ESG principles: the limits to green benchmarking

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Abstract

Taxonomy and efficiency assessments provide financial intermediaries (FIs) with guidance to grant funds according to the Environmental, Social and Governance principles. The EBRD provides a classification of industries according to a priori potential risk (low, medium or high). Using a panel of 28 industries in Luxembourg (2008-2019) and National Account data (NA), we challenge this taxonomy. We compute Data Envelopment Analysis (DEA) efficiency scores indicating if an industry could increase output while simultaneously lowering the emission of greenhouse gases. Our results show that EBRD low risk industries are the most efficient ones. Surprisingly, high-risk industries are more efficient than medium-risk ones, suggesting a potential unintended outcome of the EBRD taxonomy—limiting credit to industries classified as high risk that are in fact more efficient than industries classified as medium risk.

Keywords: EBRD Risk taxonomy, Social acceptance, efficiency, bad output, credit rationing, ESG. **JEL Codes**: Q51, G11, C44.

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1 Introduction

Sustainable finance movement is a recent trend in the financial sector. Sustainable finance may be described as financial initiatives which seek to reduce the *externalities* associated with certain business practices, in particular, excess CO_2 creation (Lubin and Esty, 2011). This trend is strongly linked to the development of the Environmental, Social, and Governance (ESG) principles [1]. ESG principles incorporate non-financial ideals, such as sustainability, into financial settlements. To support this initiative, *a priori* taxonomies of industries based on ESG principles could benefit loan officers. At the same time, they could also benefit from *a posteriori* assessments of industries' economic performances given their environmental impact based on existent data. In this document, we will provide this numerical assessment of economic performances of industries in Luxembourg taking environmental impact into account.

Taxonomies are useful to provide a *natural* classification of economic activities, because they group industries that are fundamentally related. This present work uses a classification developed by the European Bank for Reconstruction and Development (EBRD) that has not made its way to the general public yet. This taxonomy provides credit officers in Financial Institutions with a guide to the expected level of inherent potential environmental, social and governance risk related to particular business activities[2]. This classification is based on expert judgements and associate to each industry (defined by its NACE revision 2 code) a level of environmental, social and governance risk. The taxonomy is industry but not country specific.

In this document, we are interested in environmental risk. Environmental risk refers to industry activities that might make any temporary or permanent changes to the landscape, atmosphere, soil, water, plants or animals. The EBRD

[1] ESG issues were first mentioned in the 2006 United Nation's Principles for Responsible Investment (PRI) report consisting of the Freshfield Report, UNEP (2005), and the "Who Cares Wins" document, IFC (2004).

[2] https://www.ebrd.com/downloads/about/sustainability/ebrd-risk-english.pdf .

considers three levels of risk: Low, Medium and High[3]. We will use this grouping of industries to compute the performances of industries in Luxembourg. Then, we will assess if there is a correlation between a priori level of risk and actual performance.

Our procedure might help Financial Institutions (FIs) to select projects to finance in particular when taxonomies are complemented by a numerical assessment taking into account the joint economic and environmental performance. The FIs will have a possibility to benchmark various industries / investment opportunities given their economic performance, but also to monitor past and present environmental developments. If FIs aim at providing sustainable finance, it will help them to channel private funds towards *leading* industries potentially best aligned with ESG principles. Actually, FIs in Luxembourg, such as Spuerkess, Banque de Luxembourg, Raiffeisen, filter out some industries based on ESG conviction (for example manufacture of weapons and ammunition)[4]. In 2021, Banque de Luxembourg indicated that 73 percent of assets under management take ESG factors into account. In 2020, The World Bank Investor Survey shows that 85 percent of investors use ESG information to assess credit risk (Hussain, 2020).

We assess the economic performance of industries by gauging their ability to turn economic resources, i.e. inputs (equipment, labour and intermediate consumptions including energy, raw materials and services) into goods and services (this is referred to as the technical efficiency of industries). However, producing goods and services comes with a negative side effect: pollution. We

[3] High Activity Risk: The customer's business activities may give rise to significant or long-term environmental impacts. These may require more specialised risk assessment, and the customer may not have the technical or financial means to manage them. Medium Activity Risk: The customer's business activities have limited environmental impacts, and these are capable of being readily prevented or mitigated through technically and financially feasible measures. Low Activity Risk: The customer's business activities have minor / few environmental impacts associated with them.

[4] See: https://blog.raiffeisen.lu/en/about-finance/steering-right-course-esg-investmentsand-aiming-returns , https://www.spuerkeess.lu/fileadmin/mediatheque/documents/about us/Sustainability/Transparence de l integration des risques en matiere de durabilite au niveau des produits.pdf and https://www.banquedeluxembourg.com/documents/ 10184/3392438/BDL_064591EN.pdf/11c93e93-3f18-312e-70cb-13e946f5b49b?t= 1638535957103 for practical implementation of ESG principles by banks.

compute indicators of efficiency that consider simultaneously the production of goods and services and the generation of a bad output. Here, pollution is measured by the amount of green-house gas emissions (GHG). GHG include CO2, methane, nitrous oxide gases and halogenated fluorocarbons, all measured in CO2 equivalent.

Data envelopment analysis (DEA) is used to compute these performance indicators. DEA is a non-parametric method developed by Charnes et al. (1978) to measure the relative technical efficiencies of a set of comparable units (firms, industries or countries). Basically, observed combinations of inputs and outputs indicate the optimal feasible productions. It identifies which industry, among similar industries, produces the most output for a given level of inputs. A set of such best-performing industries then forms a production frontier (best practice), and the distance between best-performing industries (production frontier) and industries that perform worse, measures the level of inefficiency. Using linear programming techniques, it is possible to compute industries' distances to frontier. Sickles and Zelenyuk (2019) provide a nice introduction to DEA and efficiency measurement. An extension of the DEA basic framework, the model proposed by Chiu et al. (2012), permits to simultaneously benchmark industries according to their technical efficiency (output production) and environmental efficiency (GHG emissions).

Usually it is assumed that industries share a common production technology, but operate at different levels of inputs and outputs (see Wu et al. (2015) for industry-level data and Kumar and Russell (2002) for country-level data). In other words, industries share the same technological frontier (which depicts the maximum output that can be produced for a given use of inputs). In this study, we argue that, given potential environmental risk and sizeable costs in case of adverse events, management practices will differ between two groups of industries: the low and the medium/high risk industries. Thus they will have different production technologies. This might be explained by different environmental regulations that might apply to industries (Horbach et al., 2012). Arguably, the technology might also be partly shaped to fulfil consumers expectations and needs (van den Bergh, 2008). Accordingly, we allow for heterogeneity of technologies.

