PRESS: The methodology of the Public Real Estate Sustainability Switzerland scores

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Abstract

This document presents the methodology followed in the development of the Public Real Estate Sustainability Switzerland (PRESS) scores. The PRESS scores, a pioneering initiative of the Center for Risk Management – Lausanne in collaboration with Quanthome SA, represent a breakthrough in the evaluation of sustainability performance among Swiss real estate funds. These scores, derived exclusively from publicly available data, address concerns about transparency and the lack of uniformity in the evaluation of real estate funds. The methodology spans three primary sections: quantitative indicators, offering detailed insights at the building level; textual analysis of fund annual reports, uncovering ESG strategies; and score aggregation, ensuring equal consideration of Environmental, Social, and Governance pillars. The PRESS scores foster transparency, independence, and sustainability in the Swiss real estate fund industry, serving as a crucial tool for stakeholders seeking well-informed decisions in the realm of sustainable finance.

Keywords: Real Estate, Switzerland, ESG, Sustainability, Public.

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1 Introduction

The Public Real Estate Sustainability Switzerland (PRESS) scores, an innovative initiative developed by the Center for Risk Management – Lausanne (CRML) in partnership with Quanthome SA, represent a significant advance in the evaluation of sustainability performance among Swiss real estate funds. These scores are based exclusively on publicly accessible data, guaranteeing availability to various stakeholders, including investors, regulatory bodies, and the general public. This document delineates the methodology used for each individual indicator that comprises the PRESS scores.

The inception of the PRESS scores can be traced back to the 2022 Indirect Real Estate Sustainability Report (CRML, 2023), characterized by inherent limitations. The report faced challenges primarily stemming from the lack of transparency in the assessment of real estate funds. Inaccessible internal data provided by investment vehicles precluded the public disclosure of ESG scores. Furthermore, the absence of uniform measurement methodologies hindered meaningful cross-fund comparisons, particularly with regard to CO_2 emissions (Alessandrini et al., 2023). Lastly, reliance on data provided by investment vehicles raised concerns about the independence and availability of the scoring process. Consequently, we recognize the urgent need for a more independent, transparent, and standardized approach capable of comprehensively addressing these concerns.

The PRESS scores embody a pioneering approach aimed at ensuring consistency in the scoring process across Swiss real estate funds. Our methodology hinges on the utilization of publicly available data, ensuring complete independence from the funds under evaluation. This approach fortifies the reliability and uniformity of the scores while eliminating potential biases, thus leveling the playing field for all funds. By offering these scores openly and free of charge, our objective is to equip stakeholders with the most up-to-date information necessary for well-informed decision making in the domain of sustainable finance. These scores serve as a crucial instrument in promoting transparency, accountability, and sustainability within the Swiss real estate fund industry, ultimately contributing to a more sustainable future.

The introduction of this methodology marks a significant milestone in providing a valuable resource to the market. Our focus is on real estate funds included in the SXI Real Estate Funds

Broad (2023, SWIIT) index, a carefully curated selection of funds with at least 75% of their assets invested in Switzerland. These funds play a crucial role within the Swiss economy, warranting a thorough examination of their sustainability performance.

In this methodology document, we present the construction of each indicator comprised in the PRESS scores. It is structured into three core sections. First, in Section 2 we introduce our quantitative indicators. This section delves into the specific quantitative indicators that form the foundation of the scores. These indicators are meticulously designed to offer a fine-grained analysis of real estate funds at the building level, including essential factors such as precise CO_2 emissions, building accessibility, and tenant turnover. Second, in Section 3 we expound upon our textual analysis of fund annual reports, explaining the methodology used in the examination of official reports from real estate funds. This text mining process uncovers valuable insights from fund documents, enriching our understanding of ESG strategies and the forward-looking aspects of fund operations. Third, in Section 4 we provide a detailed account of the construction of scores, clarifying how these individual quantitative and textual indicators are combined to form the overall ESG scores. This comprehensive approach ensures equal consideration of the three pillars of sustainable finance: Environmental, Social, and Governance.

2 Quantitative indicators

The quantitative indicators presented here serve to address two primary challenges encountered in the evaluation of ESG factors in the real estate sector. First, they must quantitatively and systematically represent relevant issues at the building level. Second, their aggregation should effectively capture sustainability management at the fund level and provide metrics for which real estate fund managers can reasonably be held accountable or influenced through policies, diligence, and management processes (Woodcraft, 2012). However, considering the nature of governance evaluation, three governance indicators are directly evaluated at the fund level.

Each indicator is initially computed at the building level and subsequently aggregated at the fund level. Aggregation is weighted by the heated surface area of each building (as defined in Formula 1). The use of heated area for averaging at the fund level is a common metric in various frameworks and literature.[1]

$$I_p^v = \sum_b^B I_b \times w_b \tag{1}$$

$$w_b = \frac{a_b}{\sum_b^B a_b} \tag{2}$$

where:

I_p^v : Value-weighted indicator of portfolio p

I_b : Value-weighted indicator of building b

w_b : The proportion of heated area in m^2 of building b in the portfolio

a_b : The heated area of building b.

