Essays on Job Quality

Agglomeration, Green Jobs and Labour Turnover

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Declaration of Authorship

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Statement of conjoint work

I confirm that Chapter 3 was jointly co-authored with Fabio Landini and Alberto Marzucchi. I also confirm that Chapter 4 was jointly co-authored with Femke Cnossen.

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Abstract

This dissertation contributes to the empirical literature on job quality. The first chapter introduces the broader debate and presents the overall structure of the thesis.

The second chapter examines the implications of agglomeration for job quality using an urban–rural comparative approach across multiple indicators. The results show that rural workers are better off in terms of work intensity and job satisfaction, while urban workers benefit from stronger job-match opportunities. Overall, the findings support the view that adopting a job quality lens can usefully complement assessments of the welfare desirability of urbanization.

The third chapter investigates the intrinsic value that workers derive from performing occupations that include tasks beneficial to the environment- so-called green jobs- using the concept of meaningful work. The analysis confirms that workers gain intrinsic value from green jobs, conditional on the broader social-norms/policy-context. The favourable labour supply responses associated with meaningful work suggest that workers should be considered a key lever for achieving the green transition.

The fourth chapter analyses how poor evaluations of job attributes predict labour turnover, highlighting the particular role of intangible job attributes, measured through indicators such as interesting work, learning opportunities, and leadership quality. These attributes are found to predict job separation and exits from the labour market in heterogeneous ways and to be moderated by the availability of outside options. Overall, the results underline the multiple costs and benefits associated with experienced job quality, which are particularly important to acknowledge in a context characterised by labour supply shortages.

The final section discusses avenues for future research, highlights broader policy implications and concludes the dissertation.

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1. Introduction

The welfare of almost all employed people is significantly affected by how they spend their working hours -and not just by how long they work and what they can purchase with their earnings (Steedman, 2000).

..the evaluation of labour markets and of particular jobs ought to be sensitive to a plurality of benefit and burdens of work (Gheaus and Herzog, 2016).

Most individuals need to work in order to meet their basic material needs. Beyond its material importance, however, work also represents a defining dimension of people's lives (Green, 2013). As argued by Honneth (2022), interest in the social and ethical value of labour emerged as a central philosophical concern only with the advent of modernity. Whereas for much of history labour was understood primarily as a means of subsistence, in more recent times it started to be regarded as a source of self-expression, social integration, and a prerequisite for individual autonomy.

Despite this conceptual evolution, the conventional economic approach typically reduces labour to a market transaction driven primarily by monetary considerations. This view rests on two core assumptions: first, work is inherently burdensome and therefore a source of disutility; second, individuals derive utility exclusively from consumption and leisure. This framework, which lies at the core of standard economic theory and labour supply models, ultimately returns to the conception of work as merely a means to an end (Spencer, 2004).

According to these theoretical postulates, individuals seek to maximize their utility as consumers while minimizing their costs as producers. Although seemingly neutrals at first, these assumptions constitute the foundation of modern welfare analysis (Pagano, 1985; Steedman, 2000).[1] It coveys that, the argument put forwards by Parsons (1931)- "*economics is primarily concerned with the satisfaction of individuals wants as consumers rather than as producers*"- remains highly relevant also today.

This perspective carries a main limitation such as underestimating that workers may derive direct utility from work itself and thus that their welfare is directly influenced by the working activity (Steedman, 2000; Kaplan and Schulhofer-Wohl, 2018), and not exclusively by consumption and leisure. Work is, in fact, a fundamental source of self-realization, a means of gaining social recognition, and a way of fostering a sense of usefulness to society (Spencer, 2004; Gheaus and Herzog, 2016; Lopes, 2023).

The theoretical limit of the standard economic approach to work collides with the growing interest on the future of work. This is supported by the numerous reports produced by supranational organisations such as the Organisation for Economic Co-operation and Development (OECD) (see, e.g., Berger and Frey, 2016), the International Monetary Fund (IMF) (see, e.g., Cazzaniga et al., 2024), and the International Labour Organization (ILO) (see, e.g., Messenger, 2018). The focus on the future of work and workplaces is closely tied to a set of major structural transformations that are currently taking place. Among the most debated in academic and policy discussions are: the effects of globalisation and economic integration on firms' production and location decisions (Krugman, 1992; McCann, 2008); the transformation of production systems required toward the green transition (Consoli et al., 2016; Vona et al., 2021); concerns surrounding automation and technological unemployment (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2020); the profound impact of the COVID-19 pandemic, including the widespread adoption of working-from-home (WFH) practices (Aksoy et al., 2022), and the emergence of phenomena such as the Great Resignation and quiet quitting (Klotz and Bolino, 2022). Note that these structural transformations primarily unfold within the sphere of production rather than consumption rendering the consumption-driven concept of

[1] In particular, Pagano (1985) reviews different schools of economic thought—classical, neoclassical, and Austrian—with particular emphasis on how each conceptualizes work and the resulting implications for welfare analysis.

work used in standard labour economics less appropriate to fully comprehend these developments.

By challenging the fundamental assumptions underlying the standard economic conception of work, the job quality literature offers an important theoretical and empirical advancement toward recognising the multifaceted nature of work and its centrality to overall welfare (De Bustillo et al., 2011; Green, 2013).

The concept is multidimensional (De Bustillo et al., 2011; Green and Mostafa, 2012; Green, 2013; Leschke and Watt, 2014; Cascales Mira, 2021) and as a result, it is inherently challenging defining what constitutes a "good job" (Rodrik and Sabel, 2020). Nevertheless, a very general yet useful definition of job quality is provided by Holman and McClelland (2011): "job quality refers to the impact that a job has on workers," which helps clarify that job quality is ultimately about how workers experience their jobs.

Key dimensions commonly investigated in the literature include work intensity (Green and McIntosh, 2001; Green et al., 2022), work autonomy (Bartling et al., 2012, 2014; Kwok, 2020) and workers' expectations regarding career prospects (Munasinghe, 2006; Green and Mostafa, 2012). In addition, the concept of meaningful work (Rosso et al., 2010; Spencer, 2015; Cassar and Meier, 2018) foregrounds the psychological and sociological dimensions of employment whereas the most common job satisfaction (Freeman, 1978; Borjas, 1979; Clark, 2001) encompasses workers subjective evaluations.

The aim of the dissertation is to advance the understanding of work and labour markets using a job quality perspective, applied to a set of underexplored topics. Specifically, in the second and third chapters, the dissertation offers an empirical perspective on two current defying megatrends, such as urbanisation and climate change, while in the forth chapter, the dissertation advances the understanding of the job satisfaction–labour turnover complicated nexus.

