Employment growth and the establishment of bio-refineries in the EU

March 2021 (M34)

D8.3: Case study "Bio-refineries sector"

Authors: Xinqi Zhu (TUM); Maria Vrachioli (TUM); Baldoni Edoardo; Robert M'Barek (JRC); Johannes Sauer (TUM)

Monitoring the Bioeconomy

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[1] PU = Public
PP = Restricted to other programme participants (including the Commission Services)
RE = Restricted to a group specified by the consortium (including the Commission Services)
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Document history

V	Date	Beneficiary	Author

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0 Summary

The European Commission aims to achieve climate-neutral economy by 2050 and retain the employment growth rate while reducing fossil-based production activities for each member state. Bio-refineries are considered to contribute towards this goal of the EU. This study carries out an in-depth investigation on the impact of bio-refineries on the employment rate, and other socio-economic indicators. This study contributes to the field of bio-refinery research in two ways. First, the difference-in-difference (DiD) methodological framework is applied for the first time to analyse the impact of bio-refineries on employment in a local context. In addition, a novel approach of incorporating non-binary treatment effects into the DiD model is used to provide a robust estimation of the marginal economic effects of bio-refineries. Second, this study uses a unique regional level dataset provided by EU JRC and the EH H2020 BioMonitor project to examine the impact of the bio-refinery industry on local employment. This dataset covers multiple European Member states and enables us to account for regional characteristics to assess the effects of the bio-refineries sector on the local employment. Based on our research hypothesis, previous studies might have overestimated the impact of bio-refineries on local employment by disregarding the substitution effect between fossil- and bio-based employment.

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1 Introduction

Diminishing petroleum resources and increasing greenhouse gas (GHG) emissions are critical issues for the sustainable development of humanity given the growing population and the per capita energy demand. To tackle these issues, the concept of bioeconomy, which was originally introduced by Enriquez (1998), has received the policy maker's attention. The concept of bioeconomy highlights the importance of utilizing different renewable biological resources and converting them into high-value bio-based products such as food, feed, biochemical products, and bioenergy (European Commission 2018). As summarized in the BioMonitor Deliverable D1.1, this emerging economy based on biomass is a complex system and requires a comprehensive system analysis.

The concept of bioeconomy has been popularized since the latter half of the 2000s (Fund et al., 2015). Various regions around the world have designed and adopted different strategies for promoting the bioeconomy. For example, the European Union published the report "A bioeconomy strategy for Europe" in 2012 and updated it in 2018. The U.S.A. published their report "National Bioeconomy Blueprint" in 2012.

2 Connection with other BioMonitor tasks

The ultimate goal of the BioMonitor project is to establish an efficient and robust statistical and modelling system for monitoring the bioeconomy in EU and consequently promoting its sustainable growth. The objective of work package 8 (WP8) is to test, validate, and fine-tune the operationalization of the three pillars of the BioMonitor project (design bioeconomy monitoring framework, develop bioeconomy data platform, and formulate bioeconomy modelling tool) and to provide feedback on possible improvements and recommendations for future implementation. WP8 aims to reach its objective via seven different case studies. Sector-specific and cross-sectorial cases have been strategically pre-selected to support the replication logic and the external validity of the research design. Task 8.2.2 focuses on the sector-specific case of bio-refineries, one of the key drivers of bioeconomy, to assess the impact of the establishment of bio-refineries on economic indicators such as the number of people employed.

The expected outputs of this case study that can contribute towards the WP8 objectives include:

- Lessons learnt and best practices for data collection;
- Testing and validation of bioeconomy indicators identified by Deliverable 1.1;
- Cross-validation of the BioMonitor Model Toolbox output.

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Table 1 presents the expected outputs of this case study related to the expected output identified by Deliverable 8.1. This case study contributes to the validation of the indicators that have been selected in WP1 and the data that have been collected in WPs 2 and 3. This case study will not provide new data for the models to be improved, extended, and/or newly developed as part of the BioMonitor Model Toolbox. Lastly, this case study will validate the BioMonitor Model Toolbox output at a regional level.

Table 1 – Case Studies in the BioMonitor Project and Outputs

	Sector-specific cases
Output	**Bio-refineries**
Validation of indicators and data collection	X
Providing data for models in BioMonitor Model Toolbox	
Validation of outcomes of BioMonitor Model Toolbox	X

3 Justification of research approach

In 2019, the European Commission announced the “European Green Deal” with an ambitious goal to be climate neutral by 2050, which means the amount of greenhouse gas emitted to the environment should be equal the amount of greenhouse gas absorbed by plants or buried underground by carbon removal techniques. This raised the concern of slowing down the economic growth for the EU member states, as they may have to constrain their highly polluting industries, which are energy-intensive and fossil-based. For example, the industries of steel, chemicals and cement are indispensable to Europe’s economy, as they supply several key value chains, hence, the main source of employment and economic growth. According to the European Green Deal, the European Commission claimed that decarbonisation and modernization of these sectors are essential. A potential plan is to replace fossil-based inputs in these industries with bio-based inputs. The new bio-based industries will take up the jobs of fossil-based industries and produce in a more environmentally friendly and sustainable way.

However, given the different supply chains for fossil-based and bio-based productions, the employment growth of the two types of production cannot be assessed by a trivial substitution. When replacing fossil-based production with bio-based, this might bring up competition for labour, capital, and market share in a region. Hence, despite bio-refineries can provide a certain amount of direct and indirect employment for the region, they might also eliminate some employment in the region that was previously related to fossil-based industries. For this reason, it is of great importance to understand how the establishment of bio-refineries in a region can affect the local employment.

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4 Research question

The key research question for this case study is **how establishing and operating a bio-refinery will influence employment at the regional level**. Bio-refineries are known as "an overall concept of a processing plant where biomass feedstocks are converted and extracted into a spectrum of valuable products" or "the conversion of biomass feedstock into a host of valuable chemicals and energy with minimal waste and emissions" (EU bioeconomy glossary item). Given this definition, it is widely believed that bio-refineries can promote economic growth in the rural region (Lehtonen and Okkonen, 2013). This is because the bio-refineries sector develops new feedstock processing chains for various types of biomass. For example, scattered wood chips, which previously treated as waste, can now produce energy and materials (Bailey et al., 2011). This new value chain creates new employment opportunities since it requires new technology, a new supply chain, and rising demand for wood feedstock (Thornley et al., 2013). However, at the same time, it might reduce the employment opportunities in other sectors that are involved in fossil-based production. The provision of bioplastic and biofuel constitutes another example of bio-refineries that aim to replace conventional plastic and fuel. While these new activities may increase the labour demand for the new biobased value chains, at the same time they might introduce job losses in the fossil-based counterparts of these sectors. Hence, the overall impact of establishing and operating bio-refineries on a such socio-economic indicator remains ambiguous.

Consuming indigenous biomass helps the bio-refinery to reduce its production cost by lowering transport costs and feedstock prices. For this reason, the establishment of bio-refineries have a significant impact on the local region (Cambero and Sowlati, 2016). Many studies tried to investigate the potential employment impact of bio-refineries based on industrial expert interviews. Thornley et al. (2008) investigated power only bioenergy systems and he found that they generate 1.27 worker per GWh of electricity produced regardless of technology or scale of implementation. This employment impact rises to 2 workers per GWh of electricity produced when estimating the heat and power system together. Another group of studies constructed theoretical models that assess the employment impact of the bio-refineries sector. These studies apply either an input-output or a linear programming model to simulate the impact of bio-refinery on regional employment (Bailey et al., 2011; Heijman et al., 2019; Lehtonen and Okkonen, 2013). They concluded that despite the job created by a single bio-refinery might be moderate (around 50-300 direct jobs), the indirect employment generated by the facility can be 10-100 times more direct jobs.

