Regional diversification and green employment in US Metropolitan Areas

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Abstract. Adapting or supplanting production and distribution systems to accommodate new criteria of environmental sustainability entails the search for and the recombination of know-how from a variety of domains. How this process plays out in different areas depends crucially on the specific composition of local economic activities. This paper contributes this debate by analysing whether and to what extent regional industrial and occupational diversification affects the change in green employment across 363 Metropolitan Statistical Areas (MSAs) in the United States between 2006 and 2014. Our findings suggest that industrial unrelated variety within MSAs is a positive and significant predictor of green employment growth whereas related variety has very little impact. Conversely, both related and unrelated diversification across occupations is positively associated with green employment growth. The analysis also uncovers heterogeneity across existing, new and evolving green jobs.

Keywords: Green employment; Industrial variety; Occupational variety; Diversification.

1 Introduction

The objective of this paper is to analyse whether and to what extent variety in the composition of local activities is associated with the diffusion of green jobs. Recent debates reaffirm the idea that dealing with new or revised criteria of environmental sustainability will bring about opportunities but, also, challenges associated with the necessity to adapt the structure and the organization of regional economies (Truffer and Coenen, 2012; Gibbs and O'Neill, 2017). While it is widely acknowledged that policy and regulation are critical for assisting the transition to sustainable economies (see i.e. Nesta et al., 2014; Barbieri et al., 2016), how the adaptation to new environmental criteria plays out in regional economies has received less attention. Indeed, climate change is a global phenomenon with markedly local manifestations, and regions and cities are expected to be major actors in adapting and/or anticipating the associated negative consequences.

The transition towards green economies entails the reorganisation of human capital to facilitate the adaptation of existing industrial and technological profiles to new societal goals (Feser, 2003; Asheim et al., 2011; Vona and Consoli, 2015). This is a staple in the strand of economic geography that studies how the qualitative composition of local activities enables or thwarts the potential for regional development (Jacobs, 1969; Glaeser et al., 1992). Building on the tenet that cognitive proximity and complementarity between firms' knowledge bases favour knowledge spillovers (Noteboom, 2000; Boschma, 2005), the seminal work of Frenken et al. (2007) has made headway by acknowledging heterogeneity in the forms and the effects of regional diversification. Their empirical construct of 'relatedness' has become a standard approach to measure whether and to which extent the composition of the local industry mix, and thus the attendant knowledge base, affects regional economic performance. More recently such an approach was extended to diversification between (unrelated) or within (related) occupations (Wixe and Andersson, 2017), imports and exports (Boschma and Iammarino, 2009) and technological fields (Castaldi et al., 2015).

In the present paper we blend these two strands of research to elaborate an empirical study on the relationship between the growth of green employment and regional diversification. In particular, starting from Frenken et al. (2007) we assess whether and to what extent variety in the composition of local activities is associated with green employment growth at US Metropolitan Statistical Area (MSA) level. Building on the idea that modern economies rest on the creation and diffusion of knowledge, and that work and employment are the vehicles through which individual know-how is applied to productive activities (Consoli and Rentocchini, 2015), we focus on occupational structures as a proxy of the adaptation of local knowledge bases to the green economy (Consoli et al., 2016). Moreover, we extend the framework recognising that at the heart of the greening process stand individuals that are endowed with specific skills, education and perform tasks whose demand is affected by changes in environmental-related activities (Desrochers and Leppälä, 2011). Last but not least, akin to Wixe and Andersson (2017), we move beyond the traditional remit of prior analyses based solely on industry classifications and include measures of regional variety based on occupations. That is, we test whether and to what extent occupational variety within MSAs is correlated with green employment growth.

The original contributions of the paper are three. First, we further develop the study of the dynamics of green employment (Vona et al., 2018a; Vona et al., 2018b) through the lenses of regional economic variety (Frenken et al, 2007). This way we detect different mechanisms through which the composition of local activities favours or thwarts the greening of the economy. Second, we propose a fine-grained analysis of the relationship between forms of economic variety and typologies of green jobs. To our knowledge this is the first attempt to investigate this issue which bears important policy implications in light of the substantial changes that the transition towards sustainable economies brings about, and of the distribution of costs and opportunities. Third, we extend the empirical work of Wixe and Andersson (2017) by identifying which form of diversification in regional occupational profiles is associated with green employment growth.

The main findings of the present paper are two. First, regional diversification across unrelated industries is a positive and significant predictor of green employment growth. This applies to both occupations that have an explicit green profile and to traditional occupations that are affected by the green economy via an increase in labour demand. Our result is robust to various econometric model specifications and over different time spans. Tellingly, related variety has little to no effect. The latter is in line with a small but growing (see i.e. Boschma, 2017) stream of studies that focus on the characteristics of and the enabling conditions for unrelated variety (Crespo et al., 2014; Castaldi et al., 2015; Xiao et al., 2016). The second key finding is that regional variety across related occupations is positively correlated to employment growth for jobs that are entirely new, and specific to the green economy, or that undergo qualitative transformation in their work tasks in response to climate change. At the same time, unrelated variety is associated with employment growth in traditional jobs that are connected to the greening of the economy only via growth in labour demand, thus not explicitly green.

The paper is structured as follow. Section 2 reviews the relevant literature. Section 3 describes data sources and methodologies used to measure green employment and regional variety. Section 4 presents the empirical findings and Section 5 concludes.

2 Literature review

In this section we detail key insights from relevant literature. After a review of various definitions of green jobs, we turn to studies that investigate the effect of industrial variety on regional growth in the second subsection. Finally, we focus on the empirical works on occupational variety and its effects on regional economic growth.

2.1 Green employment through occupational lens

Scholars and policy experts concur that the greening of modern economies is a gradual process characterised by the progressive take up of routines designed to deal with new or revised criteria of environmental sustainability. But in spite of growing interest on the labour market outcomes of the green transition (see e.g. Cecere and Mazzanti, 2017), the debate on what a green job is remains open (Deschênes, 2013; Vona et al., 2018b). A review by Consoli et al. (2016) finds common ground across prior empirical studies, namely the focus on the workforce of (i) industrial green processes (e.g. insulation, recycling), (ii) production or delivery of green products and services (e.g. workers producing insulation panels, hybrid vehicles) or (iii) selected green industries (e.g. manufacturing of wind turbines). The shortcoming of these studies is that green jobs are inferred from industry statistics and, thus, yield potentially incorrect estimates of the actual size of the green economy. Vona et al. (2018a) tackle this issue by proposing an alternative approach based on the task content of occupations. Using data of the Green Economy programme by the Occupational Information Network (O*NET) they identify all occupations that are affected by the greening.

The benefits of adopting an occupational-based perspective are twofold. First, it affords a more nuanced view of the compositional effects observed in local labour markets because it captures how the transition towards environmentally sustainable societies directly impacts the labour market through the creation of new jobs, changes in work activities of existing jobs and the demise of obsolete jobs.[1] Second, such a perspective captures the degree to which green activities and technologies impact the labour market. The greening of the economy affects existing non-green work tasks, brings about new (green) work tasks but, also, triggers employment demand for jobs whose nature is not necessarily defined by the demands of the green economy (e.g. natural science managers, electronics engineering technicians). In the remainder of the paper we adopt this approach to analyse how local economies adjust their structure and organization of work in response to the greening of the economy.

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[1] This approach has been well received in policy circles (see i.e. OECD blog https://medium.com/@OECD/defining-green-skills-using-data-23253591d6d2) and has been used in recent empirical studies (see Burger, 2017; Janser, 2018).

2.2 Related and unrelated variety at the industrial level

Previous literature in economic geography identifies knowledge spillovers as a precondition for the diffusion of new activities. Therein, the debate on the impact of agglomeration economies on economic growth revolves greatly around the question of whether specialisation (Marshall's externalities) or diversification (Jacobs's externalities) favour regional prosperity. The idea that a more diversified industrial composition leads to economic growth grounds on the tenet that innovation emerges from cross-fertilisation between different, local knowledge bases (Jacobs, 1969; Glaeser et al. 1992). This insight finds support in studies acknowledging that innovation stems from the recombination of bits of knowledge in different manners (Schumpeter, 1934; Usher, 1954; Nelson and Winter, 1982; Basalla, 1988; Fleming, 2001). Specifically, the emphasis is on the recombination process that reconfigures 'old' and 'new' ideas in an entirely new way leading to innovation (Weitzman, 1998).