Beyond the substantial methodological contributions devoted to the construction of indicators for measuring job quality (De Bustillo et al., 2011; Green and Mostafa, 2012; Green, 2013; Leschke and Watt, 2014; Cascales Mira, 2021), the empirical literature can broadly be organised into three main strands. The first strand focuses on the determinants of job quality (Green and McIntosh, 2001; Greenan et al., 2014; Nikolova and Cnossen, 2020; Adăscăliței et al., 2022; Nikolova et al., 2024). The second comprises a large body of work on job satisfaction and its role in shaping labour supply behaviour (Freeman, 1978; Borjas, 1979; Clark, 2001; Böckerman and Ilmakunnas, 2009). Finally, an increasingly prominent stream in labour economics seeks to estimate the value of job quality—typically conceptualised as a bundle of job amenities—using either survey data (Sullivan and To, 2014; Wiswall and Zafar, 2018; Maestas et al., 2023; Van Landeghem et al., 2024; De Schouwer and Kesternich, 2024) or experimental settings (Ariely et al., 2008; Chandler and Kapelner, 2013; Kosfeld et al., 2017; Kesternich et al., 2021; De Schouwer et al., 2025; Ashraf et al., 2025).

Overall, the dissertation primarily contribute to the first and second strands of the literature.

The second chapter investigates the job quality implication of urbanization. The latter represents the most important form of spatial organisation of population and economic activities in contemporary economies (more than half of the world population live in urban areas) and furthermore it constitutes one of the four major demographic megatrends of the century together with population growth, ageing, and international migration (UN, 2019). While a rich literature highlights the economic benefits associated with urbanisation, several dimensions of urban life also generate dissatisfaction and negative externalities, making urbanisation one of the central policy challenges of the twenty-first century (Glaeser, 2020).

The economic benefits of urbanisation are typically framed in terms of agglomeration economies, *i.e.* the productive advantages arising from the spatial concentration of economic activity and inputs. Despite the widespread view that urbanisation is overall welfare-enhancing (Ahlfeldt and Pietrostefani, 2019), a coherent and integral empirical analysis on the job quality side is missing in the literature. This represents a significant gap and it is particularly relevant in the European context, analysed here, where the urban population already accounts for approximately 70% of the total and is projected to exceed 80% by 2050 (Moonen et al., 2019).

The aim of the second chapter is to shed light on the job quality implications of agglomeration economies using an urban–rural comparative lens, drawing on evidence from the European context. The central research question is: Do agglomeration economies generate (dis)advantages in job quality?

Climate change is the second megatrend investigated in the third chapter. As highlighted in the Eurobarometer (2021) survey, 93% of the European population consider climate change to be one of the most important global threats, making it one of the more pressing contemporary issue. Addressing climate change requires production and consumption systems to substantially reduce their environmental footprint and transition towards more sustainable models (Besley and Persson, 2023). This process necessarily involves changes in production technologies and in the organisation of work, as it entails the development of new tasks and skill requirements across a wide range of occupations (Vona et al., 2021). While these tasks are expected to be beneficial to the environments, they are also likely to affect a large share of existing jobs. A central concern, therefore, is whether the emergence of "green" tasks generate benefits for workers themselves.

Beyond their environmental relevance, such tasks may contribute to a broader societal objective—namely, the mitigation of climate change—thereby making the scope of these tasks particularly valuable from a societal perspective view. At the current stage, the literature engaging with the green transition focuses primarily on the demand, namely consumers' willingness to pay for green products, and/or on technological change side of the issue (Bezin, 2019). On the contrary, much less attention has been directed to the labour supply side, particularly to issues related to production and job quality (Eurofound, 2024), particularly with respect to studies examining the social and ethical dimensions of the so-called 'green jobs'.

This gap is quite extraordinary considering the relevance of the challenge and the associated labour markets implications. Hence, the third chapter addresses the following overarching question: Do workers intrinsically value performing jobs that generate positive environmental spillovers? In addition, the chapter explores whether the relationship varies with geographical heterogeneity, specifically whether broader societal norms and national levels of policies (Persson and Tabellini, 2002; Brennan et al., 2020) shape workers' intrinsic value perceptions.

In the fourth and final empirical chapter, the thesis contributes to the job satisfaction–labour turnover literature. Labour turnover is a key reallocation mechanism of productive factors operating across firms and sectors. Yet, in many cases, labour turnover reflects workers' decisions driven by poor-quality matches as well as poorly experienced working conditions. While Eeckhout (2018) notes that hiring costs per worker can amount to multiple average salaries, Miano (2025) highlights workers' job search costs such as time, money, and stress. Taken together, these contributions point to the high socio-material losses associated with labour mobility, beyond the more commonly investigated efficiency gains.

Understanding the factors driving job separation decisions is therefore particularly valuable, especially in the presence of labour market frictions and structural shortages, which have become defining features of many advanced economies (Causa et al., 2025). While conventional approaches tend to place wages or wage dissatisfaction at the centre of explanations for worker mobility, this chapter offers a multidimensional perspective using job satisfaction measures across several job attributes. The chapter aims at addressing a series of pending questions: Is labour turnover driven by more than wage-related job attributes? Which job components are the most influential in predicting job separations? Do job attributes differently predict specific types of labour market transitions, such as job-to-job moves versus exits from the labour force? Do local labour market features moderate the relationship between job attributes and separation outcome?

Across all chapters, the dissertation consistently aims to demonstrate that a geographical perspective is beneficial to the job quality literature, and *vice versa*. Existing research on job quality predominantly examines it at the firm, occupational, or national level, while largely neglecting the spatial dimension. Three main reasons go in the direction of using a spatial lens to job quality.

First, the resurgence of geographical economics, and especially the contributions of the New Economic Geography (Krugman, 1992; Ottaviano, 2003; Fujita and Thisse, 2013), has increasingly emphasized the importance of spatial dynamics in shaping economic outcomes and the localization of production. Second, the local labour market has been increasingly recognized as a valuable territorial unit in a growing body of seminal empirical research in applied labour economics (Moretti, 2010; Autor and

Dorn, 2013; Lee and Clarke, 2019; Acemoglu and Restrepo, 2020), particularly in relation to key topics such as job polarization, wage inequality, and job multipliers. Extending this perspective also to job quality research represents a desirable advancement for the literature. Finally, the relevance of adopting a territorial lens also has a strong policy rationale. Place-based approaches are increasingly regarded as essential tools for designing policies aimed at reducing growing spatial inequalities (Kline and Moretti, 2014; Moretti, 2024), particularly in the European context (Barca, 2009). This makes the recognition of a territorial perspective a compelling necessity for the job quality literature.

The findings, by chapter, are briefly summarised below.