Direct employment in this study includes the number of workers who are hired by the bio-refinery company to operate and maintain processing machines, managing the facilities etc. Indirect employment includes jobs in the upstream and downstream supply chain devoted to supply the necessary inputs and services for the bio-refinery. For example, contractual farmers who produce feedstock for the bio-refinery plant, delivery companies that transport feedstock, machinery companies that produce and maintain the biomass processing machinery, and advertising companies that promote the bio-based products.

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4.1 Literature review on bio-refineries impact on employment

Heijman et al. (2019) investigated the bio-refinery impact on rural employment in Hungary using a regional input-output model (NUTS3 level). The bio-refinery that they investigated located one hundred kilometres from Budapest. It was constructed in 2010-2011 and processes corn into bioethanol, animal feed, corn oil and other bio-based materials. The feedstock for this bio-refinery is sourced from the nearby regions of Fejér and Tolna, which are the major corn-growing regions. The major economic activities in this region are farming. Heijman et al. (2019) found that the operation of the bio-refinery helps to create employment opportunities not only through direct employment at the facility but also create and maintain jobs in farming and service industries. According to their study, the bio-refinery employed 172 people directly and created more than 5000 jobs indirectly. Hence, they believe bio-refineries can make a significant contribution to rural development.

Thornley et al. (2014) estimated the potential impact of EU bio-refinery on employment in 5 EU member states including Germany, the Netherlands, Poland, Spain and the United Kingdom using a process synthesis methodology. They focused on the biomass processing facilities that process two types of biomass, straw and softwood. In their analysis, they identified 27 process options and estimated their employment impact from its design to the construction stage to the operation stage. They also measured the direct employment and indirect employment (in the paper this was defined as induced employment) generated during these stages. The amount of employment required for each biomass processing option was measured in the unit of man-year. Process 19, which converts straw into surfactants, 2,5-Furandicarboxylic acid (FDCA), and dry lignin product, generates the highest man-year which can go up to almost 70 thousand man-years per facility. This number can be disaggregated into the direct employment at the process plant contributing over 10 thousand man-years, the direct employment in agriculture sector accounting for over 15 thousand man-years, the direct employment in the supply and logistics sector contributing roughly 10 man-years, and the induced employment was assessed to be 30 thousand man-years. However, process 19 does not provide the highest rate of return among the processing options examined by the authors. Despite the economically viable cases that do not generate as much man-year as process 19, they still generate around 25-50 thousand man-years per facility. Given the straw and softwood biomass availability, the authors estimated that up to 24 bio-refineries can be established in the targeted region they selected, which in total can generate 1.4 million man-years of employment. Roughly, one third to half of this employment was created for plant operation activities, which can be considered as long-term employment. Hence, they concluded that bio-refineries can make a significant contribution to employment generation.

Studies targeting regions outside the EU also reached a similar conclusion. Bailey et al. (2011) projected the impact of establishing 6 lignocellulosic bio-refineries each with an annual

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production capacity of 189 dam3[1] on local employment in the US using IMPLAN[2], an input-output model. They estimated that 2666 new jobs will be created in Alabama with 891 of them sourcing from the logging sector and 1217 being indirect jobs sourcing from other sectors that have a connection with the logging sector. While more people being employed, 588 more jobs can be created to satisfy the increasing demand of worker's needs such as food and services. The authors also did a comparative analysis by changing the location of the envisaged bio-refineries to regions characterized by both abundant timber resources and persistent rural poverty. They concluded that regions with homogeneous economic activities enjoy a greater benefit in output, employment, income, and indirect business taxes compared to regions with a more diverse economic activity.

Cambero and Sowlati (2016) developed a multi-objective mixed-integer linear programming model to quantify the potential social, economic, and environmental impacts of constructing forest-based bio-refineries to the interior region of British Columbia, Canada. They found that by optimizing different objectives, such as net present value, GHG emission savings, social benefits, or total job creation, the number of jobs created also can vary. Maximizing total job creation generates the highest amount of new jobs (239 jobs), followed by maximizing social benefits (238 jobs), GHG emission savings (203 jobs), and net present values (82 jobs). The majority of the created jobs were for entry-level jobs such as logging machinery operators, heavy equipment operators, and truck drivers. Since the entry-level jobs retain a high unemployment rate in British Columbia, the authors believe jobs created by the bio-refineries can potential be of great significance for the region.

5 Context

Biorefinery technology and innovations

Currently, the common classification of the types of bio-refineries is based on three of their main features: products (energy products, material products); feedstock (dedicated crops, residues); and technology processes (thermochemical, biochemical, chemical and mechanical processes) (IEA, 2019).

The technology readiness level (TRL) varies across different types of bio-refineries with higher TRL representing more mature technologies. Conventional bio-refineries, which utilize starch and sugar, have the highest TRL level 9. Oleochemical bio-refineries that utilize oil crops have the second-highest TRL level ranging from TRL 7 to 9. Whole crop bio-refineries, which use whole crop cereals such as rye, wheat and maize, can reach a TRL level that ranges from 7 to 8. Lignocellulosic bio-refineries that are based on lignocellulosic rich biomass such as straw, chaff, reed, miscanthus, and wood could potentially reach aTRL level between 6 to 8. Green bio-refineries whose activities are based on wet biomass such as grass, lucerne and clover, and sugar beet leaf can characterized by TRL levels of 5 to 7. Marine bio-refineries that process

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[1] dam3 = Cubic decametre

[2] Economic Impact Analysis for Planning (IMPLAN) is a sophisticated economic input-output model use to evaluate the impact of forest management on rural development. URL: https://blog.implan.com/what-is-implan

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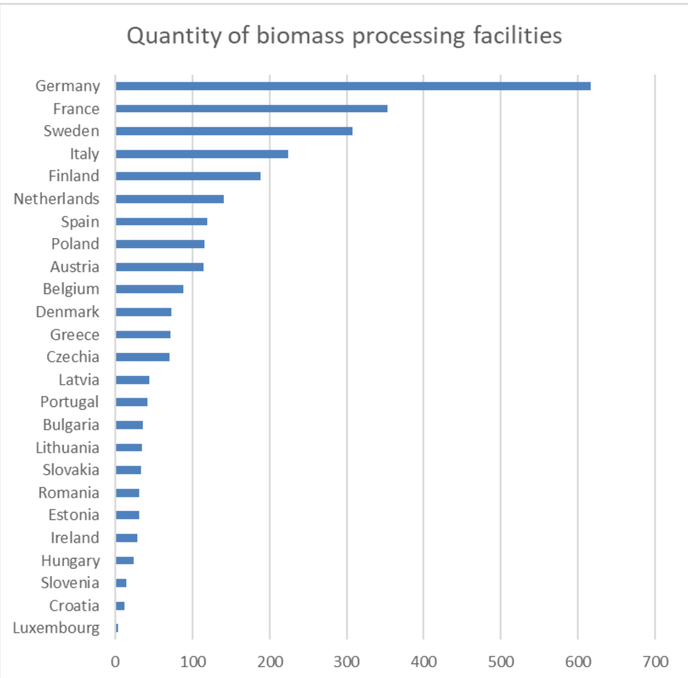
aquatic biomass (mainly microalgae and macroalgae) have the lowest TRL level ranging from 5 to 6.