Whereas externalities arising from agglomeration, especially in the form of knowledge spillovers, are considered an 'engine of growth' (Romer, 1986), geographical proximity is a key precondition for knowledge transfer. The theoretical background behind the relationship between agglomeration externalities and regional growth is further extended by the consideration of regional 'relatedness' (Frenken et al., 2007). Starting from the idea that repeated interaction between agents is most effective within delimited geographical and cognitive spaces (Noteboom, 2000; Boschma, 2005), this approach uncovers different types of variety associated with the degree of relatedness between industrial knowledge bases. In turn, whether and how much spillovers facilitate structural change depends on the type of complementarity that binds together key change actors within a region (Iammarino and McCann, 2006; Aarstad et al., 2016; Boschma, 2017). The evidence in this stream of studies points to a distinction between related variety - viz. within-industry diversity due to connection among activities that share similar resource bases – and unrelated variety - viz. between-industry diversity, which instead calls upon spanning a wider spectrum of different, possibly not hitherto connected, capabilities (Boschma and Frenken, 2011; Boschma and Capone, 2015; Boschma, 2017).

Exploring the regional determinants of green employment calls for a thorough assessment of how existing industrial and institutional settings shape the environment in which green activities emerge. According to the OECD (2011), achieving green growth entails catalysing investments and innovation to foster economic growth and development while ensuring efficient use of natural resources. However, the transition to the new model will draw from a variety of domains in a recombinant fashion, and local sectoral composition will likely affect the rate and direction of this process. Crucially, both the transfer of know-how and the development of new shared routines will depend on the degree of cognitive proximity across sectors.

In this paper we operationalise these ideas by studying the effect of regional industrial variety on green employment growth. Diversification stemming from related variety confronts lower costs and uncertainty compared to diversification that thrives on new connections in the space of regional activities. However, because of the tacit nature of knowledge in early stages of major transitions – and the shift to green economies is understood to be at early stage (see review by Barbieri et al., 2016), unrelated variety is key to enhance employment growth due to the disruptive new technological paradigm. A recent study by Castaldi et al. (2015) lends support to this conjecture. Therein, related variety and unrelated variety are found to be complementary for innovation, and contingent upon life-cycle type of dynamics. In particular, related variety in the regional knowledge base concerns innovations that develop incrementally out of established cognitive structures across connected domains while unrelated variety, though more uncertain and initially costly, can be a catalyst for breakthroughs that span, by necessity or by design, new functionalities. On these grounds Castaldi et al. (2015) conclude that unrelated variety paves the way to frontier activities that will become more related as they transition through stages of the life cycle. A recent paper by Barbieri et al. (2018) tests the difference between green and non-green technologies and finds that environmental-related technological activities are more complex, more radical and exert higher impacts on subsequent technologies than non-green ones.

These findings support the intuition that green innovation arises from more diversified knowledge sources and pervades a higher variety of technological domains. Moreover, dealing with environmental problems adds complexity in terms of the knowledge components that are recombined in the new invention. These characteristics of green innovation motivate our interest in assessing which type of variety is correlated to green employment growth. Indeed, the growth effect arising from knowledge spillovers and innovation may in this case be favoured by a knowledge base that is diversified across unrelated industries due to the higher complexity of green innovation.

Building on these insights, the present paper aims to address the following propositions:

Proposition 1. Unrelated variety measured by employment by industry in MSAs is associated with green employment growth due to the higher complexity that characterises green technologies.

Proposition 2. Related and unrelated industrial variety in MSAs exert different effects on green employment depending on the typology of green jobs under analysis.

2.3 Related and unrelated variety at the occupational level

The central tenet of the literature described above is that knowledge spillovers are more likely when industrial knowledge bases are complementary in terms of competences (Frenken et al., 2007). This idea is operationalised through the concept of related (and unrelated) variety that characterises sectors among which learning processes and interactions are fostered by (not too much) cognitive proximity (Iammarino and Boschma, 2009). However, by looking merely at the learning processes of firms overlooks an important aspect concerning the fact that knowledge spillover and transfer are eventually carried out by individuals (Wixe and Andersson, 2017). Even though industries are related in terms of industrial knowledge base, knowledge exchanges and learning processes occur when employees are located in the same regional environment, or move from one firm to another (Duraton and Puga, 2007). It follows that individual skills and human capital are crucial input that foster knowledge spillovers and innovation (Becker, 1962) and thus, regional growth (Boschma et al., 2014).

The importance of individuals as agents of knowledge spillovers finds support in the labour mobility literature. For an individual, switching job implies that some skills and human capital may become redundant and therefore he/she will choose new jobs that require similar skills and human capital (Lazear, 2009; Neffke et al., 2017). Due to the similarity between skills and human capital required in job switching, cross-industry labour flows are often used as a proxy for relatedness across industries (Neffke et al., 2013). Boschma et al. (2014) provide evidence of the positive effect of labour flows across skill-related industries on regional growth, pointing out that "the matching of skills […] promotes complementarities that stimulate productivity growth" (Baschma et al., 2014: pp.1686).

Following Wixe and Adersson (2017), the present paper investigates the extent to which relatedness between individual know-how, skills and tasks, as captured by regional occupational profiles is associated to green employment growth. In particular, given the heterogeneous effects of the greening process on the labour market, we assess whether related and unrelated variety favour different types of green jobs depending on the extent to which green activities and technologies lead to the emergence of new green jobs, increase the relative importance of green tasks in existing jobs, or enhance employment in occupations that are indirectly impacted by the green economy. Building on these premises, the paper addresses the following propositions:

Proposition 3. Regional diversification across related and unrelated occupations is associated with green employment growth.

Proposition 4. Depending on the type of green job, regional diversification across related and unrelated occupations is differently associated with green employment growth.

3 Methodology

We analyse the relationship between regional variety and green employment in 363 Metropolitan Statistical Areas (MSAs) of the United States.[2] This unit of analysis is deemed appropriate for three reasons. First, MSAs are areas with considerable occupational distinctiveness and heterogeneous occupational structures across units (Markusen and Schrock, 2006). Second, they are nationally consistent entities that are widely used to study local labour markets (see among others Demin and Kahn, 2018). Third, they are the geographical unit for which US Bureau of Labor Statistics (US BLS) data on employment disaggregated at a very detailed occupational level are available. This information is crucial to estimate green employment using occupational data (Vona et al., 2018b). Data on green employment are drawn from the 'Green Economy' programme of the Occupational Information Network (O*NET) and the Occupation Employment Statistics programme of the US BLS. Moreover, regional industrial structures are built using data gathered from the County Business Patterns (Source: US Census Bureau). The rest of the section provides further details on these data sources and describes the methods employed to construct green employment and regional diversification variables.

3.1 Measuring green employment

We build the database on green employment by combining the methodologies of Consoli et al. (2016) and Vona et al. (2018b). Before focusing on the regional dimension of green employment, we investigate the channels through which the green economy pervades the labour market. The objective of this phase is to analyse to what extent green activities and technologies affect occupational requirements in order to detect those occupations that are closely related to the greening of the economy. To do so, the main data source is the 'Green Economy' programme of O*NET which consists of a comprehensive list of occupational categories that are affected by the greening of the economy. Therein, green occupations are detected through an in-depth review of the different sources ranging from academic articles, industry white paper, to internet sources. [3] This leads to the identification of three types of occupations affected by the greening process.

The 'Green Economy' O*NET database of occupations is designed to account for multiple labour market outcomes. At one end of the spectrum are 'Green New & Emerging' (GNE) jobs that carry a

[2] These geographical units are delineated by the U.S. Office of Management and Budget (OMB) based on the population size of the area and the degree of socio-economic integration with adjacent areas. To be classified as MSA a county or a group of adjacent counties must comprise at least one urbanised area with population of 50,000 or more, and have strong commuting ties with the core area. Alaska and Puerto Rico are not included in the sample.

