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Juillet
2024

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A critical assessment based on French data

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218

Document de travail

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DOCUMENT DE TRAVAIL

N° 218

Juillet 2024

Directrice de Publication : Christine ERHEL
Secrétaire de rédaction : Bilel OSMANE

ISSN 1629-7997
ISBN 978-2-11-167225-3

UTILISER LES TÂCHES ET EMPLOIS VERTS D'O*NET EN EUROPE ? UNE ÉVALUATION CRITIQUE À PARTIR DES DONNÉES FRANÇAISES

Mathis Bachelot

RÉSUMÉ

Dans la littérature internationale et européenne sur les emplois verts, de nombreux travaux empiriques s'appuient sur une adaptation des catégorisations O*NET, qui (i) identifient trois groupes d'emplois verts et (ii) distinguent les tâches vertes des tâches non-vertes, pour chaque emploi. Or, ces données standardisées sont basées sur – et donc dépendantes de – la nomenclature états-unienne des professions. Ainsi, l'application de ces catégorisations à d'autres pays nécessite tout un processus de correspondance. Des méthodes ont été développées et opérationnalisées, mais aucune n'exploite pleinement toutes les possibilités, ni n'évalue réellement la précision de ces adaptations. Profitant de la richesse des données françaises, cet article propose une adaptation minutieuse et transparente des catégorisations O*NET *via* la nomenclature internationale ISCO-08, en présentant l'ensemble du processus méthodologique de manière claire et accessible. En outre, en France, une institution appelée Onemev a établi une liste *ad hoc* d'emplois verts, intégrée depuis 2021 dans toutes les grandes enquêtes de la statistique nationale et couvrant le « cœur » des emplois verts. En exploitant les données de l'Enquête Emploi française, nous utilisons cette liste comme un point de comparaison pour évaluer la pertinence de l'adaptation des catégorisations vertes O*NET. Nos résultats révèlent des décalages importants entre la liste de l'Onemev et les catégorisations proches de l'O*NET, mettant en évidence et étayant des limites tant conceptuelles que méthodologiques. Cela remet en question la pertinence de certaines études qui ont utilisé ces méthodes de correspondance d'une manière moins granulaire et prudente.

Mots-clefs : emplois verts, nomenclature professionnelle, méthode de correspondance, O*NET, ISCO-08

N.B. : L'accès à certaines données utilisées dans le cadre de ce travail a été réalisé au sein d'environnements sécurisés du Centre d'accès sécurisé aux données – CASD (Réf. 10.34724/CASD). Ce projet bénéficie du soutien de la Région Hauts-de-France et de la Plateforme Universitaire des Données de Lille. L'auteur remercie Mathilde Guergoat-Larivière et Thomas Amossé pour leurs relectures et commentaires.

*Using O*NET green jobs and tasks in Europe? A critical assessment based on French data*

ABSTRACT

In the international and European literature on green jobs, many empirical works rely on an adaptation of O*NET categorisations, that (i) identify three groups of green jobs and (ii) distinguish green from non-greens tasks. However, these useful standardised data are based – and thus dependent – on the US occupational nomenclature. Hence, applying these categorisations to other countries require a whole crosswalk process. Methods have been developed and operationalized, but none of them fully exploits all the possibilities, nor do they really assess the accuracy of these adaptations. Taking advantage of the richness of French occupational data, this article proposes a meticulous and transparent adaptation of O*NET categorisations through the ISCO-08 international nomenclature, presenting the entire methodological process in a clear and accessible manner. Besides, in France, an institution called Onemev has established an *ad hoc* list of green jobs, integrated within all major national statistics surveys since 2021 and covering the 'core' of green jobs. Exploiting French Labour Force Survey data, we use this list as a benchmark for assessing the relevance of the adaptation of O*NET green categorisations. Our results reveal significant mismatches between the Onemev list and close O*NET categorisations, highlighting and documenting both conceptual and methodological shortcomings. This casts doubt on the relevance of some studies that have used the crosswalk method in a less granular and cautious way.

Key words : green jobs, occupational classification, crosswalk methodology, O*NET, ISCO-08

N.B.: Access to some of the data used in this work was carried out in secure environments provided by CASD – Centre d'Accès Sécurisé aux Données (Ref. 10.34724/CASD). This project is supported by the Hauts-de-France Region and the Lille University Data Platform. The author thanks Mathilde Guergoat-Larivière and Thomas Amossé for their proofreadings and comments.

INTRODUCTION

To analyse the effects of the ecological transition on employment, a US institution called O*NET (Occupational Information Network) compiled a list of jobs based on the literature about the world of work and the green economy. After having sorted and clustered this list, occupational analysts identified three categories of green jobs:

(i) The *green new and emerging* (GNE) category, which is supposed to group jobs that are new because of the ecological transition. In practice, this corresponds to occupations whose titles were new relative to the (previous) O*NET taxonomy, and whose objectives and tasks were thus significantly different from those of occupations already covered.

(ii) The *green enhanced skills* (GES) category, which identifies already existing jobs whose tasks and skills are evolving internally to adapt to the environmental challenge. Here, it includes occupations whose titles were "a close match to [a previously] existing O*NET occupation, but had aspects that could merit task list updating and/or alternate title changes" (Dierdorff et al., 2009, p. 32).

(iii) The *green increased demand* (GID) category, which refers to jobs that are expected to grow in volume to support the expansion of the first two categories, but for which the nature of work does not change. In this case, occupations were already appropriately identified within the O*NET taxonomy.

This categorisation is based on the extensive database provided by O*NET, which contains specific and standardised descriptions of over a thousand occupations covering the entire US labour market. Each occupation is assigned a list of tasks and, within this framework, each occupation belonging to the two 'directly' green categories (GNE and GES) was also assigned green tasks (O*NET, 2010). This task-based information offers a more granular view of the ecological dimension of these occupations.

Particularly used and recognised in academic literature, using these O*NET categorisations for countries other than the US would be interesting, both for international comparisons and for the analytical relevance of such a division into three groups and into green and non-green tasks. One way of doing this is to recreate similar categorisations for the target country on an *ad hoc* basis. But this is a very costly and time-consuming process as it means starting from scratch[1]. Conversely, it is also possible to convert O*NET categorisations into foreign nomenclatures, using mappings between the different occupational classification systems. To do this, one can rely on ISCO (International Standard Classification of Occupations), as has been done in many studies (*e.g.* de la Vega et al., 2024; Elliott et al., 2021; Hancké & Bowen, 2019; Lobsiger &

[1] In the European Union, there is no standardised list of green jobs or green tasks that can serve this purpose. The only approximation would be a list of 'green skills' that is developed by the European Commission based on the ESCO classification, and that can easily be linked to the ISCO nomenclature. However, this is a different perspective, and one cannot reasonably deduce a comparable list of green jobs from these green skills. Following Autor (2013), Apostel & Barslund (2024) indeed point out that "green tasks refer to the actual green activity found in a particular job, while green skills can be seen as capturing the degree to which green activities could potentially be performed" (p. 5). This is why, for instance, Lobsiger & Rutzer (2021) prefer to talk of 'green potential' rather than 'green jobs' when developing an O*NET green skill-based approach.

Rutzer, 2021; OECD, 2023; Scholl et al., 2023; Sofroniou & Anderson, 2021; Valero et al., 2021; Vona, 2021).

However, to ensure the 'accuracy' of the adaptation, it is useful to have a baseline for comparison. Indeed, a major criticism of studies adapting O*NET categorisations to European data is precisely that their crosswalks suffer from many shortcomings, which lead to problematic aggregation bias. This is mainly because nomenclatures cannot be matched for the same levels of aggregation, and because occupations do not match one-to-one either. As a result, Vona (2021) usually observes that estimates of "the size of green employment appears much larger in the [target country] than in the US, which is a red flag on the poor quality of the crosswalk" (p. 24). Yet, it is normal for green employment to vary from country to country and, more importantly, this comparison in volume says nothing about the type of jobs that are 'wrongly' considered to be green due to this biased crosswalk.

In this regard, France is an interesting case for two reasons. On the one hand, it has "rich occupation-level data that can be used to impute O*NET-based measures through cross-walking" (Vona, 2021, p. 33). Hence, using French Labour Force Survey (LFS) allows matchings at a lower level of aggregation than other studies which generally use European LFS data and are therefore constrained to the 3-digit level of the ISCO nomenclature. On the other hand, France has an institution – called Onemev (*National Observatory for Employment and Professions of the Green Economy*) – dedicated to identifying and monitoring green jobs. Since 2020, it has established a list of more than 140 green occupations, updated each year and defined at the most detailed level of the French nomenclature (that of occupational titles)[2]. This narrow list mostly covers the 'core' of green jobs, *i.e.* the greenest ones, those that could somehow be related to the GNE category[3].

This French green jobs' list, which can be assumed to be relatively precise since it is narrowly defined and purposely created for the French economy, is useful as a benchmark for assessing the relevance of the adaptation of O*NET green categorisations. Not only does it allow to compare the respective volumes of jobs in the same sample, but it also allows to identify which jobs are considered green for all O*NET and Onemev categories, and which are green only for part of them. This detailed analysis of overlaps can help to illustrate the shortcomings in the adaptation and can show where the aggregation bias is distributed[4].

[2] The list of all green jobs is available on the Insee website: https://www.insee.fr/fr/information/6050093

[3] This list also includes some 'greening' jobs (thus more related to GES), as shown by the fact that some occupational titles are similar to those of the former 'Métiers verdissants' Onemev category, discontinued since 2020.

[4] In the same vein, Østergaard et al. (2021) apply different green jobs approaches on a same Danish data set. They analyse the resulting overlaps and conclude that they are limited, so that it would be "a sign that green jobs are diverse and spread across the economy" (Apostel & Barslund, 2024, p. 10). However, they do so to compare occupation-based (bottom-up) and entity-level (top-down) approaches, whereas our objective is different: we want to compare different occupation-based approaches with each other to assess the relevance of a given crosswalk.

1. CROSSWALK ISSUES AND OBJECTIVES

Two main steps are required to adapt O*NET categorisations to French data: (i) moving from the 8-digit O*NET-SOC classification to the 6-digit US SOC classification; (ii) moving from the 6-digit US SOC classification to the 4-digit ISCO-08 classification[5].

Indeed, O*NET green categorisations (GNE/GES/GID and green/non-green tasks) are available for the 8-digit level O*NET-SOC 2010 classification, but the official crosswalk to ISCO-08 is only available at the 6-digit level of US SOC 2010. This means that O*NET categorisations must first be adapted to the US SOC level, and then to the 4-digit ISCO-08 one. However, as mentioned above, given that correspondences between nomenclatures are not perfect (there are some many-to-many matchings), methodological and aggregation issues arise in trying to remain as faithful as possible to initial categorisations.

<u>Box 1: The different existing matching methods</u>

To adapt the green jobs categorisations created by O*NET to other nomenclatures (or simply to operationalise them on US employment data), it is necessary to go through aggregation processes that require some methodological choices. Methods have already been proposed in the literature, and Valero et al. (2021) distinguish three approaches: (i) *green max*, (ii) *green mean*, (iii) *green mean weighted*.

(i) The first, known as the *green max* approach, is notably used by Hancké & Bowen (2019). It simply consists of designating as 'green' any aggregate occupation that includes at least one 'green' sub-occupation. The problem is that this method is too generous in that "entire occupational categories are considered green even if only one sub-category is considered green in O*NET" (Valero et al., 2021, p. 25).

(ii) The second, more cautious, is the *green mean* approach. It considers that if an aggregate occupation includes *x* sub-occupations, then it is green only in proportion to the number *y* of sub-occupations that are green themselves. This method therefore results in a green score between 0 and 1 which, in this case, is equal to *y/x* (Valero et al., 2021, p. 50).

However, in doing so, we assume that each sub-occupation has the same weight, which biases the final estimate. As Vona (2021) writes, "it leads to a large over-estimation of the real size of the green economy because occupations with higher greenness are usually much smaller than occupations with lower or zero greenness within [the aggregate occupation]" (p. 26).

(iii) Thus, a third aggregation method called *green mean weighted*, developed in another context by Dingel & Neiman (2020), can also be applied here: it involves weighting sub-occupations by their share of employment in the calculation of the aggregated ratio.

[5] Here, SOC is the US 'Standard Occupational Classification' while ISCO stands for 'International Standard Classification of Occupations'.

Although not mentioned by Valero et al. (2021), the same approaches apply if the starting point is not binary green categories (GNE/GES/GID) but a continuous score based on the percentage of green tasks in an occupation. In this work, we present and discuss in more detail the *green mean* and *green mean weighted* methods applied to the French case, through several binary and task-based continuous green categorisations.

The problem is that, until recently, no study fully exploited all the potentialities of crosswalks. Firstly, as mentioned above, many are based on European data and are thus forced to use the 3-digit ISCO level, due to European LFS data availability. Secondly, until last year, none of these adaptations used the green mean weighted approach: in the green jobs' literature, its principle was only stated but never applied. Whether they start from a binary categorical assignment or from a continuous task-based index, studies confined – at best – to the green mean approach.

For instance, Sofroniou & Anderson (2021) directly provide a "classification of relevant ISCO-08 minor groups by green occupation category" (p. 41) but, apart from being at the 3-digit ISCO level, they do not explain how they manage to assign each subgroup to only one category of green occupations. Hancké & Bowen (2019) propose a more transparent method, but because of their focus on the European level, they are ultimately forced to use the 3-digit level too[6]. Moreover, they adopt the green max approach, which considerably overestimates the range of occupations associated with green categories. In the second part of their report, Valero et al. (2021) do better by adopting the green mean approach, but they still have to restrict to the 3-digit ISCO level as they focus on the European level.

There are, however, studies that implement crosswalks at a less aggregated level. This is the case for the first part of Valero et al. (2021) report, which applies the same green mean method to UK data and sticks to the 4-digit level for aggregation, but they do so using the UK nomenclature. Staying with ISCO-08, there is the article from Elliott et al. (2021) on Dutch data, which adapt both binary O*NET categories and task-based scores to the 4-digit ISCO level with a green mean method. Although it is certainly one of the most meticulous adaptations, Vona (2021) remains very critical, saying – for reasons already exposed – that "the aggregation bias is evident" (p. 27) and that "detailed cross-validations are not performed" (p. 24).

More recently, Scholl et al. (2023) crosswalked O*NET green mean weighted indicators to the 4-digit ISCO level on Portuguese data. Although they indeed implemented what we do as well, their objective is not the same: they want to assess whether different greenness measures and weighting options lead to significantly different results. To do so, they build a wide range of greenness indicators and then empirically test their robustness by checking whether they all show a similar relationship with productivity. They conclude that it does, so that "if one is

[6] The same limitation applies to the OECD (2023) report, which adapts the O*NET task-based approach. Authors however state that, according to their task-based method, "less detailed employment data does not have a strong effect" on overestimation (p. 87). To support this, they show that employment volumes in the US and Canada differ only slightly (maximum 3 percentage points) depending on whether we consider the 5, 4 or 3-digit level of their occupational nomenclature. But this analysis does not take account of crosswalks to other nomenclatures, which can then widen the gap.

interested in economy-wide average levels of greenness, picking one measure or the other may not make a big difference" (p. 18).

However, the fact that all these greenness measures are relatively consistent with each other does not mean that they are 'faithful' to the initial O*NET categorisations. Although it contributes to the 'detailed cross-validations' asked by Vona (2021), this method does not fully clarify the accuracy of the crosswalk. In contrast, our objective in this article is to select a more limited number of greenness measures, and specifically to focus on the most 'refined' ones, in order to compare them with the French *ad hoc* categorisation and to provide another – complementary – angle on the reliability of the crosswalk.

Besides, even if Scholl et al. (2023) test a lot of measures, they do not crosswalk the three original O*NET categories (GNE, GES, GID), but only consider greenness as a whole (*i.e.* belonging to GNE or GES without distinction, or the share of green tasks – thus completely excluding GID). Here, we also want to crosswalk these three categories, because many other authors have done so, and because they are original and symbolic of O*NET seminal categorisations. Also, they rely on Vona et al. (2018) greenness measures, while we prefer starting from Vona et al. (2019) – hereafter VMC[7]. The first difference is that Vona et al. (2018) only consider specific tasks in their measures, while VMC consider all of them[8].

