Environmental, social and governance (ESG) anomaly detection

With the increased market demand for reliable environmental, social and governance (ESG) data, a new challenge has emerged: determining the trustworthiness of this data. We used best in class ESG dataset from Refinitiv®, an LSEG business, in the application of our anomaly detection tool. The tool is at its infancy, proof of concept stage, and we are looking to enhance further as we complete the journey of feedback and validation.

LSEG

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1. ESG data

1.1 Growing importance

As issues such as climate change, social inequality, diversity and inclusion are placed in the spotlight, investors, corporations and banks alike are realising the importance of sustainable investment. The demand for global change is fuelled by environmental, social and governance (ESG) data, an increasingly important element in the reporting and analysis process. As millennials lead a drive to invest in ESG-focused companies, organisations seek to improve their ESG scores and performance.

Companies with strong ESG performance have demonstrated higher returns on their investments, lower risks and better resiliency during a crisis. From 2018 to 2020, investments in ESG strategies grew by 42%, and a third of assets under management are invested in ESG strategies. LSEG (London Stock Exchange Group) recognises the critical importance of transparent, accurate and comparable ESG data and analytics for the financial industry, a key focus in 2022 and beyond, with the proven potential for excess returns.

1.2 Trust issue

A common pain point for investors is the lack of reliable ESG data to help them make meaningful decisions. Despite an abundance of disclosure and ratings data from various sources, investors find it hard to assess the credibility of companies' compliance with ESG criteria when they lack confidence in the data.

Investors have the right to question ESG data, and it is not uncommon for the scores to contain anomalies. What defines an anomaly is dependent on the use case. With this in mind, one can define an anomaly as a significant difference between the observed and the expected, be it a textual or a numerical value. These differences show up due to unexpected changes over time or appear inconsistent compared to peer companies. While not an exhaustive list, these are just a few reasons why anomalies may occur:

- Inaccurate data due to unintentional errors
- First time reporting
- Significant changes within a company motivated by strategy or operations
- Structural changes within an industry group
- Greenwashing

1.3 Refinitiv's ESG data

Refinitiv provides ESG scores for close to 12,000 companies globally, with time series data going back to 2003.

Figure 1: Structure of Refinitiv's ESG data

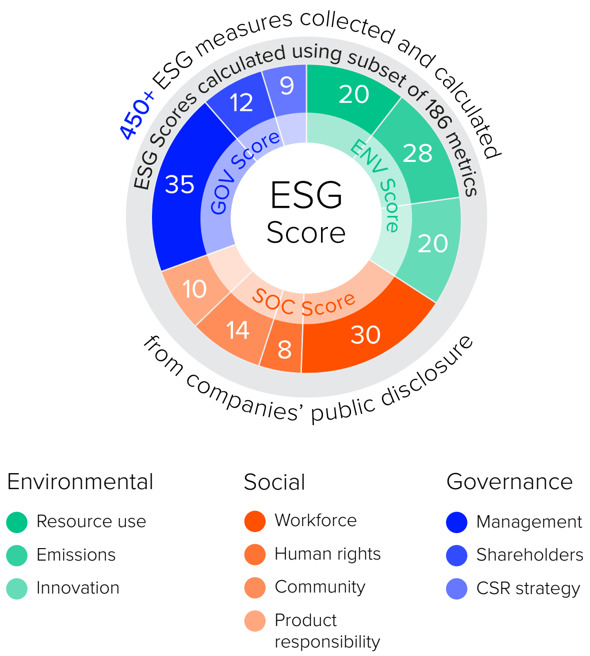


Figure 1 shows the structure of the ESG dataset. A company's ESG score is calculated as a weighted sum of three pillar scores: environmental, social and governance. The pillars are further broken down into multiple category scores shown on the right-hand side. Categories are further split into 186 metrics in total which are based on more than 500 ESG measures. Industry group-specific weights define how much impact a category has on the ESG score. For example, in emission-intensive industry groups such as oil and gas, the emissions category has a greater weight than the financial industry group.

The coverage of this data is continuously expanding, making it time-consuming for various groups of users to identify and verify anomalies to make informed decisions. LSEG Labs recognises there is an opportunity to create value for various stakeholders by enabling them to process high volumes of data efficiently across multiple entities and timeframes, providing a consistent view of the ESG space.

To this end we have created a tool that automatically detects anomalies and identifies the reasons behind them allowing users to enhance their understanding of the ESG scores. In the following sections, we will first describe how anomaly detection works before we elaborate on the applications of this tool in section 2.