Drawing micro-level data from the 2015 wave of the European Working Conditions Survey (EWCS) on 34 European countries, the second chapter tests the urban-rural job quality differentials along four dimensions: work intensity, job match, career prospects, and job satisfaction. The analysis identifies three main spatial disparities which are consistently supported by an extensive set of robustness checks. Overall, rural workers are better-off in terms of lower work intensity and higher job satisfaction, while urban workers benefit from considerable job matching advantages. Career prospect does not vary on a territorial base.

To provide a purely illustrative sense of the magnitude of these gaps, the urban penalty in work intensity is similar in size to the female–male difference (about 80%). In terms of job satisfaction, the urban penalty is about half the size of the difference between workers with and without a tertiary degree. Finally, the urban premium in job match corresponds to almost the 70% of the premium observed for tertiary-educated workers.

Although assessing the welfare implication of the agglomeration-job quality nexus is extremely challenging, the chapter suggests that urban workers, relative to the rural, may face important job quality disadvantages. Each job quality dimension carries socio-economic implications which might translate into externalities, as in the case of the health costs associated with higher work intensity (Hunt and Pickard, 2022) or lower job satisfaction (Fischer and Sousa-Poza, 2009). These disadvantages should be interpreted as undesirable from a welfare point of view and as possible negative externalities associated to agglomeration.

The third chapter uses the concept of meaningful work (Rosso et al., 2010) as a proxy for capturing workers' intrinsic values. To measure the green content of occupation, the chapter employs data on green tasks from the European Skills, Competences, Qualifications and Occupations (ESCO) database. These informations are then combined with micro-level information from the 2015 and 2021 waves of the European Working Conditions Survey (EWCS).

The empirical analysis is built upon an extension of the standard meaningful framework (Cassar and Meier, 2018), using insights from the recognition theory (Honneth, 1995), by formalizing the idea that green tasks may generate additional meaning to work because they contribute to a socially valuable collective objective, namely the mitigation of climate change. This mechanism operates through enhanced individual self-esteem but conditional on the external societal attitudes towards environmental protection. The contextual dimension is captured using the OECD Environmental Policy Stringency (EPS) Index.

Using an instrumental variables approach, the analysis finds that a one standard deviation increases in green skills intensity—approximately a 4% percent increase in green skill content—is associated with a 6% percent increase in perceived meaningful work. In line with the formulation, the positive relationship remain consistent only in countries characterised by higher environmental policy stringency, highlighting the centrality of the societal context.

Overall, the findings carry interesting implications, showing that workers value the societal impact of their green jobs, conditional on a favourable policy environments. These results suggest that workers and the broader cultural–societal context may represent important levers for advancing the green transition and, as such, constitute relevant policy objectives.

Finally, the fourth chapter builds on Mas (2025) job value approach which defines job as a bundle composed of wages, tangible, and intangible job attributes. Drawing on the Netherlands, over the period 2014–2023, and relying on a novel linked dataset combining survey micro-data from the Dutch Working Conditions Survey with administrative records, the empirical analysis uses a job satisfaction framework, as a proxy for realised utility, to test the prediction based on a simple search model.

The findings highlight that dissatisfaction with intangible job attributes—such as interesting work, leadership quality, and learning opportunities—predict an higher probability of separation, in between 3% and 5% respective to the average value (20%) of satisfied workers. These results are stable across different specification and more consistent with respect to the other job components. When differentiating by mobility destinations, dissatisfaction with interesting work and leadership quality are both associated with an higher probability of entering unemployment and respectively education and self-employment. Finally, the dissatisfaction with learning opportunities and job separation relationship is moderated by the available outside options, captured with a tightness indicator at the local labour market level.

These results are particularly informative in the current context marked by persistent labour supply shortages (Gonne, 2023). Recognising the importance of intangible job attributes may provide policymakers with additional tools to design interventions aimed at fostering more stable and efficient labour markets, with potential benefits for both workers and firms. Furthermore, the direction of the mobility associated to intangibles attributes (exit) should invite to acknowledge the public-side implications of job intangibles with respect to social security and education policies.

The dissertation proceeds with the three empirical chapters. The concluding section discusses the study's limitations, outlines avenues for future research, and policy implications.

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2. The urban-rural job quality differentials in Europe

Davide Lunardon

Abstract

The paper provides an analysis on urban-rural differentials in terms of job quality using EWCS 2015 data. Overall, the paper highlights that urban workers are worse-off in term of intensity at work and job satisfaction while they are better-off in term of job-match possibilities. No spatial differentials is captured for career prospects. In the context of rising urbanization, the paper highlights the multiple 'hidden' societal costs implications of job quality for urbanisation which may represent a new form of agglomeration diseconomies.

Keywords: Job quality, Urban-Rural divide, Agglomeration (dis)economies, Europe, EWCS

JEL Codes: J20, J28, J32, J81

2.1 Introduction

Urbanization is one of the defining demographic trends of the 21st century. According to UN (2019), more than half of the global population currently resides in urban areas, with projections indicating this share will rise to approximately 70% by 2050. In Europe, urbanization levels are already higher, and the share is expected to reach around 83% by 2050 (Moonen et al., 2019). The global expansion of trade, rapid technological advancements, and the remarkable growth of the service economy have played major roles in driving urbanization by reinforcing the centripetal forces that draw productive input factors toward large agglomerations (Krugman, 1992). Today more than ever, large urban areas serve as primary catalysts and engines of economic growth (Lucas Jr, 1988; McCann, 2008; Fujita and Thisse, 2013).

Urban economists insist on the idea that workers benefit from working in cities based on productive advantages associated with density and proximity, known as agglomeration economies (Duranton and Puga, 2004; Rosenthal and Strange, 2004). Urban workers are more productive due to improved occupational matching, greater returns to learning, and access to higher quality local public goods.[1] Notwithstanding the huge literature on agglomeration economies acknowledges the high 'social costs' of working and living in the city connected to pollution, congestion, crime and higher cost of living, these 'negative externalities' rarely enter into the extensive literature on the urban wage premium (Melo et al., 2009; Donovan et al., 2024). If anything, the negative agglomeration externalities are used to motivate the lower subjective well-being/life satisfaction associated to living in urban areas (Sørensen, 2014; Loschiavo, 2021; Lenzi and Perucca, 2022).

The general idea is that workers (will) continue to concentrate in urban areas because the monetary returns are large enough to outweigh the social costs associated with the *diseconomies* of agglomeration (Duranton and Puga, 2020) and that densification policies are overall welfare enhancing (Ahlfeldt and Pietrostefani, 2019).

The aim of this paper is to include within this analysis a new side of the problem, namely the existence of agglomeration externalities associated to job quality.

[1] Education facilities for instance, see Van Maarseveen (2021).