Thus, we estimate group-specific (low and high to medium risk industries) technical frontiers. Within each industry group, we then estimate industry specific inefficiency, that is the distance between the group's technical frontier (maximum possible production defined by best performing industries within group) and position of an individual industry (Chiu et al. (2013) provide a related framework). We call this distance the managerial inefficiency because we assume that industries within each group share the same technology. If they had access to the same technology, they should be able to produce the same as the most efficient industries within a group. Given that they do not, this must be due to poor managerial practices[5]. Finally, O'Donnell et al. (2008) show how we can join technical frontiers of the two groups of industries (low and high to medium risk industries) into a single global technical frontier. We then call the distance between the technical frontier of the industry group (e.g. frontier of the high to medium risk industries) and the global frontier, the technical gap. Every industry is able to approach the global technology, to fill the technological gap, by innovation (Lee and Choi, 2018). If we sum together this technical gap (distance between group's frontier and global frontier) and managerial inefficiency (distance between industry and group's frontier) we arrive at total inefficiency. The total inefficiency of a single industry can therefore be decomposed into managerial inefficiency and technical gap.

The present study draw to close by discussing how the taxonomy complemented by efficiency analysis might impact decision processes of FIs when allocating funds. In particular, we examine the case when high or medium risk industries present sizeable inefficiencies in producing goods and services while minimising green house gas emissions. If FIs hold on ESG principles it might results on credit rationing that cannot always be solved by public subsidies as often advocated.

This issue has recently gain importance with the implementation of a new EU directive about social and environmental risk reporting by firms (including financial intermediaries). The Corporate Sustainability Reporting Directive CSRD (January 2023) ensures that investors have access to the information they need to assess financial risks and opportunities arising from climate change and other sustainability issues. Ghosh (2023), for the case of MENA countries, indicates that climate legislation implementation lower lending by 5 percent. When data are lacking, banks often relies to expert advices (ECB, 2023). To our knowledge, our study is the first to use data envelopment

[5] Note that, we assess in each group the ability of an industry to turn inputs into outputs while minimising GHG emissions, it is a joint economic and environmental efficiency.

analysis and official National Accounts data to challenge a priori expert information used when allocating funds[6].

This paper is organised as follows: Section 2 presents the data and gives an overview of the Luxembourgian economy in terms of environmental risks. This section also present the model to compute efficiency scores. The following section summarizes results comparing risk groups. The last section hypothesizes what could be the perverse outcomes of an excessive reliance on such taxonomies and benchmarks.

2 Data and models

2.1 High, Medium and Low environmental risk industries in Luxembourg

Data used in this analysis come from Luxembourg's National Accounts. They include observations on output, capital stocks, hours worked, intermediate consumption and GHG emissions for 28 industries covering almost all industries in Luxembourg (insurance services and households as employers are excluded, as information on GHG emissions are missing for these industries). The data cover the years from 2008 to 2019. Table 1 lists industries by degrees of environmental risk, according to the EBRD taxonomy.

[6] Some studies have assessed the (non) consistency of different ESG and corporate social responsibilities ratings of firms but do not elaborate on contrasting a priori expert views with official National Accounts data (such studies are, for example, Chatterji et al. (2016) or Berg et al. (2022).

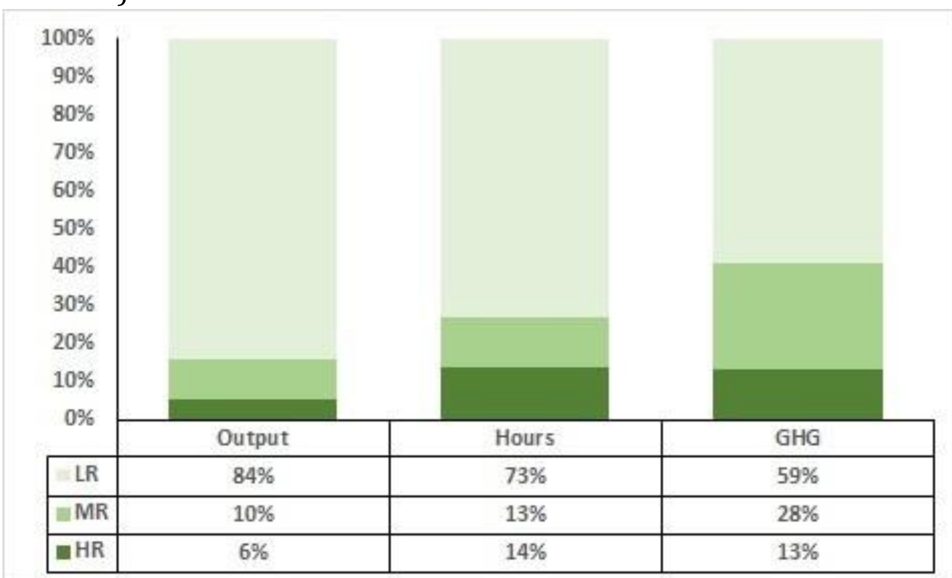
Table 1: Environmental risk by industries in Luxembourg.

Industries	Name	Risk
Manufacturing Industries		
A 01	Agriculture	Medium
A 02	Forestry	High
B	Mining and Quarrying	High
C 10-18	Manufacturing food products to Printing	Medium
C 19-22	Manufacturing chemicals and pharmaceutical products to plastics	High
C 23-32	Other manufacturing	Medium
C33	Repair and installation of machinery and equipment	Low
D	Electricity, Gas, Steam and Air Conditioning Supply	High
E 36	Water Supply	Medium
E 37-39	Sewerage, Waste Management and Remediation Activities	High
F	Construction	High
Services		
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	Low
H	Transportation and Storage	Low
I	Accommodation and Food Service Activities	Low
J	Information and Communication	Low
K	Financial Activities	Low
L	Real Estate Activities	Low
M	Professional, Scientific and Technical Activities	Low
N	Administrative and Support Service Activities	Low
O	Public Administration and Defence; Compulsory Social Security	Low
P	Education	Low
Q 86	Human Health	Medium
Q 87-88	Social Work Activities	Low
R	Arts, Entertainment and Recreation	Low
S	Other Service Activities	Low

Note: Taxonomy based on EBRD Environmental and Social Risk Categorisation List.