2. A tool that harnesses AI to detect and explain anomalies

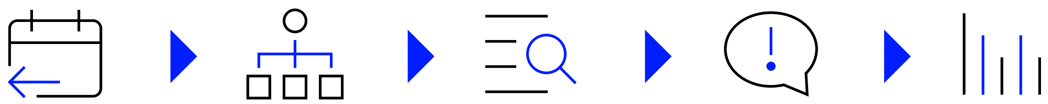
We apply machine learning (ML) and statistical data analytics to provide users a quick overview of all ESG reporting anomalies across a set of companies. Anomalies are characterised by their magnitude and polarity. The magnitude describes the severity of an anomaly — the higher this value, the more unusual the company's scores. The polarity shows if there is an unusual increase or decrease of scores associated with the anomaly. We provide more detailed explanations in section 3 to show how the user can verify what can trigger an anomaly detection.

In addition to anomaly detection analysis, we have developed a feature that allows users to assess and calibrate the carbon emission intensity of a portfolio by adjusting the weights of multiple stocks to ensure the portfolio is compliant with regulations. You will find more details under section 3.2.

2.1 How does anomaly detection work?

The goal of anomaly detection is to highlight unusual changes in ESG scores of a company compared to a group of peer companies in the same industry. Anomalies are characterised by their magnitude and polarity. To dive deeper and verify why anomalies occur, we quantify how much each ESG category contributes to an anomaly.

Figure 2: Anomaly detection steps



Change in score compared to **previous years**	Compare score change within **industry group**	**Apply ML model** to detect anomalies	**Apply ML explanation** tool to quantify impact of each category	Map model outputs to **magnitude and polarity score**

Figure 2 summarises the five steps in detecting and explaining ESG anomalies.

We train the ML model on over 18 years' worth of ESG data. It returns a score for each company and year to quantify the extent to which the category scores of each company have changed within that year. Category weights are considered as well, which means that a score change in a category with a higher weight contributes more to the anomaly score than a category with a lower weight. The advantage of using a ML model compared to a statistical model is that the ML model does not require any assumption regarding the distribution of score changes and assesses the combination of all score changes of a specific company.

This model is then input to the explanation tool to quantify how much each category contributes to the model's output. With this, the impact of every category is quantified by a value between 0 and 1. A value of 0 means that the respective category did not impact the detected anomaly, while a value of 1 means that this category exclusively caused the detection of an anomaly.

To make the results easily interpretable, we transform the model outputs into two different scales: the anomaly magnitude and the anomaly polarity. The anomaly magnitude has a range between 0 and 1 and describes how much the ESG scores of one company have changed compared to its industry group peers. The higher this value, the more the scores have changed. Anomaly polarity ranges between –1 and +1, and describes the trend of the score changes compared to companies in the same industry group. The more the scores have decreased, the lower the polarity; while the more scores have improved, the higher the polarity.

2.2 Anomaly detection example

To illustrate how anomaly detection works, we chose two examples. The first shows a company in whose ESG scores no anomaly was detected. This case has a low anomaly magnitude and neutral anomaly polarity. The second example has a high anomaly magnitude and is therefore considered an anomaly.

2.2.1 Low anomaly magnitude

We selected Haw Par Corporation Ltd as an example with low anomaly magnitude. In 2020, the anomaly magnitude output by the model was 0.11. Compared to other companies, this is a low value. Hence, we consider this example to be non-anomalous.

Figure 3: Time series of ESG score and pillar score of a non-anomaly for Haw Par Corporation Ltd