Broadly speaking, job quality is defined as the multiple impacts that a job has on an individual (Holman, 2013). The economic logic behind the concept acknowledges that individuals do not uniquely exchange 'working time' for monetary rewards but on contrary that labour is a production activity which involves spending considerable amount of the daily time in a workplace interacting with other persons - peers, managers or customers-, dealing with capital goods (machinery, buildings, vehicles and so on) and complying with organizational rules. The paper investigates, in the European context, multiple urban-rural gaps in job quality while considering three labour markets features associated to agglomeration -urban rat race (Rosenthal and Strange, 2008), better job-match (Andini et al., 2013) and job satisfaction externalities (Dalmazzo and de Blasio, 2011)- on four job quality dimensions: intensity at work, job-match/career prospects and job satisfaction. The paper uses individual-level data from the European Working Conditions Survey which is the most used data source to study job quality in Europe. The worker-centred perspective in job quality analysis necessitates the use of interview-based data, aligning with the growing trend of incorporating subjective well-being measures to complement traditional indicators of economic and social progress (Graham and Ruiz Pozuelo, 2017). The main analysis is carried out using the 2015 wave while, 2010 and 2021 waves are used as complements.

The empirical analysis highlights that overall urban workers report lower job quality as compared to their rural counterparts. The formers are worse-off in terms of intensity at work and job satisfaction. In line with the expectations, urban workers benefit from higher job match while surprisingly, no urban career premia is captured. Although, the results remain descriptive, the empirical analysis addresses some endogeneity problems - mostly omitted variable bias and sorting- by including wage level and a measure of consumption frequency, used as a proxy for the presence of local amenities, as controls. The overall findings are confirmed and remain robust across a variety of checks and further specifications.

When replicating the main analysis, the paper finds support for external validity using the 2010 data, confirming the stability of the results across time. In contrast, the restricted analysis using 2021 data - due to survey limitations - only on intensity and career prospects, do not fully support the main results. Specifically, the lack of any urban career premia is confirmed while the intensity gap is not captured any more. The latter finding is interpreted not as contradictory, but rather as reinforcing the original conclusions drawn from the 2015 data and confirm using 2010 EWCS wave. Specifically, it is acknowledged that temporary disruptions caused by the Covid-19 pandemic —particularly the widespread shift to remote work and changes in workplace location— significantly reduced the relevance of work intensity as a signalling strategy in the urban context, as postulated by the urban rat race theory (Rosenthal and Strange, 2008).

By providing a comprehensive analysis on the agglomeration - job quality multiple relationships, this paper contributes to two strands of literature. Firstly, on the limited literature in urban economics that investigates beyond-wage labour market dimensions. Specifically, the paper brings new evidence on the urban rat race dynamics for the European context, after the seminal work of Rosenthal and Strange (2008) on the US. However, the results differ from two main points: while the original work documents a 'localization' effect on work intensity at extensive margin -i.e. more hours worked-, this paper captures an 'urbanization' effect at the intensive margin using a demanding work measure of intensity.

The results on job-match extend the unique findings of Andini et al. (2013) and point to the beyond-wage advantages of agglomeration in terms of long-term income and employment security. Finally, the paper finds a job satisfaction penalty for urban workers which rejects the original findings of Dalmazzo and de Blasio (2011). The latter suggests that it might be appropriate to include job-related downside aspects within the more general subjective well-being and happiness studies side of agglomeration, beside the most investigate impact of public goods externalities. This paper adds a job quality perspective on the broader discussion on the 'Urban Paradox' (Sørensen, 2014; Carlsen and Leknes, 2022*b*,*a*).

The paper contributes to a second strand of literature, the labour economics branch dealing with job quality (Green, 2006; Cassar and Meier, 2018; Nikolova and Cnossen, 2020). To the best of author knowledge, this is the first work that provides systematic evidence on multiple job quality outcomes while considering the role played by the concentration in space of economics activities beyond the commonly space-neutral examined state level. The urban-rural dichotomy underscores the significance of labour market sizes for workers and their reported job quality. Recognizing the impact of agglomeration economies on job quality is essential when considering potential policy interventions. As documented in a sustained literature (Freeman, 1978; Green, 2006; De Bustillo et al., 2011; Cassar and Meier, 2018; Nikolova and Cnossen, 2020), job quality has significant implications for labour supply behaviours, firm's performance and, in general, on economic outcomes.

In a phase of increasing urbanization in Europe and worldwide, the work highlights the necessity to provide further evidence on the agglomeration job quality externalities and at the same time to extend beyond the idea that agglomeration makes workers better-off while applying wage (consumption) as the only evaluative parameter. The job quality analysis invites to take into consideration also the welfare implications associated to production (Steedman, 2000).

The remainder of the paper proceeds as follows. Section 2 reviews the literature on the complex agglomeration economies and job quality. Section 3 discusses the data and the variables used for the empirical analysis. Section 4 discusses the empirical strategy. Section 5 presents the main results and a series of robustness checks. Section 6 concludes and discusses policy implications.

2.2 Related literature

2.2.1 Agglomeration and Job Quality

There are several theoretical and empirical contributions in economics that highlight the multiple advantages of working in cities as compared to rural areas. These benefits are commonly summarized with the key concept of agglomeration economies, *i.e.* the positive external economies that spur from the concentration in space of economic activities (Marshall, 1890; Duranton and Puga, 2004). Specifically, workers benefit from higher job opportunities, higher possibility to accumulate human capital and from more learning opportunities. Notwithstanding the mechanisms in place are complex and variegated, the large majority of empirical analysis end up measuring these favourable labour market conditions using wage levels for capturing the so-called "urban wage premium" (Glaeser and Mare, 2001; Duranton and Puga, 2004; Rosenthal and Strange, 2004; Gould, 2007; Roca and Puga, 2017; Duranton and Puga, 2020; Dauth et al., 2022; Papageorgiou, 2022). Reducing the analysis only to the monetary gains from agglomeration may represent a shortcoming. In fact, while wage is a key aspect for the decision to exchange labour, it is not the only dimension that matters for workers. The working activity encompasses multiple non-wage aspects that are also relevant to acknowledge (Green, 2006; De Bustillo et al., 2011; Kaplan and Schulhofer-Wohl, 2018).

While the literature that investigates the 'urban wage premium' is huge, the part focusing on job quality is scant. Thus, to infer that working in urban areas makes workers better-off while referring only at the wage dimension might be incorrect or at least questionable. In support of this, three main arguments can be used to discuss the job quality implications of agglomeration. The first theory is the urban rat race, theorised and tested in the seminal contribution of Rosenthal and Strange (2008). Accordingly, agglomerated workers behave in more competitive and rivalry way manifesting in an higher intensity at work supplied. The rat race hypothesis is taken from the job signalling model of Akerlof (1976) where intensity is used as a 'signal' for ability. By signalling 'hard working', employers are likely to infer that these workers are highly productive and consequently they are more prone to reward them with higher wages. This creates an ongoing competition among peers which will strive for being recognized as hard workers.

