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Using Natural Language Processing to monitor circular activities and employment

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ABSTRACT

In Europe, NACE codes are used for the official classification of sectors, however, the circular economy is not sufficiently captured in this classification. Therefore, this paper improves previous attempts for defining circular activities and jobs by web scraping techniques applied to each company in Belgium. We analyze their first, second, and third official NACE codes and compare these to the NACE codes they should have been allocated to according to the web scraping data. Subsequently, we calculate circularity scores for every sector to construct an indicator for the number of circular companies and jobs. The results show that the number of circular companies is lower than the baseline from official statistics when we only consider the companies' first and main NACE code. The estimates are higher than the baseline when we also take the second and third NACE codes into account and the estimated number of circular jobs is far higher than the baseline. This research upgrades previous classifications of circular sectors and demonstrates how web scraping and novel data might improve our understanding and capacity to build data. Based on the results in this paper, we recommend a uniform data collection such as reporting standards, and an inclusion of all circular strategies in sectoral classifications.

1. Introduction

Currently, there is no commonly accepted definition of what circular activities entail, nor what sectors can be considered as circular. Nevertheless, policy measures often are designed at sectoral level. For example, the Circular Economy Action Plan from the European Green Deal focuses on some key sectors such as textiles, electronics, construction, recycling, … (European Commission, 2020). In the documentation of the European CE Monitoring Framework of Eurostat, the Circular Economy Economic Sector is defined as *"The circular economy goods and services sector is a subset of the whole economy. Economic goods and services of the circular economy sector are those that maintain the value of products and materials as long as possible and minimize waste and resource use, thereby, closing or narrowing the [raw] material cycle."* (Eurostat, 2022b).

In Europe, sectors and activities are classified by "NACE" codes: "Nomenclature générale des Activités économiques dans les Communautés Européenes" or "statistical classification of economic activities in the European Community" (Eurostat, 2008). On the most detailed level, the NACE codes consist of five digits and the most recent version of the classification is called NACE Rev. 2. Using this classification, several studies and monitoring frameworks have tried to estimate the size of the circular economy (CE) of the European Union or its member states by calculating indicators of NACE codes considered as circular (Delahaye et al., 2023; Tsironis et al., 2022; Vanhuyse, 2023). For example, the Circular Economy Monitoring Framework relies on the NACE codes for its calculations and find that in 2021 in Belgium, 1.4 % of GDP are related to private investments of CE sectors (Eurostat, 2022b). The total gross value added of circular economy sectors makes up 1.7 % of GDP in 2021. For Flanders, the CE Monitor shows that 3.7 % of the total turnover and 1.5 % of total employment can be attributed to CE sectors, calculated by NACE codes (CE Center, 2023).

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However, Korhonen et al. (2018) state that material and energy flows do not respect these man-made sectoral borders. Therefore, these previous calculations have some limitations that follow directly from the limitations of NACE codes. Three limitations about matching company activities with NACE codes arise. First, companies can choose themselves which NACE codes they belong to. As there are 943 different codes to choose from, companies do not always make a correct choice (Battiston et al., 2022). Second, the activities of a company may change over time while the companies do not change their NACE codes accordingly (VLAIO, 2023b). Third, companies are free to choose a second or third NACE code which resembles their activities, however, this is not obligatory. Therefore, if a company with a focus on several activities only chooses one NACE code, its other activities are not reflected or captured in the database (Christensen, 2013). It is furthermore expected that all employees perform the activity of the first NACE code, but this is not always the case (Komorowski, 2020).

This research shows how policy measures for the (CE) might miss their effects if they stay depend on rigid classification systems which insufficiently capture circular activities. For example, in Brusselaers et al. (2022), a Computable General Equilibrium model (CGE) is used where two additional sectors and three additional goods are added to increase the level of detail for repair activities. Consequently, a combination of several taxes is modelled to encourage repair activities and discourage conventional household goods. However, as we will see later in this paper and in Annex S2, the repair sector should contain more companies than it does officially, which means that a tax decrease on the sector of repair will not benefit all repair companies.

Therefore, in this paper, we aim to improve the mapping of Belgian circular activities by using Natural Language Processing (NLP) and web scraping. According to the definition given by Chowdhary (2020), NLP is "an area of research and application that explores how computers can be used to understand and manipulate natural language text or speech to do useful things". We will use this method to first scrape websites of Belgian companies to correct their self-declared NACE code, and consequently we will apply NLP to extract keywords and understand the text. Subsequently, we will develop an indicator for the number of circular companies and the number of employees in the CE. With this information, we will aim to provide an answer to the following research question: Can we build a methodology to monitor circular activities and employment with NLP data applied to alternative information flows?

We start from a study of Willeghems and Bachus (2019) where several NACE codes were tagged as circular to calculate the number of circular jobs. Their selection of NACE codes has been used as a basis for many applied indicators on the number of companies, the turnover, and the number of jobs in Belgium in the CE (CE Center, 2023; Multani et al., 2021). In this paper, we use alternative information flows and NLP to correct the NACE codes of the Belgian companies, and we consequently use the list of circular NACE codes from Willeghems and Bachus (2019) to count the number of circular companies and jobs. With this exercise, we illustrate how this novel approach allows to get a better picture of the sectoral activities which complements previous indicators with new quantitative data. As a result, we have an assessment of the appropriateness of the current classification systems in the context of circularity assessments and a quantification of the number of circular companies and jobs in Belgium.

This research is the first large-N study (82,509 observations) to use NLP in the context of circular indicators and circular business models. The goal of this study is to build on the existing literature and to get a deeper understanding of the implementation of circular activities in businesses. This paper contributes to the field of the CE by being the first to provide a new dynamic classification system which allows identification and assessment of circular activities within the broader economy. The dynamic classification system can be used to develop a new type of indicators, which is more flexible and responsive to adapt to new evolution in the realm of circular activities. Our research allows to translate these new evolutions into new codes for the existing classification (or completely change that classification). This is of importance to policymakers and investors to direct their support for circular innovation towards specific sectors and to demonstrate how digitalization might improve the mapping of the CE. For example, investments in product passports or product-service systems towards the whole sector cannot be applied today as that NACE code does not exist, and also governments use these codes for distributing subsidies and levying taxes (VLAIO, 2023b). The case of Belgium serves as an example for other small, open economies with a large share of SMEs in the urban and industrial landscape.

In what follows, we first elaborate on a literature study which includes a translation of NACE codes to other classifications such as NAICS (North-America) or ICIS (global), and an overview of current estimates for circular activities. Thereafter, we propose the dataset obtained with web scraping. Consequently, we present and discuss the results. Finally, we conclude with the limitations of this method and recommendations for future research.

2. Literature review

2.1. CE indicators

Circular indicators can focus on economic, environmental, and social aspects. Several authors have done a systematic literature review and have found that circular indicators are often focused on the economic aspect and to a lesser extent on the environmental and social aspects (De Oliveira et al., 2021; De Pascale et al., 2021; Kristensen and Mosgaard, 2020). When we look at the social dimension on the one hand, Calzolari et al. (2022) found that indicators for employment opportunities in the supply chain are the most common indicators in this category, such as the share of domestic jobs in international value chains and the loss in jobs through more recycling and reuse (Geerken et al., 2019). On the other hand, indicators such as the number of companies with a circular activity might fit in the economic/environmental nexus. The limited focus on social indicators is a drawback because the social impacts are interlinked with the product system and should therefore be accounted for in systemic shifts such as the CE, and because political objectives are often focused on employment and education (De Oliveira et al., 2021; De Pascale et al., 2021). Furthermore, the number of circular jobs can also be seen as being positioned at the economic-social nexus.

