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LABOR MARKET IMPACTS OF THE GREEN TRANSITION IN THE MENA

Shireen AlAzzawi and Vladimir Hlasny

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CONTENTS

Abstract

As global decarbonization intensifies, Middle East and North Africa (MENA) economies face mounting pressure to decouple their development from oil dependence. This paper provides the first comprehensive assessment of green employment across the region, analyzing longitudinal data from Egypt, Jordan, Palestine, and Tunisia. By adapting a skill-greenness classification derived from the U.S. O*NET database to local labor market surveys, we utilize both binary prevalence indicators and continuous task-intensity measures to map the regional green landscape.

The findings reveal that while 17% to 29% of occupations in these countries contain at least one green task, the actual green task intensity remains low, consistently falling below 7%. A significant demographic divide characterizes the green transition. Contrary to earlier estimations, men are two to three times more likely to hold green jobs than women, who are largely sequestered in «grey» sectors such as education and health. Furthermore, a distinct age gap exists; while prime-age adults are more likely to hold green positions, youth are disproportionately concentrated in «brown» or polluting occupations. Our analysis also uncovers that informal jobs exhibit a higher prevalence of both green and brown tasks compared to formal employment, suggesting that much of the region's environmental labor occurs without social protections. These results indicate that the green transition in the MENA region currently risks exacerbating existing inequalities. To ensure an inclusive shift, we provide policy recommendations focused on greening female-dominated sectors, aligning vocational training with green technical needs for youth, and formalizing the informal green workforce.

Keywords: Green jobs, Task-based approach, green transition, Decarbonization, MENA region.
JEL Classification: J24, O14, O53, Q52.

Résumé

Alors que la décarbonation mondiale s'intensifie, les économies du Moyen-Orient et de l'Afrique du Nord (MENA) font face à une pression croissante pour dissocier leur développement de la dépendance au pétrole. Cet article propose la première évaluation complète de l'emploi vert dans la région, en analysant des données longitudinales provenant d'Égypte, de Jordanie, de Palestine et de Tunisie. En adaptant une classification des compétences « vertes » dérivée de la base de données américaine O*NET aux enquêtes locales sur le marché du travail, nous utilisons à la fois des indicateurs binaires de prévalence et des mesures continues d'intensité des tâches pour cartographier le paysage régional de l'emploi vert.

Les résultats révèlent que, bien que 17 % à 29 % des professions dans ces pays comportent au moins une tâche verte, l'intensité réelle des tâches vertes reste faible, se situant systématiquement en dessous de 7 %. Une fracture démographique significative caractérise la transition verte. Contrairement aux estimations antérieures, les hommes ont deux à trois fois plus de chances d'occuper des emplois verts que les femmes, qui sont largement cantonnées à des secteurs « gris » tels que l'éducation et la santé. En outre, un écart d'âge marqué apparaît : si les adultes en âge actif sont plus susceptibles d'occuper des postes verts, les jeunes sont de manière disproportionnée concentrés dans des emplois « bruns » ou polluants. Notre analyse montre également que les emplois informels présentent une plus forte prévalence de tâches vertes et brunes que l'emploi formel, ce qui suggère qu'une grande partie du travail environnemental dans la région s'effectue sans protection sociale. Ces résultats indiquent que la transition verte dans la région MENA risque actuellement d'aggraver les inégalités existantes. Afin d'assurer une transition inclusive, nous formulons des recommandations de politique publique axées sur la « verdisation » des secteurs à prédominance féminine, l'alignement de la formation professionnelle sur les besoins techniques verts des jeunes, et la formalisation de la main-d'œuvre verte informelle.

الملخص

(MENA) مع تصاعد وتيرة إزالة الكربون عالميًا، تواجه اقتصادات منطقة الشرق الأوسط وشمال إفريقيا ضغوطًا متزايدة لفصل مسار التنمية عن الاعتماد على النفط. يقدم هذا البحث أول تقييم شامل للوظائف الخضراء في المنطقة، من خلال تحليل بيانات طولية من مصر والأردن وفلسطين وتونس. ومن خلال تكييف تصنيف الأمريكية مع مسوح سوق العمل المحلية، نستخدم O*NET المهارات «الخضراء» المستمد من قاعدة بيانات .مؤشرات ثنائية للانتشار ومقاييس مستمرة لكثافة المهام لرسم خريطة المشهد الإقليمي للوظائف الخضراء

تكشف النتائج أنه رغم أن ما بين 17% و29% من المهن في هذه البلدان تتضمن مهمة خضراء واحدة على الأقل، فإن الكثافة الفعلية للمهام الخضراء تظل منخفضة، حيث تقل باستمرار عن 7%. وتُميز الانتقال الأخضر فجوة ديموغرافية واضحة. فعلى خلاف التقديرات السابقة، فإن الرجال أكثر احتمالًا بمقدار مرتين إلى ثلاث مرات لشغل وظائف خضراء مقارنة بالنساء، اللواتي يتركزن إلى حد كبير في قطاعات «رمادية» مثل التعليم والصحة. كما يظهر فرق عمري ملحوظ؛ إذ يميل البالغون في سن العمل إلى شغل وظائف خضراء بدرجة أكبر، بينما يتركز الشباب بشكل غير متناسب في وظائف «بنية» أو ملوِّثة. ويُظهر تحليلنا أيضًا أن الوظائف غير الرسمية تسجل انتشارًا أعلى لكل من المهام الخضراء والبنية مقارنة بالعمل الرسمي، ما يشير إلى أن جزءًا كبيرًا من العمل البيئي في المنطقة يتم دون حماية اجتماعية

تشير هذه النتائج إلى أن الانتقال الأخضر في منطقة الشرق الأوسط وشمال إفريقيا قد يؤدي حاليًا إلى تفاقم أوجه عدم المساواة القائمة. ولضمان انتقال شامل، نقدم توصيات للسياسات تركز على «تخضير» القطاعات التي تهيمن عليها النساء، ومواءمة التدريب المهني مع الاحتياجات التقنية الخضراء للشباب، وإضفاء الطابع الرسمي على القوى العاملة الخضراء غير الرسمية

INTRODUCTION AND MOTIVATION

The heightened threats of climate change have escalated the imperative for global decarbonization, prompting nations around the world to increasingly adopt policies that facilitate their green transitions. National governments in the Middle East and North Africa (MENA) are increasingly committing themselves to climate action and green transition initiatives as part of their broader development plans. This commitment is reflected in various national strategies, announcements of Nationally Determined Contributions (NDCs) and regional collaborations. Over the last several years there has been a notable increase in the number of countries making announcements about “net-zero” plans, including the UAE and Oman by 2050, and Saudi Arabia, Kuwait and Bahrain by 2060 (WEF 2023).

Others have also made strong commitments to reducing greenhouse gas (GHG) emissions and increasing their renewable energy mix. Egypt's Vision 2030 strategy exemplifies this trend, incorporating sustainability and environmental protection as core components. This includes substantial investments in renewable energy, particularly solar and wind power, with projects like the Benban Solar Park, expected to be one of the largest solar installations in the world (AfDB 2023). Jordan and Tunisia have also committed to climate action, with Jordan aiming for 10% of its energy to come from renewable sources by 2025 (Jordan Green Growth National Plan 2021-2025), and Tunisia setting a target to reduce its carbon intensity to 45% by 2030 compared to 2010 levels (Republic of Tunisia 2021), planning to generate 30% of its electricity from renewables by 2030.

While these commitments and policy transitions are commendable responses to the impending climate crisis, there is limited analysis of how such structural shifts will affect economic sectors and labor markets. This transition will create both winners and losers, and the impact will differ significantly across regions, industries and between groups within labor markets (Fragkos et al. 2021). While advanced economies have demonstrated a steady growth in environmentally sustainable employment (Dicce and Ewers 2021), transitional economies in the Middle East and North Africa (MENA) face unique structural challenges in adapting to this "green megatrend". For decades, these nations have remained tethered to carbon-intensive development models, driven either by direct resource extraction or reliance on remittances from oil-rich neighbors. However, recent commodity-price volatility and a deepening global commitment to low-carbon production have increased the pressure on MENA governments to decouple economic growth from fossil fuel dependence.

Despite these policy pronouncements, the regional labor market impact remains under-researched, representing a critical gap in our understanding of how a "just transition" might unfold. The move toward a green economy inevitably creates a dichotomy of winners and losers, as traditional fossil fuel industries face disruption while emerging sectors like renewable energy and sustainable construction offer new, albeit skill-intensive, opportunities (Robertson and Acevedo 2024). This paper provides the first comprehensive, longitudinal assessment of green employment in the MENA region to systematically address this gap. By analyzing data from Egypt (2018, 2023), Jordan (2010, 2016), Palestine (2021), and Tunisia (2014, 2022, 2023), we offer a detailed view of the region's occupational evolution over a critical decade of climate policy development.

Our methodological approach extends previous literature by applying a high degree of granularity and measurement diversity. Utilizing a skill-greenness classification derived from the U.S. O*NET database, we impute job greenness at the 4-digit occupational-code level. Crucially, we move beyond simple binary indicators of "green" versus "non-green" roles to implement a continuous metric of green task intensity. This facilitates a distinction between occupations that merely contain environmental elements and those characterized by high-intensity green functions. Furthermore, our analysis identifies "brown" or polluting occupations, providing a comprehensive map of the regional labor market's environmental footprint across different sectors and socioeconomic groups.

The results of this study challenge several prior assumptions regarding the green transition in developing contexts. While the binary prevalence of green jobs in the region is comparable to some European benchmarks, we find that actual green task intensity remains low, consistently falling below 7%. Moreover, our findings uncover a stark demographic divide. Contrary to earlier, more optimistic projections, we find that men are two to three times more likely to hold green jobs than women, who remain largely sequestered in "grey" sectors like education and health. We also identify a "youth paradox," where younger workers are disproportionately concentrated in polluting brown industries, while green roles are predominantly occupied by prime-age adults in managerial positions. Additionally, the data reveals a surprising concentration of green tasks within the informal sector, suggesting that a significant portion of the region's environmental labor occurs without the benefit of formal social protections.

By synthesizing these findings, this paper provides critical insights into the potential for the green transition to exacerbate existing regional inequalities. The evidence suggests that while the foundation for a green economy is being laid, the transition is currently shallow and demographically imbalanced. Consequently, this study concludes with targeted policy recommendations aimed at greening female-dominated sectors, facilitating youth transitions out of brown industries, and formalizing the green workforce. These interventions are essential to ensuring that the shift toward a low-carbon future in the MENA region is both economically sustainable and socially inclusive.

The remainder of the study is organized as follows. Section 2 reviews the relevant literature on the prevalence of green skills, green jobs, and the distributional effects of decarbonization on various classes of workers, and the prevailing methodological approaches. Section 3 introduces the data and methods used to classify jobs and as 'green,' and explain workers' propensity to be match with green roles. Section 4 provides a detailed description of the datasets. Section 5 presents the empirical results of the classification across worker types, followed by the results of the regression models. Finally, Section 6 synthesizes the key results and suggests pertinent policy responses.

LITERATURE REVIEW

Green transformation is projected to be a megatrend that will redraw the industrial and labor-market organization of economies worldwide, just as prior energy transitions and technological and trade shocks have done (Bartik et al. 2019; Hanson 2023; Altieri et al. 2016). Just as during those prior transformations, our understanding of the prospects and risks is constrained by the fuzzy delineation of green and non-green occupations.[1] This is despite a longstanding academic and policy debate over the criteria for greenness of occupations in private-sector enterprises (Renner et al. 2008; Georgetown–CEW 2010; Vona 2021). Prior studies have undertaken the identification of sustainable sectors, and the analysis of energy content of production (share of energy in costs). For instance, PWC (2023) has developed a Green Jobs Barometer of the sectors, and occupations in them, susceptible to the green transition. However, it has been recognized that the greenness of occupations varies greatly within narrow sectors rather than only across them. The US Bureau of Labor Statistics (BLS; 2013) promulgated an input–output definition considering whether the occupations serve to produce green goods and services and use green technologies and practices.

Compared to the green-output or green-process delineations of green occupations, recent studies have adopted a skill-content based approach. The former approaches are arguable sensitive to the delineation of green enterprises and occupation codes, and assumptions regarding their future classification as green. The skill content approach accounts flexibly for changes in workforce capacities and composition amid the gradual emergence of the green technology paradigm, and the emerging work tasks and task requirements of all occupations (LoBello et al. 2019). One approach has involved focusing on workers' possession of a critical number of green skills as well as those demanded by employers (ILO 2011a,b; CEDEFOP 2018; LinkedIn Economic Graph 2023). The European National Energy and Climate Plans (NECP) have emphasized the need for a transition to new skills and the development of these new skills, particularly soft 'green skills' such as collaboration, teaming, ethical judgement, and communication (Rotatori et al. 2021) for 'green jobs' in energy intensive industries (European Commission 2019). Jobs skills vary in the degree with which they should be updated in the decarbonization process (Branca et al. 2022).