The second – more critical – difference is that VMC correct some of the 'problematic occupations' issues that we will present later, and in this way mitigates a significant risk of aggregation bias. While Scholl et al. (2023) adopt the hypothesis that "employees are uniformly distributed across 8-digit occupations within each 6-digit SOC occupation" (p. 8), VMC are more cautious and manually correct – using a predefined method – for these overestimates. Indeed, one of the problems is the aggregation bias caused by the standard green mean method when moving from the 8-digit to the 6-digit US nomenclature. As explained in Box 1, it strongly overestimates the share of green jobs. But VMC propose a way of correcting for this: we will use what we call a 'corrected mean aggregation method' and, more broadly, their resulting greenness scores. In doing so, we will present their method in detail, allowing us to identify some practical inconsistencies and to propose (justified) corrections.

The objective of this methodological work is therefore, thanks to the detailed data available in France, to adapt O*NET green categorisations in the most transparent and rigorous way possible – as well as presenting it in a clear and accessible manner. To do so, we will apply a crosswalk at the 4-digit ISCO-08 level while mobilising the most advanced methods developed: weighting by employment shares, using both binary categorisations and continuous task-based indexes, comparing them on the same database, etc. The *ad hoc* list of green jobs provided by Onemev will then provide a benchmark for assessing the relevance of results, and by extension will provide a critical perspective on other European studies that have already adapted these O*NET categorisations in a less cautious way.

[7] As we will rely a lot on Vona et al. (2019), we will shorten its name to 'VMC' (for Vona, Marin & Consoli).

[8] As they explain, in the O*NET database, occupations "include both 'specific' and 'general' tasks. 'General' tasks are common to all occupations, whereas 'specific' tasks are unique to each occupation" (Scholl et al., 2023, p. 7). VMC thus include both general and specific tasks in their measures, which makes more sense for grasping the whole picture of a job's (green) practices.

These new results will help to support or nuance the general conclusion that "the quality of the crosswalk is not sufficient to use it to measure green employment in Europe" (Vona, 2021, p. 24). In this way, we also follow the recommendations made by Apostel & Barslund (2024) in their literature review on green jobs, who suggest that "it would be desirable if work in this area not relying on the O*NET-list would explicitly state (1) how the identified green occupations differ from O*NET green occupations; (2) why using O*NET is not desirable in the specific context of the research; and (3) what the likely impact in terms of aggregate employment/employment characteristics of this choice implies" (p. 14).

2. THE STARTING POINT: O*NET BINARY CATEGORIES AND CONTINUOUS TASK-BASED SCORES

Before thinking about *how* to methodologically adapt and interpret, we first need to think more precisely about *what* to adapt. The first and most common option is to start with the binary assignment of jobs to the three O*NET green categories presented above – namely GNE, GES, GID (and, in fact, a fourth category including all occupations that do not belong to any of the three previous ones).

But this strict separation between categories has sometimes been criticized, especially as O*NET also provides some more granular information, *i.e.* on green tasks. This information on the tasks performed by each occupation allows to construct another greenness categorisation, which is a continuous score based on the percentage of green tasks among all tasks of an occupation. This is precisely what VMC develop, with two additional features also available in the O*NET database: (i) they weight each task by the importance score assigned to it; (ii) they distinguish two indicators, the first including all the tasks associated with the given occupation (Green tasks index), and the second one keeping only what are considered to be core tasks for this occupation (Core green tasks index).

While authors agree that weighting by the importance score generally "yield qualitatively the same results as the unweighted shares" (OECD, 2023, p. 43), with cases of correlation exceeding 99% (de la Vega et al., 2024, p. 5), thus "making the use of such weights unnecessary" (Vona, 2021, p. 14), we will still use them as the greenness weighted scores are made available by VMC. Thus, we re-use the two task-based greenness scores as provided in the article.

Hence, to get the most complete overview possible, and to allow comparisons with the various approaches used in the literature, we have decided to start both from:

2.1. Binary green categories (GNE, GES, GID)
2.2. The two task-based continuous measures of VMC – the 'Green tasks' and 'Core green tasks' indexes

3. FROM THE 8-DIGIT TO THE 6-DIGIT LEVEL OF THE US NOMENCLATURE

For this first step, it should be noted that there is a direct correspondence between the two levels of the US nomenclature that are O*NET-SOC for the 8-digit level and US SOC for the 6-digit level. In other words, each occupation at the 8-digit level belongs to one and only one occupation at the 6-digit level: this connection can be identified by the first 6 digits of the occupation code, which are the same.

3.1. The simple mean aggregation

The simplest option to aggregate into 6-digit occupations is by averaging greenness of all their associated 8-digit sub-occupations.

To give a particularly telling example for readers of this article, the 6-digit occupation 'Economists' (19-3011) groups together two sub-occupations from the 8-digit level: 'Economists' (19-3011.00) and 'Environmental economists' (19-3011.01). Here, only the latter is considered green: it is attached to the GNE category, and all its tasks are labelled green by O*NET (*i.e.* a task-based greenness score of 1). Since no administrative or survey data are available to indicate the number (or proportion) of workers for these two sub-occupations in the US, it is impossible to apply a weighting on this basis so that the aggregate 'green score' of the 6-digit occupation would respect the distribution of workers at the 8-digit level. As a result, we have to initially apply a simple averaging method as presented and illustrated by Valero et al. (2021):

> "We first compute the share of greenness of each 6-digit US occupation based on the share of 8-digit occupations that are green and are mapped to it. For example, the occupation '11-3051: Industrial production managers' has five green sub-occupations out of seven that are GNE, such as '11-3051.02: Geothermal production managers'; one sub-occupation which is GID, and one sub-occupation that is not green. We thus consider that occupation 11-3051 is 0.85 green as it is 14% GID [1/7] and 71% GNE [5/7]" (p. 52)

Each 6-digit occupation is thus assigned a greening score between 0 and 1 for each O*NET category (GNE, GES, GID). This method was applied based on the list of green jobs provided by the O*NET Resource Center[9], as well as on the O*NET-SOC 2010 Occupation Listing[10] which lists the number of 8-digit occupations associated with each 6-digit occupation[11].

We proceed the same way for the two continuous task-based indexes. For instance, 'Civil engineers' (17-2051) is composed of two sub-occupations: 'Civil engineers' (17-2051.00) with a task-based greenness score of 0.45, and 'Transportation engineers' (17-2051.01) with 0.18. Hence, the 6-digit occupation green tasks index is the average of its two sub-occupations, here 0.315.

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[9] See here: https://www.onetcenter.org/dictionary/22.0/excel/green_occupations.html

[10] See here: https://www.onetcenter.org/taxonomy/2010/list.html

[11] A discussion on the number of occupations to be selected will be developed in the following section.

3.2. The corrected mean aggregation method of Vona et al. (2019)

In any case, the simple mean method suffers from the aggregation bias already described (Box 1). Based on the information on (green) tasks made available by O*NET for each 8-digit occupation, VMC propose a way of limiting the over-estimation of green occupations in the aggregation process:

> "In these problematic cases [where matching is not direct], we generally take the greenness of the most general occupation to avoid over-estimation of green employment. Examples of problematic cases are 'Sales Representatives of Technical and Scientific Products' (SOC 41-4011), containing 'Solar Sales Representatives' (SOC 41-4011.07), or 'Chief Executives' (SOC 11-1011.00), containing 'Chief Sustainability Officers' (SOC 11-1011.03). Accordingly, we devised a procedure to address each of the following circumstances:
>
> 1. When the 6-digit occupational group (*i.e.* the 8-digit SOC occupation that ends with '.00') has zero or few (much less than other 8-digit occupations) green tasks, we attribute zero greenness to all the 8-digit occupations within that group to avoid over-estimation of the greenness;
>
> 2. When the number of green tasks of 6-digit occupations is greater than zero and not substantially smaller than the one for other 8-digit occupations, we attribute to each 8-digit occupation the average greenness of all the occupations within their 6-digit group" (p. 48-49, working paper version)

This method was designed for the continuous task-based approach, but we can also extend it to binary categories so that they can still be used, but more carefully. This only requires an adaptation to account for the GID category, which is not considered by VMC who base their criteria on green tasks, while GID occupations do not have any green tasks. Hence, where GID aggregations were not one-to-one and needed the choice of a method, we adopted the simple mean aggregation. Once decided for this minor adaptation, the same task-based correction can be applied to the aggregation of binary categories.

To better illustrate the issue, we can re-use our previous example of economists. If we apply the simple mean method (3.1), then the 6-digit occupation 'Economists' (19-3011) should be 50% GNE, or have a 50% task-based greenness score. Conversely, following VMC, it would be 0% green for both because the most general profession, *i.e.* 'Economists' (19-3011.00), does not contain any green task.

In addition to simply using scores as given in their article, we also kept a close eye on their method and how they applied it to each 'problematic occupation'. Indeed, several questionable choices were made without directly meeting their stated criteria. This may stem from the relative vagueness of the terms used, for instance those highlighted in the following quotes: "zero or *few* (*much less* than other 8-digit occupations) green tasks" and "greater than zero and not *substantially smaller* than the one for other 8-digit occupations". Hence, we correct VMC's greenness scores for some occupations – for more detail, see Table A1 in Appendix.

3.3. Restricting O*NET categorisations to some sectors only?

One aspect that is not always made clear in the literature is whether the O*NET-SOC green occupations are meant to concern all sectors or, conversely, whether they should be limited to the twelve initial sectors[12] investigated in the seminal O*NET work from Dierdorff et al. (2009). Because of their importance in the literature, these sectors were supposed to offer a "precise view of green economy activities [and technologies that] allows for a more thorough determination of potential occupational implications" (Dierdorff et al., 2009, p. 13). But the restriction issue is not directly addressed in this report: on the contrary, it is explained that "this list [of twelve sectors] is not meant to be exhaustive" (Dierdorff et al., 2009, p. 12), which is more of an incentive to apply O*NET green categorisations to all sectors. This is precisely what most studies do, whether they deal with the US or with other countries that require crosswalks.

As recognized by Hancké & Bowen (2019), "O*NET focused on certain industry sectors that are deemed to be more heavily involved in the green transformation", but actual implementations "have reasoned [as if] any occupation that is identified as green in these industries is likely to be green in other industries" (p. 21) – without necessarily saying so. While this is not problematic for occupations whose identification title is already specific enough, this can lead to significant overestimates for occupations with a broader title, such as managers, whose greenness in the sectors initially investigated makes sense, but whose extension to the whole economy no longer reflects any of this.

To some extent, the second updating report by Dierdorff et al. (2011) is more explicit: it states that "a review of green research conducted since 2009 suggested that the 12 green sectors previously identified in the 2009 report were comprehensive and no new sector additions were required" (p. 6) – although, since 2011, things may have changed. Hence, one could rely on the online appendices to this report[13], which exhaustively indicate to which of the twelve sectors each green job and green task listed belong. However, given that studies never apply this restriction, we will not do it either, in order to stay within a more comparable framework[14].

[12] These twelve sectors are: (1) renewable energy generation; (2) transportation; (3) energy efficiency; (4) green construction; (5) energy trading; (6) energy and carbon capture and storage; (7) research, design, and consulting services; (8) environmental protection; (9) agriculture and forestry; (10) manufacturing; (11) recycling and waste reduction; (12) governmental and regulatory administration.

[13] See here: https://www.onetcenter.org/reports/Green2.html

[14] Although we sometimes decide to (slightly) adapt the methods used in other studies, we do so to pursue and 'perfect' their approaches, in order to be as 'up to date' as possible with the literature. Here, restricting green jobs and tasks to the sectors to which they were initially assigned might make sense, but it would constitute a far too strong departure from the studies we want to shed light on – especially as none of them has outlined such a restriction perspective. Besides, and in anticipation of the issues that will arise later (see 6.3), restricting the crosswalk to a limited number of sectors could certainly increase the proportion of Onemev green jobs within O*NET categories (Table 4b), but this would not – in any case – increase the total volume of Onemev green jobs covered by O*NET categories (Table 4a), which is the main indicator of the vagueness of the adaptation.

Table 1. List of occupations whose categorical greenness score changes with the corrected mean aggregation method

US SOC code	Occupation title	GNE score with simple mean (3.1)	GNE score with correction (3.2)	Evolution of GNE score	GES score with simple mean (3.1)	GES score with correction (3.2)	Evolution of GES score
11-1011	Chief Executives	0.5	0	Decrease	0	0	Stable
11-2011	Advertising and Promotions Managers	0.5	0	Decrease	0	0	Stable
11-3051	Industrial Production Managers	0.71	0	Decrease	0	0	Stable
17-2072	Electronics Engineers, Except Computer	0	0	Stable	0.5	1	Increase
17-3027	Mechanical Engineering Technicians	0.5	0	Decrease	0	0	Stable
19-2099	Physical Scientists, All Other	0.5	0	Decrease	0	0	Stable
19-3011	Economists	0.5	0	Decrease	0	0	Stable
19-3099	Social Scientists and Related Workers, All Other	0.5	0	Decrease	0	0	Stable
41-3099	Sales Representatives, Services, All Other	0.5	0	Decrease	0	0	Stable
41-4011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	0.5	0	Decrease	0.5	1	Increase
47-1011	First-Line Supervisors of Construction Trades and Extraction Workers	0.5	0	Decrease	0	0	Stable
49-9099	Installation, Maintenance, and Repair Workers, All Other	0.5	0	Decrease	0	0	Stable
51-9199	Production Workers, All Other	0.5	0	Decrease	0	0	Stable
53-1021	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	0.5	0	Decrease	0	0	Stable

3.4. Summary

All these quasi-*ad hoc* aggregation choices cause the greenness score of some US SOC occupations to change with respect to the simple mean method (3.1). Table 1 therefore lists all the US SOC occupations for which the greenness score for GNE and GES categories changes when using our corrected aggregation method and not that of the simple mean[15]. The score for the GID occupations is not shown because, having applied the simple mean method, they never vary[16]. For the continuous task-based indexes, we have directly applied the corrected aggregation method from VMC, so there is no comparison with the simple mean method to provide.

4. FROM THE US NOMENCLATURE TO THE INTERNATIONAL ONE

At the end of the previous step, whichever of the starting point or aggregation method is chosen, several greenness scores (depending on the combination) ranging from 0 to 1 are obtained for each 6-digit SOC occupation.

For this second step, the availability of employment data at the 6-digit US SOC level allows for weightings to be applied in order to fairly distribute greenness within the 4-digit ISCO-08 level. This is the green mean weighted approach that Valero et al. (2021) present as an adaptation of Dingel & Neiman (2020). Here, the difficulty lies in the fact that this is not a one-to-one mapping, in the sense that a US SOC occupation would only be associated with a single ISCO-08 occupation – as is the case when aggregating from one level to another in the same nomenclature. Indeed, the official crosswalk provided by the US Bureau of Labor Statistics[17] indicates that different ISCO-08 occupations can be associated to the same US SOC occupation.

For instance, US SOC occupation 19-1013 ('Soil and plant scientists'), which has a GES score of 1 and a core green-task index of 0.64, is linked to ISCO occupations 2131 ('Biologists, botanists, zoologists and related professionals') and 2132 ('Farming, forestry and fisheries advisers') – these two ISCO occupations being in turn linked to respectively 10 and 3 US SOC occupations. It follows that a weighting method only relying on US SOC employment data would create double-counting, giving a greater weight to occupations associated with more ISCO occupations. Dingel & Neiman (2020) summarize the problem and propose to solve it as follows[18]:

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[15] See Table A2 in Appendix to have a more complete (although not exhaustive) picture of the crosswalk.

[16] Nor are the GID occupations involved in joint aggregations with other O*NET green categories that would be subject to the corrected aggregation method.

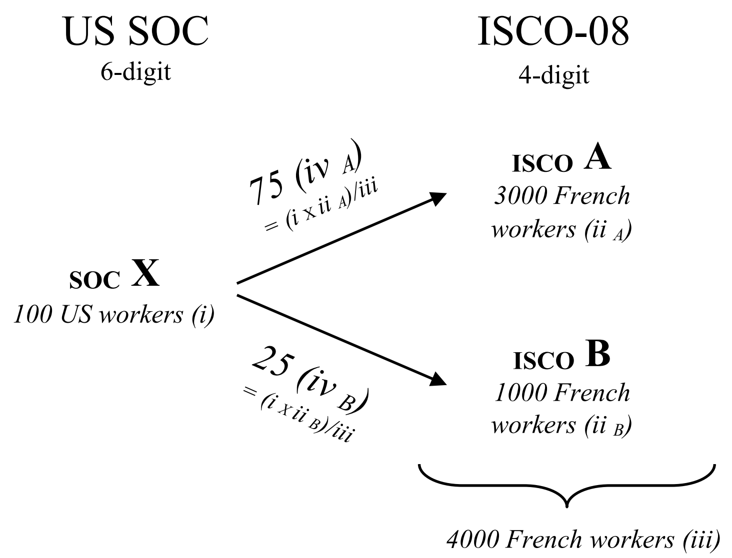
[17] Click here to download the conversion table in Excel format.