On the European level, the Circular Economy Monitoring Framework of Eurostat (2022a) contains an indicator "Persons employed in circular economy sectors" as a percentage of total employment. They measured circular employment by mapping activities against the integrated system of economic classification and linking it with NACE, CPA, and PRODCOM codes (Eurostat, 2022b). They chose the activities to consider as circular by an extensive literature review of definitions and narrowed the list by the availability of data. Eventually, they had a list of 77 NACE codes to consider circular, however, activities such as "ozone for water desinfection", "architectural services", and "building of ships and floating structures" were also included, among others. We therefore pose that although the goal of their indicator was to analyze very specific activities, the categorization of the NACE codes does not suffice.

Furthermore, the European Environment Agency presents indicators that are not covered by Eurostat in their Circularity Metrics Lab (European Environment Agency, 2023). One such indicator is "SMEs offering green products or services", and the data is obtained from the Flash Eurobarometer. A disadvantage of the Eurobarometer questionnaires, however, is that they are not conducted on a regular basis, and the questions change over time. Therefore, it is not possible to draw a timeseries.

The implementation of such CE indicators in current policy frameworks in Belgium is multifold. In Flanders, a region of Belgium, several indicators exist to measure the size and state of circular activities. These indicators are collected in the "CE Monitor" and the most important indicators for this research are "Employment in the circular economy", "Turnover in the circular economy", and "Implementation of circular economy strategies by companies" (CE Center, 2023). The first two are calculated by respectively summing up the number of employees, the turnover and the number of companies which are officially categorized in one of the sectors tagged as circular by Willeghems and Bachus (2019). These sectors consist of NACE codes for, among others, repair and maintenance, waste collection and treatment, repair activities, rental activities, sale of waste, parts and accessories, and sale of second-hand goods. As a result, the CE Monitor reports a turnover of 17.8 billion euro in 2019 and 43,261 employees in 2020.

The third indicator of the CE Monitor of the implementation of CE strategies by companies is presented by a business survey by the Foundation Innovation & Work. Businesses participating in this survey had to indicate which circular strategies they use, choosing from 10 different circular strategies: (i) Ensuring that products purchased are easy to disassemble and can be dismantled or repaired, (ii) Collaboration for sharing logistic means, (iii) Collaboration for sharing space and buildings, (iv) Ensuring that products sold are easy to disassemble and can be dismantled or repaired, (v) Collaboration for sharing machinery and tools, (vi) Reusing waste, residual or by-products for the same process, (vii) Reusing waste, residual or by-products for a different process, (viii) Using raw materials or materials which are waste, residual or by-products for other companies, (ix) Selling waste, residual or by-products, and (x) Offering product-service combinations. However, as this survey is only executed every two years and the questions change over time, it is not possible to develop a timeseries indicator with this data.

2.2. Circular activities and Natural Language Processing

Literature on the nexus between CE and text mining is relatively recent, although text mining has already been used in several ways for analyzing the CE. Here, we distinguish three topics for which text mining has helped research on the CE. A first topic is related to using text mining to make an inventory of studies on CE. In their paper, Mahanty et al. (2021) analyze the label "circular economy" and the textual elements that are attached or detached to this label by topic modelling using Latent Dirichlet Allocation (LDA). LDA groups words from a document into a topic and assumes that every document has multiple topics. The goal of their paper is to track the evolution of the concept of CE in academic literature between 2005 and 2021, and they find that in 2014–2015 there was a shift in the CE literature towards a European context and industrial ecology. Furthermore, there is an increased focus on micro-level interventions such as circular product design, business models, and supply chain from a Chinese predominance. Performed. Similar studies map the scientific discussion on waste management or in the field of fruit by-products (Ranjbari et al., 2021; Villegas-Yarlequé et al., 2023).

A second topic in which text mining has helped research on the CE, is by using NLP to categorize documents to develop typologies. A first example is for government roadmaps for the CE, such as by Abu-Bakar et al. (2023) who combined NLP with topic modelling to analyze 398 CE documents for a more coordinated CE transition. The method allowed to make a typology of Circular Economy Roadmaps which increased alignment of sustainability agendas and benchmarking of CE ambitions. The same can be done for corporate reporting, as done by Santos et al. (2023) and Caferra et al. (2023) who used text mining to analyze, respectively, management reports and mission statements to develop typologies of these companies. A last example is developing a typology of scientific articles for CE definitions, as seen in Alizadeh et al. (2023) where 172 definitions between 2015 and 2023 were gathered and analyzed with topic modelling and LDA. The results show that the definitions can be classified in 12 topics with each 10 keywords.

A last interesting point of view, and related to this paper, is the perspective of text mining to analyze circular business models (CBMs). With the use of text mining, the activities and business model of a company can be revealed, for example by scraping their communication from LinkedIn. One such study extracted data from LinkedIn of all companies in the EU28 who had "circular economy" in their description (Tsironis et al., 2022). Information was downloaded on the employees, date of foundation, and the activities. In total, they found 3727 circular companies in the EU28, with 124,306 employees. For Belgium they report 269 companies with 24,151 employees or 11,248 employees if they distribute employees of multi-national companies according to each country's population. In their follow-up paper with the same data, the results for one country (Germany) were analyzed (Knäble and Tsagarakis, 2023). Taking a similar approach but instead with keywords, Blasi et al. (2021) scraped companies' websites to analyze their communication on CE for 168 Italian manufacturing companies and tested the relation with economic performance. First, the companies were selected and subsequently, the web scraping was performed using CULTR, a web-based application for crawling websites. In total, they looked for 26 keywords. The approach of keywords is similar to the web scraping analysis of the Netherlands Environmental Assessment Agency (2019) and the study of Statistics Netherlands (2023). The first one used circular keywords and found that there were 85,000 circular activities, representing 420,000 jobs. The second study used the circular R-strategies to scrape the websites of companies and analyze their level of implementation of the R-strategies and found that there were 4980 companies that communicated about circular activities in the Netherlands. However, these studies present snapshots of the economy but do not translate into indicators.

2.3. NACE classification and link with other classifications

Other classifications of activities exist in different parts of the world. The most well-known classifications are NAICS (nomenclature of economic activities in North America) and ISIC (International Standard Industrial Classification of All Economic Activities). Mapping the relation between NAICS, ICIS, and NACE is not straightforward because the relationships are of type 1 → n, n → 1, or 1 → 1 (Pachot et al., 2021). Some NACE codes may have a one-on-one relation with a NAICS or ICIS code, while other codes may correspond to multiple NAICS or ICIS. The other way around, multiple NAICS or ICIS codes may correspond with one NACE code. However, several authors have built correspondence tables between these different classifications, such as Pachot et al. (2021) for NACE and NAICS, and Squicciarini and Asikainen (2011) for the correspondence between NACE, ICIS, and NAICS in the construction sector.

3. Methods

In this paper, we propose an alternative mapping of circular activities of all Belgian companies by using NLP to perform a semantic analysis in two different ways. In section S1 of the supplementary information, we explain in detail the model that was used for the web scraping. In this section, we explain the resulting two datasets and how they are used to construct the indicators.

3.1. Dataset 1 (1 NACE)

In this first dataset (1 NACE), all websites and Facebook accounts of Belgian companies were scraped by the algorithm in April 2021 by the company Inoopa under supervision of 10 experts in the field of circular economy in Belgium and the Netherlands. The results were repeatedly discussed with all the experts and the method was updated iteratively.