Bio-refineries can mix and match the aforementioned feedstocks for their production porcesses. Hence, utilizing single/multiple feedstock(s) to produce single/multiple product(s) can be possible. According to the IEA TEE assessment of bio-refinery concepts (2019), utilizing single feedstock helps bio-refineries maximizing their economy of scale. Sugar, pulp and paper industries can be some good examples of single feedstock bio-refineries. These bio-refineries have a similar production concept compared to oil refineries. Hence, they are characterized by large production sizes and have high margins of economic profitability. Bio-refineries utilizing multiple feedstocks are the opposite of the single feedstock bio-refineries and mainly utilize biomass available locally. These multiple feedstock bio-refineries help to fill the gaps in biomass utilization.

Bio-refineries' market organization

The JRC DataM biorefinery database (2020) identified 2362 biomass processing facilities among all EU member states including pulp and paper, bio-methane (used mainly as the feedstock for biogas production), starch and sugar, bio-based chemical, timber, liquid biofuels, and composites and fibres. Some facilities produce multiple products. The majority of them (92.5%) are at the commercial scale and the remaining are pilot/demonstration plants. R&D facilities occupy only 1.8%. Most of the facilities are located in Germany (617), France (353), and Sweden (307) (Figure 1). In terms of the density of biomass processing facilities, the Netherlands, Belgium and Germany rank top three within the EU (Figure 2).

Figure 1: Number of biomass processing facilities in the EU



Source: JRC DataM Bio-based Industry (https://datam.jrc.ec.europa.eu/datam/mashup/BIOBASED_INDUSTRY/index.html)

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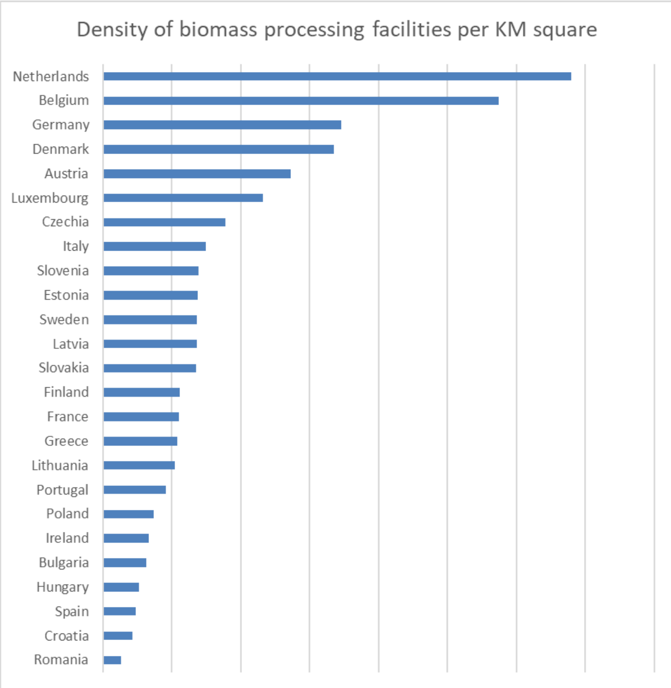
Figure 2: Density of biomass processing facilities per square KM in EU



Source: JRC DataM Bio-based Industry (https://datam.jrc.ec.europa.eu/datam/mashup/BIOBASED_INDUSTRY/index.html)

Bio-refinery economic impact

According to the EU bioeconomy job and wealth data from the JRC DataM database, the EU bioeconomy sector employed 2.56 million workers in 2017 (Ronzon et al., 2020). The EU bioeconomy sector includes bio-based textiles, wood products and furniture (including paper), bio-based chemicals, pharmaceuticals, plastic and rubber, liquid biofuel and bio-based electricity. Together they generated €136 billion value-added and over €462 billion turnovers. These figures were estimated based on the NOVA bio-based share and Eurostat business statistics.

5.1 Data collected

This case study adopted a holistic single case design defined in BioMonitor Deliverable D8.1. We investigated the bio-refinery sector development across all EU member states. We used the information about the year of establishment of bio-refineries within Europe from JRC. There are 1005 biorefineries in the database, which produce bioenergy, bio-methane, biochemical, biofuel, and bio-based components. We excluded the sugar, and pulp and paper industries in this case study since these conventional bio-refineries do not initially aim to replace fossil-based production. Many of them have also been established before the concept of bioeconomy emerged.

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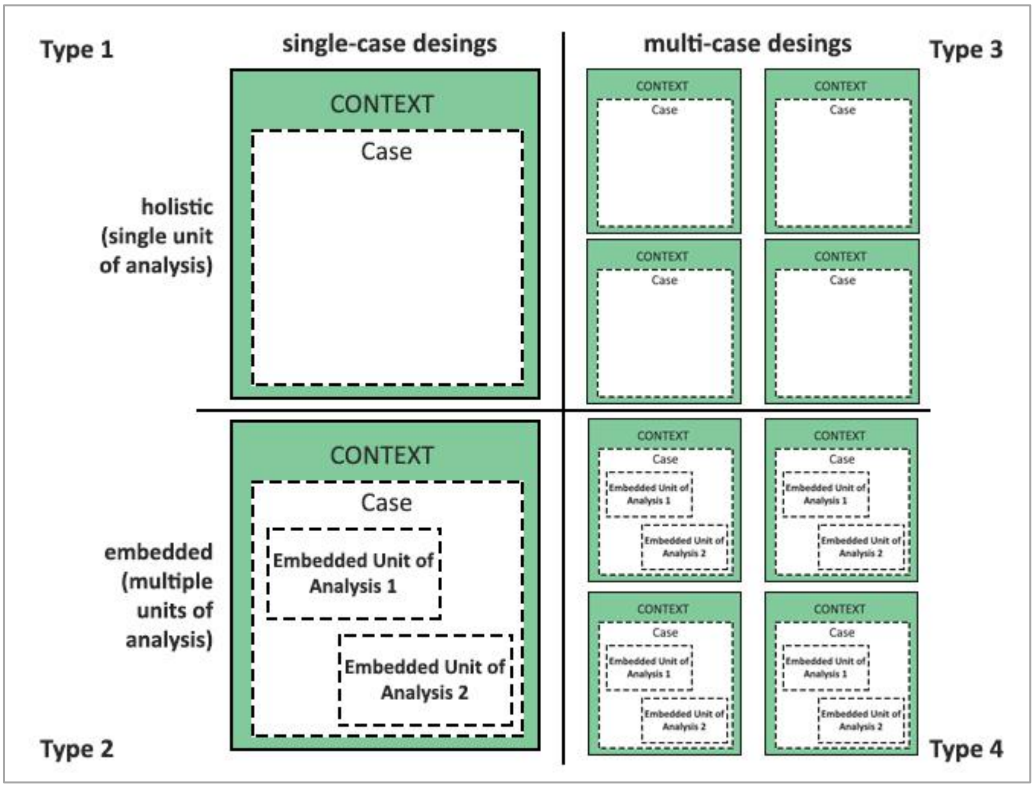
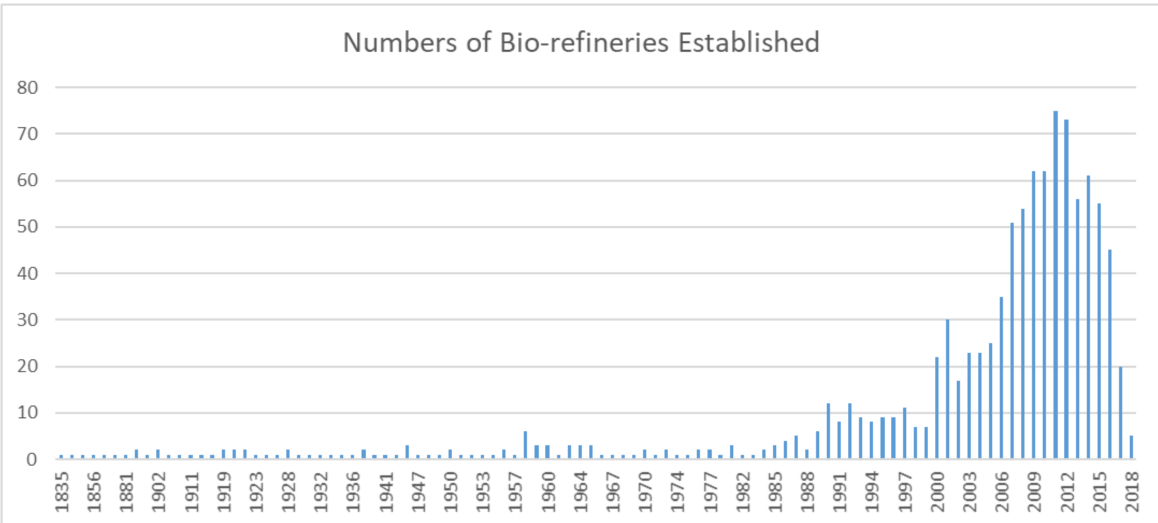
Figure 3: Types of Case Studies Designs