The EBRD taxonomy allows us to describe Luxembourg's economy in terms of output, labour and pollutant emissions. In 2008, in Luxembourg, 84 percent of output are produced by low risk (LR) industries, about 9 percent by medium risk (MR) industries and the remaining 6 percent by high risk (HR) industries. Shares remain relatively constant from 2008 to 2019. For total hours worked the repartition is the following: 73 percent in LR industries, 13 percent in MR industries and 14 percent in HR industries. Also, these shares remain stable across time. If we describe Luxembourg's economy in terms of two important economic indicators, labour and output, the economy is mainly characterized by low environmental risk activities. This is because Luxembourg is a service economy. In terms of GHG emissions, in 2008, LR industries emitted 52 percent of total emissions and reached 69 percent in 2019. Conversely, for HR this share decreased from 18 percent to 6 percent. For MR industries the share moved from 30 percent to 25 percent.

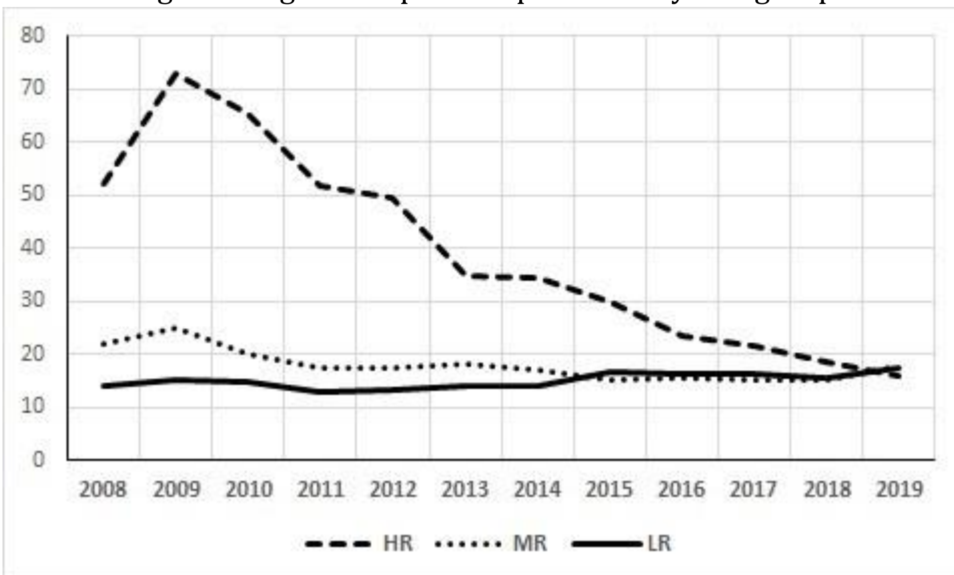
Figure 1: Average shares of output / hours worked / GHG by risk group (2008-2019)



Note: STATEC National Accounts data.

Interestingly, if we compute the ratio of GHG emissions per unit of output (the carbon intensity of output produced), this ratio increased on average by 2 percent for LR industries and decreased by -1 and -9 percent for MR and HR industries respectively. This large decrease is due to the rapid increase of output and to a lower extent to improvements in GHG emissions for some HR industries.

Figure 2: Kg of CO2 per unit produced by risk group



Note: STATEC National Accounts data.

We use these data to estimate managerial inefficiency, technological gap and total inefficiency.

2.2 The metafrontier model

To evaluate the performance of industries, we follow Chiu et al. (2012) using DEA and a meta-frontier framework. Traditional models require that the units being assessed operate with the same technology (the same frontier). In this paper, we argue that, according to their level of environmental risk, industries will adopt relatively different technologies and management practice. In particular, if industries care about risk, high environmental risk industries will pay greater attention to possible GHG emissions than low environmental risk industries. There is also a (meta)technology that encompasses group technologies and indicates economy wide best practices. The idea of using a metafrontier is not new, but, in many cases the split of industries is based on their geographical location (e.g. Wang et al. (2013), Li et al. (2017)). To the best of our knowledge, nobody has used the EBRD environmental taxonomy to split industries into groups.

We first compute a model that benchmarks one industry compared to all other industries, an economy-wide meta frontier. It assumes that industries seek to produce the maximum output possible given quantity of inputs used (output orientation) while keeping green-house gases emissions as low as possible. Variable returns to scale are also assumed. Let x_{in}^{k} be inputs of industry n in group k (capital, labour and intermediate consumption), y_{rn}^{k} is the good output (total output) and b_{fn}^{k} is the bad output (GHG emissions). The model can also handle multiple goods and bad outputs. The corresponding model is:

$$
\begin{aligned}
&\mathbf{Max}\vec{D}^{m}(x_{io}^{k}, y_{ro}^{k}, b_{fo}^{k}) = \beta^{m} \\
&\mathbf{s.t.} \sum_{k=1}^{K} \sum_{n=1}^{N_k} \lambda_n^k x_{in}^k \leq x_{io}^k, i = 1, \dots, M, \\
&\sum_{k=1}^{K} \sum_{n=1}^{N_k} \lambda_n^k y_{rn}^k \geq (1+\beta^m) y_{ro}^k, r = 1, \dots, S, \\
&\sum_{k=1}^{K} \sum_{n=1}^{N_k} \lambda_n^k b_{fn}^k = (1-\beta^m) b_{fo}^k, f = 1, \dots, F, \\
&\sum_{k=1}^{K} \sum_{n=1}^{N_k} \lambda_n^k = 1, k = 1, \dots, K, \\
&\lambda_n^k \geq 0, n = 1, \dots, N_k,
\end{aligned}
\qquad (1)
$$

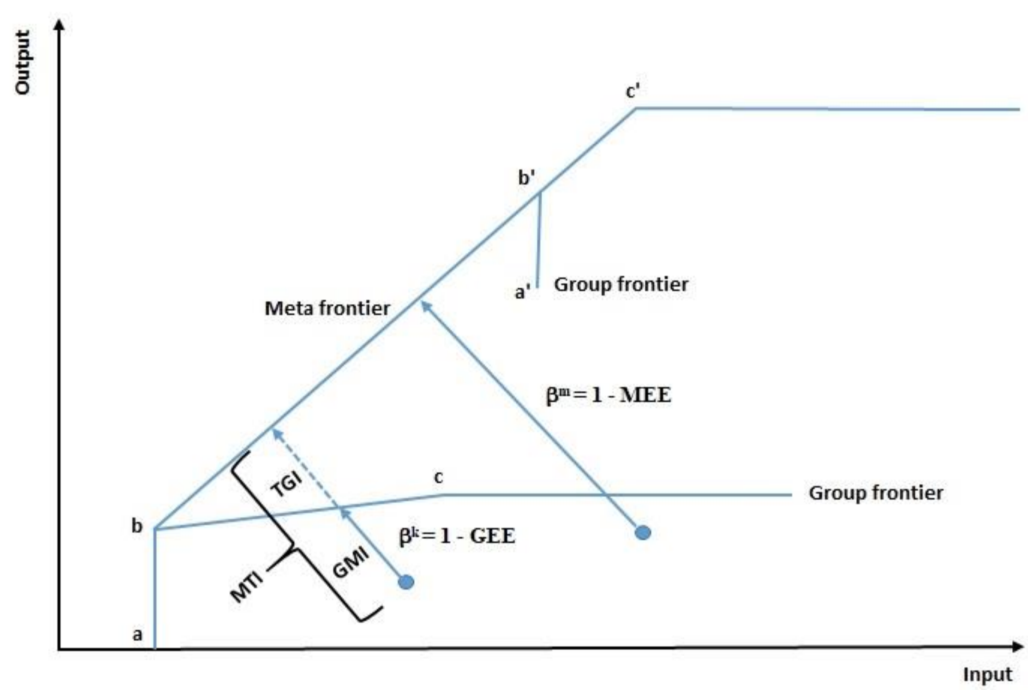
In a second step, we compute efficiency scores by groups of industries. To have enough industries in each group we consider one group including LR industries (17 industries) and a second group with all MR and HR industries (respectively 5 and 6 industries). Then we have two groups, and, efficiency scores in each group are computed according to the following model:

$$
\begin{aligned}
&\mathbf{Max}\vec{D}^{k}(x_{io}^{k}, y_{ro}^{k}, b_{fo}^{k}) = \beta^{k} \\
&\mathbf{s.t.} \sum_{n=1}^{N_k} \mu_n^k x_{in}^k \leq x_{io}^k, i = 1, \dots, M, \\
&\sum_{n=1}^{N_k} \mu_n^k y_{rn}^k \geq (1+\beta^k) y_{ro}^k, r = 1, \dots, S, \\
&\sum_{n=1}^{N_k} \mu_n^k b_{fn}^k = (1-\beta^k) b_{fo}^k, f = 1, \dots, F, \\
&\sum_{n=1}^{N_k} \mu_n^k = 1, \\
&\mu_n^k \geq 0, n = 1, \dots, N_k,
\end{aligned}
\qquad (2)
$$

From these two models several indicators can be computed. Model (1) gauges the inefficiency of an industry due to not using the best available technologies in the economy as evaluated by the meta-technology: $MEE = 1 - \beta^m$. Efficiency scores indicate if an industry could increase simultaneously output while lowering the emission of greenhouse gases (given the available best technology in the industry, model 1, or in the economy, model 2). If there is no room for improvement the industry is said to be efficient.

The second indicator based on model (2) indicates the inefficiency in using the technology available to specific industries in the same environmental risk group: $GEE = 1 - \beta^k$. The case of one good output and one input allows us to graph the two (in)efficiency measures (see figure 3). The points (abc) define one group frontier whereas the points (a'b'c') define a second group frontier, the meta-frontier is defined by points (abc') and encompasses the two group frontiers. β^k is the efficiency of one industry given to its group frontier, if the industry is on the frontier $\beta^k = 1$ then $GEE = 0$. β^m is the efficiency of one industry given to the global meta-frontier, if the industry is on the frontier $\beta^m = 1$ then $MEE = 0$.

Figure 3: Meta and group-frontiers, inefficiency measures



These two measures can be combined in a ratio, the meta-technology ratio MTR.

$$0 < MTR = \frac{MEE}{GEE} \leq 1$$

The closer to 1 the ratio is, the less heterogeneity there is between the group technology and the economy-wide technology. If the two frontier are indistinguishable, in this case efficiency scores are the same and the ratio is equal to 1. We can also compute inefficiency originating from the technical gap between the meta-frontier and the group-specific frontiers (TGI). This technology gap can be closed by innovation.

$$TGI = GEE \cdot (1 - MTR)$$

Last, inefficiency can be attributed to managerial failure (GMI).

$$GMI = 1 - GEE$$

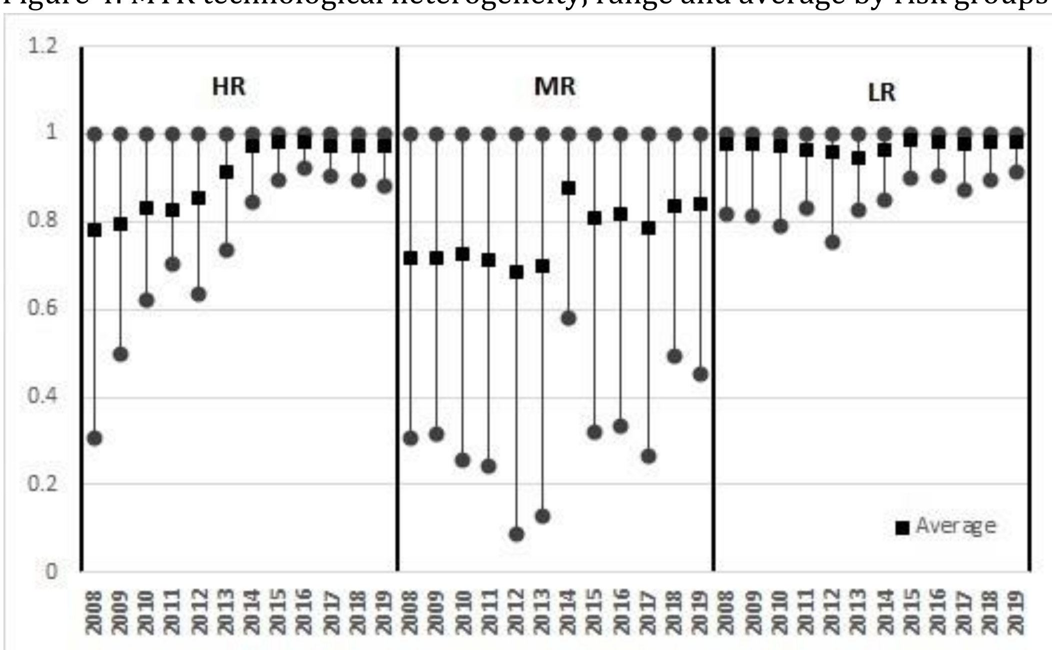
Thus, total inefficiency is MTI = TGI + GMI. An industry that has a total inefficiency of zero, conversely a total efficiency of 1, is labelled *green-efficient*. The three inefficiency measures are pictured in figure 3 (assuming one output and one input for the sake of simplicity).

3 Results

This section presents results on industries' efficiency to mobilise resources to produce output compared to industries in the same environmental risk group (GMI). We also compute the inefficiency due to not using the best technologies available in the economy (TGI). Last, we evaluate to what extent a group technology deviates from the optimal economy-wide technology.