Thereafter, the database was constructed by linking every company to its "declared" first, second, and third NACE. This is the NACE code they are officially categorized in. Furthermore, the algorithm links every company to a "first best NACE", "second best NACE" and "third best NACE", where it proposes a new first, second, and third NACE code. That newly allocated NACE code can be equal to or different from the declared NACE. Every newly proposed NACE code furthermore receives a score between 0 and 1 for their relevance to the company and how well the vector of words from the website matches the word cloud of the NACE sector. This score is a normalized reflection of the number of hits of the keywords from a website with the word cloud from a specific sector. The closer the score is to 1, the better the match between the vector of words from the website and the word cloud from a specific sector. The relevance of the company and its keywords in the word clouds of the economic sectors is an indication of the extent to which the company performs an activity under a specific NACE code.

Finally, data cleaning was employed to delete inactive companies, companies amidst a legal process (e.g. for bankruptcy), or companies protected by GDPR legislation to make their NACE code invisible. Deletion of these companies resulted in a dataset of 35,714 companies that have a “best NACE”, according to the algorithm, from one of the circular NACE codes from Willeghems and Bachus (2019), as seen in Table S1. We note that this results in both a positive and a negative correction; it is possible that firms which were originally not classified as circular according to their declared NACE, are now tagged as circular according to the algorithm and vice versa.

3.2. Dataset 2 (1–3 NACE)

Often in the development of indicators, only the first activity of the company is considered to determine whether a company is circular or not (Multani et al., 2022). In this second dataset (1–3 NACE) we overcome this problem by looking at the first, second, and third NACE codes in order to capture multiple side-activities. The technical description of the second dataset (1–3 NACE) is similar to that of the first, however, this dataset includes all the companies with a first, second, and third best NACE code from Table S1. This results in a dataset of 93,549 companies or 82,509 companies after deleting companies without an official NACE code. This dataset allows us to detect companies active in circular sectors while not referring to them as their main activity.

3.3. Data validation

We performed some checks for several companies to validate the trustworthiness of the data. In this section we illustrate two examples of these checks. First, in 2015 Philips introduced “Light as a Service” (LAAS) together with RAU Architects (Philips Lighting, 2020). However, we do not find Philips in our two datasets. Therefore, we checked their website manually and saw that they do not mention LAAS on their website. When we further looked into this, we see that Philips and RAU Architects founded a CE consultancy organization called Turntoo which manages the LAAS activities for Philips. Turntoo is a Dutch company and has no branches in Belgium. Therefore, we do not see these activities reflected in our datasets. Another problem with servitisation, is that there is no explicit NACE code for this. We also do not see Peerby, which is a platform offering shared tools and bikes for neighbors to share, among others, for neighbors to share. They have an officially declared NACE code 70220 Council for Business and other management consultancy. This NACE code does not fit their activities, however, there is no alternative available. The same goes for Juunoo which produces circular walls for companies and offers these walls as a service. Officially, they have the declared NACE 43320 Joinery. The NLP dataset predicts the same best NACE. This check confirms that the NACE codes do not include all circular activities, and therefore, a better suited NACE cannot be found for this company.

We also performed checks for companies for which we know they do not have circular activities. For example, several companies that produce cars are included in the dataset, such as Volvo, Honda, BMW, Mercedes, Kia, Audi, … All of them have a predicted and official NACE code of 45,310 or other codes starting with 45 for retail maintenance, and repair in the automotive industry. We conclude that their official NACE codes correctly reflect their communication of their activities, however, the inclusion of trade of automotive equipment in the circular NACE codes by Willeghems and Bachus (2019) should be put up for discussion.

Also, typical linear companies focused on consumption such as Coca Cola and McDonald’s are not included in the datasets. While manually checking their websites and characteristics of the companies, we see that the Coca-Cola Company has multiple spin-offs with a branch in Belgium, however, their website with an extensive page on sustainability and recycling is linked to the Coca-Cola Company which does not have a branch in Belgium. The same goes for McDonald’s.

Finally, companies concerned with waste collection and recycling are all included in the datasets, some with official NACE codes starting with 38 (Recupel, Renewi), others with official NACE codes starting with 46 of wholesale of waste (Ecoo, Ecolux). These companies all receive a NACE code from the algorithm starting with 38.

3.4. Circularity scores

With our two datasets, we first construct circularity scores for every NACE code. These circularity scores are the share of companies that should have a circular NACE score according to the algorithm, relative to the total number of companies in that year according to Statbel (2023). For example, for the first dataset (1 NACE), if the algorithm says that 10 companies that have an official first NACE code of 01100 (not circular) should have a first NACE code of 33,110 (circular) and in total there are 1000 companies in 01100 (10 circular and 990 not circular), then the sector receives a circularity score of 1 %. These scores are only constructed for 2021, as this is the year that the web scraping was performed. The circularity scores can be found in Table 2 for every section, Annex S2 reports the circularity scores on a more detailed level for every subclass. All subsequent calculations have been done on the most detailed level of subclasses, however, as there are 934 different subclasses, we display them in the Annex S2 to improve the readability and only show the results here for the level of sections.

Consequently, the scores can be used to construct the indicator for the number of circular companies every year in a linear manner. If the next year there are 1100 companies in 01100, and we assume that the circularity score is still representative, then we may assume that 11 companies are circular. In this paper, we construct this indicator for 2015 until 2022, but we note that the circularity scores should be updated more frequently (e.g. every 3 years or every year). That way, a more realistic indicator can be developed, when there is an additional update of the circularity score.

For the number of circular jobs, we opted to use the data from the National Bank of Belgium (NBB, 2023) which depicts the number of employed people. The reason for this choice is that Statbel or other databases only offers insight into the number of employees in Belgium while we also want to take into account the sole proprietorships to be able to count the total number of circular jobs. Another reason is that the NBB shows the results on the level of division of NACE codes (two digits). Other datasets offer a more detailed view, but because of privacy reasons the numbers are often unavailable. By using the more aggregated data from the NBB, we can find the full totals per division. We follow the implicit assumption made in Vona et al. (2018) and Vona et al. (2019) that the share of an activity in an occupation is proportional to the time spent doing this activity. As a consequence, we can pose that the circularity of an occupation is the fraction of time spent on circular activities. According to this view, aggregated circular employment can be estimated as the sum of the share of employment of all occupations reweighted by their circularity score.

For the indicator of the number of circular companies, we allocated the whole company to the new NACE code to calculate the number of CE scores. However, a company has multiple activities and therefore not all the employed people can be considered circular for the indicator of the number of circular jobs. The NLP data provides a score between 0 and 1 for the fit with the predicted first, second, and third NACEs for their

Table 2
The circularity score and the weighted circularity score for every section and dataset.

