodology

3.3.1 Data

In this study, data from four sources in the Netherlands were utilized: transaction data from the Land Registry Office (Cadastre)/Statistics Netherlands (CBS), property information from the Key Register Addresses and Buildings (BAG), official valuations (WOZ) from Dutch municipalities, and urbanity and proximity to facility statistics from CBS. The observations span the years 2008 to 2023, resulting in a final dataset comprising 478,744 transacted properties in 308,225 transactions.

The primary data source is the Land Registry Office, which records all legal transfers of plots/parcels in the Netherlands from notary deeds. These deeds provide details on the involved parcels, the exact legal rights transferred, and the agreed prices. In their registration process, the Land Registry Office links plots to the structures on them. This process is characterized by a many-to-many relationship: one plot could have multiple structures, and one structure could span multiple plots. Using this information, we identified portfolio sales. First, we selected deeds involving transfers of property rights. Second, we counted the involved properties and recorded the corresponding prices in the deeds. This enabled us to differentiate between single-object sales (one property, one price) and portfolio sales (multiple properties, one price). Although we apply a strict definition of portfolio sales here (one price for multiple properties), this approach also allows us to distinguish between small and large portfolios.

Secondary information was obtained from the BAG, WOZ, and urbanity and proximity of facilities statistics. This information was used to run hedonic regression models with control variables, as described in Section 3.3.2. The BAG provides information on all buildings in the Netherlands, including floor surface, construction year, and property type. The WOZ contains annually updated valuations of all buildings, which we used to classify neighborhoods by average real estate value (low, medium, high, etc.). This creates a specified location variable which proved to be a significant predictor of real estate prices. Lastly, urbanity and proximity to facilities statistics from CBS were used, specifically the degree of urbanity and distance to train stations (CBS, 2024b). These variables serve as explanatory variables for real estate prices, which is elaborated in the next paragraph.

In addition to the microdata discussed above, two macro-level series were used for comparison purposes. First, the commercial property price indices (CPPIs) published by Statistics Netherlands were used as a reference (CBS, 2024b). These CPPIs are calculated for rental dwellings, offices, retail, and industrial buildings based on the same data used in this study. Second, a business cycle indicator composed by CBS was used as a reference. This indicator estimates the performance of the Dutch economy and is based on a wide range of important economic information published by CBS, calculated as the deviation from the long-term trend (CBS, 2024a) [9]. Both the developments of the CPPIs and the business cycle indicator are compared to the development of portfolio sales over time. The results are presented in the next section.

9 The underlying indicators are: consumption, hours worked, turnover temping agencies, producer confidence, exports, unemployment, consumer confidence, bankruptcies, investments, house prices, manufacturing output and job vacancies.

3.3.2 Methodology

The data discussed in the previous paragraph is initially used to count the number and total value of portfolio sales over time. Comparing these figures with single object sales provides insight into the economic importance of portfolio sales. Additionally, we will compare the development of portfolio sales numbers and values with price developments (CPPIs) and economic performance (business cycle indicator) to gain a preliminary understanding of what might explain the trends in portfolio sales.

To determine whether portfolio sales involve a price premium or discount, we performed hedonic regression analysis. In hedonic regression, real estate is treated as a bundle of characteristics (which remain constant over time in the model), and the price of a property is explained as the sum of the values of these characteristics. Hedonic regression is often used in price index construction to adjust for quality or compositional changes. In this study, we use hedonic regression to isolate the effect of portfolio sales on transaction prices. For this purpose, we adapted the hedonic models used by Statistics Netherlands to calculate CPPIs (CBS, 2024b) by adding an indicator that denotes whether a transacted property was part of a portfolio to determine the price effect of portfolio sales.

It is important to note that this portfolio indicator is not included in the models used by Statistics Netherlands because the distribution of portfolio versus single property sales is not something that should be adjusted for in a price index. If a shift in this distribution leads to a price change, this should be reflected in the price index rather than corrected for in the model. The model with the portfolio indicator is presented by the following equation:

$$ln P_i^t = \alpha + \sum_{k=1}^{K} \beta_k c_{ik} + \beta_l s_{il} + \varepsilon_i^t, \qquad (t = 0, \ldots, T) \tag{3.1}$$

where:

- $ln P_i^t$ = the natural logarithm of the real estate price for property i at period t
- α = the intercept
- β_k = the regression coefficient for control variable k
- c_{ik} = control variable k for real estate property i
- β_l = the regression coefficient for portfolio indicator l
- s_{il} = portfolio dummy l for real estate property i
- ε_i^t = standard error for real estate property i at period t

The control variables k include the most significant estimators of building prices, such as floor area, construction age, and location. Two important variables are absent from the hedonic model: time and property type. Time is excluded as a separate indicator because the regressions were run for each quarter, allowing P^t to be estimated for the entire time series between 2008 and 2023. This enables us to analyze the differences in the price effects of portfolio sales over time. Property type is also excluded as a separate indicator because the regressions were run separately for each property type, which is beneficial given the heterogeneity of commercial real estate. Running regressions separately for each property type also allows for customized models, with parameters expected to differ between property types (and years). These models, adapted from Statistics Netherlands, are the same models used to calculate and publish CPPIs. The models for each property type are presented in Table 3.1.

TABLE 3.1 Hedonic models per property type for commercial property price indices of Statistics Netherlands. Source: adapted from CBS (2024b). Retrieved from: https://www.cbs.nl/en-gb/about-us/innovation/project/measuring-commercial-property-prices

		Rental dwellings	Industrial buildings	Office buildings	Retail buildings
1	Ln(floor area)	✓	✓	✓	✓
2	Residential region	✓			
3	Industrial region		✓		
4	Neighborhood segment 3	✓			✓
5	Neighborhood segment 10			✓	
6	In Amsterdam	✓	✓	✓	✓
7	In The Hague	✓			
8	In Utrecht	✓			
9	Transaction type	✓			
10	Construction year classification 1		✓		
11	Construction year classification 2			✓	
12	Degree of urbanity				✓
13	Office density		✓		
14	Retail density				✓
15	Distance to nearest train station			✓	

In addition to the hedonic regression results, Pearson correlation analyses were performed to interpret the output. We used the business cycle indicator and CPPIs by property type as reference indicators. These reference indicators were related to the economic activity in portfolio trading (number and value of portfolio sales). Correlations were calculated for both absolute figures and year-on-year changes across all series. The idea behind these comparisons is to explore how portfolio trading and pricing relate to the economic state.

3.4 Findings

3.4.1 Composition of portfolio sales

We defined a sale as a portfolio sale if it involved more than one property. However, an investor's intention may not always be to create and trade a portfolio. For instance, if two adjacent buildings are constructed by the same developer in the same year, selling them together is logical but does not necessarily indicate portfolio creation. Understanding the composition of portfolios can shed light on investment behavior regarding portfolio trading. Table 3.2 shows the number of properties involved in a transaction (portfolio size) alongside the number of occurrences. It reveals that most transactions are single property sales and that most portfolio transactions include only a small number of properties.

TABLE 3.2 Size of portfolio sales between 2008-2023 in the Netherlands. Source: authors' own creation.

Number of properties in transaction	Number of occurrences	Value of occurrences (billion)
1	274,158	€ 216
2	19,935	€ 42
3-5	8,188	€ 30
6-10	2,802	€ 13
11-50	2,707	€ 24
>50	435	€ 16
Total	**308,225**	**€ 342**
Single	274,158	€ 216
Portfolio	34,067	€ 125

Table 3.3 offers more insight into the composition of portfolio sales by breaking down the number of different property types and cities in a portfolio. The table indicates that most portfolios contain properties within the same city and of the same property type. However, it also highlights the diversity of portfolios, as many include multiple property types and span several cities. The maximum number of cities in a single portfolio exceeds 60, while the maximum number of property types in one portfolio is over 9 out of the 12 defined types.

TABLE 3.3 Diversity of portfolio sales over property types and regions in the Netherlands (2008-2023). Source: authors' own creation

Number of property types in portfolio	Number of occurrences	Number of cities in portfolio	Number of occurrences
1	17,669	1	31,716
2	13,982	2	1,322
3	1,808	3	435
4	397	4	192
5	111	5	97
>6	100	>6	305
Total	**34,067**	**Total**	**34,067**

3.4.2 Market share of portfolio sales

The market share of portfolio sales can be measured by transaction numbers, the number of sold properties, or the total value of transactions. Each measure offers useful insights into the role of portfolio sales in the commercial real estate market. The first measure, the share in transaction numbers for the years 2008 up to 2023, is provided in Table 3.2. With 274,158 single property transactions compared to 34,067 portfolio transactions, the shares are 89% and 11%, respectively. Although portfolio transactions account for a small percentage by transaction number, their share in total value averages 37%.

Figure 3.1 illustrates the distribution of transacted properties in portfolios versus single-object transactions per year. Notably, around 50% of all transacted properties are part of portfolios, indicating a significant market presence. Additionally, the share of transacted properties in portfolios fluctuates over time. In 2015, portfolio sales peaked at nearly 60%, while in 2021, they dropped to 34%. A visual comparison with commercial real estate price developments suggests a correlation: prices declined until 2015 as the share of portfolio sales increased, and from 2016 onward, prices rose as the share of portfolio sales decreased. These observations are supported by statistical correlations, which show a negative relationship between prices and the share of portfolio sales. These figures are provided in Figure 3.1. In all cases, the correlation is negative. In other words, when the prices go up, the share of portfolio sales goes down.

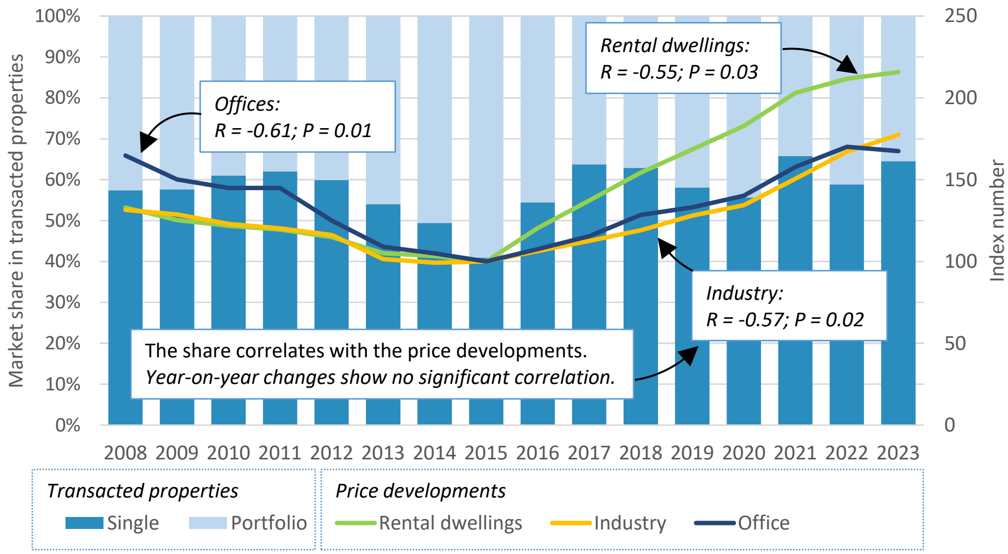

FIG. 3.1 Distribution of portfolio/single property by transacted properties and price indices, 2015=100 in the Netherlands. Source: authors' own creation.

Figure 3.2 shows the total value of portfolio transactions and single-object transactions. Here, the share of portfolios is slightly smaller compared to the number of transacted properties. The share of portfolio sales also varies over time, showing similar peaks and dips as in Figure 3.1. The value of portfolio sales is compared to the Dutch business cycle, and a visual correlation between property values and the business cycle is apparent, particularly the dip in 2013 and the peaks in 2018. These observations are again supported by statistical correlations, which show a positive relationship between the economy's upward trends and the values of both single property sales and portfolio sales. In all cases, the correlation is now positive. In other words, when the economy is in an upward trend, the value of both single property sales and portfolio sales also goes up.

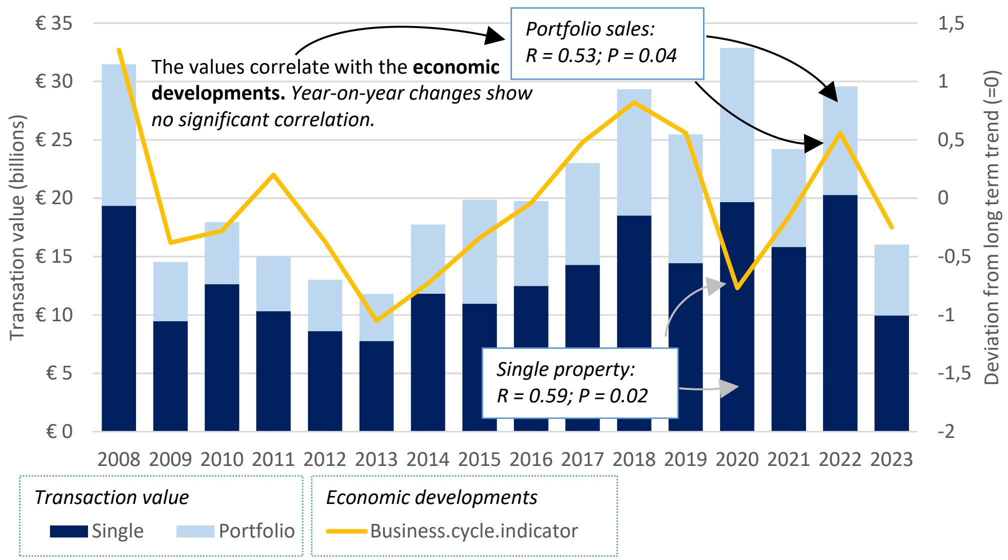

FIG. 3.2 Value of portfolio/single property and the business cycle in the Netherlands. Source: authors' own creation.

3.4.3 Price influence of portfolio sales

To estimate the influence of portfolio sales on pricing, we performed regressions as outlined in Section 3.3.2. These regression models were adapted from those used by Statistics Netherlands to estimate and publish commercial property price index figures. The models cover the four major property types: rental dwellings, industrial buildings, office buildings, and retail buildings. We included a binary indicator for portfolio sales to further explain pricing. The regressions were conducted for each property type and for each quarter from 2008 to 2023.

On average, the adjusted R-squared values for all quarters were 0.70 for rental dwellings, 0.78 for industrial buildings, 0.78 for office buildings, and 0.66 for retail buildings. The regression coefficient estimates of the portfolio indicator are presented in Figure 3.3.[10] Since prices are transformed using the natural logarithm, the coefficients can be interpreted by taking the exponent of the coefficients (discount/premium $= e^{\beta} - 1$). For rental dwellings, this indicates an average discount

10 For all quarters in the years 2015-2020, model R^2's and regression coefficient estimates for the floor area indicator are enclosed in annex 1 and annex 2.

of 14.8% between 2015 and 2020. For industrial buildings, office buildings, and retail buildings, the average discounts are 19.1%, 17.6%, and 21.1%, respectively. Insignificant estimates (p-value > 0.05) were excluded from the figure. The results indicate that the price effect of portfolio sales is generally negative, supporting our first hypothesis that portfolio sales involve a price discount.

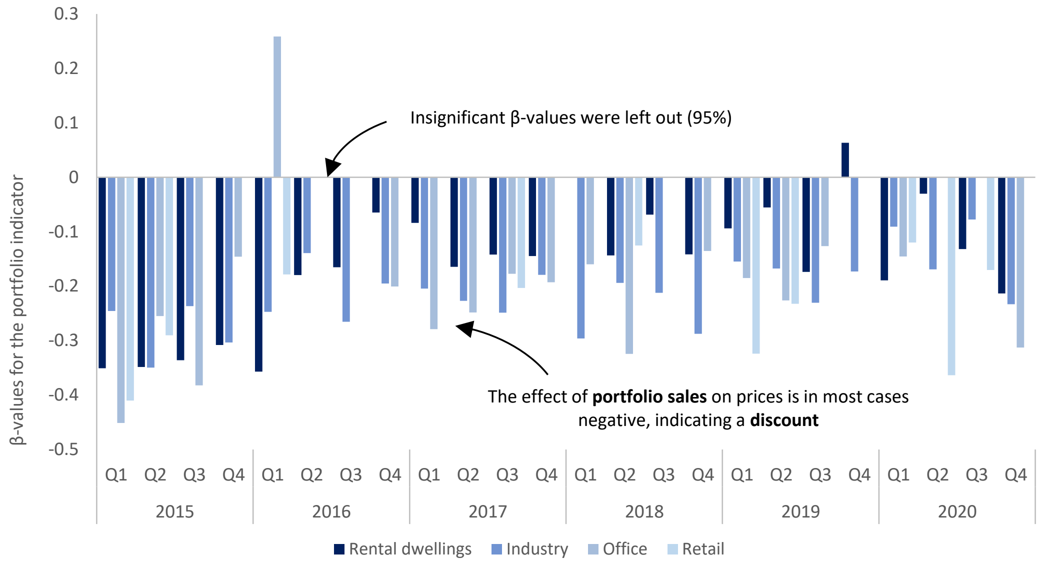

FIG. 3.3 Influence of portfolio sales on the price in the Netherlands. Source: authors' own creation.

To further explore the discount effect, we conducted several additional regressions. First, we differentiated portfolios by regional dispersion: portfolios with properties located close to each other versus those spanning greater (but domestic) distances. Both groups showed a discount, but there was no significant difference between them, indicating that regional dispersion does not affect the discount size. Second, we categorized portfolios by property types: portfolios with only one property type versus those spanning multiple property types. Both groups again showed a discount with no significant difference, suggesting that diversification by property type does not impact the discount. Third, we split portfolios by the number of involved properties: small portfolios with up to 5 properties versus larger portfolios with more than 5 properties. While results for industrial buildings, office buildings, and retail buildings were inconclusive, results for rental dwellings revealed a pattern as shown in Figure 3.4. The figure shows the regression coefficient estimates of the portfolio indicators 'small' and 'large.' Insignificant estimates (p-value > 0.05) were excluded.

The results indicate that large portfolio sales generally have a larger price discount than small portfolio sales, supporting our second hypothesis that, based on prospect theory, larger portfolio sales involve a greater price discount.

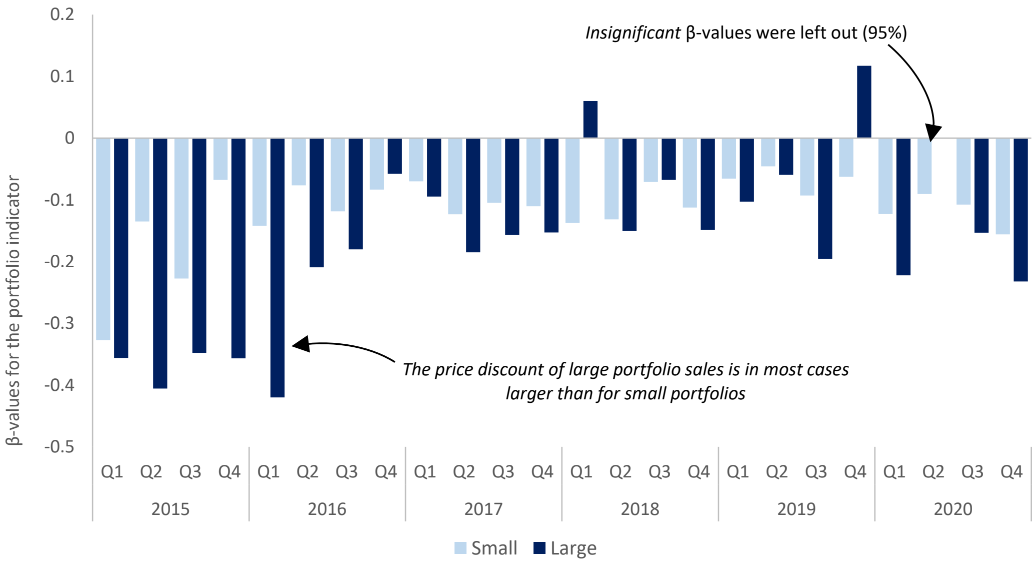

FIG. 3.4 Influence of small and large portfolio sales on the price of dwellings in the Netherlands. Source: authors' own creation.

3.5 Conclusions and discussion

3.5.1 Portfolio sales and price effects

In this study, we aimed to investigate the phenomenon of portfolio sales, focusing specifically on their composition, market share over time, and price effect on included properties.

The results on the composition indicate that most portfolios are simple in terms of diversity, though highly diverse portfolio sales do exist. In this study, portfolio diversity is measured by the number of included properties, the variety of different property types, and geographic dispersion.

The findings on market share reveal that portfolio sales constitute a substantial portion of the commercial real estate trading market, representing 30% to 60% of total transactions. The share of portfolio sales correlates with the state of the economy: during economic downturns, real estate prices decline, and the share of portfolio sales rises. Conversely, in an upward-moving economy, the share of portfolio sales declines. Statistical correlations were observed between the share of portfolio sales, commercial real estate price developments, and the Dutch business cycle indicator. This pattern aligns with the concept of buyers' and sellers' markets: in economic downturns, falling prices create a buyers' market, making it an opportune time for portfolio acquisitions, which (this study showed) are often more favorable to buyers. Consequently, the increase in portfolio sales aligns with the characteristics of a buyers' market (and conversely for a sellers' market).

Regarding price effects, properties in portfolios are generally sold at a discount. The results align with Akerlof (1970) who described how information asymmetry between buyers and sellers results in a price discount. Furthermore, the results also align with a recent study on REITs by Huerta & Mothorpe (2023), who also found a discount in real estate bundling, particularly for geographically diversified REITs. The discounts align with this study, but the relationship with geographical diversification was not observed in our study.

The results imply that portfolio sales are a significant and distinctive part of the market, with a share that fluctuates along with the economic cycle and different price developments compared to single object sales. These findings show that portfolio sales are distinctive from single property sales. Therefore, portfolio sales should be included in CPPIs in order to represent the entire commercial real estate market. From a financial stability monitoring perspective, the representativeness of CPPIs is essential.

This study also raises the broader topic of portfolio measurement in statistics. Portfolio sales occur in real estate and similar types may be prevalent in other areas, such as consumer and producer prices, where bundle sales are common. It could also apply to building permits as these often apply to large projects involving multiple dwellings. This study shows that the size of portfolio sales is related to real estate market behavior, which may also hold true for bundle sales in other markets.

3.5.2 Limitations and future research

The conclusions of this study apply to the real estate market in the Netherlands. Previous research has shown that portfolio forming in real estate is common (Brown & Mathyslak, 1995; Geltner, 1997; Eurostat, 2017), suggesting that real estate portfolio trading might also be globally common. However, this can only be confirmed with similar studies in other countries. Legislation differences may affect portfolio sales, leading to varying results.

As with any study, our research was limited by available data. While the number of observations was sufficient (data length), more detailed information per observation (data width) would have been beneficial. For example, data on estimated returns, rent income, occupancy, or other measures of liquidity were not available and could have further explained the price discount of properties in portfolios.

TOC

4 Including portfolio sales in commercial property price statistics

The previous chapter addressed both issues of low observation numbers and heterogeneity in the data phase by focusing on portfolio sales. This study showed that real estate sold in portfolios generally yield a price discount. As a consequence, if we want to construct CPPIs that reflect the market, we should include portfolio sale observations to ensure that changes in the discount rate are treated as price changes.

This chapter builds on to this finding by exploring methods to include portfolio sales into CPPIs. The potential methods are also assessed on its usability by discussing the advantages and disadvantages. A model-based bootstrap is used as a resampling method to assess the imputations methods.

4.1 Introduction

In the last two decades there has been a growing interest in official statistics on commercial real estate. This interest intensified during the global financial crisis that began in 2008, although the roots of the crisis extended back much further. Approximately 15 years before the crisis, a real estate price bubble was forming: sale prices were becoming increasingly disconnected from fundamentals such as income and equity (Acharya & Richardson, 2009). This bubble was facilitated by financial firms engaging in innovations that masked risks (Baily et al., 2008). The bankruptcy of these firms and the subsequent exposure of these risks led to a global wave of financial losses, sparking the financial crisis. In an effort to learn from this crisis and potentially minimize the impact of future crises, decision-makers became more interested in the phenomenon of real estate price bubbles. To detect these bubbles, the G20 agreed on the need for indicators to monitor the real estate market, covering both the residential and commercial markets. Among these indicators, price indices are seen as some of the most crucial (FSB & IMF, 2009). These price indices must be measured accurately to reflect market prices and thereby identify potential bubbles.

In constructing commercial property price indicators (CPPIs), official statistical offices face multiple challenges, as the commercial real estate market[11] differs significantly from the owner-occupied housing market. These differences are particularly evident in data collection and processing. For instance, commercial real estate data is characterized by intracompany transactions (Bisat, 1968; Grubert, 2003), sale-and-leaseback transactions (Tipping & Bullard, 2007, Sanderson et al., 2019), quick resales (Wong et al., 2022), and share deals (Ishaak et al., 2023). Another major difference is the presence of portfolio sales (Brown & Matysiak, 1995; Geltner, 1997). As shown in chapter 3, portfolio sales form a large share of the market and should, therefore, not be neglected in the construction of CPPIs.

Including portfolio sales in CPPIs, however, is troublesome for several reasons. First, portfolio sales span multiple property types. Since commercial real estate is even more heterogeneous than residential real estate, dividing data into property types is essential. Therefore, it seems that portfolio sales should be split during

11 Commercial real estate includes rental housing besides the more traditional types, such as industrial, office and retail buildings. Rental housing concerns income producing real estate and is, therefore, considered as part of the commercial real estate market.

data processing. Second, price indices are often calculated using hedonic methods (Eurostat, 2013b, 2017). In this methodology, the price of a property is explained as the sum of the value of corresponding attributes, such as floor area and location.

However, as portfolios are diversified, properties in a portfolio could be located in multiple cities, making the attribute 'location' sometimes impossible to assign to an entire portfolio. Third, the measurement unit of a portfolio is at the transaction level. An assumption in index compilation is that the unit of measurement should be held constant. If a hedonic variable, for instance, refers to floor area, the unit of measurement should either be square meters or square feet, but never a combination of both. In the case of a portfolio, we should be aware of such a combination, since each portfolio is composed differently in each transaction. For example, in period 1, a portfolio might consist of properties A, B, and C. In period 2, another portfolio sale might include the same properties A, B, and a different property D. In period 3, property A could be sold individually. This frequent change in unit composition is undesirable from an index perspective.

While several studies have identified the complexities of portfolios and suggested methods to address them (Kallberg et al., 1996; Kołodziejczyk et al., 2019), the treatment of portfolio transactions for CPPIs is understudied. Goetzmann (1992) illustrated a way to incorporate portfolios in calculations, but the frequent change in unit composition presents a clear benefit to process portfolio data before calculating indices. Despite attention to portfolios in real estate economics, there has been little focus on processing portfolio sales for CPPIs. Now that CPPIs are being developed worldwide, it seems appropriate to study this phenomenon, along with associated issues, processing methods, and techniques for testing and assessing these methods.

Therefore, the research question of this study is: What are legitimate methods to process data on portfolio sales for the compilation of CPPIs? We use official data on CRE transactions from the Land Registry Office in the Netherlands to experiment with imputation and assessment methods. The results show to what extent certain methods are suitable for including portfolio sales into CPPIs. The provided methods will offer CPPIs compilers guidance on how to handle portfolio sales, and the assessment techniques will provide a way to evaluate the results.

4.2 Background

4.2.1 Data structure of portfolio sales

To investigate methods for processing portfolio sales in the compilation of CPPIs, it is important first to describe the data these methods must handle. In the data, the most characteristic feature of a portfolio sale is that it involves multiple properties. Additionally, a portfolio sale typically does not provide individual prices for each property; instead, it offers a single price for the entire portfolio. This structure can be understood through the following example.

Imagine you are shopping for clothes. A shirt costs €20, and matching pants cost €10. Since both items complement each other, they are combined into a bundle priced at €25. In this bundled offer, the individual prices no longer apply. Because this bundle includes a discount, the sum of the original prices exceeds the new bundled price. While it is possible to use the original individual prices to estimate the new individual values, the key point is that such estimations are inevitable.

In real estate, the information available is even more limited than in the above example, as the initial prices of individual properties remain unknown. We have identified three potential scenarios in which a portfolio sale can appear in the data.[12] These scenarios are illustrated in Tables 4.1, 4.2 and 4.3, where portfolio A, consisting of properties A1 (dwelling), A2 (dwelling), and A3 (office), is sold for a total amount of €10,000,000.

12 The authors have also witnessed these structures in various data sources.

TOC

TABLE 4.1 Portfolio data scenario 1. Source: authors' own creation.

Transaction	Transaction price	Number of properties	Property type
A	€ 10,000,000	3	Dwelling, office

TABLE 4.2 Portfolio data scenario 2. Source: authors' own creation.

Transaction	Property	Transaction price	Property type
A	A1	€ 10,000,000	Dwelling
A	A2	€ 10,000,000	Dwelling
A	A3	€ 10,000,000	Office

TABLE 4.3 Portfolio data scenario 3. Source: authors' own creation.