[3] https://www.onetcenter.org/dictionary/21.3/excel/green_occupations.html See Deirdoff et al. (2009) for a detailed review of these studies.

specific environmental orientation. Examples of this type of jobs would be ‘Biofuels Production Managers’ (SOC 11-3051.03) or ‘Energy Brokers’ (SOC 41-3099.01). Green activities and technologies significantly impact the world of work in such a way to create the need for specific work and worker requirements, i.e. a new occupation. Another possible outcome is the qualitative transformation in the work content of existing jobs to accommodate growing demand for environmental criteria. Instances of these ‘Green Enhanced Skills’ (GES) jobs are ‘Soil and Water Conservationists’ (SOC 19-1031.01), ‘Architectural and Engineering Managers’ (SOC 11-9041.00). The greening of the economy does not affect the purpose of the jobs but implies a change in tasks, skills, knowledge, etc. Yet another circumstance contemplated in O*NET is that jobs do not perform bespoke environmental-related activities but rather work tasks that are general, yet complementary to green, nature. ‘Industrial Production Managers’ (SOC 11-3051.00), ‘Chemical Engineers’ (SOC 17-2041.00) are good cases in point of these ‘Green Increased Demand’ (GID) occupations. Work and worker requirements are substantially unaltered but employment is expected to grow due to an increase in labour demand driven, among others, by the greening of the economy.

O*NET information on green occupations are provided at national level and do not vary over time. To address this shortcoming, we use time-varying data on employees by occupation in each US MSA from BLS Occupation Employment Statistics. Green employment is measured by collecting MSA employment data for each O*NET green occupation explored above. However, whereas the Occupational Employment Statistics provides data at the 6-digit level of the Standard Occupational Classification (SOC), the information on green occupations from the ‘Green Economy’ programme of the O*NET is available at the SOC 8-digit level. By merging the two sources we identify three main cases. First, there are occupations at the SOC 6-digit level that include only green occupations (at SOC 8-digit). In this case the assumption is that the SOC 6-digit occupation is a green job (e.g. SOC 19-2043 “Hydrologists”). The second cases concern all the SOC 6-digit occupations without any green 8-digit occupations. Accordingly, the occupation is considered as a non-green job (e.g. SOC 19-3091 “Anthropologists and Archaeologists”). Third, there are SOC 6-digit occupations that contain both green and non-green 8-digit occupations. In such cases we follow Consoli et al. (2016) to address this mismatch by assuming a uniform distribution of 8-digit occupations within the same 6-digit occupation. That is,

$$Green\_occ\_share_{6dig} = \frac{ONET\ green\ occupations_{8dig}}{total\ number\ of\ occupations_{8dig}} \tag{1}$$

where $Green\_occ\_share$ is the share of employment for a 6-digit occupation that is devoted to green activities. The indicator ranges from zero, when all 8-digit occupations within the 6-digit occupation are non-green, to one, when all 8-digit occupations within the same 6-digit occupation are $ONET\ green\ occupations$. To illustrate: 'Advertising and Promotions Managers' (11-2011.00) and 'Green Marketers' (11-2011.01) are classified in the same SOC 6-digit code, 11-2011. Since the 6-digit code 11-2011 includes no other occupations, and since 'Green Marketers' is a green occupation in O*NET, we assume that workers are equally distributed across the two 8-digit occupations. The final $Green\_occ\_share$ score of the 6-digit occupation is 0.5 meaning that half of the workers carry out a green job. Although this happens in only 45 cases (0.5% of all 6-digit occupations) we propose two alternative measures to check the robustness of our results to this choice. That is, we calculate the upper bound of green employment considering all employees within these 45 occupations as performing green jobs (i.e. $Green\_occ\_share$=1) and the lower bound of green employment hypothesising that all workers are employed in non-green jobs (i.e. $Green\_occ\_share$=0). In Appendix A we show that this choice does not alter our results.

Further, following Vona et al. (2018b), we compute a spatial measure of green employment share (GS) as follows:

$$GS_{it} = \sum_{k} Green\_occ\_share_k \times \frac{L_{kit}}{L_{it}} \tag{2}$$

where L_{kij} is the employment in occupation k, US MSA i at time t. As stated above the variable $Green\_occ\_share$ relies on the information on green occupations of the O*NET Green Economy programme. This is constant over time and does not vary across MSA since it is measured at the level of occupations. Therefore GS variation across US MSAs and over time depends entirely on differences in the composition of the local labour force.

The national share of green jobs in our sample of 841 6-digit SOC occupations is about 20%.[4] Figure 1 shows their distribution across all major occupational groups (2-digit SOC). The first feature that stands out is that only 14 out of 22 macro categories include green occupations. Second, green occupational categories encompass an ample spectrum ranging from high-skill Management jobs [SOC 11] (2.5% employment share) to mid-skill occupations like Transportation & Material Moving [SOC 53] (3.5%), Production [SOC 51] (2.8%) and Office & Administrative Support [SOC 43] (1.8%). Green jobs are also present in two low-skill jobs categories: Construction & Extraction [SOC 47]

[4] Our analysis is based on the full sample of green occupations available in O*NET. Other studies use a different selection: Consoli et al. (2016) leave the Green Increased Demand group out of their analysis while Vona et al. (2018a) use O*NET data on skills to build an entirely novel measure of green employment. As a result, figures concerning the relative magnitude of the green economy tend to differ across these studies. We think that these differences can be reconciled in light of the still open nature of the debate on green employment.

(2.5%) and Installation, Maintenance and Repair [SOC 49] (2.2%). Looking within occupational macro-groups we observe that the lion share of green employment is made up of existing jobs. Indeed, ‘Green New and Emerging’ jobs are the smaller category, and are most prominently featured among high-skill occupational groups like Management, Architecture & Engineering, Business & Financial Operators and Sales. Conversely, ‘Green Increased Demand’ jobs are overrepresented among mid-skills occupations, especially Transportation and Material Moving, Production and Office & Administrative Support. Low-skill occupational categories exhibit a more balanced profile with almost equal shares of ‘Green Increased Demand’ and ‘Green Enhanced Skills’ jobs.

FIGURE ONE ABOUT HERE

3.2 Measuring diversification

To measure diversification in MSA we rely on the entropy approach (Jacquemin and Berry, 1979; Attaran, 1986) along other studies on related and unrelated variety (Frenken et al., 2007; Boschma and Iammarino, 2009). These works use entropy (or Shannon index) to measure diversification in industries (Frenken et al., 2007; Boschma and Iammarino, 2009), occupation and education of workers (Wixe and Andresson, 2017) import and export (Boschma and Iammarino, 2009) and technological fields (Castaldi et al., 2015). We adopt this approach in order to measure between and within diversification of industries (Frenken et al., 2007) and of occupations (Wixe and Adersson, 2017) at the local level. The advantage of the entropy measure is that it is decomposable and enables accounting for both absolute and relative abundance of groups (Wixe and Andersson, 2017). By employing a hierarchical structure, such as the industry classification, unrelated variety in each MSA measures diversification ‘between’ broad (i.e. low number of digits) industries, whereas related variety measures diversification of narrow industries (i.e. higher number of digits) ‘within’ each of these broad industries. In the same vein, when the occupational structure of regions is used to calculate diversification, unrelated variety measures diversification between more broad occupations and related variety within narrow occupational profiles.