		Dataset 1 (1 NACE) - Circularity score	Dataset 1 (1 NACE) - Weighted circularity score	Dataset 2 (1–3 NACE) - Circularity score	Dataset 2 (1–3 NACE) - weighted circularity score
A	Agriculture, forestry and fishing	0.05 %	0.03 %	1.82 %	0.43 %
B	Mining and quarrying	1.90 %	0.91 %	9.00 %	2.39 %
C	Manufacturing	7.45 %	5.48 %	13.53 %	7.02 %
D	Electricity, gas, steam, and air conditioning supply	0.44 %	0.24 %	2.57 %	0.71 %
E	Water supply; sewerage; waste management and remediation activities	68.62 %	56.12 %	86.01 %	62.06 %
F	Construction	1.19 %	0.73 %	9.72 %	2.72 %
G	Wholesale and retail trade and repair of motor vehicles and motorcycles	9.49 %	7.61 %	17.43 %	9.67 %
H	Transporting and storage	0.55 %	0.29 %	5.23 %	1.42 %
I	Accommodation and food service activities	0.14 %	0.07 %	1.88 %	0.48 %
J	Information and communication	0.13 %	0.07 %	3.21 %	0.74 %
K	Financial and insurance activities	0.43 %	0.22 %	4.19 %	1.12 %
L	Real estate activities	0.21 %	0.12 %	2.19 %	0.58 %
M	Professional, scientific and technical activities	0.05 %	0.03 %	1.11 %	0.26 %
N	Administrative and support service activities	7.17 %	5.36 %	12.03 %	6.61 %
O	Public administration and defense; compulsory social security	0.33 %	0.19 %	9.35 %	3.11 %
P	Education	0.05 %	0.03 %	1.80 %	0.42 %
Q	Human health and social work activity	0.10 %	0.06 %	1.44 %	0.39 %
R	Arts, entertainment and recreation	0.22 %	0.12 %	4.02 %	1.02 %
S	Other services activities	6.81 %	4.84 %	8.03 %	5.18 %
T	Activities of households as employers; undifferentiated goods – and services – producing activities of households for own use	6.87 %	3.73 %	16.79 %	6.92 %
U	Activities of extraterritorial organizations and bodies	0.00 %	0.00 %	0.00 %	0.00 %
	Grand Total	3.26 %	2.48 %	7.54 %	3.53 %

relevance to the company and how well the vector of words from the website match the word cloud of the NACE sector. Subsequently, we use this score to recalculate the number of CE jobs, as also done by Statistics Netherlands (2023). For example, if a company has a 60 % fit with a predicted best NACE tagged as circular, a 10 % fit with a secondary NACE not tagged as circular, and a 5 % fit with a third NACE tagged as circular, then the normalized score for the best NACE will be 60 %/(60 % + 10 % + 5 %) or 80 % and the normalized score for the third NACE will be 6.66 %. The total weighted CE score for this company will be 86.66 %. Using these scores on a sectoral level, we multiply the average weighting with the circularity scores to obtain a weighted circularity score per sector. These weighted circularity scores can also be found for every section in Table 2 and for every subclass in Annex S2. As the scores are weighted with a number between 0 and 1, the weighted circularity score is always lower than the unweighted circularity score. We apply these weighted circularity scores to the number of jobs. For example, if a company has 100 people employed, and a company has a set of first, second, and third NACE codes with a weighting of 86.66 % circularity, then we pose that 87 people perform a circular job by working on the circular activities. We note the possibility of, for example, greenwashing, which might increase the match between the companies' websites and circular sectors, and therefore increase the circularity scores.

4. Results

4.1. Number of companies

In 2015, Statbel reports that there were 869,652 companies in Belgium and 1,143,138 in 2022 (Statbel, 2022, 2023). In Table 3 we see the number of companies for every year and for every region. We construct a baseline calculation by counting the official number of companies in the NACE codes that were tagged as circular by Willeghems and Bachus (2019). We see that the number of companies within the sectors defined as circular in the CE is 31,988 in 2015 (3.68 % of total) and 38,341 in 2022 (3.35 % of total). In absolute terms, we see that the number of circular companies increases every year, while relatively it decreases every year. This signifies that the total number of companies increases more than the number of companies in the sector that is considered as circular.

In Table 4 we find the results from the first dataset (1 NACE). We immediately see that these results are lower than the baseline, in 2015 there are 30,898 circular companies (3.56 % of total) and in 2022 this is 36,435 (3.19 % of total). There are two opposite effects, namely, the companies that officially have a NACE code from the list of Table S1, but do not have a NACE code from this list according to the NLP data, are subtracted from the total. On the other hand, the companies that officially have a non-circular NACE code but should have one according to the NLP data, are added to the estimates. We see that the negative effect is larger than the positive one, and therefore, we have a lower estimate than the baseline. Below in Table 4 we see the results for the second dataset (1–3 NACE). We see that these results are higher than the baseline and the first dataset (1 NACE). In 2015 there are 69,637 circular companies (8.00 % of total) and in 2022 this is 84,797 (7.42 %).

The results for every sector can be found in Fig. 2 and Fig. 3 for respectively the first and the second dataset (1–3 NACE). The sections in the Fig. 3 of the second dataset (1–3 NACE) are the first official NACE codes of the companies. We see that for the first dataset (1 NACE), most of the circular companies can be found in the section 'wholesale and retail trade repair of motor vehicles and motorcycles'. The growth over time in the number of circular companies is a consequence of a growth in this section, and the section 'manufacturing'. For the second dataset (1–3 NACE) we see that the companies are more diverse over the sections, however, the section 'wholesale and retail trade repair of motor vehicles and motorcycles' has the largest share followed by the section 'construction'. The growth in the number of companies is the

Table 3
Baselines estimates for the number of CE companies per region. Sources: Statbel (2022, 2023); Willeghems and Bachus (2019).

	2015	2016	2017	2018	2019	2020	2021	2022
Total number of companies	**869,652**	**905,840**	**941,894**	**976,162**	**1,010,464**	**1,050,533**	**1,094,339**	**1,143,138**
Flanders	524,613	547,483	570,296	593,007	617,595	646,460	678,941	713,916
Walloon	232,975	240,968	248,742	255,385	260,694	269,226	279,379	290,354
Brussels-Capital	97,170	101,127	104,699	108,226	110,802	113,163	115,511	118,259
Foreign or unknown	14,894	16,262	18,157	19,544	21,373	21,684	20,508	20,609
Baseline - Number of CE companies	**31,988**	**32,830**	**33,538**	**34,300**	**35,347**	**36,452**	**37,585**	**38,341**
Flanders	18,856	19,419	19,882	20,548	21,602	22,561	23,515	24,114
Walloon	9949	10,120	10,317	10,395	10,370	10,540	10,754	10,938
Brussels-Capital	2841	2909	2925	2923	2916	2898	2876	2818
Foreign or unknown	342	382	414	434	459	453	440	471
Baseline – Share of CE companies	**3.68 %**	**3.62 %**	**3.56 %**	**3.51 %**	**3.50 %**	**3.47 %**	**3.43 %**	**3.35 %**
Flanders	3.59 %	3.55 %	3.49 %	3.47 %	3.50 %	3.49 %	3.46 %	3.38 %
Walloon	4.27 %	4.20 %	4.15 %	4.07 %	3.98 %	3.91 %	3.85 %	3.77 %
Brussels-Capital	2.92 %	2.88 %	2.79 %	2.70 %	2.63 %	2.56 %	2.49 %	2.38 %
Foreign or unknown	2.30 %	2.35 %	2.28 %	2.22 %	2.15 %	2.09 %	2.15 %	2.29 %

Table 4
Estimates for the first and second dataset (1–3 NACE) for the number of CE companies per region. Sources: Statbel (2022, 2023); Willeghems and Bachus (2019).