The urban rat race finds empirical support from an analysis on US metropolitan statistical areas. Specifically, Rosenthal and Strange (2008) capture a 'localization effect' on intensity at work for professional-high skills workers using respectively an occupational density and hours worked per week measures. The overall estimated 'urban rat race' effect is quite remarkable since it is equivalent to an increase of supply of labour by a standard work week over the course of the year. According to the authors, their findings offer a new explanation for why cities tend to be more productive than less urbanized or rural regions, beyond the well-known production benefits linked to urban areas.

The second theory is better job matching, which is arguably one of the most thoroughly explored aspect in the standard agglomeration literature. Better job matching captures both quantitative and qualitative benefits associated with large and dense labour markets (Kok, 2014*a*; Abel and Deitz, 2015; Papageorgiou, 2022; Dauth et al., 2022). On the quantitative side, it implies that in denser local markets there is a sustained labour demand leading to both higher wages and a greater number of vacancies—thus more job opportunities. On the qualitative side, the larger market size allows for greater division of labour and higher levels of specialization which lead to longer and more stable career prospects (Kok, 2014*b*,*a*). Both aspects are typically used to explain the urban wage premia literature (Abel and Deitz, 2015; Dauth et al., 2022; Papageorgiou, 2022) but rarely measured directly.

A unique contribution in this context is the work of Andini et al. (2013), who use rich and purpose-specific survey data from Italy. Among multiple findings, they show that urban workers enjoy an advantage in terms of job matching, using a variable that captures how easily a workers can find a job with a similar salary level in the event of job loss. Note that while this type of variable is used to capture job-match (Andini et al., 2013), it can also be used to capture employment security (Schmidt, 1999).

Furthermore, Andini et al. (2013) highlights a possible downside of agglomeration: higher labour turnover. This opens to consideration regarding career prospects. As emphasized by Munasinghe (2006), the perception of having career prospects is fundamental for evaluating the quality of a match. Perceiving long-term career opportunities reflects a medium- to long-term match, which is indicative of a good match. Contrary of Andini et al. (2013), a series of empirical works support the agglomeration premia in term of career prospects (Rosenthal and Strange, 2008; Kok, 2014*a*,*b*), although the Andini et al. (2013) evidence on turnover seems to question this. On this matter, the literature is lacking further evidences.

The third and final arguments considered is the job satisfaction externalities, drawn from the empirical work of Dalmazzo and de Blasio (2011). Focusing on Italy, they offers a unique analysis on the city size-job satisfaction relationships focusing mainly on high-skilled workers. The authors find a positive return in terms of satisfaction for urban high-skilled workers, with the gains deriving from a more favourable social environment. Specifically, the analysis reveals that urban high-skilled workers report better outcomes in terms of physical and social conditions, feeling valued by others, and reduced concerns about job loss. These are all critical aspects of working life that hold significance beyond simple wage considerations. Interestingly, the job satisfaction premia is specific to high-skill workers while it goes away when medium and low skill workers are considered. This approach aligns with the early 2000s very influential literature on the consumer city and agglomeration consumption externalities (Glaeser et al., 2001; Krupka, 2009) and support the main idea of cities making people 'happier' (Glaeser, 2011), also from a job satisfaction perspective view. However, a notable shortcoming of this work is that it only focuses on high-skill workers.

2.2.2 The social-economics of job quality

Measuring job quality represents a fundamental step to gain a comprehensive understanding of individual working well-being and, in a broader context, the overall well-being of our societies (Clark, 2015). As emerged from the review of existing empirical works in the previous section, multiple are the job quality dimensions that can be affected by agglomeration economies. This aligns well with the idea of job quality as a multidimensional concept (Green, 2006; De Bustillo et al., 2011; Green and Mostafa, 2012). Still, a key point to acknowledge is that each single job quality dimension carries specific socio-economic significance which are useful to acknowledge for interpreting the results. [2]

Work intensity holds significant job quality meaning due to its connection with productivity but especially with its long-term effects on physical and mental health (Green, 2006; Fur and Trannoy, 2024). While work intensity is measured using hours

[2]Please note that while the job quality literature encompasses a broad range of topics that goes from the psychological aspects to human and labour rights dimensions (De Bustillo et al., 2011), the job quality dimensions used in this chapter relates only to those that can actually be reconciled with the urban economic theoretical and empirical literature, as discussed in the section "Agglomeration and Job Quality". It is beyond the scope of the chapter to speak to all the segments of the job quality literature.

worked in the standard economic literature[3], in the job quality literature it takes a work demanding connotation (Green and McIntosh, 2001; Adăscăliței et al., 2022). The latter is usually measured combining dimensions such as: speed at work working and meeting tight deadlines.

The original contribution of Rosenthal and Strange (2008), from which the urban rat race hypothesis is derived, uses a standard measure of working hours and finds that urban workers supply relatively more hours, emphasizing in particular the productivity advantages and their positive welfare implications. However, it largely overlooks the associated mental and physical health consequences (Fur and Trannoy, 2024). While the productivity dimension is of central importance, within the job quality framework and from the perspective of the demanding work approach, higher work intensity is interpreted primarily as a negative outcome rather than a positive one (Green and McIntosh, 2001; Adăscăliței et al., 2022). This is due to its adverse effects on workers' well-being as well as its potential implications for public health. Within this framework, the findings of Nagler et al. (2025)—showing that workers sort into higher-pressure jobs in exchange for additional monetary compensation despite the associated negative health outcomes—are still interpreted as evidence of the negative consequences of work intensity. Hence, the overall idea is that an higher intensity is a negative job quality outcome.

Two job quality dimensions are mentioned when discussing the better job-match mechanism associated to agglomeration. The first, the job-match à la Andini et al. (2013) -how easy is to find a job with a similar salary- exerts interesting workers welfare implications. In fact, an easier match endows workers with a pool of potential benefits: long-term job and income security (Schmidt, 1999), reduction of the psychological cost of becoming unemployed [4] and increase the workers bargaining power vis-à-vis employers, particularly in terms of wage determination (reservation wage) and improved working conditions (Spencer, 2002; Yamaguchi, 2010). These are all positive outcomes in term of job quality.

[3] In the standard labour supply model, work intensity or effort is assumed to negatively affect utility (Green and McIntosh, 2001).

[4] The latter has been shown to have a cost beyond monetary terms, negatively impacting overall life satisfaction (Knabe and Rätzel, 2011).