Transaction	Property	Transaction price	Property type
A	A1	€ 5,000,000	Dwelling
A	A2	€ 3,000,000	Dwelling
A	A3	€ 2,000,000	Office

In *scenario 1*, the data is stored at the transaction level, providing only an aggregate price. While the number of individual properties is (or could be) available, the property types are consolidated into a single cell due to limitations on the extent of information that can be stored at the property level. In *scenario 2*, the data is stored at the property level. It includes information about the parent transaction, but the prices at the property level refer back to the transaction-level prices. This scenario reveals the distribution of property types, unlike scenario 1. In *scenario 3*, the data is also stored at the property level and contains information about the parent transaction. Unlike scenario 2, however, the prices refer to individual property prices. While this may seem ideal, caution is recommended: someone or some algorithm must have made imputations, as there is no agreed-upon price at the portfolio level. Even if this information is obtained from the buyer or seller, its reliability is questionable due to potential biases, such as tax-related agendas.

4.2.2 Price index methods

To investigate methods for processing portfolio sales in the compilation of CPPIs, it is appropriate to briefly introduce some of these compilation methods (i.e., price index methods). While not all methods will be discussed, we will focus on two extremes: a simple, yet unfavorable method lacking sufficient quality correction, and a favorable but more complex method with adequate quality correction. The simple method for price index compilation involves calculating price developments using a mean or median price per period (Eurostat, 2013b). Due to its insufficient quality correction, this method is generally avoided in official statistics. However, it serves as a useful example to illustrate the problem that arises when attempting to include portfolio sales (as discussed in section 4.2.3). An index based on a simple mean only uses prices, and the equation is:

$$I_{0,t} = \frac{\sum_{i=1}^{N_t} p_t / N_t}{\sum_{i=1}^{N_0} p_0 / N_0} \tag{4.1}$$

where:

- $I_{0,t}$ = the price index between period 0 and period t;
- p_t = the price of the i^{th} property sold in period t;
- N_t = the number of properties sold in period t;

An index method that does correct for quality change is the hedonic price index (Eurostat, 2013b). There are many different variations of a hedonic price index, but in all cases, a regression is performed with the price as dependent variable and a few price determinants as independent variables. An index based on hedonic regression, thus, uses auxiliary information besides prices and the equation for this regression is:

$$\ln p_t^i = \beta_t + \sum_{k=1}^{K} \beta_t^k x_{\mathrm{t}}^{ik} + \varepsilon_t^i \tag{4.2}$$

where:

- β_t = the intercept term in period t;
- β_t^k = the coefficient of the k^{th} characteristic in period t;
- x_{t}^{ik} = the k^{th} characteristic of the i^{th} property sold in period t;
- ε_t^i = a random error term of the i^{th} property sold in period t, with $\varepsilon_t^i \sim N(0,\sigma)$.

Examining the methods above, allows us to better understand the complexities and considerations necessary for including portfolio sales in CPPI compilation.

4.2.3 Problems using unprocessed portfolio data in price index methods

Combining the data structure of portfolio sales with the two price index methods introduces potential issues that can impact the reliability of the resulting indices. These issues primarily revolve around stratification and the unit of measurement.

The table below summarizes the issues when applying the index methods to the three scenarios of portfolio data described in Section 4.2.1.

TABLE 4.4 Problems in portfolio sale data. Source: authors' own creation.

Data	Method	Stratification issue	Measurement unit bias
Scenario 1	Simple mean	✓	✓
Scenario 2	Simple mean		✓
Scenario 3	Simple mean		
Scenario 1	Hedonic regression	✓	
Scenario 2	Hedonic regression		✓
Scenario 3	Hedonic regression		

Stratification issues occur when data lacks sufficient detail for categorization. This issue is prominent in scenario 1, where different property types are stored in a single variable. This type of registration makes it impossible to disaggregate the total transaction price across different property types. Consequently, it is impossible to create distinct stratified indices, which is necessary since different property types are assumed to have varying price developments. Both the simple mean and hedonic regression methods face this stratification issue in scenario 1 (Table 4.1).

Measurement unit bias occurs when different units of measurement are used in the same calculation, potentially distorting the resulting indices. In scenario 1 (Table 4.1), the simple mean method is subject to this bias, as it treats the entire portfolio as a single transaction. Since the index is based on a simple mean, it combines portfolio-level prices with single property prices, leading to major differences in levels between periods. These differences cannot solely be attributed to price changes, but also to different sizes of portfolios across periods. Hedonic regression helps mitigate this bias in scenario 1 by incorporating the property type variable to better 'explain' the total transaction price. Scenario 2 (Table 4.2) encounters the measurement unit bias in the mean approach, as the prices are still at the transaction level. For the hedonic approach, the transaction-level price does not align with the unit at which the characteristics are registered, resulting in inaccurate regression results since property-level characteristics do not predict the portfolio price.

These problems do not appear to exist in scenario 3 (Table 4.3). This scenario provides the most granular data, with prices and characteristics assigned to individual properties. Therefore, it is the preferred scenario. However, caution should be exercised when receiving the data, as someone or an algorithm likely already imputed the data. Ideally, data should be transformed into this format. This requires imputation methods that must also be assessed for quality. Suggestions for such imputation and assessment methods are discussed in Section 4.3.

4.3 Data & methodology

4.3.1 Data

For this study, we primarily used official registers from the Netherlands. We utilized transaction data from the Land Registry Office (Cadastre)/Statistics Netherlands (CBS), property information from the Key Register Addresses and Buildings (BAG), and official valuations (WOZ) from Dutch municipalities. The observations span from 2008 to 2023, encompassing 478,744 transacted properties across 308,225 transactions. Of these 308,225 transactions, 274,158 were single property transactions, and 34,067 were portfolio transactions. These 34,067 portfolio transactions involved 204,586 properties.

The key information is retrieved from the Land Registry Office, which registers all legal transfers of parcels in the Netherlands from notary deeds. These notary deeds contain information on the involved parcels, the exact legal rights transferred, and the corresponding agreed prices. The structure of the portfolio data resembles scenario 2, as presented in Section 4.2.1 and Table 4.2: observations are registered at the property level, but the corresponding price is at the transaction level, thus referring to multiple properties.

Secondary information is retrieved from the BAG and the WOZ. This information is used to run hedonic regression models with control variables, as described in Section 4.3.2. The BAG contains information on all buildings in the Netherlands, from which we used floor surface and property type. The WOZ contains valuations of all buildings in the Netherlands, which are updated annually. In this study, we used the WOZ to impute portfolio prices at the property level, as explained in Section 4.3.2.

4.3.2 Methodology

To address the research question, *"What are legitimate methods to process portfolio sales in the compilation of CPPIs?"*, a simple answer might be to not process them at all; just disregard the portfolio sales and base price estimations on single property sales. However, in chapter 2 we showed that portfolio sales form a significant and distinctive part of the market. Therefore, it is necessary to impute the values. These imputations involve estimating prices at the property level, as they are initially only available at transaction level. The following paragraphs discuss a few imputation methods and methods to assess their quality. Finally, the methods used to calculate price indices are explained, complementing the discussion in Section 4.2.2. The price indices are used to compare price developments based on single property sales, portfolio sales, and a combination of both.

Imputation methods

In Scenario 2, the data resembles Table 4.2. A transaction price is provided, which applies to all properties in the portfolio. The goal is to distribute the transaction price among the properties such that their sum equals the transaction price. The basic approach is to construct a distribution key, which requires additional data. Obvious data sources include valuations and floor area. Less obvious and more creative keys could be based on average square meter prices in the neighborhood, plot size, or cubic meters. In practice, a combination of these sources may be necessary due to missing data. For instance, if the key is based on valuations and one is missing, the remaining keys would be overestimated. In such cases, additional data could help either to impute the missing valuation or to base the keys on a different source. This study tests the obvious data sources of valuations and floor area. An illustration of the distribution keys and derived price imputations is provided in Table 4.5.

TABLE 4.5 Problems in portfolio sale data. Source: authors' own creation.

Transaction	Property	Transaction price	Property type	Distribution key	Property price imputation
A	A1	€ 10,000,000	Dwelling	20%	€ 2,000,000
A	A2	€ 10,000,000	Dwelling	30%	€ 3,000,000
A	A3	€ 10,000,000	Office	50%	€ 5,000,000

Given the inevitability of combining data sources in practice, quality measures are essential to determine an order: start with data source A for imputing property prices, and if data is missing, continue to data source B, and so on. Methods for such quality assessment are provided in the next paragraph.

Assessment method: resampling and model-predicted bootstrapping

The first assessment method is a variation of a resampling method described by James et al. (2021). According to them, resampling involves *"...repeatedly drawing samples from a training set and refitting a model of interest on each sample to obtain additional information about the fitted model"* (James et al., 2021, p. 197). This study is inspired by bootstrapping, a specific form of resampling, as described by Efron and Tibshirani (1993), Hastie et al. (2017) and James et al. (2021). Bootstrapping enriches resampling by producing multiple samples, allowing the examination of the behavior of these samples (and thus model fits). The application of resampling and bootstrapping in this study is described below.

The data can be split into two subsets: 204,586 observations within portfolios and 274,158 single property sales. The prices of observations within portfolios must be imputed, while single property sales provide observed prices. The single property sale dataset can be used to assess portfolio imputations by simulating these sales as if they were portfolios. The method consists of five steps:

1. **Determine the number and size of portfolios** from the portfolio dataset for each period. For example, 2020 Q4 might contain two portfolios: one with 2 properties and one with 10 properties.
2. **Draw a random sample without replacement** from the single property dataset, matching the number and size of observed portfolios for each quarter, creating a simulation dataset. For instance, the simulation dataset for 2020 Q4 would also contain two portfolios: one with 2 properties and one with 10 properties.
3. **Calculate a fictional portfolio price** in the simulation dataset by summing all observed individual prices. The simulation dataset now contains information similar to that available for portfolios.
4. **Calculate imputed prices** for the simulated observations using the imputation methods described earlier, based on valuations and floor area.
5. **Compare imputed and observed prices** in the simulation dataset.

This comparison is visualized in Figure 4.1. The figure presents all observed and imputed prices within a fictitious portfolio, consisting of properties A to J, on the x-axis. The y-axis shows the value for each property, with green dots representing observed values and red dots representing imputed values. The figure illustrates how well the imputations approximate the observed values by examining the differences between the two dots for each property.

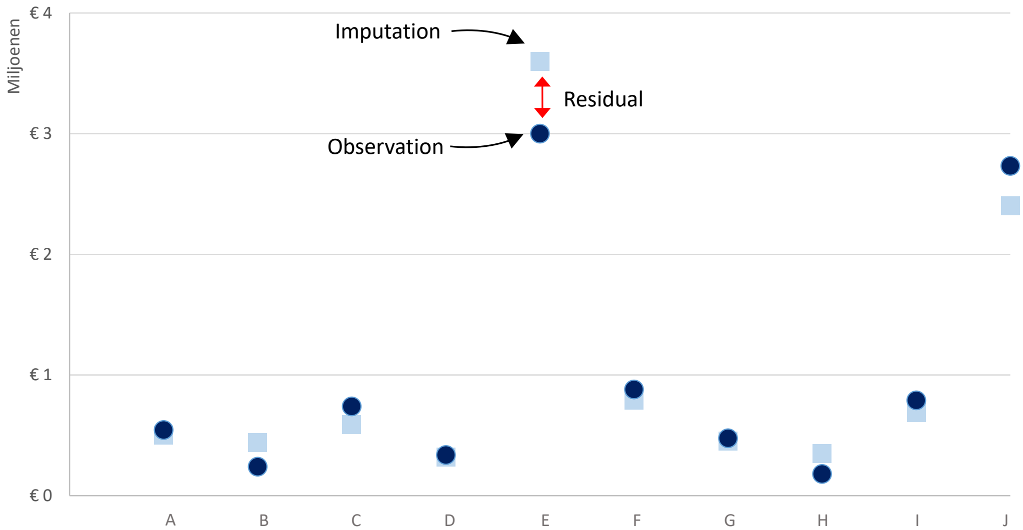

FIG. 4.1 Fictitious observations, imputations and residuals. Source: authors' own creation.

These differences resemble regression output, similar to the difference between observed values and model predictions or residuals. In regressions, the common way to assess residuals is by calculating the R^2, a measure of the variation in the dependent variable predicted by the independent variables. In our case, the residuals can be calculated as follows.

$$R^2 = 1 - \frac{\sum_k \left(O_k - I_k\right)^2}{\sum_k \left(O_k - \bar{O}\right)^2} \tag{4.3}$$

where:

- R^2 = the coefficient of determination;
- O_p = the observed price of the k^{th} property;
- I_k = the imputed price of the k^{th} property;
- $\bar{O}$ = the mean observed price for all properties.

By calculating these measures for each period and each imputation method, we can assess the stability of the imputation methods over time and compare their performances. The results are presented in Section 4.4.

Price index methods

To further assess the impact of portfolio sales on price indices, we calculated several variations: indices including only single property sales (1), only portfolio sales (2), and a combination of both (3). The price index methods used in this study are the hedonic double imputation Fisher method (Eurostat, 2013b) and the Hedonic Multilateral Time series Splicing (HMTS) method (Ishaak et al., 2024).

In the hedonic double imputation Fisher method, transaction prices are modelled as a function of the real estate's characteristics. In our study, these transaction prices are observed for single property sales and imputed for portfolio sales. By controlling for characteristics, a hedonic regression estimates what the price of real estate would have been if those characteristics had remained constant over time. The double imputation element involves model estimates for both the initial period and the reporting period. In literature, there are three variations:

- **Laspeyres Index**: Keeps the characteristics of the initial period constant (initial period = base period) (Laspeyres, 1871, as referenced in Fisher, 1921).
- **Paasche Index**: Keeps the characteristics of the reporting period constant (reporting period = base period) (Paasche, 1874, as referenced in Fisher, 1921).
- **Fisher Index**: Combines the Laspeyres and Paasche indices by taking the geometric mean of the results (Fisher, 1921).

This method is recommended by Eurostat (2013b) and is used in official real estate statistics (CBS, 2024b, 2024c), making it appropriate for our study. We constructed price indices for offices using the same characteristics as Statistics Netherlands for their CPPI for offices. These characteristics include floor surface, neighborhood segment, a dummy for Amsterdam[13], classification by construction year, and distance to the nearest train station.

13 Other large cities were also tested but showed no significant contribution to the model.

TOC

While the hedonic double imputation Fisher method is widely used for house price indices, it often results in volatile indices for commercial real estate. To provide more stable indices, we employed the HMTS method by Ishaak et al. (2024). This method also uses hedonic regression and double imputation similar to the Fisher method, but it improves stability by considering every possible period as the base period. It uses time series analyses to enhance the estimations and takes the geometric mean of every possible outcome as the final index. Although relatively new, this method is already used in official statistics for small domains (CBS, 2024c).

In this study, we applied both the Fisher and HMTS methods to construct price indices for offices. The same set of characteristics was used for both methods to ensure consistency. By comparing the results of these methods, we aim to understand the impact of including portfolio sales on the stability and accuracy of commercial property price indices. This comparison will help determine the most effective method for processing portfolio sales in the compilation of CPPIs, providing insights into price developments based on single property sales, portfolio sales, and a combination of both. The detailed results and analysis are presented in the following sections.

4.4 Findings

4.4.1 Model-predicted bootstrapping

The model-predicted bootstrapping process provided us with residuals, an example of which is visualized in Figure 4.1. Bootstrapping was performed over 64 quarters (from 2008 to 2023), and histograms showing the distributions of residuals are presented in Figure 4.2. The histograms indicate that the residuals from valuation-based imputations are more concentrated around zero, indicating better performance compared to floor area-based imputations.

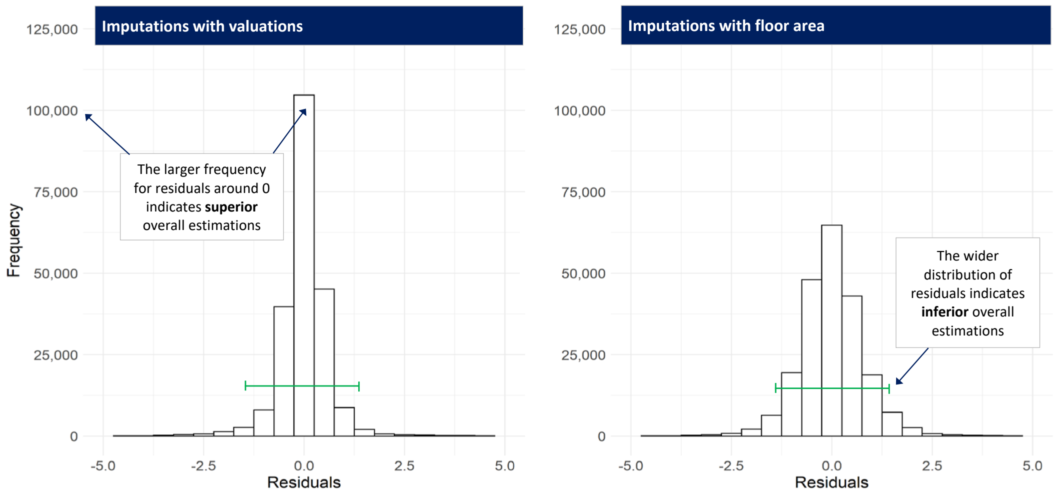

FIG. 4.2 Histogram of residuals for valuation and floor area based imputations. Source: authors' own creation.

To ensure the robustness of the outcomes, the model-predicted bootstrap was simulated 100 times. The distribution of the residuals and the quality of the estimations remained stable throughout these simulations. Valuation-based imputations showed superior performance with an average R^2 of 0.69, an average AIC of 379,954, an average intercept value of 2.25, and an average β-coefficient of 0.82. In contrast, floor area imputations had an average R^2 of 0.49, an average AIC of 508,964, an average intercept value of 5.18, and an average β-coefficient of 0.59. The R^2 and β-coefficient estimates for 20 random simulations are visualized in Figure 4.3.

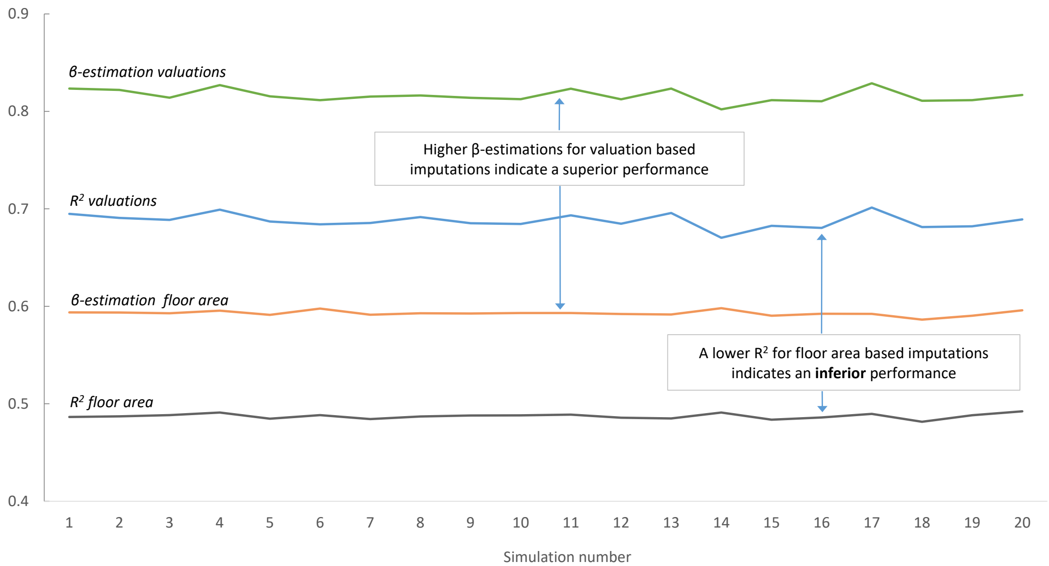

FIG. 4.3 R2 and β-estimates for 20 random simulations. Source: authors' own creation.

4.4.2 Price indices

Indices for office buildings, based on the Fisher hedonic double imputation method, are shown in Figure 4.4. These indices were calculated for single property sales, portfolio sales, and a combination of both. Although Statistics Netherlands publishes indices for office transaction prices, the results in this study differ due to different data selections and slightly different imputations methods[14]. Both use the same population, but Statistics Netherlands removes specific observations through data cleaning. To maintain consistency for portfolio and single property sales, this study deliberately omits this step, resulting in slightly more volatile indices. This volatility is most noticeable in the first quarter of 2010, where prices seem to increase drastically. Additionally, the estimations for single property sales appear more stable than those for portfolio sales. Two potential explanations exist for this: (1) Volatility could be introduced by the imputations. Since imputations come with a prediction error, the hedonic model cannot produce the same stable estimations as it does for directly observed values. (2) Portfolio sales may inherently have more volatile prices than single property sales.

14 The imputation methods used by Statistics Netherlands are more complex in detail, but the use of a distribution key is essentially the same. The difference is that Statistics Netherlands uses multiple imputation methods step-by-step: if number one does not work, the next one comes into effect.

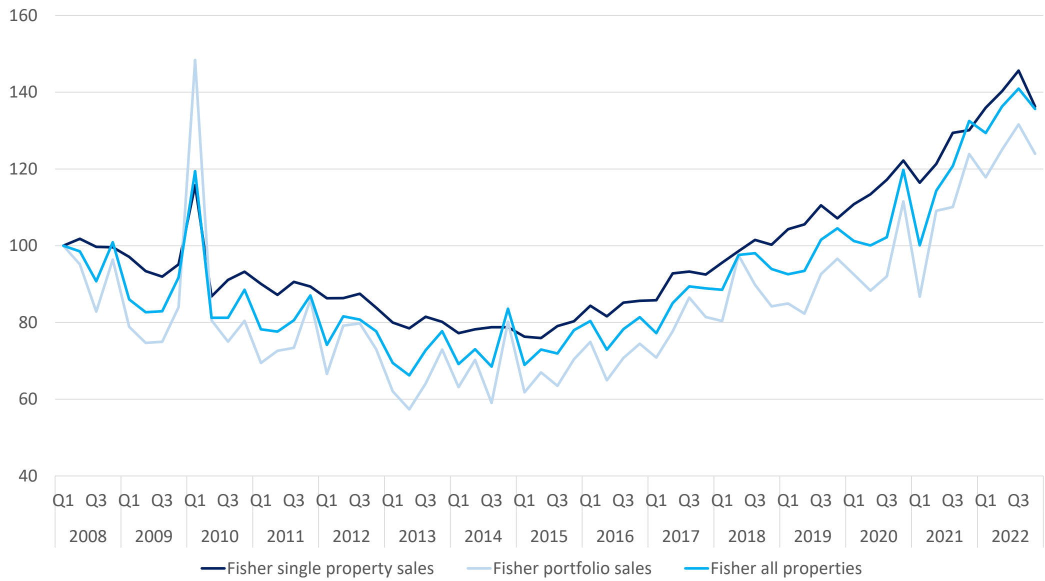

FIG. 4.4 Hedonic Fisher double imputation indices for offices in the Netherlands, 2008Q1=100. Source: authors' own creation.

Figure 4.4 also displays more stable versions of the price developments due to the HMTS method (Ishaak et al., 2024). This figure reveals long-term trends and differences in price developments between single property sales and portfolio sales. Compared to 2008, portfolio sale property prices decreased faster until 2013 than single property sale prices. Even after 2013, portfolio sale prices remained lower compared to 2008. These results support the findings in chapter 2, where we found that portfolio sales often come with a discount. They also observed that during crises, like in 2013, the market share of portfolio sales increased substantially. Therefore, it makes sense that the price indices for portfolio sales show a larger decrease between 2008 and 2013 than single property sales.

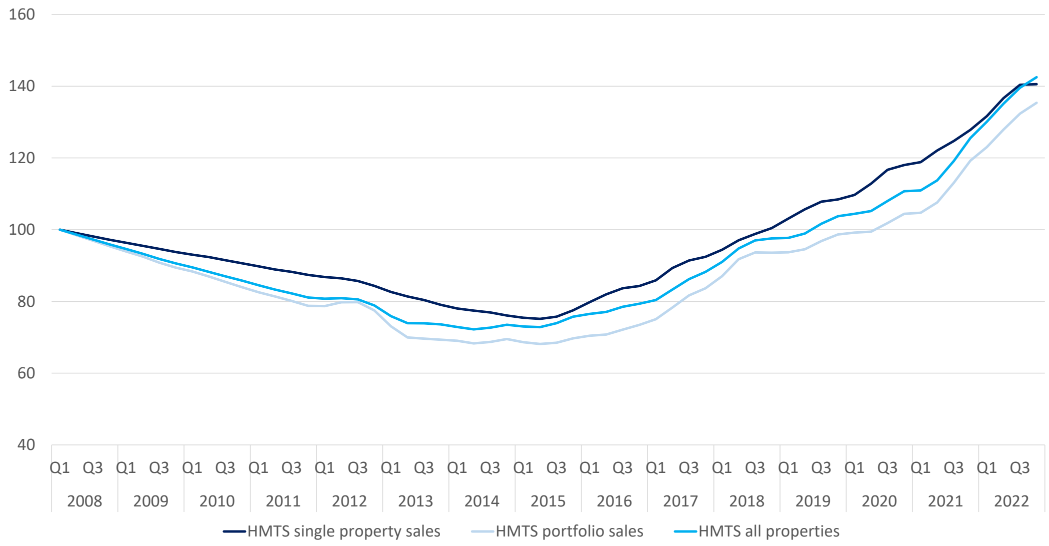

FIG. 4.5 HMTS indices for offices in the Netherlands, 2008Q1=100. Source: authors' own creation.

4.5 Conclusions and discussion

In this study, we explored imputation methods for including portfolio sales in commercial property price indices (CPPIs) and developed methods to assess these imputations. Our findings indicate that the assessment methods provide robust indicators for evaluating imputation methods. Specifically, imputations based on valuations outperform those based on floor area, likely because valuations capture more comprehensive information about the property, while floor area only reflects one characteristic. The results also reveal that CPPIs based on portfolio sales differ from those based on single property sales. A CPPI that includes both types of sales shows slightly different price developments.

Based on these findings, we suggest that CPPIs could be improved by incorporating portfolio sales. Since data restrictions (missing information) may prevent a single imputation method from always being effective, the assessment method allows for the prioritization of imputation methods by quality, enabling the use of a secondary method if the primary one fails.

The imputation methods introduced in this study provide new approaches to handling portfolio sales in the compilation of CPPIs. Additionally, the assessment methods present novel variations of resampling techniques. These methods address the research question by establishing the legitimacy of the imputation methods. However, it is important to note that this study was conducted in the Netherlands, and data from other countries may differ in quality, potentially leading to different results.

This study represents one of the first attempts to address portfolio sales in the context of CPPIs. Nevertheless, further research is recommended due to certain limitations. The study is based solely on data from one country, and only two indicators (valuations and floor area) were available to form a key for distribution within portfolios. Other indicators, such as rent or return values, could also be effective predictors of property sale prices. Therefore, further research on data from other countries, potentially with more variables for distribution keys, is suggested.

Despite the focus on portfolio sales in real estate economics, there has been little attention given to processing portfolio sales for CPPIs. Since CPPIs are now being developed worldwide and statisticians often face the issue of portfolio sales, this study fills a crucial gap by demonstrating the potential for including portfolio sales in CPPIs. This inclusion would improve CPPIs, allowing for more accurate tracking of real estate market developments.

5 A suitable method for official commercial property price indices

The previous chapter addressed both issues of low observation numbers and heterogeneity in the data phase by focusing on the inclusion of portfolio sales in commercial property price indices. The study shows that there are multiple ways to include portfolio sales, and that this inclusion is necessary to construct representative market figures.

This chapter addresses again both issues of low observation numbers and heterogeneity, but now in the method phase. In this study, a method is presented to construct price indices that is suitable for small domains and suits the needs for official statistics.

TOC

5.1 Introduction

In the construction of real estate price indices, hedonic regression methods are quite common and widely used. In fact, these are highly recommended methods for the compilation of official residential property price indices (Eurostat, 2013b). In case of commercial real estate, however, hedonic regression does not always lead to the desired results regarding official statistics. This is because, opposed to residential real estate, two specific complications typically occur: a limited number of observations (small domains) and heterogeneity of real estate transactions/objects that are observed (Eurostat, 2017). Heterogeneity is usually reduced by stratifying observations into more homogeneous groups. This solution, however, further decreases the number of observations and thus makes it even more problematic to create a reliable index. A small number of observations often causes hedonic models to inadequately capture relations and thus results in an inaccurate index. This can be resolved by pooling the data of all periods in a hedonic time dummy model (Eurostat, 2013b). The side effect, however, is that this method involves backward revision. After all, once a period is added, the pool of data changes and thus the model outcomes change for all periods in the data pool. These constant revisions are undesirable from a user's point of view. The rolling time dummy method (RTD) (Shimizu et al., 2010; O'Hanlon, 2011; De Haan, 2015; R. J. Hill et al., 2022) partly resolves this issue by pooling the data in a specified time window. In this method, the data and the outcomes of periods outside of the window remain unchanged. This method, however (like most other methods), was primarily constructed for residential property. An application to commercial property still often results in a volatile index, because of the small number of observations and high degree of heterogeneity in real estate (an application of the RTD method and a presentation of the corresponding issues is provided in Section 5.4). In practice, the shortcoming of current methods becomes apparent from the limited number of countries that have succeeded in publishing commercial property price indices (CPPIs). In October 2009, the Financial Stability Board and International Monetary Fund expressed the need for CPPIs. Eurostat, in response boosted the development of CPPIs in EU member states (FSB & IMF, 2022). In a progress report of Eurostat from December 2021, it was mapped that – twelve years later – only 4 of 24 member states had succeeded in publishing a CPPI (European Commission, 2021). In addition, even published CPPIs have drawbacks. For example, the Netherlands, who is one of the four, publishes a volatile index alongside a smooth trend line (CBS, 2024b). So even though this counts as a publication, the Netherlands has not succeeded in calculating a single reliable CPPI. The reason for this, it that small numbers of transactions and heterogeneous markets are considered as main challenges.