B : The number of buildings of portfolio p.

This notation will be used consistently throughout the definition of all indicators. To ensure the robustness of our analysis, we identify potential outliers in heated area measurements using the interquartile range (IQR) as outlined in Equations 3, 4, and 5:

$$IQR = Q_3 - Q_1 \tag{3}$$

$$\text{Upper outliers} = Q_3 + 1.5 \times IQR \tag{4}$$

$$\text{Lower outliers} = Q_1 - 1.5 \times IQR \tag{5}$$

where Q_1 and Q_3 represent the 1^{st} and 3^{rd} quartiles of the heated area distribution. Subsequently, we subject all potential outliers to individual scrutiny, distinguishing between plausible observations and data errors. Errors are systematically excluded from our dataset.

[1] This approach might be limited by an initially low coverage of heated area data. In cases of missing values, an estimate is derived by multiplying the number of floors by the floor area. An alternative aggregation option could have been using the sum of the dwelling area in each building or their market value. However, using dwelling area may be less appropriate when funds also invest in non-residential buildings, and market value can be influenced by external macroeconomic factors. Such metrics are also less commonly used for weighted aggregation in the ESG framework of Real Estate.

2.1 Environmental indicators

Environmental impact assessment in the real estate sector primarily revolves around two key indicators: energy consumption and CO_2 emissions. Therefore, this section introduces two indicators that are designed to estimate the energy intensity and CO_2 emissions of each fund. We acknowledge that the scope of the environmental influence of real estate extends beyond these metrics to encompass aspects such as biodiversity, resource depletion, and land use, among other dimensions. These additional issues will be progressively added to the qualitative indicators as information becomes available. We also mitigate the impact of such missing information by using a textual measure.

2.1.1 Energy intensity

Regarding energy consumption, real estate bears significant responsibility, accounting for approximately 40% of the final energy consumption in Switzerland (OFEN, 2023a). In alignment with the Swiss Energy Strategy 2050, which seeks to reduce this consumption by around 28% by 2050, the energy intensity indicator plays a critical role in encouraging fund entities to improve their energy efficiency efforts. Data on energy intensity are not reported by the funds at the building level, only at the fund level. As our CO_2 intensity indicator is measured at the building level, we also calculate the energy intensity at the building level since this is a component of the CO_2 intensity indicator that we cover in the next section.

To construct the energy intensity indicator, we rely on two primary datasets. The first dataset, known as the Geneva Buildings Dataset, comprises a collection of 11,750 buildings located within the canton of Geneva. This dataset provides building level information, such as energy intensity values, and serves as the foundational data source for our estimations. The second dataset comprises a list of 42 real estate investment funds, each fund associated with its reported average energy intensity value in kWh/m_2. This secondary dataset serves as a benchmark role in validating our results.

Our methodology employs a Gradient Boosting Algorithm model, a machine learning approach known for its effectiveness. This algorithm iteratively utilizes decision trees to predict energy intensity values with a high degree of accuracy. Within our model, we consider a total of 16 features, encompassing various aspects such as construction year, ground area, Minergie label, building class (e.g. residential or commercial) and surface-related characteristics. This indicator is initially estimated at the building level using our model and is subsequently aggregated at the entity level, as defined in Formula 1. This multi-tiered approach ensures that the indicator is both granular and representative of the fund's overall energy efficiency performance.

The energy intensity indicator, though insightful, has inherent limitations. Relying on the Geneva Buildings Dataset introduces a potential geographic bias which might limit generalizability. The western part of Switzerland, including Geneva, may have lower renovation rates compared to the rest of the country, potentially leading to a slight overestimation of our model's representation of the overall market. Interpretation should consider the data's origin and potential regional variations in renovation practices within Switzerland.

2.1.2 CO_2 intensity

The real estate sector carries significant responsibility for the ongoing climate crisis, primarily due to its substantial contribution to greenhouse gas emissions (GHG), particularly CO_2. In Switzerland, the real estate sector alone accounts for approximately a quarter of the country's CO_2 emissions (FOEN, 2023b). The imperative to address GHG within this sector goes beyond climate change mitigation; it also involves recognizing these emissions as a potential risk and considering potential future regulations mandating their reporting and reduction.

GHG classification encompasses three distinct scopes: scopes 1, 2, and 3. Scope 1 emissions refer to emissions directly related to the operations of real estate funds. Scope 2 emissions represent emissions arising from electricity and energy consumption used for heating and cooling within these entities. Scope 3 emissions include emissions generated during both upstream and downstream activities (GRESB, 2018).[2] Nevertheless, the lack of uniformity in the approaches used by funds to measure emissions remains a challenge (for more details on measurement diversity, refer to Alessandrini et al., 2023). However, our computational method offers a stan-

[2] Significantly, Scope 3 emissions constitute the majority of total emissions from the property sector worldwide, with an average of 86% among the 200 largest listed real estate companies that disclose their emissions (Robecco, 2023). In particular, within the scope 3 emission category, 53% are attributed to downstream operations, occurring mainly during the building use phase. Given these statistics, the measurement and assessment of the emissions from scope 3 may imply substantial significance.

dardized CO_2 metric, which facilitates meaningful comparisons.