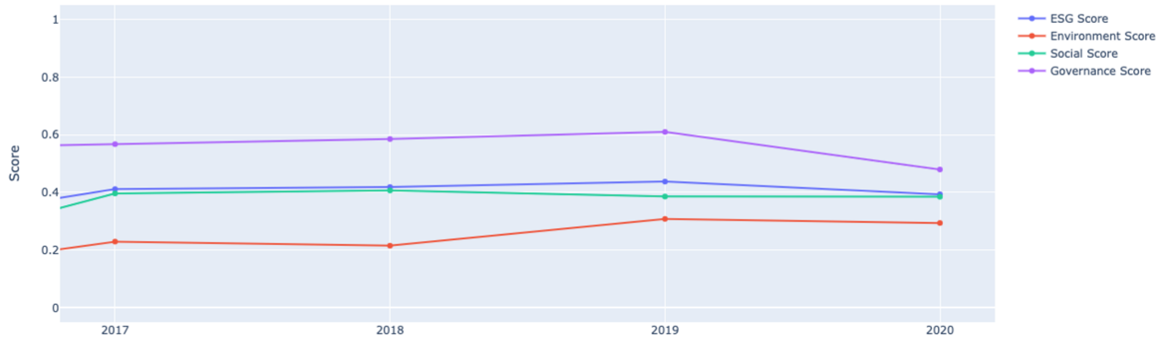
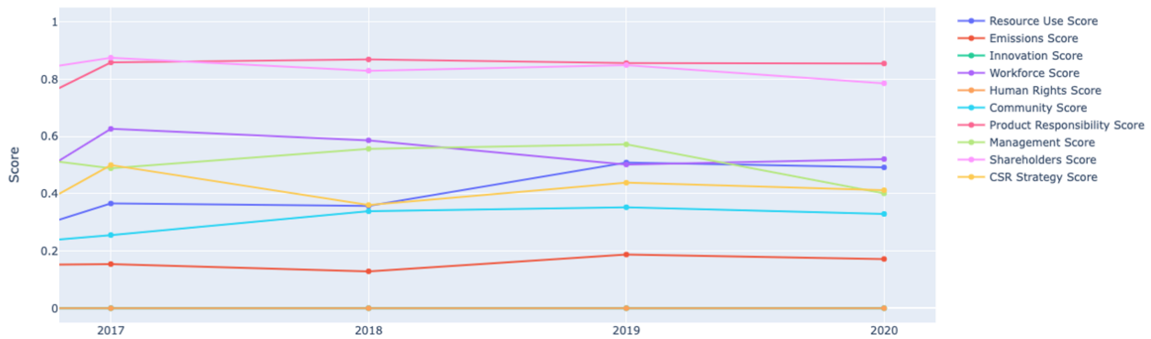


Figure 3 shows the time series of this company's ESG score and pillar score between 2017 and 2020. All scores showed only minor changes over the years.

Figure 4: Time series of ESG category scores of a non-anomaly for Haw Par Corporation Ltd



To confirm that there are no anomalies, the user can explore one level deeper: from the pillar scores to the category scores. Figure 4 shows the time series of these scores. On this level, there are only minor changes. This means the ESG scores of this company are as expected and it is safe to have confidence in their ESG reporting.

2.2.2 High anomaly magnitude

In contrast to the previous example, Kingboard Holdings Ltd showed numerous unusual changes in their ESG scores. The anomaly magnitude was 0.59, which is an unusually high value considering the 75th percentile within this industry group is 0.29. The anomaly polarity was at 0.01, almost neutral. This means that despite some unusual changes in individual category scores, the overall ESG scores showed very little variation in either direction.

Figure 5: Time series of ESG score and pillar scores of a detected anomaly of Kingboard Holdings Ltd, Electronic Equipment & Parts

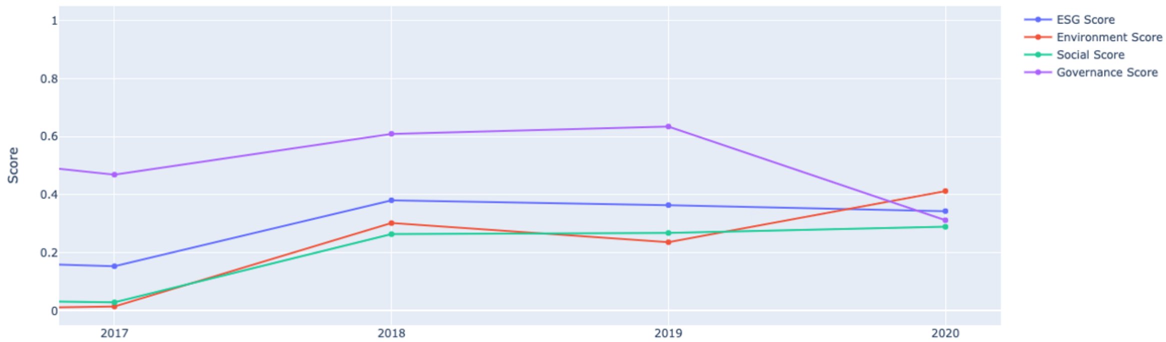
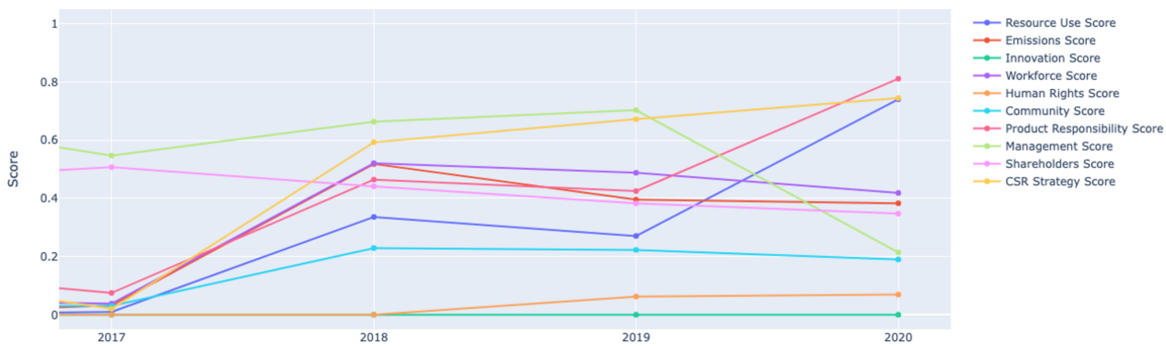