Existing price index methods, thus, do not seem to meet the desired properties of official statistics when it comes to commercial real estate. The aim of this study is to develop a method that does. In official statistics, a few practical properties often make the difference (in addition to methodological properties) for the successful adoption of an index by the users. Therefore, in this study the desired properties are split up into methodological and practical properties.

The methodological properties are formed by index axioms or tests as mentioned by Balk (1995, 2012). An example is the identity test, which states that if the prices of period A are equal to the prices of the same products of period B, then the index figures of both periods should be equal. Another example is the time reversal test, which states that if you would reverse the calculation from 'period A relative to period B' to 'B relative to A', the outcomes should be exact opposites of each other. A third example is the circularity test, which states that the multiplication of a price index between period A and B with a price index between period B and C, should be equal to a direct price index calculation between period A and C. There are many other axioms and tests for index methods. A motivation on the choice of tests for this study is provided in Section 5.2.1. An important note here is that no single index formula meets all axioms (Wald, 1937; De Haan & Van der Grient, 2008). Therefore, in choosing/developing an index, fulfilling methodological axioms is a matter of choice/preference. As each axiom has its own advantages, certain axioms should be valued higher than others in order to choose an index method. Although it is a matter of choice, testing the performance of an index on the axioms provides useful information on the quality and behavior of the index. An elaboration of the desired methodological properties and the advantages and disadvantages is provided in Section 5.2.

A first desired practical property is a price index that does not suffer from volatility, except volatility caused by market fluctuations. If the volatility in an index is not a market reflection but an intrinsic part of the index, it could indicate a flaw in the method. Aside from the methodological deficiency, a volatile index is also undesirable from a publication stance. A price index should provide users with information about the underlying evolution of the market. Volatility prevents users from making such an assessment, unless, of course, the market is truly very volatile. A second desired practical property is that the index is only subject to revision to a limited extent. Some hedonic methods, for instance the time dummy model, lead to revisions of previously estimated indices each time a period is added at the most recent end of the series (even though the data itself from the older periods is unchanged). This is a major disadvantage from a publication perspective. It makes the initial estimation less reliable in the eyes of the user. Most statistics published by National Statistical Institutes (NSIs), therefore, are only revised up to a certain point. A third desired practical property is that the index should enable an early detection of turning points. Although a price index can be seen as a report of developments that occurred in the past, it is often used as a monitoring tool to assess where the developments are heading in the (near) future. Even though a price index should not contain predictions itself, it shouldn't lag or over extensively smooth real developments either. This would prevent an early detection of turning points.

The main question of this study is: how can we construct a price index for small, heterogeneous domains that balances the most desired practical and methodological properties? The most important practical properties are a limited backward revision, minimal index volatility caused by model deficiencies and an early detection of turning points. The commonly most important methodological properties are the identity test, the time reversal test and the circularity test. The motivation for choosing these tests is elucidated in Section 5.2. A price index that balances above properties will be of use in monitoring financial stability and will, therefore, be suitable for the use in official statistics. An attempt to construct such an index for commercial real estate has not been made before and realizing it will aid statisticians in constructing publishable CPPIs or will at least provide some handles to rethink which properties should be desired for official CPPIs.

5.2 Background

In this section, some background is provided on the practical and methodological properties. Through a brief literature review, explanations are provided on how its performance on these properties is crucial for the success of a CPPI.

5.2.1 Desired methodological properties

From a methodological perspective, many possible properties for official statistics can be imposed. In index theory literature, these criteria are referred to as axioms or tests. In general, the axioms/tests describe scenario's that feel logical. It was Laspeyres (1871, as referenced in Diewert 2007) that first spoke of an *identity test* for assessing an index. The identity test states that, if the prices in period A and B are equal, the price index figure between period A and B should be equal too (as in there is no price development between the two periods). The consequence of an index meeting the identity test is that there is an immediate response to the data. This is an advantage if the data is an accurate reflection of the market. In the presence of transaction noise (discussed in Section 5.2.2), meeting the identity test may actually be a disadvantage.

After the identity test, Westergaard (1890, as referenced in Diewert 2020) followed by proposing a *circular (or transitivity) test*. In this test, the results between three periods should be consistent: multiplying the index between A and B with the index between B and C should be equal to the direct index between A and C. The consequence of an index meeting the circularity test is that the index does not depend on one or a few base periods. Especially in small domains, this may prove to be a useful index property as there is a chance that first period (likely the base period) does not contain the best data. Even in Paasche like indices, where the base period alters from reporting period to reporting period, the index figures are still based on one base period at a time. In small domains, this will lead to the use of at least some base periods based on small samples.

After the circular test, it was Pierson (1896) who proposed an additional *time reversal test*, stating that the price index of period A relative to B should be the opposite of the price index of period B relative to A. In other words, reversing the periods in the data should not change the relation between the two periods. The consequence of an index meeting the time reversal test is that again the index does not rely on one base. Whether A serves as base or B, the outcome is the same in time reversible indices.

Fisher (1922, as referenced in Diewert 2007) bundled these tests (Fisher's system of tests) and added a few other tests. In the years after, many authors followed by proposing new tests. Eichhorn (1976) made a distinction between axioms and tests. Axioms are claimed to be self-evident, and tests are more debatable. In his review on 'axiomatic price index theory', Balk (1995) listed 6 axioms and 4 tests. Diewert (2007) surpassed that and reported 21 tests (without making a distinction with axioms). An important note regarding these tests is that they cannot be met simultaneously. Wald (1937) proved this with just the older tests of Fisher's system of tests. For example, index cannot simultaneously satisfy the identity test, the circularity test and the product test (a test which considers quantities in an index) (Balk, 1995). To exemplify, the three most famous index variations are Laspeyres, Paasche and Fisher. In the table below, the properties of the three hedonic index methods are presented, showing that these variations do not pass all tests.

TABLE 5.1 Index test results for Laspeyres, Paasche and Fisher. Adapted from: de Haan and van der Grient (2008, p. 14).

	Laspeyres	Paasche	Fisher
Identity	Yes	Yes	Yes
Time reversibility	No	No	Yes
Circularity	No	No	No

Fisher's system of tests is mostly included in regulations for official statistics (e.g. ILO et al. 2020; Eurostat 2022). In this paper we, therefore, focus on the identity test, the time reversal test and the circular test.

5.2.2

5.2.2. Desired practical properties

Looking beyond methodological properties has not always been common. In the last decade, attention for the practical side, however, grew. In its 'Quality Framework and Guidelines for OECD Statistical Activities', the OECD stated that 'Quality is defined as "fitness for use" in terms of user needs (OECD, 2012, p. 7). It is also the first principle in the UN's 'Fundamental Principals of Official Statistics' that 'official statistics should meet the test of practical utility' (UN 2014, p. 2). For successfully compiling official statistics, it is, therefore, recommended to also consider practical components.

The first practical property, we denote in this study, is a *stable index*. If price developments go up for 10% in one period and go down by 20% in the next period, it is difficult for users to assess how the market is evolving. The aim for index construction is, however, not to remove market volatility, but only to remove volatility that is intrinsic to the index method or *non-existing volatility*. The more *existing volatility* is removed, the more it leans towards smoothing. Over the years, this trade-off has been discussed in various studies. Silver (2016) warns for the effects of adding stability trough smoothing. He states that there is a loss of credibility if apparent volatility is not mirrored in the index. Schwann (1998) also mentions disadvantages of forcing stability and acknowledges there is a trade-off: smoothing in essence is undesirable, because it will deviate from the true (to be estimated) index. On the other hand it enhances accuracy (an elaboration on this is provided in Section 5.3.3). Both authors seem to refer to real market volatility and not volatility that is intrinsic to the method. On the other hand, smoothing has at least two advantages: making the underlying trend visible and averaging inaccurate estimates. Regarding the latter, Francke (2010) explains how index modelling can lead to volatility. If regression models are used, the estimated regression coefficient is sensitive to transaction noise. In broad pricing context, noise refers to information that misrepresents the underlying trend. This is caused by the coincidental distribution of observed prices across periods. As a consequence, observed transaction prices differ from its true (and to be estimated) market prices and thus, basing an index on only observed prices can lead to inaccurate estimates. Regarding trends, from the perspective of official statistics, in the CPI manual it is stated that for some purposes, "measuring core inflation is desirable from an economic stance" and "central banks use measures of the general trend of inflation when setting monetary policy" (ILO et al., 2020, p. 329). In CPIs, core inflation is commonly captured by excluding prices of items that are deemed volatile. In other words, these are items that are susceptible to short-term shocks (ILO et al. 2020, 30). Measuring core inflation, in that sense, aligns with the goals of our study. Given that banks will be main users of CPPIs, this argues for the use of an indicator that captures the trend, but not the volatility. From these perspectives, estimating true market prices is favorable, but it should be done with cautiousness not to remove useful market information.

The second practical property is to create an index that is not overly *subject to revision*. To be clear, we are not talking about revisions due to mistakes, but revision that are inherent to the index method. Index methods that suffer from this issue are, for example, hedonic time dummy and repeat sales. Every time a new period is added, the model has to be re-estimated, and it leads to changes to the entire – previously estimated – index series. In its guideline on revision policy for Principal European Economic Indicators (PEEIs: indicators which are essential for monitoring, such as real estate prices), Eurostat (2013a, p. 5) states that "revisions are something of a double-edged sword". The estimation is improved, but if it results in "a different assessment of the state of the economy", it can "damage the credibility of the statistical data". In addition, from a user's perspective, "too many revisions create uncertainty" (Eurostat, 2013a, p. 7). Silver (2016, p. 20), however, states that a "problem" with the revision "should not be overstated" as there are many real estate price indices in the Unites Stated that suffer from continuous revision and it is without any complaints of users. Clapham et al. (2006), on the other hand, state that 'index stability' (in terms of limited revisions) is often overlooked in index construction. Given the wide use of real estate indices, limiting revisions is highly relevant. Deng et al. (2008) provide further explanation: the initial estimations of real estate price indices are mostly used. If a month later the initial estimation is revised, people don't pay much attention to the revision as the focus is on the price development of the most recent period. Revisions, therefore, are mostly informational. Moreover, if revisions tend to be large, the usefulness of the index becomes compromised. Therefore, EU member states are by legislation

TOC

bound to only one preliminary period for the House Price Index (HPI) (European Union, 2023). Given that development of HPIs is more advanced than CPPIs, CPPIs can be expected to have the same restrictions in the future. From these perspectives, it can be concluded that limited revision of an index is favorable, but there should be awareness not to give in on accurateness.

The third property is the ability of detecting *turning points* in an early stage. An early detection of turning points has the particular interest of users involved in management in the real estate economy. In the use of CPPIs, "the focus of much of the analysis … is on trends and turning points. In this context users need regular and timely data … for the detection and identification of economic relationships" (Eurostat, 2017, p. 27). A turning point is, in this study, defined as a 'structural' change in the price development from positive to negative or the other way around. The term 'structural' closely relates to the first property of a stable index. In a volatile index, changes from positive to negative occur often. Structural changes are, therefore, hard to detect in an unstable index. Some cautiousness is, however, appropriate in making indices more stable by smoothing. Eurostat (2017, p. 120) notes "late detection or turning points due to systematic smoothing of the index" as a potential issue. The type of smoothing that is referred to is, however, caused by using valuations as data source rather than smoothing as a method. Hill and Steurer (2020) and Francke (2010) then again, notice that certain index models (namely Repeat Sales models) can also cause lags, which prevents an early detection of turning points.

5.3 Methodology

There are several possible approaches in constructing a price index for small, heterogeneous domains that meet the most desired practical and methodological properties. In this study, we propose a 4-step procedure. We base each of these steps on existing techniques, which we alter for our present purpose. In sequential order, these steps are (1) hedonic imputations, (2) multilateral imputations, (3) time series re-estimated imputations and (4) window splicing. This is the first study that combines above techniques to construct a price index. An overview of the steps and summary of the effects is provided in Figure 5.1. Each step is discussed in detail in below paragraphs.

TOC

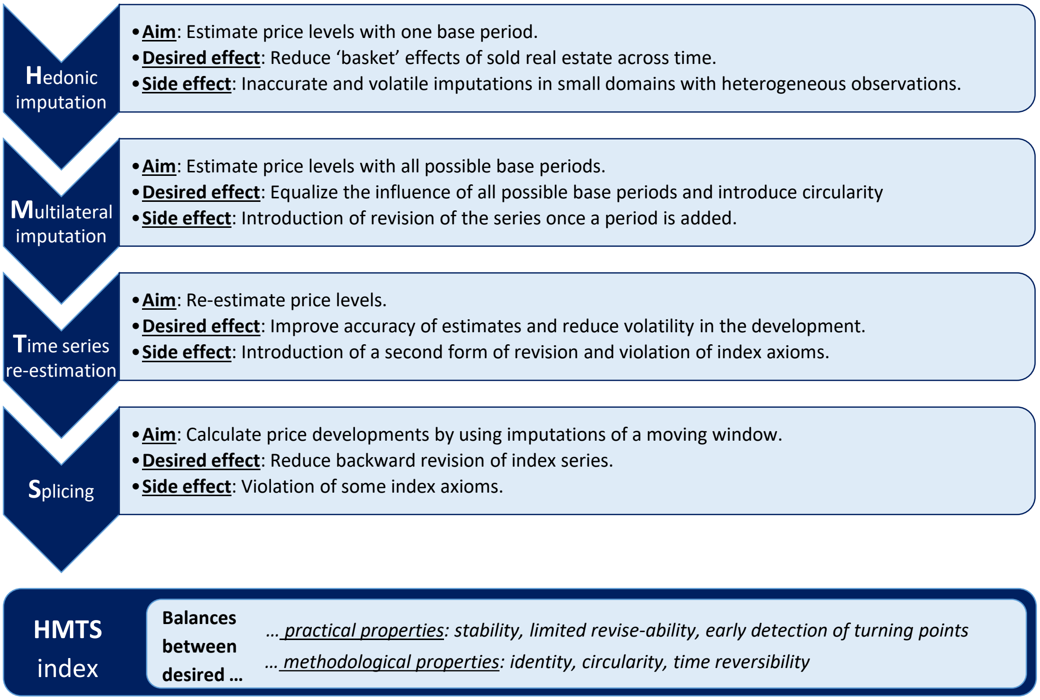

FIG. 5.1 HMTS procedure. Source: authors’ own creation.

5.3.1 Step 1 – Hedonic imputations

The aim for a Commercial Property Price Index (CPPI) is a constant quality price index. In other words, the purpose is to measure pure price changes of real estate and not changes in quality. Therefore, a comparison of sold real estate between periods should be adjusted for changes in quality between the periods. For the measurement of non-durable goods, this is less of an issue as the exact same product can be purchased in succeeding periods. For real estate this is problematic, because every real estate object is unique and, in every period, a different selection of real estate is sold. As a first step, hedonic regression is introduced in this procedure to adjust for the quality changes between periods. Hedonic regression is in essence a breakdown of complex good (such as real estate) into its components. These are, for example, size, location, building age and so on. The composition of a hedonic model is actually a very important, but different topic. The hedonic model should contain important and statistically significant attributes of real estate prices and the assumptions for hedonic modelling should be tested. Miyakawa et al (2022), for one, show the diversity of attributes that could be taken into account for explaining commercial transaction prices. Once the model is adequately formed, one can proceed to the next step.

The value or sale price can be expressed as an additive function of these characteristics. Linear regression (OLS: Ordinary Least Squares) is used to an averaged value addition for all components. These averages are then used to calculate model prices or *imputed prices* for each observation. A common logarithmic-linear model, based on Eurostat (2013b, p. 50), which is used to calculate the averaged value additions (β) per period, is:

$$\ln p_t^i = \beta_t + \sum_{k=1}^{K} \beta_t^k x_{\mathrm{t}}^{ik} + \varepsilon_t^i \qquad (5.1)$$

where:

- p_t^i = the price of the i^{th} property sold in period t;
- β_t = the intercept term in period t;
- β_t^k = the coefficient of the k^{th} characteristic in period t;
- x_{t}^{ik} = the k^{th} characteristic of the i^{th} property sold in period t;
- ε_t^i = a random error term of the i^{th} property sold in period t, with $\varepsilon_t^i \sim N(0,\sigma)$.

To understand the application of above regression in the HMTS method, it helps to first understand the basics of the Laspeyres and Paasche hedonic double imputation (HDI) method. In both methods, the regression is run for each period, and the model prices are estimated (or imputed) with the retrieved intercept and coefficients. The difference between the two is the base period. In Laspeyres indices, the characteristics of the first period are kept constant. In Paasche indices, the characteristics of the reporting period are kept constant. The index formulae of both are presented below.

$$I_{0,t}^{L} = \overline{\widehat{p}_{t(0)}} \Big/ \overline{\widehat{p}_{0(0)}} = \frac{exp\,\widehat{\beta}_t exp\left[\sum_{k=1}^{K} \widehat{\beta}_t^k \overline{x_0^k}\right]}{exp\,\widehat{\beta}_0 exp\left[\sum_{k=1}^{K} \widehat{\beta}_0^k \overline{x_0^k}\right]} \qquad (5.2)$$

$$I_{0,t}^{P} = \overline{\widehat{p}_{t(t)}} \Big/ \overline{\widehat{p}_{0(t)}} = \frac{exp\,\widehat{\beta}_t exp\left[\sum_{k=1}^{K} \widehat{\beta}_t^k \overline{x_{\mathrm{t}}^k}\right]}{exp\,\widehat{\beta}_0 exp\left[\sum_{k=1}^{K} \widehat{\beta}_0^k \overline{x_{\mathrm{t}}^k}\right]} \qquad (5.3)$$

TOC

The added terms, compared to Equation (5.1), are:

- $I^{L}_{0,t}$ = Laspeyres HDI price index number between period 0 and t;
- $\overline{\hat{p}}_{t(0)}$ = average imputed price of period t with base period 0;
- $\overline{x}^{k}_{0}$ = average of the k^{th} characteristic in period 0. This is calculated by $\sum_{i=1}^{N_t} x^{ik}_{0} / N_0$, with N_0 representing the number of observations in period 0.

As can be seen, the variations between Laspeyres and Paasche are caused by variating in base periods. In Laspeyres, the characteristics, $\overline{x}^{k}_{0}$, are kept constant in both the numerator and the denominator at period *0*. This results in price imputations, $\overline{\hat{p}}_{t(0)}$, with base period *0*. In words, the mix of sold real estate in period *0* is tracked through time. Its prices are imputed in the next periods as if they were sold in another period. These imputations are made by using the regression coefficients, $\hat{\beta}^{k}_{t}$, which are obtained by Ordinary Least regression (OLS). In the case of Paasche (equation 5.3), this is turned around and the mix of sold real estate in period t is tracked through time. A schematic overview of all imputations of four sequential periods (0 < 1 < 2 < 3), required for a Laspeyres and a Paasche index, is provided in below table.

TABLE 5.2 Matrix with Laspeyres and Paasche imputations. Source: authors' own creation.

		Reporting period				Used to calculate:
		0	1	2	3	
Base period	0	$\overline{\hat{p}}_{0(0)}$	$\overline{\hat{p}}_{1(0)}$	$\overline{\hat{p}}_{2(0)}$	$\overline{\hat{p}}_{3(0)}$	Laspeyres (I^{L}_{0-3})
	1	$\overline{\hat{p}}_{0(1)}$	$\overline{\hat{p}}_{1(1)}$			Paasche ($I^{P}_{0,1}$)
	2	$\overline{\hat{p}}_{0(2)}$		$\overline{\hat{p}}_{2(2)}$		Paasche ($I^{P}_{0,2}$)
	3	$\overline{\hat{p}}_{0(3)}$			$\overline{\hat{p}}_{3(3)}$	Paasche ($I^{P}_{0,3}$)

Note that the Laspeyres index uses only imputations in one row, indicating that there is only one imputation for each period. This is in contrast to the Paasche index that uses imputations in multiple rows, because each addition of a period creates a new version of the imputed price in period *0* ($\hat{p}_0$). In this study, equations (5.2) (Laspeyres) and (5.3) (Paasche) are not performed to construct the HMTS index. Only the element of imputed prices is used. In Table 5.2, these are presented as the values for $\overline{\hat{p}}$.

5.3.2 Step 2 – Multilateral imputations

Table 5.2 shows a common characteristic in both the Laspeyres and the Paasche index: there is a large dependency on the imputations in period *0*. In the Laspeyres index, period *0* is used as base period and in the Paasche index, the imputations of period 0 are recalculated in each reporting period. Especially when using small datasets, the use of one base period can be perceived as a deficiency as is the case with Laspeyres and Paasche indices. In Laspeyres, the selection of transacted real estate in period *0* is tracked through time in the entire index series. If the data is limited, the possibility grows that this selection does not resemble the stock of real estate or the sold real estate in other periods. In Paasche, the selection of real estate in period *t* is tracked, but in every calculation, it uses regression results of period *0*. If the data is limited, the possibility grows these regression results lack accuracy. A common way to mediate between Laspeyres and Paasche is to calculate a Fisher index, which is the geometric mean of the Laspeyres and Paasche index. As the Fisher index is composed from the Laspeyres and Paasche index, it also inherits the mentioned deficiencies. In all three indices, the choice of base period is arbitrary. To fix this dependency on one or a few base periods, we propose a multilateral approach, which is achieved by filling the blanks in Table 5.2 as illustrated in Table 5.3. By completing the matrix, every reporting period is calculated with every possible base period. This results in multiple series, and all of these cover the complete time span, hence the term 'multilateral'.

TABLE 5.3 Matrix with multilateral imputations. Source: authors' own creation.

		Reporting period			
		0	1	2	3
Base period	*0*	$\overline{\widehat{p}}_{0(0)}$	$\overline{\widehat{p}}_{1(0)}$	$\overline{\widehat{p}}_{2(0)}$	$\overline{\widehat{p}}_{3(0)}$
	1	$\overline{\widehat{p}}_{0(1)}$	$\overline{\widehat{p}}_{1(1)}$	$\overline{\widehat{p}}_{2(1)}$	$\overline{\widehat{p}}_{3(1)}$
	2	$\overline{\widehat{p}}_{0(2)}$	$\overline{\widehat{p}}_{1(2)}$	$\overline{\widehat{p}}_{2(2)}$	$\overline{\widehat{p}}_{3(2)}$
	3	$\overline{\widehat{p}}_{0(3)}$	$\overline{\widehat{p}}_{1(3)}$	$\overline{\widehat{p}}_{2(3)}$	$\overline{\widehat{p}}_{3(3)}$

Added compared to the Laspeyres or Paasche calculation as presented in Table 5.2.

This approach is inspired by the multilateral GEKS (Gini 1931; Eltetö and Köves 1964; Szulc 1964 as referenced in de Haan and van der Grient 2011) method as described by Willenborg (2017, 2018). In his study, Willenborg explains the

GEKS method as completing a matrix with index figures based on all possible base periods. By taking the geometric mean of all possibilities for each reporting period, *circularity* is realized (Table 5.1 shows that Laspeyres, Paasche and Fisher do not pass the circularity test). A direct price development between period *0* and *2* equals a multiplication between direct indices between period *0* and *1* and period *1* and *2*. The formula for retrieving each imputation is provided in equation (5.4).

$$\overline{\widehat{p}_{t(b)}} = exp\,\widehat{\beta}_t exp\left[\sum_{k=1}^{K}\widehat{\beta}_t^k\,\overline{x_b^k}\right] \tag{5.4}$$

Opposed to equations (5.2) and (5.3), the base periods are flexible as it can have any value between *0* and *t*. Calculating one single imputation for period t is achieved by taking the geometric mean of all variations with different base periods, illustrated in equation (5.5).

$$\overline{\widehat{P}_t} = \left(\prod_{b=0}^{T}\overline{\widehat{p}_{t(b)}}\right)^{1/T}, \text{ with } t = 0,1,\ldots,T \tag{5.5}$$

With $\overline{\widehat{P}_t}$, a circular index $I_{0,t}$ can be constructed according to equation (5.6).

$$I_{0,t} = \overline{\widehat{P}_t} \Big/ \overline{\widehat{P}_0} \tag{5.6}$$

In this study, equations (5.5) and (5.6) are not performed at this stage for the final index. The imputations resulting from equation (5.4) are used in the next step.

5.3.3 Step 3 – Time series re-estimated imputations

The result of equation (5.6) is a circular index that does not heavily rely on one base period. However, the individual imputations in step 1 may still lack accuracy and thus a resulting index still shows volatile developments. This is especially the case if hedonic regression is performed on small datasets with a high degree of heterogeneity. Time series analysis, and in particular state space modelling is used in this step to improve the price imputations in terms of accuracy, reliability and validity. A few notes on the latter concepts seem appropriate at this point and Babbie (2014, pp. 140–143) provides definitions that we will use to describe how time series re-estimations will enhance the index.

Accuracy often refers to the proximity of a measurement to the true value. As we are aiming for trend like behavior of the price developments, moving away from volatility seems to add accuracy. This is not to be confused with precision. Precision reflects the closeness of multiple observations to each other. E.g. estimating a man as '36 years old' is more precise than 'in his thirties'. If the man is in fact 39 years old, the latter estimation is, however, the only accurate one. In our case, the introduction of time series re-estimations adds accuracy, but hands in on precision.

Reliability refers to whether a technique, applied repeatedly to the same observation, yields the same result. The re-estimation reduces volatility and, therefore, also variance in outcome. This leads to more similar results when simulations are run with in-sample variations. This analysis is further described in section 5.4.2 (Figure 5.5 – confidence intervals).

Validity refers to the extent to which a measure reflects the real meaning of the concept. The concept we are aiming to measure is price developments in the real estate market. Again here, volatility prevents us from capturing the real underlying market developments. Due to low numbers and heterogeneity, a volatile index rather captures momentarily developments of incidental transactions.

In time series analysis, all values in the series are assumed to be related, i.e. there is a correlation between adjacent periods. State space models make a general distinction between observed and unobserved variables. The former is model input and the latter is model output. A simple state space model (in this case a random walk plus noise model) is represented in equations (5.7) and (5.8) (Commandeur & Koopman, 2007, p. 9).

$$y_t = \mu_t + \varepsilon_t , \qquad \varepsilon_t \sim NID\left(0, \sigma_\varepsilon^2\right) \tag{5.7}$$

$$\mu_{t+1} = \mu_t + \xi_t , \qquad \xi_t \sim NID\left(0, \sigma_\xi^2\right) \tag{5.8}$$

The terms in these formulae are:
- y_t = the observed value in period *t*;
- μ_t = the unobserved level in period *t*;
- ε_t = the observation disturbance in period *t*;
- ξ_t = the level disturbance in period *t*;
- $NID()$ = indication that the disturbance terms are normally and independently distributed.

Equation (5.7) is called the measurement or observation equation. It separates the observed series y_t into a signal (μ_t) and a noise component. The essence of above model is that the signal is described by a series of unobserved states μ_t that evolve through time. This is done by the second equation (5.8), called the transition equation. It describes how the unobserved state μ_t depends on the previous value of μ_t. The amount of change between consecutive values of μ_t is determined by a series of random shocks ξ_t.

We are interested in the unobserved states and are able to estimate these with help of the observed series. In our case, the observed states y_t refer to the estimated average hedonic price levels, resulting from equation (5.5). Following equation (5.7), we assume the series of observed price levels y_t contain noise or observation disturbances. The state space assumption is that we cannot observe the true states (unobserved levels) directly and these should be estimated.

Regarding reducing volatility, these state space methods as described by Commandeur and Koopman (2007) and Durbin and Koopman (2012), show great potential, because the unobserved levels tend to be smoother than the observed levels. With the assumption that there is correlation within the time series, the estimated unobserved levels are most likely also more accurate estimates of the price developments. Francke & De Vos (2000), Francke (2010), Rambaldi and Fletcher (2014) and Hill et al. (2021) already proved that integration of hedonics and state space methods can result in stable estimates of growth rates.