Many studies have gone deeper in the analysis of occupations and adopted task-based measures of green employment that give a more nuanced view of the true 'green' content of occupations (Vona 2021). Workers' ability to perform green tasks (Lobsiger and Rutzer 2021), or the number of green tasks required of workers (Autor 2013; Autor and Dorn 2013; Dicarlo et al. 2016) were assessed. Dierdorff et al. (2009, 2011) adopted the task-based delineation of occupations and considered how

[1] The challenge of identifying occupations vulnerable to labor demand changes amid technology and trade shocks has been studied extensively (Goldin and Katz 1998; Autor et al. 2003; Autor and Dorn 2013; Lu and Ng 2013).

green activities and technologies affected the demand for, the context of, or even the task content of occupations (thus, broadly, the 'greening' of occupations as an output of decarbonization).

Most studies of occupational green-task content have been conducted in industrialized countries, especially the US (Walker 2013; Hartley et al. 2015; Consoli et al. 2016; Bowen et al. 2018; Vona et al. 2018, 2019; Upton and Yu 2021; Bergant et al. 2022; Suassay et al. 2022; WSJ 2023), but also the UK (PWC 2022), Germany (Böhringer et al. 2013), or groups of European countries (Bontadini and Vona 2020; Gilli et al. 2020; Serrano 2022).

Evidence from developing countries is weaker, not least because of sparser data. Bluedorn et al. (2023) used labor force surveys from 31 countries, mostly European countries but including two from the global south – Mexico and South Africa[2] – to study the implications of job greening for different socioeconomic groups, for workers' earnings, and for their dirty–to–green transition. De la Vega et al. (2024) developed a task-based green potential index for two-digit occupation groups in Argentina and estimated workers' likelihood of benefiting from the green transition.

Given the focus on developing economies in the MENA region and the implementation of a task-based green-potential index, this study is most closely related to the data-driven skill-identification framework proposed by De la Vega et al. (2024). This research extends the existing methodological landscape by providing a comprehensive, longitudinal assessment of green employment across the region. The study offers several distinct contributions to the literature. First, it achieves a significant degree of granularity by imputing job greenness at the 4-digit occupational-code level, adapting global standards to the specific data constraints of MENA labor markets. Second, the analysis utilizes a diverse variety of indicators to identify not only green jobs but also brown, or polluting, occupations, providing a more balanced view of the environmental labor landscape. Third, the methodology moves beyond simple binary prevalence by incorporating a continuous metric for task intensity, which allows for a more nuanced measurement of the actual «greenness» of work performed. Finally, by examining multiple countries over several years, the study captures the temporal dynamics of the green transition across different national contexts, providing essential evidence from an understudied region of the world.

[2] The included countries were AUT, BEL, BGR, CHE, CYP, CZE, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IRL, ISL, ITA, LTU, LUX, LVA, MLT, MEX, NOR, POL, PRT, ROU, SAR, SVK, SWE, USA.

METHODS

Our empirical strategy comprises three main steps. First, we define a set of green skills based on existing data on the prevalence of green tasks by occupation, using data from the US O*NET database (Peterson et al. 2001) based on the seminal work of Vona et al. (2018, 2019). Next, we crosswalk this US occupational classification-based data to ISCO occupational classifications using a set of mapping assumptions as in Scholl et al. (2023). We report the prevalence of green jobs by country and for various industries and socioeconomic groups. Finally, third, we use regression analysis to study the determinants of workers attaining a green job at the individual level. These steps are motivated and described in the following subsections.

GREEN JOBS VS. GREEN SKILLS

The International Labor Organization defines green jobs as "decent jobs that contribute to preserving or restoring the environment". These jobs can be both in traditional sectors such as agriculture or manufacturing, or in new and emerging sectors such as renewables: solar and wind energy industries or in industries that enhance energy efficiency (ILO 2016, 2018). Thus, green jobs can produce goods or provide services that benefit the environment, but also 'non-green' jobs in 'non-green' sectors created due to greening[3] (Auktor 2020). The BLS initiated its "Green Jobs Initiative" in 2010 to gather information about size and industrial, occupational and geographic distribution of green jobs. The BLS relied on its "Green Goods and Services Survey" that it distributed to enterprises in such green product and service production activities, based on their North American Industrial classification system (NAICS). The survey uses an output and process approach that defines green jobs as either (a) jobs in businesses that produce goods or provide services that benefit the environment or conserve natural resources, or (b) jobs in which workers' duties involve making their establishment's production processes more environmentally friendly or use fewer natural resources (BLS 2013).

This definition is however heavily dependent on how researchers define and delineate the green economy, as well as their assumptions about its growth trajectory (Deschenes 2013). Moreover, this methodology overlooks the complex and varied nature of skills and expertise required within occupations. It fails to account for the ways in which different types of knowledge contribute to human labor, which is a critical theme in task-based models commonly used in the literature to examine the role of skill-biased technological change (Autor et al. 2003; Acemoglu and Autor 2011; Autor and Dorn 2013; Beaudry et al. 2013) and international trade (Autor et al. 2013; Lu and Ng 2013) on labor market gains and losses.

[3] For example, industries along the supply chain that provide intermediate products such as cables, engines, metals, etc. to renewable energy firms.

Defining «green skills» is less straightforward, as there is no standard definition. In principle, such skills ought to be those especially important within green occupations. Following the seminal work of Vona et al. (2018, 2019), our approach relies on identifying green skills based on their importance in green jobs.

We utilize the 'Green Economy' program developed by the Occupational Information Network (O*NET) under the auspices of the US Department of Labor. The O*NET database is a rich source of occupation-level information on skill requirements and tasks, which facilitates identifying the skill content of green jobs. The Green Economy project defines green jobs as falling into three groups (Dierdoff et al. 2009, 2011): (i) current occupations with increased demand due to the shift towards sustainability ('increased demand' occupations), without that entailing significant changes in the work and worker requirements of the occupation; (ii) occupations anticipated to undergo substantial alterations in their task profiles ('green enhanced'); and (iii) newly emerging occupations within the green economy ('new and emerging').

O*NET provides a detailed exposition of green activities by offering insights into both tasks (demand side) and the required skills (supply side). Tasks are categorized as "general" (common across all occupations) or "specific" (unique to each). Additionally, for 'new and emerging' and 'green-enhanced' occupations, O*NET distinguishes between specific tasks related to green activities and those that are not.

MEASURING OCCUPATIONAL GREENNESS AND BROWNNESS

Following Vona et al. (2018), our classification method is based on the green tasks identified by the Green Economy Project. We update their results by utilizing the most recent available classification (O*NET release 24.1, November 2019), which distinguishes between green and non-green specific tasks for 'new and emerging' and 'green-enhanced' occupations. Figure 1 provides a schematic visualization of the construction of the green indictors used in this study, and their mapping across classifications.

We define two measures of occupational greenness at the detailed 8-digit Standard Occupational Classification (SOC) level (level 2 of Figure 1), using the task-based approach, which allows us to pinpoint general skills particularly linked to greener occupations. The first is a measure of the intensity of green tasks within the occupation, defined as the ratio of green-specific tasks to the total specific tasks performed in occupation k:

$$\text{Greenness}_k^{\text{SOC8d}} = \frac{\text{number of green specific tasks}_k}{\text{total number of specific tasks}_k} \qquad (1).$$

This intensity measure identifies the green-skill intensity of various jobs, aligning with the framework suggested by Vona et al. (2018, 2019) and Vona (2021). It is a continuous measure that relies on an assessment of the environmental relevance of the tasks conducted within each occupation.

The second measure is a binary variable, where an occupation is classified as green if it contains *any* green task at the SOC 8-digit level, or equivalently if $Greenness_{k.}^{SOC8d} > 0$.

$$AnyGreen^{SOC8d} = \begin{cases} = 1 \text{ if SOC8d occupation K has any green task} \\ = 0 \text{ if SOC8d occupation K has no green task} \end{cases} \quad (2).$$

The binary green measure is employed to establish a consistent, low-threshold classification that parallels the binary definitions of brownness and greyness, as explained below, facilitating comparative analysis.

These green measures are defined at the 8-digit SOC level. MENA countries however typically classify occupations according to the International Standard Classification system (ISCO). The US Bureau of Labor Statistics (BLS) publishes a cross walk between the less detailed 6-digit SOC level and the ISCO 4-digit level. We therefore need to first crosswalk these greenness measures to the 6-digit SOC level, and then further to the 4-digit ISCO level to match with labor market surveys available for the MENA developing countries.

To derive a measure of greenness at the 6-digit SOC level from the 8-digit level scores (level 3 of Figure 1), the $Greenness_k^{SOC8d}$ score must be aggregated across nested 8-digit SOC categories. Ideally, this would use a weight derived from employment data, reflecting the relative size of each 8-digit occupation within the 6-digit one. However, due to the lack of publicly available 8-digit employment data (BLS only publishes 6-digit data), the 8-digit scores are simply averaged without weighting, assuming a uniform distribution of 8-digit occupations within each 6-digit SOC, as shown in Equation 3:

$$Greenness_k^{SOC6d} = \frac{1}{N_k^{SOC8d}} \sum_{k \in SOC6d} Greenness_k^{SOC8d} \quad (3).$$

This method aligns with the approach used by Vona et al. (2018). They justified this assumption by arguing that most of the variation in green skills occurs at the 6-digit level, and therefore the unweighted average is unlikely to significantly distort the resulting indicators.

Using the binary green measure ($AnyGreen^{SOC8d}$) established at the 8-digit level, two additional measures are constructed at the 6-digit SOC level.[4] The first measure is a continuous variable derived by calculating a simple, unweighted average of the 8-digit binary green variable across all nested 8-digit SOC categories within a specific 6-digit SOC. This resulting continuous score effectively represents the share of 8-digit occupations classified as green (based on the presence of any green task) within the broader 6-digit occupation. We refer to this variable as *share_green8d*^{SOC6d}. The second measure is a binary variable that mirrors the original 8-digit definition. This variable,

[4] The methodology followed in this section follows closely that in Scholl et al. (2023) and we wish to thank the authors for kindly sharing their data and methods with us. However, our results differ slightly in that we use the O*NET 24.1 release which has updates to the green tasks by occupation. More importantly we use employment weights from each of the countries in our sample to account for the employment weighted green indices.

$AnyGreen^{SOC6d}$=1 if $Greenness^{SOC6d}$>0. This leaves us with 3 green indicators at the SOC6d level as depicted in Figure 1 (level 3).

Cross-walking SOC to ISCO occupation codes

Next, the crosswalk between the 6-digit SOC and the 4-digit ISCO classification available from BLS, together with employment data at the 6-digit SOC is used to translate the SOC measures to ISCO measures (level 4 of Figure 1). The assumption of a uniform distribution of nested occupations from lower to higher levels, which was previously made when aggregating from SOC 8-digit to SOC 6-digit, is no longer necessary. Instead, greenness scores can be aggregated using employment weights.

The conversion of our 6-digit SOC measures of greenness to the ISCO 4-digit is complicated by the many-to-many mapping between the two systems. If the mapping were one-to-one, we could simply compute a score for a 4-digit occupation by averaging the scores of its constituent 6-digit occupations. However, a single 6-digit SOC code can map to multiple 4-digit ISCO occupations, and vice-versa, which necessitates a procedure to correctly allocate the greenness score of a SOC occupation without double counting. We employ the employment-weighted approach, following the methodology developed by Dingel and Neiman (2020) (henceforth referred to as DN) which effectively uses a double-weighting scheme to map the score at the SOC 6 digit to the destination ISCO codes without double counting. The DN methodology treats the U.S. employment count as the base weight that must be 'fractionalized' across the multiple 4-digit ISCO occupations it maps into. This distribution is proportional to the total employment shares of those 4-digit ISCO occupations that map to that SOC, within each country in our analysis.

Suppose a SOC 6-digit occupation *SOC6d*, that has US employment count L_{SOC6d}, maps into a set of ISCO 4-digit occupations, $\Phi(SOC6d)$. The portion of L_{SOC6d} allocated to a specific ISCO occupation (*i4*) is proportional to the local employment of *i4* relative to the total local employment of all occupations within the set $\Phi(SOC6d)$. The allocated employment weight is therefore calculated as:

$$w^{i4}_{SOC6d} = L_{SOC6d}\left(\frac{E_{i4}}{\sum_{i \in \Phi(SOC6d)} E_i}\right) \quad (4)$$

Where E_{i4} is the local employment count in ISCO occupation *i4* that maps to the SOC 6-digit occupation. The denominator is the sum of the local ISCO employment counts of all occupations in $\Phi(SOC6d)$. This calculation ensures that the entire employment weight is fractionalized and fully allocated ($\sum w^{i4}_{SOC6d} = L_{SOC6d}$).

Numerical Example

To clarify, suppose a 6-digit SOC occupation (SOC X) has 500 U.S. employees (L_X=500). This SOC maps to two 4-digit occupations in Country N: ISCO A, which has 3000 employees (E_A=3000) and ISCO B which has 1000 employees (E_B=1000). The allocated weight for ISCO A would be 500 · (3000/4000)= 375, and for ISCO B: 500 · (1000/4000) = 125. These allocated values (375 and 125) are then used as SOC X's weighted contribution when calculating the employment-weighted average of the green measure across all SOC's that map into each respective ISCO for that country.

To illustrate the fact that one ISCO can also map into multiple SOCs, suppose further that ISCO A maps into two SOC's: SOC X (discussed above) and SOC Y. If SOC Y maps only to ISCO A, its entire US employment weight (L_y) would be allocated to ISCO A. In this case the total SOC employment contribution to ISCO A's final score would be the sum of the allocated weights: $Lx * \frac{3000}{4000} + L_y$ This process ensures that a 6-digit SOC occupation's score is accurately fractionalized and allocated to the correct categories based on actual observed employment patterns in the destination ISCO codes, which vary by country and year. This avoids double counting and provides accurate, country- and time- specific green indicators at the 4-digit level.