The challenge of computing overall CO_2 equivalent emissions arises due to limited data availability. Consequently, a proxy for CO_2 emissions is developed, using energy sources for heating and hot water from the Federal Building and Housing Registry (RegBL).[3] Furthermore, the energy intensity demand for heating and hot water demand, estimated from our Gradient Boosting Algorithm model, is incorporated.

Each energy source is associated with a CO_2 equivalent (CO_2e) factor per square meter of the heating area. This measure covers both scope 1 and scope 2 emissions. Emissions factors are sourced from Intep (2022) and recommended by the recent Swiss Asset Management Association directive (AMAS, 2023). The CO_2 intensity indicator is calculated at the building level using Formula 6 and subsequently aggregated at the fund level using Formula 1.

$$I_b^{CO_2} = w_b \times f_{sw} + h_b \times f_{sh} \tag{6}$$

where:

$I_b^{CO_2}$: CO_2e emission intensity indicator in building b

w_b: Estimated hot water demand for building b

h_b: Estimated heating demand for building b

f_{sw}: Emission factor for heating system s

f_{sh}: Emission factor for water heating system s.

We note that RegBL collects information on primary and secondary heating systems, which could be different for hot water and heating. Therefore, we allow different emissions factors when this is the case. The proportion of hot water as a source of CO_2 emissions is approximated to be 12.8% of heating, according to the factors of energy demand in OFEN (2023b).

[3] The RegBL dataset contains unique identifiers for buildings and housing, along with key information such as addresses, construction years, floor counts, and heating systems. Managed by the Federal Statistical Office, RegBL plays a crucial role in population censuses and serves as the foundation for the country's building and housing statistics. See FSO (2022) for further details.

2.2 Social indicators

This section delves into the social dimension of real estate and introduces indicators designed to assess its impact. Specifically, the selected indicators aim to capture the accessibility of assets, rental pricing strategies, the exposure of building occupants to noise pollution, and the tenant policy. It is important to note that while these indicators provide valuable information on user well-being, they do not encompass critical variables such as community engagement, neighborhood integration, or the ratio of rents to income, among others. At this stage, data on employee policy, such as salary or training programs at the fund management level, are not included as quantitative indicators. However, they are captured through the textual indicator.

2.2.1 Accessibility

Accessibility is defined as the ability of individuals to reach goods, locations, and services. It is influenced by characteristics of urban planning, such as proximity to stores, educational institutions, healthcare facilities, and recreational areas. Additionally, individual-specific factors, including ability, income, and knowledge, can impact a person's accessibility to these locations. Achieving inclusive accessibility requires consideration of these characteristics in the development of urban areas (Access to Services, 2023). Mixed-use development projects, for example, can reduce the reliance on fuel-based transportation, enhance accessibility, and stimulate the local economy (Herndon, 2011).

This indicator takes into account various forms of accessibility, as shown in Figure 1, including access to healthcare, education, social activities, and transportation. To measure accessibility, we count the number of service entities within a 10-minute walking radius (approximately 700 meters) from the building's location.[4] OpenStreetMap data and RegBL building coordinates are used for these calculations.

Different accessibilities are calculated as shown in Formula 7, and subsequently are aggregated at the building level using Formula 8. Finally, this indicator is aggregated at the portfolio

[4] In order to prevent a disproportionately high score resulting from the dominance of a single service type, we have instituted an upper limit of 10 entities. This decision aligns with the understanding that, within a 10-minute walking radius, the marginal utility of an additional service diminishes significantly in areas already characterized by a substantial concentration of that particular service.

level using Formula 1.

$$A_b^c = \frac{\sum_{t=1}^{t_c} s_b^t}{t_c} \tag{7}$$

$$A_b = \frac{\sum_c^C A_b^c}{C} \tag{8}$$

where:

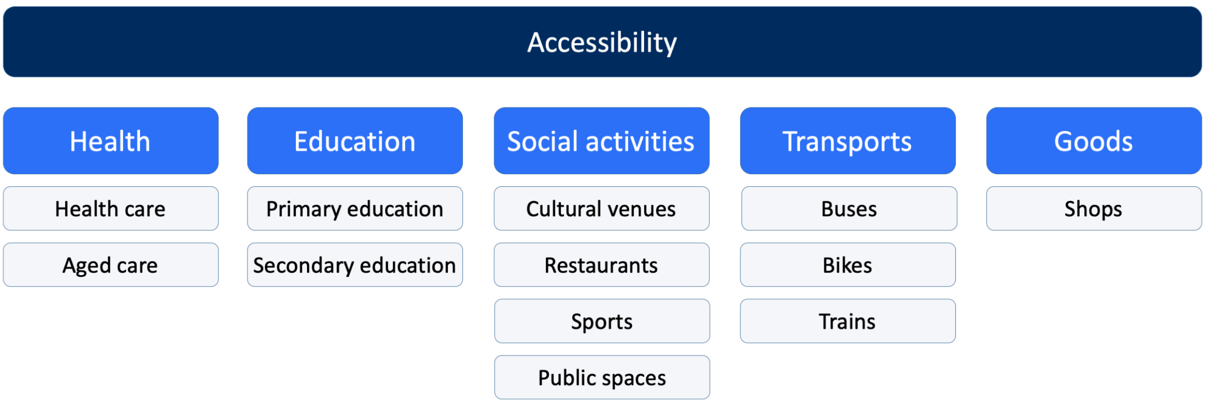
A_b: Accessibility for building b

s_b^t: Number of entities for the type of service t within a radius of 700 m for the building b