Source: BioMonitor Deliverable D8.1

Figure 4: Biorefineries



Source: JRC owned database

Figure 4 shows the year of establishment of all the bio-refineries that produced bioenergy, bio-methane, biochemical, biofuel, and bio-based components within our database. Before the concept of bioeconomy was introduced and established, there were a few bio-refineries that were established. Hence, their impact on regional employment considered as very limited. The number of bio-refineries established has prompted after 2000 and reached its maximum in 2011 where 74 bio-refineries were established only that year. For this reason, we

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are more interested in the employment impact introduced by the bio-refineries after 2000. This also concides with the period of interest for the BioMonitor project.

In the aim of isolating the causal effect of bio-refinery establishing on regional employment, we also control for other regional characteristics that might influence the regional employment. This includes population, disposable income, education, business birth rate and survival rate. These variables were selected based on a literature review that selected variables that may have an explanatory power on employment change (Biag and Lucifora, 2008; Fritsch and Schindele, 2011; Torp, 1994).

We also collected three additional variables on patents, motorways and railways since they are key determinants of where a bio-refinery can be located (Serrano-Hernandez et al., 2017). These variables were used for matching purposes in order to account for the possibility that some regions have a higher possibility to accommodate the needs of a bio-refinery establishement.

All the aforementioned variables were collected from the Eurostat at the NUTS 2/3 level. Table 2 presents a detailed description of these variables.

Table 2: Definition of Variables

Variable name	Unit	Description
Employment	Thousands of employees	Number of people employed for all NACE activities
Bio-refinery	Number	Number of bio-refineries established based on their year of foundation
Population	Thousands of people	Average annual population
Disposable income	EURO	Purchasing power index, per inhabitant
Education	Percentage	Percentage of economically active population with tertiary education (ISCED level 5-8)
Patent	Number	Number of patent applications per million inhabitants
Business birth rate	Number	Number of births of enterprises in t
Business survival rate	Number	Number of enterprises newly born in t-3 having survived to t
Motorways	Kilometres	Kilometres per thousand square kilometres
Railway	Kilometres	Kilometres per thousand square kilometres

Table 3 presents the descriptive statistics of the raw dataset. For each year from 2000 to 2018, we have a range of 192 to 240 observations. The mean employment for each year ranges from 753.88 to 857.41 thousand people. The mean number of bio-refinery establishments per year ranges from 0.01 to 0.25. This number was calculated by dividing the number of bio-refineries established in that year by the total number of observations. The mean population in our data for each year ranges from 1682.19 to 1851.12. The mean disposable income for each year ranges from 10745.6 to 15932.5, while the mean population with tertiary education ranges from 9% to 13%. The number of patent applications per million inhabitants stays between 103.92 to 129.46 applications per year with data not being available after 2012. The number

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of newly introduced bio-refineries per year is between 646.03 to 952.88 for the 2000-2018 period. The number of enterprises with at least a 3-year survival rate varies from 443.44 to 591.47. The data for business birth and survival rates were only available from 2008 onwards. The mean motorways kilometres per thousand square kilometres ranges from 27.24 to 33.35, while the mean railways kilometres per thousand square kilometres ranges from 55.8 to 79.23.

Due to the amount of data missing in our database, we aggregated NUTS 3 level data into NUTS 2 level. We then further filled the missing data with multiple imputation methods using Stata. Details of the multiple imputations can be found in the Appendix of this report. We imputed each observation 20 times and took the average of the results. The cleaned dataset contains 3421 observations, which covers 222 NUTS2 regions from 2000 to 2018. This is an unbalanced panel dataset since some regions do not have data available for each of the years within the period of interest. The maximum number of observations for each region is 19 with an average of 15.4. Table 4 presents the descriptive statistics after cleaning the dataset using the multiple imputation method.

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Table 3: Descriptive summary of raw data

	Obs	Employment	Bio-refinery	Population	Disposable income	Education	Patent	Business birth rate	Business survive	Motorways	Railway
2000	193	753.88	0.04	1682.19	10745.6	0.09	120.05	missing	missing	29.33	56.26
2001	193	760.6	0.07	1683.82	11262.69	0.09	110.86	missing	missing	29.88	55.8
2002	193	760.16	0.02	1686.39	11567.36	0.09	110.25	missing	missing	27.24	55.88
2003	193	763.77	0.07	1692.76	11948.19	0.09	114.23	missing	missing	29.11	57.12
2004	192	770.74	0.04	1706.62	12320.83	0.09	122	missing	missing	28.5	56.67
2005	192	778.3	0.05	1713.17	12753.13	0.1	124.94	missing	missing	28.07	72.63
2006	193	789.47	0.07	1710.83	13320.21	0.1	126.82	missing	missing	29.9	71.5
2007	193	804.66	0.07	1718.24	13833.16	0.1	129.46	missing	missing	30.43	69.57
2008	193	811.06	0.11	1725.6	14380.31	0.11	125.5	792.62	505.48	32.59	79.23
2009	193	793.77	0.18	1729.8	14072.54	0.11	124.87	646.03	485.66	32.99	71.34
2010	193	786.37	0.16	1732.28	14211.92	0.11	128.58	721.56	539.3	33.35	71.61
2011	193	785.53	0.25	1733.99	14405.18	0.11	128.09	730.97	529.84	31.65	72.04
2012	196	773.94	0.22	1710.2	14328.57	0.12	103.92	702.79	443.44	31.46	70.25
2013	196	770.05	0.2	1712.05	14397.45	0.12	missing	778.22	468.55	31.59	70.12
2014	196	776.89	0.17	1714.18	14595.92	0.12	missing	894.67	515.57	31.68	66.25
2015	223	812.5	0.13	1808.46	14973.99	0.13	missing	830.3	486.63	29.88	66.1
2016	240	832.17	0.1	1844.88	14965	0.13	missing	915.76	536.67	28.23	65.3
2017	240	845.66	0.03	1847.87	15436.25	0.13	missing	918.7	591.47	27.71	66.87
2018	240	857.41	0.01	1851.12	15932.5	0.13	missing	952.88	545.54	29.53	66.02

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Table 4: Descriptive summary of data processed with multiple imputations