	2015	2016	2017	2018	2019	2020	2021	2022
Baseline - Number of CE companies	**31,988**	**32,830**	**33,538**	**34,300**	**35,347**	**36,452**	**37,585**	**38,341**
Flanders	18,856	19,419	19,882	20,548	21,602	22,561	23,515	24,114
Walloon	9949	10,120	10,317	10,395	10,370	10,540	10,754	10,938
Brussels-Capital	2841	2909	2925	2923	2916	2898	2876	2818
Foreign or unknown	342	382	414	434	459	453	440	471
Dataset 1 (1 NACE) – Number of CE companies	**30,898**	**31,633**	**32,229**	**32,915**	**33,818**	**34,739**	**35,714**	**36,435**
Flanders	18,292	18,788	19,190	19,792	20,712	21,517	22,381	22,956
Walloon	9454	9597	9754	9826	9795	9944	10,105	10,268
Brussels-Capital	2800	2857	2861	2851	2840	2815	2781	2735
Foreign or unknown	351	390	424	446	471	463	448	476
Negative correction	−3944	−4123	−4294	−4459	−4680	−4979	−5208	−5391
Positive correction	2855	2926	2986	3076	3152	3267	3378	3486
Dataset 2 (1–3 NACE) – Number of CE companies	**69,637**	**71,503**	**73,110**	**75,039**	**77,300**	**79,894**	**82,508**	**84,797**
Flanders	41,713	42,886	43,913	45,454	47,511	49,679	51,933	53,743
Walloon	20,124	20,507	20,871	21,124	21,217	21,663	22,116	22,579
Brussels-Capital	6720	6922	7026	7085	7104	7119	7108	7086
Foreign or unknown	1080	1187	1300	1375	1468	1433	1351	1388

consequence of a growth in the section ‘administrative and support service activities’, section ‘wholesale and retail trade repair of motor vehicles and motorcycles’, and section ‘construction’.

4.2. *Circular jobs*

Table 5 shows the results for the circular jobs between 2015 and 2021. For 2022, the data is not yet available. We see that the baseline results from NBB (2023) are lower than the results from our datasets. For a total number of employed people in 2021 of 4,989,300, we see that our first dataset (1 NACE) reports 120,690 (2.42 %) circular jobs and the second dataset (1–3 NACE) reports 335,619 (6.73 %) circular jobs. When the results are weighted for the share of circular activities performed in a company, the first dataset (1 NACE) still shows 89,348 (1.79 %) circular jobs and the second dataset (1–3 NACE) 45,718 (2.92 %). Surprisingly, we see a decrease in circular jobs in 2020 in all datasets, although there is no decrease in the total number of employed people in 2020. We will further elaborate on this finding in the discussion section.

The reason for this large difference in the baseline and the web scraping data is twofold: on the one hand, we chose to work with data from the NBB which includes all the working people in the economy instead of only the employees, and on the other hand by using more aggregated data, we do not have the problem of privacy of the social balance of the annual accounts. The large difference between the baseline and our estimates is an important conclusion for policy makers and educational institutions that measures targeted at circular jobs need to take more people into account than originally thought.

In Fig. 4 and Fig. 5 we again see the results per section. Fig. 4 depicts the number of circular employed people per section from the first dataset (1 NACE) between 2015 and 2021 unweighted (left) and weighted (right) while Fig. 5 shows the number of circular employed people per section from the second dataset (1–3 NACE) between 2015 and 2021 unweighted (left) and weighted (right). We see in Fig. 4 that the distribution over the sections is similar, with the largest shares for the section ‘wholesale and retail trade repair of motor vehicles and motorcycles’, section ‘water supply; sewerage; waste management and remediation activities’ and section ‘manufacturing’. The growth in jobs is mainly a consequence of a growth in section ‘administrative and support service activities’, ‘wholesale and retail trade repair of motor vehicles and motorcycles’, and ‘manufacturing’. The decrease in 2020 is mainly a consequence of a decrease in ‘administrative and support service activities’ and ‘manufacturing’. The second dataset (1–3 NACE) in Fig. 5 again displays a higher diversity in sectors. Besides sections ‘wholesale and retail trade repair of motor vehicles and motorcycles’, ‘manufacturing’, ‘water supply; sewerage; waste management and remediation activities’, and ‘administrative and support service activities’, we also see a high number of circular jobs in section ‘public administration and defense; compulsory social security’.

5. Discussion

5.1. *An indicator for circular companies*

In the results, we see that the number of circular companies deviates from existing estimations based on the current NACE codes (the baseline). When we only look at companies who should have a circular

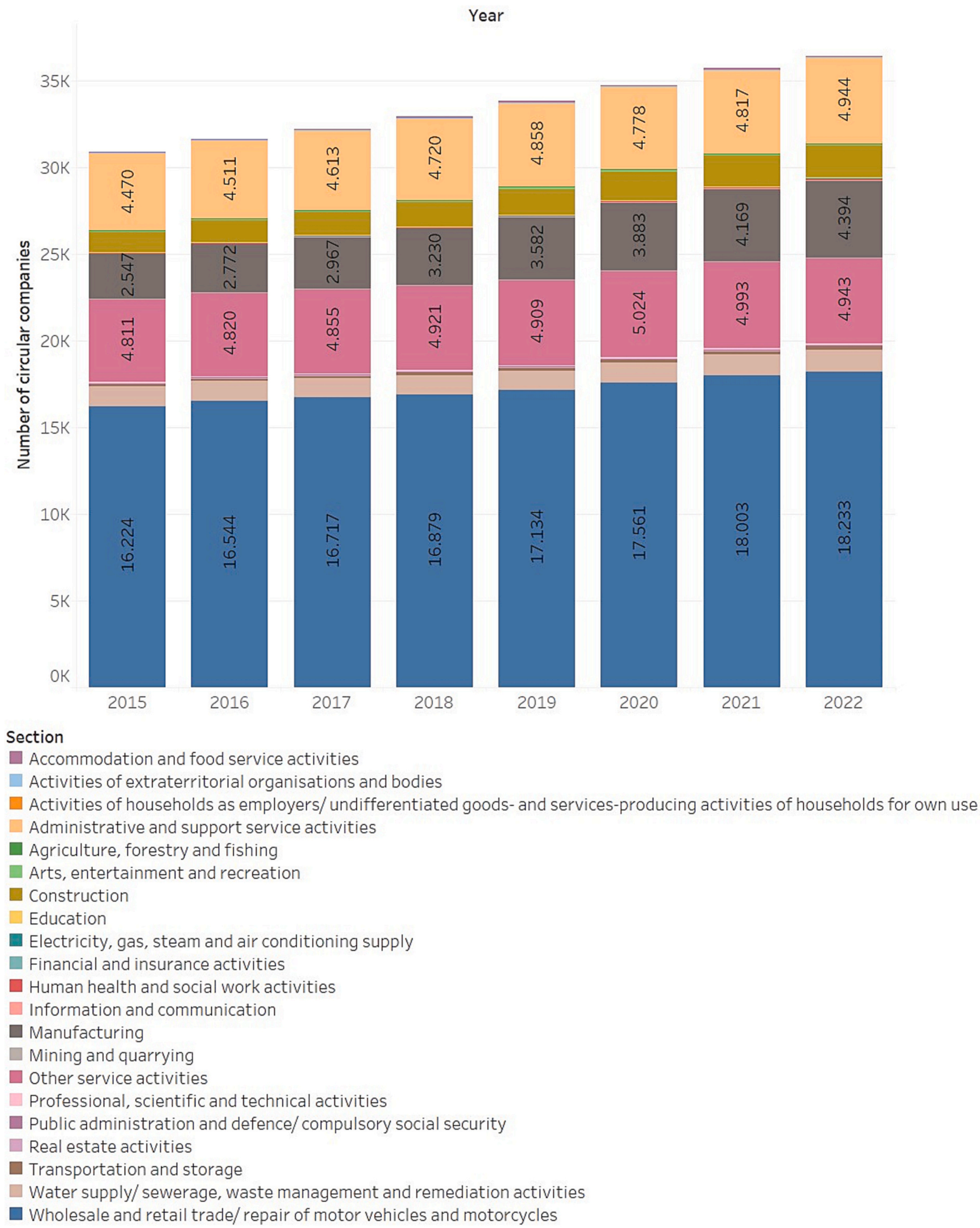

Fig. 2. Number of circular companies from the first dataset (1 NACE).

primary NACE code, we see that our estimations are lower than the baseline. The reason for this is that the negative correction is larger than the positive correction. The negative correction refers to the number of companies which officially have a circular NACE code but should not have that primary code according to the algorithm. The positive correction refers to the number of companies who do not have an official circular NACE code but should have such a code. When we only correct the primary NACE codes according to companies' websites and Facebook pages, fewer companies seem to perform a circular activity compared to the official statistics.