Figure 5 shows the company's overall ESG score and its constituent pillar scores between 2017 and 2020. The ESG score itself has changed only from 0.36 to 0.34 between 2019 and 2020, as is reflected by the almost neutral polarity. The figure also shows, however, significant changes in the environmental and governance scores. As the former score increased, the latter score decreased effectively balancing out each other's impact on the overall score. As a result, the ESG score remained almost constant.

This anomaly would not have been identified by an analyst looking only at the overall ESG score. However, since the anomaly detection model considers category score changes at a more granular level, it can detect such cases and highlight them to the user.

Figure 6: Time series of ESG category scores of a detected anomaly Kingboard Holdings Ltd, Electronic Equipment & Parts



The user thus gains a clearer understanding of the change in pillar scores by digging a level deeper into the ten categories presented in Figure 6. Here we can clearly see unusual changes in the Product Responsibility score, Resource Use score and Management score.

Figure 7: Weights and anomaly importance of each ESG category, Kingboard Holdings Ltd, Electronic Equipment & Parts

To better understand unusual changes in the scores, the anomaly detection application provides an overview that explains the importance of each category when it detects an anomaly. This is illustrated by the lower bar chart of Figure 7, which highlights the importance of the Resource Use score and Management score.

Although the Product Responsibility score also changed significantly, its category importance is lower than those of Resource Use and Management. This can be explained by the category weights which are shown in the upper bar chart in the same figure. The category weights define the impact a category has on the ESG score. Resource Use and Management have higher weights than Product Responsibility; hence these anomalies are more relevant.

3. Applications of anomaly detection

According to customer success managers, portfolio managers and various LSEG stakeholders, it can be challenging to identify and interpret ESG anomalies during portfolio optimisation. With our anomaly detection tool, LSEG Labs hopes to address these concerns.