Our key explanatory variables are calculated using employment by industry statistics at MSA level from the US County Business Patterns survey (source: US Census Bureau) and employment by occupation statistics at MSA level from the US Occupational Employment Statistics (source: US BLS). For each MSA, we calculate related and unrelated variety to capture within and between diversity across industries and occupations using, respectively, employment data at two and four digits of the

North American Industry Classification System (NAICS) and employment data at two and six digits of the Standard Occupational Classification (SOC).[5]

Following Frenken et al. (2007), let each four-digit sector i be exclusively part of a two-digit sector, S_g, where $g = 1, \dots, G$. The two-digit shares of employment P_g can be obtained by summing the four-digit shares p_i:

$$P_g = \sum_{i \in S_g} p_i \tag{3}$$

Unrelated variety is measured as follows:

$$UV = \sum_{g=1}^{G} P_g \log_2 \left(\frac{1}{P_g} \right) \tag{4}$$

whereas related variety is computed as:

$$RV = \sum_{g=1}^{G} P_g H_g \tag{5}$$

where:

$$H_g = \sum_{i \in S_g} \frac{p_i}{P_g} \log_2 \left(\frac{1}{p_i / P_g} \right) \tag{6}$$

As a robustness check, in Table 3, we measure regional related and unrelated variety using the number of establishments[6], rather than employment data as input (Aarstad et al., 2016). The main difference between variety measured using employment by industry data and number of establishments by

[5] Data availability for employment by occupation in MSAs is more detailed than for employment by industry. We recognise that measuring variety at different levels (i.e. 2 and 4 digits of the NAICS classification and 2 and 6 digits of the SOC classification) may cast some doubts into the comparability of the results. However, the calculation of the entropy at different level of the hierarchical structures is not new in regional studies (see i.e. Wixe and Andersson, 2017). We provide robustness checks in Appendix A in which we calculate related and unrelated variety in occupations at the same group-level employed to calculate diversification within and between industries.

[6] The US Census Bureau defines the establishment as “a single physical location at which business is conducted or services or industrial operations are performed. It is not necessarily identical with a company or enterprise, which may consist of one or more establishments.” (US Census Bureau - https://www.census.gov/programs-surveys/cbp/about/glossary.html)

industry data is that P_g and P_i are the share of establishments at two and four digits of the NAICS classification.

3.3 Empirical strategy

The estimated model takes the following form:

$$\Delta GS_{i,s,t} = \alpha + \beta_1 UV_{i,t} + \beta_2 RV_{i,t} + \beta_3 Controls_{i,t} + \gamma_s + \delta_t + \varepsilon_{i,t} \quad (7)$$

where ΔGS is the long-difference of green employment share in US MSAs i within state s over the periods 2006-2010 and 2010-2014.[7] We use as dependent variable changes in green employment share in all occupations, Green Increased Demand, Green Enhanced Skills and New and Emerging Green occupations.[8]

The long-difference of green employment share enables us to net out the unobservable fixed characteristics of local labour markets (Vona et al., 2018b). UV and RV, the explanatory variables of main interest, capture unrelated and related variety in industries (or occupations) and are calculated at the beginning of each period (i.e. 2006 and 2010) for each MSAs. $Controls$ refers to a set of controls to take into account potential drivers of green employment growth other than UV and RV. In particular, we include the share of employment in R&D sectors[9] and in manufacturing, population density and share of green employees at the beginning of the period.[10] Moreover, we control for the growth rate of total employment in the MSAs that captures the overall trend of the local labour market.[11] δ_t is a time dummy variable to control for unobservable heterogeneity that varies over time and is constant across MSAs. Finally, following Autor and Dorn (2013) and Vona et al. (2018b), we include a set of state dummies (γ_s) to account for unobservable state-level policy implementation. After this inclusion, the coefficients of interest β_1 and β_2 capture within-state cross-MSAs variation. Finally, $\varepsilon_{i,t}$ is the error term. Each regression is weighted by total employment at the beginning of the period and the parameters are estimated using Ordinary Least Squares (OLS) with standard errors clustered at the US

[7] Different time spans are tested as robustness check in Table A1 in the Appendix

[8] We thank one anonymous referee for this suggestion.

[9] We use employment in the NAICS code 5417 titled 'Scientific Research and Development Services'. The 4-digit code includes R&D activities in Physical, Engineering, Life Sciences, Biotechnology, Nanotechnology, Social Sciences and Humanities.

[10] Data on employment in R&D sectors and employment in manufacturing are obtained from the County Business Patterns (US Census Bureau). Population density is built using data from US Census Bureau.

[11] Our dependent variable, i.e. the long-difference in the share of green employment over total employment, captures the relative changes of green employment, i.e. the greening of the local labour market. However, given the way in which we calculate green employment this measure does not take into account the level of the change in total employment. We thank an anonymous referee for pushing us to clarify this.

Federal State level.[12] In Appendix A we show that our results are robust to different model specifications.

4 Results

In this section we first explore through a descriptive lens the characteristics of green employment share and its relationship with related and unrelated variety. Second, we report the results of the econometric analysis and discuss the findings.

4.1 Descriptive analysis

Before turning to the results of the regression analysis, let us provide an overview of the main empirical trends at hand. Table 1 contains these descriptive statistics computed over all 363 MSAs. Figures 2 and 3 show the geographical distribution of green employment shares and industrial variety over MSAs. State boundaries are outlined in grey and the interior of each area is shaded according to its decile rank in the distribution of the relevant dimension. Colour coding is darker for higher deciles and progressively lighter for lower ones.

TABLE ONE ABOUT HERE

As mentioned above, over the period 2006-2014 the mean green employment share (GS) in the US is about 20%, it declines between 2006 and 2010 – coinciding with the onset of the global financial crisis – and grows in the period 2010-2014. MSAs in the top decile of GS account for about 27% of overall green employment over the period under analysis. This cluster exhibits some degree of persistence, as about 50% of areas stay in the top 10% both in 2006 and in 2014. Compared to the bottom 90%, areas in the top decile lose GS more than 4% than the others and greater growth by 2014 (+11%). Looking at the geographical distribution, top GS areas both in 2006 and in 2014 are mostly in the right-hand side quadrant coinciding with the territories of the Midwest, the South and the Northeast (Figure 2). A notable feature is that throughout the period the cluster of top GS areas includes mostly second-tier cities, with the exception of Detroit, Houston and Memphis. Indeed, the mean population density of MSAs in the top 10% of GS is 40% lower than all the remaining ones in 2006 (25% in 2014).

Next, we explore the distribution of sectoral diversification as captured by means of related and unrelated variety (Figure 3). Recall that according to Frenken et al. (2007) related variety, entropy at four-digit level, captures variety within each of the two-digit sectors in an area, i.e. diversification across sub-sectors that share similar know-how. By contrast, unrelated variety – or entropy at two-digit

[12] In order to allow for serial correlation we run the model with alternative standard errors clustered at the MSA level. The statistical significance of the coefficients does not vary. Tables are available upon request.

of the industrial classification – measures the extent of diversification of activities carried out within a MSA. The latter relies on complementarities of different knowledge bases within a region, and for this is considered strategically important to mitigate the risk of mass unemployment, especially during a downturn (Frenken et al, 2007).

Unrelated variety stays around a mean value of 3.9 over the period under analysis. The cluster of top decile by unrelated variety exhibits a high degree of persistence, with about 70% of MSAs in the top 10% both in 2006 and in 2014. In general, unrelated variety is found to be higher in the MSAs of mid-tier cities such as Charlotte, Portland, Denver and Kansas City. With the exception of Los Angeles, Dallas, Houston, Atlanta and Seattle, most of the largest US cities do not rank high in unrelated diversification. The figure also shows that unrelated variety is on average higher in the right-hand side portion of the map, and thus in the territories of the Midwest, the South and the Northeast (Upper panel, Figure 3). MSAs in the top decile of unrelated variety account for about 22% of green employment in 2006 (21.4% in 2014). Lastly, while the decline of overall GS in the period 2006-2010 was 5% higher in the top unrelated variety decile relative to the remaining areas, by 2014 GS growth was 28% higher in MSAs in the top decile. These observations lead to expect that the change of GS is correlated with initial levels of unrelated variety.

Turning to the other measure of diversification, related variety is on average lower than unrelated variety, with mean around 2.6. The degree of persistence in the top decile of related variety is 68%, somewhat lower than that of unrelated variety. Areas in the top decile of related variety are about 70% more dense compared to the rest. Indeed, different from what was observed in the case of unrelated variety, the vast majority of US cities with higher population density are concentrated in the top 10% (i.e., Los Angeles, Chicago, Philadelphia, Cleveland, New York, Pittsburgh and Miami). Still in the top decile are mid-tier large areas like Providence, New Haven, Buffalo and Milwaukee. This cluster of areas accounts for a mean share of green employment of about 19%, slightly below that of all the remaining MSAs (20%). Also, their mean growth of GS is only 10% higher than that of all other areas. As the lower panel of Figure 3 shows, related variety is more concentrated on the two coasts and the Midwest. All in all, these descriptive statistics do not hint at a strong correlation between GS and related variety.