On the other hand, when we also consider the second dataset (1–3 NACE) which also takes the second and third official NACE codes into account, we notice an increased number of circular companies compared to the baseline. We conclude that companies often undertake circular activities on the side and companies do not sufficiently value the use of the different codes, nor are circular activities sufficiently captured in these codes (Battiston et al., 2022). Christensen (2013) checked this claim for Danish firms and found that 94 % of the firms assigned only

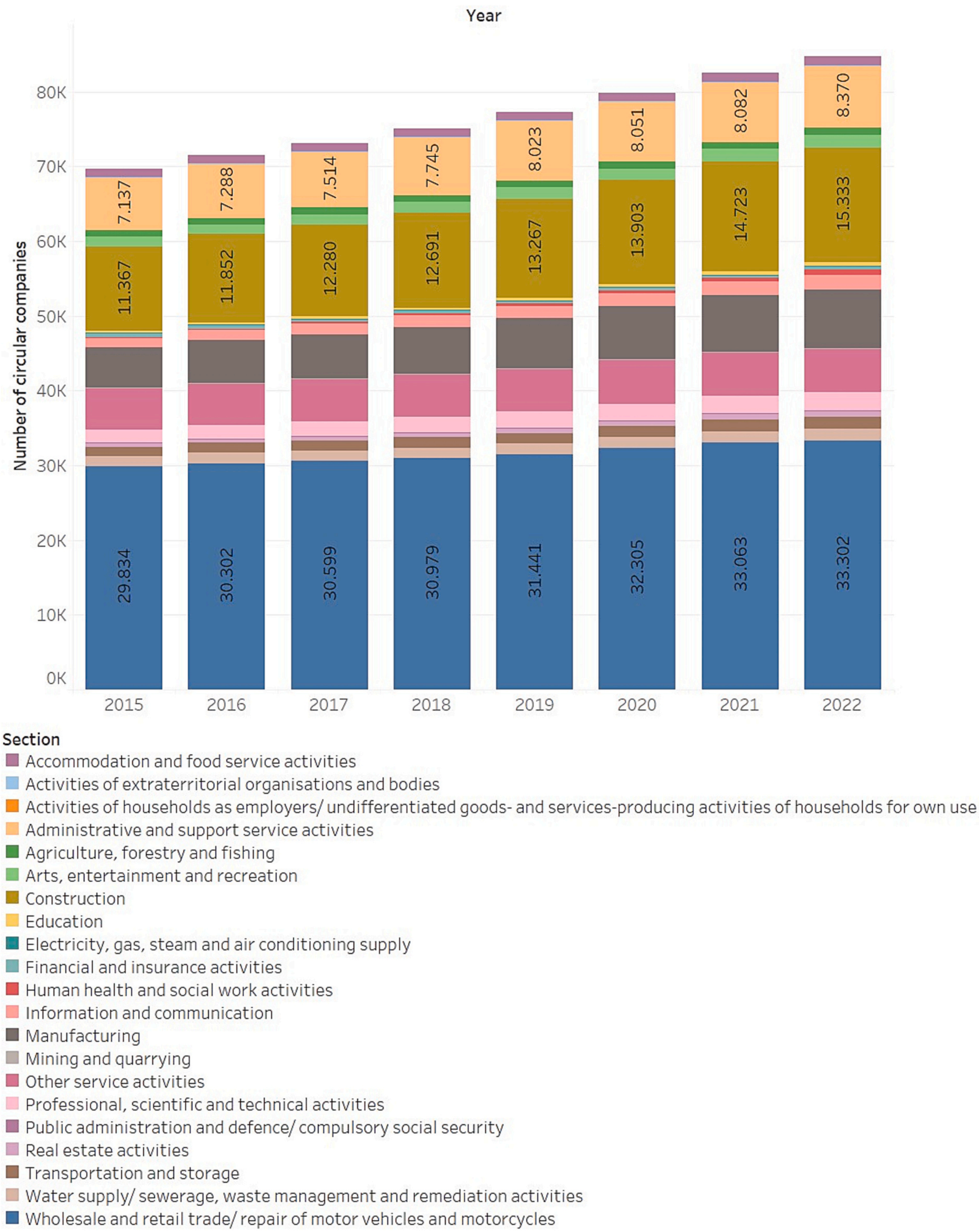

Fig. 3. Number of circular companies from the second dataset (1–3 NACE).

one NACE code while less than 1 % reported more than two NACE codes. Therefore, it is important for policy design, policy measures and policy analysis to consider multiple corrected NACE codes instead of only considering the primary NACE code and it is important for companies to update their NACE codes regularly (VLAIO, 2023a). For example, a company selling electrical products may also offer repair activities for customers with broken products. This company will typically have a primary NACE code in retail and maybe a related second or third NACE code. If policy measures would be targeted at stimulating repair activities, these companies will not be targeted if they did not update their NACE codes to include their repair activities or they will not be targeted if only the primary NACE codes are considered. Therefore, this research shows how policy measures for the CE might prove to be ineffective if they stay dependent on rigid classification systems which insufficiently capture circular activities. The web scraping data used in this research can assure a more accurate follow-up of economic activities if the data is updated regularly.

Regarding the number of circular jobs, in all datasets we see a

Table 5
Estimates for the number of circular jobs. Sources: NBB (2023); Willeghems and Bachus (2019).

	2015	2016	2017	2018	2019	2020	2021
Total number of employed people	4,617,700	4,675,400	4,748,200	4,818,200	4,895,100	4,898,300	4,989,300
Baseline circular jobs	63,253	66,382	68,422	70,947	74,296	75,182	77,162
Dataset 1 (1 NACE) – circular employment	111,840	113,455	116,424	118,309	121,870	120,303	120,690
Dataset 1 (1 NACE) – weighted circular employment	82,784	83,952	86,182	87,590	90,268	89,104	89,348
Dataset 2 (1–3 NACE) – circular employment	317,646	320,297	325,438	329,470	335,376	333,199	335,619
Dataset 2 (1–3 NACE) – weighted circular employment	136,670	138,122	140,947	142,927	146,250	144,947	145,718