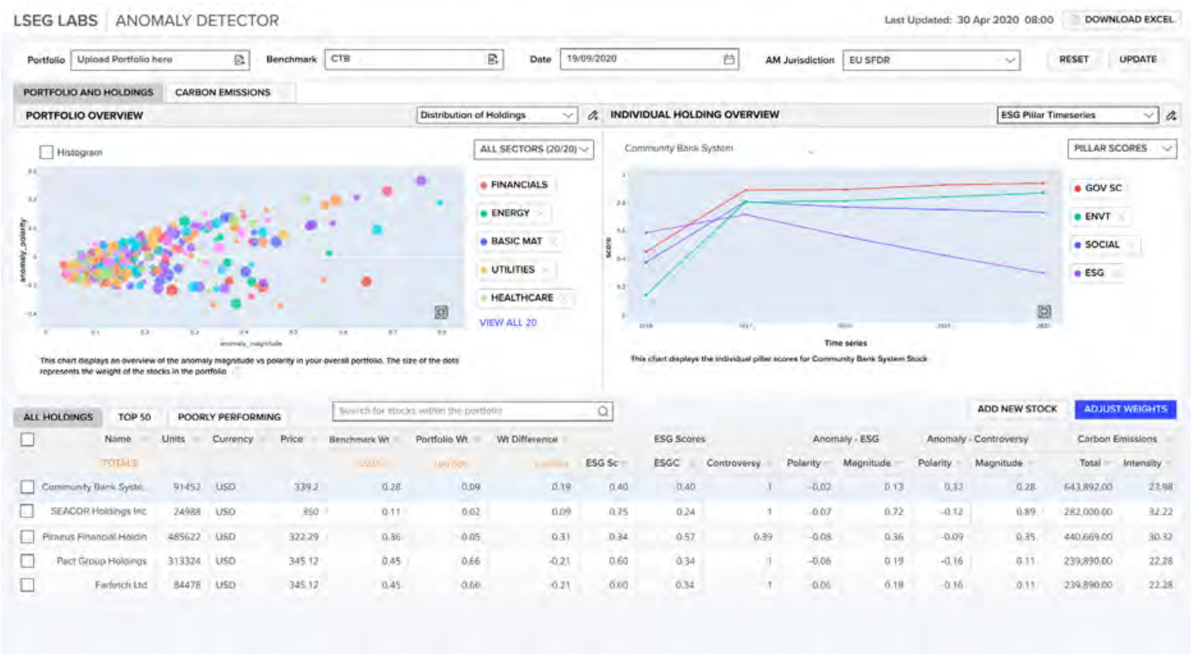
This paper presents two use-cases for the tool:

– Portfolio and Individual Holding Overview: Gives an overview of your portfolio in terms of anomalies
– Stock Weight Adjustment: Adjusts the weight of your stocks within the portfolio to achieve the desired result against a specific benchmark of your client's choice

These use cases represent typical scenarios in which users may be interested in investigating possible anomalies while checking their portfolios against a specific benchmark to comply with a given ESG regulation.

3.1 Portfolio and individual holding overview

Figure 8: Landing page, consisting of portfolio overview (left) and individual holding overview chart (right)

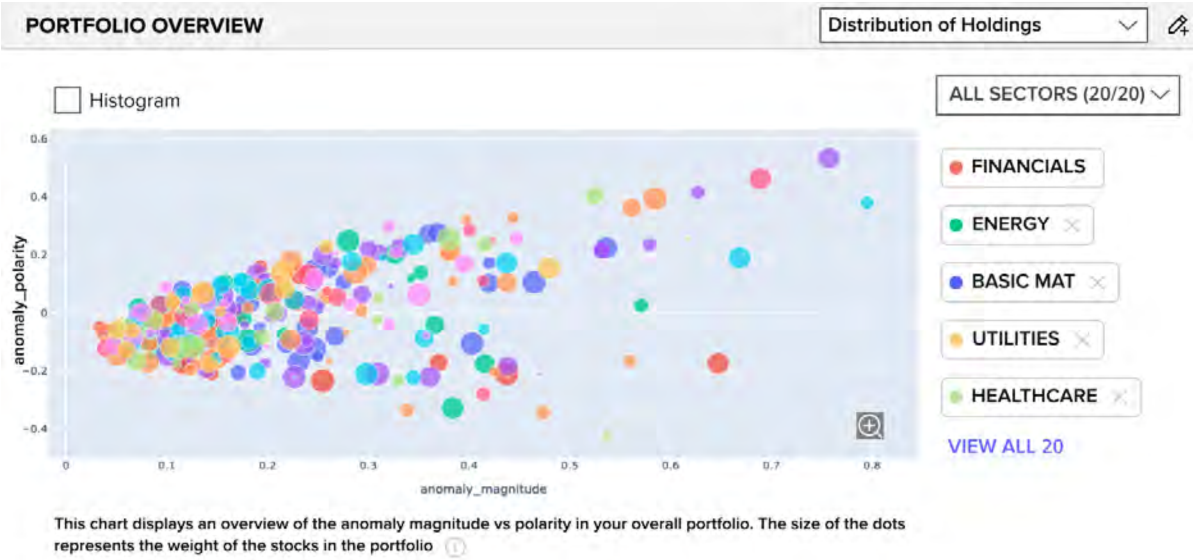


From Figure 8, users can:

– Identify quickly which stocks may present ESG anomalies (left chart)
– Investigate in detail why anomalies have been detected (right chart)

Let us zoom into the Portfolio Overview chart.