FIGURES TWO AND THREE ABOUT HERE

4.2 Econometric analysis

In this section we explore the results of the econometric analysis of the relationship between regional industrial and occupational diversification and green employment growth. Table 3 illustrates the results of the model estimation using long-difference of green employment share as dependent variable. Green employment share provides more useful insights with respect to the level of ‘green’ employees because it better captures the catching up on the part of regions that are at early phase of the green transition.

Our favourite specification in Column 1 (Table 3) shows that the coefficient of unrelated variety calculated using employment by industry in MSAs is positive and statistically significant, highlighting that an increase of ten per cent in the MSA diversification of the industrial knowledge base is associated with an increase of 0.8 per cent in green employment share over the next four years – holding other variables constant.[13] This result confirms that green employment growth, which as has been argued (Section 2) is one of the ways in which the transition to green economies manifests itself, is correlated with diversification across sectors (in the sense of connecting industries that are otherwise unrelated). Moreover, contrary to unrelated variety, industrial related variety seems not to matter in the green transition of local labour markets. Although this seems to counter studies showing that relatedness is a crucial driver of employment growth, the context of the green economy is one in which technological change plays an even more crucial role (Popp et al., 2010). As previously stated, the channel through which agglomeration economies impact regional growth concerns the extent to which industrial knowledge base diversification triggers knowledge spillover between and within industries, i.e. at different degrees of cognitive proximity (Frenken et al., 2007). Therefore, in the transition towards green economies, regions that diversify their industrial structure across unconnected industries and broaden their knowledge space are more likely to spur the recombination process that underlies the early phases of radical change (Castaldi et al., 2015). This resonates with evidence that green technologies exhibit higher complexity compared to non-green technologies since they require more diversified knowledge sources and recombine a higher number of knowledge components (Barbieri et al., 2018).[14] In line with this framework, our analysis confirms that due to the complex characteristics of green innovation, regional diversification across unconnected industries facilitates recombination and knowledge spillovers.

The coefficients of the control variables in Table 3 have the expected sign. In particular, the R&D employment is positively associated with green employment share growth, providing an insight into the importance of more analytical knowledge for green jobs. Urbanisation economies, captured by

[13] Since collinearity may inflate the variance of regression coefficients, we calculated the variance inflation factors (VIF). The VIF of each independent variable is below the threshold value of five, with a mean value of 2.63, suggesting collinearity does not affect our results. Table 2 reports the correlation matrix.

[14] Although Barbieri et al. (2018) do not differentiate between related and unrelated variety, they measure complexity using the number of technological classification codes assigned to patents (Lerner, 1994; Trajtenberg et al., 1997). Their result confirms that green technologies recombine a greater variety of technological fields with respect to non-green ones.

population density variable, show no association with green employment share growth. Conversely, the share of employees in manufacturing is positively correlated with green employment growth. In addition, green employment share at the beginning of the period has a negative and statistically significant effect on green employment growth. This result is in line with the fact that a sort of catching up is in progress for which regions that lag behind in terms of green employment experience a glowing greening process. Finally, the growth rate of total employment has a significant and positive correlation with green employment. This is in line with the occupational perspective employed to measure green jobs. As stated in Section 4.1 the majority of green employment is accounted for by jobs that are affected by the green transition via changes in the skill content of jobs or via an increase in labour demand.

The relevance of unrelated variety on changes of green employment is confirmed when we measure regional industrial variety using the establishments by industry instead of the number of employees (Column 2 of Table 3). The coefficient of unrelated variety is positive and significant whereas related variety seems to be ineffective to explain green employment growth. An increase of ten per cent in unrelated variety is associated with an increase of almost two per cent in green employment share, holding other variables constant. Robustness checks in Appendix A confirm this finding.

TABLES TWO AND THREE ABOUT HERE

It is noteworthy that engaging green activities entails a closer focus on skills and human capital that differ from those used by non-green jobs (Consoli et al., 2016). Column 3 in Table 3 points at a different relationship between diversification and green employment growth when the variety in regional occupational profiles is accounted for. In this case both related and unrelated variety are positive and significant. This highlights that green employment growth is correlated with both variety across unrelated occupations and related occupations. In interpreting this finding we recall that the greening of the economy affects jobs in different ways. Using the green job categorisation of O*NET enables us to delve into this issue.

Table 4 shows the relation between industrial and occupational variety and the changes in green employment at the local level for: (i) green new jobs (GNE); (ii) green enhanced skills (GES) jobs that experience a change in the task content to adapt to the green economy; (iii) green increased demand (GID) jobs, or traditional occupations that do not undergo transformations in the type of work tasks but that are more in demand as green activities expand. As far as industrial variety is concerned, unrelated variety is correlated to the growth of green employment. As stated above this may arise from the fact that higher complexity of green innovation calls upon a diversified industrial knowledge base across unconnected industries. The result holds when we consider separately the component of green employment growth, namely New and Emerging and Green Increased Demand occupations. However, Table 4 shows that unrelated variety in occupations is associated with green employment growth in Green Increased Demand occupations. On the other hand, jobs with a marked environmental character (i.e. Green Enhanced Skills and New and Emerging Green) emerge from diversification across related occupations.

The effect of occupational unrelated variety on employment growth in Green Increased Demand jobs is in line with the finding of Wixe and Andersson (2017) who provide evidence of a positive correlation, although not robust to different specifications, between unrelated variety in education and occupations and employment growth. Indeed, we find that Green Increased Demand jobs are not directly impacted by the green economy in term of tasks content or skills requirement but only through the increase of labour demand. Put otherwise, this category contains non-green jobs that are complementary to green activities (Consoli et al., 2016). In this case, green employment grows in regions endowed with a heterogeneity of skills and human capital. On the other hand, we find that related variety favours employment growth for environment-related occupations (i.e. Green New and Emerging and Green Enhanced Skills). Cognitive proximity in terms of skills and human capital is important to foster green employment in jobs that are directly impacted by the greening of the economy. The life-cycle heuristic can be again useful to interpret this result: at an early stage of development, green know-how is still limited in its diffusion within regions and the boundaries between different occupational profiles are difficult to be overcome. Hence, 'speaking the same language' favours knowledge spillovers and pure-green employment growth.

TABLE FOUR ABOUT HERE

5 Concluding remarks and the way ahead

This paper has explored whether and to what extent the organization of local activities influences the transition towards environmentally sustainable economies. This question was operationalised by using the growth of green employment share as dependent variable and regional related and unrelated variety as the main explanatory variables in a regression analysis on 363 US metropolitan areas over a nine-year period. The econometric analysis shows heterogeneous effects based on the type of green jobs under investigation. Thereby the employment growth of jobs that are impacted by the greening of the economy in terms of tasks content or skills requirements is associated with a regional industrial structure diversified across unrelated industries and an occupational structure diversified across related occupations. This implies that the greening of regional economies is favoured when individuals, who are the principal agents through "knowledge in the air" is recombined, are surrounded by heterogeneous productive knowledge bases and by similar, but still diversified, capabilities, work activities and skills. On the other hand, employment in jobs complementary to green activities and technologies (i.e. whose tasks and skills are not directly impacted by the green economy, though the transition leads to increased labour demand) are correlated with industrial and occupational unrelated diversification.

Our study provides insights on the know-how that is needed to deal with the complexity of existing and emerging green technologies (Barbieri et al., 2018): regions need a higher variety of previously unconnected industrial knowledge bases to foster their transition towards sustainability. At the same time, given the early stage of maturity of green economies, knowledge spillovers need some degree of complementarity and relatedness in terms of work tasks and skills of individuals. This is achieved when regions are characterised by related variety in occupational profiles.