After equation (5.8), there are many different models to choose from. In our study, many models were tested, and the best model was chosen by looking at the most suitable fit. The model showed, among which, the lowest AIC (presented in appendix 2). The model of choice is a local linear trend model. In this model, another term, the slope component, is introduced to further improve the estimation of the trend. In general, the addition of a slope is more suitable for long term and changing trends. Furthermore, the model sets a hyperparameter of the level component equal to zero, while the slope component remains stochastic. This model is also known as a smooth trend model, and since the slope disturbances affect the level component indirectly, generally yield a smoother estimate of the level component. Equations (5.9), (5.10) and (5.11) represent this model applied to the price imputations resulting from step 2.

$$\overline{\widehat{p}_{t(b)}} = \mu_{t(b)} + \varepsilon_{t(b)}, \qquad \varepsilon_{t(b)} \sim NID\left(0, \sigma_{\varepsilon}^{2}\right) \tag{5.9}$$

$$\mu_{t+1(b)} = \mu_{t(b)} + v_{t(b)} \tag{5.10}$$

$$v_{t+1(b)} = v_{t(b)} + \zeta_{t(b)}, \qquad \zeta_{t(b)} \sim NID\left(0, \sigma_{\zeta}^{2}\right) \tag{5.11}$$

The added terms in these formulae are:

- $\overline{\widehat{p}_{t(b)}}$ (observed values);
- $\mu_{t(b)}$ = the unobserved level in period t for the series with base period b;
- $\nu_{t(b)}$ (deterministic) for the series with base period b;
- $\zeta_{t(b)}$ = the slope disturbance in period t for the series with base period b.

In equation (5.9), the observed values y_t are replaced by the imputed prices $\overline{\widehat{p}_{t(b)}}$ retrieved from the previous step. Opposed to equation (5.8), the estimation of $\mu_{t(b)}$ is now expanded with slope $\nu_{t(b)}$ in equation (5.10). Slope $\nu_{t(b)}$ depends in its turn on the previous estimation of $\nu_{t(b)}$. The model can be estimated by applying a two-step procedure. First, the hyperparameters, i.e., the variances of the error terms, are estimated via a Maximum Likelihood procedure. Then the Kalman filter (Kalman, 1960) is applied to estimate the state variables (level and slope). The Kalman filter is a recursive algorithm that first applies a forward pass to the time series, from *t*=1 to *t*=T, and at each step updates the estimates of the state variables. This is called filtering. The estimates at time *t* are thus only based on information up to that period. Then a backward pass is applied from *t*=T to *t*=1, in which the filtered estimates are updated using all available information. This is called smoothing. In our case we are interested in these smoothed estimates, since this is the added value of step 3 (capturing the trend). Once the model is estimated, the re-estimated imputations can be derived as follows.

$$\widetilde{\overline{\widehat{p}}}_{t(b)} = \widehat{\mu}_{t(b)} = \overline{\widehat{p}_{t(b)}} - \widehat{\varepsilon}_{t(b)} \tag{5.12}$$

The term $\widetilde{\overline{\widehat{p}}}_{t(b)}$ represents the re-estimated price imputation in period *t* with base period *b*. A schematic overview of all re-estimated price levels of four sequential periods (0 < 1 < 2 < 3) with the same number of base periods is provided in below table.

TABLE 5.4 Matrix with re-estimated multilateral imputations. Source: authors' own creation.

		Reporting period			
		0	1	2	3
Base period	0	$\widetilde{\overline{\widehat{p}}}_{0(0)}$	$\widetilde{\overline{\widehat{p}}}_{1(0)}$	$\widetilde{\overline{\widehat{p}}}_{2(0)}$	$\widetilde{\overline{\widehat{p}}}_{3(0)}$
	1	$\widetilde{\overline{\widehat{p}}}_{0(1)}$	$\widetilde{\overline{\widehat{p}}}_{1(1)}$	$\widetilde{\overline{\widehat{p}}}_{2(1)}$	$\widetilde{\overline{\widehat{p}}}_{3(1)}$
	2	$\widetilde{\overline{\widehat{p}}}_{0(2)}$	$\widetilde{\overline{\widehat{p}}}_{1(2)}$	$\widetilde{\overline{\widehat{p}}}_{2(2)}$	$\widetilde{\overline{\widehat{p}}}_{3(2)}$
	3	$\widetilde{\overline{\widehat{p}}}_{0(3)}$	$\widetilde{\overline{\widehat{p}}}_{1(3)}$	$\widetilde{\overline{\widehat{p}}}_{2(3)}$	$\widetilde{\overline{\widehat{p}}}_{3(3)}$

From these re-estimated imputations, an index can be constructed according to equations (5.5) and (5.6). In this study, equations (5.5) and (5.6) are not performed at this stage for the final index. The imputations resulting from equation (5.12) are used in the final step.

5.3.4 Step 4 – Window splice

At this point in the procedure, the method is expected to provide more stable indices. However, the other practical property of limited revisions is not met. The previous steps of multilateral calculations and time series re-estimations both cause revisions once a period is added.

For multilateral calculations the mechanism is as follows: once a reporting period is added, a series is added with another base period. This is demonstrated in Table 5.3: adding a column (reporting period) also means adding a row (series with upgraded base period). Calculating the geometric mean of all possibilities for period *0*, now includes one extra figure (with base period *t*). This occurs in all periods and therefore the figures of all periods are revised.

For the time series re-estimations, the mechanism is as follows: once a reporting period is added, the calculation of the previous period is adjusted as each unobserved value is calculated with information of the preceding and succeeding period. This occurs in all periods and therefore the figures of all periods are revised.

A rolling window approach or window splicing is introduced in this study to avoid revision of the entire series every time a reporting period is added. As shown by Shimizu (2010), Ivancic et al. (2011), Krsinich (2016), Chessa (2021), Bentley (2022) and Diewert and Fox (2022), splicing is well known in index construction, especially in combination with multilateral methods. Hill et al. (2022) report that the technique is also widely used in official statistics (at least in the form of a rolling time dummy method). The main idea of window splicing is to keep a limited number of periods provisional instead of the entire time series. To bypass the revisions caused by the multilateral calculations, the final averaged index number is not based on all possibilities of an imputed price, but on a selection.

This selection is performed in a 2-step procedure. First, to bypass the revisions caused by the multilateral time series re-estimation, the series for each base period will not endlessly be updated. An example to illustrate this: a window is determined at 3 periods. In other words, once period t is calculated for the first time it is provisional. In this period and the next two periods, the figure for period t is subject to revision. In period $t+1$, the series with base period t is extended with reporting period $t+1$. In period $t+2$, the series with base period t is extended again with reporting period $t+2$. In both calculations, the figure for period t is revised. This will be the last time, since the series with base period t is fixed from that point on. An illustration of this update scheme is provided in Table 5.5.

TABLE 5.5 Matrix with update scheme of re-estimated multilateral imputations. Source: authors' own creation.

		Reporting period					
		0	1	2	3	4	5
Base period	0	$\widetilde{\widetilde{\hat{p}}}_{0(0)}$	$\widetilde{\widetilde{\hat{p}}}_{1(0)}$	$\widetilde{\widetilde{\hat{p}}}_{2(0)}$ *			
	1	$\widetilde{\widetilde{\hat{p}}}_{0(1)}$	$\widetilde{\widetilde{\hat{p}}}_{1(1)}$	$\widetilde{\widetilde{\hat{p}}}_{2(1)}$	$\widetilde{\widetilde{\hat{p}}}_{3(1)}$		
	2	$\widetilde{\widetilde{\hat{p}}}_{0(2)}$	$\widetilde{\widetilde{\hat{p}}}_{1(2)}$	$\widetilde{\widetilde{\hat{p}}}_{2(2)}$	$\widetilde{\widetilde{\hat{p}}}_{3(2)}$	$\widetilde{\widetilde{\hat{p}}}_{4(2)}$	
	3	$\widetilde{\widetilde{\hat{p}}}_{0(3)}$	$\widetilde{\widetilde{\hat{p}}}_{1(3)}$	$\widetilde{\widetilde{\hat{p}}}_{2(3)}$	$\widetilde{\widetilde{\hat{p}}}_{3(3)}$	$\widetilde{\widetilde{\hat{p}}}_{4(3)}$	$\widetilde{\widetilde{\hat{p}}}_{5(3)}$
	4	$\widetilde{\widetilde{\hat{p}}}_{0(4)}$	$\widetilde{\widetilde{\hat{p}}}_{1(4)}$	$\widetilde{\widetilde{\hat{p}}}_{2(4)}$	$\widetilde{\widetilde{\hat{p}}}_{3(4)}$	$\widetilde{\widetilde{\hat{p}}}_{4(4)}$	$\widetilde{\widetilde{\hat{p}}}_{5(4)}$
	5	$\widetilde{\widetilde{\hat{p}}}_{0(5)}$	$\widetilde{\widetilde{\hat{p}}}_{1(5)}$	$\widetilde{\widetilde{\hat{p}}}_{2(5)}$	$\widetilde{\widetilde{\hat{p}}}_{3(5)}$	$\widetilde{\widetilde{\hat{p}}}_{4(5)}$	$\widetilde{\widetilde{\hat{p}}}_{5(5)}$

** In practice, the initial time series are much longer than 3 periods. Above scheme is implemented in practice with around 20 starting periods.*

Second, the above imputations are transformed into index figures. This is achieved by dividing the imputation of the reporting period by the imputation of the first period as shown in equation (5.17). At this point, a transformation into indices is necessary, because in the next step – equation (5.18) -, the multilateral series, all with different base periods, are merged into final index figures. The imputations, presented in Table 5.5, are comparable over time within its own series using its own base period. The imputations are not comparable over time across different base period series. A transformation into index figures makes the series comparable and ready for the final step.

$$I_{0,t(b)} = \widetilde{\widetilde{\hat{p}}}_{t(b)} \Big/ \widetilde{\widetilde{\hat{p}}}_{0(b)} \qquad (5.17)$$

After the index transformation, the windows are created. The final index is the geometric average of a window of index mutations. For example, if the window length is 3 periods, the index figure of reporting period t ($I_{0,t}$) is the geometric average of the indices with base period $t-2$ until base period t: $I_{0,t(t-2)}$, $I_{0,t(t-1)}$ and $I_{0,t(t)}$. The formula to construct the price index according to the proposed method multilateral hedonic imputation with time series re-estimation and window length w, is provided in equation (5.18).

$$I_{0,t}^{MHIT-w} = \left(\prod_{b=t-(w-1)}^{T} I_{0,t(b)} \right)^{1/w}, \quad \text{with } t = w-1, w, \ldots, T \tag{5.18}$$

Above equation is not applied to the first set of windows as this would imply that first windows would be based on fewer periods then the window length. E.g. following equation (5.18) for reporting period *0*, would result in a window from period *-2* to *0*. Since there are no negative periods, period *0* remains and the window would include just one period. To solve this, the first windows ($t<(w-1)$ are calculated with altered equation (5.19).

$$I_{0,t}^{MHIT-w} = \left(\prod_{b=0}^{w-1} I_{0,t(b)} \right)^{1/w}, \quad \text{with } t = 0, \ldots, w-2 \tag{5.19}$$

Table 5.6 illustrates a window splice of three periods and the calculation of the final index. The resulting index is from now on referred to as the HMTS method (Hedonic Multilateral Time series Splice). At this point, the choice of a three-period window splice is purely for illustration purposes. The choice of window length is rather important in the index construction. Bentley (2022), for one, acknowledges this and notices that there are no criteria set in official statistics to determine a window length (other than that it should yield reasonable results). He also lists arguments in favor of a shorter or longer window. The most important one, in case of the HMTS, is that greater transitivity goes along with a longer window. On the other hand, a shorter window minimizes the number of revisions. Hill et al. (2022) point out that a longer window generally increases the robustness of the index, while a shorter window increases the current market relevance. They also present a method to determine the optimal length a of window. Another way to look for an optimal window length – and specifically applied to the HMTS – is presented in Section 5.4.2.

TABLE 5.6 Index matrix with a 3-period window splice.

		Reporting period					
		0	1	2	3	4	5
Base period	0	$I_{0,0(0)}$	$I_{0,1(0)}$	$I_{0,2(0)}$			
	1	$I_{0,0(1)}$	$I_{0,1(1)}$	$I_{0,2(1)}$	$I_{0,3(1)}$		
	2	$I_{0,0(2)}$	$I_{0,1(2)}$	$I_{0,2(2)}$	$I_{0,3(2)}$	$I_{0,4(2)}$	
	3				$I_{0,3(3)}$	$I_{0,4(3)}$	$I_{0,5(3)}$
	4					$I_{0,4(4)}$	$I_{0,5(4)}$
	5						$I_{0,5(5)}$
Final index		$I_{0,0}^{HMTS(w=3)}$	$I_{0,1}^{HMTS(w=3)}$	$I_{0,2}^{HMTS(w=3)}$	$I_{0,3}^{HMTS(w=3)}$	$I_{0,4}^{HMTS(w=3)}$	$I_{0,5}^{HMTS(w=3)}$

Equation 5.18 *Equation 5.19*

5.4 Data and empirical findings

The analyses in this section are presented and assessed by the practical and methodological properties in below paragraphs. We will present results for our four-step approach, and for each of these steps compare the outcomes to results from the standard approach where only the first step is applied, i.e., a hedonic imputation method such as Laspeyres or Paasche index is computed. First, a description of the data is provided.

5.4.1 Data: Office building transactions in the Netherlands

To test the index procedure, data on commercial real estate in the Netherlands is used. The data consists of transactions that are reported on a quarterly basis and span the years of 2008 until 2022. As the focus of this study is on small domains, we selected the subgroup of office buildings – containing limited numbers of observations – to run the calculations. The number of observations ranges from approximately 150 to 1.100 per quarter. These data are also used by Statistics Netherlands to calculate the published CPPIs and have already been cleaned. The cleaning process comprises of correcting data errors, excluding false observations and transforming portfolio sales into useable transactions (CBS, 2024b). The hedonic variables – as used by Statistics Netherlands for a Fisher Hedonic Double Imputation (HDI) method – were used as input for the hedonic model in step 1. The regression model and its results are enclosed in appendix 1. The time series analyses results are enclosed in appendix 2.

The HMTS method relies on a solid hedonic model. Running hedonic diagnostic tests prior to implementing the HMTS method is, therefore, required. Analyses show, however, that the HMTS method performs well even with the most basic hedonic variables: floor area, location and building age. The results of an index with these variables resembles an index with many additional variables.

5.4.2 Results step 1 to 4

The HMTS index with 3 preliminary periods (4 period window splice) is presented in Figure 5.2. The stepwise results (from H to HMTS) show that the index corrects for quality changes, detaches from one base period, adds stability and has a limited revision.

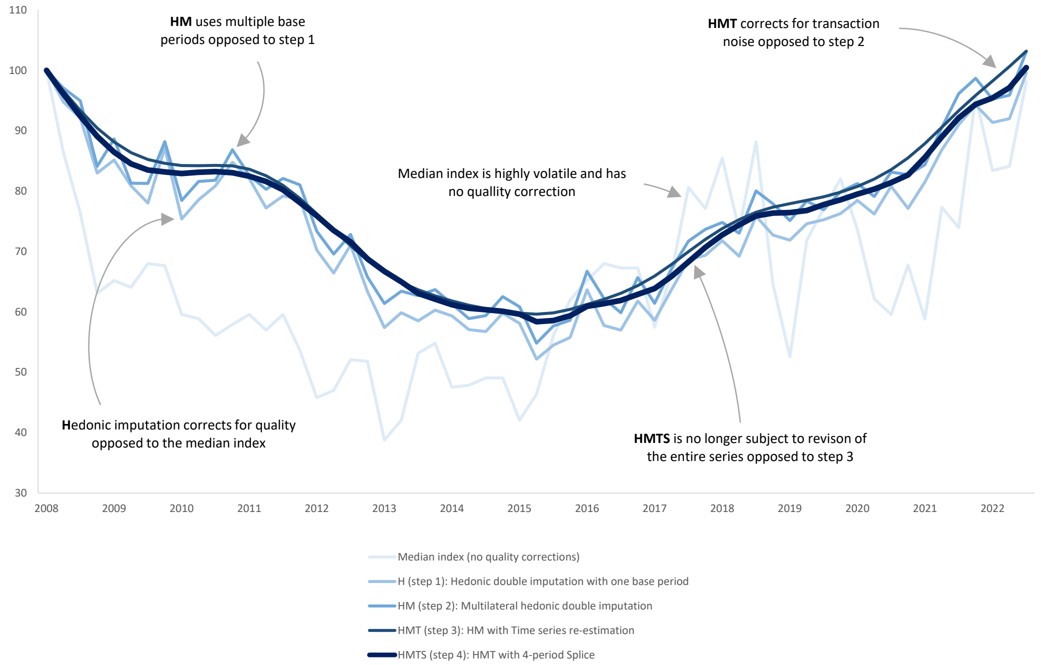

FIG. 5.2 From median index to HMTS index, 2008Q1=100. Source: authors' own creation.

5.4.3 Assessment of practical properties

To assess the HMTS index on revisions and the ability to detect turning points, the years around 2015 are more closely analyzed. Both the Fisher HDI and HMTS detect a downward peak in 2015 Q2 (lowest point) and a first rise in 2015 Q3. The latter period is, therefore, marked as a turning point. Figure 5.3 shows the results of a simulation between 2014 and 2016. The index is calculated with three preliminary periods. Each index point, therefore, has four estimations:

- The *first* estimation is made in the corresponding calculation period;
- The *second* estimation is made once the calculation period is one period ahead;
- The *third* estimation is made once the calculation period is two periods ahead;
- The *final* estimation is made once the calculation period is three periods ahead.

In this turbulent period, including a turning point, the first estimations are on average 0.82 index point off from the final estimation. As expected, the revision decreases at the second (0.29) and third (0.03) estimation. Given that, the index figures are only subject to a very slight revision after the third estimation, two or three preliminary periods seem to be appropriate in the HMTS index construction.

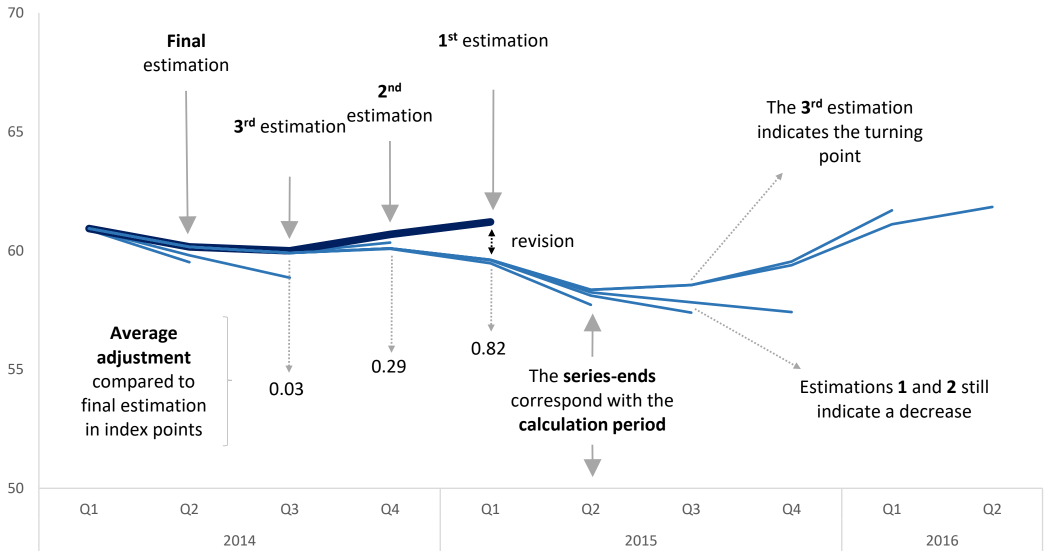

FIG. 5.3 Revisions and turning point detection. Source: authors' own creation.

Although the turning point is in the second quarter of 2015 and the index should show an increase, the first two estimations of the HMTS index indicate a downward development. The third estimation is corrected upwards, indicating a turning point. After the revisions the index gets more accurate and above simulation shows that the desired accuracy lags two periods. Even though the HMTS index does not indicate the turning point immediately, the turning was expected after looking at the mutations. Figure 5.4 shows the changes compared to the same quarter of the previous year for the HMTS index and the Fisher HDI index. Because of the trend-like development of the HMTS index, a clear development towards a turning point can be distinguished. The Fisher index, on the other hand, shows a distorted development.

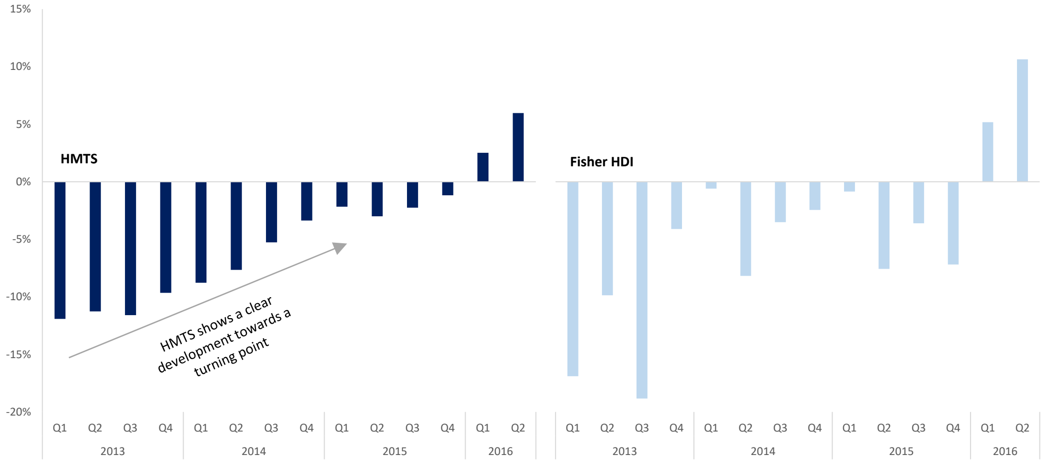

FIG. 5.4 Changes compared to the previous year (%). Source: authors' own creation.

To assess the HMTS index on its reliability, stability and robustness, *confidence intervals* were calculated. The interval was calculated according to the bootstrap method as described by Efron and Tibshirani (1994) and executed by Johnson (2001) and Willenborg and Scholtus (2018). In essence, the intervals are obtained by simulating variations, using the variability in the data. The index series are calculated 500 times, and, in each calculation, the original input is altered by sampling with replacement until the original sample size is reached. Calculating the variance of the 500 index series allows us to construct confidence interval as presented in Figure 5.5. It shows that the HMTS has an improved reliability compared to a Fisher HDI.

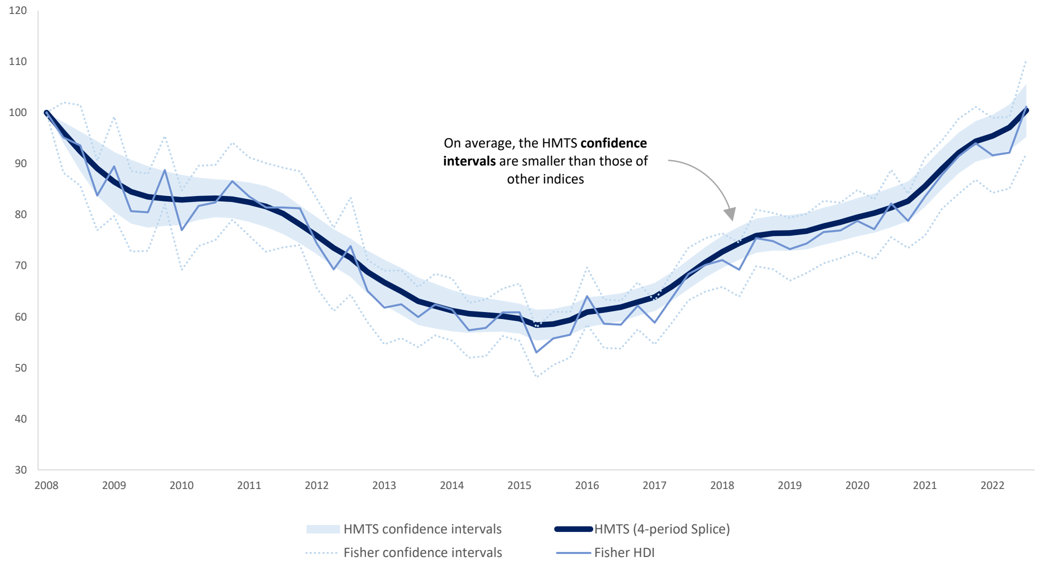

FIG. 5.5 Confidence intervals (95%), 2008Q1=100. Source: authors' own creation.

The robustness of the index is also tested by running calculations on a randomly selected subset of the data with 50 observations per quarter. The result, presented in Figure 5.6, shows that the index is somewhat less stable than the original one (yet not extremely) and in certain years the trend is slightly different. For comparison purposes, the Fisher index is also calculated with the same reduced dataset. It shows that reducing observations, causes more peaks, which indicates the presence of transaction noise.

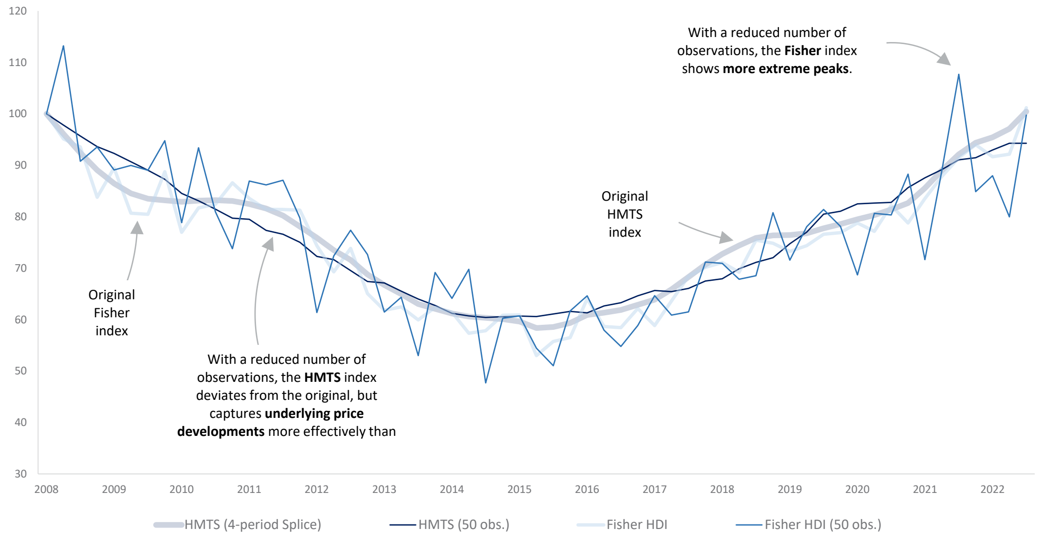

FIG. 5.6 Simulation with 50 observations, 2008Q1=100. Source: authors' own creation.

Yet, another way to get an idea of the robustness of the index is to calculate the share of each observation in the index mutation. This type of calculation is often used in official statistics to detect suspicious observations, which should be (manually) checked. The approach to calculate the shares is similar to the bootstrap simulation: the index is calculated as many times as there are observations, and each iteration observations are alternately excluded. This way, the effect of each observation becomes visible by comparing the alternative index to the original index. Calculations performed on the Fisher HDI and the HMTS shows that the range at which observations affect the index decreases with approximately 50%. In the Fisher HDI, the observation's share in the index ranges from -0.67 to 0.27 index point. On average, the absolute share of individual observations in the index is 0.06 index point. In the HMTS, shares range from -0.4 to 0.2 index point. On average, the absolute share of individual observations in the index is 0.03 index point.

5.4.4 Assessment of methodological properties

The identity test states that once the prices of period *t* return to the state of period 0, the index should also return to 100. Due to the multilateral approach, the re-estimations and window splicing, the identity test does not hold anymore in its strict form. That is, if the prices in the data return to the state of period 0, the index does not (necessarily) return to 100. Only in the scenario where all multilateral re-estimations return to the state of period 0, the index does return to 100. This resembles the multiperiod identity test as described by Diewert (2020). In most cases, however, even though the observed prices of both periods are the same, the transaction noise in period 0 will likely differ from the noise in period t. This is because the noise is determined with help of the adjacent periods. Since the adjacent periods differ, so will the noise. Figure 5.7 shows an empirical test: the prices from period 2020 Q1 and onwards are set to the state of 2008 Q1. As illustrated, the Fisher index returns immediately to 100. The HMTS index returns very slowly to the original state. The question here is whether the development of the Fisher index is realistic. The prices of period 2020 Q1 indicate that the prices suddenly peak, but the re-estimations method uses information from other periods as well. The HMTS index, therefore, indicates that a sudden increase is not realistic, but if the prices keep indicating this level, the index eventually returns to the same level. The size of lag depends on the size of the development. Below example could be considered extreme. To conclude, the HTMS does not meet the identity test. This sacrifice is made to gain stability. The risk is that responds with a lag to extreme price changes

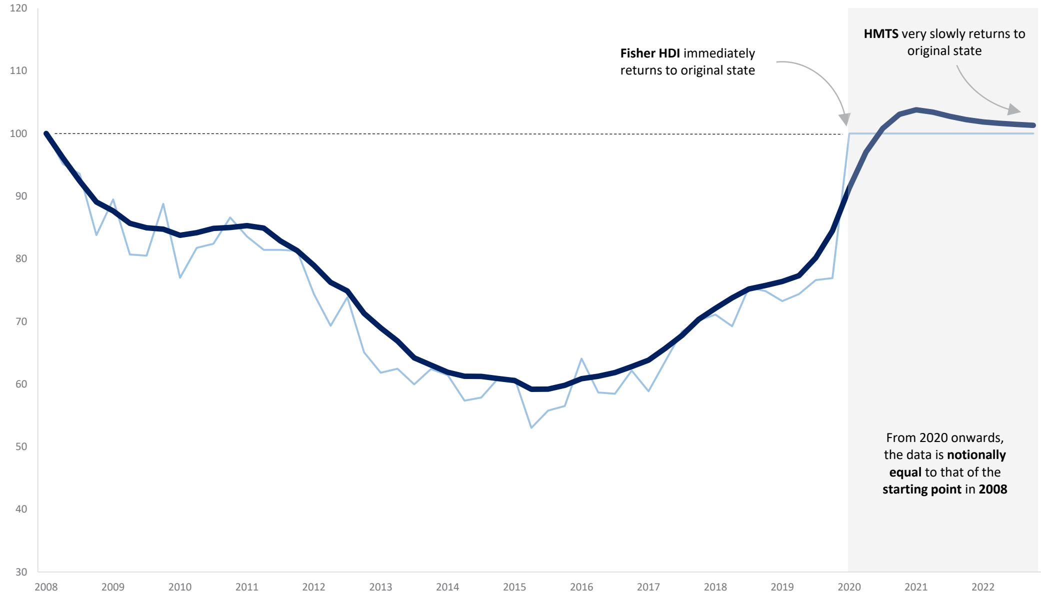

FIG. 5.7 The identity test, 2008Q1=100. Source: authors' own creation.