Figure 9: Top left chart of the main screen (portfolio overview scatter-plot)



This scatter-plot in Figure 9 shows the distribution of all stocks within a portfolio, with each dot representing a stock. The position is defined by the anomaly magnitude and polarity, while the size of the dot is relative to its portfolio weight. (The bigger the dot size, the greater the weight). Each dot is also colour-coded to reflect the relevant industry sector.

In this example, most of the stocks are concentrated towards the left along the median line, indicating that the probability of their being anomalous is low.

The stocks which do require attention are distributed on the right-hand side of the chart. The stocks on the top right of the median line represent an increase in the scores, and the stocks on the bottom right of the median line represent a decrease in the scores.

Figure 10: Top right chart of the main screen (individual holding overview – ESG Pillars Timeseries selected)

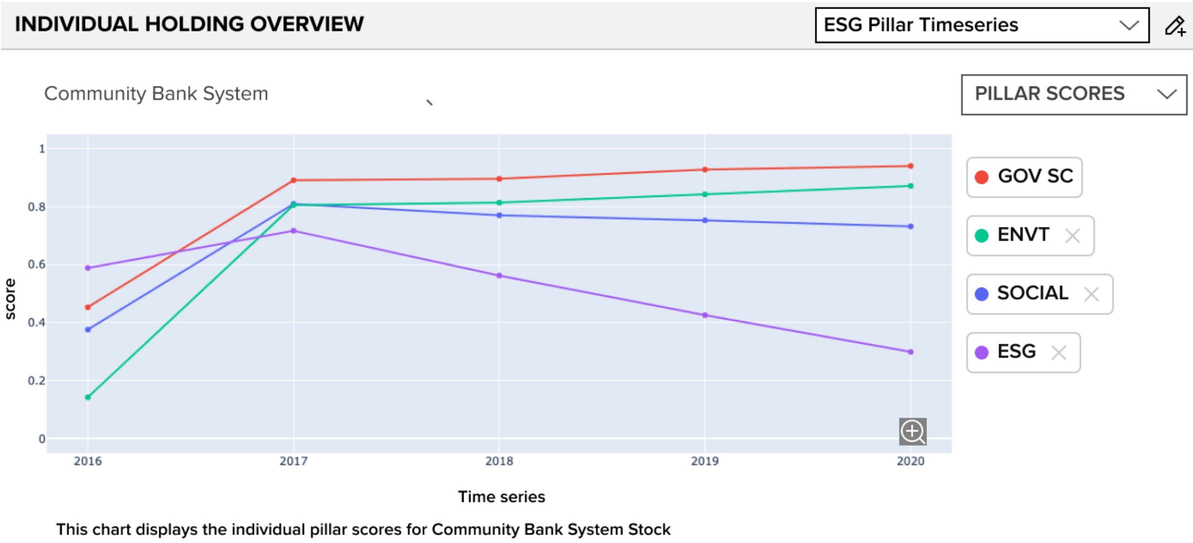


Figure 10 shows the ESG Pillar Timeseries chart. In addition, there is a series of charts (not shown) which reflect the details of stock across different criteria. Different charts provide different visualisation types and help users identify and investigate fluctuations in the scores. A user can click the drop-down arrow of the ESG Pillar Timeseries box to view the other charts:

– ESG Category Scores Timeseries – ESG and individual pillar scores
– Weight & Importance Chart – relative importance of different category scores (emissions, resource use etc.) to detect significant anomalies
– ESG Categories Peers Band – changes to ESG category score of one stock over multiple years
– Controversies Time Series – changes to ESG Controversy score of one stock over multiple years

Figure 11: List of all portfolio holdings – bottom table of the main screen

ALL HOLDINGS | TOP 50 | POORLY PERFORMING | Search for stocks within the portfolio | ADD NEW STOCK | ADJUST WEIGHTS

Name	Units	Currency	Price	Benchmark Wt	Portfolio Wt	Wt Difference	ESG Scores			Anomaly - ESG		Anomaly - Controversy		Carbon Emissions	
TOTALS				100.00%	100.00%	100.00%	ESG Sc	ESGC	Controversy	Polarity	Magnitude	Polarity	Magnitude	Total	Intensity
Community Bank Syste..	91452	USD	339.2	0.28	0.09	0.19	0.40	0.40	1	-0.02	0.13	0.32	0.28	643,892.00	23.98
SEACOR Holdings Inc	24988	USD	350	0.11	0.02	0.09	0.75	0.24	1	-0.07	0.72	-0.12	0.89	282,000.00	32.22
Piraeus Financial Holdin	485622	USD	322.29	0.36	0.05	0.31	0.34	0.57	0.39	-0.08	0.36	-0.09	0.35	440,669.00	30.32
Pact Group Holdings	313324	USD	345.12	0.45	0.66	-0.21	0.60	0.34	1	-0.06	0.19	-0.16	0.11	239,890.00	22.28
Farfetch Ltd	84478	USD	345.12	0.45	0.66	-0.21	0.60	0.34	1	-0.06	0.19	-0.16	0.11	239,890.00	22.28