The second, career prospect, can be used to capture: a form of long-term matching and the alignment between current employment and workers' future expectations (Green and Mostafa, 2012). The benefits associated to long-term employment relationships are multiple and include both wage and non-wage rewards that accumulate through experience, human capital development, and integration into an organization's routines and practices. Given the fundamental—and often costly—decision workers face when quitting a job, considerations about career prospects play a crucial role (Munasinghe, 2006). Overall, these have far-reaching consequences in workers' lives, future expectations and consumption decisions. Jobs that allow higher career prospects increase the job quality of workers.

Finally, job satisfaction is by far the most studied dimension of job quality (Green, 2006; Muñoz de Bustillo et al., 2011). Analysing job satisfaction offers valuable insights into the overall well-being of workers. Its importance often extends beyond work-related factors, as it is widely considered a broader indicator of both individual and societal well-being (Clark, 2015), closely linked to concepts of happiness and life satisfaction. Numerous studies emphasize the economic significance of job satisfaction, not only in terms of work performance but also in influencing labour supply behaviours such as job quitting and absenteeism (Freeman, 1978; Hacket, 1989; Clark, 2001; Theodossiou and Zangelidis, 2009).

2.3 Data

To assess the urban-rural gaps in job quality I gather the data from the European Working Conditions Survey (EWCS) 2010, 2015 and 2021 waves. EWCS is conducted every five years since 1990s and it is the most relevant and widely used source for studying the job quality in Europe (Green and McIntosh, 2001; De Bustillo et al., 2011; Green et al., 2013; Greenan et al., 2014; Lopes et al., 2014*a*,*b*; Aleksynska, 2018; Nikolova and Cnossen, 2020; Adăscăliței et al., 2022; Nikolova et al., 2022). The EWCS is a country representative survey. To ensure the representativeness of the sample, the EWCS survey design is based on complex sampling strategies which ensure that each person have the same probability to be included in the sample, assuring the randomness of the sample selection. The sample average per country is around 1000 workers but the number tends to vary depending on the waves. Usually the larger countries in terms of population have larger sample size. The countries surveyed are basically always the same, the EU-27 plus the UK and other extra-EU European countries such as Norway, Albania, Montenegro, Croatia, Turkey, Switzerland and Serbia.[5] EWCS provides micro-level information on multiple socio-demographics and work related characteristics.

In order to ensure a stable and reliable comparisons among workers, I adopt some sample size restriction criteria. Specifically, I include in the analysis workers between 18 and 70 years old, with a formal contract [6], working between 20 and 60 hours per week and with no regular second job. Furthermore, I exclude from the analysis workers employed in the agriculture, extra territorial industrial sectors and armed force occupations. Clearly, this strategy leads to reduce the sample sizes considerably. To account for this issue, in the robustness checks, the analysis is repeated using the non-restricted sample (Panel e Table 2.A.7).

Note that the empirical analysis primarily relies on the 2015 wave of the European Working Conditions Survey (EWCS), while the 2010 and 2021 waves are used to address concerns related to external validity. The choice of the 2015 wave as the main data source is motivated by two key considerations. First, the focal regressor capturing agglomeration economies is only available from the 2015 wave onwards. Second, the 2021 edition—conducted as a telephone-based survey (European Working Conditions Telephone Survey)—is less reliable due to substantial missing data and the omission of several key questions, which restrict the scope of the main analysis. These limitations stem during the challenging context of the Covid-19 pandemic. [7]

[5]For more information about sample size, country observations and more general sample selection characteristics, please refer to technical reports (Eurofound, 2012, 2015, 2022).

[6]EWCS surveys also informal workers.

[7]While the 2010 and 2015 use similar multi-stage, stratified, random sample strategy the EWCTS 2021 used a different strategy using computer randomly generates telephone numbers that match the configuration of telephone numbers in a country. The traditional face-to-face interviews were changed with computer assisted interviews that affected the sample selection and response rate (Eurofound, 2022)

For these reasons, the main analysis is carried out using 2015 data. The final sample size for the main analysis consists of a total of 30,815 observations.

2.3.1 Variables

Dependent variables

The paper examines multiple dimensions of job quality selected based on the empirical literature reviewed in Section 2.2.1. These dimensions are specifically used to test the urban rat race, job matching and satisfaction externalities evidence.

To capture the urban rat race effect, I rely on a well-established indicator in the job quality literature that captures the quantitative demands of work combining *speed at work* and *working to tight deadlines* dimensions (Green and McIntosh, 2001; Adăscăliței et al., 2022). The combination is made by averaging the two questions.[8] To assess job matching, I rely on a job match question closely mirroring the one used by Andini et al. (2013), together with a standard question on career prospects. Finally, to test satisfaction externalities, I use the question on *satisfaction with working conditions* as a proxy for overall job satisfaction. All the elements are summarised in Table 2.1.

Note that most of the EWCS questions used yield ordinal variables. Following De Bustillo et al. (2011). I rescale every dimension to range from 0 to 100 for ease of interpretation and comparability.[9] Table 2.1 lists for each job quality dimension the respective EWCS questions used and number of answers available per question, these varies between 4 and 7.

[8]Note that this measure of work intensity differs from the original one (Rosenthal and Strange, 2008). However, this indicator better fits with the original *rat race model* of Akerlof (1976) that considers the speed at work as the factor revealing 'ability'. The use of working hours in a cross-countries context such as Europe is difficult due to different regulations and institutions rendering the working hours an indicator subject to many complications. Refer here to acknowledge the differences in working hours per country: `https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20240530-1`.

[9]To ensure the coherence of the results, after the baseline analysis, I repeat the analysis using an ordered logit model. The ordered logit estimates are qualitatively consistent with the OLS results, yielding similar signs and patterns of statistical significance across specifications. see Table 2.A.6.

Table 2.1: Job quality variables

Indicators	EWCS questions	N. of answers	Related literature
Intensity	a. Does your job involve to work at high speed? [a]	7 categories	Green and McIntosh (2001)
	b. Does your job involve working to tight deadlines?	7 categories	Adăscăliței et al. (2022)
Job match	a. If I were to lose or quit my current job, it would be easy for me to find a job of similar salary	5 categories	Andini et al. (2013)
Career prospect	a. My job offers good prospects for career advancement	5 categories	De Bustillo et al. (2011)
Job satisfaction	a. On the whole, how satisfied are you with working conditions?	4 categories	Dalmazzo and de Blasio (2011)

Notes: "Does your job involve working at a high speed?". Seven answers: "all of the time," "almost all the time,"around three-quarters of the time," "around half of the time," "around a quarter of the time," "almost never," and "never." These have been re-scaled to 100, 90, 75, 50, 25, 10, and 0, respectively. In the case of 5 answers, the scale used is 100, 75, 50, 25, 0. Own elaboration from EWCS 2015.