t_c: Number of types of services accessible in category c (e.g., healthcare and age care as types of accessibility within the category health)

C : Number of accessibility categories.

Figure 1: Accessibility criteria at the building level



2.2.2 Rental pricing

The rental pricing indicator evaluates how rents of individual dwellings within a fund's portfolios compare to the average rent of buildings in their respective quarter or municipalities. This comparative analysis assesses whether funds' pricing strategies impose rental premiums or offer discounts to their tenants. The indicator plays a pivotal role in providing stakeholders with insights into the implications of these pricing strategies for tenants within their portfolios.

The methodology for this indicator relies on data collected by Quanthome from rental housing advertisement as well as data from RegBL. The indicator is formally defined as the disparity between the rental price per square meter for a dwelling contained within the investment portfolio of a fund and the mean rental price per square meter for properties situated within the locality.[5] For the ten most populous cities, the locality corresponds to the urban quarter.[6] For the other municipalities, the locality aligns with the boundaries of the same municipal area.[7] Rental prices are normalized to a standard three-room apartment to ensure consistent and meaningful comparisons. A positive rental difference indicates that the fund charges a premium on rental price compared to the average of the locality, while a negative rental difference suggests potential tenant discounts.

A positive premium, which would be perceived as negative from the tenant's standpoint, could reflect compensation for higher living standards in the building, which should be captured by other indicators. If living standards are not higher, the higher rental price only reflects the pricing strategy of the fund and negatively impacts the S score.

The calculation of the rental pricing indicator is performed at the building level using Formula 9. Subsequently, the indicator is aggregated at the portfolio level using Formula 1.[8]

$$R_b = r_b - r_l \tag{9}$$

where:

R_b : Rental premium or discount for building b

r_b : Rental price per m^2 for building b in locality l

r_l : Average rental price per m^2 for locality l.

[5] For our computations, we utilize the gross rental price, a customary and extensively utilized metric in housing advertisements. This choice is made to mitigate the potential inconsistencies that arise from the heterogeneity between net rent and additional charges, ensuring that disparities in rental prices predominantly signify pricing strategies rather than specific characteristics of the building.

[6] For the precise delineation of quarters boundaries, we rely upon a the FSO (2017) database. This database provides neighborhood boundaries for the following major cities: Basel, Bern, Biel/Bienne, Genève, Lausanne, Lugano, Luzern, St. Gallen, Winterthur, and Zürich.

[7] We employ the municipal level as it represents the lowest geographical tier at which we can establish well-defined boundaries for these entities.

[8] To address potential bias from the commercial nature of a fund, we adjust the indicator based on the proportion of residential dwellings in the portfolio. Consequently, a fund exclusively focused on commercial properties is considered neutral for this indicator.

2.2.3 Outdoor noise pollution

In Switzerland, a significant proportion of the population — approximately 1 in 7 individuals — is exposed to noise pollution originating from road, air, and train traffic during both daytime and nighttime hours in 2015 (FOEN, 2015). Extensive research has shown the various adverse effects of exposure to noise on critical aspects of health and well-being. For example, noise pollution has been linked to potential impacts on mental well-being of children (Lim et al., 2018) and has been associated with sleep disorders that increase the risk of cardiovascular disease (Hume et al., 2012). Furthermore, noise disturbances can compromise the overall productivity and comfort of individuals (Mohamed et al., 2021).

Within the realm of real estate, property owners have several avenues for addressing noise-related concerns. They can invest in improving the quality of the building envelope to create sound-insulated living environments or promote sustainable and noise-reducing transportation solutions, such as slow and electro-mobility (FOEN, 2023a). Property owners can also leverage their property rights to influence local regulations, thus directly contributing to the reduction of noise pollution at its source. This underscores the role that real estate entities play in mitigating the impact of noise pollution and fostering healthier living environments for tenants.[9]

To calculate the outdoor noise pollution indicator, we have collected the following maps published by the Federal Office of the Environment (FOEN, 2022): Daytime and nighttime road traffic noise and daytime and nighttime train traffic noise in decibels (dB). These estimates are based on traffic data, vehicle category and type, and location-specific characteristics, such as obstacles or road coverings (FOEN, 2023a).