We believe that the connection between regional diversification and the transition to environmentally sustainable economies can enrich ongoing scholarly and policy debates. When it comes to greening of the economy, the key question is how regions develop new growth paths, and why they differ in their ability to do so. In the economic geography literature such a question is framed in terms of whether and to what extent locally related activities can act as an enabling factor in the search for these paths. By and large, empirical works corroborate the hypothesis that relatedness is an important driver of regional diversification across a broad spectrum of dimensions (e.g., products, industries, technologies) and of spatial units (e.g., countries, regions, cities, labour market areas) of analysis (see reviews by Content and Frenken, 2016). The common finding in this stream of research is that related diversification is a stronger driver compared to unrelated diversification. This is, to some extent, not surprising considering the nature of both constructs. As Boschma (2017) puts it, diversification is an uncertain process that can be better dealt with by relying on available local resources, and on well-tested connections across them, both trademark features of related variety. Unrelated diversification, on the other hand, entails implementing new forms of coordination across different and formerly unassociated capabilities (Desrochers and Leppälä, 2011). As Castaldi et al. (2015) argue, however, the two forms of regional diversification need not be seen as opposites in a static fashion but rather as complementary forms of organizing and creating resources in a dynamic process.

Our results fit this framework and reinforce the conjecture that the transition towards environmentally sustainable production is, broadly speaking, still at early stages. No doubt, this complex process entails adaptations at many levels, not just within firms and industries but, ultimately, in the attendant cognitive and organizational dimensions. We focus on changes in the labour force to keep track of how local economies transform their routines to accommodate new criteria for environmental sustainability. At this early stage of the transition towards greener economies, the scope of the adaptations that need be made is still open to negotiation, and its costs and benefits are not totally understood. Thus, the room for trial and error is bigger, and so is the need to tap into different pools of knowledge. This is the part of the process where unrelated variety is more potent vehicle, in spite of the possible shortcomings due to experimenting and failing with untried combinations. If this logic holds, as the scope of the adaptation narrows, and stable routines emerge, recombining closely related knowledge should become a more viable strategy in the future. As already hinted at in the introduction, the path towards green growth does not happen in vacuum but, rather, on top of existing systems for extracting and transforming resources. This will entail partly dismantling pre-existing structures and partly setting up new ones. The present paper reinforces the claim that underneath the visible changes that this transition will ignite in technology, institutions and business firms is the evolution of the knowledge base and, thus, the relevant skills as well as the forms of organizing workers' know-how.

A full discussion of the policy implications that can be derived from these findings is beyond the scope of the current paper. Further research is needed to probe the validity of the findings about the effects of related variety and unrelated variety on the green employment. This is crucial to inform policy, and can be done by exploring different avenues. First, our methodology could be replicated in the context of countries other than the US. An analysis of different institutional settings will surely enrich the debate on the nature and the extent of green employment. Second, the analysis could be extended to explore the effect of 'green knowledge' endowment and innovation. Investments in research and development in the domain of environmental sustainability are growing fast, and various forms of innovation are already visible in the horizon. Understanding the extent to which specialization or diversification favour or hamper green local innovation capacity would contribute a great deal to the formulation of policy. Third, the effects of variety could be analysed at different levels of geographical aggregation. Moving beyond metropolitan statistical areas, one could resort to alternative, smaller spatial units, for example travel-to-work areas that are constructed by calibrating economic and social characteristics of geographical areas so as to increase the potential for policy impact. These are but a few possible avenues in which research on regional diversification and on environmental sustainability can enrich each other. We hope that the present paper has provided useful insights to further develop this exciting research agenda.

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Figures

Figure 1. Green employment share across 2-digit SOC codes (2014)