Using these allocation weights, we end up with a Greenness score at the 4-digit ISCO occupation level as an employment weighted average of the 6-digit SOC occupation scores from equation (3),

$$Greenness\_ew_{i4}^{ISCO4} = \sum_{SOC6d \in \mathrm{I}(i4)} w_{SOC6d}^{i4} \cdot Greenness_k^{SOC6d} \quad (5)$$

where I($i4$) is the set of all 6-digit SOC occupations[5] that match with the 4-digit ISCO occupation $i4$. We will refer to this employment weighted greenness measure as "$greenness_{ew}$". This measures the green intensity of *employment*: that is the average share of green tasks done by workers in each occupation.[6]

When the occupation itself is the unit of interest, rather than the employment size, we utilize a frequency-weighted measure of Greenness. This approach ignores the country-specific employment sizes of the occupations. The frequency-weighting approach calculates the ISCO 4-digit score as a simple average of all SOC 6-digit scores that map into it, deliberately ignoring the double-counting issue inherent in the many-to-many crosswalk. This measure is useful for examining the average green intensity or the simple prevalence of 'green' SOC occupations (defined by the existence of any green task) within an ISCO group, irrespective of how many workers are in that occupation.

The frequency-based greenness score is given by:

$$Greenness_{i4}^{ISCO4} = \frac{1}{|\mathrm{I}(i4)|} \sum_{SOC6d \in \mathrm{I}(i4)} Greenness_k^{SOC6d} \quad (6)$$

[5] In the above example I($i4$) contains SOC X and SOC Y, while Φ($SOC6d$) contains ISCO A and ISCO B.

[6] We also examined the impact of using an alternative employment weighting approach: specifically, weighting only by the size of the 6-digit SOC and ignoring the relative size of the 4-digit ISCO occupations it maps to. This method, termed the "uniform weighting" approach by Scholl et al. (2023), is typically used when data on the relative sizes of occupations within the country of interest are unavailable. However, the results vary significantly when uniform weights are applied, consistently yielding higher measures of greenness across all countries and survey years in our study compared to those using the DN employment weights in equation 5. To maintain clarity and conserve space, we have chosen not to report the results based on the uniform weights, but they are available from the authors upon request.

This "*greenness*" measure essentially records the average green intensity of the underlying SOC 6-digit occupations, within each 4-digit ISCO occupation group.

If the worker-focused (employment-weighted) "$greenness_{ew}$" measure yields a higher average score than the occupation-focused (frequency-weighted) "*greenness*" measure, it indicates that green SOC occupations, on average, have a larger number of workers than non-green occupations in the observed economy.

These two weighting methods-the frequency weights and the employment weights, can also be applied to the binary indicator that measures whether the occupation has any green task, either at the 8-digit or 6-digit SOC occupation level. Using the DN employment weighting method, we get variables that measure the *share of green employment* within the ISCO 4-digit occupation. $Emp\_shr^{8d}_{ew}$ is an employment weighted aggregation of the binary variable at the 8-digit SOC level, using DN employment weights as in equation (4), while $Emp\_shr^{6d}_{ew}$ is the analogous measure using the 6-digit SOC binary variable. Similarly, we calculate frequency weighted measures of the respective binary variables to get $Share\_green_{8d}$ and $Share\_green_{6d}$ for each ISCO 4-digit occupation.

Finally, we also define a binary indicator green=1 if the ISCO 4-digit occupation includes any green task, i.e. if the frequency-based *Greenness*>0. The bottom panel of figure 1 depicts the construction process of these variables. Table 1 provides a summary of all measures used and how to interpret them for ease of reference.

DEFINING BROWN AND GREY OCCUPATIONS

Brown occupations (i.e., polluting jobs) are defined following Vona et al. (2018) at the 6-digit SOC level, based on industry-level pollution data (4-digit North American Industry Classification System (NAICS)). This measure is binary. They first identify Brown industries as those in the 95th percentile of pollution intensity, measured in terms of pollution per worker, for at least three air pollutants.[7] An occupation is then classified as Brown if the share of its employment in these polluting industries is at least seven times higher than the average share across all occupations.[8]

Next, the brown indicator is cross walked to the ISCO 4-digit classification using a similar set of steps and the same correspondence tables as that for green measures. For many to many mappings, we again use both the employment weights and frequency weights as explained above. Since we start from SOC 6-digit occupations (level 3 of Figure 1) and only one binary indicator of brownness, applying the two

[7] The pollutants examined include Carbon Dioxide (CO_2) and several criteria pollutants regulated by the Environmental Protection Agency: Carbon Monoxide (CO), Volatile Organic Compounds (VOC), Nitrogen Oxides (NOx), Sulfur Dioxide (SO_2), and Particulate Matter (PM10 and PM2.5), as well as lead. These emissions are used to label industries as brown when their pollution intensity ranks highly for at least three of these pollutants.

[8] Vona et al. (2018) tested various thresholds, such as 5- or 10-times higher employment shares, but found the chosen threshold was optimal. Higher cutoffs caused clearly polluting occupations (like mining) to be excluded from the brown classification, while lower cutoffs included irrelevant occupations (like microbiologists).

weighting systems yields only two brownness indicators: the DN employment weighted measure, and the $Emp\_shr^{6d}_{ew}$ frequency weighted measure, $Share\_brown_{6d}$, in addition to the binary variable *Brown*=1 if any underlying 6-digit occupation within the 4-digit ISCO is brown.[9]

Finally, an occupation is defined as *Grey* if it is neither *Green* nor *Brown* by the binary measures discussed above, or if it is defined as both *Green* and *Brown* according to these classifications systems.

ISCO GREEN AND BROWN STATISTICS

Our classification procedures yield a set of green and brown indicators for each of the 437 ISCO 4-digit occupations. Out of these, 91 (20.8%) are classified as green only (containing any green task or equivalently greenness >0), 41 (9.4%) are classified as brown only, leaving the remaining 69.8% as grey (see Table 2). Only 12 of the classified occupations involve both green and polluting (brown) activities, with the vast majority of grey occupations being neither green nor brown.

The frequency-based measures provide further detail: Aggregating the SOC 8-digit binary green measure to the ISCO 4-digit level shows that, on average, 13.8% of the underlying SOC 8-digit occupations are green. Notably, aggregating the SOC 6-digit binary measure yields a higher average share: 15.8%. Aggregating the brown binary variable indicates that on average 7.3% of the ISCO's underlying SOC 6-digit occupations are brown. The frequency-weighted green task intensity measure (*greenness*) implies that the average ISCO 4-digit occupation has a relatively low green task intensity of just 5.5%. Among the 91 strictly green occupations, however, the mean green task intensity rises substantially to nearly 25%, with the frequency-weighted share of green underlying occupations being 62% ($Share\_green_{8d}$) and 72% ($Share\_green_{6d}$).

Next, we provide the country and year specific versions of these indicators. We map this 4-digit occupation-level information to nationally representative labor surveys across the region to classify individual workers based on whether they perform green tasks or engage in polluting activities. The resulting frequency and employment weighted measures will vary based on the occupational distribution within each country and survey year and will be used to analyze differences across groups such as by gender and age, and by employment characteristics, such as industry and formality.

Mapping of the green jobs and skills on labor surveys allows us to report the prevalence of green jobs and green skills among the current workforce, disaggregating results by sex, age, region of residence within country, sector of employment, and educational attainment. Stylized facts on workers' and employers' other selected characteristics are reported.

[9] We do not show the construction of $Emp\_shr\_brown^{6d}_{ew}$ and $Share\_brown_{6d}$ in Figure 1 to avoid cluttering the figure, but their construction is analogous to that of $Emp\_shr^{6d}_{ew}$ and $Share\_green_{6d}$, except that they start with. binary measure of brownness as explained in the text. The binary variable brown is depicted in the bottom level on the right.

Applying regression analysis to the merged microdata, we study the determinants of having a green job at the individual level. Differences in green job potential by individual and household characteristics such as gender, age, education, sector of employment, family background and region of residence are examined. This offers insight into the characteristics of individuals and households that have low green job potential and therefore allow a concise targeting strategy for policy makers looking to mitigate the impact of decarbonization on specific classes of workers and households.

DATA

Microdata on individual workers' detailed occupation group are available from Labor Market Panel Surveys (LMPS) for Egypt (2018, 2023), Jordan (2010, 2016) and Tunisia (2014), as well as from the Palestine Labor Force Survey (LFS) (2021) and the Tunisia Labor Force Surveys for 2022 and 2023. The LMPS for Egypt, Jordan and Tunisia (2014) are harmonized and use the same ISCO 2008 classification system. The Egyptian survey has the most detailed disaggregation of occupations, at ISCO 6 digits, while the Jordanian and Tunisian (2014) are available at the 4-digit level.

The Tunisian 2022-2023 LFS data uses the National Nomenclature of Occupations (NNP-2014) at the 5-digit level. The NNP is similar but not identical to ISCO. We first aggregated the 5-digit NNP occupations to the 4-digit level. We then translated the descriptions from French to English, merged the 4-digit NNP occupation codes with the ISCO counterparts by code number, and utilized an AI tool to verify that the NNP occupation descriptions matched those of the analogous ISCO codes. We then manually checked each of the 437 occupations to ensure consistency. There were 11 occupations that did not have direct matches in the ISCO 2008 classification, and for these the final match was determined through manual review of the occupation descriptions to find the nearest match.[10] The Palestinian LFS data are at the 2-digit ISCO classification. Information on the task content of SOC 8-digit occupation groups is taken from the O*NET (2019) database version 24.1, which is the latest version to have the green task classification.

Finally worth noting, the nature of green jobs expected post-decarbonization will depend on the conditions in economic sectors at large, due to the evolving degree of competitiveness, engagement in global value chains, technology and regulation, among other factors. Furthermore, skills in high fossil footprint sectors are already showing signs of greening up (Elliott et al. 2021). These projection challenges are mitigated by the relatively short time window of our forecasting, and relatively broad categories of green/brown jobs. Nevertheless, we attempt to account for these prospects by using alternative definitions of job greenness over time across multiple countries at varying degree of progress towards the green transition.

[10] We also attempted to use data from Iraq, Sudan and Mauritania, but the data on occupational classification is only available at the 1 -digit level and hence these would lead to extremely crude estimates that we chose not to report due to lack of reliability. An earlier version of this paper also used data for the State of Palestine, which had information on occupations at the 2-digit ISCO level. We decided to remove this analysis from the current version given the massive impact of the Gaza war on the Palestinian economy over the last two years, rendering any results using data from before 2023 irrelevant.

RESULTS

DESCRIPTIVE ANALYSIS

Figure 2 presents the binary indicators green, brown and grey for each country and year. In Egypt in 2018 17% of occupations had at least one green task, 5% of occupations were brown (polluting) and the remaining 78% were grey. By 2023 the share of green occupations had increased slightly to 18.6%, and that of brown occupations had decreased slightly to 4.9%. In Jordan in 2010 22.7% of occupations were green and 7.4% were brown. By 2016 here was a slight increase of green occupations to 24.1%, while brown occupations increased notably to 11.7%. In Palestine in 2021 16.9% of occupations were green, while 8.2% were brown. In Tunisia in 2014 26.4% of occupations were green and this share rose to 27.5% in 2022 and then rose further to 28.8% in 2023. The share of brown occupations also increased notably from 3.4% in 2014 to 6.2% in 2023. For comparison, the share of green occupations in Portugal, using the same methodology adopted here, was 19% in 2011 and fell to 17.9% in 2017. The share of brown occupations also fell from 11.6% in 2011 to 10.8% in 2017 (Scholl et al. 2023).

Examining the distribution by sex (Figure 3), most women in all three countries and all years are in grey occupations (80-91%). This is not surprising as large groups of women in these countries are concentrated in clerical work, education and health occupations (AlAzzawi and Hlasny 2025), which are classified as neither green nor brown. In all countries the share of men in green occupations is 2 to 3 times higher than women, and has been rising over time, except Tunisia where it fell between 2022 and 2023. The share of men in brown occupations has also been largely rising, but most notably in Jordan where it almost doubled, increasing from 8.7% in 2010 to 13.7% in 2016.

Figure 4 shows the distribution by age group. In all countries and years adults (30-65 years old) are more likely to have green jobs, while youth (15-29) are more likely to be in brown jobs, except in Jordan in 2016. Informal jobs (figure 5) are more likely to be green and brown in all countries and years, except Egypt in 2018. Most formal jobs are grey in all countries. Examining the prevalence of green jobs by region of residence (figure 6), urban areas appear to have higher shares of green jobs across all countries, and in Jordan also higher shares of brown jobs.

Figure 7 presents the distribution by 1-digit ISCO occupation. Green jobs are most heavily concentrated among Managers in all countries and years. Brown jobs are heavily concentrated among Crafts and related occupations, and in Tunisia also among skilled agriculture and forestry workers. In Egypt, the share of green jobs among Managers increased by over 10 percentage points between 2018 and 2023, while it decreased among by even more among Technicians. In Jordan the share of green jobs among Managers dropped significantly between 2010 and 2016 by over 20 percentage points, while it increased among Sales and Service workers and Technicians. In Tunisia, the most notable change between 2014 and 2023 was increased share of brown jobs among Crafts, Machine Operators, Skilled Agricultural workers and Technicians-these were much lower or mostly green and grey in 2014.