Regarding the heterogeneity of technologies (or to what extent the group frontier coincides with the meta-frontier, MTR), the LR technology is, on average, almost coincident with the global technology (see figure 4). Over the whole period, the average value of MTR is 0.97, the minimum average value is 0.84 for the Arts, entertainment and recreation industries. We observe that the HR industries are converging towards the global technology. The average MTR index is getting closer to 1. This suggests that these industries are innovating to become more environmentally / economically efficient (the average value grows from 0.72 to 0.97). The observed improvements come mainly from the mining industries. MR industries are not catching-up and some industries belonging to this group are very far from the global frontier. This indicates that these industries were not able to follow and adopt best environmental technologies. The most *heterogeneous* industry is by far agriculture with an average score of 0.35. Indeed, agriculture is known to be a major contributor to greenhouse gas emissions: livestock generates methane emissions (Lassey, 2007), nitrogen fertilizers are essential to improve and sustain crop yields but result in volatilisation of nitrous gases (Vergé et al., 2007). To cope with these issues, the national energy and climate plan of Luxembourg considers measures to reduce nitrogen load from fertilisation and manure management, and sets a targets for organic cultivation to reach at least 20% of agricultural land by 2025 and 100% by 2050[7]. These results support our assumption of a metafrontier and group technologies. If MTR scores where all *close* to 1, then it would have been sufficient to consider only a country wide frontier to benchmark simultaneously all industries.

Figure 4: MTR technological heterogeneity, range and average by risk groups

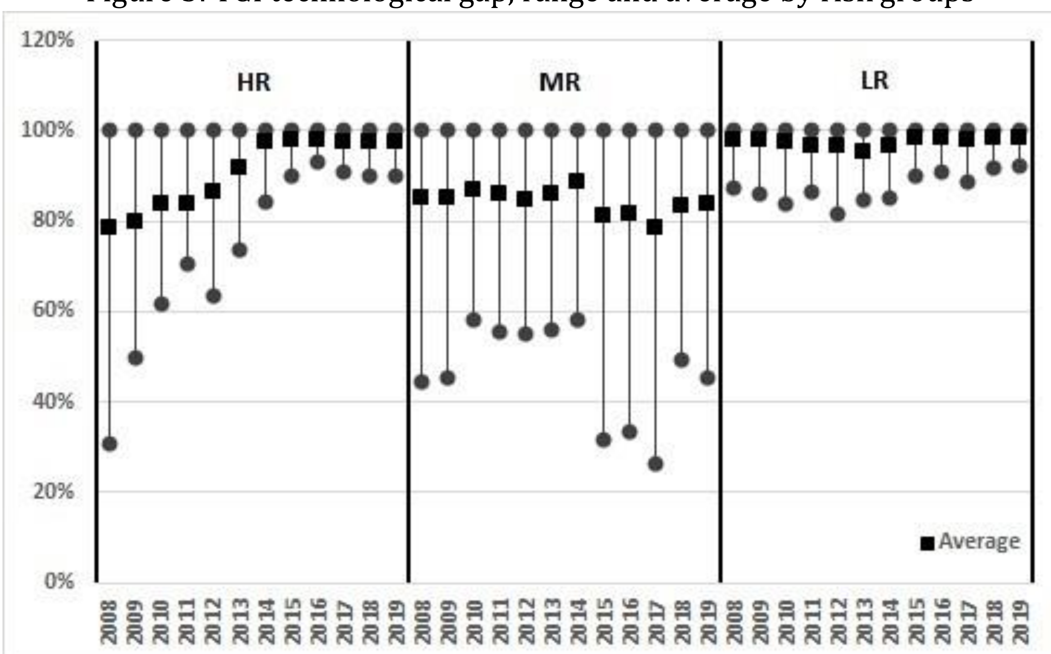


[7] https://energy.ec.europa.eu/system/files/2021-01/staff_working_document_assessment_necp_luxembourg_en_0.pdf

Note: Author's computations. A value of 1 indicates absence of heterogeneity. Squares are group simple averages, circles picture the minimal and the maximal value computed for each group.

The technological heterogeneity is confirmed by the observation that the technological gap is almost non-existing for LR industries for all years (see figure 5). The technological gap indicates if a specific industry is far from the meta-frontier. For HR industries the gap was closed in relatively few years and remained close to zero in the last years. This is explained by the adoption of greener technologies by the mining industry to reduce GHG emissions when using energy. For MR industries, on average, the technological gap slightly deteriorated. Once again, this result is driven by agriculture.

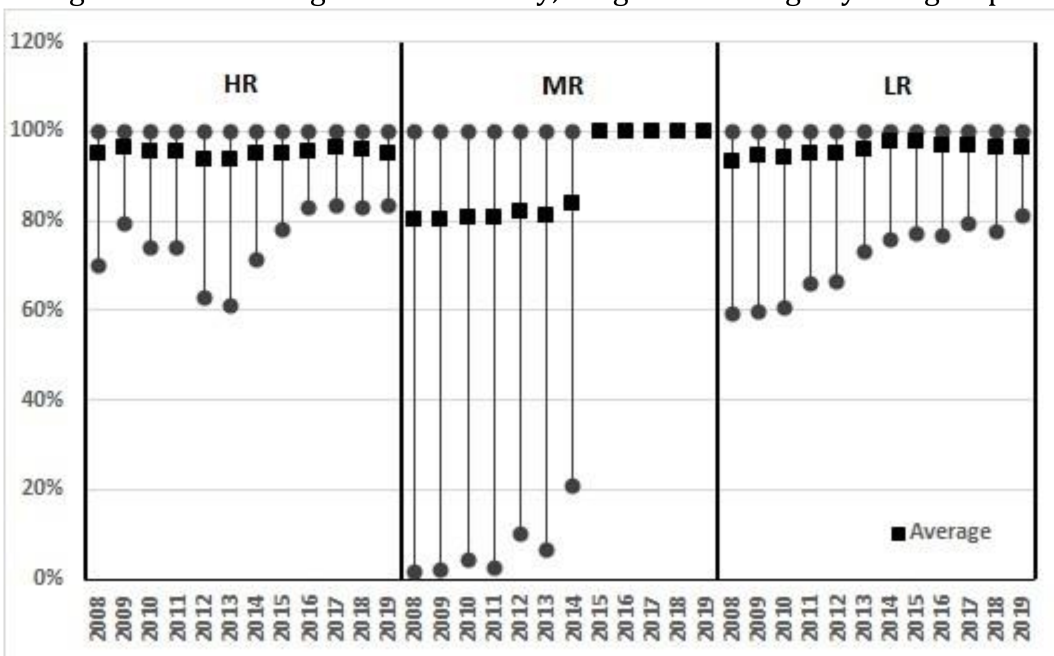
Figure 5: TGI technological gap, range and average by risk groups



Note: Author's computations. A value of 100% indicates absence of technological gap. Squares are group simple averages, circles picture the minimal and the maximal value computed for each group.