Independent variables

The main explanatory variable is a dummy variable named *Urban*, that is used for measuring urban-rural differentials in job quality and as proxy for agglomeration economies. This variable is based on the Degurba methodology that is developed by EUROSTAT and classifies local administrative units (municipalities) based on a combination of criteria of geographical contiguity and minimum population threshold applied to 1 km^2 population grid cells. This approach goal is to avoid distortions arising from how differently administrative geographical units are specified and so to enable a more robust comparison of locations across Europe.[10] The Degurba methodology identifies three levels of urbanization: urban, intermediate and rural. An area is defined as urban based on the following criteria: 1) there is a minimum contiguity of population of 50,000 inhabitants and 2) the density is higher than 1500 inhabitants per km square for at least 50 % of the total population. Conversely, a rural area is defined when there is not contiguity among cells and the density

[10]The degree of urbanization is derived from the Global Human Settlement Layer (GHSL) programme, developed within the European Space Agency's Copernicus Earth Observation Programme. The primary objective of this instrument is to provide a standardized tool for the comparison of urban and non-urban settlements worldwide. Further details are available at the following link: https://human-settlement.emergency.copernicus.eu/index.php.

per km squared is lower than 300 inhabitants (Eurostat, 2023). The third category, intermediate, stays in between. Figure 2.1 shows how the European continent is classified with Degurba methodology.[11] In this case, it is fundamental to recall that this indicator is used to capture an 'urbanization effect' connected to agglomeration economies (Rosenthal and Strange, 2004) and it provides a measure that combines size and density simultaneously and can be considered as capturing the concentration of population and economic activities in space.

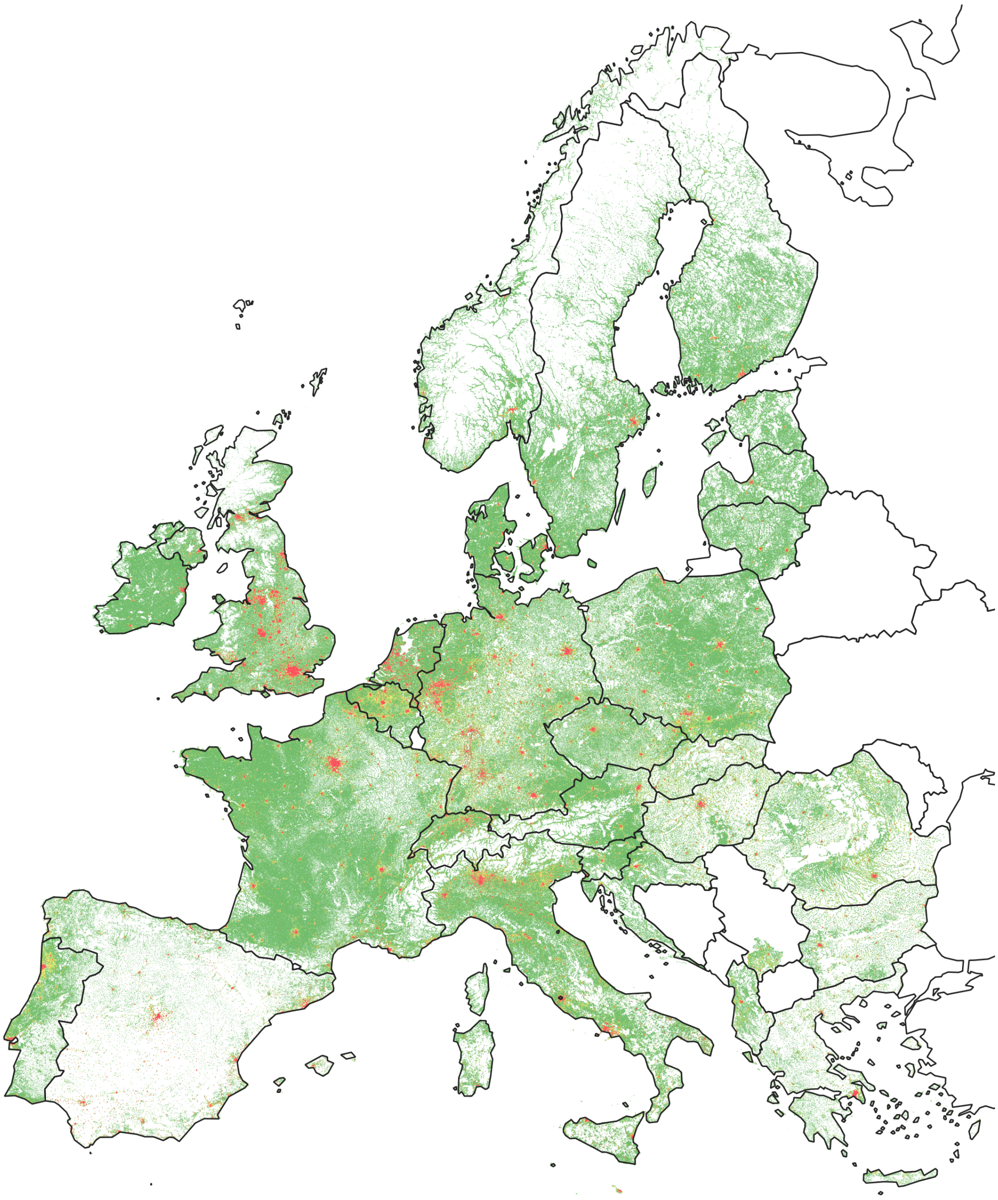
According to the Degurba classification in 2015, more than 40 % of European population live in urban areas, more than 31 % in intermediate areas and the remaining 28 % in rural areas.[12] Note that these proportions are reflected in the EWCS sample.

For the main analysis, the intermediate category is eliminated because I intend to minimize any potential interference or noise, given that agglomeration economic forces, although to a lesser extent, may also be at play in intermediate areas, particularly those situated in proximity to urban centers (Rosenthal and Strange, 2020). As it has been highlighted in important contributions (Rosenthal and Strange, 2003, 2004), the geographical extent of agglomeration is still a hot debate in the literature. The general idea, however, is that agglomeration effects decay with distance and are stronger in proximity to the center. By referring to Figure 2.1, the possible source of noise deriving form intermediate areas might be particularly pronounced in country such as Belgium, Netherlands, Germany and Italy. In order to avoid this problem, the intermediate category has been removed from the main analysis. The final sample is composed by 21,000 workers, 61 % of them in urban areas and the remaining 39% in rural areas. As a robustness check, the analysis is repeated with the inclusion of the intermediate (see Panel a and b Table 2.A.7).

[11]Note that the map classifications (cities-towns and suburbs) correspond to urban and intermediate classification. Not all the countries surveyed in the EWCS are highlighted in the map. Turkey, Serbia, North Macedonia and Montenegro are shown separately in Figure 2.A.1 and 2.A.2.