The time reversal test states that the price index of period A relative to B should be the opposite of the price index of period B relative to A. Since the prices are re-estimated with help of the entire series, time reversibility can't be proven mathematically. Figure 5.8, therefore, shows an empirical test. A version of the index is calculated where all periods are reversed. The resulting index is then reversed again, and the figures are compared to the original index. The figure shows that the indices without splice resemble the original index. In numbers, the indices are fully alike up to 7 decimals for the entire index series. Adding the splice, violates the time reversibility. This was expected as the splices of the time reversed index, are shifted and contain (slightly) different information. The consequence is that the HMTS index is not fully independent of a base period. It does rely on the events to occur in one chronological order (and luckily, they do). In terms of index properties, this is a disadvantage, but like the identity test, this is a sacrifice that is likely worth it (given all benefits discussed Section 5.2.2).

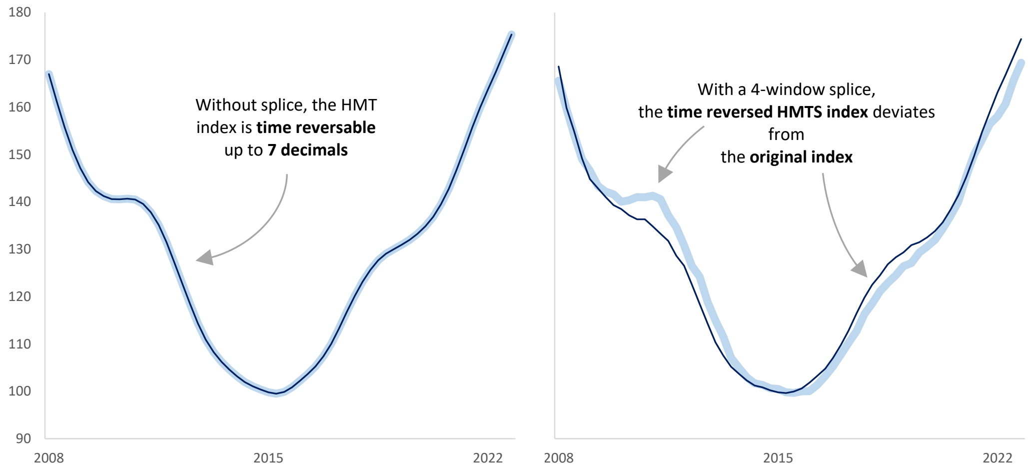

FIG. 5.8 The time reversal test, 2015=100. Source: authors' own creation.

The circular test states that the results between three periods should be consistent: multiplying the index between A and B with the index between B and C should be equal to the direct index between A and C. Circularity is introduced in the multilateral imputations step, but after the re-estimation and the window splice, the index loses this characteristic. Figure 5.9 shows an empirical test: indices are calculated with different starting points: 2008, 2009, 2010 and 2011. If circular, the indices should exactly overlap. The figure shows, however, that the indices do not overlap and thus the index is not circular. However, it also shows that the effect of using different base periods is minimal. This indicates that a certain level of circularity is retained. The indices differ the most at the start of the series. This is because the HMTS uses information of adjacent periods. As the series start in later periods, information is missing. Soon after the start of the series, the index levels and developments are quite similar.

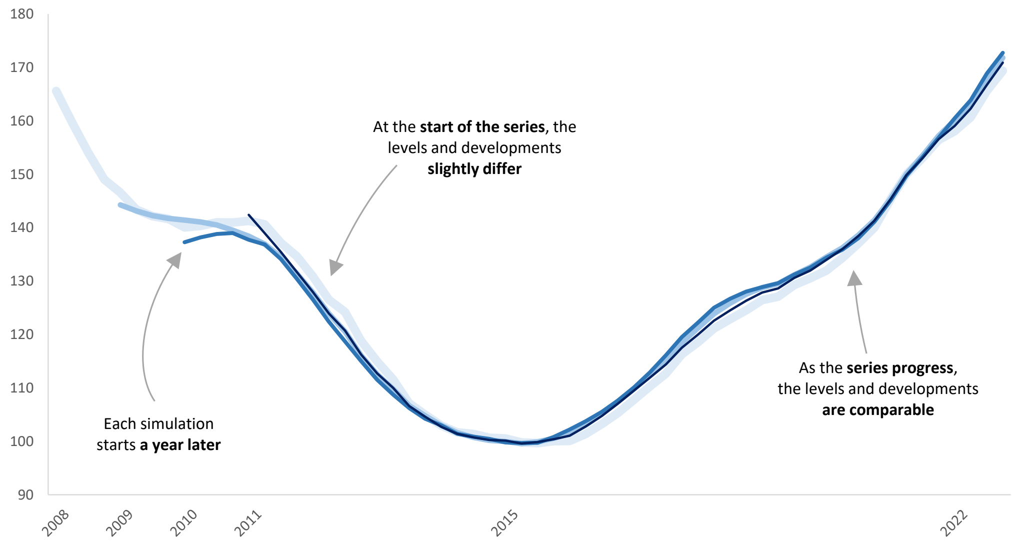

FIG. 5.9 Circularity test, 2015=100. Source: authors' own creation.

5.4.5 Reference comparisons

The Rolling Time Dummy (RTD) method (De Haan, 2015; Hill et al., 2022) is one of the most serious alternatives when it comes to small domains and heterogeneous markets. The multiperiod regression increases the sample size (thus lowering the effect of small domains with heterogeneous markets) and the rolling window prevents continues revisions. Figure 5.10 shows the HMTS index alongside the RTD index and the Fisher HDI index. The RTD is calculated with a window length of 3 periods and a movement splice as described by de Haan (2015). The RTD index still shows volatility similar to the Fisher HDI index. In addition, the RTD shows drift, caused by 'weak' periods in 2013. The Fisher index has no drift (by definition) and, therefore, illustrates the impact of the RTD's drift. The RTD was also calculated with increased window lengths. Each window-increase caused the index to be closer to the Fisher index. This proves the sensitivity of the RTD to drift. The HMTS index is stable and shows no sensitivity to drift.

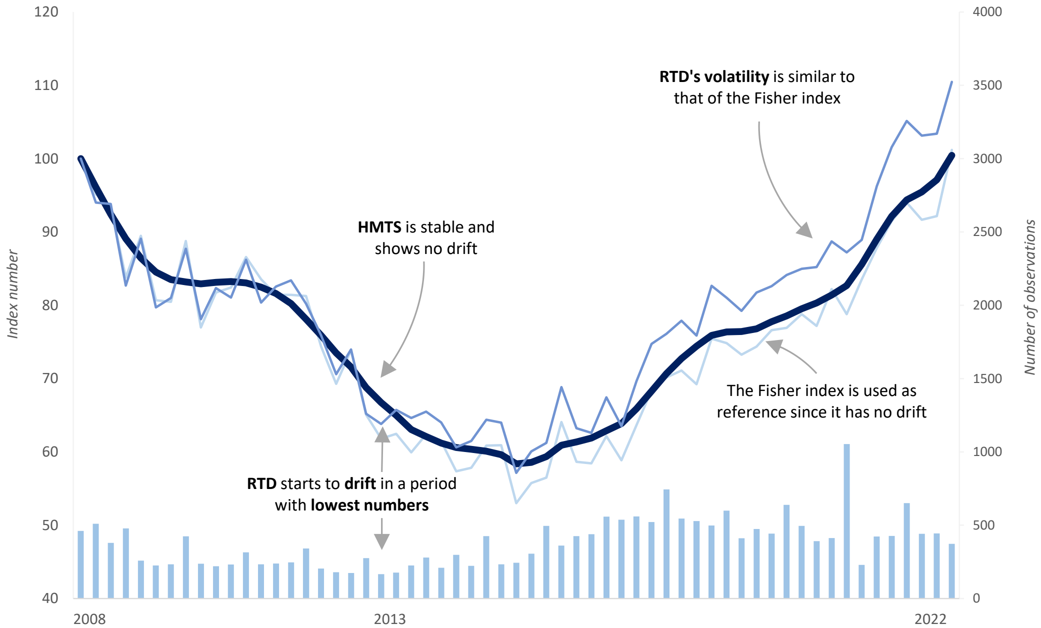

FIG. 5.10 HMTS, Fisher HDI and 3-window Rolling Time Dummy (RTD) for offices in the Netherlands. Source: authors' own creation.

As time series re-estimation is introduced in step 3 of the method, there may be a concern for delay in the HMTS index. By looking at Figure 5.10, there is no solid way to tell if the HMTS lags the Fisher index. A test for Granger causality as used by Shimizu, Nishimura and Watanabe (2010) is also performed in this study to investigate lead-lag relationships. The tests were run pairwise on the HMTS and a *hedonic double imputation* index with the first period as base period (step 1), a *multilateral hedonic double imputation* index (step 2) and *Fisher* hedonic double imputation index, Both possible lead and lag role for the HMTS were tested. With p-values of respectively *1.371 x 10^-4*, *5.827 x 10^-4* and *1.657 x 10^-06*, a lag role of the HMTS is in all cases significant. However, with p-values of respectively *3.154 x 10^-13*, *5.127 x 10^-16* and *1.678 x 10^-12*, this shows that there is no clear lag of the HMTS. If any, the HMTS leads the other indices, most likely due to minimal volatility: a Fisher peak is, for example, a rise followed by a drop. If there was a downward trend before, the HMTS probably shows a drop twice and thus leads the Fisher index.

5.5 Conclusion

5.5.1 Main conclusions

The HMTS index shows several practical advantages. There is an option to reduce and lengthen the number of provisional periods. Furthermore, stability is introduced without losing market information like a timely detection of turning points. It also reduces the reliance on the base period. This can be beneficial in case of insecurities about data quality or representativeness. Regarding CRE, this is often the case. The methodological index tests on the other hand, are not strictly (mathematically) met by the HMTS method. Analyses show, however, that the time reversal test is approximately (numerically) met in practice without splice. The splice creates a loss of time reversibility. This property of the HMTS shows that a sequential order of time is important. It is, however, good to see that right before slicing, time reversibility is mostly retained. The circular test is not fully met in practice, but analyses show that a large amount of circularity is retained in the index construction. Independence of one base period is especially important in small domains and the result in the circularity test shows the effectiveness of the HMTS in this regard. The identity test is not mathematically nor numerically met. Certainly, in cases of small domains with heterogeneous observations, the identity property may not be the index characteristic to primarily aim for. As shown in the analyses, identity-proof indices directly reflect changes in prices, regardless of the trend. If an index level is at 150 and the prices indicate a drop by 50%, an index that meets the identity test returns to 100 immediately. This is exactly what makes an index volatile. The assumption in the HMTS method is that the observations are subject to transaction noise. The lower the transaction numbers and higher the degree of heterogeneity, the safer this assumption seems to be. All in all, the methodological properties are not mathematically met, but in cases of small domains and heterogeneous markets (such as in commercial real estate) it may be worthwhile to loosen the desirability of these properties and balance it with practical properties.

The HMTS index is constructed with the desired properties of statistical agencies in mind. As the results seem adequate and the index outperforms the alternatives at some critical points, the HMTS index may aid statistical agencies in constructing reliable CPPIs. Complexity of the method and many hours of required coding can be considered disadvantages of the method. Code in R programming language is, therefore, available at request from the authors.

The HMTS could be applied beyond commercial real estate. A next best application would be for the construction of house price indices at a lower regional level, which can also be small domains. This relates to the strategic goals of statistical agencies and user's needs to measure phenomena at a more regional level. As long as a hedonic model is used, the HMTS is applicable. Beyond real estate, however, it has not been studied. This is a topic for future study. A remark on using the HMTS method, is that if a common index method is sufficient, this probably has the preference. Primarily in case of small domains and heterogeneous goods, and when common index methods fail at capturing realistic price developments, the HMTS may provide a solid alternative.

5.5.2 Research limitations

In cases where there are (almost) no observations, the HMTS index in its current form does not work. Each period should have a few observations with explanatory variables that show variation. A possibility to solve this, is to implement a multiperiod regression in the hedonic imputation: if a period does not have sufficient observations, the observations of the adjacent periods are added to complete the regression. This possibility has not been fully studied yet.

TOC

6 Sustainability as a price component of commercial real estate

The previous chapter addressed both issues of low observation numbers and heterogeneity in the method phase by presenting a new method to construct price indices. The study shows that a combination of existing techniques produces accurate price development estimates for small domains.

This chapter addresses the issues of heterogeneity in the method phase. As hedonic models generally deal with heterogeneity, this study focusses on the possible enrichment of hedonic models for price indices with sustainability indicators.

6.1 Introduction

In recent years, there has been a growing emphasis on the need for more sustainable buildings. On international level, sustainability is a very well embedded topic on the political agenda as the United Nations (UN) stated that making real estate more sustainable is key to achieving global climate goals (ILO & United Nations Environment Programme Finance Initiative, 2022).

In the Netherlands, this has led to a bundle of sustainability regulations regarding the built environment. These regulations often specifically target energy performance for housing and office buildings. Previous studies have shown that energy efficiency generally has a positive effect on the value of residential property (Aroul & Rodriguez, 2017; Pride et al., 2017; Cajias et al., 2019; Mironiuc et al., 2021; Lambourne, 2022). Many studies also show a similar effect of energy on offices (Chegut et al., 2014; Devine & Kok, 2015; Eichholtz et al., 2010; Kok & Jennen, 2010; Fuerst & McAllister, 2011b; Holtermans & Kok, 2019; Mangialardo et al., 2019; Lambourne, 2022; Overbeek et al., 2023).

Sustainability, however, is much broader than energy efficiency. For instance, aspects regarding the environment, health, user quality and the adaptability of a building are also considered aspects of sustainability. Yet, little is known about the effects of sustainability measures, other than energy efficiency, on residential real estate and offices. Moreover, property types other than residential property and offices also play a role in achieving the global climate goals. Even less is known about the effects of sustainability performance on the value of these property types.

Our aim, therefore, is to investigate the relationship between sustainability measures (in a broad sense) and real estate values for commercial real estate (also in a broad sense[15]). The focus is on the transaction price as an approximation of the value. In the remainder of this chapter, we therefore use the term transaction price instead of value. We pursued the aim by using official data on commercial real estate transactions from the Dutch Land Registry Office in the Netherlands and sustainability assessment scores from a Dutch real estate consultancy.[16] The latter data source

15 The definition for commercial real estate, that is followed in this study, is provided by Eurostat(2017, p. 32): commercial property is … “all property other than owner-occupied housing and property used in non-market activity”. This definition includes rental housing.

16 The reason for conducting this study in the Netherlands, is as follows: the data that is used in this study, is retrieved from statistics Netherlands. Statistics Netherlands has spent many years on processing commercial real estate data and improving the data quality. Given that the data is cleaned up and that it includes transaction prices and sustainability scores, makes it a suitable case for this study.

allowed us to examine the effect of multiple sustainability dimensions on real estate prices with hedonic regression models with the goal to answer the following question: how do sustainability measures affect commercial property prices?

Section 6.2 provides an elucidation of the broad concept of sustainability and the definition and dimensions used in this study. In Section 6.3, the data and methodology are further elucidated and in Section 6.4, the findings are presented. Section 6.5 closes with conclusions and further discussions proposed by the results.

6.2 Background

6.2.1 The definition of sustainability

Sustainability is a very broad concept. Many studies have focused on gathering used definitions, extracting common grounds, identifying dimensions and formulating better fitting definitions. Warren-Myers (2012) and Berardi (2013) found that there are over one hundred definitions of sustainability. Moore et al. (2017) selected over 200 studies and identified 24 different definitions. One of the simplest definitions they found was: "… sustainability is the capability of being maintained at a certain rate or level" (Gruen et al., 2008, p. 1580). Regarding real estate development, the question arises what it is that should be maintained. In this regard, Ruggerio (2021) points out that sustainability and sustainable development are often used as synonyms, but that the contamination of sustainability and development can be perceived as contradictory: it is impossible to pursue economic growth in a limited world. Redclift (2006) explains this by stating that growth of the global population will inherently lead to increased strain on the environment. Also, as technology advances, the people's expectations and needs increase. The production of goods (or development of real estate) is therefore inherently unsustainable. One might argue that sustainability can be achieved by downsizing consumption, but others suggest that downsizing has limits for a society to function effectively (Redclift, 2006). Contradictory or not, there is more awareness nowadays for sustainable development of real estate. To structure these developments, the World Commission on Environment and Development (WCED: World Commission on Environment and Development, 1987) categorized sustainability into social, economic and ecological dimensions.

Considering our aim – investigating the relationship between sustainability measures and real estate prices – a multidimensional approach to sustainability broadens the scope of this study. Various sustainability aspects could have different effects on prices and, furthermore, the effects could be different on different types of real estate (housing, office, industry, etc.). From these many relations (Figure 6.1), mainly the relationship between the ecological dimension (energy in particular) and residential property and office buildings have been studied so far. This study contributes to the body of knowledge by looking at multiple aspects of sustainability and multiple property types.

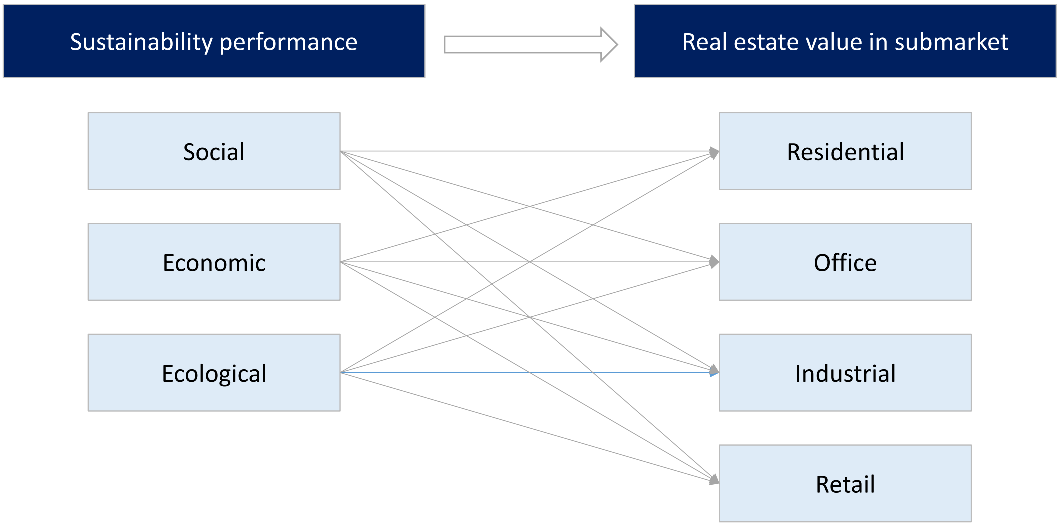

FIG. 6.1 Relationship sustainability and real estate submarket price. Source: Authors' own creation.

6.2.2 Implications of sustainability performance

Enhancing sustainability could mean that buildings become more energy-efficient, healthier, more environmentally friendly and all in all less damaging for the planet. From investors' point of view, it would be very welcome if sustainability would provide financial benefits. Such benefits could increase the demand for sustainable buildings and could boost sustainability in real estate in general. Aliagha et al. (2013) mention the lack of interest or demand as one of the barriers in the development in sustainable buildings. Aliagha et al. (2013) and Yudelson (2016) also point out that limited awareness and understanding of sustainable property could be a cause. Regarding awareness, Falkenbach et al. (2010) notice that there is a lack of evidence that sustainability measures in general increase the value of real estate. Since then, there were no studies found that investigated the effect of sustainability on prices in a broad sense. If this study could determine the financial value of sustainability measures, it will increase understanding of sustainable property and may, therefore, contribute to breaking down the barriers of sustainable development.

6.2.3 Effects of certification

Many studies focus on environmental certification as predictor of real estate value (Fuerst & McAllister, 2011a; Chegut et al., 2014; Devine & Kok, 2015; Holtermans & Kok, 2019; Mangialardo et al., 2019; Overbeek et al., 2023). These certifications cover most, if not all, dimensions of sustainability. BREAAM certifications, for instance, cover *management*, *energy use*, *health and well-being*, *pollution*, *transport*, *land use*, *ecology*, *materials* and *water* (Sayce et al., 2007, p. 631). Studies on the effect of such certificates, however, also measure something else than merely the sustainability of real estate. They measure the psychological effect of a certificate on the real estate value. E.g. if two buildings have exactly the same sustainability performance, but only one is certified, this one may be valued higher, because there is an actual proof of sustainability. Benefield, Hefner and Hollans (2019) proved this effect for green certified homes. This study contributes to the body of knowledge by not looking at the certification status, but only looking at the sustainability scores.

6.3 Data & methodology

6.3.1 Data

Data from three sources in the Netherlands were used in this study: transaction data from the Land Registry Office (Cadastre), property information from the Key Register Addresses and Buildings (BAG) and sustainability scores from the real estate consultancy firm W/E advisors. The transaction prices from the Cadastre are used as approximation for real estate values. The sustainability scores from W/E advisors are used as independent variables. The information from the BAG is used to control for other effects (other than sustainability) that may influence the price.

In total, W/E advisors reported 3,473 projects in the database. Projects refer to buildings that they assessed on their sustainability performance in the years between 2010 and 2022. Some buildings are entered into the database two or more times, because they were assessed before and after a renovation. These double entries were not removed, because the assessment scores are not duplicates. They differ before and after a renovation and are useful in the analyses if the price of the building in the according year is selected (price before renovation and price after renovation). The sustainability assessment is performed on five main scores, which are linked to the categories as provided by the WCED (1987). These scores are Energy, Environment (ecological), Health, User quality (social) and Future prospects (economic) as illustrated in Figure 6.2. As shown, the scores were built up in the data from lower sub scores.

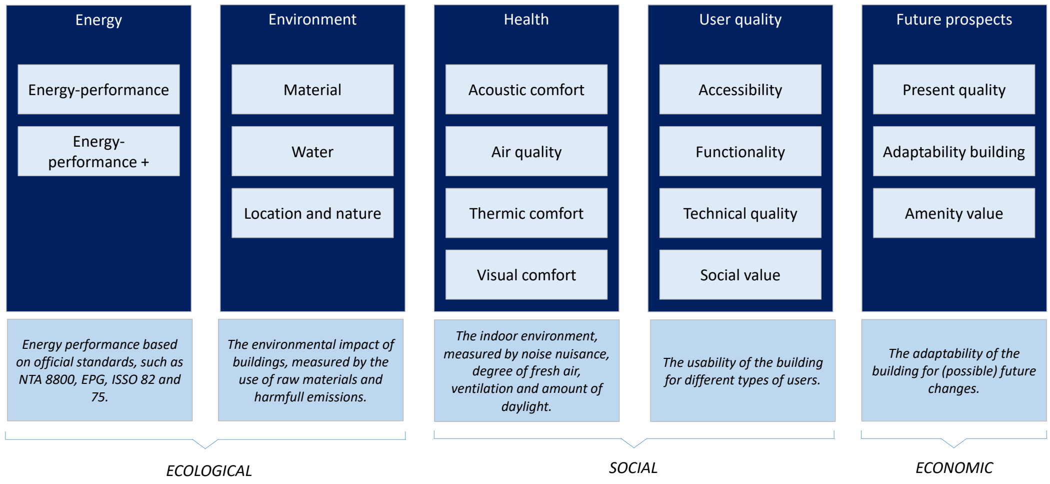

FIG. 6.2 Sustainability measures. Source: Adapted from W/E advisors, translated by authors.

The 3,473 projects were linked to addresses (BAG), which correspond to 79,866 individual buildings. The observations were then linked to real estate transactions (Cadastre) and corresponding transaction prices in the years between 2010 and 2022. After that, observations with pre-renovation sustainability scores were linked to transactions from before the assessment dates. Observations with post-renovation sustainability scores were linked to transactions that occurred after the assessment dates. After these filters and other data cleaning (removal of incomplete cases/omitted variables) 10,652 observations remained for the final analyses. The observations seem randomly distributed over the Netherlands (Figure 6.3).

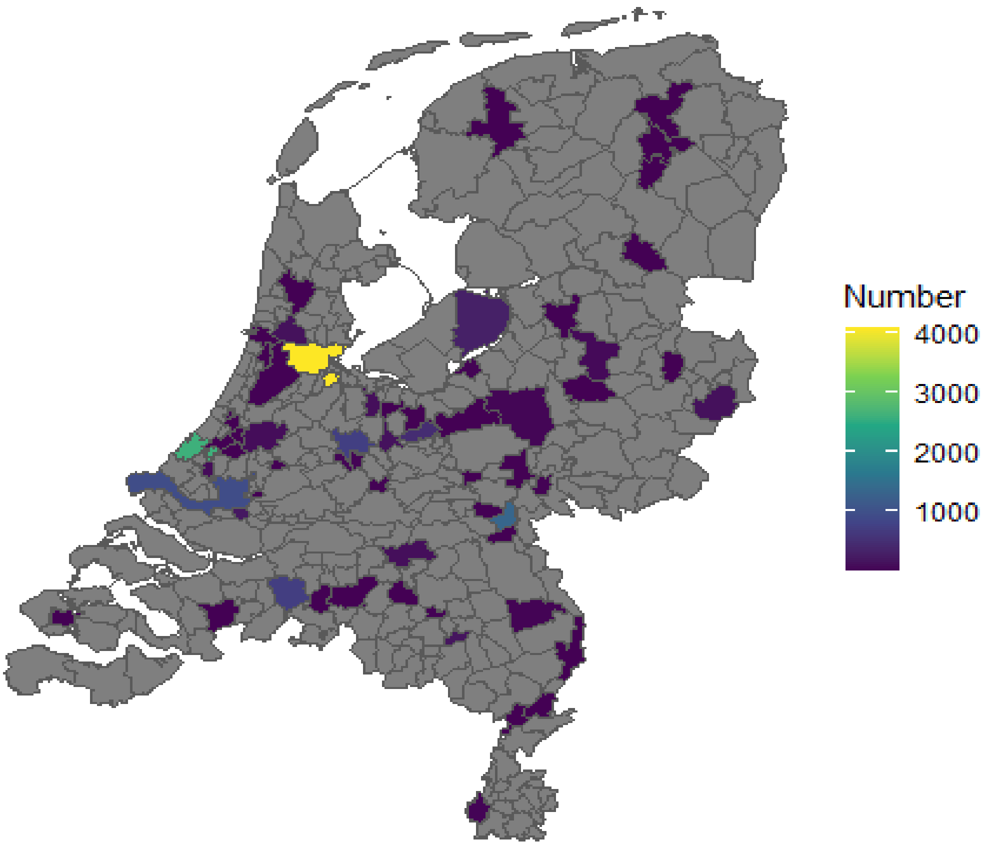

FIG. 6.3 Spatial distribution of observations in the Netherlands. Source: Authors' own creation.

6.3.2 Methodology

To analyze the effect of sustainability performance on real estate price, linear regressions and hedonic imputations were performed.[17] Both techniques are described in the subparagraphs below.

17 A difference-in-difference approach was also considered and pursued, but due to a lack of a solid panel data structure, this approach was not feasible.

Hedonic regressions

The starting point of the analyses is a log-linear regression function as denoted in equation (6.1).

$$lnP_i^t = \alpha + \sum_{t=1}^{T} \delta^t D_{it} + \sum_{k=1}^{K} \beta_k c_{ik} + \beta_l s_{il} + \varepsilon_i^t, \qquad (t = 0, \ldots, T) \tag{6.1}$$

where:

- lnP_i^t = the natural logarithm of the real estate price for property i at period t;
- α = the intercept;
- δ^t = the regression coefficient for time dummy period t;
- D_{it} = the time dummy for property i at period t;
- β_k = the regression coefficient for control variable k;
- c_{ik} = control variable k for real estate property i;
- β_l = the regression coefficient for sustainability score l;
- s_{il} = sustainability score l for real estate property i;
- ε_i^t = standard error for real estate property i at period t.