What is striking is that managerial inefficiency has disappeared in MR industries (see figure 6). Unfortunately industries have moved to the part of the group frontier that is not catching-up with the global frontier[8]. In general, managerial inefficiencies are small.

Figure 6: GMI managerial inefficiency, range and average by risk groups

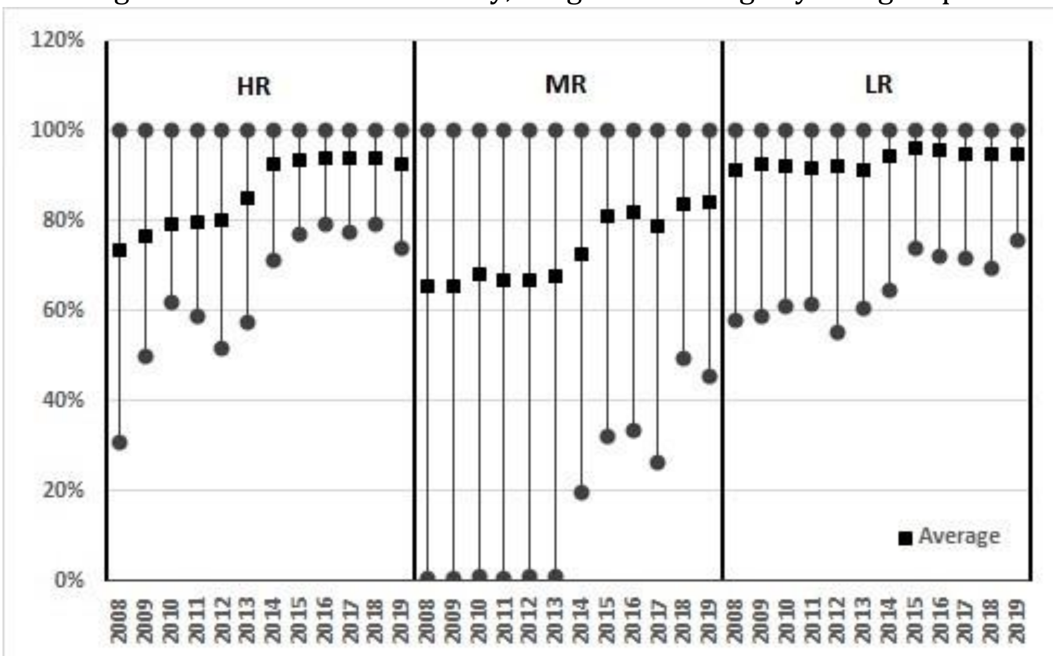


Note: Author's computations. A value of 100% indicates absence of managerial inefficiency. Squares are group simple averages, circles picture the minimal and the maximal value computed for each group.

Combining the two sources of inefficiency, we obtain total inefficiency (see figure 7).

[8] Again, this is due to the fact that agriculture has no more managerial inefficiencies. In fact, agriculture is doing so bad that it is to be compared to itself and is on the frontier. To avoid this paradoxical result, one could compute an anti-efficiency frontier that defines the worst practices. It will be very likely that agriculture will be on both frontiers, the efficient and the anti-efficient (see Shen et al. (2016) for the definition of anti-efficiency). Agriculture is the best industry among the worst when compared to itself.

Figure 7: MTI total inefficiency, range and average by risk groups



Note: Author's computations. A value of 100% indicates absence of inefficiency. Squares are group simple averages, circles picture the minimal and the maximal value computed for each group.

In terms of total efficiency (managerial and technical), about 50 percent of LR industries are green-efficient (efficiency score equal to 1). This proportion is only 33 percent for HR industries and 40 percent for MR industries (see table 2). The less efficient industry is agriculture with a dramatic score of 0.17, followed by Arts, entertainment and recreation industries (0.66) and Manufacturing industries food - textile - paper (0.67).

The main result is the following, belonging to a specific a priori risk group does not necessarily imply a lower or an higher efficiency score. Public administration (LR industry) is fully green efficient as well as forestry (HR industry) or water supply (MR industry). Sewerage, waste management and remediation activities (HR industry), Manufacturing industries food - textile - paper (MR industry) and Accommodation and food service activities (LR industry) have relatively similar efficiency scores (respectively 0.69, 0.68, 0.67). Taxonomies provide an interesting framework but do not reflect the *true* performances of industries. DEA benchmarking adds to a priori classification. Table 2 provides summary statistics for individual industries.

Table 2: Efficiency scores by industries (average 2008-2019, %).

risk group	Industry	MTR	TGI	GMI	MTI
High	Forestry	100.0	100.0	100.0	100.0
	Mining and quarrying	83.1	83.1	100.0	83.1
	Manufacture of chemicals and pharmaceutical products	80.2	80.5	96.2	76.8
	Electricity, gas steam and air conditioning supply	100.0	100.0	100.0	100.0
	sewerage, waste management and remediation activities	91.1	93.4	75.6	69.0
	Construction	88.1	88.1	100.0	88.1
	Average High	89.4	90.9	95.3	86.2
Medium	Agriculture	34.6	71.9	45.6	27.5
	Manufacturing industries food - textile - paper	67.0	67.0	99.9	67.0
	Manufacturing industries other	82.7	82.7	100.0	82.7
	Water supply	100.0	100.0	100.0	100.0
	Human health activities	100.0	100.0	100.0	100.0
	Average Medium	69.8	84.3	89.1	73.4
	Average Medium and High	80.5	87.9	92.5	80.4
Low	Trade	100.0	100.0	100.0	100.0
	Transportation, Storage and postal activities	100.0	100.0	100.0	100.0
	Accommodation and food service activities	92.7	94.4	73.3	67.7
	Publishing activities	96.5	96.6	98.4	94.9
	Telecomunications and IT services	99.6	99.6	99.3	98.9
	Financial service activities	100.0	100.0	100.0	100.0
	Activities auxiliary to financial services	100.0	100.0	100.0	100.0
	Professional scientific activities	100.0	100.0	100.0	100.0
	Administrative, technical and support service activities	99.3	99.4	92.5	91.8
	Public administration	100.0	100.0	100.0	100.0
	Education	100.0	100.0	100.0	100.0
	social work activities	96.2	96.2	98.9	95.1
	Arts, entertainment and recreation	85.9	89.3	76.9	66.2
	Sports activities and amusement and recreation activities	90.9	91.3	96.2	87.5
	Activities of membership organisations	93.3	93.7	93.3	87.1
	Repair of computers and personal and household goods	100.0	100.0	100.0	100.0
	Other personal service activities	97.9	97.9	100.0	97.9
	Average Low	97.2	97.6	95.8	93.4
	Average all industries	92.1	93.8	94.5	88.3

Note: Author's computations. A value of 100% indicates absence of inefficiency. MTR: technological heterogeneity, TGI: technological gap, GMI: managerial efficiency, MTI=GMI+TGI-100.