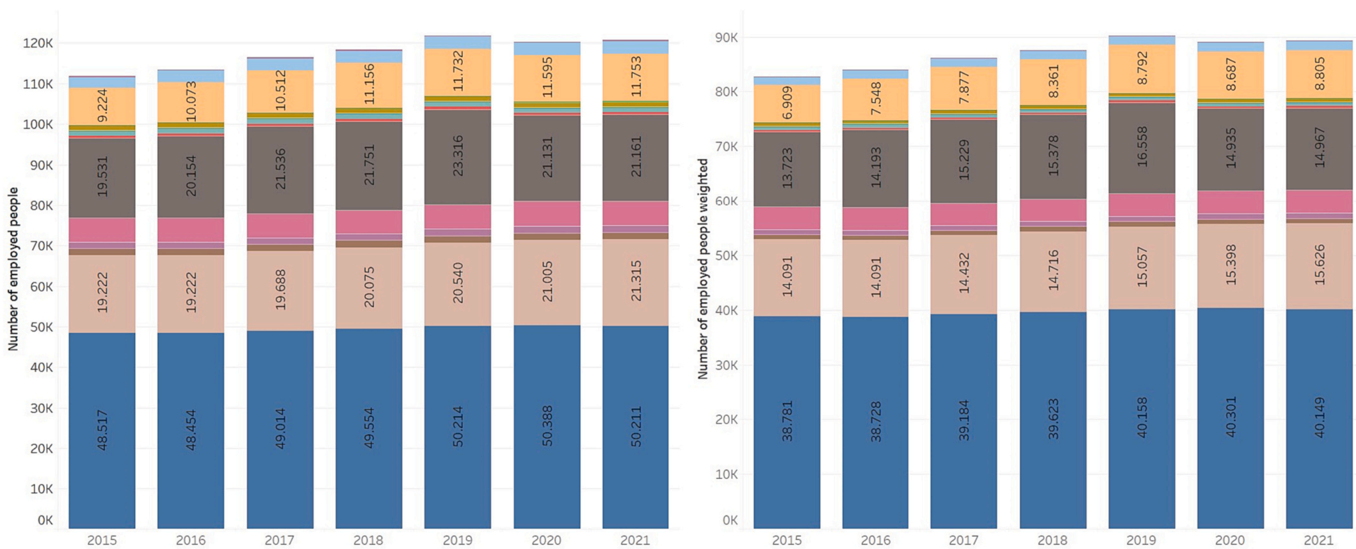

Fig. 4. Number of employed people unweighted (left) and weighted (right) from the first dataset (1 NACE).

decrease in circular jobs in 2020 during the COVID-pandemic, although there is no decrease in the total number of employed people in 2020 nor in the baseline estimations. This observation is confirmed by CE Center (2023), who observed a decrease in the Flemish indicator for the number of circular jobs and the turnover in the circular economy while simultaneously witnessing an increased turnover of the total Flemish economy in 2020. However, this statement requires further research since this result contradicts the results of Borms et al. (2023a) who showed that circular companies have a significantly higher resilience score than less circular companies. The method in this paper does not allow to conclude that there is a decrease in circular jobs during COVID, we can only deduce with certainty that a sector with a relatively high percentage of circular jobs has been affected by the pandemic.

The employment effect in the CE is an important part of the social role that the CE plays. Aguilar-Hernandez et al. (2021) analyzed 300 CE scenarios in their large literature review and structured the macroeconomic and social results of the CE by 2050. However, with “social results”, they only incorporate employment effects. Several authors have estimated the increase or decrease in employment caused by the transition to a CE. Dubois and Christis (2014) for example estimated an Input-Output model and that a CE would create 26,573 jobs in Flanders, which is more than 1 % of the total Flemish employment. For Europe, Cambridge Econometrics (2018) used an econometric model E3ME and estimated that a CE would generate 700,000 jobs in Europe by 2030, on top of the already 4 million jobs in 2018. When we look at the contents of the job, Borms et al. (2023c) used survey-based research and found that several circular strategies will require more technical skills, IT skills, logistics, and R&D. Borms et al. (2023b) on the other hand used macroeconomic modelling and found that most circular skills are related to typical investment sectors, such as construction and services, and to the targeted sector. A different type of employment impact was researched in Van Opstal and Borms (2022) where the effect of circular strategies was analyzed for collaboration between startups and Work Integration Social Enterprises.

Other social dimensions of the CE not related to employment include, among others, the sharing economy and participative democratic decision-making (Korhonen et al., 2018). According to Millar et al. (2019) the current framework of the CE could contribute to several SDGs, although the link is currently weak, especially with the social dimensions of the SDGs. Schroeder et al. (2019) analyzed the link between the CE and the SDGs, and found that the link is strongest for SDG 6 (Clean Water and Sanitation), SDG 7 (Affordable and Clean Energy), SDG 8 (Decent Work and Economic Growth), SDG 12 (Responsible Consumption and Production), and SDG 15 (Life on Land). The current weak link explains the limited focus on social aspects beyond employment. Also Padilla-Rivera et al. (2020) and Mies and Gold (2021) found that the current CE framework does not include social well-being and human rights for this generation and the next. From another perspective, CE can also be linked to spatial planning and sustainable communities, such as by Vanhuyse et al. (2021) who researched the social impact of the CE in cities.

5.2. Limitations and further research

The previous results clearly show the importance of a correct and uniform data collection for four reasons: (i) to develop indicators which reflect reality, (ii) to develop indicators that allow to track the evolution over time, (iii) to be able to target the appropriate groups with policy measures, (iv) to be able to target the relevant groups for education. In this section we further explain these four reasons and show how our research improves the current data collection, its limitations, and improvements for future research to strengthen the dataset and our current understanding of corporate communications on CE.

For the first reason to develop indicators which reflect reality, we

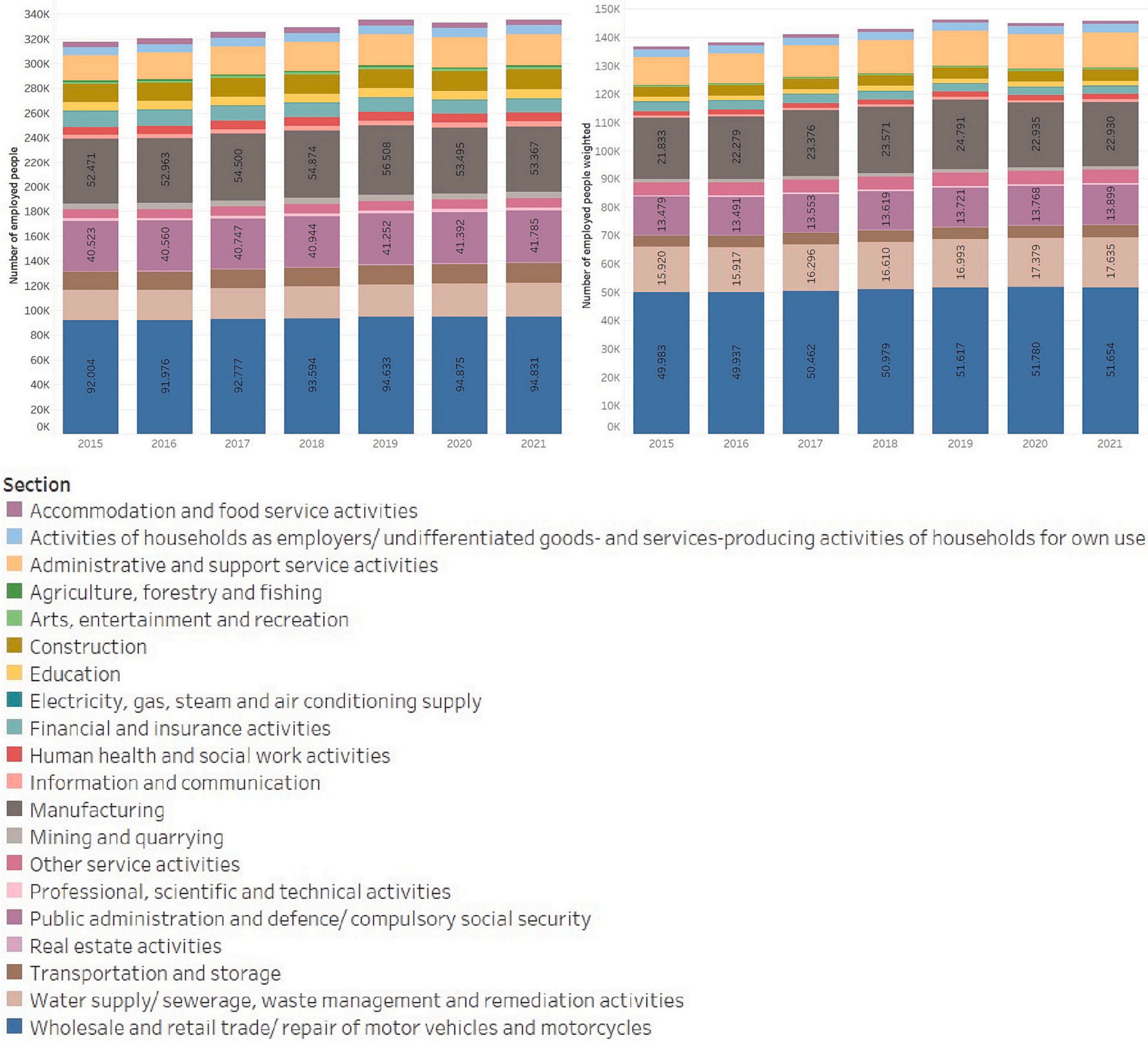

Fig. 5. Number of employed people unweighted (left) and weighted (right) from the second dataset (1–3 NACE).