In this equation, real estate is considered as a bundle of characteristics. The price of the property can be explained as the sum of these characteristics. The main characteristics in above equation are time, control variables and sustainability. The aim is to determine the relationship between sustainability and price. This is achieved by including time and (other) control variables and, therefore, ‘removing’ other components that affect the price. Time is an important component as prices fluctuate through time. Property type is one of the most important control variables as different property types also have different price effects. Other variables, such as building age, floor area and location have proven to be good control variables in former studies (Eurostat, 2017; Porumb et al., 2020; Overbeek et al., 2023) and are, therefore, included in the model. In total, there are 25 versions of sustainability score l. These versions correspond to the scores and sub scores in figure 6.2. The model with a breakdown of all variables is provided in figure 6.4.

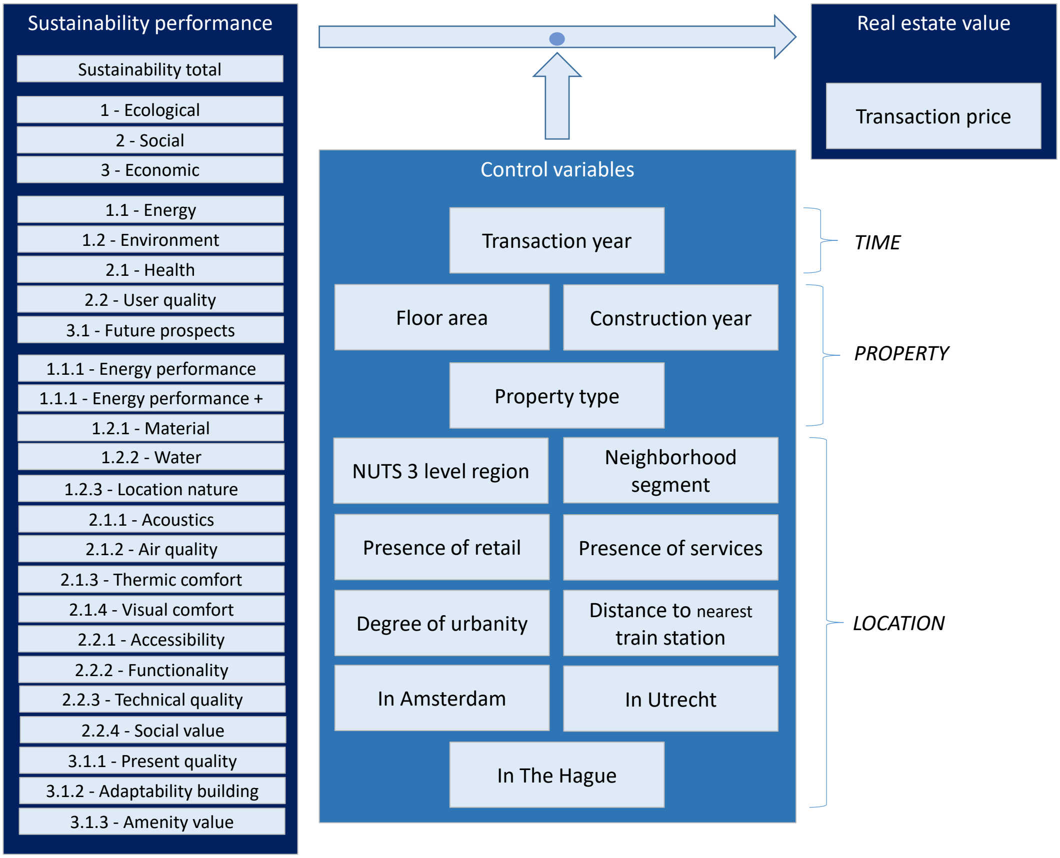

FIG. 6.4 Conceptual model. Source: Authors' own creation.

The rich source of sustainability scores implies many possible regression models to test the effect of sustainability on prices. It also involves two potential problems: multi-collinearity and complex/non-linear relationships. Multi- collinearity on 5 aspects is shown in Figure 6.5 and the possible existence of non-linear relationships between sustainability and prices is presented in annex 3.

To solve the problem of non-linearity, so-called step functions, as explained by James et al. (2021), were introduced in the sustainability variables. In the step function process, the variables were split up into three parts, based on the percentage distributions of the score: ‘low’, ‘medium’ and ‘high’.[18] Other solutions to tackle this issue would have been polynomial regression functions or regression splines (James et al., 2021). In our case (given the high number of to be tested scores), step functions performed better in terms of understanding, interpreting and reporting the results. Furthermore, polynomial regressions were performed, but did not led to different conclusions.

To avoid the problem of multi-collinearity, the sustainability scores were entered into the basic regression model one at a time (so not simultaneously). Another option would have been to include all scores simultaneously (within the same aggregation level) and investigate a deeper relationship by adding interaction terms. This solution, however, in our case would lead to a confusing number of possibilities. To illustrate this: if we run a regression with interaction terms on the 5 main scores, it leads to 25 interaction terms (energy*environment, energy*health*user quality, and so on). In addition, we split the scores up into 3 categories (low, medium and high). In practice, we therefore deal with 15 scores (5*3) and possibly end up with 225 interaction terms (energy-low*environment-medium, and so on). In our case, performing separate regressions worked better in terms of understanding, interpreting and reporting the results. Furthermore, interaction terms were tested, but did not lead to different conclusions.

18 Four and five categories were also tested but given the number of observations and variation in the scores, three categories had the best performance. The percentage distribution for each sustainability score was examined in order to distribute steps according to natural break points.

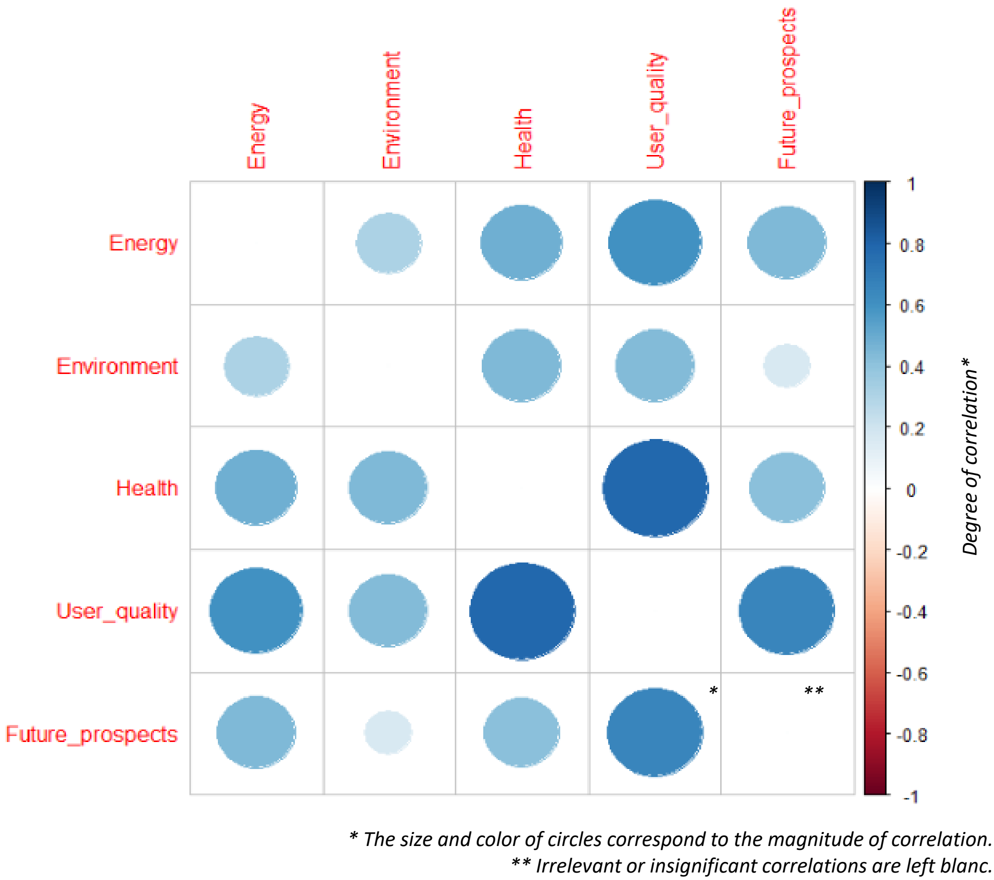

FIG. 6.5 Multi-collinearity between sustainability scores in the Netherlands. Source: Authors' own creation.

Hedonic imputation

The above regressions were troublesome to run per property type due to low observation numbers and limited variation in hedonic variables within property type strata. Therefore, all property types were pooled in one regression model and the differences in property types are captured in a 'property type'-dummy. To examine how a particular score affects the average value for different types of property when a particular sustainability score changes, we use a hedonic imputation approach. Hill et al. (2023), recently used a very similar approach to predict transaction prices if

EPC recommendations were implemented. In this study, hedonic imputation is used to predict transaction prices if a sustainability score was increased.

In the first step, the regression model outcomes are used to predict (or impute) prices for all observations for the current sustainability state X. These imputations are then used to calculate the geometric mean corresponding to state X.[19] Compared to the base regression model, presented in equation (6.1), the term z was added. This term denotes the level within the data: 'low', 'medium' or 'high'. This means that prices for state X are estimated per level. For instance, $P^t_{z=low,X}$ delivers estimates for all property with low sustainability scores at the current sustainability state X. Step 1 is denoted in equation (6.2).

$$\overline{\ln \widehat{P}^t_{z,X}} = \alpha + \sum_{t=1}^{T} \delta^t \overline{D_{z,t}} + \sum_{k=1}^{K} \beta_k \overline{c_{zk,X}} + \beta_l \overline{s_{zl,X}}, \quad (t = 0,\ldots,T) \qquad (6.2)$$

In the second step, the model is used to calculate prices for state Y. In this step, the sustainability scores are fictitiously (one at a time) increased by 1 level (from 'low' to 'medium' or from 'medium to 'high'). For instance, observations with Energy level 'low' (state X) are fictitiously increased to level 'medium' (state Y). In another version, observations with Energy level 'medium' (state X) are fictitiously increased to level 'high' (state Y). Step 2 is denoted in equation (6.3). The difference with equation (6.2) is that all control variables $\overline{c_{zk,X}}$ are kept constant at state X and only the sustainability scores $\overline{s_{zl,Y}}$ have moved to state Y. All coefficients β remain the same as well as they are based on the same model (the regression is run only once on the original data).

$$\overline{\ln \widehat{P}^t_{z,Y}} = \alpha + \sum_{t=1}^{T} \delta^t \overline{D_{zt}} + \sum_{k=1}^{K} \beta_k \overline{c_{zk,X}} + \beta_l \overline{s_{zl,Y}}, \quad (t = 0,\ldots,T) \qquad (6.3)$$

After the second step, there are two versions of prices for the same set of observations: $\overline{\ln \widehat{P}^t_{z,X}}$ and $\overline{\ln \widehat{P}^t_{z,Y}}$. This allows us to determine the price effect of an energy increase from 'low' (state X) to 'medium' (state Y) for each property type. This price effect is determined by calculating a price ratio $I^P_{z,X \to Y}$ as denoted in equation (6.4). This method resembles a commonly used hedonic imputation price index method (Eurostat, 2013b; CBS, 2024b). Only here, instead of calculating price developments over time, X and Y represent different versions of calculations (and not different periods).

$$I^P_{z,X \to Y} = \overline{\ln \widehat{P}^t_{z,X}} \,/\, \overline{\ln \widehat{P}^t_{z,Y}} \qquad (6.4)$$

19 In practice, the prices are imputed on the level of individual observations. After that, the geometric mean is calculated to retrieve <<Eqn329.eps>>. This bypasses the obstacle of averaging dummies.

At this point, the price difference – which is independent of time t - indicates the effect of a sustainability score increase by one level. Another step is necessary to standardize the ratio, because the levels of sustainability are allocated differently for each property type and each score. For example, Energy in office could have a 'low' and 'medium' level that corresponds to average scores 3 and 7. Health in retail could have very different levels as 'low' and 'medium' could correspond to average scores 5 and 6. A standardization is performed by dividing price ratio $I^{P}_{z,X\rightarrow Y}$ by the corresponding sustainability ratio $I^{S}_{z,X\rightarrow Y}$. The result is a ratio of price and sustainability R_{PS}. The equation for standardization is shown in equation (6.5).

$$R_{PS} = \frac{I^{P}_{z,X\rightarrow Y}}{I^{S}_{z,X\rightarrow Y}} = \frac{\overline{\ln \widehat{P}^{t}_{z,X}} \,/\, \overline{\ln \widehat{P}^{t}_{z,Y}}}{\overline{S^{t}_{z,X}} \,/\, \overline{S^{t}_{z,Y}}} \tag{6.5}$$

The results are presented in the next section.

6.4 Findings

6.4.1 Descriptive statistics

Table 6.1 shows a distinction between real estate with high sustainability scores and low sustainability scores. This distinction is made by calculating the geometric mean of all five sustainability scores for each property (creating a total sustainability score). Every property below the mean is included in the lower group and every property above the mean is included in the higher group. The table shows some differences between the higher and lower class of sustainable real estate. An expected result is that younger buildings show on overage a higher degree of sustainability. An unexpected result is that for offices, retail and residential property, lower average prices were found in higher sustainability segments. Even if we correct for square meters, office and retail buildings still show lower prices in higher sustainability segments. These results indicate that a more sustainable property may be valued higher for these property types. Descriptive information is, however, not sufficient to base conclusions on as the average prices are not corrected for quality adding features. This is added in the regression analyses (Section 6.4.3).

TABLE 6.1 Descriptive statistics: low vs. high sustainability scores in the Netherlands. Source: Authors' own creation.

Property type	Sustainability segment	Value (€/ million)	Value / m^2 (€)	Construc-tion age	Floor surface	Energy	User quality	Environ-ment	Health	Future prospects
Industry	*bottom 50%*	1,625	1,058	31	4037	5.7	6.1	6.2	4.5	6.6
	upper 50%	1,980	1,524	18	1608	8.7	8.2	8.4	8.1	8.2
Office	*bottom 50%*	1,893	15,77	91	338	4.9	7.1	4.9	5.0	7.3
	upper 50%	1,824	7,652	14	471	6.3	7.5	6.2	7.5	8.2
Retail	*bottom 50%*	1,559	11,74	77	209	7.3	7.3	5.8	5.9	7.6
	upper 50%	610	6,116	18	141	7.7	8.2	7.4	6.5	7.6
Dwelling	*bottom 50%*	707	4,475	22	190	6.2	7.0	5.9	6.4	6.1
	upper 50%	584	5,008	11	137	7.4	7.8	6.7	7.7	6.9

6.4.2 Sustainability over time

Buildings are expected to improve in terms of sustainability over time. The relationship between the five sustainability scores and time is shown in Figures 6.6, 6.7, 6.8, 6.9 and 6.10. On the left side, a linear relationship is assumed and on the right side, a flexible model with a second-degree polynomial (or quadratic) regression is plotted. Following the linear relationships, the figure supports the idea of a positive relationship.[20]. The flexible model shows that the relationship for some sustainability aspects is more complex. This is the case for User Quality, Environment and Health. For User Quality the relationship for the lower class is flatter and the positive relationship only becomes apparent in the upper class. For Environment and Health, the relationship is opposite. For the lower classes, there is a strong positive relationship. Towards the middle, it flattens and in the upper class the relationship is negative, indicating that more recently sold buildings perform worse regarding these sustainability scores. In general, the figure shows that time has a significant impact on the sustainability score. Moreover, time has a significant impact on the real estate prices (CBS, 2024b). Therefore, time is entered in the regression model as a control variable.

20 95% confidence intervals are plotted as well but could be too small to observe. This, however, does indicate a good fit of the models on the data.

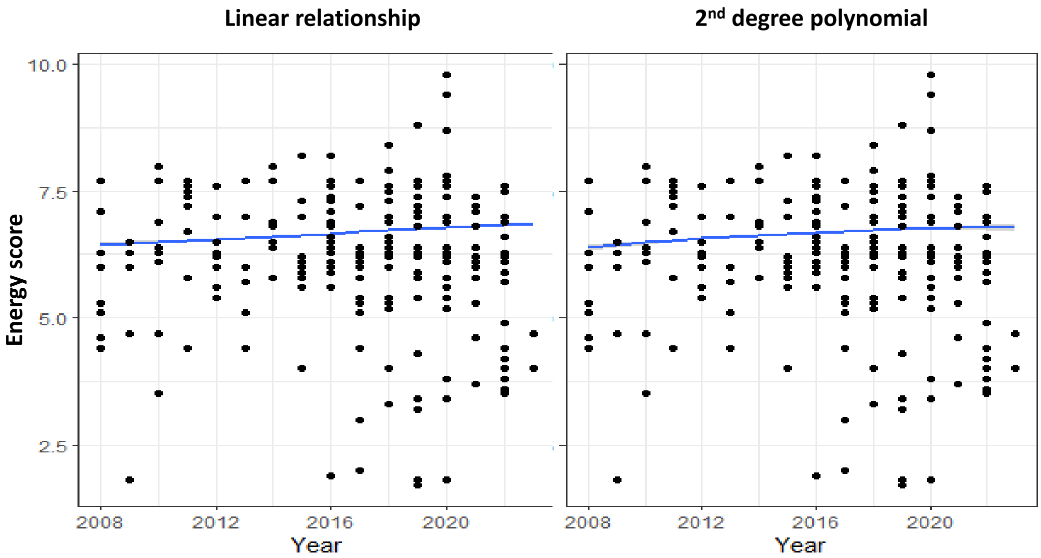

FIG. 6.6 Energy scores over time in the Netherlands. Source: authors' own creation.

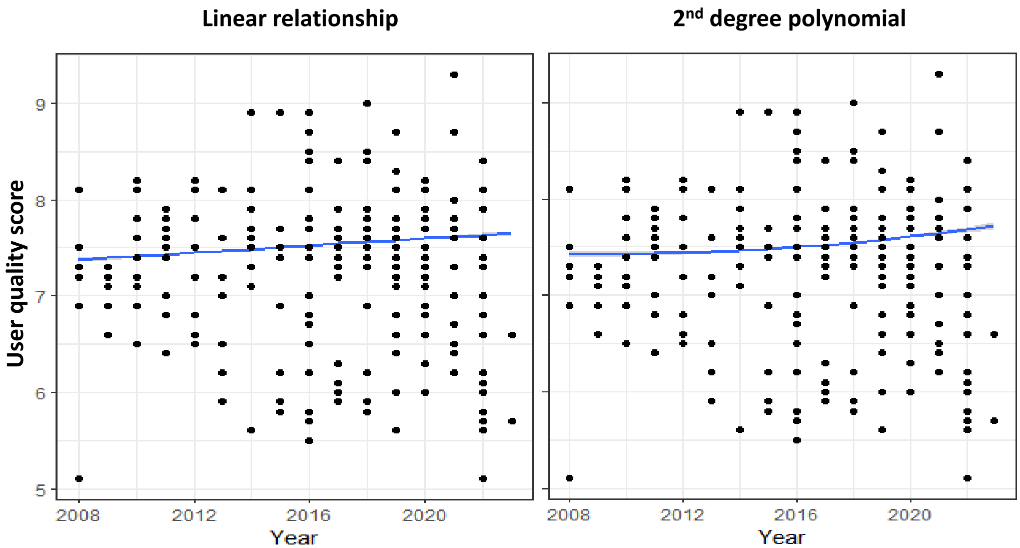

FIG. 6.7 User quality scores over time in the Netherlands. Source: authors' own creation.

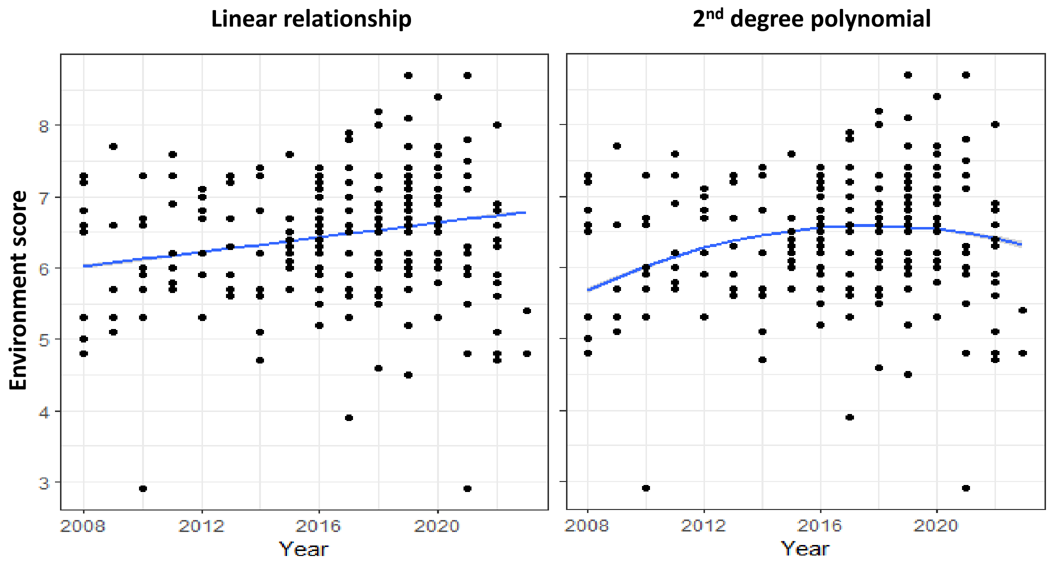

FIG. 6.8 Environment scores over time in the Netherlands. Source: authors' own creation.

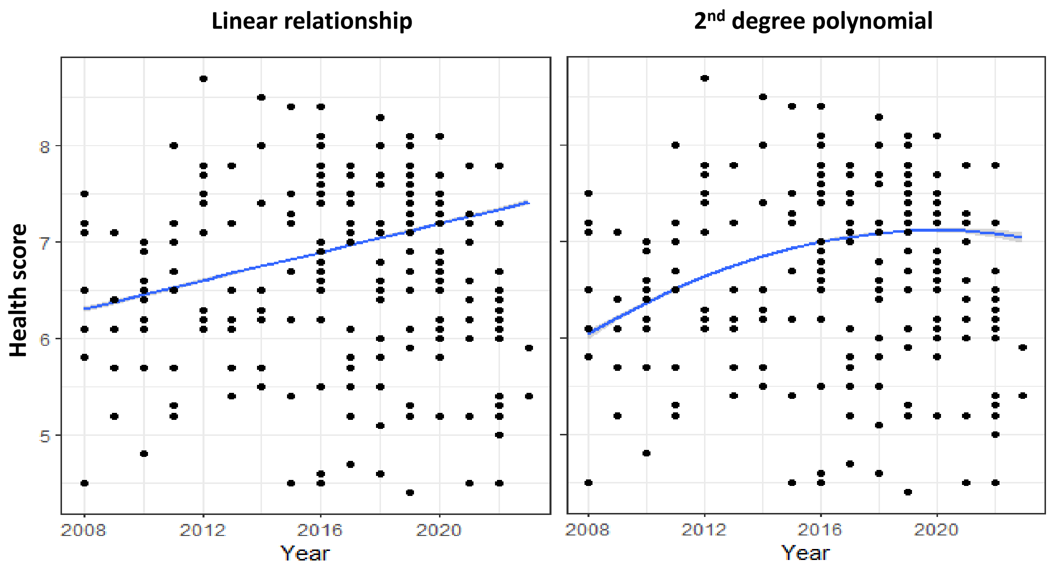

FIG. 6.9 Health scores over time in the Netherlands. Source: authors' own creation.

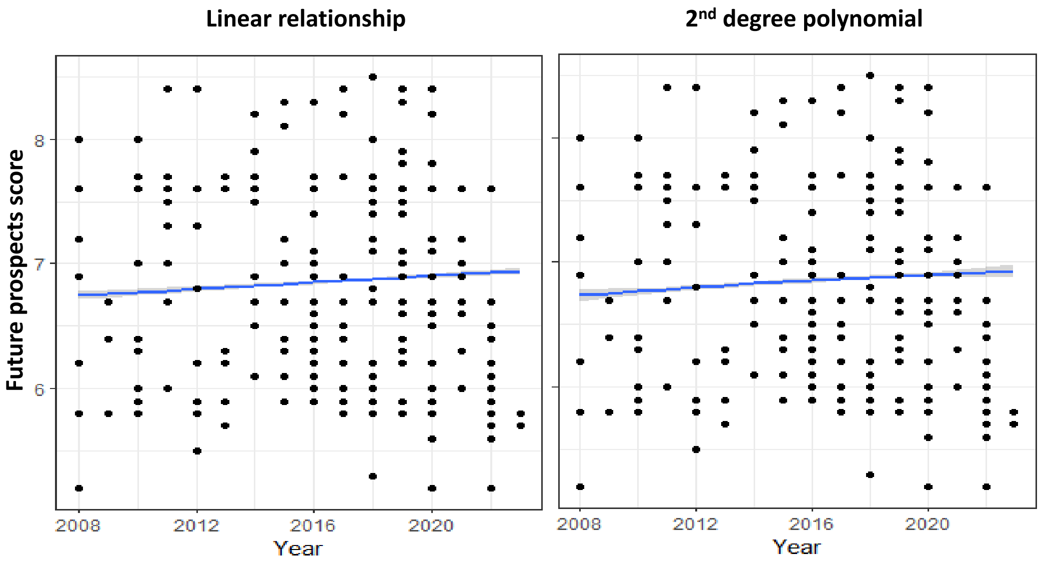

FIG. 6.10 Future prospects scores over time in the Netherlands. Source: authors' own creation.

6.4.3 Regression analyses

Table 6.2 shows the results of different models related to the natural logarithm of transaction prices. The first model contains no sustainability scores. The explanatory variables already provide a solid explained variance with an adjusted R-squared of 0.73. In each model 2 to 26, a single sustainability score is added one at a time. Table 6.2 shows only the corresponding control variables of these models. The estimates are summarized and a range (lowest : highest) of all models is presented in the estimates column. The estimates show that the control variables remain stable, and it shows that adding sustainability scores, slightly enhances both the adjusted R-squared and BIC.[21]

21 Next to R^2, BIC is often used to evaluate regression models. BIC (Bayesian Information Criteria) is a variant of AIC (Akaike Information Criteria) with a stronger penalty for extra variables in the model. For BIC applies: lower indicates a better model accuracy.

TABLE 6.2 Regression without sustainability scores in the Netherlands. Source: Authors' own creation.

	(1) without sustainability		(2 - 26) + sustainability scores	
	Estimate (β)+	Sign.	Estimate (β)++	Sign.
Intercept	9.3	***	8.7 : 13.2	***
Year	YES	***	YES	***
Floor surface (log)	0.4	***	0.4 : 0.4	***
Type: industry	1.6	***	-0.9 : 2.3	.
Type: community	6.0	***	2.9 : 6.7	***
Type: office	2.2	***	0.6 : 2.8	***
Type: education	2.2	***	-0.4 : 2.2	***
Type: retail	0.5	***	-1.7 : 1.1	
Type: house	1.7	***	-0.8 : 2.1	***
Type: care	2.3	***	-0.7 : 2.8	***
Construction year category	YES	***	YES	*
NUTS3 region	YES	***	YES	***
Neighborhood segment	YES	***	YES	***
Share service sector	-2.7	***	-3 : -0.3	***
Urbanity degree	-0.1	***	-0.3 : 0.1	
Distance to train station	0.0	***	0.0 : 0.1	***
In Amsterdam	-2.3	***	-3.7 : -1.9	***
In The Hague	-0.8	***	-2.4 : -0.3	***
In Utrecht	-0.4	***	-0.5 : 0.4	***
Adjusted R2	0.73		0.73 : 0.75	
BIC	17,342		16,450 : 17,303	
Number of observations	10,652		10,652	

+ Estimates are transformed by the natural logarithm. To relate the outcomes to actual prices, the estimates have to be exponentiated. For instance, the intercept of 9.3 equals a starting point of a price at € 10,938.

++ For models 2-26, the range of coefficients (minimum - maximum) is presented.

. Significant at 90%-level.

* Significant at 95%-level.

*** Significant at 99.9%-level.

Table 6.3 shows the corresponding estimates for the sustainability scores. For presentation purposes, the estimates 'medium' and 'high' are placed alongside of each other instead of on top of each other. The level 'low' does not have estimates as this level is used as reference category. A notable result from this table is that a switch from low to medium is often accompanied by a negative movement of the transaction price. As we look at the category 'high', we see that the negative relationships have mostly been converted into positive relationships. Unfortunately, these results do not provide insight into the relationships per property type. The results in the next section will.

TABLE 6.3 Regression with sustainability scores in the Netherlands. Source: Authors' own creation.