	Obs	Employment	Bio-refinery	Population	Disposable income	Education	Patent	Business birth rate	Business survive	Motorways	Railway
2000	168	778.9	0.05	1735.22	11267.26	0.1	126.29	1138	660.31	31.95	81.72
2001	168	786.65	0.08	1737.31	11785.71	0.1	121.3	1117.55	650.28	32.93	82.59
2002	170	787.23	0.02	1737.84	12050.59	0.1	120.65	1133.78	655.65	31.46	81.88
2003	170	791	0.08	1745.04	12435.29	0.11	126.11	1149	662.08	32.63	81.41
2004	169	799.79	0.04	1759.98	12857.99	0.11	133.06	1117.25	649.46	33.2	80.45
2005	170	806.19	0.06	1764.29	13278.82	0.12	136.22	1125.58	653.38	32.6	86.39
2006	171	820.71	0.07	1768.78	13832.75	0.12	138.95	1101.52	641.68	35.15	88.29
2007	172	834.91	0.08	1774.03	14313.37	0.12	140.97	1124.48	660.58	35.57	86.06
2008	173	841.01	0.13	1778.13	14857.23	0.13	136.51	995.64	596.23	35.96	91.8
2009	174	826.68	0.2	1788.52	14503.45	0.13	132.94	909.62	587.64	35.71	86.75
2010	175	819.03	0.18	1788.86	14645.71	0.13	135.59	949.78	614.25	36.92	86.84
2011	176	819.01	0.27	1795.83	14817.05	0.13	133.81	974.43	618.06	36.29	87.54
2012	178	817.08	0.25	1801.27	14600	0.14	111.26	946.61	567.76	36.74	86.12
2013	178	812.9	0.22	1803.55	14655.62	0.15	174.36	963.71	576.19	36.89	86.04
2014	175	828.46	0.18	1825.92	14926.86	0.15	175.67	1016.28	588.71	36.88	86.16
2015	196	883.2	0.14	1961.17	15354.08	0.15	180.14	995.31	586.8	35.77	86.75
2016	212	901.49	0.11	1992.79	15328.3	0.15	181.39	1031.45	595.88	34.26	86.6
2017	214	902.02	0.03	1964.36	15788.79	0.16	189.03	1038.33	641.25	34.46	86.73
2018	212	925.77	0.01	1988.79	16436.32	0.15	199.96	1071.19	618.07	36.49	83.47

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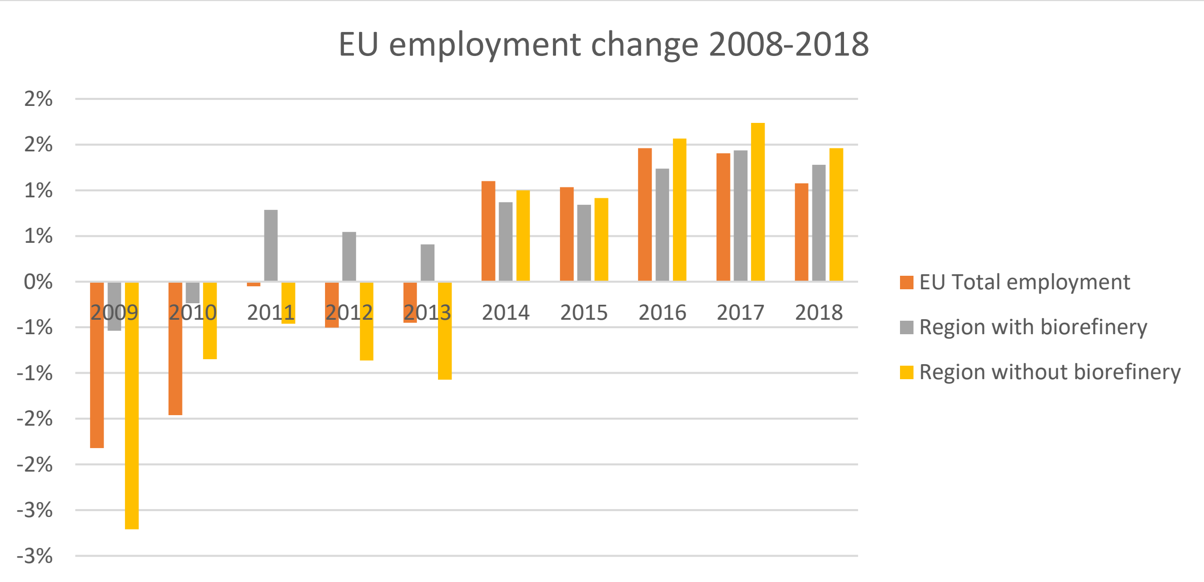
Bio-refineries impact

We compared the overall employment change in the EU with the regional employment change. We divided the regions into those having at least one biorefinery established and those that have not had any bio-refineries established within the period of interest. By comparing the employment change, regions with bio-refineries perform better when overall employment decreases (less employment loss or employment growth). Regions without bio-refinery establishments have a higher employment growth when overall employment increases.

Figure 5: Employment change



Source: Eurostat

Demographics of bio-refinery regions

Bio-refinery regions have higher employment compared to non bio-refinery regions. Table 5 shows that only population and education are insignificant different between bio-refinery regions and non bio-refinery regions. Employment, disposable income, patent tendency, business birth and survival rates, motorways and railways are all significantly different.

Table 5: Region gemographics

	Biorefinery region		Non-biorefienry region		
Variable name	Mean	Std. Dev.	Mean	Std. Dev.	t-test
Employment	873.9593	546.3924	809.5082	792.277	0.01
Population	1761.857	1012.939	1861.248	1759.619	0.0637
Disposable income	15550.04	4205.051	13338.75	3738.583	0
Education	221.1502	119.7349	212.1427	218.7479	0.1728
Patent	196.9443	131.8483	119.5729	99.34823	0
Business birth rate	1093.509	425.1121	1016.861	579.4171	0
Business survival rate	652.9145	250.2445	602.3811	352.0921	0
Motorways	37.87755	23.70831	33.0411	27.76143	0
Railway	114.7579	87.10307	67.62009	43.47597	0

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In this case study, the contextual factors that can influence the methodological framework used and the unit(s) of the analysis are:

- *Changing NUTS code:* Since this study analyses the impact of bio-refineries on socio-economic factors based on the current NUTS code, a change in the NUTS code might introduce biases in the estimated results.
- *Fluctuation of biomass or fossil fuel price*: Bio-refinery production costs are mainly affected by the cost of the biomass feedstock. A huge fluctuation in biomass or fossil fuel prices might affect the entry and exit of bio-refineries since many bio-based products are direct substitutes of fossil-based products. Hence, it might affect the fundamental business environment for bio-refineries.
- *Policy and regulation*: Policies, such as a blend mandate, can have a strong impact on the supply and demand of bio-based products. It might also change the business environment that bio-refineries operate.
- *Consumer preferences*: A critical factor for the success of bio-refineries is the demand for bio-based products. Consumer preferences indicate and can alter the demand for bio-based products.
- *Technology innovation*: The development of technology might influence the profitability and environmental impact of bio-refineries. It might also influence decisions on where the bio-refinery will be allocated.

6 Analysis Method

Our analysis begins by investigating how the establishment of bio-refineries correlates with regional employment. To do this, we first apply a multivariate linear regression model, as presented in Equation (1):

$$Employment = \beta_0 + \beta_1 Biorefinery + \beta_2 Population + \beta_3 Disposable\ income + \beta_4 Education + \beta_5 Busines\ birth + \beta_6 Business\ survive + \varepsilon \quad (1)$$

With this model we can identify how changes in employment can correlate with changes in the number of bio-refinery establishments, while holding all other factors fixed. Population, income, education, business birth and survival rates are included as control variables.