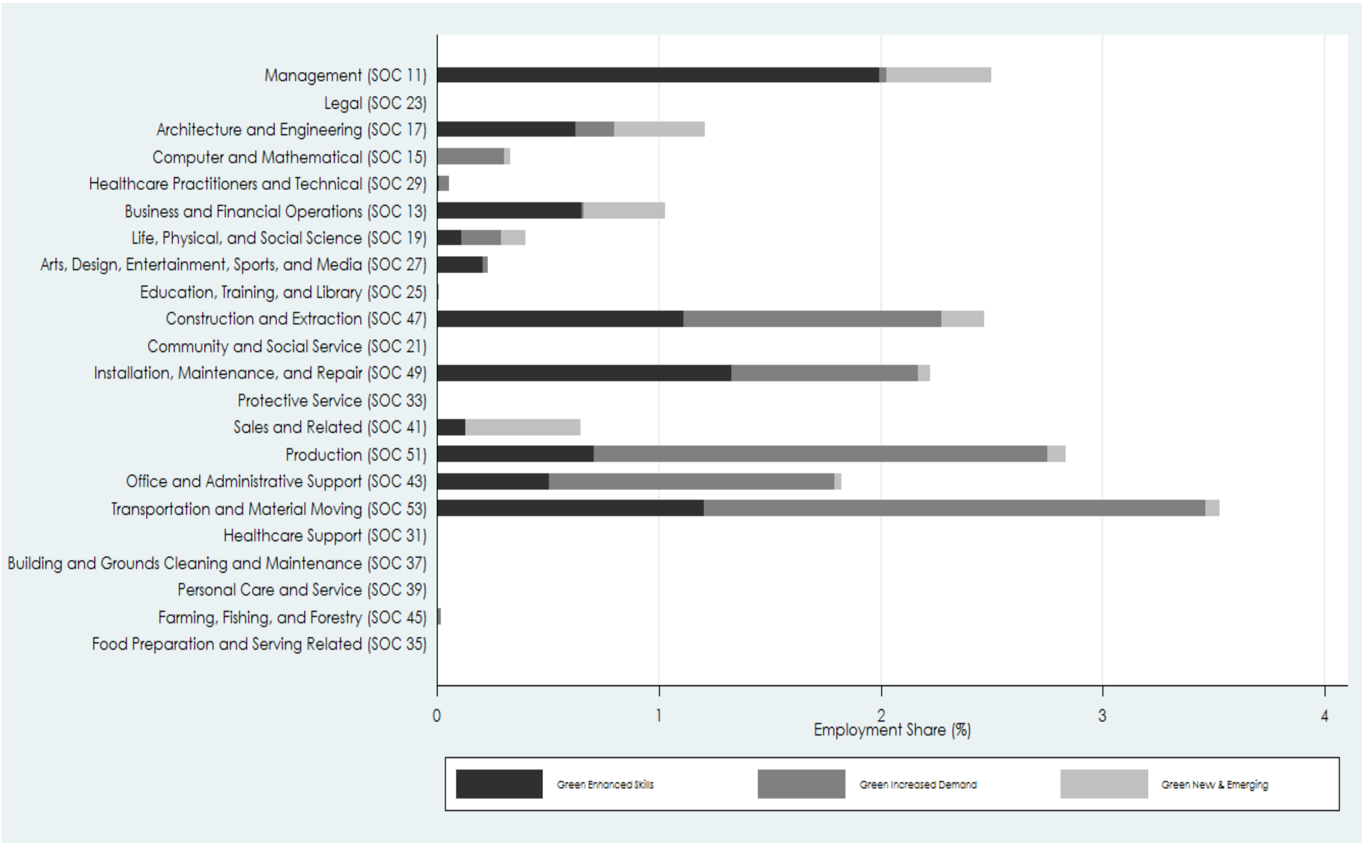


Figure 2. Geographical distribution of Green Employment Share, 2006-2014

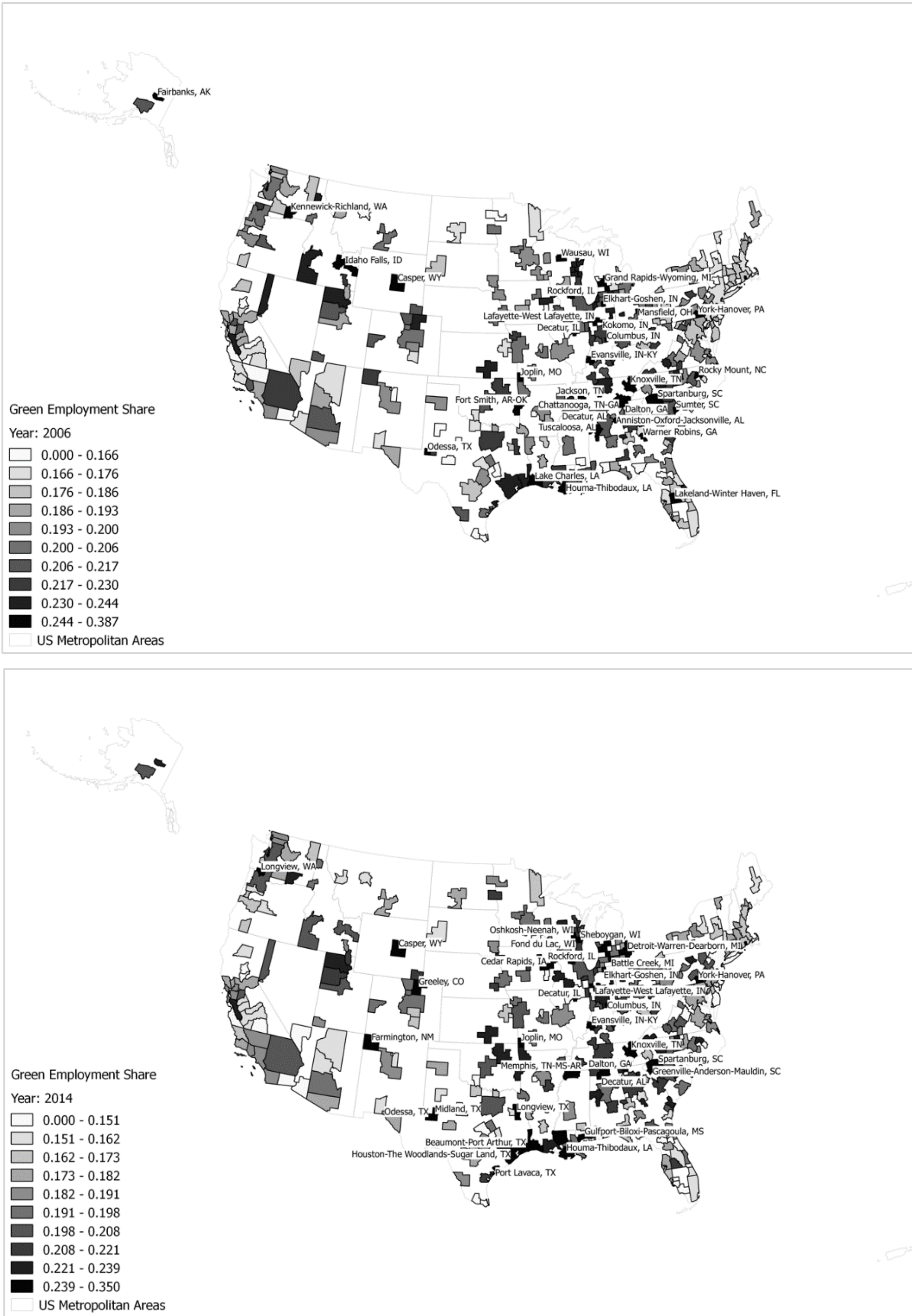
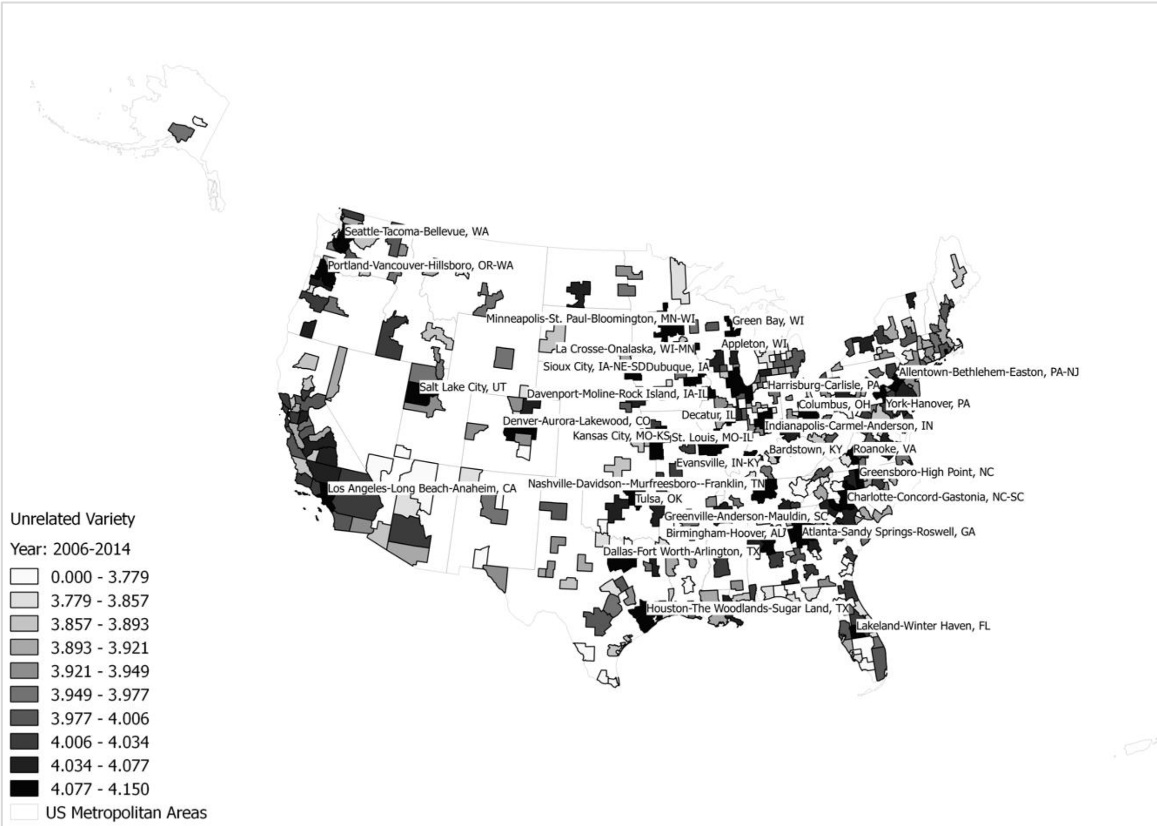


Figure 3. Geographic distribution of Unelated (Upper panel) and Related Variety (Lower panel)



Tables

Table 1. Descriptive statistics

Variable	Description	Obs	Mean	St Dev	Min	Max
Changes in Green employment share (2006-2010 & 2010-2014)						
ΔGS	Green employment share changes in occupations	726	-.0048	.0185	-.088	.071
ΔGS GNE	Green employment share changes in Green New and Emerging occupations	726	.0001	.0038	-.038	.039
ΔGS GES	Green employment share changes	726	-.0012	.0087	-.031	.036
ΔGS GID	Green employment share changes in Green Increased Demand occupations	726	-.0037	.0128	-.066	.057
Related Variety (2006 & 2010)						
RV IND	Employment by industry	726	2.66	.166	1.78	3.01
RV EST	Number of establishment by industry	726	2.84	.069	2.49	2.98
RV OCC	Employment by occupation	726	3.71	.148	3.17	4.04
Unrelated Variety (2006 & 2010)						
UV IND	Employment by industry	726	3.92	.132	3.08	4.16
UV EST	Number of establishment by industry	726	3.86	.058	3.59	3.99
UV OCC	Employment by occupation	726	3.90	.096	3.31	4.09
Control Variables (2006 & 2010)						
R&D EMP	Share of employment in the R&D sector	726	.003	.007	0	.094
MANUF	Share of employment in the manufacturing sector	726	.180	.063	.038	.579
DENS	Population density	726	.296	.332	.006	2.83
GR SH	Share of green employment	726	.194	.033	.107	.386
EMP GW	Growth in employment (2006-2010 & 2010-2014)	726	.010	.075	-.271	.349

Table 2. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
∆GS	1									
UV IND	0,07	1								
RV IND	-0,04	0,34	1							
UV OCC	0,21	0,32	0,38	1						
RV OCC	-0,02	0,47	0,54	0,24	1					
R&D EMP	0,03	-0,02	0,08	0,20	0,16	1				
MANUF	0,03	0,11	0,36	0,16	0,40	0,19	1			
DENS	-0,17	0,05	-0,13	-0,47	0,06	-0,14	-0,20	1		
GR SH	-0,24	0,22	-0,10	-0,30	0,29	-0,02	-0,09	0,63	1	
EMP GW	0,53	0,02	-0,09	0,07	-0,10	0,07	-0,03	-0,28	-0,16	1