		Medium		High	
		Estimate (β)+	Sign.	Estimate (β)+	Sign.
Sustainability total (2)		-0.8	***	-0.4	***
1	Ecological (3)	-0.9	***	-0.3	***
2	Social (4)	-0.6	***	0.0	
3	Economic (5)	-0.3	***	0.0	
1.1	Energy (6)	0.1	***	0.9	***
1.2	Environment (7)	-1.2	***	-0.7	***
2.1	Health (8)	-0.9	***	-0.3	***
2.2	User quality (9)	-0.4	***	0.3	***
3.1	Future prospects (10)	-0.3	***	0.0	
1.1.1	Energy performance (11)	0.0		0.8	***
1.1.1	Energy performance + (12)	0.2	***	0.4	***
1.2.1	Material (13)	-0.6	***	-0.3	***
1.2.2	Water (14)	-0.2	***	0.4	***
1.2.3	Location nature (15)	0.4	***	0.8	***
2.1.1	Acoustics (16)	-0.8	***	-0.4	***
2.1.2	Air quality (17)	-0.6	***	0.4	***
2.1.3	Thermic comfort (18)	0.4	***	0.6	***
2.1.4	Visual comfort (19)	-0.6	***	-0.7	***
2.2.1	Accessibility (20)	0.3	***	1.0	***
2.2.2	Functionality (21)	-0.8	***	0.3	***
2.2.3	Technical quality (22)	-0.4	***	-0.3	***
2.2.4	Social value (23)	0.2	***	0.4	***
3.1.1	Present quality (24)	0.3	***	0.6	***
3.1.2	Adaptability building (25)	-0.1	**	0.2	***
3.1.3	Amenity value (26)	-1.3	***	-0.7	***

\+ *Estimates are transformed by the natural logarithm. To relate the outcomes to actual prices, the estimates have to be exponentiated. For instance, the intercept of 9.3 equals a starting point of a price at € 10,938.*

** *Significant at 99%-level.*

*** *Significant at 99.9%-level.*

6.4.4 Hedonic imputation

Table 6.4 shows the price changes that correspond to a change from level 'low' to level 'medium'. The scores are corrected for the level grades: a level increase from 'low' to 'medium' could correspond to an increase from 2 to 6 or from 4 to 5. The results are relative and should be interpreted as follows: a score increase of 1% corresponds to a price development as presented in the table. For example, the price development of 'sustainability total' in the top left corner of -3.68%, corresponds to a 'sustainability total' increase of 1%. The number between parentheses are one sides 95% confidence intervals.[22] The reported -3.68 could, therefore, be -0.13 or +0.13 within 95% certainty. For industry, confidence intervals could not be calculated due to too low numbers for 10-fold cross validation.

A very remarkable result is that most scores relate negatively to prices on the low end of sustainability. Although remarkable, it does correspond to the previous reported regression results (Section 6.4.3). From the 5 aggregate dimensions of sustainability, 'Energy' is the only one that shows price increases.

22 The margins are calculated with a 10-fold cross-validation as described in James et al. (2021).

TABLE 6.4 Hedonic imputation results: lower segment price changes per property type in the Netherlands. Source: Authors' own creation.

		Residential	Office	Industry	Retail
Sustainability total		-3.68 (0.13)	-2.38 (0.50)	-4.52 (.)	-7.01 (1.67)
1	Ecological	-3.63 (0.16)	-2.28 (0.31)	-5.06 (.)	-5.27 (1.3)
2	Social	-2.94 (0.22)	-1.97 (0.31)	-2.31 (.)	-6.63 (1.66)
3	Economic	-2.05 (0.27)	-1.62 (0.39)	-1.4 (.)	-1.57 (0.88)
1.1	Energy	0.89 (0.23)	0.52 (0.14)	2.89 (.)	3.17 (1.35)
1.2	Environment	-3.77 (0.24)	-2.91 (0.31)	-2.83 (.)	-3.76 (0.86)
2.1	Health	-2.48 (0.09)	-1.17 (0.25)	-2.05 (.)	-5.99 (1.12)
2.2	User quality	-2.94 (0.40)	-6.29 (2.11)	-2.22 (.)	-3.48 (0.86)
3.1	Future prospects	-2.05 (0.34)	-1.62 (0.39)	-1.4 (.)	-1.57 (1.46)
1.1.1	Energy performance	-0.12 (0.10)	-0.09 (0.08)	-0.31 (.)	-0.33 (0.32)
1.1.1	Energy performance +	1.18 (0.29)	0.75 (0.24)	. (.)	2.39 (1.84)
1.2.1	Material	-1.2 (0.10)	-4.85 (0.93)	-2.41 (.)	0 (1.33)
1.2.2	Water	-4.93 (1.07)	-0.37 (0.06)	-0.87 (.)	-0.6 (0.09)
1.2.3	Location nature	1.86 (0.34)	0.92 (0.23)	27.11 (.)	1.26 (0.24)
2.1.1	Acoustics	-1.26 (0.10)	-0.28 (0.07)	. (.)	-1.31 (0.21)
2.1.2	Air quality	-1.91 (0.27)	-1.62 (0.58)	-1.03 (.)	-8.19 (11.67)
2.1.3	Thermic comfort	2.74 (0.58)	0.86 (0.47)	1.09 (.)	3.27 (1.39)
2.1.4	Visual comfort	-1.41 (0.09)	-2.55 (0.21)	-5.4 (.)	-2.46 (1.33)
2.2.1	Accessibility	1.28 (0.26)	1.46 (0.40)	. (.)	3.62 (0.69)
2.2.2	Functionality	-13.54 (0.77)	-4.65 (1.57)	-9.52 (.)	-6.42 (1.53)
2.2.3	Technical quality	-0.99 (0.09)	-0.74 (0.10)	. (.)	-2.07 (0.53)
2.2.4	Social value	2.14 (0.79)	1.64 (1.47)	0.33 (.)	1.29 (0.47)
3.1.1	Present quality	0.78 (0.15)	0.5 (0.11)	1.05 (.)	5.05 (2.53)
3.1.2	Adaptability building	-0.83 (0.35)	-2.31 (1.58)	-1.01 (.)	-1.34 (0.64)
3.1.3	Amenity value	-6.17 (0.32)	-3.24 (0.19)	-2.62 (.)	-11.96 (5.04)

Table 6.5 shows the price changes that correspond to a change from level 'medium' to level 'high'. It is immediately noticeable that nearly all sustainability scores now show a positive relationship with transaction prices.

TABLE 6.5 Hedonic imputation results: higher segment price changes per property type in the Netherlands. Source: Authors' own creation.

		Residential	Office	Industry	Retail
Sustainability total		4.56 (0.84)	17.31 (16.16)	1.2 (.)	62.62 (24.15)
1	Ecological	8.41 (0.70)	10.3 (3.21)	2.62 (.)	27.4 (1.57)
2	Social	14 (2.02)	19.22 (6.47)	2.68 (.)	7.02 (.)
3	Economic	3.8 (0.61)	19.25 (.)	4.77 (.)	10.2 (1.98)
1.1	Energy	4.6 (0.86)	15.28 (6.32)	2.54 (.)	86.1 (63.47)
1.2	Environment	4.97 (0.64)	7.37 (3.44)	4.51 (.)	8.4 (1.15)
2.1	Health	6 (1.16)	31.17 (14.78)	1.37 (.)	39.88 (6.35)
2.2	User quality	13.17 (2.57)	10.18 (5.03)	4.4 (.)	11.32 (.)
3.1	Future prospects	3.8 (1.23)	19.25 (.)	4.77 (.)	10.2 (2.11)
1.1.1	Energy performance	4.94 (0.58)	11.73 (3.16)	2.39 (.)	16.51 (.)
1.1.1	Energy performance +	1.32 (0.36)	1.62 (0.44)	. (.)	3.54 (0.72)
1.2.1	Material	1.9 (0.23)	1.67 (0.52)	2.08 (.)	2.63 (0.78)
1.2.2	Water	8.25 (0.90)	8.71 (2.38)	1.31 (.)	16.93 (3.07)
1.2.3	Location nature	3.8 (0.77)	3.7 (1.25)	0.69 (.)	21.38 (7.39)
2.1.1	Acoustics	2.94 (0.38)	3.67 (1.15)	. (.)	. (.)
2.1.2	Air quality	23.64 (2.75)	16.17 (4.63)	1.86 (.)	39.99 (13.74)
2.1.3	Thermic comfort	1.46 (0.46)	2.47 (0.57)	0.7 (.)	2.8 (0.94)
2.1.4	Visual comfort	**-0.31 (0.30)**	**-0.45 (0.45)**	**-0.3 (.)**	**-1.01 (1.99)**
2.2.1	Accessibility	3.24 (0.63)	4.2 (1.03)	. (.)	14.74 (.)
2.2.2	Functionality	17.4 (1.09)	60.65 (14.27)	9.69 (.)	. (.)
2.2.3	Technical quality	. (.)	1.47 (1.35)	. (.)	2.86 (1.47)
2.2.4	Social value	3.5 (1.53)	3.06 (1.11)	. (.)	. (.)
3.1.1	Present quality	1.02 (0.45)	. (.)	1.32 (.)	1.79 (0.76)
3.1.2	Adaptability building	2.97 (0.43)	10.92 (2.01)	. (.)	6.56 (2.90)
3.1.3	Amenity value	7.26 (0.45)	32.59 (.)	7.62 (.)	14.08 (0.88)

6.5 Discussion and conclusions

6.5.1 Main conclusions

In this study, the aim was to investigate the relationship between sustainability measures and real estate transaction prices for commercial real estate. The results show that this relationship is complex. Whether there is a positive or negative effect on prices, varies between specific sustainability measures and property types. The effect in the lower sustainability segment also differs from the effect in the higher sustainability segment. Of the five main sustainability scores, 'energy' is the one that shows a consistent positive effect for all property types and in both the low and high segment. This is in line with previous studies that already show a positive relationship between energy efficiency and property value (Eichholtz et al., 2010; Kok & Jennen, 2010; Fuerst & McAllister, 2011b; Chegut et al., 2014; Devine & Kok, 2015; Pride et al., 2017; Aroul & Rodriguez, 2017; Cajias et al., 2019; Holtermans & Kok, 2019; Mangialardo et al., 2019; Mironiuc et al., 2021; Lambourne, 2022; Overbeek et al., 2023). The other sustainability scores, for which the price effects have not been studied before, show mostly negative relations in the low sustainability segment. This indicates that for most sustainability measures, there is no clear financial incentive to start investing in sustainability.

Referring back to the barriers in the development of sustainability, these results indicate that is it is not likely that the barriers will be broken because of financial benefits. An intervention of an outside actor, most likely the government, is very welcome when it comes to increasing sustainability other than energy efficiency. A first step would be creating more awareness on sustainability other than energy efficiency by consistently measuring these aspects. Based on a study on rating tools, Myers et al. (2010) argue that government input is needed here as well to achieve real change in the real estate sector.

Although this study provides new insights on the various effects of sustainability (in a broad sense) on transaction prices, it should be noted that there are some studies that show similar, negative price effects. Zheng et al. (2012), for instance, found that 'buildings that score high on the green index sell for a price premium at the presale stage, but they are subsequently leased or resold for a price discount'. This result not only shows that negative price effects also occur elsewhere, but also shows that the relationship is complex: there is a positive effect at presale, but a negative effect after that. Yoshida & Sugiura (2015) and Evangelista et al. (2022) found similar negative price effects. They found, like this study, that price discounts typically occur at the lowest quantiles of the price distribution. Zheng et al. (2012) and Yoshida & Sugiura (2015) also provide explanations: green technologies can reduce user costs but can also increase user costs. For instance, replacement costs of sustainable materials could be higher. Another example is that a central air conditioning system that is sustainable given the air quality, consumes more electricity and thus is less sustainable in another sense. All in all, sustainability sometimes induces higher life cycle use costs.

6.5.2 Limitations and further research

Although this study is one of the first attempts to grasp the effect of the broad concept of sustainability on transaction prices, it has a few limitations.

First, the results could be distorted by scarcity of real estate in the Netherlands. As a study of Colliers (2023) recently showed, rental prices for housing do not tend to be lower for houses with a low energy label. The measured average rent was even higher for low energy labels. They suggest that this may be caused by scarcity in the Dutch market: investors will retrieve high income anyway, so there is no incentive to increase sustainability. A follow up study on transaction prices could be conducted on whether the scarcity effect could also have distorted the results of this study.

Second, a possible explanation is that sustainability measures could increase user costs and, therefore, may not lead to a price increase. Further research on this possible explanation is recommended, for instance, by measuring user costs alongside sustainability measures and analyzing the relationship between the two.

7 Discussion and conclusions

The previous chapters addressed various challenges in the construction of commercial property price statistics. These challenges are classified into data and methodological challenges. The studies show opportunities to overcome these challenges.

This final chapter summarizes and combines these findings to answer the overall research question: what opportunities are there to construct reasonably accurate commercial property price indicators for official statistics?

7.1 Answers to research questions

Below, the research questions addressed in chapters 2 to 6, are discussed briefly and answered in relation to the main aim of the dissertation.

Question 1: To what extent does the absence of share deals distort commercial real estate (CRE) statistics?

Chapter 2 focuses on a specific aspect of commercial real estate data collection and analysis: share deals. Share deals involve the transfer of company shares, where the company's sole purpose is to hold real estate. Transfers of these companies, known as Single Purpose Entities (SPEs), essentially represent real estate transfers. However, because they are technically company transfers, they do not appear in traditional real estate transaction registers, which register only asset deals, and are generally absent in the compilation of real estate price indicators.

This study examines the impact of share deals on price indicators. The foremost challenge was to obtain data and to identity share deals from the data. This process required linking multiple datasets and establishing specific rules for selecting real estate share deals. Key data sources include the General Business Register (ABR) and property transfer tax data from the Dutch Tax Authorities. While both sources contain valuable information, it was essential to link them with the Key Register Cadaster (BRK), the Key Register Addresses and Buildings (BAG) and the Key Register 'Waardebepaling Onroerende Zaken' (WOZ) to accurately identify real estate share deals.

The results show that share deals in the Netherlands account for up to approximately 34% of the CRE trading market, with popularity varying by property type. Thus, adding share deals would increase volume and value indicators. For financial stability assessments, this would also mean a more accurate reflection of market risks, highlighting the importance of incorporating share deals into commercial property price indicators. However, reliable and valid prices for real estate share deals are challenging, if not impossible, to obtain, as they often do not exist independently. A real estate share deal involves the transfer of a company that holds real estate, meaning that the transfer price primarily reflects the company's value, not solely the real estate. This company transfer price likely includes costs unrelated to the real estate itself, so any real estate-specific price in a share deal would typically need to be an estimate. Moreover, the contribution of share deals to a CPPI aggregate would be minimal, as the total value of asset deals surpasses that of share deals. This implies that including share deals would enhance volume and value indicators more than it would improve price indices.

Contribution of chapter 2 to the dissertation’s main aim

These findings highlight one reason why commercial real estate (CRE) suffers from low transaction numbers: not all transactions are recorded in common registers. An opportunity to address this issue would be to include share deals to increase transaction numbers. However, the study also showed that collecting and processing share deal data is very challenging. Additionally, obtaining accurate prices for share deals is nearly impossible, as these prices encompass more than just real estate. Therefore, despite the potential advantages, adding share deals to CRE indicators in the Netherlands is not recommended due to data issues and relatively low frequency of real estate share deals. A limitation of the study is linked to its scope, as it was conducted solely in the Netherlands. As the study revealed, legislation regarding share deals varies among countries. For example, in the Netherlands, property transfer tax generally applies to share deals. In countries without such legislative restrictions, there may be a greater incentive to prefer share deals over asset deals. Therefore, in other countries, including share deals might still be a viable option to increase transaction numbers in CRE statistics.

Question 2: What is the market volume and value of portfolio sales and what is its impact on real estate pricing?

Chapter 3, like chapter 2, focuses on another specific aspect of commercial real estate data collection and analysis: portfolio sales. Portfolio sales involve transactions of multiple properties, such as office buildings, retail spaces, and rental dwellings, bundled together. A key characteristic of these sales is that there is only one agreed-upon price: the total price for the entire portfolio. This type of registration is often unfit for direct inclusion in index calculations. Therefore, the most pragmatic solution is to exclude portfolio sales and base index calculations solely on single-property sales. However, the validity of discarding portfolio sales depends on the magnitude and distinctiveness of portfolio sales within the market.

This study examines the market volume and value, as well as the price effect of portfolio sales compared to single property sales. The findings show that portfolio sales typically occur at a discount. Additionally, the market share of portfolio sales, in terms of volume, is around 11%. In terms of value, the share is on average 37%. The study also reveals that this share is not fixed but fluctuates with economic developments.

Contribution of chapter 3 to the dissertation's main aim

These findings show that portfolio sales are a significant part of commercial real estate transactions. Excluding portfolio sales from real estate indicators not only reduces the number of observations but, given their magnitude, also results in an underestimation of volume indicators. The underestimation is even more pronounced for value indicators. Moreover, excluding portfolio sales from price indices results in inaccurate estimations of price developments. This is because portfolio sales are a distinctive group in terms of pricing. Omitting them creates a bias in the estimations. Therefore, it is recommended to include portfolio sales in CRE statistics.

A limitation of this study is that the discount associated with portfolio sales could not be fully studied from the available data. We explored potential explanations related to geographical diversity and variations in building types, but did not identify any significant relationships. While the discount has a theoretical foundation in information asymmetry theory (Akerlof, 1970) and prospect theory (Kahneman & Tversky, 1979) and the regression results were quite convincing, additional information such as estimated returns, rental income, or occupancy rates could provide further clarity on the discount effect. Moreover, uncovering a comprehensive explanation may require a qualitative research approach, which could involve gathering insights directly from investors.

Question 3: What are legitimate methods to process portfolio sales in the compilation of CPPIs?

Chapter 4 focuses again on portfolio sales, building on the findings from chapter 3. Chapter 3 concludes that portfolio sales should be included in CRE statistics, and chapter 4 develops methods to process these observations. The study demonstrates how valuation data and floor area information can be used as keys to distribute the total price and impute prices for constituting properties in a portfolio. Additionally, it provides a method to assess the accuracy of these imputations using a model-based bootstrap. This assessment method helps to prioritize imputation methods based on quality. It also allows for a backup method to be used if the primary one doesn't work.

Contribution of chapter 4 to the dissertation's main aim

These findings show how portfolio sales can enrich CRE data. Firstly, including portfolio sales in volume indicators increases the number of observations. Secondly, it helps reduce heterogeneity in the data by disentangling various observations so they can be categorized into separate groups. For example, portfolio sales might include both offices and dwellings. Disentangling the portfolio allows for the separate compilation of office and dwelling indicators that then would include (part of) portfolio sales. Therefore, the first recommendation is to process portfolio sales by imputing prices for constituting properties in a portfolio. We have demonstrated that this approach is feasible by using additional data as distribution keys, preferably valuations. The second recommendation is to prioritize various imputation methods by assessing them through bootstrapping. In some cases, the primary method may fail due to insufficient data. In such cases, a secondary method could be employed.

A limitation of this study is that potentially more effective distribution keys were not explored due to limited data availability. Indicators such as rent or return values could also be effective predictors of property sale prices and thus, could potentially also serve well as distribution keys. Nonetheless, if these indicators become available in the future, the assessment method remains applicable.

Question 4: How can we construct a price index for small, heterogeneous domains that balances the most desired practical and methodological properties?

Chapter 5 focuses on a methodological opportunity to deal with small domains while meeting desired theoretical and practical properties. The theoretical properties are formed by extensive mathematical research over many years, as comprehensively reviewed by Diewert (2007, 2020). This is also referred to as the axiomatic index approach. The discussed desired theoretical properties include identity, circularity and time reversibility. Although many other properties were developed over the years, these three are considered as foundational and serve as a reliable guide for developing indices. The practical properties are formed by the needs of official statistics, emphasizing stable and minimally revisable price estimations and the early detection of turning points. These practical foundations are grounded in user requirements and are essential for the successful development of official statistics.

The results show that the developed method, the Hedonic Multilateral Time Series Splice (HMTS), balances all desired properties better than existing price index methods. It delivers stable indices, is not overly subject to revisions, detects turning points early, and aligns closely with the desired theoretical properties. It is important to note that if the desired properties were to change, a different methodology might be preferred. The primary scientific contribution of this study is its demonstration that index theory and time series approaches can be effectively combined. Index theory typically considers two points in time, limiting its effectiveness in terms of data utilization. Conversely, time series approaches inherently violate index axioms, making them less suitable for index construction. The development of the HMTS illustrates that how these approaches can cooperate by adopting useful components from both approaches and tailoring them to specific needs.

Contribution of chapter 5 to the dissertation's main aim

The developed method contributes to the compilation of CPPIs by addressing the most important needs in official statistics and demonstrating that index theory and time series approaches can be combined. Therefore, the HMTS method may aid statistical agencies in constructing reliable CPPIs. A disadvantage of the method is its complexity, which can be a barrier to transform the method into usable code. To mitigate this, the code developed in this research in the R programming language is available upon request and is designed to be user-friendly. In the near future, this code will be made publicly available on CRAN.

Question 5: How do sustainability measures affect commercial property prices?

Chapter 6 focuses on a methodological development, specifically exploring the usefulness and testing of a presumed valuable hedonic indicator: sustainability. Sustainability in real estate has become a prominent topic over the last few decades, as making real estate more sustainable is key to achieving global climate goals (ILO & United Nations Environment Programme Finance Initiative, 2022). While many studies have demonstrated the positive impact of energy efficiency on real estate pricing, other aspects of sustainability—such as environmental factors, health, user quality, and building adaptability—are understudied.

The results of this study show that the relationship between real estate pricing and sustainability is complex. The impact on prices varies between specific sustainability measures and property types, with differing effects in the lower and higher sustainability segments. Energy efficiency is the only sustainability measure that consistently shows a positive effect on prices.

Contribution of chapter 6 to the dissertation's main aim

These findings indicate that using sustainability as a hedonic indicator for price indices is challenging. In hedonic index construction, a straightforward linear relationship with price is preferred, but the study show the relationships are not always linear. A possible solution to fit sustainability in a linear model is to use step functions. This involves breaking up sustainability in multiple parts, such low sustainable properties and high sustainable properties. Using step functions is, however, only a partial solution since the size of steps varies across object types and may change over time. Given the consistent relationship between real estate prices and energy efficiency, energy efficiency emerges as the most promising independent variable to add to a hedonic model.

A limitation of this study is its geographical scope, as it was only conducted in the Netherlands. Specifically for the Netherlands, the results could be influenced by real estate scarcity in the residential market. A recent study by Colliers (2023) showed that rental prices for housing do not tend to be lower for houses with a low energy label; in fact, the measured average rent was higher for low energy labels. They suggest this may be due to scarcity in the Dutch market: investors can command high income regardless, so there is no incentive to increase sustainability. All in all, sustainability may not be an obvious variable to add to a hedonic model.

7.2 The main aim: opportunities to improve CPPIs

In the introduction of this dissertation (Section 1.4, Figure 1.4), a research framework based on Bertalanffy's general systems theory (1950) was presented. This framework organizes systems into three stages: input, throughput, and output. Throughout the study, this model was used to structure the process of creating statistics: retrieving data (input), performing calculations (throughput), and delivering statistics (output).

The first three research questions specifically address the input phase, exploring opportunities in data collection and processing of share deals and portfolio sales. It was found that adding share deals to CRE indicators has potential benefits; however, it is not recommended in the Netherlands due to data issues. In contrast, while adding portfolio sales also presents challenges, these issues can be managed, making it beneficial to include them. The scientific contributions involve the development of imputation techniques and assessment methods based on bootstrapping.

The last two research questions address the throughput phase, exploring methodological opportunities. A method was developed that balances the needs of official statistics and accurately reflects price developments for commercial real estate. This also contributes to academic literature by demonstrating that index theory and time series approaches can be combined. Additionally, sustainability was investigated as a hedonic indicator. This proved less successful, as the relationship between sustainability and real estate pricing is too complex.

A summary of these findings is visualized in an updated version of the research framework (Figure 7.1), now highlighting the key findings.

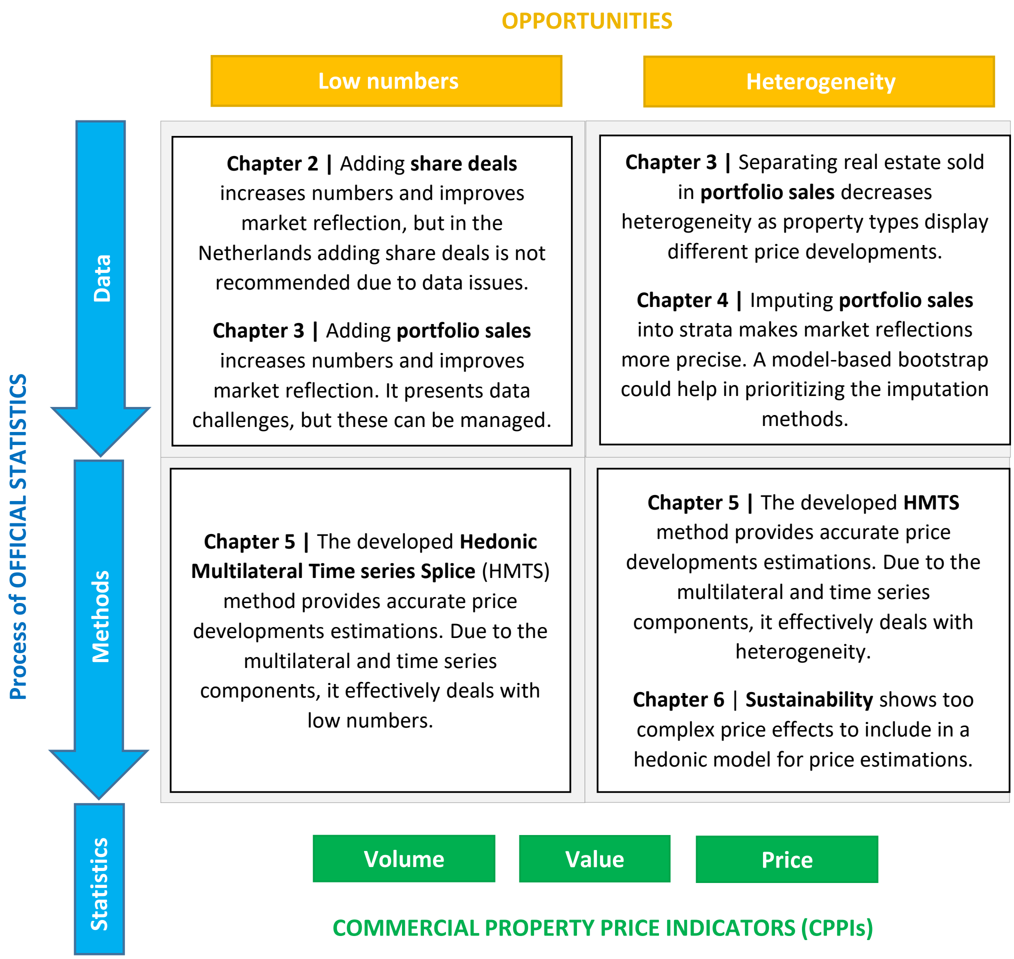

FIG. 7.1 Research framework with key findings. Source: author's own creation.

7.3 Applications of research findings

In 2016, the European Systemic Risk Board (ESRB) issued a formal recommendation to address data gaps in real estate, specifically urging EU countries to establish legislation for the publication of official CRE statistics. Following this recommendation, numerous studies—primarily conducted by National Statistical Institutes (NSIs)—have focused on developing real estate indicators. The studies in this dissertation are among these efforts and provides valuable input for legislation that is currently (in 2024) being drafted to standardize CRE statistics across EU countries. The proposed legislation includes the three primary indicators of volume, value, and price indices, which are also the main focus of this dissertation. This dissertation's contributions to the legislative framework can be categorized into two key areas: data and methodology.

On the data side, a key element in shaping the legislation is defining the target population of these indicators. The topics of share deals and portfolio sales examined in this dissertation directly inform the ongoing discussions on these definitions within the legislative process. Furthermore, many countries encounter portfolio sales in their data and face challenges in processing them effectively. The findings in this study offer statisticians guidance on establishing or enhancing CPPIs through proposed methods for incorporating and assessing portfolio sales data.

In terms of methodology, a key contribution of this research is the HMTS method. Although developed for CRE, the HMTS method has broader applicability to price indices for all small domains. Statistics Netherlands already uses the HMTS method to publish HPIs at the municipal level (CBS, 2024c; CBS, 2024d) and plans to apply it to CPPIs in 2025. Both HPIs for municipalities and CPPIs require price development estimations for small domains, underscoring the method's value. Another practical implication of this study lies in its input for academic discussions on sustainability's role in real estate valuation and price index modelling. As buildings become more sustainable, they increase in quality, a factor that should be reflected in price index models. The findings contribute to ongoing debates about the suitability of sustainability as a hedonic indicator.

7.4 Future research

In this final section, three suggestions for future research are elaborated upon.

Geographical scope

The studies in this dissertation were all performed on data for the Netherlands. While many sources and high-quality data were available, limiting the study to one country poses a challenge for generalizability. For example, chapters 2, 3, and 4 thoroughly examined share deals and portfolio sales, but the recommendations are based solely on data from the Netherlands, making their applicability to other countries uncertain. Similarly, the study on the relationship between sustainability and real estate pricing may be influenced by the Dutch real estate market, again making its applicability to other countries uncertain.

Different legislation across countries can also lead to variations in data structures. For instance, if laws require portfolio sales to register prices at the property level, it will significantly alter the analysis. Beyond data structure, legislation can greatly affect the magnitude of observed phenomena. For example, in countries with fewer legislative restrictions, the prevalence of share deals might exceed the market share observed in the Netherlands.