The formula 10 computes the outdoor noise pollution indicator at the building level and formula 1 aggregates the indicator at the fund level.

$$I_b^n = \frac{\sum_c^C N_{b,c}}{4} \tag{10}$$

where:

I_b^n : Aggregate of the four types of noise in dB at the building level

[9] In Switzerland, residential noise level limits are set at 60 dB during the day and 50 dB during the night.

$N_{b,c}$: Noise of type c in dB for building b

C : Types of night or day train and road noise.

2.2.4 Tenant policy

The decision to relocate is influenced by a variety of factors, including personal circumstances, family changes, and job opportunities. However, the tenant's satisfaction with their current living or working environment can also play a crucial role and sometimes be the reason for seeking a change.

An article published by Raiffeisen Bank highlights that 13% of individuals decide to move due to dissatisfaction with their current living conditions or property management (Neff, 2020). To capture this effect, two sub-indicators, "New residents delta" and "Rental advertisement delta", have been developed. Each of these metrics assesses the number of individuals or advertisements per dwelling or heated area in relation to the same metric at the municipality level. These metrics indicate whether a building experiences more or fewer moving than the average of the municipality.[10]

2.2.4.1 New residents delta

The new residents delta sub-indicator relies on the STATPOP dataset from 2021, specifically the number of residents living in a hectometer for less than a year, assumed to be new residents. To estimate the number of new residents for each building, the value at the hectometer level is attributed to the building based on its share of dwellings in the hectometer, as described in Equation 11. Then the average number of new residents per municipality is calculated, as shown in Equation 12.

Finally, the indicator, which represents the difference between these two metrics, is calcu-

[10] In alignment with the rental pricing indicator, we rescale tenant policy metrics with the proportion of residential properties, thereby mitigating bias arising from a commercial focus.

lated at the building level using Equation 13.

$$R_b = R_{hm} \times \frac{D_b}{\sum_b^{B \in hm} D_b} \tag{11}$$

$$R_m = \frac{\sum_{hm}^{HM \in m} R_{hm}}{\sum_b^{B \in m} D_b} \tag{12}$$

$$R_b^{delta} = R_m \times D_b - R_b \tag{13}$$

where:

R_b : Estimated number of new residents in a building located in hectometer hm

R_{hm} : Number of new residents in hectometer hm

D_b : Number of dwellings for the building b

R_m : Average number of new residents per dwelling in municipality m

R_b^{delta} : Difference between the expected number of new residents and the actual number of new residents.

Finally, the indicator is aggregated at the fund level using Formula 1.

2.2.4.2 Rental advertisement delta

The rental advertisement delta sub-indicator relies on rental advertisements collected from rental ad websites. The methodology is similar to the one used for the new residents delta, with one distinction: the normalization of advertisements per building is done with the heated area instead of the number of dwellings. This adjustment is necessary as rental advertisements may include both residential and commercial properties, with the latter lacking dwellings.

$$I_b^{Ads} = \frac{\sum_b^{B \in m} A_b}{\sum_b^{B \in m} a_b} - \frac{A_b}{a_b} \tag{14}$$

where:

I_b^{Ads} : Building b difference from municipality m in terms of advertisement per heated surface

A_b : Number of advertisements per building b.

The indicator is aggregated at the fund level using Formula 1.

2.3 Governance

In Switzerland, real estate fund managers often delegate the direct management of their assets to property management companies (Bonnet and Pollard, 2021). As a result, evaluating governance practices using building-level data can be challenging. The indicators in this section aim to capture trends in good governance practices at the fund level.

2.3.1 Minergie

Buildings with Minergie labels are not only energy and resource efficient but also provide a comfortable living environment for tenants. Furthermore, the decision to renovate a building and label it with Minergie, or to purchase or construct a Minergie-compliant building lies within the hands of the fund's managers. Additionally, the greenness of assets shows a positive correlation with good governance practices (Robinson and McIntosh, 2022).

To build the Minergie indicator, the share of the surface labeled with Minergie is used.[11] As most of the buildings with the Minergie label adhere to the Minergie standards, no differentiation is made between the different labels.

$$Minergie_p = \sum_{b}^{B} m_b \times w_b \tag{15}$$

where m_b is a variable equal to 1 if building b has a Minergie label. Last, the indicator is aggregated at the fund level using formula 1.

2.3.2 Board gender

The board gender indicator is a quantitative metric used to assess gender diversity within the composition of the board of directors collected at the fund level. This indicator is designed to evaluate the extent to which a real estate investment fund's board of directors reflects gender parity or deviates from it. To calculate the Board Gender Gap, comprehensive data on the com-

[11] Our data is cross-referenced with the figures presented in the annual reports. In the event of inconsistencies, the highest value is selected.

position of each investment fund's board of directors are collected, including the total number of board members and the number of male and female directors.

$$BoardGenderGap_p = |0.5 - ShareOfWomen_p| \tag{16}$$

where:

$ShareOfWomen_p$: Share of women in the fund board of portfolio p

$BoardGenderGap_p$: Deviation from perfect parity in absolute percentage point.

A Board Gender Gap of 0 indicates perfect gender parity, meaning that the board of directors has an equal representation of male and female members. Positive values indicate an overrepresentation of male or female directors on the board.