To confirm the absence of full correspondence between risk group and efficiency we estimate a simple Tobit model stacking each year[9]. To get a censored variable, we take the inverse of total efficiency, this variable takes value 1 (full efficiency) and the more inefficient the industry is, the higher this score is (if the industry is fully inefficient the variable tends to infinity). We regress this variable on time dummies and a dummy that takes value 1 if the industry belongs to the high risk group and a second dummy that has for value 1 if the industry is labelled as medium risk. Table 3 shows that some time dummies are significant but, in particular, if the coefficient associated to the dummy for high risk group is not significant, it is highly significant for medium risk group and positive. We clearly show that inefficiency is higher for medium risk industries compared to high and low risk industries, and, then there is no full correspondence between level of risk and (in)efficiency scores.

[9] It would have been possible to develop a Monte-Carlo procedure in line of the work (Simar and Wilson,1998) to get the *correct* inference, but it would not change dramatically the results presented here.

Table 3:Tobit inefficiency scores.

Variable: inverse of total efficiency	Coefficient	Std. Error	z-Statistic	Prob.
High risk (0-1)	3.05	4.40	0.69	0.48
Medium risk (0-1)	23.7	4.47	5.29	0.00
Year 2008	-5.56	5.94	-0.93	0.34
Year 2009	-9.66	6.06	-1.59	0.11
Year 2010	-12.41	6.11	-2.03	0.04
Year 2011	-9.68	6.06	-1.59	0.11
Year 2012	-11.73	6.10	-1.92	0.05
Year 2013	-11.38	6.09	-1.86	0.06
Year 2014	-19.43	6.37	-3.04	0.00
Year 2015	-24.79	6.88	-3.60	0.00
Year 2016	-19.67	6.40	-3.07	0.00
Year 2017	-22.86	6.68	-3.41	0.00
Year 2018	-22.96	6.69	-3.43	0.00
Year 2019	-21.22	6.52	-3.25	0.00
Error Distribution				
SCALE:C(15)	27.61	1.56	17.68	0.00
Mean dependent var	3.72	S.D. dependent var		19.79
S.E. of regression	19.52	Akaike info criterion		5.14
Sum squared resid	122402.50	Schwarz criterion		5.31
Log likelihood	-849.92	Hannan-Quinn criter.		5.21
Avg. log likelihood	-2.52			
Left censored obs	175	Right censored obs		0
Uncensored obs	161	Total obs		336

Note: Author's computations.

4 Discussion

The starting point of this paper is that, assuming that financial intermediaries (FIs) stick to ESG principles, FIs might be interested in using taxonomies to benchmark industries and channel funds to *sustainable industries* (low risk industries), and/or, towards industries where measured economic and environmental performances are high. We rely on the EBRD risk categorisation taxonomy and DEA to provide such benchmarking. We use industry level data for Luxembourg to compute efficiency scores. We consider heterogeneous technologies, based on potential environmental risk as defined by the EBRD and we show that potential risk (as defined by the EBRD taxonomy) and a posteriori DEA evaluations do not coincide. Belonging to a specific risk group does not imply a better or a worst performance compared to industries in other risk groups. We now discuss how and why the use of taxonomies and benchmarking might lead to an inefficient allocation of funds to investor.

This problem is a consequence of *rating addiction* or *regulatory obsession* (Cole and Cooley, 2014). This happen when regulators incorporate (credit) ratings into their regulatory processes to a point whereby they essentially outsource their lending decision (Cash, 2018), prohibiting their asset managers from investing in or retaining bonds of less than a specific rating (Fridson, 1999). This is the case for all types of financial assets (bonds, shares, loans). Basically, asset managers might delegate their responsibilities to third parties to quantify risk and to invest. They might disregard the standard desk review when receiving funding request. Based on a priori information FIs might try to roughly improve risk-adjusted returns of investments using exclusion a priori rules (Polbennikov et al. (2016), Giese et al. (2019b)). The idea of applying strict exclusionary screens to portfolios was typically used in the 1990s (Giese et al., 2019a). For example, based on these ESG principles, FIs declare to exclude a priori some industries such as the manufacture of weapons, the tobacco industry and the gambling industries[10]. This exclusion rule is clearly indicated in the EBRD taxonomy.

Amel-Zadeh and Serafeim (2018), using survey data from mainstream investment organizations, show that twice more investors use ESG principle for negative screening (exclusion) rather than for positive screening (30% compared to 13% of respondents). As the EU directive that makes ESG disclosure compulsory just came into force (January 2024) only anecdotal evidence can be presented. A recent European Central Bank lending survey of 2023Q2 indicates that climate risks of euro area firms had a net tightening impact on credit terms and conditions for loans to brown firms. This survey

[10] In passing, exclusion might concerns specific firms rather than industries, Some assets are black listed by investment firms based on ESG principles, for example, McDonalds', WalMart or RioTinto see https://www.wealthmanagement.com/equities/top-20stocks-blacklisted-esg-funds

also underline that, according to the banks, to assess the climate risk for loans to SMEs, sector-average information were often used[11]. In our case, the EBRD taxonomy would refrain FIs to invest in high risk industries whereas our benchmarking indicates that they perform better than medium risk industries and as well as low risk industries due to impressive improvements from year to year. A priori exclusion is not aligned with real data evaluation and might generate unjustified credit rationing. This phenomenon is not restricted to the Euro area, Degryse et al. (2023) using a large international sample of syndicated loans over the period 2011–2019, find that green banks indeed reward firms for being green in the form of cheaper loans with fewer covenants. Similar evidence for quoted firms in China is provided by Huang et al. (2023) and Xiaoyu (2023).

For the case of Luxembourg, evidence of credit rationing is scarce as bank do not communicate on their refusal rate and their decision process on providing funds or not. However, the World Bank Enterprise survey provide us with some crude information [12] . If we split the sample by a priori environmental risk, we find that medium and low risk industries declare that access to finance is not a problem for respectively 68 and 62 percent of firms while it is only 55 percent for high-risk industries in 2022. The EIB investment survey also provide some interesting information: Q23. Factors influencing firms' ability to carry out planned investment: political and regulatory climate, do you think that the situation will improve, stay the same, or get worse over the next 12 months? ”Net effect” is defined as the share of ”positively” responses minus the share of ”negatively” responses[13] . The net effect is -25 percent in Luxembourg. In addition, according to the same survey, less than 29 percent of firms set and monitor targets for respective GHG emissions. Therefore it is reasonable to conclude the use of a priori information will constrain lending despite “true” performance of industries.