[18] For a less literary and more formalized version, the Stata code from Dingel & Neiman (2020) is available on the following Github: https://github.com/jdingel/DingelNeiman-workathome. More specifically, we relied on the 'country_measure' part by adapting the crosswalk to the 4-digit ISCO level (and not 2-digit, as is the case in their article). See also Scholl et al. (2023, p. 9‑ 11).

> "Ideally, each SOC would map to a unique ISCO, so that we could simply calculate the ISCO share as a weighted average of SOC shares, using the SOCs' US employment counts as the weights. However, given the many-to-many mapping, this approach would put disproportionate weight on those SOCs that happen to map to a larger number of ISCOs. To address this issue, when an SOC maps to multiple ISCOs, we allocate the SOC's US employment weight across the ISCOs in proportion to the ISCOs' employment shares in the "target" country. For instance, if a particular SOC has 100 US employees and is associated with two ISCOs that have respective totals of 3000 and 1000 employees in a country, we allocate 75 of the SOC's US employees to the larger ISCO and 25 to the smaller one. Those values of 75 and 25 are then used as that SOC's weight when calculating the average across all SOCs within each ISCO for that country" (p. 6)

Figure 1 below schematically illustrates these many-to-many mappings and the weighting method used. We can see that several variables need to be collected or constructed in order to finally obtain the weighting (iv) that will be applied when calculating the mean greenness of each 4-digit ISCO occupation. We can now describe in more detail the practical construction of these various variables.

Figure 1. Weighting method of the 'green mean weighted' approach



Source: author's realisation based on Dingel & Neiman (2020)

(i) US employment figures for each 6-digit SOC occupation

For this purpose, we use BLS data at a national level for the year 2012, which are directly reported at the 6-digit US SOC level[19]. Indeed, 2012 is the last year to provide employment figures for a version of the US SOC 2010 nomenclature similar to that used for the O*NET green categories (O*NET 18.0). Furthermore, this categorisation was updated at the end of 2011 (Dierdorff et al., 2011), so using 2012 statistics allows us to approximate the state of the economy and occupations at the time they were assigned to their O*NET binary categories. We call this variable:

[19] Available here: https://www.bls.gov/oes/tables.htm

SOC_Empl_US

(ii) French employment figures for each 4-digit ISCO occupation

This variable was created on the basis of the merged 2021 and 2022 French LFS[20]. To obtain the number of individuals in a given group (here within an ISCO occupation), we need to sum the individual weights of the individuals belonging to this group – this individual weight being the ‘EXTRI’ variable. We call this variable:

ISCO_Empl_FR

(iii) For each SOC occupation, the sum of the number of workers in the ISCO occupations associated with it

For the weight to be distributed among ISCO occupations in proportion to their share of employment in France, it is not enough to have French employment for each ISCO occupation. To avoid double-counting, we also need to know what share of employment this ISCO occupation represents among all the ISCO occupations linked to the US SOC occupation. To do so, for each SOC we need to sum up all the ‘ISCO_Empl_FR’ values (ii) linked to it *via* the corresponding ISCOs[21]. We call this variable:

ISCO_SumFR_perSOC

(iv) The final weighting variable

Once the three previous variables have been constructed, we can create the one that will be used to calculate the weighted greenness scores of each ISCO occupation. This new variable, for which each ISCO-SOC combination has its own value, is calculated as follows:

$$\text{Weighting} = \frac{\text{SOC\_Empl\_US (i)} \times \text{ ISCO\_Empl\_FR (ii)}}{\text{ISCO\_SumFR\_perSOC (iii)}}$$

(v) The calculation of each ISCO occupation’s weighted greenness

Finally, to get the green mean weighted values of each ISCO occupation, we simply take the weighted average of all the SOC green mean values associated with it – these values being scores from 0 to 1 obtained at the end of the first step[22].

[20] To get data at such a detailed level, we used the LFS available on the *Centre d’Accès Sécurisé aux Données* (Insee, 2022).

[21] Each ISCO must give its ‘ISCO_Empl_FR’ value only once when calculating the sum.

[22] de la Vega et al. (2024) applied the same method for the Argentinian 2-digit ISCO level and then checked the difference between this weighted adjustment and the unweighted version: they found that “the correlation [ranges] from 82 to 90 percent” (p. 5).

5. BACK TO BINARY ASSIGNMENTS: INTERPRETING THE GREENNESS OF ISCO OCCUPATIONS

Once all these steps have been applied, we obtain a greenness score on a scale of 0 to 1 for each 4-digit French occupation of the ISCO-08 nomenclature. Whether the starting point is the binary green categories or the continuous index of green tasks, we can interpret that the closer to 1 the score, the greener the occupation is – in the sense that, according to this method, it is estimated that a greater proportion of its related jobs or tasks are associated with the O*NET initial categorisation.

But this continuous score can complicate interpretations, especially when it comes to analysing the characteristics of jobs that we could consider green (in O*NET sense), and for which we would like to retain a sample. Indeed, an occupation can have values between 0 and 1 for all its categories (as long as their sum does not exceed 1): for instance, ISCO 1324 ('Supply, distribution and related managers') has a greenness of 0.33 for GNE, 0.67 for GES and 0 for GID. To simplify interpretation and follow the literature, we can thus create (new) binary green categories, assigning (or not) each occupation to them based on its continuous greenness scores.

5.1. Concerning the binary green categories approach, we propose that an ISCO occupation is assigned to an O*NET category (GNE, GES, GID) if its score is equal or greater than 0.5 for this same category – or to say it differently, if it is estimated that at least half of the French jobs associated with this occupation belong to the initial O*NET category[23].

5.2. Regarding the continuous index of green tasks, we try two alternatives from the literature, which we will refer as 'average task-based' (5.2.1) and '10% task-based' (5.2.2) green categories:

5.2.1. The first one, found in Elliott et al. (2021), considers an occupation to be green if its task-based greenness score is greater than the average for the list of all 4-digit ISCO occupations. In our case, it means having a greenness value greater than 0.0308 for all tasks, and greater than 0.0217 for core tasks[24].

5.2.2. The second one, found in OECD (2023), proceed differently and define green-task jobs as "occupations with at least 10% of their tasks considered green" (p. 52)[25]. This fixed threshold is useful as it "helps make estimates comparable across countries with different occupational employment" (p. 35).

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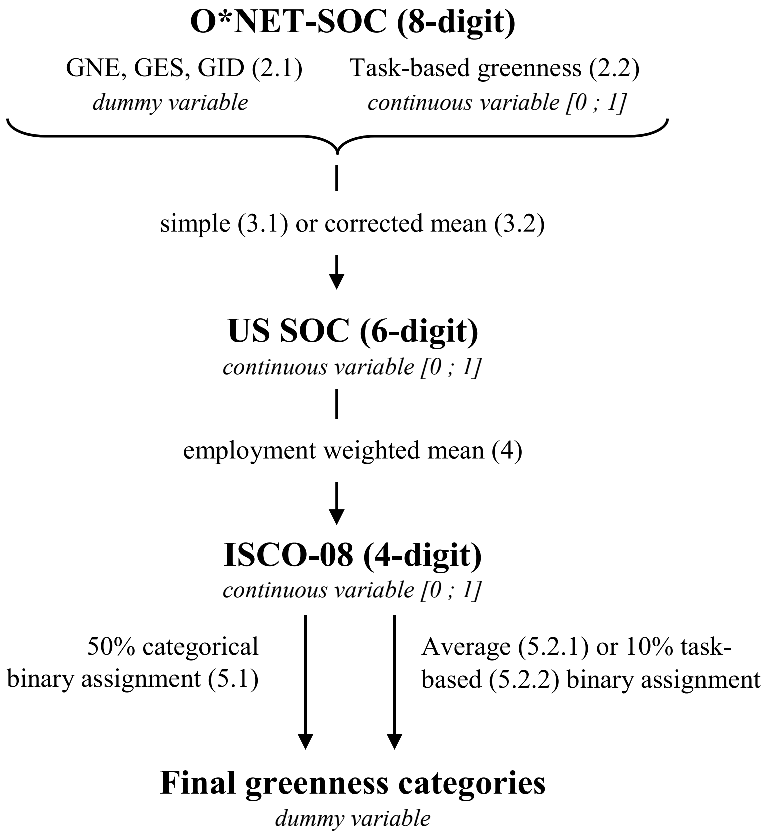
[23] There is a situation in which an ISCO occupation is assigned to two O*NET categories at the same time: it must have a greenness score of 0.5 for both. The occupations concerned, with the corrected mean aggregation method and before weighting (which reduces the number of cases), are: 2142 & 2143 for the GNE/GES combination; 7411 for GNE/GID; and 2114, 3114, 3131, 3155, 3522, 8211 for GES/GID. See footnote n°32 (p. 26) to find the occupations that keep this double assignment in the French data after employment weighting.

[24] More recently, de la Vega et al. (2024) identified green jobs as occupations "with [task-based] greenness scores greater than the 75th percentile" (p. 6).

[25] At first sight, following Apostel & Barslund (2024, p. 9), one may adopt the first formulation of this threshold, which suggests that the green task index must be *strictly greater* than 10%: "an occupation is considered green if its green intensity is *larger than* 10%" (OECD, 2023, p. 35). However, it is clarified in the next sentence and then several times in the report

Figure 2. Crosswalk stages



Source: author's realisation

At the end of this adaptation, it is possible to distinguish several versions of the greenness indicator, depending on whether we started from dichotomous categories (2.1) or continuous task-based indexes (2.2), whether we consider only core tasks or all of them for the latter, whether aggregation from the 8-digit to the 6-digit US nomenclature has been corrected (3.1 or 3.2), whether the adaptation from the US nomenclature to the international one has been weighted by employment shares (4), and depending on the binary assignment ultimately used (5). Figure 2 provides a schematic summary of all the stages (and thus choices) in this adaptation.

Ideally, analyses should be based on the most rigorous indicators, *i.e.* the ones resulting from both the correction and the weighting (of employment shares). But perhaps even more instructive would be the comparison between different versions, to see to what extent these methodological choices modify greenness measures and hence the final sample. Although there seems to be a consensus on the fact that weighting for task importance does not significantly modify scores (de la Vega et al., 2024; OECD, 2023; Scholl et al., 2023; Vona, 2021); and that Scholl et al. (2023, p. 7) state that using Vona et al. (2018) greenness measures rather than VMC do not change their results, hence suggesting that the corrected mean method is not essential; it is still worth testing some variations on our French sample. Indeed, and more

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that an occupation must have "*at least*" such a share of green tasks, thus including those with a green score of precisely 10%. In any case, it is unlikely to significantly change the results: in our case, no ISCO occupation has a green task index precisely equal to 0.1, so this has no effect on the resulting sample of green jobs.

importantly, Scholl et al. (2023) actually recognize that the – rarely used – employment weighting method consistently gives lower scores, and that "this result critically hinges on the employment distribution across 4-digit occupations in Portugal, and may change in the context of a different economy with a different industrial structure" (p. 18).

6. AN EMPIRICAL TEST OF THESE INDICATORS ON FRENCH DATA

What lessons can be drawn from the operationalisation of these correspondence methods on data from the merged 2021/2022 French LFS?

6.1. The volume of green jobs categories

The first issue concerns the range of jobs covered by our final greenness binary categories. In other words, we need to examine which jobs are considered green and which are not, and therefore what proportion of total employment each adapted category covers. These different options can be represented in the following table:

Table 2. Shares of employment by categories and aggregation methods

	O*NET binary categories			Task-based approaches			
				Green tasks		Core green tasks	
	GNE	**GES**	**GID**	**10%**	**Average**	**10%**	**Average**
W_C[26]	1.3	10.7	8.0	9.8	16.9	5.5	12.2
NW_C	2.2	10.8	6.6	10.1		7.3	
W_NC	2.3	9.5	8.0				

Source: author's realisation based on French 2021/2022 Labour Force Surveys (Insee, 2022)

Several observations can be made. Concerning O*NET binary categories, the first is that the corrected mean does not modify the GID perimeter ($\text{GID}_{\text{W\_C}} = \text{GID}_{\text{W\_NC}}$) – which was, in fact, expected since this category was not treated by VMC and that we simply chose to apply the simple mean method. Conversely, the corrected mean reduces and refines the GNE perimeter ($\text{GNE}_{\text{W\_C}} < \text{GNE}_{\text{W\_NC}}$). However, and more surprisingly at first sight, the corrected mean increases the number of jobs belonging to the GES category ($\text{GES}_{\text{W\_C}} > \text{GES}_{\text{W\_NC}}$). There are two reasons for this, both of which are illustrated in Table 1. On the one hand, the only aggregations to which a score of zero is assigned (which is the main contribution of the correction) concern GNE occupations, therefore leaving the greenness scores of GES occupations unchanged. On the other hand, and more importantly, the choice of assigning the greenness of the most general sub-occupation when aggregating (see Appendix) concerns two

[26] Rows distinguish combinations of aggregation methods between 'weighted and corrected' (W_C), 'non-weighted but corrected' (NW_C) and 'weighted but non-corrected' (W_NC). For instance, with correction (3.2) and weighting (4), the adapted GNE category covers 1.3% of French total employment. About the sample, we do not exclude individuals with no greenness score (because they have an ISCO code that is not detailed enough, and therefore does not allow such precise crosswalk), but we proceed as if their greenness score is zero.

GES occupations, and it increases their level of greenness: US SOC 17-2072 goes from a GES score of 0.5 to 1 with this correction, and US SOC 41-4011 goes from 0.5 in GES and GNE to 1 in GES.

In turn, weighting reduces the perimeter of GNE ($GNE_{WC} < GNE_{NW\_C}$) and GES ($GES_{WC} < GES_{NW\_C}$), but increases that of GID ($GID_{W\_C} > GID_{NW\_C}$) – which means that the crosswalk to ISCO underestimated the weight of occupations associated with the GID category in France. If we adopt the most refined version, the weighted and corrected one, O*NET categories therefore cover 20% of French employment, *i.e.* a volume very close to the less precautious adaptation made by Valero et al. (2021). But it should be noted that the distribution between categories is very different: they found 5% for GNE, 9% for GES and 7% for GID.

Concerning the adapted task-based approaches, the average binary assignment method of Elliott et al. (2021) results in large volumes of jobs, both for green tasks (16.9%) and core green tasks (12.2%), even exceeding the sum of GNE and GES categories. While this is not problematic *per se*, it is likely that the threshold is too low, especially as "the correct task-based approach to measure green employment indicates that only 2-3% of the US workforce is green and [that] it is in line with accurate survey-based measures" (Vona, 2021, p. 25). Although we might like to have a broader picture of jobs using green tasks, this somehow loses the granularity of this approach. With this in mind, we decide to rather focus on the 10%-threshold version from OECD (2023), which gives more confined perimeters, and to retain the weighting, which has a similar effect of reducing the sample[27].

6.2. The nature of adapted green jobs

But it is essential to go beyond the volume of employment alone if we are to assess the coherence of the occupations identified. Table 3 shows the main occupations included in our weighted and corrected green categories[28]. More precisely, for each category, we list the ten most numerous occupations as a weighted share of its total employment, both according to ISCO-08 – which is used for the crosswalk – and according to the 4-digit PCS level, which is more representative of French practices[29]. So, what does all this reveal?

[27] However, one should note that the OECD (2023) task-based adaptation, which relies on the 3-digit ISCO level, is uncorrected and unweighted (neither by importance score for the 8-to-6-digit SOC aggregation, nor by employment shares for the SOC-to-ISCO crosswalk). Hence, it results in very large volumes of green-tasks jobs, with around 24% for France (p. 54).

[28] All the following analyses are based on these 'weighted & corrected' (W_C) versions for the French 2021/2022 LFS.