Figure 8 shows the distribution of green jobs by industry. In Egypt the Construction, Electricity, Water and Waste industries have the highest concentrations of green jobs. Brown jobs were highly concentrated in Mining and Manufacturing, and in 2023 in Construction. There were notable increases in green job concentrations in 2023 in ICT, Mining and the Construction sectors and notable increases in brown jobs in the Electricity sector by 2023. In Jordan in 2010 Water and Waste, ICT and Mining had the highest concentrations of green jobs while Construction and Electricity, followed by Manufacturing, had the highest concentrations of brown jobs. By 2016 the green of green jobs fell notably in ICT, and increased in Arts and Recreation, Finance, and Manufacturing. In Palestine, green jobs were most prevalent in Finance, Electricity, ICT and Construction. Brown jobs were most prevalent in Manufacturing, Electricity, Mining and Construction. In Tunisia[11] Electricity, Construction, ICT and Mining had the highest concentrations of green jobs in 2014, while brown jobs were in Manufacturing and Mining. By 2023 the share of green jobs had declined notably in Electricity and ICT but increased in Water and Waste. Brown jobs had increased in Agriculture, Electricity and Water and Waste.

Next we present the results of the green intensity of occupations, greenness and employment $greenness_{ew}$, measures, as well as the binary based measures $Share\_green_{8d}$ and $Emp\_shr^{8d}_{ew}$. (Refer to Table 1 for details on interpretation). Figure 9 presents the overall statistics by country and round. The green intensity of employment, greenness, measuring how green the tasks in an occupation are, based on the Vona et. al.'s continuous greenness scores, is under 7% in all countries and years. There is a slight increase over time in Egypt and Jordan but decrease in Tunisia. The employment weighted measure, $greenness_{ew}$, is slightly lower, suggesting that less than 5% of workers' tasks in these countries are green. Again, these shares rose slightly over time in Egypt and Jordan but have declined in Tunisia. For comparison, in Portugal in 2017 the average green intensity of occupations is just 3% and the intensity of green employment is 1.5% (Scholl et. al. 2023).

Moving to the binary based indicators, 13% of ISCO occupations in Egypt are classified as Green (having any green task) in the underlying 8-digit SOC occupation, 15-16% in Jordan, 10% in Palestine and 15-20% in Tunisia. Very similar share of employment is Green in each country when using the employment weighted binary based measure ($Emp\_shr^{8d}_{ew}$). These shares are also relatively higher than Portugal in 2017, where the shares were 8.7% and 10.1% respectively.

Figure 10 present these shares by sex and confirm the earlier findings that men have higher greenness intensity of occupations and employment, both by the continuous measures and the binary measures. In Egypt, these shares are falling over time for women, while they are rising for men. In Jordan the green

[11] We omit 2022 as it was almost identical to 2023 to save on space.

intensity of occupations and employment are rising over tie for both men and women. The binary based measures show little change over time. In Tunisia women's green intensity of occupations and employment rose over time, as well as their share of Green occupations and employment (binary based measures), while that of men fell over time.

Figure 11 shows the greenness indicators by age group. Once again, in all countries and years, adults are more likely to be in occupations or employment with higher green task intensity, or to be in occupations with at least one green task. Figure 12 reports the greenness indices by formality status of employment and confirms the earlier finding that informal jobs are somewhat more likely to have higher green task intensity or to be in occupations with at least one green task. There are slight variations by country and year, but the differences are most pronounced in Jordan where the binary based measures are much higher for informal jobs in both years.

Figures 13a and 13b present these measures by 1-digit ISCO occupation. Across all countries, years and using the measures based on the continuous green intensity scores (figure 13a), Managers have the highest green intensity of occupations and employment. This is followed by Elementary occupations and Crafts in Egypt, by Professionals in Jordan, and by Crafts in Tunisia. Using the measures based on the binary Green indicator (figure 13b) the patterns are similar with the exception of Jordan in 2016 where Service and ales workers has slightly higher shares of occupations with underlying Green SOC occupations and of workers in Green occupations.

REGRESSION ANALYSIS

In this section we present regression analysis examining the individual-level correlates of having a green or brown job, and of the green intensity of occupations and employment. The results in Tables 4-7 include individual characteristics such as age group :15-29 (omitted), 30-44 and 45-64), sex (omitted: male), education group: low, which is less than intermediate (omitted), medium, which is an intermediate level and high which is above intermediate, region of residence (urban is omitted, except in Palestine where the third category refugee camps is the omitted category), broad industry of employment (omitted: agriculture), as well as occupation. Models 1 and 2 are probit regressions showing the probability of holding a green or brown job by worker characteristics. Models 3 and 4 are OLS regressions of the correlates of the green intensity of occupations and employment, respectively. Standard errors are adjusted for 11 clusters of industry.

Results vary somewhat across countries, but largely confirm the descriptive statistics presented earlier. Older adults, men, those residing in urban areas, informal workers, professionals, those employed in construction, transportation and communication are more likely to have green jobs. Brown jobs (table 5) are more prevalent among younger workers, those with less education, men, crafts and related workers, machine operators, in mining, manufacturing and public utilities.

Models 3 and 4 (Tables 6 and 7) examine the determinants of the green intensity of occupations and employment based on the continuous greenness scores. Older adults, especially in Jordan are more likely to have jobs with high green intensity. Women, rural residents and highly educated adults are less likely to have jobs in high green intensity. Green intensity of occupations and employment is relatively higher in Public Utilities, construction and in manufacturing in Jordan and Palestine, but lower in Education and Health.

SUMMARY, POLICY RECOMMENDATIONS AND CONCLUSION

The descriptive and regression analyses reveal that while the MENA region exhibits a relatively high share of occupations containing at least one green task, the actual intensity of green work remains low. Across Egypt, Jordan, Palestine, and Tunisia, the binary prevalence of green jobs—ranging from approximately 17 to 29 percent—exceeds benchmarks found in some European countries like Portugal. However, the continuous greenness scores, which measure the actual proportion of green tasks within an occupation, consistently fall below 7 percent. This suggests that while a significant portion of the workforce is engaged in roles that have been «touched» by the green transition, very few workers are employed in positions dedicated exclusively to environmental functions. The results also show that brown or polluting jobs remain a significant presence, particularly in Jordan and Tunisia, where their share has seen notable increases in recent years.

A stark demographic divide characterizes the green labor market in the region, particularly regarding gender and age. Women are overwhelmingly concentrated in grey occupations, which comprise 80 to 91 percent of female employment across all surveyed countries. This concentration is largely due to the clustering of women in education, health, and clerical roles that currently lack defined green task profiles. Consequently, men are two to three times more likely than women to hold green jobs. Furthermore, the data reveals a youth paradox; while older adults are more likely to secure green positions—often in managerial or professional capacities—young workers aged 15 to 29 are disproportionately represented in brown industries. This indicates that the current green transition is favoring established workers with higher seniority and education, while the youth are entering the labor market through traditional, more polluting sectors.

The socio-economic characteristics of green employment also highlight significant challenges related to informality and geography. Informal jobs are more likely to be classified as green or brown compared to formal jobs, which are predominantly grey. This suggests that a substantial amount of the region's environmental labor, such as that found in waste management or certain agricultural practices, is occurring outside of regulated frameworks and social protections. Geographically, green jobs are heavily concentrated in urban areas, leaving rural populations at a disadvantage. Sector ally, while construction and utilities show high green potential, the declining green intensity in sectors like ICT and the rise of brown tasks in manufacturing suggest that the transition is uneven and potentially regressing in certain industrial clusters.

POLICY RECOMMENDATIONS FOR AN INCLUSIVE GREEN TRANSITION

To address the gender gap, policymakers should focus on greening the sectors where women are already most active rather than solely focusing on shifting women into male-dominated technical fields. This involves updating the occupational standards and curricula for the education and health sectors to incorporate environmental sustainability, green health management, and climate education. By formally recognizing these as green-intensive roles, governments can elevate the status of women's work within the green economy. Additionally, providing targeted financial incentives and mid-career training for women in the green ICT and finance sectors could help increase their representation in high-intensity green roles where they currently have a smaller footprint.

Regarding the youth, the priority must be creating clear pathways from brown to green employment. Given that young workers are currently concentrated in polluting crafts and machine-operating roles, vocational training programs must be redesigned to provide the specific technical skills required for green construction and renewable energy installation. Governments should implement «green apprenticeship» subsidies for firms that hire young workers into environmental roles, ensuring that the next generation is not locked into declining brown industries. By aligning the skills of young workers with the high-intensity tasks found in the utilities and waste management sectors, the region can transform its youth bulge into a primary driver of the ecological transition.

Finally, structural reforms are needed to support informal workers and rural communities. Policymakers should introduce simplified registration processes and social security incentives for informal green workers, effectively formalizing the environmental labor that is already taking place. To counter the urban bias of green jobs, investment should be directed toward rural green infrastructure, such as sustainable agribusiness and decentralized renewable energy projects. These efforts would ensure that the benefits of the green economy are distributed more equitably across the population. By integrating these demographic and structural considerations into national climate strategies, MENA countries can achieve a transition that is not only ecologically sound but also socially just.

CONCLUSION

The findings of this study provide a critical baseline for understanding the greening of labor markets in the MENA region. While the presence of green tasks is widespread, the low task intensity and significant demographic disparities suggest that the transition is still in its infancy and risks reinforcing existing inequalities. The concentration of green roles among older, urban men and the exclusion of women and youth from high-intensity green work present a significant barrier to inclusive growth. However, the high binary prevalence of green jobs indicates a strong foundation upon which to build. By implementing targeted policies that green women-dominated sectors, retrain youth for environmental roles, and support the informal workforce, MENA countries can harness the green transition to promote broader economic and social development.

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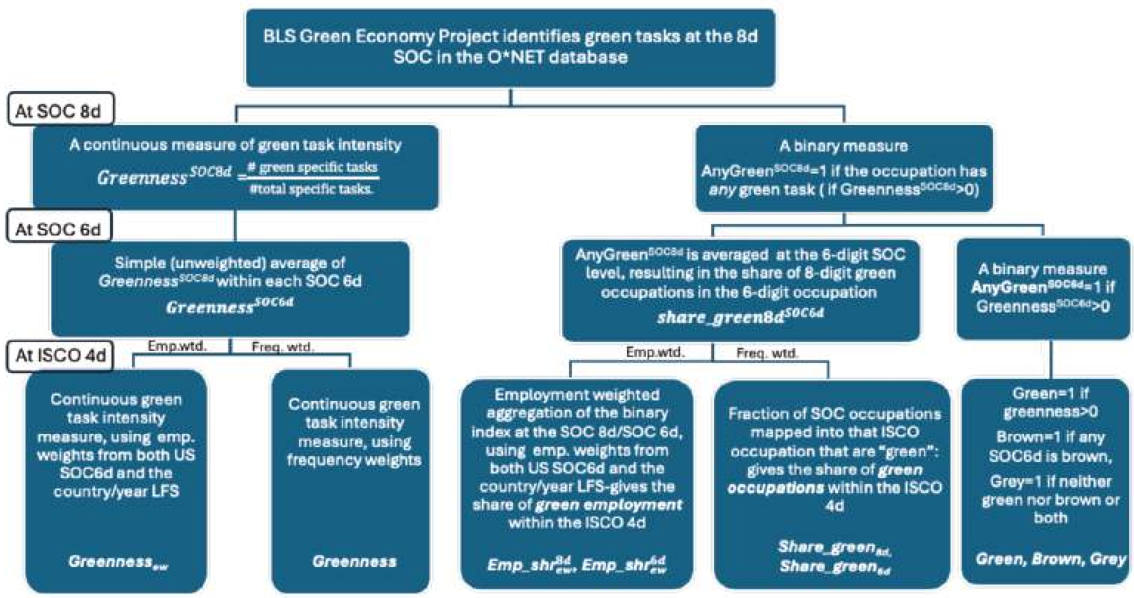
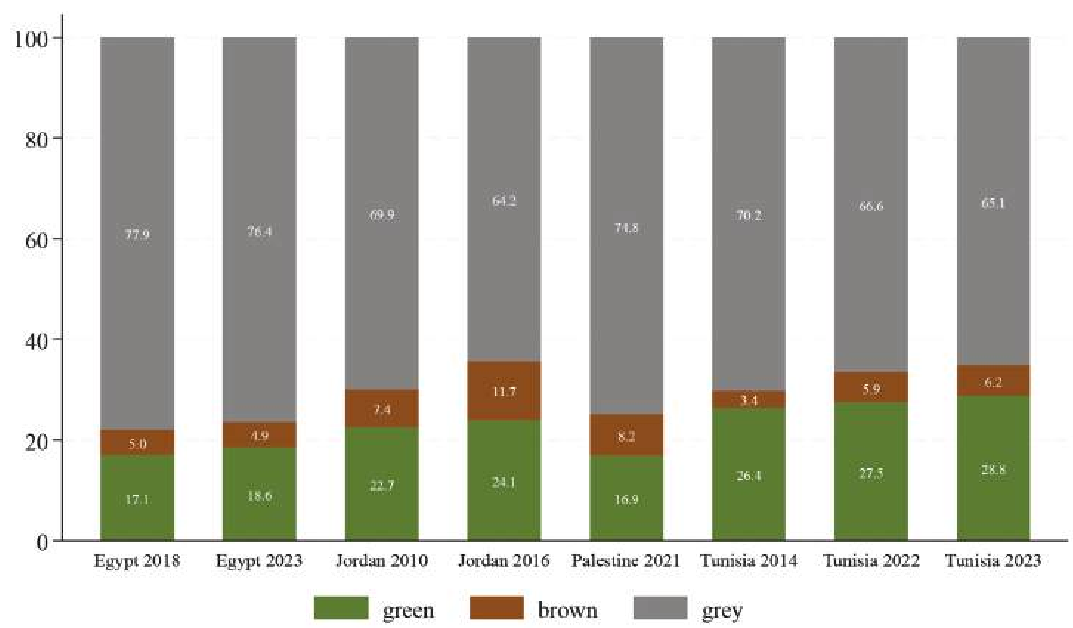
Figure 1. Visualization of Mapping Procedure Green Occupations