[11] https://www.ecb.europa.eu/stats/ecb_surveys/bank_lending_survey/html/ecb.blssurvey2023q2~6d340c8db6.en.html

[12] We use the term crude as the sample is very limited, about 170 firms, and the split by industry is not very detailed. Data are available at https://login.enterprisesurveys.org/ .

[13] https://data.eib.org/eibis/graph.

When a priori evaluation translated in a taxonomy is actually aligned with an a posteriori assessment (for example using DEA) and credit rationing seems to be justified, it might pose problems to policy makers. We take the example of agriculture. Agriculture is classified as a medium risk industry and the DEA efficiency assessment indicates this industry as the worst performance compared to all other industries. These two reinforcing negative signals are a clear incentive for FIs to avoid investing in agriculture. This might explain

why agriculture suffers from a lack of funds as pointed out in a recent European Report made by the European Investment Bank (EIB, 2020). To have an order of magnitude, the financing gap for the agriculture sector has been estimated to be in the order of EUR 19.8 to EUR 46.6 billion for the EU 24 in 2020 (EIB, 2020). However, it is obvious that agriculture is necessary to satisfy food needs. A study made by WorldBank (2008) indicates that the world will need 70 to 100 percent more food by 2050. If countries aim at sustainability, what is needed, is a more sustainable agriculture (Gomiero et al., 2011) that will require substantial investments (Huang and Wang, 2014). Public subsidies/funding are often advocated to solve lack-of-capital problems (for the case of Italy see Trovato and Alfo (2006)). For the specific case of agriculture, the support from the Common Agricultural Policy (direct payments, investment support, and start-up support) clearly contributes to improving the situation by facilitating farmers' access to lending as the support increases their cash flow and loan repayment capacity (EIB, 2020).

In such a case, taxonomies and benchmarking can reinforce each other as tools to justifying credit rationing and suggesting public subsidies/funding. If public funding has to be substituted to private funding, one of the major challenge for public authorities and government agencies is the social acceptance of subsidies. It might not be socially acceptable to subsidise industries that harm the environment or in general are labelled high risk industries. The main difficulties lies in the fact that, as explained by Huijts et al. (2007), Social acceptance is not just a matter of individual feelings and perceived risks and benefits, but predominantly is a social process. Beliefs being very persistent and are not necessarily related to factual risks (Flynn et al., 2006). An example is the development of nuclear energy, a highly subsidised industry in early development stages. Subsidies have a low social acceptance often due to the history of its development and previous accidents related with nuclear power plants (Jun et al., 2010). However, William

Magwood, Director-General, OECD Nuclear Energy Agency, stated in 2021 that nuclear energy has an important role to play in the transition to net-zero emissions by 2050[14]. For the case of agriculture (in particular farming), social acceptance of subsidies is decreasing with an increasing criticism about modern animal farming practices, such as the way farm animals are treated and used for production (see Boogaard et al. (2011)). Ethical concerns such as animal rights and welfare explain social (non) acceptance(Kendall et al., 2006).

Nonetheless, it would be wrong to believe that ESG principles always refrain FIs to invest and/or to provide funds to specific firms and industries. Recently, Kumar et al. (2018), provide several example of firms that should be either excluded or at minima labelled as high risk. The Boeing Company and Lockheed Martin are ranked first and second largest firms in the manufacture of weapons industry. According to the EBRD risk classification they should be excluded from financing. Boeing is classified at high ESG risk by Sustainalytics[15] but classified as one of the best airline stocks to buy. Monsanto (acquired by Bayer in June 2018) produces glyphosate-based products and is, according to Sustainalytics, a severe risk ESG company but can still be part of many portfolios. It generates for FIs the challenge to keep a robust ESG profile and a positive ESG trend while maintaining minimal exclusions. Cappucci (2018) indicates that in 2017 about 87 percent of Managers of hedge funds and absolute returns financial vehicles working for Mercer Global Investment do not use ESG principles. Incidentally, from the perspective of investment analysts, ”it is rare that a company’s failure to manage environmental and social issues has led to an inability to repay creditors” (McCluskey, 2012). Cynically, YoungFerris and Roberts (2021) suggest that FIs should present ESG integration as something that effectively addresses environmental and social issues, rather than merely financial materiality. Cappucci (2018) indicates that a significant number, and perhaps a majority, of investment managers in the US, view ESG as primarily a client relation matter.

To conclude, we believe that taxonomies, benchmarking, ratings are interesting and may provide useful information. It combines a priori valuable warning signals contrasted by a numerical evaluation of performance using actual data. However, we would like to highlight that taxonomies might lead to a priori exclusion of some firms/industry from access to finance while the

[14] https://www.oecd-forum.org/posts/the-role-of-nuclear-energy-in-mitigating-climate-change

[15] urlhttps://www.sustainalytics.com/esg-rating/the-boeing-company/1008249103

same industries are successful in reducing their environmental impacts. For the case of Luxembourg, the mining and quarrying industry is a striking example, a high-risk industry that manages to dramatically increase its efficiency. In addition, least performing industries can also be seen as, potentially, industries that might be the solution to meet the objective of an economy with net-zero greenhouse gas emissions by 2050 (for example agriculture, Gorjian et al. (2021)) and might require substantial investments. If FIs exclude theses industries based on ESG principles, the solution lies in public subsidies. However, policy makers will face the issue of social acceptance of subsidies.

The non-acceptance of subsidies might block such policies amplifying credit rationing. Chen et al. (2009) propose a convincing model where upon receiving loan request from applicants, banks always conduct a standard desk review (first-stage credit evaluation) on information provided in the application forms and related documents. Then they undertake a second-stage credit evaluation such as hiring external auditors or independent credit-rating agency, which enhances the quality of credit decision and contributes to reduce the financing gap. Thus, taxonomies and benchmarking exercises are useful tools and do not replace or overcome decisions from a preliminary careful desk review. It might also be interesting to extend the coverage of ESG principles to investments that are relevant for the sustainable economic development of the country (e.g. to develop sustainable agriculture) even if they seem to be in contradiction with ESG principles. One can imagine a public agency providing a rating to firms in line with national priorities for national economic development as an incentive for FIS to provide funding to these specific firms.

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