[29] We are not providing it according to job titles (*libellés des professions*) because, although more precise, its lack of aggregation would further reduce the overall view, making it more difficult to present the sample. In this sense, the 4-digit PCS level seems to be a good compromise between precision and aggregation.

Table 3. Most represented occupations in O*NET adapted categories (as weighted share of the category)

	GNE		GES		GID		Green tasks – 10%		Core green tasks – 10%	
ISCO-08	Title	%	Title	%	Title	%	Title	%	Title	%
	1349 Professional services managers, not elsewhere classified	22.8	8332 Heavy truck and lorry drivers	11.3	2141 Industrial and production engineers	18.0	7231 Motor vehicle mechanics and repairers	7.2	2432 Public relations professionals	10.9
	1439 Services managers, not elsewhere classified	22.3	2433 Technical and medical sales professionals (excluding ICT)	10.6	7233 Agricultural and industrial machinery mechanics and repairers	11.2	5221 Shopkeepers	6.6	2422 Policy administration professionals	8.9
	2142 Civil engineers	21.2	5221 Shopkeepers	6.0	7115 Carpenters and joiners	9.5	1420 Retail and wholesale trade managers	6.3	3339 Business services agents, not elsewhere classified	8.9
	1431 Sports, recreation and cultural centre managers	9.9	1420 Retail and wholesale trade managers	5.8	8344 Lifting truck operators	7.8	2432 Public relations professionals	6.1	1323 Construction managers	8.3
	2149 Engineering professional, not elsewhere classified	9.8	2432 Public relations professionals	5.6	3122 Manufacturing supervisors	7.3	7126 Plumbers and pipe fitters	5.5	1324 Supply, distribution and related managers	8.1
	2133 Environmental protection professionals	8.8	7126 Plumbers and pipe fitters	5.1	7411 Building and related electricians	7.0	2422 Policy administration professionals	5.0	1349 Professional services managers, not elsewhere classified	5.4
	1213 Policy and planning managers	2.4	1120 Managing directors and chief executives	4.3	9333 Freight handlers	5.7	3339 Business services agents, not elsewhere classified	5.0	1439 Services managers, not elsewhere classified	5.3
	3116 Chemical engineering technicians	2.2	1323 Construction managers	4.3	4323 Transport clerks	5.6	1323 Construction managers	4.6	2142 Civil engineers	5.1
	2143 Environmental engineers	0.6	1324 Supply, distribution and related managers	4.2	8342 Earthmoving and related plant operators	3.8	1324 Supply, distribution and related managers	4.5	2161 Building architects	5.1
			9622 Odd-job persons	4.1	3111 Chemical and physical science technicians	3.5	9622 Odd-job persons	4.4	3119 Physical and engineering science technicians, not elsewhere classified	4.7
Total		100		61.3		79.4		55.2		70.7
PCS4 (in French)	38C1 Ingénieurs et cadres d'études du BTP	12.0	64B1 Conducteurs de poids lourds	10.5	65B1 Caristes	7.8	63C2 Réparateurs qualifiés de véhicules et de biens d'équipement du foyer	4.1	54D1 Employés administratifs des services commerciaux	5.7
	33B1 Ingénieurs et cadres techniques de la fonction publique	9.0	38F5 Ingénieurs commerciaux et cadres technico-commerciaux	5.0	47D3 Techniciens d'installation et de maintenance (hors informatique)	6.1	54D1 Employés administratifs des services commerciaux	3.2	37D5 Cadres de la communication, de la publicité et des relations publiques	5.1

	22D5 Gestionnaire d'autres établissements de service	8.5	46C1 Représentants, technico-commerciaux de la vente de biens auprès de professionnels	3.8	38D1 Ingénieurs et cadres de production	5.0	22B2 Commerçants de biens pour la personne	2.9	46E1 Assistants de la communication, de la publicité et des relations publiques	4.7
	38D1 Ingénieurs et cadres d'études, recherche et développement de l'industrie	5.8	22B2 Commerçants de biens pour la personne	2.7	38D2 Ingénieurs et cadres d'études, recherche et développement de l'industrie	4.8	37D5 Cadres de la communication, de la publicité et des relations publiques	2.9	21B7 Artisans tout corps de métier du bâtiment et artisans des travaux publics	4.3
	21E5 Artisans du nettoyage, de la récupération et des services divers	4.6	37D5 Cadres de la communication, de la publicité et des relations publiques	2.6	67E2 Manutentionnaires peu qualifiés et professions assimilées	3.9	63B4 Plombiers, chauffagistes qualifiés	2.7	33B1 Ingénieurs et cadres techniques de la fonction publique	4.0
	37C2 Cadres généralistes et services administratifs	3.7	46E1 Assistants de la communication, de la publicité et des relations publiques	2.4	62E5 Ouvriers qualifiés de maintenance et d'entretien des équipements industriels	3.7	63B7 Ouvriers qualifiés d'entretien général des bâtiments	2.7	33C2 Cadres administratifs des collectivités territoriales et des hôpitaux publics	3.9
	38B1 Ingénieurs et cadres techniques de l'agriculture, de l'aquaculture, des forêts et de la protection de l'environnement	3.5	63B7 Ouvriers qualifiés d'entretien général des bâtiments	2.4	63B3 Menuisiers qualifiés du bâtiment	3.6	46E1 Assistants de la communication, de la publicité et des relations publiques	2.6	47B2 Techniciens de chantier du BTP	3.3
	43D1 Directeurs et cadres du travail social et de l'animation socio-culturelle	3.2	21B7 Artisans tout corps de métier du bâtiment et artisans des travaux publics	2.3	48C1 Agents de maîtrise de fabrication industrielle	3.4	46B1 Responsables (non-cadres) de magasins	2.5	33C1 Cadres administratifs de l'Etat	3.2
	35C1 Cadres de la presse, de l'édition, responsables de la production et de la programmation audiovisuelle et des spectacles	3.1	46B1 Responsables (non-cadres) de magasins	2.3	62A1 Conducteurs d'engins de chantier des travaux publics	3.3	21B7 Artisans tout corps de métier du bâtiment et artisans des travaux publics	2.4	38C1 Ingénieurs et cadres d'études du BTP	3.1
	38C3 Ingénieurs et cadres de chantier du BTP	2.8	63B4 Plombiers, chauffagistes qualifiés	2.2	38F3 Ingénieurs et cadres du contrôle-qualité et de la prévention des risques	3.1	33B1 Ingénieurs et cadres techniques de la fonction publique	2.3	38D1 Ingénieurs et cadres d'études, recherche et développement de l'industrie	2.3
Total		56.2		36.2		44.7		28.3		39.6

Source: author's realisation based on French 2021/2022 Labour Force Surveys (Insee, 2022)

While the GNE category does indeed refer to occupations with a relatively explicit environmental content, identifiable by both the ISCO nomenclature (2133, 2143) and the PCS one (21E5, 38B1), this is not so obvious for a large proportion of them. In fact, despite a relatively small sample, the GNE category identifies many jobs whose green status is abused and therefore overestimated. This is the case for the numerous directors' occupations (1349, 1439, 1431) which are included in the correspondence with the ISCO nomenclature, and which represent more than half of the sample – despite that there is nothing to support their green nature, and even less their 'new and emerging' one. If we follow the assignment path in our method, we can explain it with US SOC 11-9199 ('Managers, all other') which, being 6/10 GNE and in line with VMC, gave the GNE category to all these managerial occupations *via* the crosswalk to the ISCO nomenclature.

As did the French Onemev former definition of greening occupations (*métiers verdissants*), the GES category identifies some transport drivers, who here occupy first place in the sample with both nomenclatures. Although the reasons for this choice are questionable, especially as it represents a large number of workers, it is methodologically consistent with the initial O*NET category, which includes 'Heavy and tractor-trailer truck drivers' (53-3032.00). There are also other occupations on which we can agree that they are (or should be) adapting to the environmental challenge. This is the case, for example, in the construction sector (1323, 9622), which is one of the few sectors (along with energy, transport and agriculture) where there is a consensus in France – and more widely in developed countries – on the need for a massive ecological transformation (Hentzgen et al., 2023).

Nevertheless, the GES category still includes many directors and managers, particularly in the retail sector. This is not to say that practices and tasks in these occupations do not need to adapt: on the contrary, their "functional contribution to consumerism and over-exploitation of nature" (Coutrot, 2021) emphasises this need, and assigning these occupations to GES thus makes more sense than for GNE. Still, there are legitimate doubts about the reality of the adaptation of these occupations and whether they are already effective and substantial, particularly in view of the level of aggregation of the ISCO categories used for the crosswalk.

In a way, the same observation as for the GES category can be made for the two task-based categories, with a relative bias towards high-skilled workers as well[30], in particular for the core-tasks sample. In these two categories, we obviously find occupations also covered by GNE and GES (especially GES: 2432, 1323, 1323, etc.), but also other occupations that emerge due to the change in method. And finally, the GID category – which is of less interest to us – seems relatively consistent with its initial list.

[30] It should be noted that this high-skill 'bias' is not the result of an inappropriate crosswalk (Vona et al., 2019, p. 9). On the contrary, it is in line with the fact that, in the GNE category in particular, "there is more of a bias towards professional and associate professional occupations but [that] this may simply reflect the development stage at which many green technologies [had] reached" (Cambridge Econometrics et al., 2011, p. 104).

6.3. Cross-checks with the French *ad hoc* list of green jobs

Another way of assessing the consistency of this crosswalk is to compare occupations identified by these adapted categories with those covered by the French Onemev definition of green jobs. Indeed, Onemev has a particularly precise identification method that is suited to French data (see Box 2 below). As such, its perimeter can provide a good basis for judging the relevance of applying the O*NET adapted categories to the French case – and, more generally, to other countries.

The point is not to say that adapted categories should perfectly overlap with the Onemev definition, but rather that if there are significant divergences even for the categories that are supposed to share a common inspiration, then it legitimately questions the relevance of the crosswalk both for other less similar categories, and for other countries with no such benchmark to assess the accuracy of their adaptation. In particular, the Onemev definition shares a common inspiration with the GNE category from O*NET, both seeking to identify what would be the 'greenest' occupations (Apostel & Barslund, 2024, p. 8; Bachelot, 2023, p. 29). The fact that these are particularly small groups confirms this intuition: the GNE has the fewest jobs of the three adapted binary categories, and the Onemev definition only represents 1.5% of French employment.

However, one should not forget the differences between the two approaches, so that Onemev green jobs falling into the GES and GID adapted categories is not a problem *per se* – in fact, we expect this to happen to a certain extent, as already suggested (see footnote n°3). More specifically, a rarely mentioned point that illustrates these differences is the fact that, unlike the Onemev:

> "The O*NET approach is not designed to identify what might be called 'historic' green jobs, *i.e.* occupations that do indeed have an environmental purpose and whose tasks are geared in this direction, but which are neither new (they have existed for a long time), nor greening (they were already green), nor necessarily expected to grow. In other words, they do not significantly reflect the effects of the ecological transition on employment. Although most green occupations, even the oldest, do meet one of these three criteria, this is not the case, for example, with "Landscaping and groundskeeping workers" [37-3011.00], who are not covered by O*NET but are by Onemev" (Bachelot, 2023, p. 27)

Hence, the O*NET and Onemev categorisations are intrinsically different: they do not really have the same 'philosophy', nor were they constructed at the same period, so that it is normal that their perimeters vary – within a reasonable range. Two sources of mismatch therefore exist – and cumulate: (i) the methodological limitations of the crosswalk; (ii) the conceptual (and political) differences between O*NET and Onemev categorisations, in terms of what is initially considered as 'green' and what is not[31]. It is important to bear this in mind to avoid misinterpreting subsequent results.

[31] More fundamentally, both are dependent on how occupations are broken down and identified in each nomenclature, as it affects the crosswalk possibilities as well as the level of granularity with which greenness can be captured.

Box 2: The identification of 'green jobs' by Onemev

Developed as part of the 2020 occupational nomenclature change (PCS 2020), the Onemev approach identifies green jobs based on job titles (*libellés de professions*) – the most detailed level of the French nomenclature. This coding of green jobs is directly integrated into official statistics surveys and is publicly available on the Insee website. It aims to identify "jobs which, through their purpose and/or the skills they use, contribute to measuring, preventing, controlling and correcting negative impacts and damage to the environment" (Insee, 2024). This list of job titles was constructed "on the basis of an automated textual analysis of job titles collected in the Generation surveys using a lexicon of 'green' keywords". This procedure "enabled the identification of more than 2,500 job titles", which was then reduced to "a smaller list, suitable for an *ad hoc* indicator of green jobs" (Amossé et al., 2019, p. 77‑78). In 2022, the finalised list contained 143 job titles, rising to 145 in 2023 and 150 in 2024.

Are occupations identified by the Onemev method also found in the adapted O*NET categories (in particular GNE), and *vice versa*? To what extent, and for which occupations, is this the case or not? Tables 4 and 5 answer these questions.

Table 4 indeed confirms that the Onemev definition is closest to GNE: it is the adapted category that proportionally includes the most individuals working in green jobs as defined by Onemev (10.5%). The other categories, although they include more green jobs in volume (4a), are far behind relative to their size (4b).

Table 4. Overlaps between adapted categories and Onemev green jobs (as a share of the 'within' sample)

(4a)

within… / Proportion of…	**Onemev green jobs**
GNE	8.5
GES	10.7
GID	15.6
Double assignment[32]	1.1
Belonging to none	64.3
Green tasks – 10%	22.3
Core green tasks – 10%	19.3

(4b)

Proportion of… / within…	**Onemev green jobs**
GNE	10.5
GES	1.6
GID	2.8
Green tasks – 10%	3.3
Core green tasks – 10%	5.1

Source: author's realisations based on French 2021/2022 Labour Force Surveys (Insee, 2022)

[32] Occupations that are assigned to two O*NET binary categories are counted only once, in this 'double assignment' category (the sum of all white rows being 100): this concerns ISCO 2142 and 2143 which are GNE and GES; and ISCO 3114, 3155 and 3522 which are GES and GID.

Table 5. Job structures of adapted categories and Onemev green jobs

	Onemev green jobs	GNE	GNE & GES	Green tasks – 10%	Core green tasks – 10%
Socio-professional category					
Craftsmen, shopkeepers, heads of business	5.7	23.8	18.5	20.5	15.9
Managers and higher intellectual professions	18.1	59.2	33.4	30.9	44.3
Middle-level occupations	16.7	6.8	19.8	22.8	26.6
Skilled clerical, sales and services workers	1.3	0.1	0.7	3.9	6.1
Unskilled clerical, sales and services workers	0.4	0	1.0	1.3	0.1
Skilled industrial and blue-collar workers	52.4	0.1	21.4	15.0	4.7
Unskilled industrial and blue-collar workers	5.4	0	5.1	5.6	2.4
Mean wage	1785€	2940€	2519€	2377€	2597€

Table 6. Main occupations identified as green by one category and not others

(6a)

	Onemev green jobs not covered by GNE & GES adapted categories	
	Title	**%**
Job titles (PCS)	Landscaper (*paysagiste*)	25.7
	Green spaces maintenance agent (*agent d'entretien des espaces verts*)	15.4
	Gardener (*jardinier*)	14.7
	Total	55.8
ISCO-08	Gardeners, horticultural and nursery growers (6113)	53.4
	Garden and horticultural labourers (9214)	24.5
	Environmental and occupational health inspectors and associates (3257)	4.7
	Total	84.6

(6b)

	GNE jobs not covered by Onemev green jobs	
	Title	**%**
Job titles (PCS)	Technical services manager (*responsable des services techniques*)	9.0
	Building design engineer (*ingénieur d'études du BTP/bâtiment*)	8.8
	Leisure centre director (*directeur de centre de loisirs*)	3.4
	Total	21.2
ISCO-08	Professional services managers, not elsewhere classified (1349)	28.3
	Civil engineers (2142)	26.0
	Services managers, not elsewhere classified (1439)	19.3
	Total	73.6

(6c)

	Onemev green jobs not covered by the 'Core green tasks 10%' category	
Job titles (PCS)	Environment officer (*chargé de mission environnement*)	8.8
	Refuse collector (*ripeur éboueur*)	8.7
	Waste sorting agent (*agent de tri des déchets*)	8.0
	Total	25.5
ISCO-08	Environmental protection professionals (2133)	34.2
	Refuse sorters (9612)	21.8
	Life science technicians, excluding medical (3141)	13.5
	Total	69.5

(6d)

	'Core green tasks 10%' jobs not covered by Onemev green jobs	
Job titles (PCS)	Communication officer (*chargé de communication*)	3.5
	Government qualified architect (*architecte DPLG*)	2.9
	Roofer (*couvreur*)	2.9
	Total	9.3
ISCO-08	Public relations professionals (2432)	12.8
	Constructions managers (1323)	9.7
	Supply, distribution and related managers (1324)	9.7
	Total	32.2

Source: author's realisation based on French 2021/2022 Labour Force Surveys (Insee, 2022)

The most striking thing, however, is the fact that 64.3% of Onemev green jobs (or rather of individuals occupying them) do not belong to any adapted O*NET binary category. This is even more surprising that the Onemev definition, which is fairly restrictive, is not supposed to overestimate jobs – quite the contrary. The fact that more than half of them is not attached to any of our adapted categories clearly is problematic. As does the fact that, conversely, 89.5% of jobs belonging to GNE are not covered by the Onemev definition.