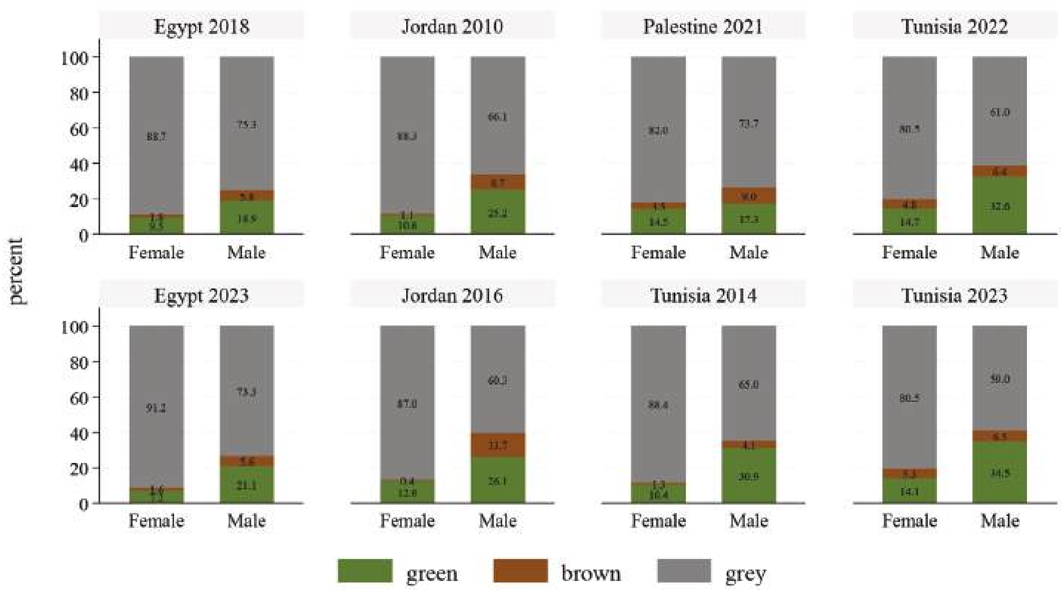
Source: Authors based on methodology described in the text

Figure 2. Prevalence of Green, Brown and Grey Occupations by country and year



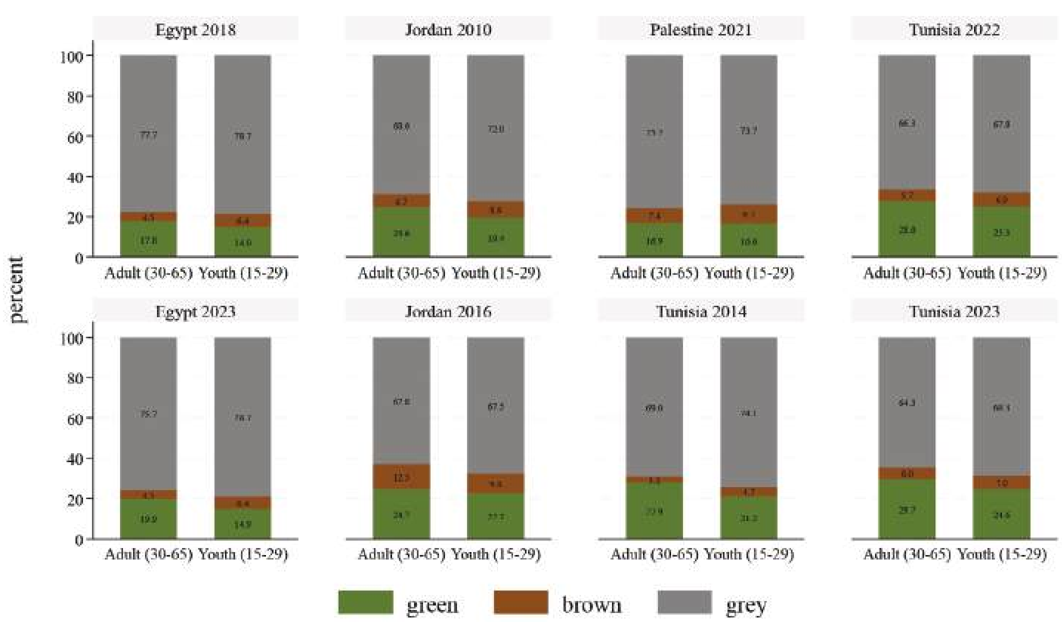
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 3. Prevalence of Green, Brown and Grey Occupations by sex, country and year



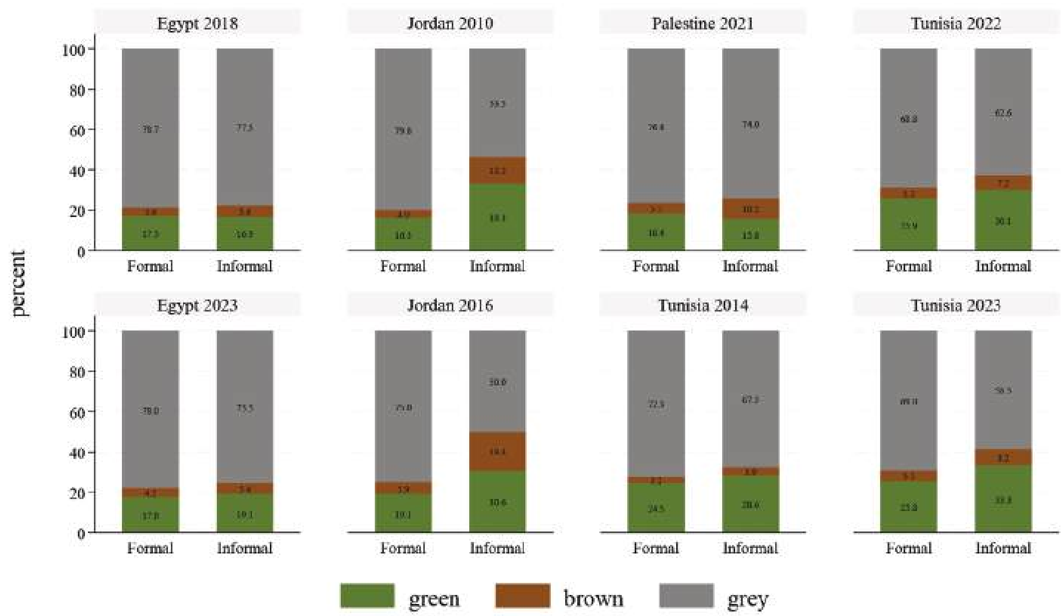
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 4. Prevalence of Green, Brown and Grey Occupations by age, country and year



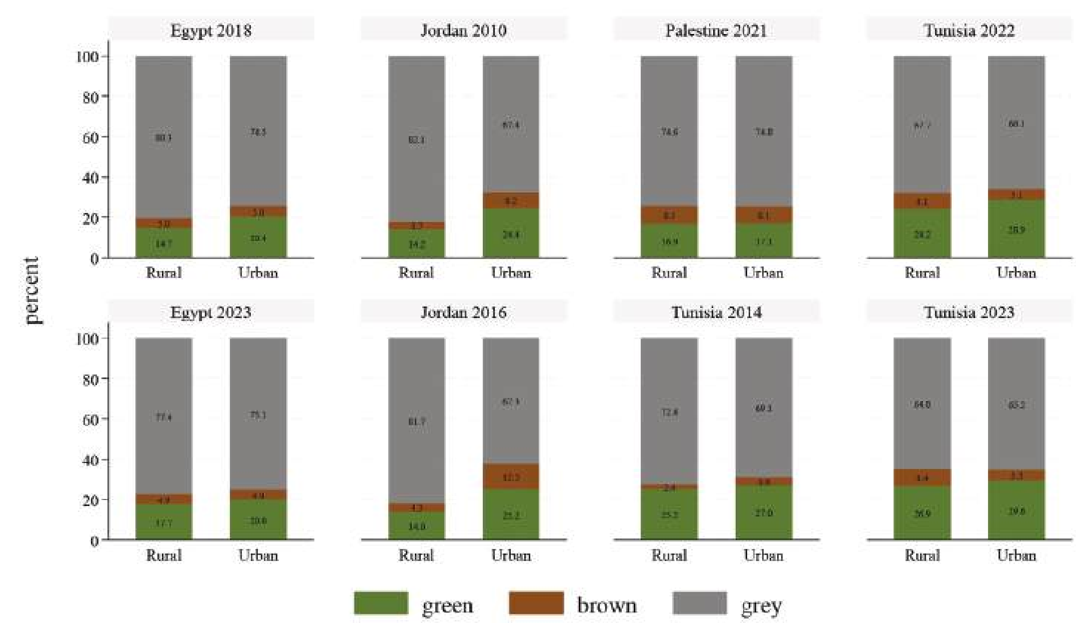
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 5. Prevalence of Green, Brown and Grey Occupations by formality of employment, country and year



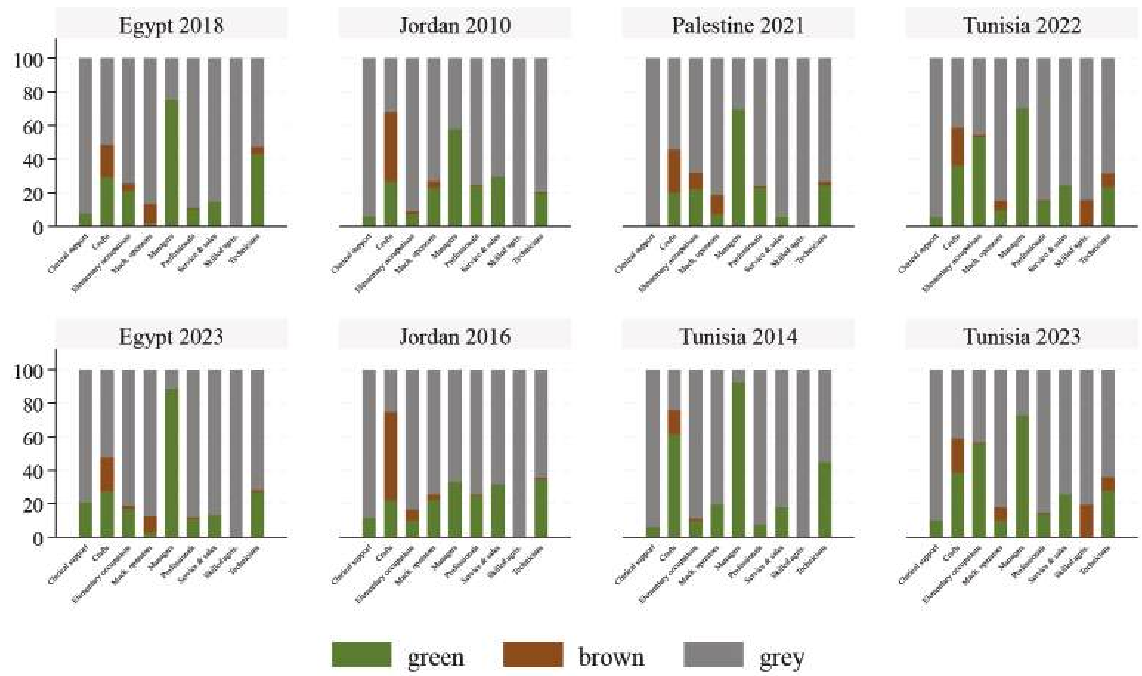
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 6. Prevalence of Green, Brown and Grey Occupations by region of residence, country and year