As well as the charts, users can select an individual stock from the table at the bottom of the screen (see Figure 11) by scrolling through the table or typing the security name in the search field. If a user clicks on a table row, it will display the ESG pillar scores on the right-hand chart (default view) and highlight the relative dot on the scatter plot on the left side of the screen. Users can also filter the columns or toggle between the 'All Holdings', 'Poorly Performing' and 'Top 50' tabs.

3.2 Stock weight adjustment

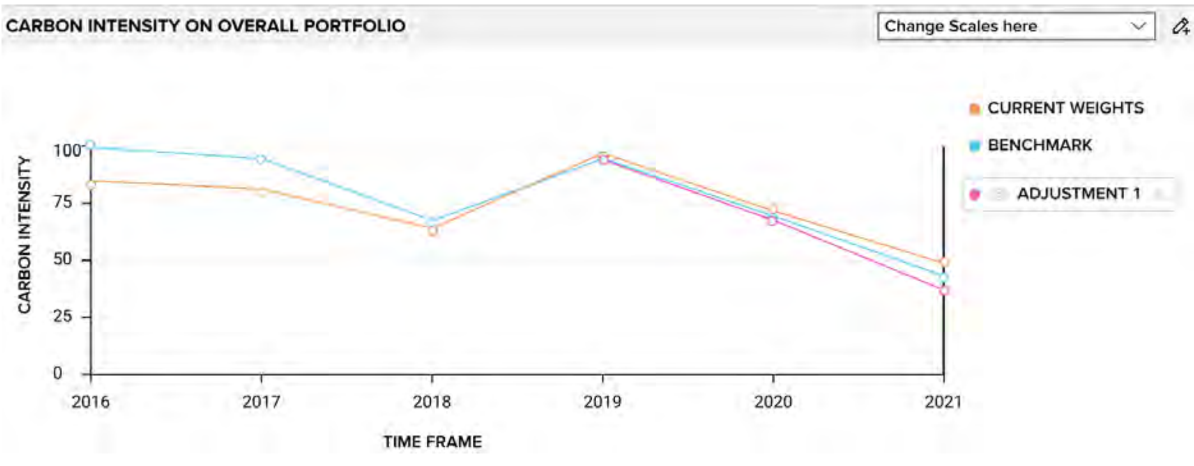


Figure 12: Carbon intensity on overall portfolio with current weights and benchmark lines

While the previous use case focuses on gathering high-level information about the portfolio and inspecting individual stocks, Stock Weight Adjustment focuses on adjusting the weights of one or multiple securities to bring the overall portfolio in alignment with or below the benchmark line (in blue). Figure 12 uses the Climate Transition Benchmark (CTB), a benchmark included in the European Union's Sustainable Finance Action Plan, as an example.