Table 6: Multivariate linear regression results

Employment	**Estimated coefficient**	**t-test**
Biorefinery	17.43***	2.95
Population	0.44***	181.06
Disposable income	0.02***	24.60
Education	218.45***	5.68
Business birth rate	-0.04***	-3.03
Business survive	0.14***	5.30
No. Obs	3421	
R^2	0.9502	

Significant level: ***=1%, **=5%, *=10%

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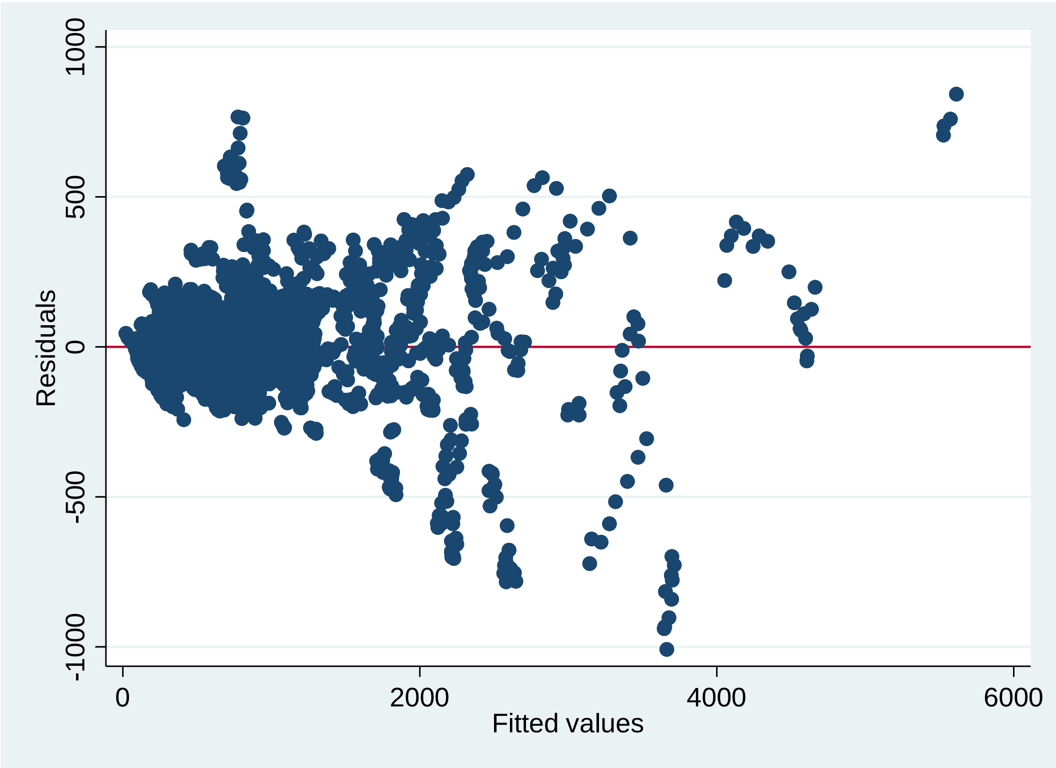
The coefficient for bio-refinery is significant according to the regression results of Table 6 suggesting a positive correlation between employment and bio-refinery establishments.

Figure 6: Regression residuals



According to the residual plot (Figure 6), we observe that there might be a heteroscedasticity problem in our data. We also performed standard Breusch-Pagan tests for heteroscedasticity and the chi-square test statistic rejected the null hypothesis. This indicates that there is a heteroscedasticity problem in our data. This problem might source from individual heterogeneity. Hence, we applied a fixed-effects panel regression model with time dummies to account for the unobserved factors, which might influence regional employment that is invariant over time. For example, culture and labour preference (Brügger, 2009; Van de Walle, 2015). We checked whether these time-invariant are not correlated with the error term by performing the Hausman test suggesting a fixed-effects model instead of random effects model.

$$\begin{aligned} Employment_t &= \alpha_i + \beta_{1t}Biorefinery + \beta_{2t}Population + \beta_{3t}Disposable\ income \\ &+ \beta_{4t}Education + \beta_{5t}Busines\ birth\ rate + \beta_{6t}Business\ survive \\ &+ \beta_{7t}Time\ dummy + \varepsilon \end{aligned} \tag{2}$$

We introduce the variable Bio-refinery in two different ways in the fixed effect model analysis. This difference is based on whether we assume there is a persistent impact of bio-refinery on employment after its establishment. If no persistent impact, the bio-refinery variable is equal to the number of bio-refineries established in year t. If we assume persistent impact then the bio-refinery variable will be equal the sum of bio-refineries established up until year t. For instance, if a region has one bio-refinery established in 2005 and another one established in

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2010, the number of bio-refineries established will be 0 before 2005; equal 1 from 2005 to 2009; equal 2 from 2010 onwards if we use the persistent impact framework.

Table 6: Fixed effect model results

	WITHOUT TIME DUMMY		WITHOUT PERSISTENT IMPACT		WITH PERSISTENT IMPACT	
	Estimated coefficient	t-test	Estimated coefficient	t-test	Estimated coefficient	t-test
Biorefinery	2.11	1.6	6.61***	4.25	4.159***	2.81
Population	0.32***	7.98	0.35***	9.04	0.356***	9.31
Disposable income	0.01***	10.51	0.02***	8.16	0.016***	7.87
Education	2.11	-0.86	43.31*	1.75	53.865**	2.3
Business birth rate	0.32**	-2.21	-0.03***	-2.75	-0.033***	-2.72
Business survive	0.01**	2.55	0.06***	2.83	0.053***	2.77
2001			-2.67*	-1.75	-1.976	-1.37
2002			-4.99*	-1.87	-4.319*	-1.69
2003			-10.91***	-2.96	-9.598***	-2.76
2004			-14.30***	-3.02	-12.866***	-2.88
2005			-17.12***	-2.96	-15.169***	-2.8
2006			-14.48**	-2.05	-11.797*	-1.8
2007			-10.98	-1.38	-7.741	-1.05
2008			-16.58*	-1.85	-12.793	-1.55
2009			-32.35***	-3.42	-29.527***	-3.36
2010			-41.99***	-4.23	-39.761***	-4.28
2011			-47.48***	-4.34	-45.465***	-4.42
2012			-46.13***	-4.24	-45.820***	-4.41
2013			-52.13***	-4.64	-52.903***	-4.9
2014			-48.29***	-4.29	-49.844***	-4.61
2015			-46.70***	-4.04	-48.605***	-4.38
2016			-41.24***	-3.42	-43.398***	-3.75
2017			-38.29***	-3.01	-40.214***	-3.3
2018			-33.23**	-2.46	-34.552***	-2.7
No. Obs	3421		3421		3421	
Groups	222		222		222	
R2 within	0.4608		0.5045		0.5181	
R2 between	0.9570		0.9572		0.9582	
R2 overall	0.9490		0.9500		0.9508	

Significant level: ***=1%, **=5%, *=10%

With employment being a time-variant variable, without taking into account the time dummy, the bio-refinery variable does not have a significant impact on employment. Hence, we introduce time dummies to the fixed effect model. The significance of the time dummies indicates that employment increases over time. The bio-refinery variable also becomes significant. Based on the results presented in Table 6, the establishment of bio-refineries has