Another way of illustrating the fact that green jobs clearly differ between categories is to compare their job structures in terms of socio-professional categories or average wage. This is what Table 5 does, indeed showing that, although volumes sometimes get closer, differences between O*NET adapted categories and Onemev green jobs remain very significant: while the former exhibit a high-skill bias, it is rather the opposite for the latter. In fact, this helps to explain why early research on green jobs in France sometimes gives contradictory results to studies on foreign countries using O*NET (Bachelot, 2023).

But, more precisely, which occupations are identified as green by one category and not by others? Table 6 lists the main occupations concerned, both according to ISCO-08 (for the same reason as mentioned in 6.2), and according to the French PCS job titles (as this is the variable used by Onemev to code green jobs). We here focus on GNE and GES, because they are the 'directly' green categories, and especially on GNE which is the greenest and closest to Onemev green jobs. For the task-based adaptation, we only present results for the 'Core green tasks – 10%' category, as it is the most similar to Onemev green jobs.

The first thing that stands out is that most of Onemev green workers which are not covered by GNE/GES adaptations (whose volume was of concern in Table 4a) are in fact gardeners or affiliates (6a) – for which it was previously explained that they were not considered by O*NET. At first sight, this could suggest that 'conceptual' differences between categorisations are the main issue, and that they alone explain (and therefore exonerate) the apparent 'poor' quality of the crosswalk. However, the picture remains similar once controlled for this 'composition effect' skewed by gardeners, who indeed account for almost 45% of French green employment.

If we ignore the volume of employment associated with each job, we still see that, of the 121 Onemev green job titles identified in the French LFS, 53 are not covered by GNE/GES adapted categories, *i.e.* 44% of them (see the list in Table 7). Also, 42 Onemev green job titles (35%) are not covered by the 10% core green tasks approach (6c).

This goes far beyond the few gardener occupations first identified, and it is difficult to imagine most of them not falling into one of the (directly) green categories. Here, it illustrates problems with the crosswalk method, especially since many of the Onemev green jobs not covered by our GNE/GES adapted groups have corresponding titles in these original O*NET categorisations.

For instance, 'Decontamination workers' from Table 7 could reasonably be considered as equivalent to 'Hazardous Materials Removal Workers' from O*NET (47-4041-00 – GES). Similarly, 'Energy research and development (R&D) engineers' and 'Agricultural and environmental engineers (IAE)' are very close to O*NET 'Energy engineers' (17-2199.03 – GNE) and 'Environmental engineers' (17-2081.00 – GES).

Table 7. Onemev green jobs not covered by GNE/GES adapted categories

PCS job titles (in French)	
Paysagiste	Horticulteur paysagiste
Agent d'entretien des espaces verts	Agent de sensibilisation en gestion des déchets
Jardinier	Entrepreneur espace vert
Jardinier municipal	Ingénieur forestier
Employé des espaces verts	Ouvrier d'entretien des espaces naturels
Jardinier paysagiste	Technicien de la pêche
Ouvrier des espaces verts	Animateur sécurité prévention environnement
Agent de nettoyage de la voirie	Artisan en parcs et jardins
Désamianteur	Assistant sécurité environnement
Responsable qualité sécurité environnement (QSE)	Chef d'exploitation d'usine d'incinération
Artisan paysagiste	Chef jardinier
Chef paysagiste	Expert forestier
Technicien environnement (protection de l'environnement)	Garde du littoral
Employé jardinier	Nettoyeur sur site nucléaire
Ingénieur de l'agriculture et de l'environnement (IAE)	Technicien en analyse des pollutions
Agent technique de l'environnement (ATE)	Technicien environnement (industrie)
Technicien des espaces verts	Technicien des espaces naturels
Chargé de mission RSE (responsabilité sociétale de l'entreprise)	Agent de sensibilisation à l'environnement
Technicien hygiène sécurité environnement (HSE)	Conseiller sécurité environnement
Technicien de rivières	Garde forestier
Animateur hygiène sécurité environnement (HSE)	Garde-pêche
Gardien des parcs et jardins	Ingénieur géotechnique
Décontaminateur	Conseiller forestier
Directeur hygiène, sécurité et environnement	Balayeur de voirie
Garde gestionnaire des espaces naturels	Technicien pollution de l'air
Agent de salubrité	Technicien du traitement des eaux usées
Ingénieur recherche et développement (R&D) de l'énergie	

Source: author's realisation based on French 2021/2022 Labour Force Surveys (Insee, 2022)

To put it simply, there are plenty of jobs whose absence or presence within O*NET adapted categories confirms doubts on the accuracy and relevance of the crosswalk. How can such differences be explained? Again, a first response would be that, because of changes in the economy and occupations, "O*NET greenness measures do not longer reflect the full set of current green employment" (Apostel et Barslund, 2024, p. 8), hence contributing to the conceptual differences identified.

While this may explain part of the problem, this work also reveals some limits directly stemming from the adaptation methods used. Going back over the assignation path precisely allows to track and explain these mismatches. Indeed, Onemev jobs are linked to ISCO-08 occupations that are green (or not) because they are attached to US SOC occupations, which must themselves include enough green sub-occupations or tasks in O*NET sense.

Table 8. Examples of crosswalks for some inappropriate categorical assignations

Final occupation	Associated ISCO	ISCO greenness (WC versions)	Associated US SOC	US SOC greenness (from Table A2)
Onemev green jobs (PCS) not covered by GNE/GES adaptations				
Technician in pollution analysis	3257 ('Environmental and occupational health inspectors and associates')	- GES = 0.36 - GID = 0.23 - GreenTasks = 0.14 - CoreGreenTasks = 0.05	29-9012	- GES = 0.33 - GreenTasks = 0.23 - CoreGreenTasks = 0.23
			45-2011	- GID = 1
			53-1031	x
			53-6051	- GES = 0,33 - GreenTasks = 0.15
Decontamination worker	9129 ('Other cleaning workers')	x	37-2019	x
			47-4071	x
GNE adapted occupations (ISCO) not covered by Onemev green jobs				
1349 ('Professional services managers, not elsewhere classified')		- GNE = 0.6 - GreenTasks = 0.35 - CoreGreenTasks = 0.31	11-9199	Same scores as ISCO greenness because one-to-one matching
2142 ('Civil engineers')		- GNE = 0.5 - GES = 0.5 - GreenTasks = 0.32 - CoreGreenTasks = 0.20	17-2051	Same scores as ISCO greenness because one-to-one matching

Source: author's realisation based on French 2021/2022 Labour Force Surveys (Insee, 2022)

To use a previous example: 'Decontamination workers' are green according to Onemev but are linked to ISCO 9129 ('Other cleaning workers') which has a greenness score of 0 for all categories. This ISCO occupation is associated to US SOC 37-2019 ('Building cleaning workers') and 47-4071 ('Septic tank servicers and sewer pipe cleaners') that contain no O*NET green occupation. On both sides, the passage through ISCO causes the loss of granularity necessary for a proper match of occupations and of their greenness.

Differently, 'Technicians in pollution analysis' are green according to Onemev and its associated ISCO 3257 ('Environmental and occupational health inspectors and associates') is not covered by GNE/GES adapted categories (6a). As Table 8 shows, this is due to the method used because its greenness score is positive for GES (and GID), but lower than the 0.5 threshold. Similar examples could be detailed for task-based adaptations, which also result in unsatisfactory mismatches, such as ISCO 2133 ('Environmental protection professionals') which is not considered green for our core green tasks approach (6c).

Still, coming back to ISCO 3257, this occupation is part of the 10% task-based green group. More broadly, task-based approaches include more of Onemev green jobs (4a). And this is not due to larger volumes of jobs: GNE & GES categories cover 12% of French employment (Table 2) but include only 19.2% of Onemev green jobs; while the 10% green-task approach cover 9.8% of French employment but include 22.3% of Onemev green jobs. What these examples first suggest is that, in general, green tasks categories may be more appropriate to capture greenness, and second and above all that binary assignments lead to the arbitrary loss of much information.

Conversely, and as previously specified, ISCO occupations 1349 and 1439 are considered GNE (6b) as they are associated to US SOC 11-9199 ('Managers, all other'), which has a GNE score of 0.6. This should have been manually corrected with the 'corrected mean aggregation' method (3.2) or, better, limited using the sector restriction (see footnote n°13).
Another last example is ISCO 2142 ('Civil engineers') that belongs to GNE *via* the US SOC 17-2051 ('Civil engineers') which is 0.5 GNE and 0.5 GES. Here, the matching coincides very

well (*i.e.* same title within ISCO and US nomenclatures), so that the divergence is due to a different (political) choice from Onemev, which decided not to count as green such a large and vague group into its green jobs' list – especially as they label 17 other 'Engineer' job titles as green.

CONCLUSION

The development and subsequent implementation of this crosswalk method from O*NET to the international ISCO-08 nomenclature using French data raises several points:

(i) It is possible, at least for countries such as France with sufficiently detailed data, to develop a more rigorous method of correspondence than has been done to date in other works dealing with European adaptations (or even in specific countries). As far as we know, we propose the most meticulous and faithful adaptations to the initial inspiration of O*NET categorisations. We explain in detail the entire methodological process and our choices, clarifying the mere references from other authors on their methods.

(ii) A careful examination of the results revealed several shortcomings, particularly regarding the GNE category, which we compared with the French Onemev fine-tuned method of identifying green jobs – that is, to a large extent, very similar in its inspiration. In fact, we have highlighted some questionable mismatches which are due both to differences in the conceptualisation and philosophy of the two categorisations and, more problematically for comparative purposes, to the difficulties and imperfections of the crosswalk method. This observation calls for caution in the use that can be made of the correspondences between O*NET and ISCO.

(iii) In France, we can therefore – and quite obviously – conclude that it is preferable to use the Onemev definition rather than any other O*NET adaptation to identify the 'core' of green jobs.

(iv) The crosswalk seems more appropriate and accurate for GES and GID categories, which have no (or no longer) equivalents in France. To some extent, this seems even more valid for binary task-based approaches.

(v) However, within this framework, assessing the relevance of these other adaptations is tricky, and the large mismatch between GNE and the Onemev list is not really reassuring. Thus, using these adapted categories with caution could be useful, although we would prefer to use an *ad hoc* French (or European) definition.

On this final point, there exists possibilities to differently identify green jobs and methodically expand their perimeter beyond the current narrow focus of the Onemev definition, potentially capturing 'indirect' green jobs as well (similarly to the GID inspiration). Provided that detailed scenarii exist, an ingenious method for doing this is to compare job changes between a business-as-usual trend and another modelling of a low-carbon trajectory. This is precisely what Hentzgen et al. (2023) did, based on the SNBC French scenario (Stratégie Nationale Bas-Carbone) applied in the 'Métiers 2030' report (Sciberras et al., 2022, p. 36).

In practice, they identify the fifteen jobs whose share of total employment increases the most with respect to the business-as-usual counterfactual. Results mainly show construction jobs (7 out of the 15), typical of greening occupations. There are also some study, research and legal staff, probably halfway between green and greening jobs. Finally, there are also what appear to be support worker positions, which could in a sense be described as indirect green jobs.

Although original and interesting, this approach bears several limits. One of the most important is that, in addition to being strongly dependent on modelling assumptions, it only considers volumes and does not account for jobs that (will) significantly change qualitatively. More practically, it identifies jobs through the 2009 FAP nomenclature (the 'Familles professionnelles' developed by the DARES), but its correspondence to PCS – used in LFS – is available only for the discontinued 2003 PCS version. Thus, it is not (yet) possible to identify and characterise these jobs in the most recent surveys (hence the pre-2020 data in the report) and, once again and among other things, to compare their sample with Onemev adapted categorisations.

Another option, rather than using multiple crosswalk methods, would either be to use textual analysis to translate and directly adapt O*NET green job titles into the French nomenclature, without using complicated and uncertain aggregation methods; or to use a new and official crosswalk directly linking O*NET-SOC 8-digit occupations with the ESCO European nomenclature[33], which can then be easily and neatly converted into ISCO.

Yet, all these methods are subject to the limits of the green/non-green binarity (Bachelot, 2023, p. 30), which may further exacerbate the imperfection of the crosswalk (see examples discussed for Table 7). A relatively simple and satisfactory solution to this problem is possible within the O*NET framework, using task-based measures but without binary assignment (5.2). Indeed, we could use them as continuous scores to better reflect and retain the heterogeneity and gradation of jobs' green practices – as recommended by Vona (2021) and done, for example, in Elliott et al. (2021). In the end, we cannot distinguish a delimited sample of green jobs (as sought in many studies), but we are able to estimate the green intensity of jobs, which can be used directly, depending on the question asked, as the variable of interest.

In any case, more investigations are still needed, and this paper was only part of it, showing how to better adapt O*NET categorisations to European and French data, while at the same time questioning the relevance, in the current state, of the adaptations already implemented and their resulting analyses.

[33] See here: https://esco.ec.europa.eu/en/about-esco/data-science-and-esco/crosswalk-between-esco-and-onet

BIBLIOGRAPHIE

Amossé, T., Chardon, O., & Eidelman, A. (2019). *La rénovation de la nomenclature socioprofessionnelle (2018-2019)* (Rapport du groupe de travail du Cnis 156). Conseil National de l'Information Statistique.

Apostel, A., & Barslund, M. (2024). "Measuring and characterising green jobs: A literature review". *Energy Research & Social Science*, *111*, 103477.

Bachelot M. (2023). « Comment définir et analyser les "emplois verts" ? Une revue de la littérature ». *Socio-économie du travail*, 13, p. 15-50.

Bowen, A., Kuralbayeva, K., & Tipoe, E. L. (2018). "Characterising green employment: The impacts of 'greening' on workforce composition". *Energy Economics*, 72, 263‑275.

Cambridge Econometrics, GHK, & Warwick Institute for Employment Research. (2011). *Studies on Sustainability Issues – Green Jobs; Trade and Labour* (Final Report for the European Commission; p. 264). DG Employment.

Coutrot, T. (2021). « Le conflit éthique environnemental au travail. Une première analyse empirique à partir de l'enquête Conditions de travail 2019 ». *Travail et emploi*, 166‑167(3‑4), 183‑206.

de la Vega, P., Porto, N., & Cerimelo, M. (2024). "Going green: Estimating the potential of green jobs in Argentina". *Journal for Labour Market Research*, 58(1), 1.

Dierdorff, E. C., Norton, J. J., Drewes, D. W., Kroustalis, C. M., Rivkin, D., & Lewis, P. (2009). *Greening of the world of work: Implications for O* NET®-SOC and new and emerging occupations*. Raleigh, NC: The National Center for O* NET Development.

Dierdorff, E. C., Norton, J. J., Gregory, C. M., Rivkin, D., & Lewis, P. (2011). *Greening of the World of Work: Revisiting Occupational Consequences at O*NET Resource Center*. Raleigh, NC: The National Center for O* NET Development.

Dingel, J. I., & Neiman, B. (2020). "How many jobs can be done at home?" *Journal of Public Economics*, 189, 104235.

Elliott, R. J. R., Kuai, W., Maddison, D., & Ozgen, C. (2021). *Eco-Innovation and Employment: A Task-Based Analysis* (IZA Discussion Paper 14028). IZA Institute of Labor Economics.

Hancké, B., & Bowen, A. (2019). *The social dimensions of 'greening the economy': Developing a taxonomy of labour market effects related to the shift toward environmentally sustainable economic activities* (European Commission and LSE Consulting). Publications Office of the European Union.