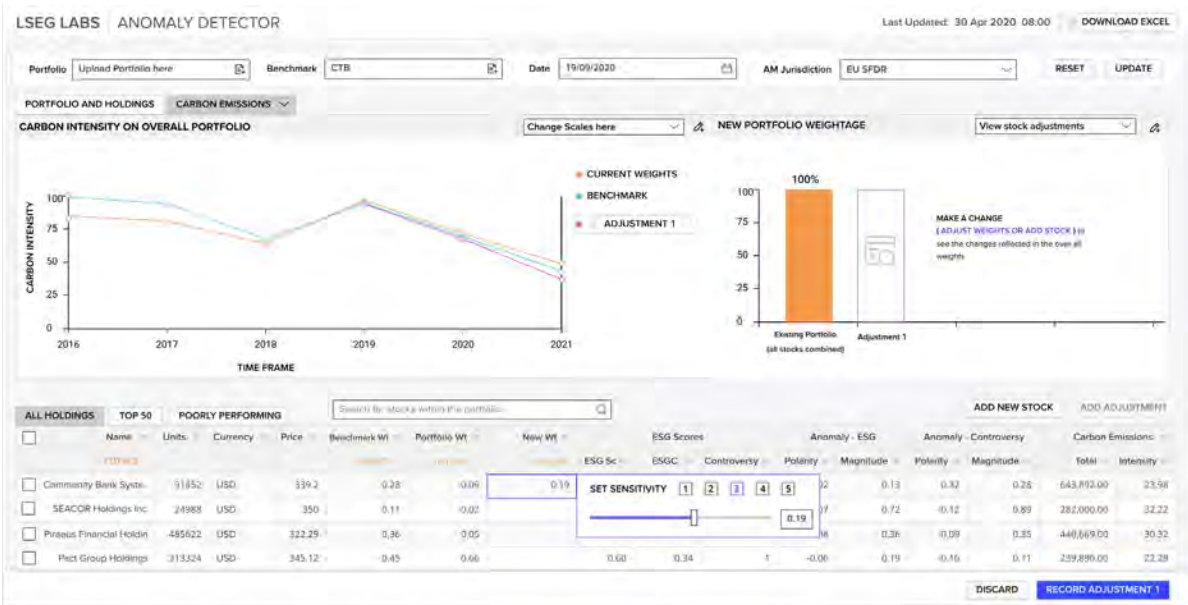


Figure 13: Stock adjustment screen – adjustment one selected

Figure 13 enables users to toggle among various adjustments and observe in real time the effects on the overall portfolio's carbon emissions on the left-hand chart. Every time an adjustment is selected, the relative deviation line is highlighted on the left, while the top right section of the screen summarises what this adjustment entails in terms of variation: which stock has been re-weighted and by what percentage. This is reflected in the overall portfolio composition.

Once the user identifies the adjustment that provides the best correction (in this case the lowest carbon emission), they can commit to it and update the new portfolio composition.

In summary, users can identify and investigate anomalies, adjust the weight of their stocks and choose the benchmark they wish to align with to bring the overall portfolio carbon emission to their desired level.

4. Conclusion and future work

Our ESG anomaly detection tool is well-positioned to enhance ESG analysis. It highlights any unusual changes in a single company's ESG score within a portfolio of hundreds of organisations and provides an added layer of clarity by identifying the sources of these anomalies. In addition, our stock weight adjustment feature allows users to assess and calibrate the carbon intensity of their portfolio, enabling them to visualise the impact of every change on this metric.

Through our tool, users can gain a broader and deeper view of their portfolios, enabling them to manage risks better, perform more incisive analysis or generate alpha.

To further expand and enhance the user experience, LSEG Labs' future research will focus on:

Expand explanation of anomalies by linking them with other sources like **news**

Widen the scope of anomaly detection from the ESG category level to the **metrics level**

Integrate a solution to **readjust stock weights** in order to improve the portfolio's **carbon emission** density while taking anomalies into account

As ESG reporting becomes more prevalent and in some cases even mandatory, companies face mounting pressure to adopt ESG policies and practices and increasing scrutiny from investors, customers, media and other stakeholders. With sustainable investment on the rise, our team believes the demand for reliable and comparable ESG data will grow exponentially in the coming years. Players with high-quality data and advanced tools to leverage this data will gain a significant competitive advantage. Through our continuous innovation, LSEG Labs is well positioned to support various players in the ecosystem as they tackle future challenges.

5. Biographies

Reinhard Sellmair, PhD, Data Scientist, LSEG Labs Singapore

Reinhard received his PhD in the field of sustainable transportation. He has many years' experience in geospatial data, agent-based simulation and optimisation.

Valerio Battagli, Senior UX Designer, LSEG Labs Singapore

Valerio is a certified UX Practitioner. He has worked in startups and MNCs such as Mastercard and EY, mainly across the Healthcare and Financial Services industries.

Mrinalini Kannan Senior UX/UI Designer, LSEG Labs Singapore

An avid storyteller, Mrinalini communicates with the end-user by building meaningful experiences. She has worked with several renowned brands as an experience designer, including DBS, Autodesk and The Walt Disney Company.

Allison Ching, Programme Director, LSEG Labs Singapore

Allison Ching has extensive programme management, business operations and communications experience across the technology and media sectors. She holds an MBA from INSEAD Business School.

Nitish Ramkumar, Lead Data Scientist, LSEG Labs Singapore

With his experience in quant finance, statistics and programming, Nitish has worked on a wide range of data science projects in the field of Equity, FX and Sustainable Finance. He is also a CFA charterholder.

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