Table 3. Regression results

	(1) ΔGS	(2) ΔGS	(3) ΔGS
UV IND (ln)	0.079***		
	(0.022)		
RV IND (ln)	0.007		
	(0.015)		
UV EST (ln)		0.197**	
		(0.076)	
RV EST (ln)		0.057	
		(0.042)	
UV OCC (ln)			0.095**
			(0.037)
RV OCC (ln)			0.051**
			(0.020)
R&D EMP	0.149*	0.169*	0.036
	(0.078)	(0.095)	(0.050)
DENS	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
MANUF	0.049***	0.028*	0.064***
	(0.017)	(0.016)	(0.018)
GR SH	-0.160***	-0.150***	-0.164***
	(0.040)	(0.046)	(0.045)
EMP GW	0.068***	0.070***	0.076***
	(0.015)	(0.015)	(0.014)
N	726	726	726
R-squared	0.589	0.592	0.592
State Dummy	YES	YES	YES
Year Dummies	YES	YES	YES

Notes: N= (363 MSAs x 2 time periods). OLS regressions at MSA level. Dependent variable: long-difference of green employment share over the periods 2006-2010 and 2010-2014. Independent variables are included at the start of the period. Robust standard errors clustered by US Federal State in parentheses. All models are weighted by MSA total employment at the start of the period. * p<0.1, **p<0.05, *** p<0.01.

Table 4. Regression results by typology of green job

	(1) ΔGS in Green New and Emerging Jobs	(2) ΔGS in Green Enhanced Skills Jobs	(3) ΔGS in Green Increased Demand Jobs	(4) ΔGS in Green New and Emerging Jobs	(5) ΔGS in Green Enhanced Skills Jobs	(6) ΔGS in Green Increased Demand Jobs
UV IND (ln)	0.014***	0.015	0.049***			
	(0.004)	(0.011)	(0.015)			
RV IND (ln)	-0.002	0.003	0.006			
	(0.003)	(0.008)	(0.009)			
UV OCC (ln)				-0.008	0.016	0.087***
				(0.016)	(0.017)	(0.031)
RV OCC (ln)				0.009*	0.020**	0.023
				(0.005)	(0.009)	(0.014)
R&D EMP	0.021*	0.036	0.092*	0.014	0.012	0.009
	(0.012)	(0.029)	(0.050)	(0.015)	(0.025)	(0.032)
DENS	0.000	0.001**	-0.001	0.000	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
MANUF	0.001	0.028***	0.019*	-0.002	0.032***	0.033***
	(0.005)	(0.008)	(0.011)	(0.007)	(0.008)	(0.012)
GR SH	-0.020**	-0.047**	-0.093***	-0.017	-0.054**	-0.093***
	(0.009)	(0.019)	(0.025)	(0.011)	(0.021)	(0.025)
EMP GW	0.002	0.022***	0.044***	0.003	0.023***	0.050***
	(0.007)	(0.008)	(0.012)	(0.007)	(0.008)	(0.011)
N	726	726	726	726	726	726
R-squared	0.200	0.431	0.583	0.196	0.435	0.587
State Dummy	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES

Notes: N= (363 MSAs x 2 time periods). OLS regressions at MSA level. Dependent variable: long-difference of green employment share over the periods 2006-2010 and 2010-2014. Independent variables are included at the start of the period. Robust standard errors clustered by US Federal State in parentheses. All models are weighted by MSA total employment at the start of the period. * p<0.1, **p<0.05, *** p<0.01.

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Appendix A– Robustness checks

Table A1 shows the results of the empirical analysis across various model specifications. Column 1 presents our preferred specification discussed in the paper. Column 2 presents the results using a shorter time span (i.e. 2006-2009 and 2010-2013) with respect to the main specification. In addition, we test whether the choice of considering green employment at 8-digit of the Standard Occupational Classification (SOC) evenly distributed within each 6-digit occupation (see Section 3.1) impacts our results. Column 3 and 4 show that using either the lower or the upper bound of green employment gives similar results. It is noteworthy, though not surprising, that the coefficient of unrelated variety in the main specification stands in the middle with respect to the coefficient of unrelated variety when we use the lower and upper bounds of green employment.

In Column 5 and 6 we report the results of the estimation of the empirical model using the average annual difference of green employment share over the two reference periods (2006-2010 and 2010-2014) and over the entire time window (2006-2014) as dependent variables. Also in these cases, unrelated variety remains a significant driver of green employment growth. This is confirmed when we employ the long-difference of green employment share over the period 2006-2014 (Column 7).

Finally, Column 8 presents the results using occupational variety calculated at 2 and 5 digits of the Standard Occupational Classification (SOC) in order to make it more similar in terms of hierarchical structure with respect to the industrial classification. The hierarchy of the North American Industry Classification System (NAICS) is structured as follows: two-digit level (Sector), three-digit level (Subsector) and four-digit level (Industry Group) – and so on. In the paper we calculate industrial variety at two and four-digit level. However, data on employment by occupation are more detailed and enable us to go in depth and calculate occupational variety at two and six-digit levels. The hierarchical structure of the SOC classification is: two-digit level (Main Group), four-digit level (Minor Group), five-digit level (Broad Group) and six-digit level (Detailed Occupation). We can observe that the NAICS counterpart at two and four-digit are the two and five-digit levels in the SOC classification. In the paper we exploit the detailed information in the data. Table A1 shows that using a similar hierarchy in both industrial and occupational structures the results do not change. Indeed, unrelated and related occupational variety are both positively and significantly associated with green employment growth (Column 8).

Table A1. Robustness checks

VARIABLES	(1) ΔGS 2006-10 & 2010-14	(2) ΔGS 2006-09 & 2010-13	(3) ΔGS Lower bound 2006-10 & 2010-14	(4) ΔGS Upper bound 2006-10 & 2010-14	(5) ΔGS Annual average 2006-10 & 2010-14	(6) ΔGS Annual average 2006-2014	(7) ΔGS 2006-2014	(8) ΔGS 2006-10 & 2010-14
UV IND (ln)	0.079***	0.078***	0.063***	0.093***	0.020***	0.092***	0.103***	
	(0.022)	(0.019)	(0.022)	(0.025)	(0.006)	(0.026)	(0.033)	
RV IND (ln)	0.007	0.003	0.005	0.008	0.002	-0.012	-0.003	
	(0.015)	(0.014)	(0.014)	(0.015)	(0.004)	(0.018)	(0.025)	
UV OCC (ln) 2 & 5 digits								0.096***
								(0.034)
RV OCC (ln) 2 & 5 digits								0.056***
								(0.017)
R&D EMP	0.149*	0.176**	0.104	0.214**	0.037*	0.190*	0.125	0.038
	(0.078)	(0.086)	(0.069)	(0.100)	(0.020)	(0.099)	(0.076)	(0.050)
DENS	0.000	0.001	0.000	0.001	0.000	0.002**	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)
MANUF	0.049***	0.051***	0.042**	0.054***	0.012***	0.021	0.023	0.066***
	(0.017)	(0.018)	(0.017)	(0.018)	(0.004)	(0.017)	(0.027)	(0.018)
GR SH	-0.160***	-0.150***	-0.131***	-0.181***	-0.040***	0.878***	-0.119**	-0.170***
	(0.040)	(0.046)	(0.040)	(0.042)	(0.010)	(0.044)	(0.059)	(0.043)
EMP GW	0.068***	0.052***	0.052***	0.081***	0.017***	0.019	0.031	0.076***
	(0.015)	(0.012)	(0.016)	(0.016)	(0.004)	(0.014)	(0.021)	(0.014)
N	726	726	726	726	726	363	363	726
R-squared	0.589	0.473	0.511	0.605	0.589	0.931	0.439	0.594
State Dummy	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES

Notes: OLS regressions at MSA level. Dependent variable: long-difference of green employment share. Independent variables are included at the start of the period. Robust standard errors clustered by US Federal State in parentheses. All models are weighted by MSA total employment at the start of the period. * p<0.1, **p<0.05, *** p<0.01.