Hentzgen, C., Orand, M., Cousin, C., Lê, J., Villedieu, P., Janelli, R., Garner, H., & Jolly, C. (2023). *Les incidences économiques de l'action pour le climat – Marché du travail* [Rapport thématique de la mission présidée par Jean Pisani-Ferry]. France Stratégie & Dares.

Insee (2022). *Enquête Emploi en continu (Base Z - Diffusion CASD) – Éditions 2021 et 2022* [Data set]. CASD. https://www.casd.eu/source/enquete-emploi-en-continu/

Insee (2024). Métiers « verts » | Insee. https://www.insee.fr/fr/information/6050093

Lobsiger, M., & Rutzer, C. (2021). "The green potential of occupations in Switzerland". *Swiss Journal of Economics and Statistics*, 157.

OECD. (2023). *Job Creation and Local Economic Development 2023: Bridging the Great Green Divide*. OECD.

O*NET. (2010). *O*NET Green Task Development Project*. The National Center for O*NET Development. https://www.onetcenter.org/reports/GreenTask.html

Østergaard, C. R., Holm, J. R., Iversen, E., Schubert, T., Skålholt, A., & Sotarauta, M. (2021). Environmental Innovations and Green Skills in the Nordic Countries. In S. R. Sedita & S. Blasi (Éds.), *Rethinking Clusters: Place-based Value Creation in Sustainability Transitions* (p. 195‑211). Springer International Publishing.

Scholl, N., Turban, S., & Gal, P. N. (2023). *The green side of productivity : An international classification of green and brown occupations*. OECD.

Sciberras, J.-C., Jolly, C., Flamand, J., Le Hir, B., Rey, M., Eidelman, A., Cousin, C., & Desjonqueres, A. (2022). *Métiers 2030 – Quels métiers en 2030 ?* [Rapport du groupe « Prospective des métiers et qualifications »]. France Stratégie & Dares.

Sofroniou, N., & Anderson, P. (2021). "The green factor: Unpacking green job growth". *International Labour Review*, 160(1), 21‑44.

Valero, A., Li, J., Muller, S., Riom, C., Nguyen-Tien, V., & Draca, M. (2021). *Are 'green' jobs good jobs? How lessons from the experience to-date can inform labour market transitions of the future*. Grantham Research Institute on Climate Change and the Environment and Centre for Economic Performance, London School of Economics and Political Science.

Vona, F. (2021). *Labour markets and the green transition: A practitioner's guide to the task-based approach*. Publications Office of the European Union.

Vona, F., Marin, G., & Consoli, D. (2019). "Measures, drivers and effects of green employment: Evidence from US local labor markets, 2006–2014". *Journal of Economic Geography*, 19(5), 1021‑1048.

Vona, F., Marin, G., Consoli, D., & Popp, D. (2018). "Environmental Regulation and Green Skills : An Empirical Exploration". *Journal of the Association of Environmental and Resource Economists*, *5*(4), 713‑753.

APPENDIX

1. Adjustments to the VMC 'corrected mean aggregation method'

Following greenness scores listed in VMC (see Table A1 of their working paper appendix), it sometimes appears that situations which are comparable with respect to their 'corrected mean aggregation method' are not treated in the same way. In most cases, we have followed choices made by VMC, but for two occupations, we have used the other method. In other cases, the occupation (and therefore the method chosen) was not presented: we then made our own choice. The different methods are summarised in Table A1 below. We explain the issues at stake in more detail next.

Table A1. Aggregation choices different from those of Vona et al. (2019)

US SOC occupation	Choice from Vona et al.	Author's choice
17-3027 Mechanical engineering technicians	Mean	Zero
19-2099 Physical scientists, All other	Not included because occupation '.00' ignored	Zero
19-3099 Social scientists and related workers, All other	Not included because occupation '.00' ignored	Zero
19-4051 Nuclear technicians	Zero	Mean
41-3099 Sales representatives, services, All other	Not included because occupation '.00' ignored	Zero
49-9099 Installation, maintenance, and repair workers, All other	Not included because occupation '.00' ignored	Zero
51-9199 Production workers, All other	Not included because occupation '.00' ignored	Zero

There are several types of cases to be distinguished:

(i) The ambiguous use of the mean method

On several instances, VMC assign to the 6-digit occupation the average greenness of its sub-occupations, although its most general occupation (the one ending in '.00') has "zero or few green tasks" (criterion 1). This is sometimes a coherent choice, given the profile of the other occupations in the group.

This is particularly noticeable for the 19-2041 aggregate occupation. Indeed, 19-2041.00 ('Environmental scientists and specialists, including health') has no green task in the O*NET database, unlike the three other occupations in the group, whose tasks are all considered to be green ('Climate change analysts', 'Environmental restoration planners' and 'Industrial ecologists'). Still, VMC opted for the mean method, and we follow their choice because it appears that the occupation with no green task is not too far from environmental issues and practices. The same applies, to a lesser extent, to occupational categories 11-9121 ('Natural sciences managers') and 43-5011 ('Cargo and freight agents'), for which we follow the authors and apply the mean method too.

Despite their choice, we do not follow this method for category 17-3027 ('Mechanical engineering technicians'). In fact, in addition to its most general occupation not being attached to any green category, this group is composed of only one other green sub-occupation: 17-3027.01 ('Automotive engineering technicians'). Given that only two occupations are included in this group, applying the mean method here would result in a significant over-estimate, especially for categories since it is associated with GNE and that the mechanical engineering sector appears (as a whole and for now) quite distant from it. For this reason and in line with the initial criteria, we give a greenness score of zero to this aggregate occupation – rather than 50% GNE.

Conversely, occupation 19-4051 ('Nuclear technicians') is given a greenness score of zero: it includes 19-4051.01 ('Nuclear equipment operation technicians') which is affiliated to the GES category and has more than 40% of green tasks, and 19-4051.02 ('Nuclear monitoring technicians') which has no green task. This choice could be consistent with initial criteria, but as we have just seen in other similar situations, mean method is sometimes used. This is what we decided to do here, because even though nuclear power is controversial and could decline depending on future energy policy decisions, its (very) low carbon footprint justifies a positive greenness score and its inclusion in a green category (here GES) just as much (if not more) than many of the other occupations selected.

(ii) Ignoring the most general occupation

In many cases, VMC do not take into account the 8-digit occupation ending in '.00'. Yet, it is this occupation, the most general one, which is supposed to serve as the basis for their criteria. Consequently, the aggregation method is not detailed for groups with only one sub-occupation other than the most general one, and they proceed as if there were no aggregation issue. This is the case for 19-2099 ('Physical scientists, All other'), 19-3099 ('Social scientists and related workers, All other'), 41-3099 ('Sales representatives, services, All other'), 49-9099 ('Installation, maintenance, and repair workers, All other') and 51-9199 ('Production workers, All other').

For instance, at the 8-digit level, 19-2099 includes two occupations: 'Physical scientists, All other' (19-2099.00) and 'Remote sensing scientists and technologists' (19-2099.01), which is GNE and has 7.16% of green tasks (0% for core green tasks). But if we do not include 19-2099.00 in the aggregation, then the 6-digit occupation 19-2099 will directly take the values of 19-2099.01.

The problem is that these 6-digit occupations can be described as 'residual' in that they include all the sub-occupations of a broader category that has not been more precisely identified elsewhere: this is the idea behind "All other"[34]. These categories bring together groups of occupations that are too heterogeneous to generalize an average greenness. This is why we assigned them a score of zero, avoiding any over-estimation and distinguishing from the simple mean method used at first.

[34] As written on O*NET website: " 'All Other' titles represent occupations with a wide range of characteristics which do not fit into one of the detailed O*NET-SOC occupations. O*NET data is not available for this type of title".

There are other cases where the '.00' occupation has not been included, but for which VMC present their method since these categories include several other sub-occupations: 13-1041, 15-1199, 19-1031, 41-3031, 43-5011, 49-3023 (and 19-4051, covered previously). Here, we follow the authors' choice of the mean method, although this is often less homogeneous with respect to environmental profiles[35].

More broadly, the question of whether the most general occupation should be accounted for is important as it affects the calculation of the mean greenness. When this occupation contains green tasks and is assigned to an O*NET category (*i.e.* 17-2051.00, 17-2072.00, 17-2081.00, 17-2141.00, 41-4011.00), the question of including it does not arise – of course we include it. When this is not the case, we can still include it but this changes the mean greenness score given that it is calculated as follows:

$$\frac{\text{Sum of the greenness of the 8-digit occupations attached to the 6-digit occupation}}{\text{Number of 8-digit occupations attached to the 6-digit occupation}}$$

Including or not this occupation affects both the numerator and the denominator. Thus, when an occupation ending in '.00' appeared to be merely the sum of the other sub-occupations, we did not include it in the calculation, considering it duplicative. For instance, it is clear that 'Heating, air conditioning, and refrigeration mechanics and installers' (49-9021.00, non-green) was only the sum of 'Heating and air conditioning mechanics and installers' (49-9021.01, GES) and 'Refrigeration mechanics and installers' (49-9021.02, GID). Here, counting the most general 8-digit occupation in the ratio is not consistent and would 'artificially' lower the greenness score.

Conversely, when it appeared obvious that this occupation covered more than just the other 8-digit occupations, we included it in the ratio. This is the case for 'Construction and related workers, All other' (47-4099.00) which was in the same group as the two GNE occupations 'Solar thermal installers and technicians' (47-4099.02) and 'Weatherization installers and technicians' (47-4099.03). In contrast to the previous example, it is clear from the titles that this 'residual' occupation ending in '.00' includes (or may include) more diverse occupations than these two green occupations only[36].

(iii) Assigning the greenness of the most general occupation

Another choice from VMC, which is not made explicit in the presentation of their method but can be found in their Table A1, is to sometimes assign to the 6-digit occupation the greenness of its most general occupation – and therefore to use neither the mean nor the zero-score method. This is the case for occupations 17-2072 et 41-4011. In these cases, the most general occupation is itself attached to an O*NET green category with green tasks. In this sense,

[35] It can be noted that there are sometimes many sub-occupations within these categories, resulting in relatively low green scores, and limiting the potential for over-estimation.

[36] More precisely, the categories for which we included the occupation ending in '.00' in the calculation – whereas VMC did not – are: 19-4041, 19-4099, 47-4099 and 51-8099 (as well as, for the simple mean aggregation method, the five 'All other' residual categories listed above). In all other cases, we have followed the authors' choice and ignored this most general occupation (as with 49-9021 in the example). For categories containing only GID sub-occupations, we decided not to count the most general occupation for the following ones: 17-2111, 17-3011, 47-2031, 51-4121.

averaging with the (lack of) greenness of another particularly minor and specific sub-occupation would mean losing the level of generality allowed by the already supposedly most representative green occupation. We therefore follow their choice for our corrected aggregation method.

2. Greenness scores of the corrected crosswalk

Table A2 gives a more complete picture of the crosswalk (and of its results) by providing greenness scores for US SOC and ISCO-08 occupations. Each row associates a given US SOC occupation with its correspondent ISCO occupation(s). This is why a same US SOC occupation can appear several times, as it can be associated with multiple ISCO codes (the variable '*multiple_isco*' is ticked with a star when this is the case).

To avoid overloading the table and ensure that it is readable, only the corrected versions of the indicators (see 3.2) are presented[37]. In addition, we dropped SOC/ISCO combinations with no positive greenness score – so that if an occupation is not listed in the table, it is because all its corrected indicators are zero.

As explained in 3.1, the initial greenness scores presented at the SOC 6-digit level were manually computed "based on the list of green jobs provided by the O*NET Resource Center, as well as on the O*NET-SOC 2010 Occupation Listing which lists the number of 8-digit occupations associated with each 6-digit occupation"[38].

Also, ISCO scores are not faithful to those used in this work because they are not weighted by US and French employment (see 4)[39]. Indeed, these versions require French employment data at the ISCO 4-digit level, which we computed in the CASD device but that couldn't be extracted for confidentiality reasons. In any case, having the final ISCO weighted scores is not very useful: to re-use such a crosswalk, they must be readapted to the target country and period.

[37] This is why variables have 'corr' in their names. Task-based indicators do not because we only applied the corrected aggregation method to them.

[38] For information on the step from the O*NET-SOC 8-digit level to the US SOC 6-digit one, see our following table: https://docs.google.com/spreadsheets/d/10gBBSkHmioYmoJj8X6RFwDAQNWnf_z1AXWsVWz3AFK8/

[39] ISCO scores from Table A2 are the non-weighted corrected versions (NW_C) from Table 2.

Table A2. US SOC and ISCO-08 occupations' corrected greenness scores

SOC_ code	GNE_ corr_soc	GES_ corr_soc	GID_ corr_soc	Task_ soc	Core_ task_soc	multiple_ isco	ISCO_ code	GNE_ corr_isco	GES_ corr_isco	GID_ corr_isco	Task_ isco	Core_ task_isco
11-1011	0	0	0	0	0	*	1112	0	0,33	0	0,04	0
11-1011	0	0	0	0	0	*	1120	0	0,5	0	0,06	0
11-1021	0	1	0	0,11	0	*	1112	0	0,33	0	0,04	0
11-1021	0	1	0	0,11	0	*	1114	0,45	0,13	0	0,28	0,23
11-1021	0	1	0	0,11	0	*	1120	0	0,5	0	0,06	0
11-1021	0	1	0	0,11	0	*	1343	0	0,5	0	0,06	0
11-1021	0	1	0	0,11	0	*	1346	0	0,5	0	0,06	0
11-1021	0	1	0	0,11	0	*	1420	0	1	0	0,11	0
11-1021	0	1	0	0,11	0	*	5221	0	1	0	0,11	0
11-2021	0	1	0	0,17	0		1221	0	0,5	0	0,09	0
11-3051	0	0	0,14	0	0		1321	0	0	0,14	0	0
11-3071	0,33	0,67	0	0,22	0,11		1324	0,33	0,67	0	0,22	0,11
11-9013	0	0,25	0	0,04	0	*	1311	0	0,25	0	0,04	0
11-9013	0	0,25	0	0,04	0	*	1312	0	0,25	0	0,04	0
11-9021	0	1	0	0,25	0,17	*	1323	0	1	0	0,25	0,17
11-9021	0	1	0	0,25	0,17	*	7111	0	1	0	0,25	0,17
11-9041	0,5	0,5	0	0,59	0,5		1223	0,42	0,25	0,17	0,46	0,42
11-9121	0,33	0	0,33	0,33	0,33		1223	0,42	0,25	0,17	0,46	0,42
11-9199	0,6	0	0	0,35	0,31	*	1114	0,45	0,13	0	0,28	0,23
11-9199	0,6	0	0	0,35	0,31	*	1213	0,6	0	0	0,35	0,31
11-9199	0,6	0	0	0,35	0,31	*	1219	0,33	0	0	0,19	0,17
11-9199	0,6	0	0	0,35	0,31	*	1322	0,6	0	0	0,35	0,31
11-9199	0,6	0	0	0,35	0,31	*	1349	0,6	0	0	0,35	0,31
11-9199	0,6	0	0	0,35	0,31	*	1431	0,51	0	0	0,3	0,26
11-9199	0,6	0	0	0,35	0,31	*	1439	0,6	0	0	0,35	0,31
13-1021	0	0	1	0	0		3323	0	0,33	0,33	0,08	0,04
13-1022	0	1	0	0,25	0,11		3323	0	0,33	0,33	0,08	0,04
13-1041	0,17	0	0	0,02	0	*	3351	0,06	0	0	0,01	0
13-1041	0,17	0	0	0,02	0	*	3353	0,08	0	0	0,01	0
13-1041	0,17	0	0	0,02	0	*	3354	0,08	0	0	0,01	0
13-1081	0,67	0	0	0,16	0,08		2421	0,44	0	0	0,11	0,06
13-1151	0	1	0	0,09	0,06	*	2356	0	1	0	0,09	0,06
13-1151	0	1	0	0,09	0,06	*	2424	0	1	0	0,09	0,06
13-1199	0,33	0	0	0,33	0,33	*	2422	0,33	0	0	0,33	0,33
13-1199	0,33	0	0	0,33	0,33	*	3339	0,27	0	0	0,09	0,08
13-2051	0	1	0	0,3	0	*	2412	0	1	0	0,21	0,03
13-2051	0	1	0	0,3	0	*	2413	0	0,33	0	0,1	0
13-2052	0	1	0	0,12	0,06		2412	0	1	0	0,21	0,03
13-2099	0,75	0	0	0,12	0,09		3339	0,27	0	0	0,09	0,08
15-1133	0	0	1	0	0		2512	0	0	0,5	0	0
15-1199	0,17	0	0	0,02	0	*	2519	0,17	0	0	0,02	0
15-1199	0,17	0	0	0,02	0	*	2529	0,11	0	0	0,02	0
17-1011	0	1	0	0,27	0,27		2161	0	1	0	0,27	0,27
17-1012	0	1	0	0,26	0,26		2162	0	1	0	0,26	0,26
17-2011	0	1	0	0,46	0,4		2144	0,33	0,33	0	0,33	0,29
17-2041	0	0	1	0	0		2145	0	0	1	0	0
17-2051	0,5	0,5	0	0,32	0,2		2142	0,5	0,5	0	0,32	0,2
17-2071	0	1	0	0,16	0		2151	0	1	0	0,16	0
17-2072	0	1	0	0,2	0,08	*	2153	0	1	0	0,2	0,08
17-2072	0	1	0	0,2	0,08	*	2152	0	0,5	0	0,1	0,04
17-2081	0,5	0,5	0	1	1		2143	0,5	0,5	0	1	1
17-2111	0	0	0,33	0	0		2149	0,73	0,07	0,02	0,31	0,25
17-2112	0	0	0,5	0	0		2141	0	0	0,5	0	0
17-2141	0,67	0,33	0	0,51	0,44		2144	0,33	0,33	0	0,33	0,29
17-2161	0	1	0	0,33	0,13		2149	0,73	0,07	0,02	0,31	0,25
17-2199	1	0	0	0,39	0,33		2149	0,73	0,07	0,02	0,31	0,25
17-3011	0	0	0,5	0	0		3118	0	0	0,1	0	0
17-3023	0	0,5	0,5	0,1	0	*	3113	0,25	0,5	0,25	0,09	0
17-3023	0	0,5	0,5	0,1	0	*	3114	0	0,5	0,5	0,1	0
17-3023	0	0,5	0,5	0,1	0	*	3155	0	0,5	0,5	0,1	0
17-3023	0	0,5	0,5	0,1	0	*	3522	0	0,5	0,5	0,1	0
17-3024	0,5	0,5	0	0,08	0	*	3113	0,25	0,5	0,25	0,09	0
17-3024	0,5	0,5	0	0,08	0	*	3115	0,74	0,07	0	0,21	0,11
17-3025	0	1	0	1	1		3119	0,53	0,12	0	0,21	0,13
17-3026	0	1	0	0,21	0		3119	0,53	0,12	0	0,21	0,13
17-3027	0	0	0	0,14	0,14		3115	0,74	0,07	0	0,21	0,11
17-3029	0,92	0	0	0,26	0,14	*	3115	0,74	0,07	0	0,21	0,11
17-3029	0,92	0	0	0,26	0,14	*	3116	0,92	0	0	0,26	0,14
17-3029	0,92	0	0	0,26	0,14	*	3117	0,78	0,1	0	0,24	0,12
17-3029	0,92	0	0	0,26	0,14	*	3119	0,53	0,12	0	0,21	0,13
19-1013	0	1	0	0,62	0,64	*	2131	0	0,1	0,1	0,06	0,06
19-1013	0	1	0	0,62	0,64	*	2132	0	0,33	0,33	0,21	0,21
19-1023	0	0	1	0	0		2131	0	0,1	0,1	0,06	0,06
19-1031	0	0,33	0	0,33	0,33		2133	0,6	0,07	0,2	0,67	0,67
19-2021	0	1	0	0,46	0,44		2112	0	1	0	0,46	0,44