discuss that the current NACE codes are not always clear for companies since they do not always choose the correct code, or they do not update their NACE codes over time (Battiston et al., 2022). Our research aims to improve these NACE codes with a focus on circularity. However, this research continues to use the NACE classification system which does not sufficiently capture circular activities and the list of circular activities by Willeghems and Bachus (2019) is rather an oversimplification. For example, product-service systems, refurbishment, and the sharing economy are not included in the NACE codes and therefore, companies that employ servitization have to choose the most relevant code for their activities, which will not reflect circularity. Other authors in different research fields found similar problems, for example Russo et al. (2022) acknowledge that the Internet of Things are not sufficiently captured by NACE codes, as well as activities related to renewable energy or sustainability (Battiston et al., 2022). Also, a company may choose the correct activity, but might offer both linear and circular activities within this activity. Our research builds upon the methodology of Willeghems and Bachus (2019) with a strong limitation of the rigidity of the codes. Future research could analyze the scraped words in the context of which circular strategy they represent. That way, we could adapt the NACE codes to reflect reality, or we could go beyond the NACE codes and towards a new classification of sectors based on their implemented circular strategies.

We follow Moraga et al. (2019) and acknowledge that we require a set of indicators to assess the CE instead of one single indicator. This research illustrates an alternative method to calculate two macroeconomic indicators. However, in policy context, also these two macroeconomic indicators should be analyzed in combination with other indicators. Furthermore, Valls-Val et al. (2022) pose that a lot of indicators have been set at the macro level but at the organizational level companies also need indicators to know their level of CE implementation so they can evaluate and communicate these results. This type of indicators is currently not reported in a coherent and structured manner.

Our previous proposed solution to analyze the scraped words in the context of which circular strategy they represent could be used to build indicators at the organizational level for corporate communication on CE. Another solution is reporting standards. Several reporting standards already exist, such as the Corporate Social Responsibility Directive (CSRD), the Global Reporting Standards, or the ISO standards (European Commission, 2023a; Global Reporting Initiative, 2020; International Organization for Standardization, 2023). However, the first one will only become operational for a selection of companies from 2024 and the results can be consulted from 2025 onwards, the second one is voluntary and the third one is still under development. We argue that these reports should include an official mission and vision statement from the company, which will eliminate uncertainty and greenwashing on websites and Facebook pages. These reports should include several elements related to sustainability and the CE, such as their production technology, the link with their social impact and the SDGs. In the absence of reporting standards, Caferra et al. (2023) used a mixed-methods approach to analyze corporate communication on LinkedIn and found that, in line with previous literature, Italian companies report on three main themes: sustainability (environmental, economic, and social), technology, and production and consumption. This research proves the need for a combination of indicators to assess multiple perspectives. Furthermore, we argue that this can be stimulated by enforcing official reporting obligations to improve data collection, away from social media data.

Secondly, a uniform and correct data collection is necessary to develop a time series. Currently, the web scraping data is real-time data taken as a snapshot on a certain point in time. Therefore, this type of data collection can be repeated at several points in time, for example every year, so that the circularity scores can be updated every year. With a frequent repetition of the web scraping and NLP analysis, we would be able to develop an indicator that guarantees the follow-up of the evolution over time. At present, the macro-economic data gathered via the NACE codes is often only available on annual or multi-annual basis. Hence, the prospect of more frequent updates would also allow to better check the respondence to specific events such as the link between circular strategies and resilience during the COVID-pandemic (Borms et al., 2023a), and increase responsiveness of policy to such shocks. Another specific policy measure is the Right to Repair by the European Commission, which consists of common rules promoting the repair of goods (European Commission, 2023b). It is expected to increase the number of companies performing repair and to increase the amount of repair performed by companies which are officially in retail or manufacturing sectors. Therefore, for this example, we expect an increase in the circularity scores for manufacturing and retail companies. We conclude that a repetition of this study is needed to update the circularity scores to calculate the number of circular companies and jobs in a non-linear way.

This brings us to the next reason of targeting the appropriate group with policy measures. Our results show some noteworthy deviations from the results of current research and it is important to get an understanding of the diverging effects to know if the current policy measures for the CE are effective. For example, Tsironis et al. (2022) found in the literature that the manufacturing sector has significant barriers to engage in circularity, while our research suggests that the manufacturing sector has high circularity scores of between 5.48 % and 13.53 %.

Furthermore, we note that our research also contains some limitations for targeting the appropriate group. Companies self-report their NACE codes, but also self-report their websites and Facebook pages. Therefore, a company doing greenwashing will have a higher circularity score in our results. In the same manner, a website that mentions that they do not perform a circular activity, will also result in a match with the word cloud of a circular sector.

Finally, we discuss the fourth reason of targeting the appropriate groups for education. Janssens et al. (2021) organized a focus group with experts in Belgium and found that there is a lack of attention towards skills for product design and knowledge about the principles of the CE. They see a role for the higher institutions for education. One such way for higher institutions to offer courses on the CE, is given by Kirchherr and Piscicelli (2019). They developed a course for the most ambitious bachelor students at the Faculty of Geosciences at Utrecht University. However, since we showed the breadth of the CE across sectors, a broad general understanding of CE across the workforce/education could help seems to be equally necessary. For that purpose, several educational tools exist to inform the wider population of the CE. Examples are Serious Games (Manshoven and Gillabel, 2021; Roba et al., 2021; Whalen et al., 2018), Hackatons (Puttonen et al., 2022), and Massive Open Online Courses (MOOCs) (Peck et al., 2020).

6. Conclusion

This paper presents an innovative way to define the companies with circular activities which allows to develop macroeconomic indicators for the CE with web scraping data. The web scraping data is used to construct weighted and unweighted circularity scores per NACE sector in order to correct the officially declared NACE codes. The circularity scores are subsequently used to estimate the number of circular companies and jobs between 2015 and 2021. The results show that the baseline estimates from the number of circular companies and the number of circular jobs are lower than our estimates with web scraping data.

This research is highly relevant for policy makers and educational institutions to correctly estimate the size of their target groups. It shows how policy measures for the CE might be ineffective if they stay focused on rigid classification systems which insufficiently include circular activities. Some key suggestions for policy makers are expanding the set of NACE codes to include a wide range of circular activities, and to base policy measures on a set of indicators and a set of NACE codes to include side activities. Furthermore, future research should be facilitated to repeat the current study at different points in time to update the circularity scores, and to capture the effects of events.

Declaration of competing interest

No potential conflict of interest was reported by the authors.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.spc.2024.02.007.

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