2.3.3 Ratification of international treaties

The indicator of ratification of international treaties assess the extent to which a real estate investment fund or fund group has committed to international treaties and agreements related to ESG factors. This indicator is designed to measure the fund's participation in global sustainability efforts and its alignment with international standards.

To calculate the number of ratified international treaties, a predefined list of international treaties and agreements related to ESG factors is used.[12] These treaties typically cover a wide range of ESG topics such as climate change, human rights, labor standards, and anti-corruption measures. Information is collected on whether the investment fund or fund group has ratified or signed these relevant international treaties. Each treaty that the fund has ratified contributes to the count. The indicator of ratification of international treaties is calculated as a simple sum of the number of treaties ratified by the fund or fund group.

A higher value for the indicator of ratification of international treaties indicates that the fund

[12] The treaties are the following: Climate Action 100, Global Investor Coalition on Climate Change, International Labour Organization, Principles For Responsible Investment, Re100, Task Force On Climate Related Financial Disclosures, UN Environment Programme Finance Initiative, UN Global Compact, World GBC Net Zero Carbon Buildings Commitment, Global Reporting Initiative, Carbon DisclosureProject, Sustainability Accounting Standards Board, Ethos Engagement Pool, Swiss Sustainable Finance.

or fund group has committed to a higher number of international treaties related to ESG factors, reflecting a stronger commitment to global sustainability and responsible investment.

2.3.4 Sustainability reporting and web communication

The indicator for sustainability reporting and web communication is used to assess the extent to which a real estate investment fund or fund group provides dedicated sustainability reporting and maintains a separate webpage dedicated to sustainability issues. This indicator aims to evaluate the fund's commitment to transparency and communication of its sustainability efforts.

To calculate the indicator of sustainability reporting and web communication, two key elements are considered: the presence of a standalone sustainability report, separate from the fund's annual report, and the presence of a webpage on the fund's website solely dedicated to sustainability-related information. Each element is assessed separately, with a binary value of 1 assigned if the element is present and 0 if it is absent.

The indicator for sustainability reporting and web communication is calculated as a simple sum of the binary values for both elements. If both elements are present, the sum is 2; if only one element is present, the sum is 1; if neither element is present, the sum is 0. This indicator is important for three main reasons. Firstly, it shows a commitment to transparency by providing a standalone sustainability report and a dedicated webpage. This transparency benefits stakeholders such as investors, regulators, and the general public, as it allows them to easily access and understand the fund's ESG efforts. Additionally, having a dedicated sustainability webpage improves the accessibility of ESG data, making it more user-friendly. Furthermore, maintaining a separate sustainability report encourages the fund to thoroughly address and report on its sustainability initiatives, promoting accountability for its ESG performance.

3 Textual indicators

This section outlines the methodology employed for our textual analysis of ESG performance in Swiss real estate funds. The focus is on three key aspects: dataset description and classification, creation of the ESG dictionary, and the text mining process. Additionally, we include a robustness check to address potential language bias.

3.1 Data

The dataset comprises disclosed statements from Swiss real estate funds that make up the SWIIT index. It encompasses various types of PDF files, including annual reports, sustainability reports, semi-annual reports, group annual reports, group sustainability reports, and factsheets.[13] The data set for each investment fund includes all available filings. The naming convention for these documents consists of an eight-character individual code for each investment, followed by the reporting year, and ending with a four-character file type code. This naming convention provides crucial information to easily identify and classify each file based on its name. The dataset encompasses files in three different languages: English, French, and German.

3.2 ESG Dictionary

In our approach to measure ESG performance through text analysis, we employ a dictionary-based method. This method uses a specific dictionary composed of words indicative of superior ESG performance. By quantifying the frequency of these dictionary words within a given text, we can infer the text's ESG performance level. Through this dictionary-based approach, dictionary enrichment via neural network techniques, and translation capabilities, our aim is to provide a comprehensive and accurate assessment of ESG performance based on textual data.

3.2.1 Description

The foundation for our initial dictionary is derived from the work of Baier et al. (2020). We utilize their updated dictionary as of July 2022, which incorporates several additional terms.[14] The initial dataset comprises 491 entries, each representing a single English word. These entries cover nouns, verbs, and abbreviations. Some words in the dictionary include meaningful inflections that capture various forms of a root word, such as ”cleaner,” ”cleanest,” and ”cleaning.” The words in the ESG dictionary from Baier et al. (2020) are categorized into three overarching topics: Environment, Social, and Governance. Furthermore, many words are subcategorized

[13] Group reports are incorporated into the database upon public disclosure of the fund's affiliation.

[14] The ESG dictionary has been sourced from Florian Kiesel's professional website Kiesel (2022), one of the co-authors of Baier et al. (2020).

into specific categories and subcategories. This classification system provides a comprehensive and granular overview of the word list, with three main topics, ten categories, and forty subcategories. By leveraging this comprehensive ESG dictionary, we gain a deeper understanding of the language and terminology associated with environmental, social, and governance aspects.