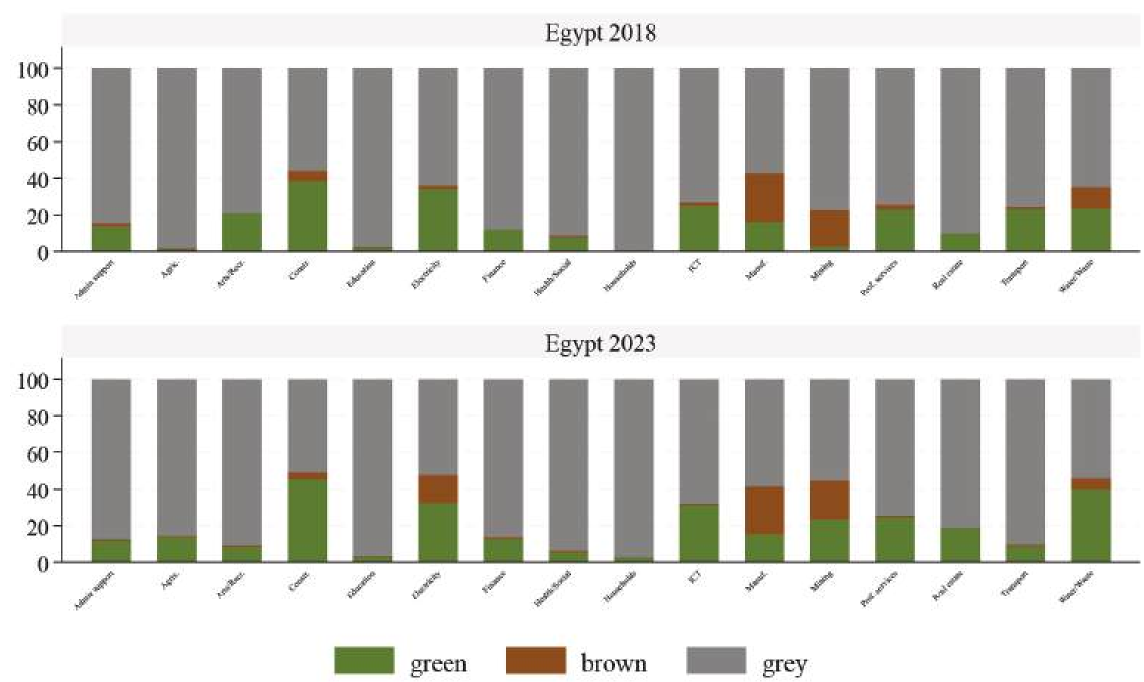
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

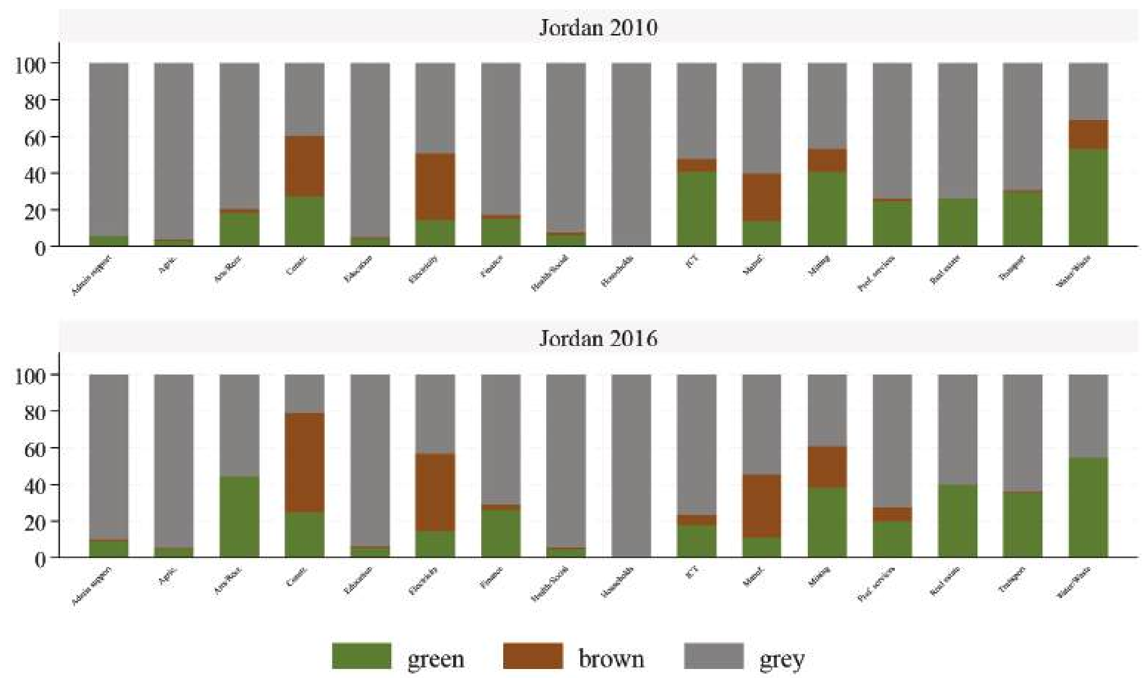
Figure 7. Prevalence of Green, Brown and Grey Occupations by broad occupation, country and year

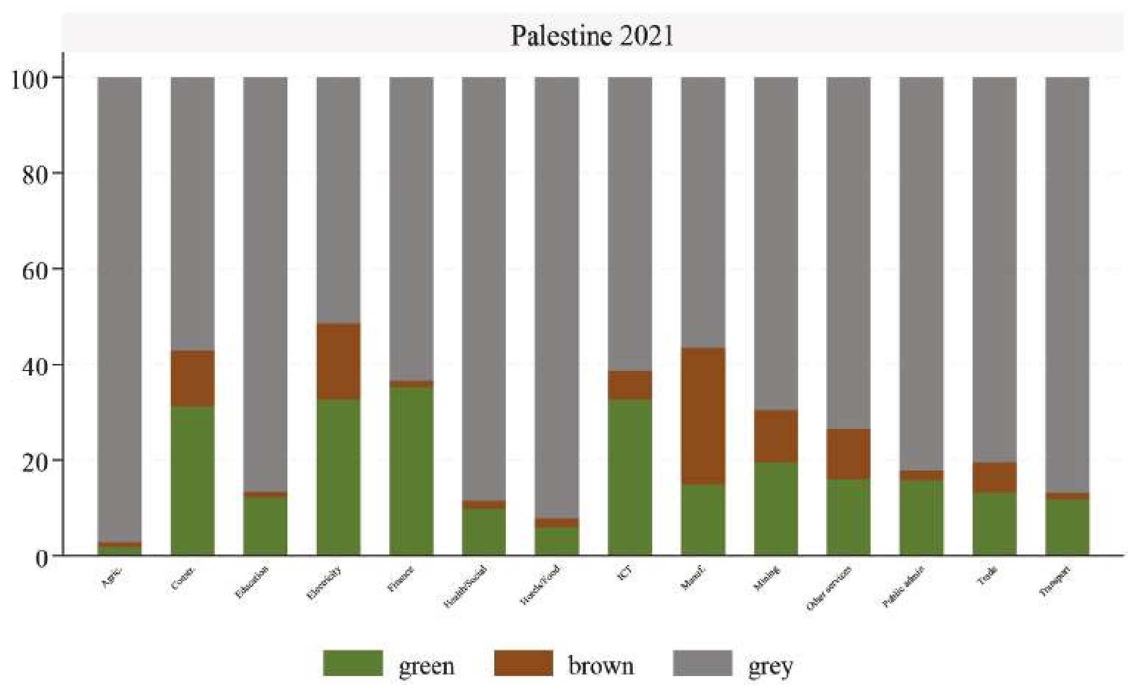


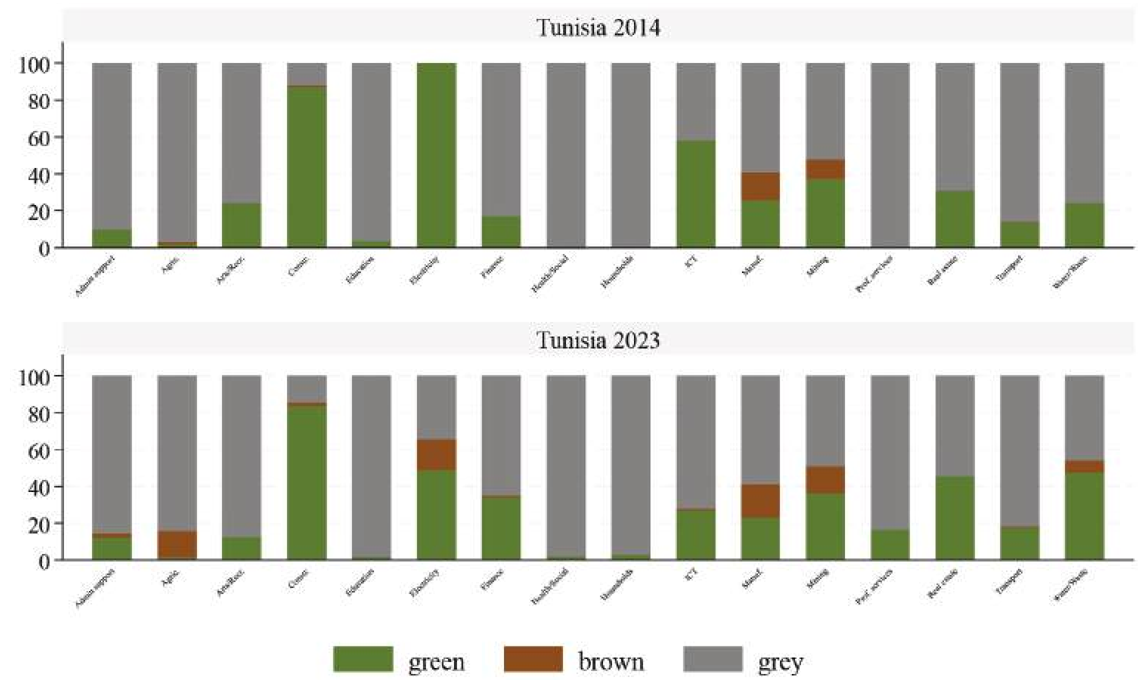
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 8. Prevalence of Green, Brown and Grey Occupations by industry, country and year



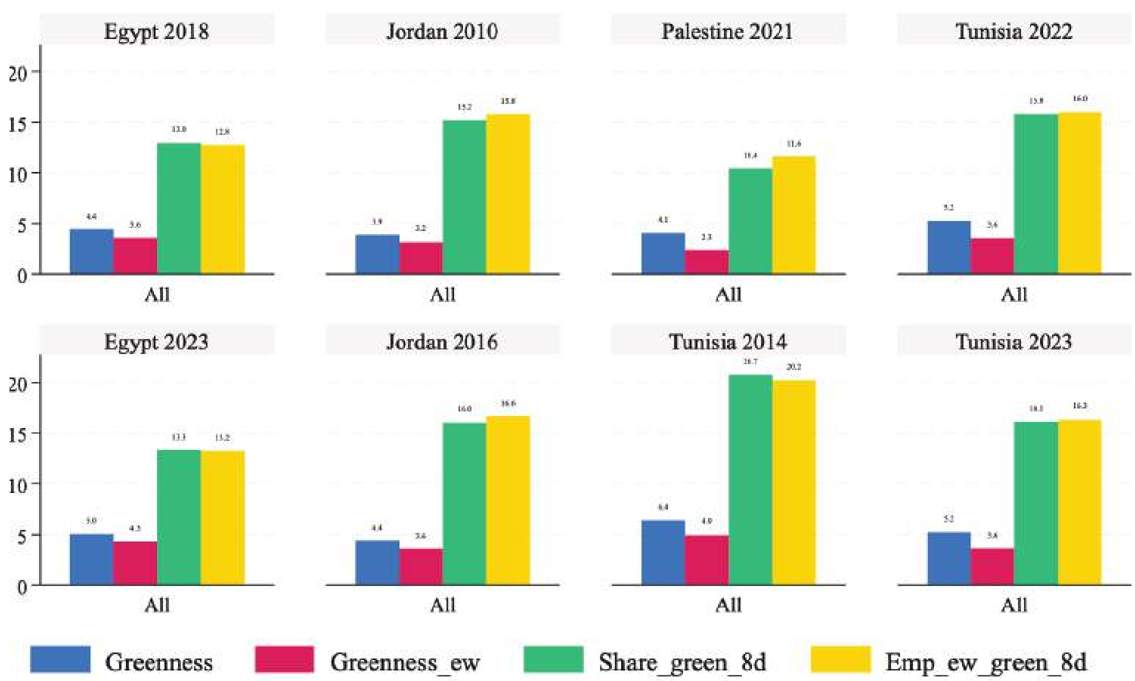

Jordan 2010
100
80
60
40
20
0
Jordan 2016
100
80
60
40
20
0
green
brown
grey


Palestine 2021
100
80
60
40
20
0
green
brown
grey



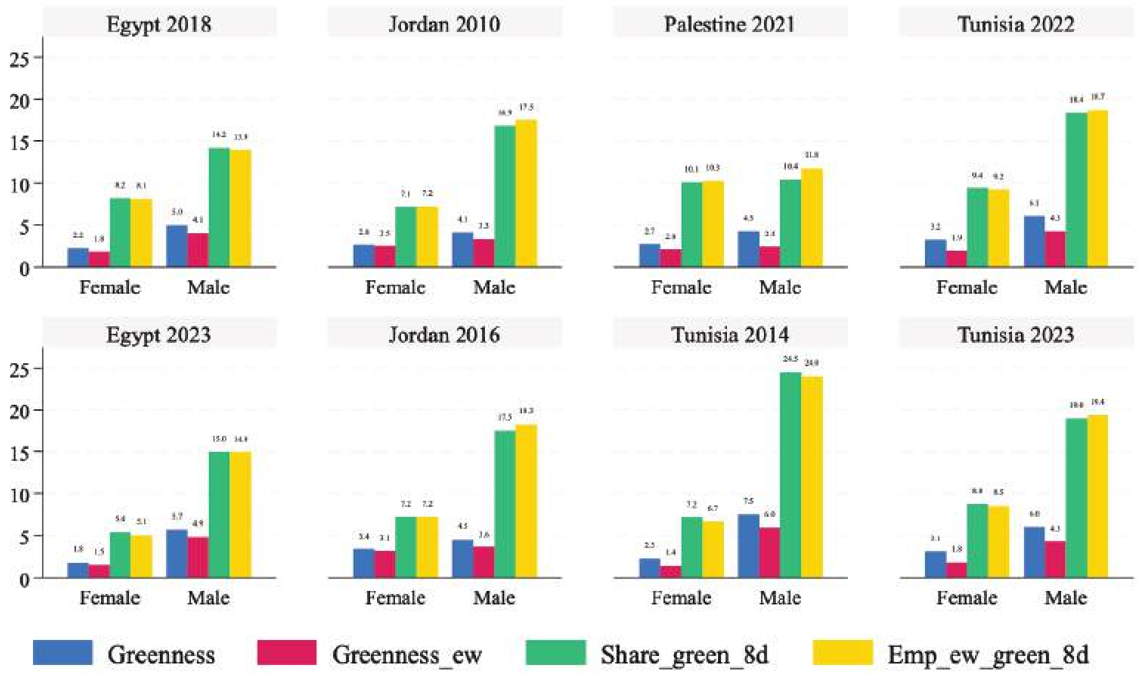
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 9. Green intensity of occupations and employment by country and year



Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 10. Green intensity of occupations and employment by sex, country and year

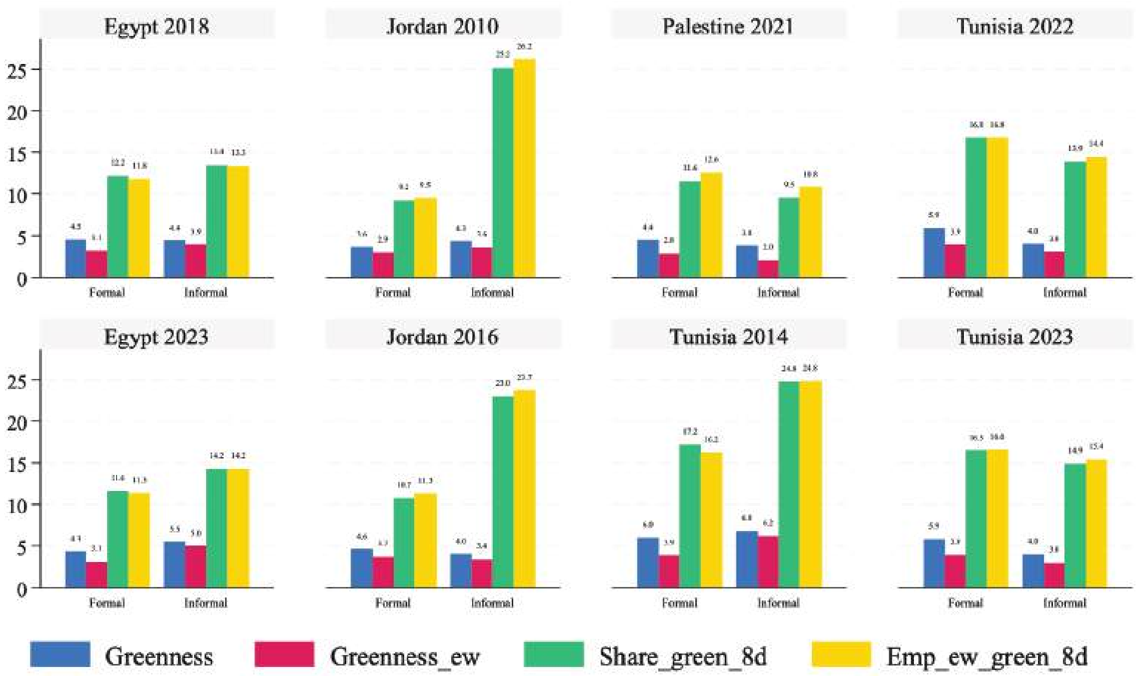


Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 11. Green intensity of occupations and employment by age, country and year

Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 12. Green intensity of occupations and employment by formality of employment, country and year



Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Figure 13a. Green intensity of occupations and employment by occupation, country and year

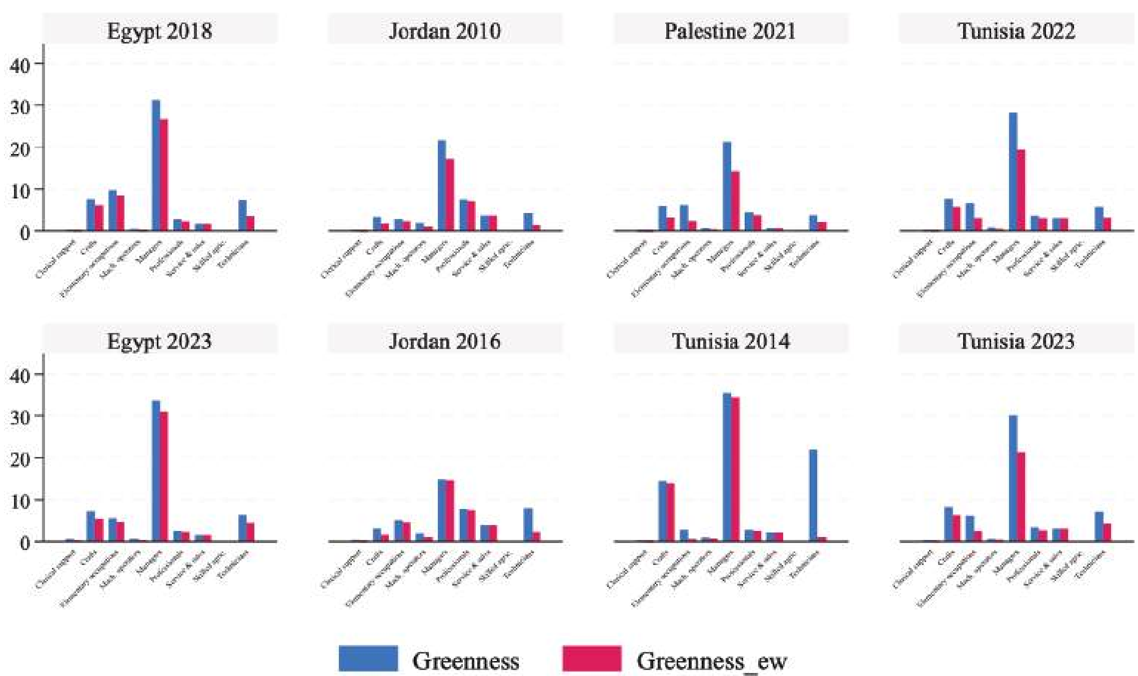
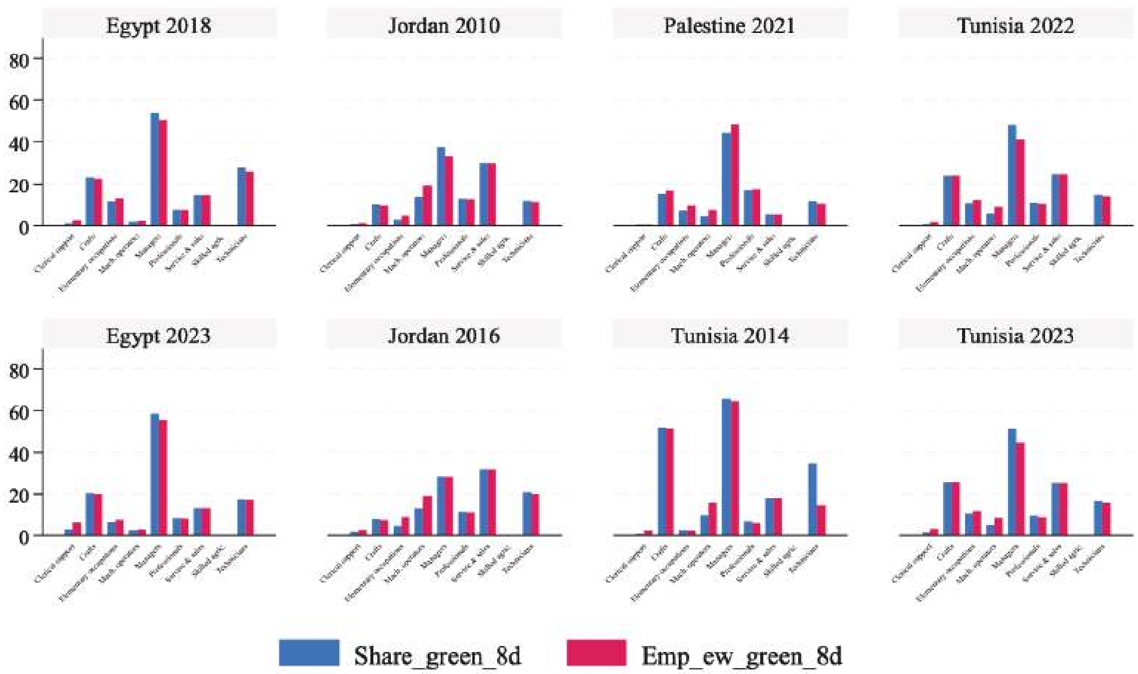


Figure 13b. Green intensity of occupations and employment by occupation, country and year



Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Table 1. Description of measures of greenness and their interpretation

Measure	Level	Type	How it's constructed	What it tells you
Share_green$_{8d}$	ISCO-4d (occupation-based)	Binary (0/1 for each SOC)	Fraction of SOC-8d occupations mapped into a given ISCO-4d that are classified as Green (i.e., contain any green task). Each SOC is counted equally, not weighted by employment.	"How green is this ISCO occupation, based on how many of its sub-occupations are green?" → Occupation-centered measure.
Emp_shr$^{8d}_{ew}$	ISCO-4d (worker-based)	Binary + DOUBLE (DN) employment-weighted	Fraction of *workers* in Green ISCO occupations who are employed in SOC-8d classified as Green. Employment weights derived from actual ISCO employment sizes from each MENA country (DOUBLE (DN) weights), rather than assuming uniform distribution.	"Among workers in Green ISCOs, what % are actually in Green SOCs?" → Worker-centered version of the binary approach using more realistic weighting where data are available.
greenness	ISCO-4d (occupation-based)	Continuous (task-share)	Average green intensity of occupations, based on Vona et al. (2018) scores, without weighting by employment.	"On average, how green are the tasks in this occupation?"
greenness$_{ew}$	ISCO-4d (worker-based)	Continuous + DOUBLE (DN) employment-weighted	Weighted average of green intensity scores, accounting for how many workers are in each SOC using DOUBLE (DN) weights based on actual ISCO employment in each MENA country.	"What share of workers' tasks are green, using real-world ISCO employment weights?"

Source: Authors based on methodology described in the text

Table 2. Sample Statistics for Occupations with at least 1 green task

Variable	N	Mean	SD	p25	p50	p75	Min	Max
greenness	91	0.25	0.25	0.07	0.16	0.35	0.01	1
share_green_8d	91	0.62	0.3	0.33	0.6	1	0.11	1
share_green_6d	91	0.72	0.29	0.5	0.67	1	0.12	1

Source: Authors based on methodology described in the text

Table 3. Sample Statistics of greenness/brownness for all ISCO 4-digit Occupations

Variable	N	Mean	SD	p25	p50	p75	Min	Max
green	437	0.208	0.407	0	0	0	0	1
brown	437	0.094	0.292	0	0	0	0	1
grey	437	0.698	0.46	0	1	1	0	1
share_green_8d	437	0.138	0.289	0	0	0	0	1
share_green_6d	437	0.158	0.322	0	0	0	0	1
share_brown_6d	437	0.073	0.222	0	0	0	0	1
greenness	437	0.055	0.153	0	0	0	0	1

Source: Authors based on methodology described in the text

Table 4. Model 1: Determinants of having a 'Green' job

	(1)	(2)	(3)	(4)
	Egypt	Jordan	Palestine	Tunisia
Age Group				
30-44	0.124*	0.109*	0.147	0.115
	(0.069)	(0.059)	(0.098)	(0.070)
45-64	0.241*	0.294**	0.178*	0.183
	(0.129)	(0.124)	(0.097)	(0.147)
Education Level				
Medium	-0.008	-0.058	0.004	-0.006
	(0.044)	(0.082)	(0.042)	(0.053)
High	-0.123*	-0.007	0.085	0.157**
	(0.071)	(0.079)	(0.104)	(0.074)
Sex				
Female	-0.306*	-0.242**	-0.009	-0.221**
	(0.173)	(0.118)	(0.190)	(0.104)
Region				
rural	-0.018	-0.096*	0.015	0.040
	(0.052)	(0.052)	(0.078)	(0.053)
urban			0.015	
			(0.044)	
Formality of employment				
Formal	-0.002	-0.129	-0.080	0.228*
	(0.096)	(0.189)	(0.177)	(0.126)
Occupation				
Managers	2.271***			
	(0.291)			