19-2031	0	0	1	0	0		2113	0	0	1	0	0
19-2032	0	0	1	0	0	*	2113	0	0	1	0	0
19-2032	0	0	1	0	0	*	2146	0	0	0,25	0	0
19-2041	0,75	0	0,25	0,75	0,75		2133	0,6	0,07	0,2	0,67	0,67
19-2042	0	1	0	0,44	0,17		2114	0	0,5	0,5	0,22	0,08
19-2043	0	0	1	0	0		2114	0	0,5	0,5	0,22	0,08
19-3051	0	1	0	0,36	0,38		2164	0	1	0	0,36	0,38
19-4011	0	0,5	0	0,06	0		3142	0	0,5	0	0,06	0
19-4031	0	0	1	0	0		3111	0,2	0,27	0,2	0,08	0,02
19-4041	0	0,67	0	0,11	0	*	3111	0,2	0,27	0,2	0,08	0,02
19-4041	0	0,67	0	0,11	0	*	3117	0,78	0,1	0	0,24	0,12
19-4051	0	0,5	0	0,16	0,15		3119	0,53	0,12	0	0,21	0,13
19-4091	0	1	0	1	1		3141	0	0,5	0	0,5	0,5
19-4093	0	0	1	0	0		3143	0	0	1	0	0
19-4099	0,5	0	0	0,1	0,04	*	3111	0,2	0,27	0,2	0,08	0,02
19-4099	0,5	0	0	0,1	0,04	*	3119	0,53	0,12	0	0,21	0,13
23-1022	0	1	0	0,03	0		2619	0	1	0	0,03	0
25-9021	0	0	1	0	0		2132	0	0,33	0,33	0,21	0,21
27-1021	0	0	1	0	0		2163	0	0	0,33	0	0
27-3022	0	1	0	0,04	0,04		2642	0	0,5	0	0,02	0,02
27-3031	0	1	0	0,21	0,2		2432	0	1	0	0,21	0,2
29-9011	0	0	1	0	0		2263	0	0	0,5	0	0
29-9012	0	1	0	0,33	0,23		3257	0	0,33	0,25	0,12	0,06
33-3031	0	0	1	0	0		5419	0	0	0,13	0	0
41-3031	0,33	0	0	0,02	0	*	3311	0,17	0	0	0,01	0
41-3031	0,33	0	0	0,02	0	*	3324	0,28	0	0	0,04	0,01
41-3099	0	0	0	0	0		3322	0	0,4	0	0,05	0,02
41-4011	0	1	0	0,11	0,04	*	2433	0	0,67	0	0,08	0,03
41-4011	0	1	0	0,11	0,04	*	2434	0	0,5	0	0,06	0,02
41-4011	0	1	0	0,11	0,04	*	3322	0	0,4	0	0,05	0,02
43-4051	0	0	0,5	0	0		4222	0	0	0,25	0	0
43-5011	0,5	0	0	0,08	0,02	*	3324	0,28	0	0	0,04	0,01
43-5011	0,5	0	0	0,08	0,02	*	3331	0,25	0,5	0	0,08	0,01
43-5032	0	0	1	0	0		4323	0	0	1	0	0
43-5061	0	0	1	0	0		4322	0	0	1	0	0
43-5071	0	1	0	0,07	0	*	3331	0,25	0,5	0	0,08	0,01
43-5071	0	1	0	0,07	0	*	4321	0	0,33	0	0,02	0
45-1011	0	0	0,4	0	0	*	6111	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6112	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6114	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6121	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6122	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6123	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6129	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6130	0	0	0,2	0	0
45-1011	0	0	0,4	0	0	*	6210	0	0	0,26	0	0
45-1011	0	0	0,4	0	0	*	6221	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6222	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6223	0	0	0,27	0	0
45-1011	0	0	0,4	0	0	*	6224	0	0	0,27	0	0
45-2011	0	0	1	0	0	*	7515	0	0	0,5	0	0
45-2011	0	0	1	0	0	*	3257	0	0,33	0,25	0,12	0,06
45-2011	0	0	1	0	0	*	3359	0	0	1	0	0
45-4011	0	0	1	0	0	*	6210	0	0	0,26	0	0
45-4011	0	0	1	0	0	*	9215	0	0	0,5	0	0
47-2011	0	0	1	0	0		7213	0	0,33	0,33	0,07	0,02
47-2031	0	0	1	0	0		7115	0	0	1	0	0
47-2051	0	0	1	0	0		7114	0	0	0,33	0	0
47-2061	0	1	0	0,16	0		9313	0	0,13	0,13	0,02	0
47-2073	0	0	1	0	0		8342	0	0	0,2	0	0
47-2111	0	0	1	0	0		7411	0,5	0	0,5	0,5	0,5
47-2131	0	0	1	0	0		7124	0	0	0,5	0	0
47-2152	0	1	0	0,24	0,03		7126	0	0,67	0	0,16	0,02
47-2181	0	1	0	0,3	0,17		7121	0	1	0	0,3	0,17
47-2211	0	1	0	0,21	0,07		7213	0	0,33	0,33	0,07	0,02
47-2221	0	0	1	0	0		7214	0	0	0,67	0	0
47-2231	1	0	0	1	1	*	7119	0,39	0,17	0	0,56	0,56
47-2231	1	0	0	1	1	*	7411	0,5	0	0,5	0,5	0,5
47-3012	0	0	1	0	0		9313	0	0,13	0,13	0,02	0
47-4011	0	1	0	0,26	0,25		3112	0	0,2	0	0,05	0,05
47-4041	0	1	0	1	1		7119	0,39	0,17	0	0,56	0,56
47-4061	0	0	1	0	0		9312	0	0	0,33	0	0
47-4099	0,67	0	0	0,67	0,67		7119	0,39	0,17	0	0,56	0,56
47-5013	0	1	0	0,05	0		8113	0	0,17	0	0,01	0
47-5041	0	1	0	0,14	0		8111	0	0,13	0	0,02	0
49-1011	0	0	1	0	0	*	7127	0	0,33	0,67	0,09	0,08
49-1011	0	0	1	0	0	*	7231	0	0,15	0,1	0,04	0,01
49-1011	0	0	1	0	0	*	7232	0	0	0,5	0	0
49-1011	0	0	1	0	0	*	7233	0,11	0	0,33	0,11	0,11
49-1011	0	0	1	0	0	*	7234	0	0	0,5	0	0
49-1011	0	0	1	0	0	*	7311	0	0	0,2	0	0
49-1011	0	0	1	0	0	*	7312	0	0	0,5	0	0

49-1011	0	0	1	0	0	*	7412	0	0	0,15	0	0
49-1011	0	0	1	0	0	*	7413	0	0	1	0	0
49-1011	0	0	1	0	0	*	7421	0	0	0,29	0	0
49-1011	0	0	1	0	0	*	7422	0	0	0,14	0	0
49-2094	0	0	1	0	0	*	7412	0	0	0,15	0	0
49-2094	0	0	1	0	0	*	7421	0	0	0,29	0	0
49-3023	0	0,5	0	0,22	0,06		7231	0	0,15	0,1	0,04	0,01
49-3031	0	1	0	0,15	0		7231	0	0,15	0,1	0,04	0,01
49-9021	0	0,5	0,5	0,13	0,12		7127	0	0,33	0,67	0,09	0,08
49-9041	0	0	1	0	0		7233	0,11	0	0,33	0,11	0,11
49-9044	0	0	1	0	0		7233	0,11	0	0,33	0,11	0,11
49-9051	0	0	1	0	0		7413	0	0	1	0	0
49-9071	0	1	0	0,13	0		9622	0	0,25	0,25	0,03	0
49-9081	1	0	0	1	1		7233	0,11	0	0,33	0,11	0,11
49-9098	0	0	1	0	0		9622	0	0,25	0,25	0,03	0
49-9099	0	0	0	0	0		9622	0	0,25	0,25	0,03	0
51-1011	0	0	1	0	0	*	3122	0	0	1	0	0
51-1011	0	0	1	0	0	*	3131	0	0,5	0,5	0,12	0,02
51-1011	0	0	1	0	0	*	3132	0,46	0	0,14	0,46	0,46
51-2011	0	1	0	0,13	0		8211	0	0,5	0,5	0,06	0
51-2022	0	0	1	0	0		8212	0	0	0,2	0	0
51-2031	0	0	1	0	0		8211	0	0,5	0,5	0,06	0
51-2041	0	0	1	0	0		7214	0	0	0,67	0	0
51-2092	0	0	1	0	0		8219	0	0	0,5	0	0
51-4011	0	0	1	0	0		7223	0	0,08	0,25	0,01	0,01
51-4031	0	0	1	0	0	*	7223	0	0,08	0,25	0,01	0,01
51-4031	0	0	1	0	0	*	8142	0	0	0,15	0	0
51-4032	0	0	1	0	0	*	7223	0	0,08	0,25	0,01	0,01
51-4032	0	0	1	0	0	*	8142	0	0	0,15	0	0
51-4041	0	1	0	0,07	0,09		7223	0	0,08	0,25	0,01	0,01
51-4121	0	0	1	0	0		7212	0	0	0,67	0	0
51-8011	0	1	0	0,28	0,08		3131	0	0,5	0,5	0,12	0,02
51-8012	0	0	1	0	0		3131	0	0,5	0,5	0,12	0,02
51-8013	0	1	0	0,2	0		3131	0	0,5	0,5	0,12	0,02
51-8021	0	0	1	0	0		8182	0	0	1	0	0
51-8091	0	0	1	0	0		3133	0	0	1	0	0
51-8099	0,8	0	0	0,8	0,8	*	3132	0,46	0	0,14	0,46	0,46
51-8099	0,8	0	0	0,8	0,8	*	8114	0,46	0	0,14	0,46	0,46
51-9011	0	0	1	0	0		8131	0	0,33	0,33	0,02	0,03
51-9012	0	1	0	0,05	0,08	*	7513	0	0,5	0	0,03	0,04
51-9012	0	1	0	0,05	0,08	*	8131	0	0,33	0,33	0,02	0,03
51-9023	0	0	1	0	0	*	8114	0,46	0	0,14	0,46	0,46
51-9023	0	0	1	0	0	*	8181	0	0	0,17	0	0
51-9061	0	1	0	0,06	0		7543	0	1	0	0,06	0
51-9199	0	0	0	0	0		9329	0	0	0,25	0	0
53-1021	0	0	0	0,5	0,5		9333	0	0	0,25	0,13	0,13
53-3021	0	0	1	0	0		8331	0	0	0,25	0	0
53-3032	0	1	0	0,09	0,04		8332	0	0,5	0	0,04	0,02
53-4011	0	0	1	0	0		8311	0	0	0,17	0	0
53-4031	0	0	1	0	0		8312	0	0	0,25	0	0
53-6051	0	0,33	0	0,15	0		3257	0	0,33	0,25	0,12	0,06
53-7051	0	0	1	0	0		8344	0	0	0,5	0	0
53-7062	0	0	1	0	0	*	9329	0	0	0,25	0	0
53-7062	0	0	1	0	0	*	9333	0	0	0,25	0,13	0,13
53-7062	0	0	1	0	0	*	9624	0	0	1	0	0
53-7081	0	1	0	1	1	*	9611	0	0,5	0	0,5	0,5
53-7081	0	1	0	1	1	*	9612	0	1	0	1	1
11-2022	0	0	0	0	0		1221	0	0,5	0	0,09	0
11-2031	0	0	0	0	0	*	1114	0,45	0,13	0	0,28	0,23
11-2031	0	0	0	0	0	*	1219	0,33	0	0	0,19	0,17
11-3011	0	0	0	0	0		1219	0,33	0	0	0,19	0,17
11-3031	0	0	0	0	0	*	1346	0	0,5	0	0,06	0
11-3061	0	0	0	0	0		1219	0,33	0	0	0,19	0,17
11-9061	0	0	0	0	0		1219	0,33	0	0	0,19	0,17
11-9071	0	0	0	0	0		1431	0,51	0	0	0,3	0,26
11-9111	0	0	0	0	0	*	1343	0	0,5	0	0,06	0
11-9131	0	0	0	0	0		1219	0,33	0	0	0,19	0,17
11-9161	0	0	0	0	0		1112	0	0,33	0	0,04	0
13-1011	0	0	0	0	0		3339	0,27	0	0	0,09	0,08
13-1023	0	0	0	0	0		3323	0	0,33	0,33	0,08	0,04
13-1051	0	0	0	0	0		3339	0,27	0	0	0,09	0,08
13-1111	0	0	0	0	0		2421	0,44	0	0	0,11	0,06
13-2041	0	0	0	0	0		2413	0	0,33	0	0,1	0
13-2061	0	0	0	0	0		2413	0	0,33	0	0,1	0
15-1122	0	0	0	0	0		2529	0,11	0	0	0,02	0
15-1132	0	0	0	0	0		2512	0	0	0,5	0	0
17-2021	0	0	0	0	0		2144	0,33	0,33	0	0,33	0,29
17-2031	0	0	0	0	0		2149	0,73	0,07	0,02	0,31	0,25
17-2061	0	0	0	0	0		2152	0	0,5	0	0,1	0,04
17-2121	0	0	0	0	0		2144	0,33	0,33	0	0,33	0,29
17-2131	0	0	0	0	0	*	2146	0	0	0,25	0	0
17-2131	0	0	0	0	0	*	2149	0,73	0,07	0,02	0,31	0,25