3.2.2 Adaption

To tailor the dictionary to the specific context of real estate, we undertake a procedure to identify potentially crucial ESG-related words that may be absent from the dictionary and incorporate them to enhance it. Both Baier et al. (2020) and Kiriu and Nozaki (2020) employ strategies that involve term-document matrix reduction to construct and refine their ESG dictionaries. However, Baier et al. (2020) does not specify the precise type of model and the specifications of the models they employ. Similarly to Kiriu and Nozaki (2020), we utilize the skip-gram model implemented through the word2vec algorithm to identify missing words and potentially enrich the dictionary.

To learn word associations from a large corpus of text and discover which words are related to specific concepts, we utilize a neural network model. This model, once trained on a dataset, can, given a word as input, produce output words that are highly correlated with the input and tend to appear in similar contexts. For this purpose, we use the word2vec library.[15] By capturing word context, the word2vec method can detect both semantic and syntactic similarities.[16,17]

After training the continuous skip-gram model on English company documents, we initially employ the words used to name the Topics and Categories, according to the procedure followed by Baier et al. (2020). To maintain the conciseness of the dictionary, we extract the top 10

[15] The word2vec method converts each word in the text into a vector, where each word occurrence is marked, effectively transforming a text into a large matrix. This matrix allows us to identify words that frequently occur in proximity to each other.

[16] Semantic similarities pertain to word meanings, while syntactic similarities relate to sentence structure and word placement.

[17] The word2vec method offers two models: the Continuous Bag-of-Words Model (CBOW) and the Continuous Skip-gram Model. The CBOW model predicts a word based on its context, while the continuous skip-gram model predicts surrounding words given the current word. According to the creator of the word2vec method Mikolov et al. (2013), apart from having greater complexity and requiring more time, the continuous skip-gram model tends to perform more accurately on semantic tasks, while CBOW excels at syntactic tasks. This suggests that the continuous skip-gram model is better suited for predicting word meanings, while CBOW is better suited for modeling word order. Therefore, the skip-gram model is more appropriate for the purpose of supplementing the ESG dictionary.

positively correlated words for each word and exclude any words already present in our dictionary. Then, we filter for meaningful additions. The recommendations of the trained model align largely with the existing dictionary, affirming that the base dictionary provided by Baier et al. (2020) is suitable for this dataset. However, we identify some valuable additions.

3.2.3 Translation

After improving the English ESG dictionary, the next step is to translate it into German and French. To accomplish this, we employ the Googletrans library in Python, which utilizes Google Translate. Once we obtain the translated word lists in German and French, we cross-reference them manually using dictionaries to ensure accuracy. In cases where different English words translate to the same foreign word, we include only one translation to prevent duplication. For example, both ”citizen” and ”citizens” translate to ”Bürger” in German. Therefore, ”Bürger” appears only once in the German dictionary to avoid double counting. Additionally, some English words have foreign translations consisting of two separate words. For instance, ”groundwater” translates to ”eaux souterraines” in French. As our model uses single words as dictionary entries, we denote such cases by introducing a hyphen, resulting in ”eaux souterraines” becoming ”eaux-souterraines” in the dictionary. This translation process ensures that the ESG dictionary covers relevant terms in German and French, enabling accurate analysis of documents in multiple languages within the model.

3.3 Text Processing

To extract information from PDF documents, we begin by using the pdfminer library in Python to extract all textual content. Our goal is to preserve as much semantic information as possible while simplifying and reducing the dimensionality of the textual data. Many words in documents are broken up by line breaks into two separate words with hyphens at each end. We identify these split words, remove the hyphens, and join them in their natural and recognizable form. To reduce data dimensionality and eliminate noise, we remove elements that do not contribute meaningful value, such as uppercase characters, punctuation, and special characters. Numbers and single-character words are also removed. We identify two-worded translation terms and replace the blank space with a hyphen to form a single word.

3.4 Information Extraction

After individually processing each document to improve textual quality and reduce data dimensionality, we proceed with information extraction. Given that sentiment analysis may not always be the most effective method for predicting firm performance, as demonstrated in Lee et al. (2018), we adopt a dictionary-based approach. In this approach, the structure of the sentence is not a primary consideration; instead, we count the frequency of each word and condense this information into a vector.

To determine the language of a fund's documents, we use the translated ESG dictionary. Specifically, for each language, we utilize the corresponding ESG dictionary to count the total number of ESG terms used in a document. The language in which the most ESG terms appear is assigned as the corresponding language of the document. Once we have a vector of translated dictionary word frequencies for each document in its respective language, we consolidate all translated dictionary word frequency vectors for funds that have multiple types of disclosed documents into a unified vector per fund. In order to reduce at maximum any language bias, we always pick English documents when available.

3.5 Computation of ESG textual indicators

The calculation of ESG textual indicators for each fund involves a step-by-step process. Initially, we obtain the total word count of the fund's documents, providing an overall measure of the available text for analysis. Subsequently, we determine the word count for each of the three ESG pillars: Environment, Social, and Governance. This entails counting the frequency of relevant words associated with each pillar within the fund's documents.