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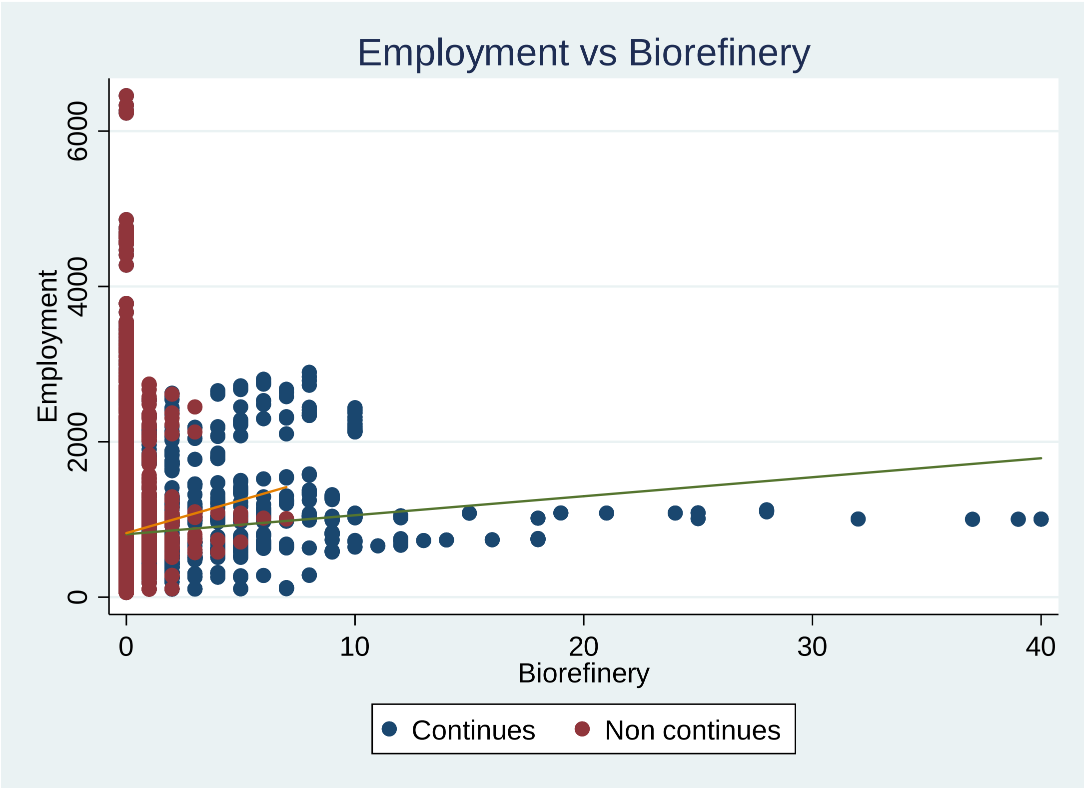
a positive impact on regional employment overall. This includes direct employment such as staff for operating the bio-refinery and indirect employment such as farmers, workers for logistics and transportation.

The persistent impact setting has a higher R^2 compared to the without persistent impact setting. This indicates the persistent impact setting explains more variation in the model, hence we are in favour of concluding there is a persistent impact of bio-refinery on employment.Figure 7 shows graphically the positive relationship between employment and bio-refinery established.

Figure 7: Employment vs Bio-refineries



In order to interpret the causal influence of bio-refinery establishment, we adopt the PSM-DID method proposed by Heckman et al. (1997, 1998). The propensity score matching (PSM) helps to eliminate the selection bias from establishing bio-refineries in certain regions with favourable characteristics. The difference-in-difference method helps to isolate the impact of the intervention, which in this case is translated as the establishment of the bio-refinery in the region. The combination of these two methods provide a more solid methodological framework in order to study how bio-refinery establishments can impact regional employment.

The key element on performing the PSM-DID method is to identify the clear cut-off for the pre-treatment period and post-treatment period. Different regions have their first bio-refinery established in different years. In order to identify the pre-treatment period and post-treatment period, we first calculate the PSM score for each region from 2000 to 2018 and get

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an average of the score for each region. These PSM scores indicate the probability of establishing bio-refineries in the region. Then we match the regions based on their PSM scores. We use nearest neighbour matching to match the treated and control region. Each control region will now have a corresponding treated region. This helps us to identify the pre-treatment period and post-treatment period. For example, if region A is a treated region that has its first biorefinery established in 2010, the pre-treatment period will be before 2010 and the post-treatment period will be 2010 and after. If region B is the corresponding control region for region A, it will have the same pre and post-treatment period.

Next we perform the kernel PSM-DID estimation following the approach of Heckman et al. (1997, 1998). We first estimate the kernel PSM using the logit model, as given in Equation (3):

$$\begin{aligned} \mathrm{P(Treated)} = \alpha + \beta_{1it} Population + \beta_{2it} Disposable\ income + \beta_{3it} Education \\ + \beta_{4it} Patent + \beta_{5it} Busines\ birth\ rate + \beta_{6i} Business\ survive \\ + \beta_{7i} Motorway + \beta_{8it} Railway + \varepsilon \end{aligned} \tag{3}$$

where P(Treated) is the propensity score estimated.

Figure 8: Sample standardized bias

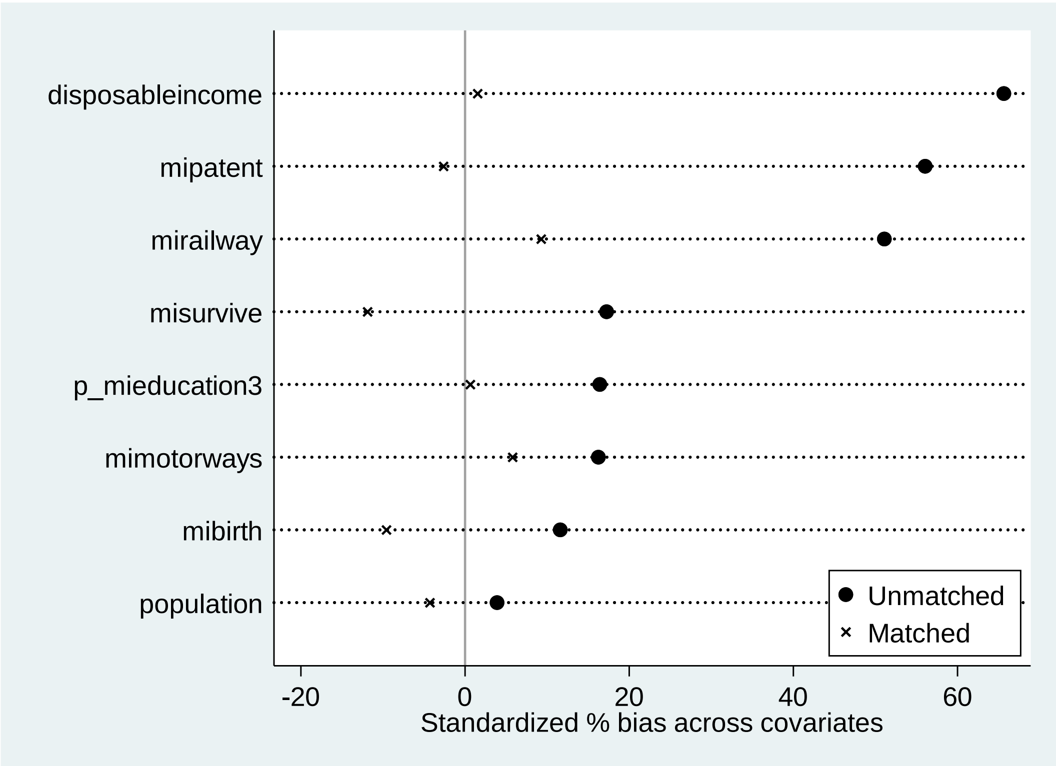

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Table 7: Matching result

	Treated mean	Control mean	Bias (%)	t-value
Population	1856.8	1916.5	-4.3	-0.81
Disposable income	16111	16050	1.5	0.33
Education	0.13752	0.1371	0.6	0.14
Patent	198.01	201.14	-2.6	-0.5
Birth	1088.4	1137.3	-9.6	-1.86
Survive	659.31	695.65	-11.9	-2.07
Motorway	37.692	36.224	5.8	1.21
Railway	108.84	102.43	9.3	1.67

Next, we test the balance of variance between the treated and control group using a two-sample t-test on pre-treatment period. Table 8 shows that there is no significant difference between the treated and control mean. This result justifies that the kernel matching helps to balance the treated and control groups.