17-2151	0	0	0	0	0		2146	0	0	0,25	0	0
17-2171	0	0	0	0	0		2146	0	0	0,25	0	0
17-3012	0	0	0	0	0		3118	0	0	0,1	0	0
17-3013	0	0	0	0	0		3118	0	0	0,1	0	0
17-3019	0	0	0	0	0		3118	0	0	0,1	0	0
17-3021	0	0	0	0	0		3115	0,74	0,07	0	0,21	0,11
17-3022	0	0	0	0	0		3112	0	0,2	0	0,05	0,05
17-3031	0	0	0	0	0		3112	0	0,2	0	0,05	0,05
19-1011	0	0	0	0	0		2131	0	0,1	0,1	0,06	0,06
19-1012	0	0	0	0	0		2131	0	0,1	0,1	0,06	0,06
19-1021	0	0	0	0	0		2131	0	0,1	0,1	0,06	0,06
19-1022	0	0	0	0	0		2131	0	0,1	0,1	0,06	0,06
19-1029	0	0	0	0	0		2131	0	0,1	0,1	0,06	0,06
19-1032	0	0	0	0	0		2132	0	0,33	0,33	0,21	0,21
19-1041	0	0	0	0	0		2131	0	0,1	0,1	0,06	0,06
19-1042	0	0	0	0	0		2131	0	0,1	0,1	0,06	0,06
19-1099	0	0	0	0	0		2131	0	0,1	0,1	0,06	0,06
19-4021	0	0	0	0	0		3141	0	0,5	0	0,5	0,5
19-4092	0	0	0	0	0		3119	0,53	0,12	0	0,21	0,13
21-1091	0	0	0	0	0		2263	0	0	0,5	0	0
27-1013	0	0	0	0	0	*	3118	0	0	0,1	0	0
27-1022	0	0	0	0	0		2163	0	0	0,33	0	0
27-1029	0	0	0	0	0		2163	0	0	0,33	0	0
27-3041	0	0	0	0	0	*	2642	0	0,5	0	0,02	0,02
33-1012	0	0	0	0	0	*	3351	0,06	0	0	0,01	0
33-1021	0	0	0	0	0	*	3112	0	0,2	0	0,05	0,05
33-1021	0	0	0	0	0	*	3119	0,53	0,12	0	0,21	0,13
33-1099	0	0	0	0	0	*	5419	0	0	0,13	0	0
33-2021	0	0	0	0	0	*	3112	0	0,2	0	0,05	0,05
33-2021	0	0	0	0	0	*	3119	0,53	0,12	0	0,21	0,13
33-2022	0	0	0	0	0		3119	0,53	0,12	0	0,21	0,13
33-3041	0	0	0	0	0		5419	0	0	0,13	0	0
33-3051	0	0	0	0	0	*	3351	0,06	0	0	0,01	0
33-9011	0	0	0	0	0		5419	0	0	0,13	0	0
33-9091	0	0	0	0	0		5419	0	0	0,13	0	0
33-9092	0	0	0	0	0		5419	0	0	0,13	0	0
33-9099	0	0	0	0	0		5419	0	0	0,13	0	0
37-3019	0	0	0	0	0	*	9622	0	0,25	0,25	0,03	0
41-1012	0	0	0	0	0	*	2433	0	0,67	0	0,08	0,03
41-1012	0	0	0	0	0	*	2434	0	0,5	0	0,06	0,02
41-1012	0	0	0	0	0	*	3311	0,17	0	0	0,01	0
41-1012	0	0	0	0	0	*	3322	0	0,4	0	0,05	0,02
41-1012	0	0	0	0	0	*	3324	0,28	0	0	0,04	0,01
41-1012	0	0	0	0	0	*	3339	0,27	0	0	0,09	0,08
41-3011	0	0	0	0	0		3339	0,27	0	0	0,09	0,08
41-3041	0	0	0	0	0	*	3339	0,27	0	0	0,09	0,08
41-4012	0	0	0	0	0		3322	0	0,4	0	0,05	0,02
41-9031	0	0	0	0	0		2434	0	0,5	0	0,06	0,02
41-9099	0	0	0	0	0	*	3339	0,27	0	0	0,09	0,08
43-4031	0	0	0	0	0		3354	0,08	0	0	0,01	0
43-4061	0	0	0	0	0	*	3353	0,08	0	0	0,01	0
43-4171	0	0	0	0	0	*	4222	0	0	0,25	0	0
43-5031	0	0	0	0	0		5419	0	0	0,13	0	0
43-5081	0	0	0	0	0	*	4321	0	0,33	0	0,02	0
43-5111	0	0	0	0	0		4321	0	0,33	0	0,02	0
45-2021	0	0	0	0	0	*	6121	0	0	0,27	0	0
45-2021	0	0	0	0	0	*	6122	0	0	0,27	0	0
45-2021	0	0	0	0	0	*	6123	0	0	0,27	0	0
45-2021	0	0	0	0	0	*	6129	0	0	0,27	0	0
45-2021	0	0	0	0	0	*	6130	0	0	0,2	0	0
45-2021	0	0	0	0	0	*	6221	0	0	0,27	0	0
45-2041	0	0	0	0	0	*	7515	0	0	0,5	0	0
45-2091	0	0	0	0	0	*	6111	0	0	0,27	0	0
45-2091	0	0	0	0	0	*	6112	0	0	0,27	0	0
45-2091	0	0	0	0	0	*	6114	0	0	0,27	0	0
45-2091	0	0	0	0	0	*	6130	0	0	0,2	0	0
45-3011	0	0	0	0	0	*	6222	0	0	0,27	0	0
45-3011	0	0	0	0	0	*	6223	0	0	0,27	0	0
45-3021	0	0	0	0	0	*	6224	0	0	0,27	0	0
45-4021	0	0	0	0	0		6210	0	0	0,26	0	0
45-4022	0	0	0	0	0	*	6210	0	0	0,26	0	0
45-4023	0	0	0	0	0		6210	0	0	0,26	0	0
45-4029	0	0	0	0	0	*	6210	0	0	0,26	0	0
45-4029	0	0	0	0	0	*	9215	0	0	0,5	0	0
47-2053	0	0	0	0	0		7114	0	0	0,33	0	0
47-2071	0	0	0	0	0		8342	0	0	0,2	0	0
47-2072	0	0	0	0	0		8342	0	0	0,2	0	0
47-2132	0	0	0	0	0		7124	0	0	0,5	0	0
47-2151	0	0	0	0	0		7126	0	0,67	0	0,16	0,02
47-2171	0	0	0	0	0		7214	0	0	0,67	0	0
47-3011	0	0	0	0	0		9313	0	0,13	0,13	0,02	0
47-3013	0	0	0	0	0		9313	0	0,13	0,13	0,02	0

47-3014	0	0	0	0	0		9313	0	0,13	0,13	0,02	0
47-3015	0	0	0	0	0		9313	0	0,13	0,13	0,02	0
47-3016	0	0	0	0	0		9313	0	0,13	0,13	0,02	0
47-3019	0	0	0	0	0	*	9312	0	0	0,33	0	0
47-3019	0	0	0	0	0	*	9313	0	0,13	0,13	0,02	0
47-4021	0	0	0	0	0		7412	0	0	0,15	0	0
47-4031	0	0	0	0	0		7119	0,39	0,17	0	0,56	0,56
47-4051	0	0	0	0	0		9312	0	0	0,33	0	0
47-4091	0	0	0	0	0	*	7114	0	0	0,33	0	0
47-5011	0	0	0	0	0		8113	0	0,17	0	0,01	0
47-5012	0	0	0	0	0		8113	0	0,17	0	0,01	0
47-5021	0	0	0	0	0	*	8111	0	0,13	0	0,02	0
47-5021	0	0	0	0	0	*	8113	0	0,17	0	0,01	0
47-5042	0	0	0	0	0		8111	0	0,13	0	0,02	0
47-5049	0	0	0	0	0		8111	0	0,13	0	0,02	0
47-5051	0	0	0	0	0		8111	0	0,13	0	0,02	0
47-5061	0	0	0	0	0		8111	0	0,13	0	0,02	0
47-5071	0	0	0	0	0		8113	0	0,17	0	0,01	0
49-2011	0	0	0	0	0	*	7421	0	0	0,29	0	0
49-2011	0	0	0	0	0	*	7422	0	0	0,14	0	0
49-2021	0	0	0	0	0		7422	0	0	0,14	0	0
49-2022	0	0	0	0	0		7422	0	0	0,14	0	0
49-2091	0	0	0	0	0		7421	0	0	0,29	0	0
49-2092	0	0	0	0	0		7412	0	0	0,15	0	0
49-2093	0	0	0	0	0	*	7412	0	0	0,15	0	0
49-2093	0	0	0	0	0	*	7421	0	0	0,29	0	0
49-2093	0	0	0	0	0	*	7422	0	0	0,14	0	0
49-2095	0	0	0	0	0	*	7412	0	0	0,15	0	0
49-2095	0	0	0	0	0	*	7421	0	0	0,29	0	0
49-2096	0	0	0	0	0	*	7412	0	0	0,15	0	0
49-2096	0	0	0	0	0	*	7421	0	0	0,29	0	0
49-2097	0	0	0	0	0		7422	0	0	0,14	0	0
49-2098	0	0	0	0	0		7412	0	0	0,15	0	0
49-3011	0	0	0	0	0		7232	0	0	0,5	0	0
49-3021	0	0	0	0	0		7231	0	0,15	0,1	0,04	0,01
49-3022	0	0	0	0	0		7231	0	0,15	0,1	0,04	0,01
49-3041	0	0	0	0	0		7233	0,11	0	0,33	0,11	0,11
49-3042	0	0	0	0	0		7233	0,11	0	0,33	0,11	0,11
49-3043	0	0	0	0	0		7233	0,11	0	0,33	0,11	0,11
49-3051	0	0	0	0	0		7231	0	0,15	0,1	0,04	0,01
49-3052	0	0	0	0	0		7231	0	0,15	0,1	0,04	0,01
49-3053	0	0	0	0	0	*	7412	0	0	0,15	0	0
49-3053	0	0	0	0	0	*	7231	0	0,15	0,1	0,04	0,01
49-3091	0	0	0	0	0		7234	0	0	0,5	0	0
49-3092	0	0	0	0	0		7231	0	0,15	0,1	0,04	0,01
49-3093	0	0	0	0	0		7231	0	0,15	0,1	0,04	0,01
49-9011	0	0	0	0	0		7412	0	0	0,15	0	0
49-9012	0	0	0	0	0		7412	0	0	0,15	0	0
49-9031	0	0	0	0	0		7412	0	0	0,15	0	0
49-9043	0	0	0	0	0		7233	0,11	0	0,33	0,11	0,11
49-9045	0	0	0	0	0	*	7233	0,11	0	0,33	0,11	0,11
49-9052	0	0	0	0	0		7422	0	0	0,14	0	0
49-9061	0	0	0	0	0		7311	0	0	0,2	0	0
49-9062	0	0	0	0	0		7311	0	0	0,2	0	0
49-9063	0	0	0	0	0		7312	0	0	0,5	0	0
49-9064	0	0	0	0	0		7311	0	0	0,2	0	0
49-9069	0	0	0	0	0		7311	0	0	0,2	0	0
49-9095	0	0	0	0	0		7119	0,39	0,17	0	0,56	0,56
49-9097	0	0	0	0	0		7412	0	0	0,15	0	0
51-2021	0	0	0	0	0		8212	0	0	0,2	0	0
51-2023	0	0	0	0	0		8212	0	0	0,2	0	0
51-2091	0	0	0	0	0		8142	0	0	0,15	0	0
51-2093	0	0	0	0	0		8212	0	0	0,2	0	0
51-2099	0	0	0	0	0		8219	0	0	0,5	0	0
51-3092	0	0	0	0	0	*	7513	0	0,5	0	0,03	0,04
51-4021	0	0	0	0	0	*	7223	0	0,08	0,25	0,01	0,01
51-4021	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-4022	0	0	0	0	0	*	7223	0	0,08	0,25	0,01	0,01
51-4022	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-4023	0	0	0	0	0	*	7223	0	0,08	0,25	0,01	0,01
51-4023	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-4033	0	0	0	0	0	*	7223	0	0,08	0,25	0,01	0,01
51-4033	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-4034	0	0	0	0	0	*	7223	0	0,08	0,25	0,01	0,01
51-4034	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-4035	0	0	0	0	0	*	7223	0	0,08	0,25	0,01	0,01
51-4035	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-4072	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-4081	0	0	0	0	0		7223	0	0,08	0,25	0,01	0,01
51-4122	0	0	0	0	0		7212	0	0	0,67	0	0
51-4191	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-4192	0	0	0	0	0	*	7213	0	0,33	0,33	0,07	0,02

51-4193	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-4199	0	0	0	0	0	*	7223	0	0,08	0,25	0,01	0,01
51-4199	0	0	0	0	0	*	8142	0	0	0,15	0	0
51-6091	0	0	0	0	0		8181	0	0	0,17	0	0
51-8031	0	0	0	0	0		3132	0,46	0	0,14	0,46	0,46
51-9021	0	0	0	0	0	*	8114	0,46	0	0,14	0,46	0,46
51-9021	0	0	0	0	0	*	8181	0	0	0,17	0	0
51-9032	0	0	0	0	0		8114	0,46	0	0,14	0,46	0,46
51-9041	0	0	0	0	0	*	8181	0	0	0,17	0	0
51-9051	0	0	0	0	0	*	8181	0	0	0,17	0	0
51-9194	0	0	0	0	0	*	8212	0	0	0,2	0	0
51-9195	0	0	0	0	0	*	8181	0	0	0,17	0	0
51-9195	0	0	0	0	0	*	8131	0	0,33	0,33	0,02	0,03
51-9198	0	0	0	0	0		9329	0	0	0,25	0	0
53-1011	0	0	0	0	0		9333	0	0	0,25	0,13	0,13
53-1031	0	0	0	0	0	*	3257	0	0,33	0,25	0,12	0,06
53-1031	0	0	0	0	0	*	8311	0	0	0,17	0	0
53-1031	0	0	0	0	0	*	8312	0	0	0,25	0	0
53-1031	0	0	0	0	0	*	8331	0	0	0,25	0	0
53-1031	0	0	0	0	0	*	8332	0	0,5	0	0,04	0,02
53-1031	0	0	0	0	0	*	8344	0	0	0,5	0	0
53-1031	0	0	0	0	0	*	9611	0	0,5	0	0,5	0,5
53-3022	0	0	0	0	0		8331	0	0	0,25	0	0
53-4012	0	0	0	0	0		8311	0	0	0,17	0	0
53-4013	0	0	0	0	0		8311	0	0	0,17	0	0
53-4021	0	0	0	0	0		8312	0	0	0,25	0	0
53-4041	0	0	0	0	0	*	8311	0	0	0,17	0	0
53-4041	0	0	0	0	0	*	8331	0	0	0,25	0	0
53-4099	0	0	0	0	0		8312	0	0	0,25	0	0
53-6041	0	0	0	0	0		3119	0,53	0,12	0	0,21	0,13
53-7031	0	0	0	0	0		8342	0	0	0,2	0	0
53-7032	0	0	0	0	0	*	8111	0	0,13	0	0,02	0
53-7032	0	0	0	0	0	*	8342	0	0	0,2	0	0
53-7033	0	0	0	0	0		8111	0	0,13	0	0,02	0
53-7063	0	0	0	0	0		9329	0	0	0,25	0	0
53-7072	0	0	0	0	0	*	3132	0,46	0	0,14	0,46	0,46
53-7073	0	0	0	0	0		8113	0	0,17	0	0,01	0
53-7111	0	0	0	0	0		8311	0	0	0,17	0	0
53-7121	0	0	0	0	0		9333	0	0	0,25	0,13	0,13

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