Professionals	0.341	-0.215	1.426***	-1.157***
	(0.254)	(0.271)	(0.219)	(0.286)
Technicians	0.998***	-0.636	1.378***	-1.131**
	(0.225)	(0.487)	(0.352)	(0.468)
Clerical	0.098	-1.497***	-1.752***	-2.005***
	(0.253)	(0.371)	(0.590)	(0.510)
Service & sales	-0.186	-1.097	0.138	-1.613**
	(0.274)	(0.906)	(0.714)	(0.695)
Skilled agric.	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Crafts	0.180	-1.044	1.958***	-1.659**
	(0.346)	(0.685)	(0.414)	(0.683)
Mach. operators	-1.132***	-1.085***	-0.046	-2.061***
	(0.204)	(0.384)	(0.755)	(0.553)
Elementary	0.000	-1.625***	0.000	-1.145**
	(.)	(0.405)	(.)	(0.446)
Industry				
Mining	-0.253***	0.814***	1.995***	1.466***
	(0.095)	(0.110)	(0.453)	(0.171)
Manufacturing	-0.668***	-0.118	1.444***	1.263***
	(0.149)	(0.101)	(0.294)	(0.244)
Public Utilities	0.090	0.418***	2.621***	1.487***
	(0.088)	(0.062)	(0.141)	(0.144)
Construction	0.349	0.375	3.556***	2.973***
	(0.284)	(0.258)	(0.074)	(0.274)
Commerce	0.048	1.435***	2.097***	1.622***
	(0.192)	(0.294)	(0.413)	(0.246)
Transport and Comm.	0.000	0.533***	3.175***	1.090***
	(0.081)	(0.060)	(0.453)	(0.241)

Financial & Professional	-0.606***	-0.140	1.086***	0.744***
	(0.076)	(0.144)	(0.147)	(0.211)
Public Administration	-0.750***	0.023	1.011***	0.623***
	(0.069)	(0.161)	(0.221)	(0.164)
Educ. & Health	-1.558***	-1.017***	0.770***	-0.642***
	(0.072)	(0.196)	(0.216)	(0.208)
Other services	-0.524***	-0.305**	0.471*	0.426***
	(0.097)	(0.148)	(0.264)	(0.153)
Round of the survey (year)=2023	-0.003			0.026
	(0.043)			(0.166)
Round of the survey (year)=2016		0.013		
		(0.033)		
Round of the survey (year)=2022				-0.022
				(0.169)
Constant	-0.853***	-0.104	-1.509***	-0.690
	(0.186)	(0.409)	(0.185)	(0.594)
Observations	26649	10724	21455	27342

Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Table 5. Model 2: Determinants of having a 'Brown' job

	(1)	(2)	(3)	(4)
	Egypt	Jordan	Palestine	Tunisia
Age Group				
30-44	-0.017	0.004	-0.163***	0.003
	(0.036)	(0.065)	(0.061)	(0.077)
45-64	0.026	0.016	-0.110	0.004
	(0.053)	(0.074)	(0.094)	(0.160)
Education Level				
Medium	0.116	0.225	-0.040	-0.063
	(0.085)	(0.144)	(0.055)	(0.055)

High	0.226	0.175	-0.221***	-0.396***
	(0.139)	(0.118)	(0.064)	(0.114)
Sex				
Female	-0.355*	-1.112***	-0.194***	-0.256
	(0.190)	(0.195)	(0.070)	(0.475)
Region				
rural	0.043	-0.082	0.098	0.072
	(0.033)	(0.112)	(0.134)	(0.088)
urban			0.043	
			(0.079)	
Formality of employment				
Formal	-0.015	-0.200	0.122	-0.115
	(0.113)	(0.179)	(0.172)	(0.117)
Occupation				
Managers	0.000			
	(.)			
Professionals	-0.311	-0.554	-2.348***	0.427
	(0.337)	(0.415)	(0.413)	(0.342)
Technicians	-0.131	-0.830*	-2.483***	1.177***
	(0.355)	(0.435)	(0.281)	(0.374)
Clerical	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Service & sales	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Skilled agric.	-1.425***	0.000	-0.799**	1.249***
	(0.187)	(.)	(0.372)	(0.162)
Crafts	1.078***	1.510***	0.000	1.628***
	(0.177)	(0.249)	(.)	(0.221)
Mach. operators	0.846**	0.025	-2.473***	0.622**
	(0.429)	(0.592)	(0.627)	(0.314)
Elementary	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)

Industry				
Mining	1.339***	0.969***	3.696***	0.672***
	(0.058)	(0.064)	(0.553)	(0.236)
Manufacturing	1.203***	0.674***	4.608***	0.588***
	(0.093)	(0.153)	(0.495)	(0.085)
Public Utilities	0.816***	1.262***	3.973***	0.904***
	(0.126)	(0.112)	(0.317)	(0.151)
Construction	-0.223	0.537***	3.962***	-1.031***
	(0.158)	(0.144)	(0.263)	(0.104)
Commerce	0.591***	-0.365**	2.151***	-0.256***
	(0.119)	(0.149)	(0.087)	(0.079)
Transport and Comm.	-0.719***	-0.324	2.427***	-0.974***
	(0.142)	(0.235)	(0.383)	(0.223)
Financial & Professional	0.320***	0.297**	3.367***	-0.739***
	(0.099)	(0.127)	(0.318)	(0.118)
Public Administration	0.040	0.173	2.947***	-0.240**
	(0.090)	(0.142)	(0.263)	(0.120)
Educ. & Health	0.069	0.031	2.271***	-1.044***
	(0.155)	(0.100)	(0.299)	(0.094)
Other services	0.503***	0.600***	3.424***	-0.216***
	(0.122)	(0.100)	(0.292)	(0.065)
Round of the survey (year)=2023	-0.121**			0.567**
	(0.053)			(0.239)
Round of the survey (year)=2016		0.264***		
		(0.095)		
Round of the survey (year)=2022				0.573***
				(0.209)
Constant	-2.460***	-2.081***	-1.614***	-2.779***
	(0.203)	(0.139)	(0.113)	(0.299)

Observations	23030	6548	12948	21661

Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Table 6. Model 3: Determinants of green intensity of occupation

	(1)	(2)	(3)	(4)
	Egypt	Jordan	Palestine	Tunisia
Age Group				
30-44	0.003	0.007***	-0.000	0.003
	(0.003)	(0.002)	(0.001)	(0.006)
45-64	0.002	0.014*	0.001	0.008
	(0.004)	(0.007)	(0.001)	(0.009)
Education Level				
Medium	-0.000	0.001	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.002)
High	-0.010*	-0.000	0.002	-0.004
	(0.005)	(0.004)	(0.001)	(0.012)
Sex				
Female	-0.010***	-0.011**	-0.010***	-0.005
	(0.003)	(0.004)	(0.002)	(0.006)
Region				
rural	-0.001	-0.003	0.001	-0.000
	(0.003)	(0.004)	(0.002)	(0.004)
urban			0.002*	
			(0.001)	
Formality of employment				
Formal	-0.004	-0.000	0.005***	0.013
	(0.006)	(0.008)	(0.001)	(0.010)
Occupation				
Managers	0.302***			
	(0.030)			
Professionals	0.035***	-0.072	-0.147***	-0.212***
	(0.009)	(0.052)	(0.021)	(0.047)
Technicians	0.057***	-0.119	-0.177***	-0.193***
	(0.013)	(0.066)	(0.019)	(0.059)

Clerical	-0.006	-0.184**	-0.217***	-0.280***
	(0.010)	(0.068)	(0.016)	(0.056)
Service & sales	-0.007*	-0.167*	-0.209***	-0.262***
	(0.004)	(0.075)	(0.015)	(0.067)
Skilled agric.	-0.049***	-0.179**	-0.166***	-0.267***
	(0.014)	(0.061)	(0.005)	(0.055)
Crafts	0.006	-0.187**	-0.169***	-0.238**
	(0.019)	(0.065)	(0.017)	(0.088)
Mach. operators	-0.023**	-0.175**	-0.214***	-0.298***
	(0.010)	(0.058)	(0.013)	(0.063)
Elementary	0.031	-0.150**	-0.158***	-0.261***
	(0.022)	(0.066)	(0.005)	(0.058)
Industry				
Mining	-0.027**	0.038***	0.051***	0.064**
	(0.012)	(0.007)	(0.007)	(0.022)
Manufacturing	-0.027*	0.021***	0.040***	0.042
	(0.014)	(0.005)	(0.010)	(0.030)
Public Utilities	0.040**	0.020***	0.122***	0.160***
	(0.013)	(0.006)	(0.007)	(0.009)
Construction	0.054**	0.071***	0.075***	0.117***
	(0.019)	(0.004)	(0.009)	(0.030)
Commerce	-0.019	0.055***	0.046***	0.026
	(0.012)	(0.016)	(0.009)	(0.018)
Transport and Comm.	-0.023**	0.011	0.056***	0.019
	(0.009)	(0.010)	(0.009)	(0.020)
Financial & Professional	-0.030**	-0.012	0.057***	-0.013
	(0.013)	(0.014)	(0.010)	(0.021)
Public Administration	-0.042***	0.014	0.064***	0.012
	(0.012)	(0.014)	(0.009)	(0.016)

Educ. & Health	-0.072***	-0.062***	0.002	-0.049*
	(0.014)	(0.017)	(0.014)	(0.023)
Other services	-0.036**	-0.004	0.054***	-0.001
	(0.011)	(0.012)	(0.010)	(0.014)
Round of the survey (year)=2023	-0.001			-0.017
	(0.003)			(0.015)
Round of the survey (year)=2016		0.002		
		(0.002)		
Round of the survey (year)=2022				-0.017
				(0.016)
Constant	0.052***	0.172**	0.166***	0.272***
	(0.016)	(0.063)	(0.005)	(0.063)
Observations	32414	11038	23061	30658

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

Table 7. Model 4: Determinants of green intensity of employment

	(1)	(2)	(3)	(4)
	Egypt	Jordan	Palestine	Tunisia
Age Group				
30-44	0.004	0.009***	0.001*	0.005
	(0.003)	(0.002)	(0.001)	(0.004)
45-64	-0.000	0.014*	0.002**	0.011
	(0.004)	(0.007)	(0.001)	(0.008)
Education Level				
Medium	-0.002	0.001	-0.000	0.001
	(0.002)	(0.002)	(0.001)	(0.002)
High	-0.015**	0.008**	-0.004	-0.001
	(0.006)	(0.003)	(0.002)	(0.007)
Sex				
Female	-0.008***	-0.006	-0.007***	-0.001
	(0.002)	(0.005)	(0.002)	(0.006)

Region				
rural	0.003	-0.003	0.001	0.001
	(0.003)	(0.003)	(0.001)	(0.005)
urban			0.001	
			(0.001)	
Formality of employment				
Formal	-0.013*	-0.004	0.004**	0.007
	(0.006)	(0.008)	(0.002)	(0.007)
Occupation				
Managers	0.259***			
	(0.034)			
Professionals	0.028**	-0.047	-0.089***	-0.156***
	(0.010)	(0.050)	(0.023)	(0.045)
Technicians	0.027**	-0.127*	-0.121***	-0.172**
	(0.009)	(0.061)	(0.005)	(0.054)
Clerical	-0.008	-0.147**	-0.145***	-0.203***
	(0.010)	(0.062)	(0.005)	(0.049)
Service & sales	-0.013***	-0.125*	-0.139***	-0.183***
	(0.004)	(0.069)	(0.008)	(0.052)
Skilled agric.	-0.072***	-0.132**	-0.127***	-0.213***
	(0.014)	(0.058)	(0.015)	(0.051)
Crafts	-0.017	-0.157**	-0.117***	-0.171**
	(0.013)	(0.056)	(0.015)	(0.075)
Mach. operators	-0.035***	-0.143**	-0.145***	-0.215***
	(0.007)	(0.057)	(0.008)	(0.052)
Elementary	0.012	-0.113	-0.123***	-0.219***
	(0.026)	(0.065)	(0.017)	(0.055)
Industry				
Mining	-0.039**	0.043***	0.024**	0.026
	(0.013)	(0.007)	(0.009)	(0.019)
Manufacturing	-0.037**	0.027***	0.011	0.006
	(0.013)	(0.007)	(0.012)	(0.022)

Public Utilities	0.008	0.031***	0.071***	0.140***
	(0.014)	(0.007)	(0.009)	(0.008)
Construction	0.039**	0.070***	0.025**	0.098***
	(0.017)	(0.007)	(0.010)	(0.022)
Commerce	-0.031**	0.055***	0.017	0.004
	(0.013)	(0.016)	(0.010)	(0.014)
Transport and Comm.	-0.032***	0.021***	0.023**	-0.002
	(0.010)	(0.006)	(0.010)	(0.015)
Financial & Professional	-0.039**	0.007	0.030**	-0.019
	(0.014)	(0.012)	(0.012)	(0.020)
Public Administration	-0.057***	0.023	0.029**	-0.021
	(0.013)	(0.013)	(0.010)	(0.015)
Educ. & Health	-0.076***	-0.046**	-0.014	-0.047*
	(0.015)	(0.016)	(0.015)	(0.022)
Other services	-0.051***	0.009	0.018	-0.010
	(0.013)	(0.012)	(0.011)	(0.012)
Round of the survey (year)=2023	0.000			-0.018
	(0.003)			(0.015)
Round of the survey (year)=2016		0.000		
		(0.002)		
Round of the survey (year)=2022				-0.018
				(0.016)
Constant	0.072***	0.124*	0.126***	0.217***
	(0.017)	(0.060)	(0.015)	(0.057)
Observations	32414	11038	23061	30658

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations, based on ELMPS 2018 and 2023, JLMPS 2010 and 2016, TLMPS 2014, Tunisia LFS 2022 and 2023 and Palestine LFS 2021.

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