Table 8: Balancing test

	Treated mean	Control mean	Difference	t-value
Employment	756.83	741.43	-15.401	0.38
Population	1618.76	1524.81	-93.944	1.14
Disposable income	14000	14000	7.914	0.03
Education	0.13	0.13	0.005	1.62
Birth	1135.53	1103.18	-32.358	1.6
Survive	651.83	635.81	-16.02	1.24

Next, we performe the DID to identify the impact of bio-refinery establishment on employment:

$$\mathrm{Y_{it}} = \beta_0 + \beta_1 T + \beta_2 D + \beta_3 DT + \beta_4 X_{it} + \varepsilon_{it} \qquad (4)$$

where Y is the employment in region i and period t, T is the time variable where T=0 if pre-treatment, T=1 if post-treatment. D is a dummy variable where D=1 if the treatment is active, otherwise D=0. X are other control variables. We are interested in $\widehat{\beta_3}$ which measures the average treatment effect on the treated (ATT).

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Table 9: Difference in Difference result

	Pre-treatment difference			Post-treatment difference		
	Difference	S. Err.	t-value	Difference	S. Err.	t-value
Control (C)	756.829			715.214		
Treated (T)	741.429			902.775		
Diff (T-C)	-15.401	38.161	-0.4	187.561***	29.692	6.32
Diff-in-Diff ($\widehat{\beta_3}$)	202.962***	48.351	4.2			

The DID result shows that there is a significant difference in employment after bio-refinery(-ies) have established. The employment is no significant different in the pre-treatment period. The ATT scores are significant positive revealing a positive impact of bio-refinery establishment on employment.

7 Caveats about study

There are several caveats we would like to make regarding this case study. First, due to data confidentiality, there is a lack of data on the bio-refinery properties available. Missing data on detailed bio-refinery properties, such as the production capacity and costs, implies that the impact of bio-refineries on employment was treated regardless of the size of bio-refinery. Hence, this case study can only identify the impact of constructing a bio-refinery on socio-economic indicators.

We also assumed that the impact of bio-refineries on regional socio-economic indicators has been constant over time. In reality, this impact might change according to changes on the production capacity, technology innovation and the exit of bio-refineries in a specific region. Another caveat exists due to the large data gap in the statistical data. Estimating the missing data can introduce some bias. This might lead to variation in the model results when replicating the estimation.

Since bioeconomy drivers are key determinants for the evolution and dispersion of bio-refineries, a shift of the drivers might also shift the estimated employment impact. These drivers include technology and innovation, market organisation, demographics, economic development and consumer preferences. Technology and innovation can drive productivity, labour demand and labour to capital ratios. If innovation moves towards capital augmented technologies, then less labour will be required for bio-refinery production. The market organisation can also drive the value chain of the bio-refineries. A change in the value chain might shift the employment multiplier and hence change the indirect employment generated from establishing bio-refineries. Demographic, economic development and consumer preferences can drive the market demand for bio-based products. A shift in the demand can lead to a shift in market equilibrium. The supply of bio-based products may also shift accordingly and the supplier – bio-refineries will be impacted.

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8 Feedback

Without a comprehensive dataset, the model can only be constructed based on some assumptions. Collecting further data on the survival are of bio-refineries or the status of bio-refineries (e.g. constructing, operating, halting or out of business) will improve the model by enhancing the boundary of analysis. Bio-based shares and regional bio-based production capacity can also help in this regard.

Currently collecting data on bio-refinery operations is difficult due to data confidentiality issues. One possible solution is the incorporation of bio-refinery data into the official national statistics offices' collection process. Since, the bio-refinery sector is strategically important for the EU, improving data availability and quality can assist research in this area. This can speed up the spreading of the concept of bioeconomy and promote the development of the bio-refinery sector. Furthermore, regarding the data collection problem, we cannot leave behind the small bio-refineries, which are usually in the need of governmental support, but missing in the dataset. While these small bio-refineries utilize much local biomass, they help to foster the biomass utilization approach and increase the utilization rate.

There is also a need to develop an estimation methodology to account for own consumption biomass. This might strengthen the biomass material flow datasets. The key sectors to focus here are biomass producing sectors such as agriculture, fishery and aquaculture, and forestry.

9 Recommendations and best practices

Our recommendation if one will replicate this case study or develop similar research is to identify a clear boundary of analysis first. This includes what types of bio-refinery to target, the temporal coverage of the analysis, the targeted regions, and the drivers of bio-refinery establishment. Adopting different boundaries of analysis will greatly influence the result, hence lead to a different conclusion.

Our second recommendation is to have a clearly defined, consolidate terminology. For example, bio-based industry and bio-refinery means the same thing but adopted by different studies and dataset. This might introduce difficulties in comparing data and results.

The method developed by this case study provides an alternative way to measure the impact of establishing bio-refineries on regional employment. The previous studies estimated employment generated by a single bio-refinery facility and aggregated it for regional employment. However, this might over/underestimate the indirect employment impact if the study fails to account for all the employment impacts between the bio-refinery sector and other sectors. For example, how bio-refinery employment substitutes fossil-refinery employment. Using econometric models helps to create a broad picture of the change in regional employment due to bio-refinery establishment. For example, indirect employment

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generated by increasing demand due to higher employment rates in regions with bio-refineries. Overall, the combination of the econometric tool applied by this case study and the tools that estimate precise bio-refinery employment developed by previous studies can provide policymakers with a comprehensive overview of the bio-refinery impact on employment.

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Appendix

Multiple imputation is a general solution to the issue of missing data that can be found in several widely used statistical sets. It aims to account for uncertainty about missing data by producing many possible imputed data sets and integrating the results from each of them appropriately. In this study, we imputed control variables education, business birth rate, business survival rate, patent, motorway, and railway. These variables are imputed with a linear regression model. We perform the imputation 20 times and calculated the average value of the imputed missing values.

The linear regression for education:

$$\text{Education} = \text{Training} + \text{Education Participation} + \text{Disposable Income}$$

The linear regression for patent:

$$\text{Patent} = \text{Biochemistry patent} + \text{Vegetable oil patent} + \text{Education}$$

The linear regression for business birth rate:

$$\text{Business birth rate} = \text{Patent} + \text{Biorefinery} + \text{Education}$$

The linear regression for business survival rate:

$$\text{Business survival rate} = \text{Population} + \text{Disposable Income} + \text{Business birth rate}$$

The linear regression for motorway:

$$\text{Motorway} = \text{Population} + \text{Disposable Income} + \text{Railway} + \text{Land}$$

The linear regression for railway:

$$\text{Railway} = \text{Population} + \text{Disposable Income} + \text{Motorway} + \text{Land}$$

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