To assess the significance of each ESG pillar, we calculate the relative frequency. This is achieved by dividing the word count for each pillar by the total word count of the documents. Our relative frequency approach offers a proportional representation of the importance of each pillar within the fund's ESG performance.

This method provides a quantifiable measure of the presence and communication of E, S, and G within official documents of a fund. A fund with a higher score in a particular pillar indicates a greater focus on addressing future challenges, implementing better disclosure practices, and employing diverse strategies to mitigate potential risks associated with that specific aspect of ESG pillars.

4 ESG scores

To provide a comprehensive assessment of each entity and facilitate cross-comparison, individual indicators are standardized onto a common scale. These standardized indicators are then aggregated to calculate ESG scores and ESG pillar scores. These scores offer a holistic evaluation of each fund.

The transformation of separate indicators into ratings occurs on a scale ranging from 0 to 10, where 0 represents the least favorable outcome, and 10 signifies the most favorable result. Our rating methodology is an adaptation of the approach outlined by Refinitiv (2020).

In our scoring methodology, we employ the percentile rank scoring method presented by Refinitiv (2020) to minimize the influence of outliers. In instances where data is missing, we assign a score of 0 to ensure that it is rated as less favorable than the least favorable data point. The final score for each indicator is determined by the percentile position of the metrics. In the case of indicators with positive polarity the score (S_f^+) is calculated as follows:

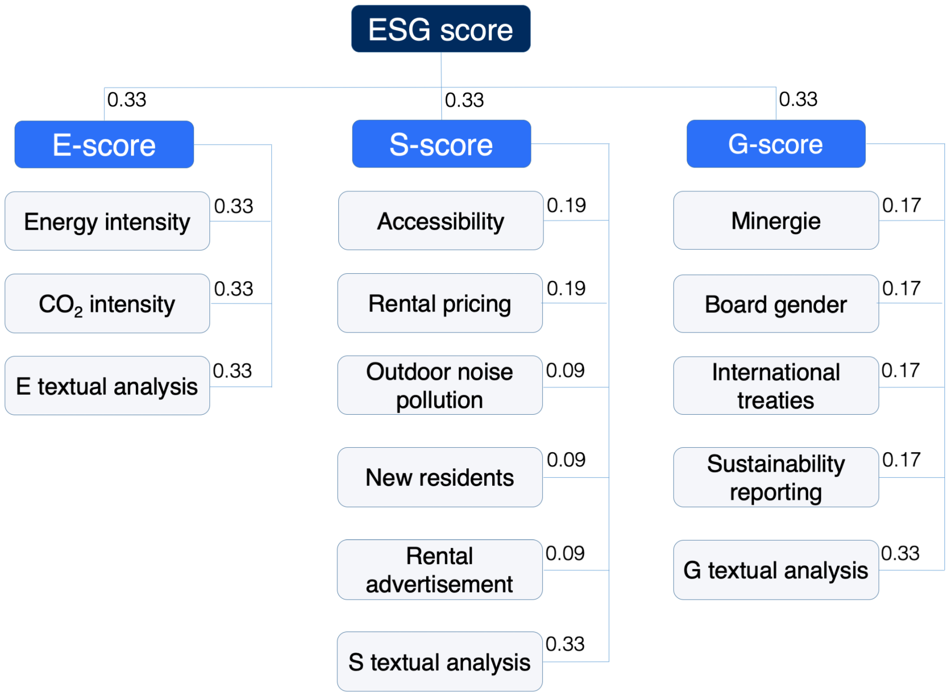
$$S_f^+ = \frac{\text{number of funds with a smaller value} + \frac{\text{number of funds with the same value}}{2}}{\text{number of funds with a value}} \times 10 \tag{17}$$

For indicators with negative polarity, the reverse percentile, denoted as S_f^-, is calculated as:

$$S_f^- = 10 - S_f^+ \tag{18}$$

The ESG pillar scores are computed as weighted averages of a set number of indicators. The Environmental pillar scores are based on 2 indicators, the Social pillar scores rely on 4 indicators, and the Governance pillar scores are determined by 4 indicators. The indicators within each pillar are assigned equal weights, ensuring that each indicator contributes equally to the final pillar score. Some exceptions apply to subindicators, where weights are distributed evenly across specific policy-related questions to maintain balance and avoid overemphasizing particular information. The resulting pillar scores range from 0 (least favorable) to 10 (most favorable). Figure 2 provides the detailed weights for each indicator.

Figure 2: Indicator weights



To enrich our quantitative scores, we incorporate results from our textual analysis. We apply the same scoring methodology, where a higher relative count of words per pillar is associated with a higher score. Textual scores contribute one third of each pillar's final score. This integration of textual analysis addresses potential backward-looking biases inherent in quantitative scores and captures additional ESG strategies that may not be fully reflected in the quantitative assessments.

The overall ESG score is an unweighted arithmetic mean of the scores from the Environmental, Social, and Governance pillars. Equal weights are assigned to the three pillar scores, ensuring a balanced consideration of all three dimensions of sustainable finance.

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