Given the geographical scope's potential influence, I recommend future studies on share deals and portfolio sales using data from countries other than the Netherlands. Expanding this research could provide insights into differences in how share deals and portfolio sales appear in data across various regions, potentially leading to the development of new techniques for managing these transactions. In Chapter 4, we proposed imputation methods and assessment techniques; studies in other countries could uncover alternative imputation methods or even innovative approaches that bypass the need for imputations altogether. Additionally, such studies might reveal new assessment techniques or methods better suited to data structures that differ from those used in this study.

TOC

Enhanced data

The data used in this study were retrieved from many sources, most of which are official sources managed by Dutch governmental institutes, with data collected on a legal basis. This provides clear advantages, such as full coverage of the Netherlands, high reliability due to official use, and consistency with published official statistics.

However, there is other valuable real estate information that has not yet been integrated into official statistics. This includes data such as estimated returns, realized yields, expert valuations, rental figures, and income—largely managed by banks and real estate agencies. For instance, expert valuations could be used to further analyze share deals and portfolio sales. Linking portfolio sales to estimated returns might yield new insights into market behavior. Similarly, connecting sustainability measures to estimated returns could highlight areas of sustainability investment that are financially advantageous.

Given the significant influence of data in this study and the continuous developments in data availability, I recommend future studies to (also) retrieve data from private data sources.

Monitoring and improving the HMTS

The developed HMTS method shows clear advantages in making price development estimations for small domains. Although this method has been tested in many simulations, using it in practice may reveal unforeseen aspects. It is also useful to see how well the index estimations perform in the event of a real-time turning point.

An improvement that could be made to the HMTS is to make it functional for periods without observations. Since small domains are always at risk of having empty periods, this is not just a theoretical situation but a very practical one. For some index methods, this leads to a small problem: the period without observations remains without a price development estimation. The problem is small because the periods with observations do have estimations. However, in coding, one period without observations could lead to an error causing the entire calculation of the index to stop. This is also the case for the HMTS method and could be solved by implementing novel methods designed for small domains, such as using observations from adjacent periods for the regression of the period without observations. Given the benefits of the HMTS method and its likely use in official statistics, I recommend future studies to use the method, identify flaws and develop improvements.

Annexes

ANNEX 1

R^2 with and without portfolio sales indicator

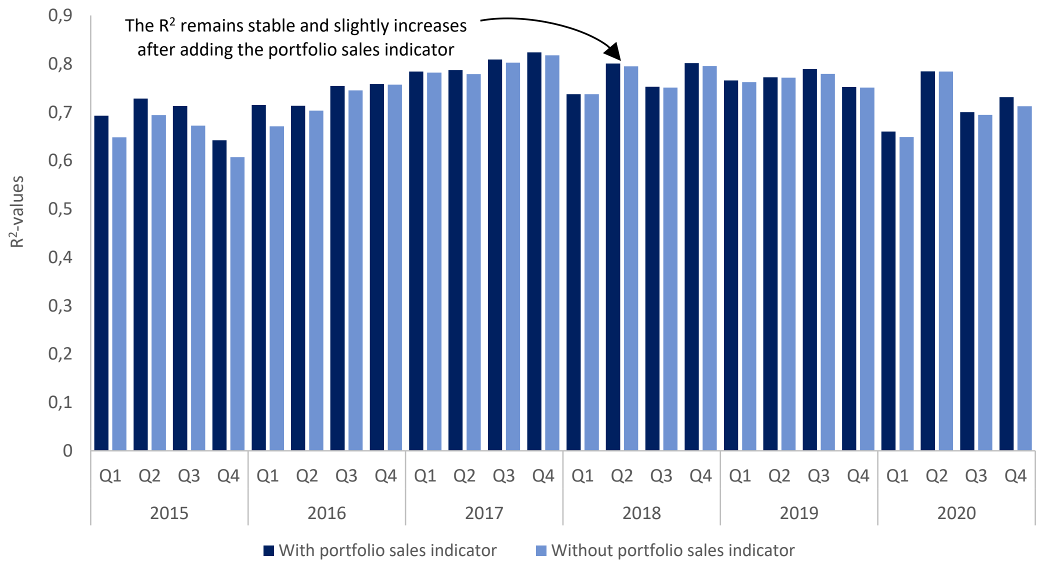

FIG. ANN.1.1 R2 **rental dwellings** with and without portfolio sales indicator. Source: authors' own creation.

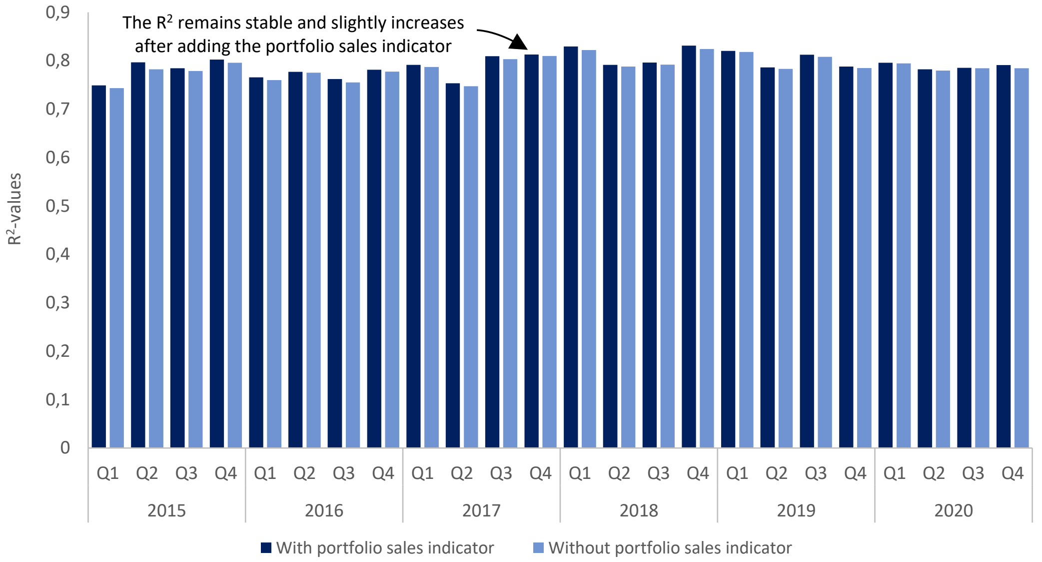

FIG. ANN.1.2 R2 **industrial buildings** with and without portfolio sales indicator. Source: authors' own creation.

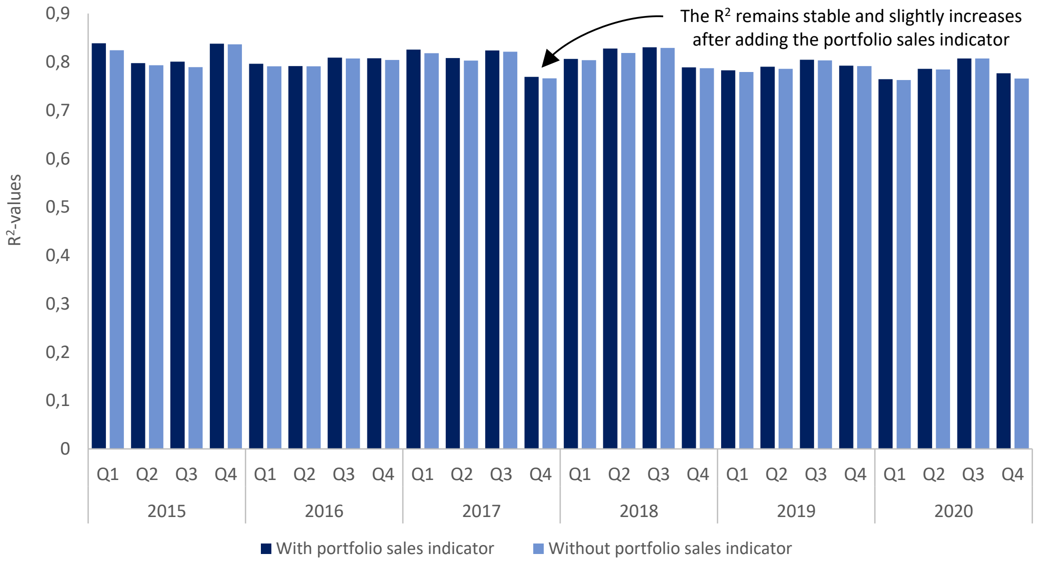

FIG. ANN.1.3 R2 **office buildings** with and without portfolio sales indicator. Source: authors' own creation.

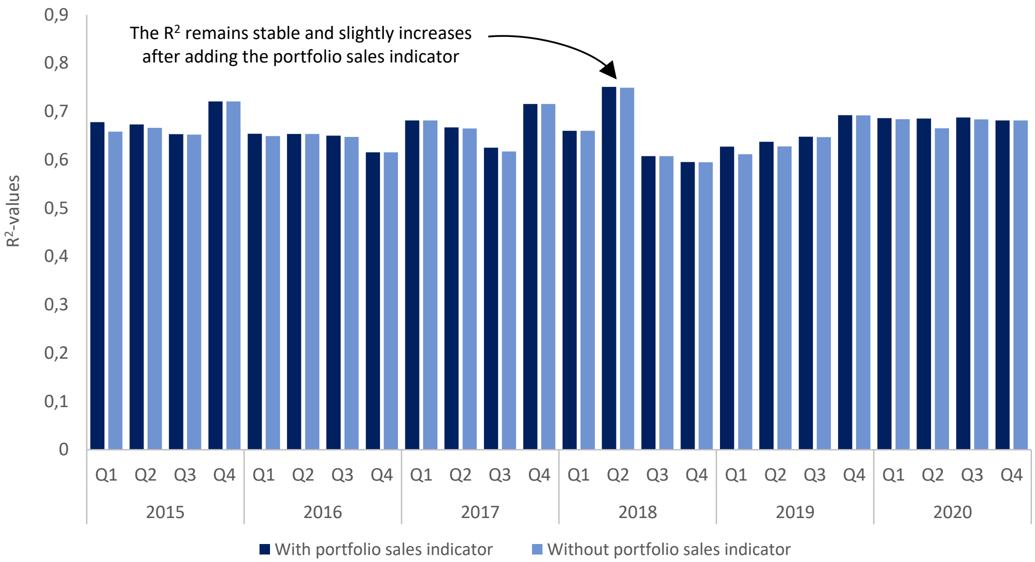

FIG. ANN.1.4 R2 **retail buildings** with and without portfolio sales indicator. Source: authors' own creation.

ANNEX 2

β-values (log) floor area indicator with and without portfolio sales indicator

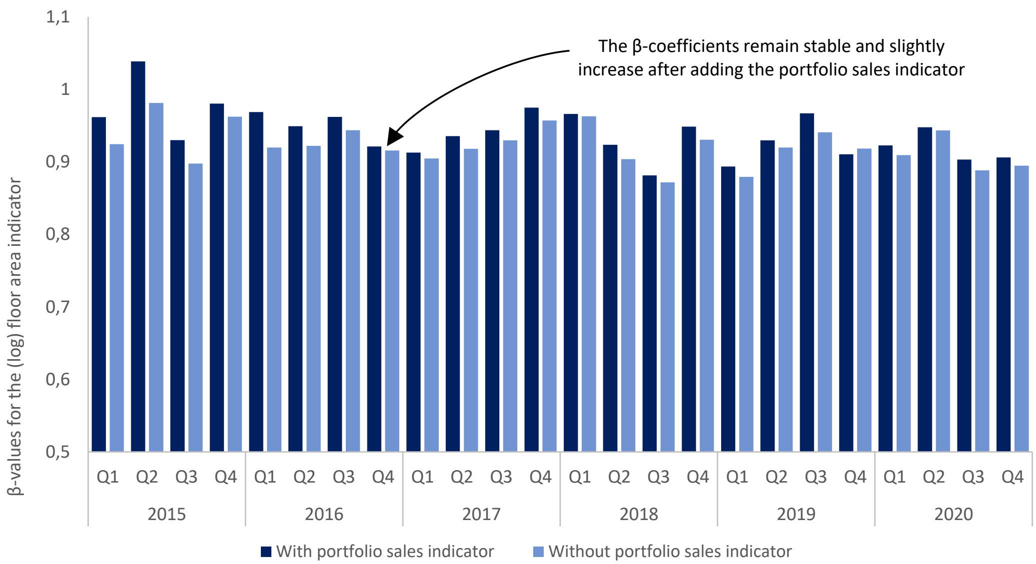

FIG. ANN.2.1 β-values (log) floor area indicator **rental dwellings** with and without portfolio sales indicator.

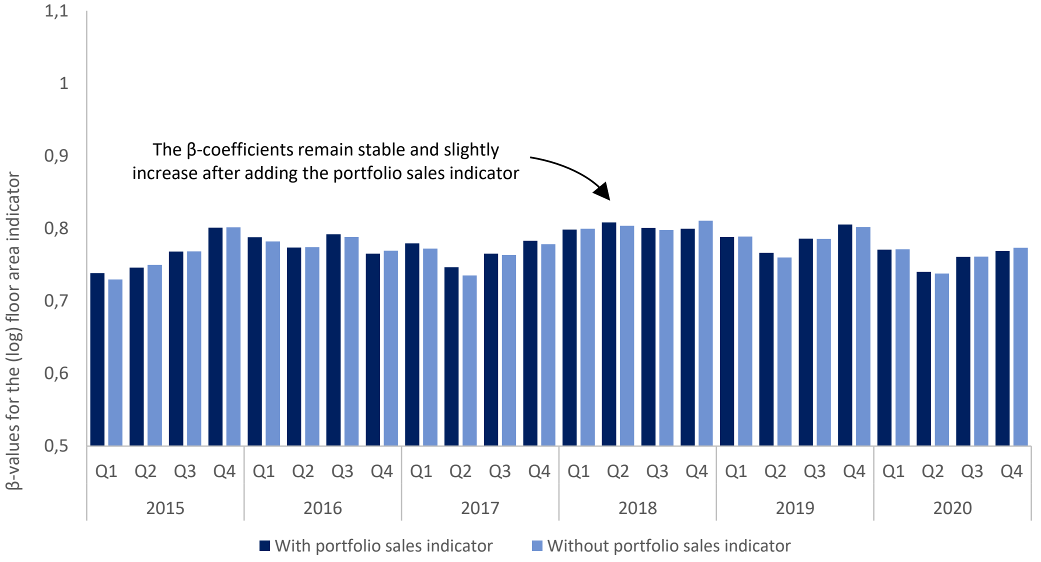

FIG. ANN.2.2 β-values (log) floor area indicator **rental dwellings** with and without portfolio sales indicator.

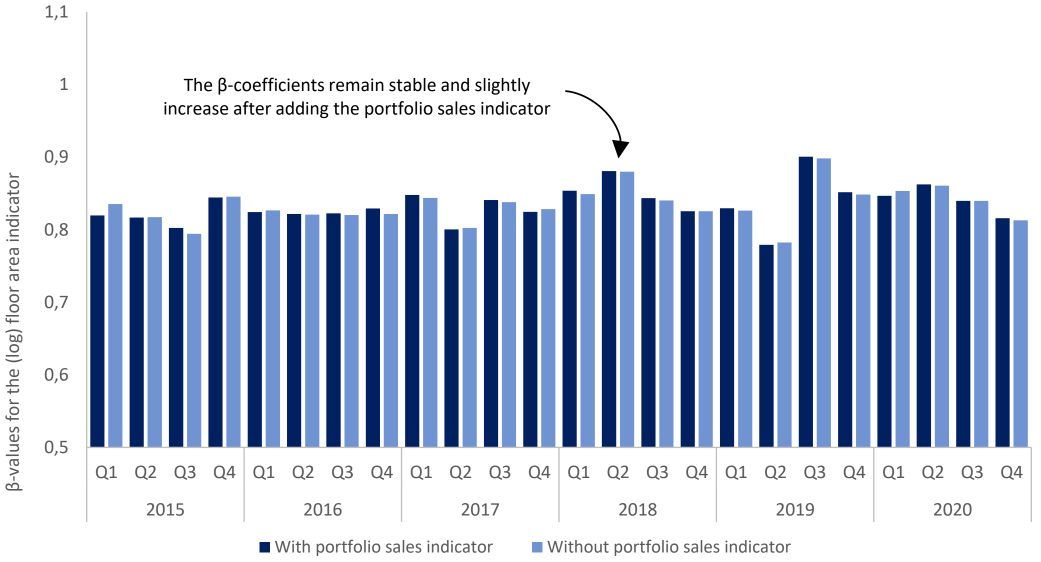

FIG. ANN.2.3 β-values (log) floor area indicator **rental dwellings** with and without portfolio sales indicator.

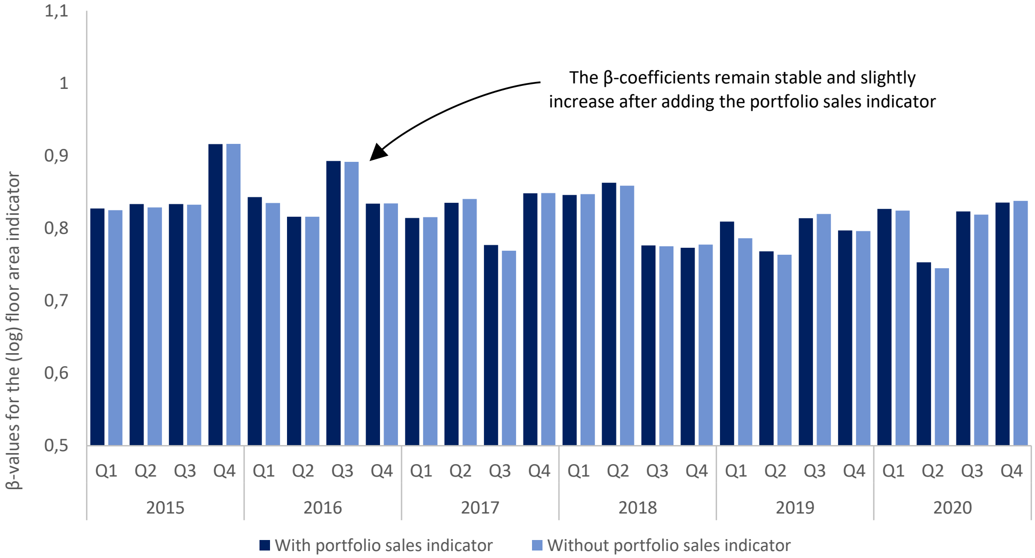

FIG. ANN.2.4 β-values (log) floor area indicator **rental dwellings** with and without portfolio sales indicator.

ANNEX 3

Relationship prices/m² and sustainability scores

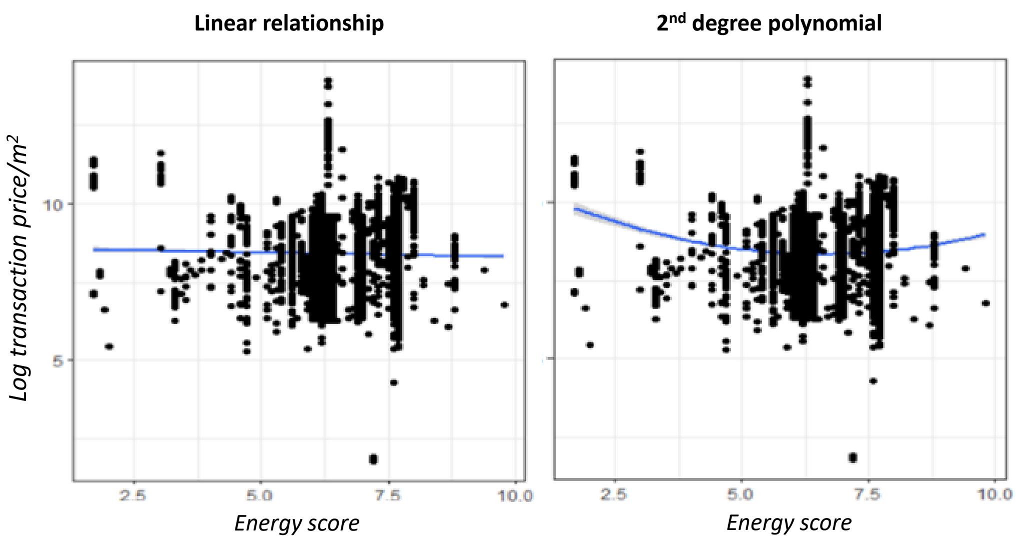

FIG. ANN.3.1 Relationship prices/m² and **energy** scores. Source: authors' own creation.

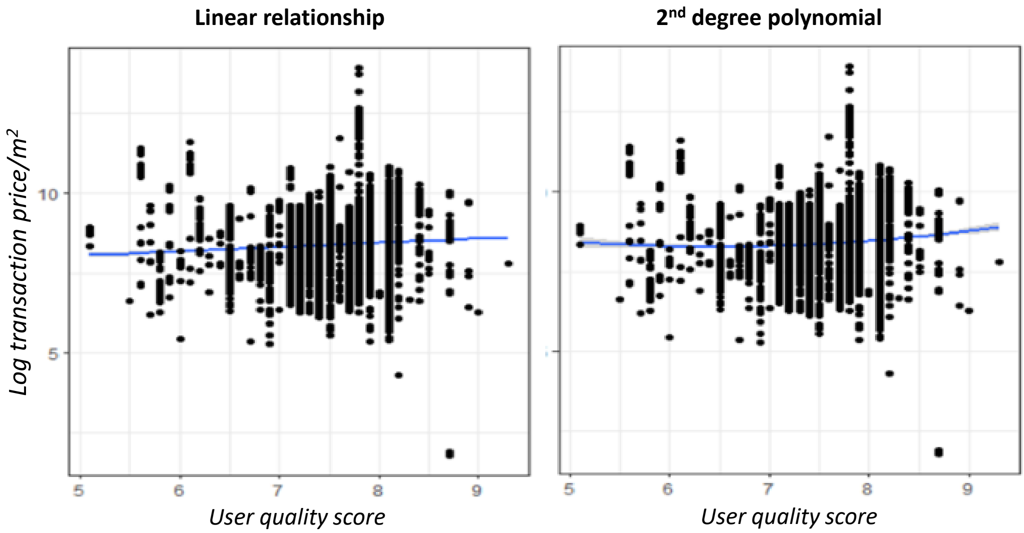

FIG. ANN.3.2 Relationship prices/m^2 and **user quality** scores. Source: authors' own creation.

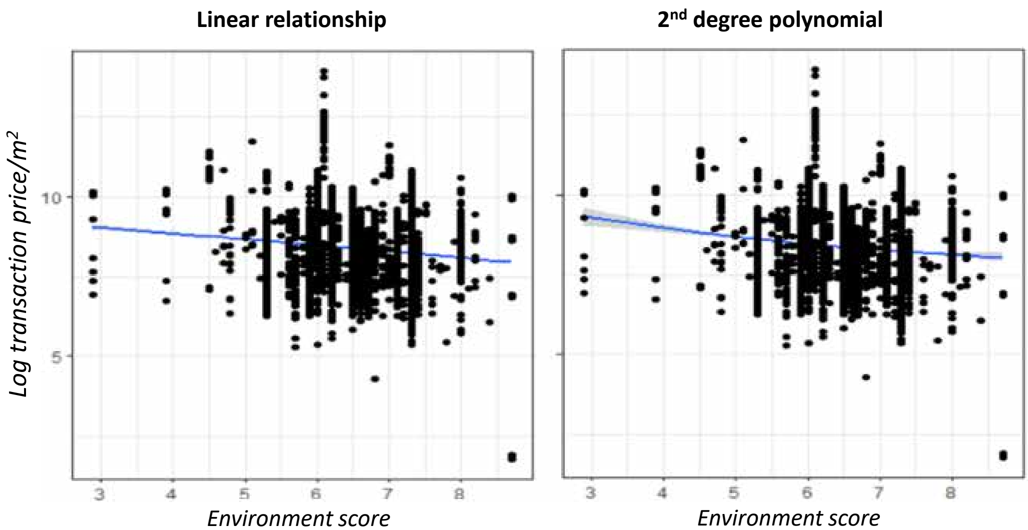

FIG. ANN.3.3 Relationship prices/m^2 and **environment** scores. Source: authors' own creation.

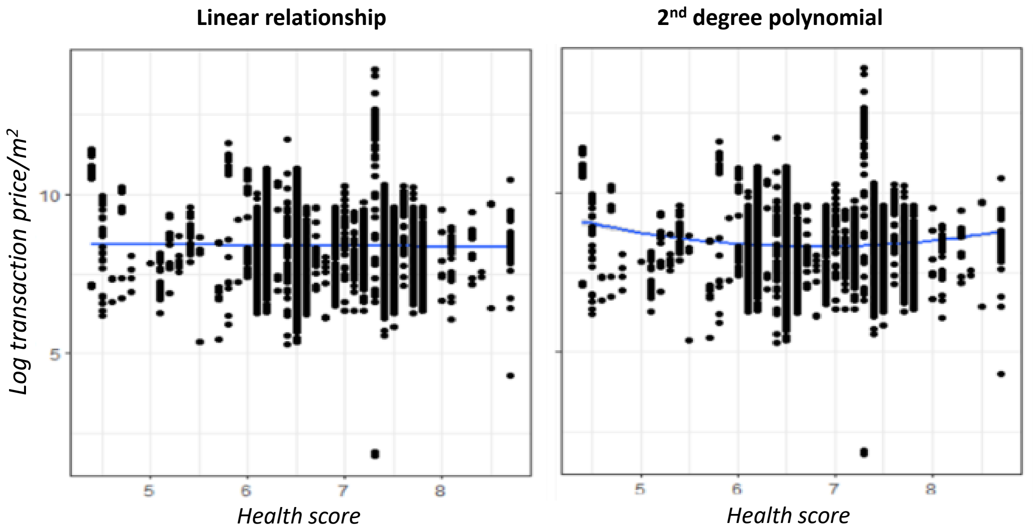

FIG. ANN.3.4 Relationship prices/m^2 and **health** scores. Source: authors' own creation.

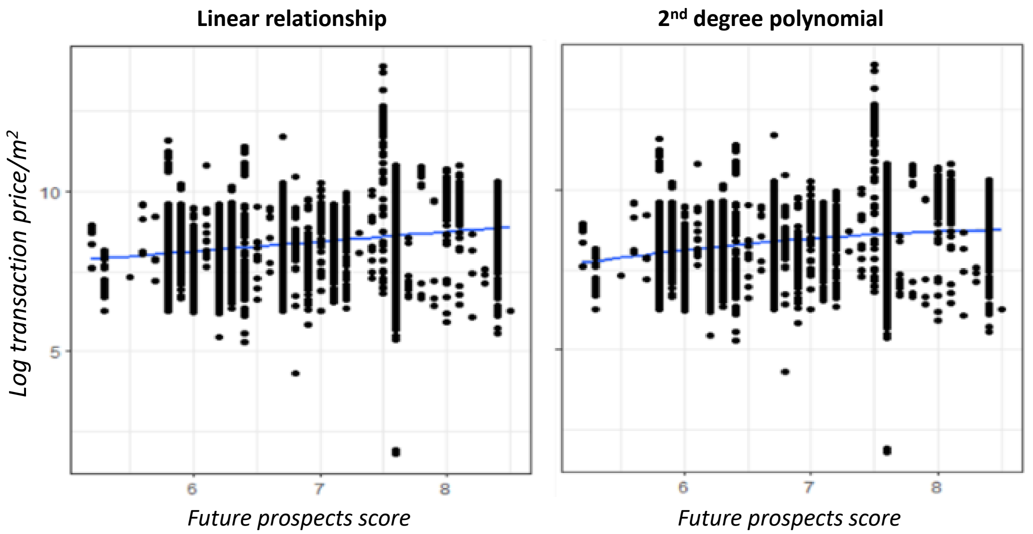

FIG. ANN.3.5 Relationship prices/m^2 and **future prospects** scores. Source: authors' own creation.

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Curriculum vitae

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2006 - present	Heldenhoek / DeeDrie Martial arts instructor
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2012 - 2013	Questionize Research Management consultant
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25#09

Improving commercial property price statistics

Farley Ishaak

Since the financial crisis of 2008, National Statistical Institutes (NSIs) have worked to develop commercial real estate (CRE) indicators for official statistics. These indicators are considered essential in financial stability monitoring and may help contain the consequences of future crises or even prevent future crises. However, progress at NSIs to develop these indicators has been slow due to challenges like low observation numbers and high heterogeneity. This dissertation addresses these challenges by exploring data issues and suggesting methodological improvements.

The first three studies focus on data challenges regarding share deals and portfolio sales. Both are real estate trading constructions that are specific to CRE. The results show that share deals and portfolio sales significantly differ from the rest of the market. Therefore, under specific circumstances, CRE indicators could benefit from including these trading types. The final two studies focus on methodological challenges regarding index construction methods and the role of sustainability in real estate pricing. The results show that, by combining established techniques, it is possible to construct price indices that meet official statistics' standards. Furthermore, the results uncover a complex relationship between sustainability and prices: while energy efficiency generally involves price premiums, others aspects like health and environment display a discount for low sustainable properties.

Overall, this dissertation contributes to the legislative framework that is currently being developed for EU countries to publish official statistics for commercial real estate and adds to the academic discussion by presenting innovative techniques for data analyses and index construction.

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