[12]Please refer to the following link: https://ec.europa.eu/eurostat/cache/RCI/#?vis=degurb.gen&lang=en

Figure 2.1: Degree of urbanization in Europe



Notes: Author's own elaboration using QGIS. The Red characterize urban areas, the yellow intermediate and the green the rural areas.

Source: https://ec.europa.eu/eurostat/web/degree-of-urbanisation/background

Table 2.A.3 shows the urban and rural means for each job quality dimension, highlighting already some discernible differences. Note that the larger gap is captured for the match indicator, more than 6 points, followed by career, 4.8, and the intensity at work, 4 points. No notable differences are visible for job satisfaction.

To isolate urban–rural differences across the various dimensions of job quality, I include a comprehensive set of control variables in the econometric specification summarized in Table 2.A.1. Consistent with prior studies —such as Rosenthal and Strange (2008); Andini et al. (2013); Dalmazzo and de Blasio (2011)— I account for individual socio-demographic characteristics, including age (and its quadratic term), biological sex, education, migrant background, marital status, and the presence of children. These controls help net out individual-level heterogeneity. Leveraging the richness of the EWCS data, I also control for key firm- and job-related characteristics. Specifically, I include firm size, weekly working hours, the frequency of working from home, and daily commuting time (measured in minutes). Finally, to account for differences in job tasks, production structures, and institutional contexts, I incorporate fixed effects for occupation (2-digit level), industry (1-digit level), and country. Summary statistics for all variables are reported in Table 2.A.4.

2.4 Empirical strategy

The empirical aim of this paper is to evaluate variations in job quality between two distinct territorial categories, urban and rural, to assess the role of agglomeration economies. I estimate a regression model by exploiting variation within occupations, industries and countries using an ordinary least square estimator. This is the typical estimator used for studying the urban wage premium and at the same time, it is also common in job quality labour economics analysis (Nikolova and Cnossen, 2020). The main baseline model is the following:

$$Y_i = \alpha + \beta_1 Urban_i + S_i + O_i + \delta_i + \varepsilon_i \tag{2.1}$$

where Y_i is the term accounting for the four different job quality dimensions;

$Urban_i$ is the term capturing the urban-rural differentials, the main interest of this analysis and S_i and O_i are respectively the vectors that contain individual socio-demographic and other controls. Finally, δ_i is the vector that contains occupation, industries and countries fixed effects. ε_i contains error terms.

The cross-sectional setting of the data does not allow to interpret by any meaning the results as causal. In this setting, endogeneity issues such as omitted variable bias and sorting are likely to bias the results. For instance, the monetary compensation plays a fundamental role in relation to omitted variable bias. In fact, wage is likely a predictor of job quality (Green and Mostafa, 2012) and at the same time, of agglomeration. To address this concerns, the log of hourly wage is included as an independent exogenous variable in the model.[13] The inclusion of wage addresses not only concerns about omitted variable bias but also touches upon issues of sorting (Rosenthal and Strange, 2008; Andini et al., 2013). Part of the urban-rural differentials may not be due to spatial configuration itself but rather driven by the sorting of more motivated, skilled, and talented workers into urban areas.

As a complement addressing the sorting part in addition is also acknowledged that workers also sort into cities attracted by urban amenities and consumption opportunities (Glaeser and Mare, 2001; Rosenthal and Strange, 2008; Dalmazzo and de Blasio, 2011). To partially account for this other sorting aspect, a variable capturing the frequency of consumption activities outside the home is included in the main model. This variable is a dummy that distinguishes workers who report engaging in sports, cultural, or leisure activities outside the home every day or weekly from those who participate monthly, less frequently, or never. The latter is used as a proxy for local amenities.

[13] With the respect of the endogeneity concerns regarding the wage level - work intensity relation, the wage level is assumed to be exogenous in this paper, in line with the efficiency wage hypothesis (Akerlof, 1984; Krueger and Summers, 1988).

2.5 Results

2.5.1 Main results

Table 2.2 presents the results of the baseline equation (1). The coefficient of the dummy variable *Urban* in column 1, capturing the urban rat race on intensity at work, is positive and statistically significant at the 1% level. Similarly, columns 2 confirms that agglomeration economies facilitate a easier job-match while, contrary to expectations, column 3 does not show any urban career premium. Finally, column 4 unveils an urban penalty, statistically significant at the 1% level, associated to job-satisfaction. Taken as all, the results support the existence of multiple urban-rural job quality differentials in the European context.[14]

But how relevant are these gaps? At first glance, these differences may appear to carry limited (socio)economic significance. To enhance the interpretability of the urban–rural gap estimates, the urban coefficients' magnitudes are compared with other important variables. Note that this remains an illustrative case rather than representing a consolidated way to interpret the spatial gaps.

For ease of comparison, the urban estimates are compared with the estimates of two other binary variables: biological sex (for work intensity) and tertiary education (for job match and job satisfaction). Referring to Table 2.2, it is notable that the urban–rural gap in work intensity is approximately 84% the size of the female–male gap in intensity. Specifically, in terms of work intensity, it is often argued that women—facing greater stigma in the workplace and broader societal pressures—must work harder than men to signal their commitment to employers (Adăscăliței et al., 2022; Heilman et al., 2024). Although anecdotal, this parallel resonates with the job-signalling framework that underpins the urban rat race theory (Akerlof, 1976).[15]

[14] Using the same econometric specification, the baseline analysis is replicated using an ordered logit model. The results, reported in Table 2.A.6, are broadly consistent with the main findings. Marginal average effects are also computed and are in line with OLS estimates.

[15] While this comparison is speculative, it is worth noting that, as highlighted by Antón et al. (2023), the gender pay gap has received increasing attention in both economics and broader discourse, yet the gender gap in general working conditions remains comparatively under-explored.

Turning to job-match, the urban premium is found well above half (i.e. 67%) of the job-match premium associated with holding a tertiary degree, while with respect to job satisfaction, the satisfaction penalty experienced by urban workers is just below 50% of the satisfaction penalty experience by no-degree holders. In both cases, the comparison puts the magnitude of the urban–rural gap into clearer perspective, comparing in it with the return from investing at least in three additional years in human capital.[16]

Overall, the emerging evidence suggests that urban workers are worse-off in term of intensity at work and satisfaction with working condition while they are better-off in term of job-match. Clearly, it is not the scope of the paper to assign to one or to other dimensions more importance. However, what's seem clear is that while the job quality dimensions of intensity and satisfaction capture current status of job quality, the better job-match dimension postpone to future possibility of job opportunity, thus refer more to future expectations, suggesting that urban workers are particularly penalized in term of experienced job quality.

As recalled in the empirical strategy section, the results may suffer from endogeneity issues related to omitted variable bias. This aspect is particularity relevant while analysing work intensity. In fact, higher work intensity might indicate that urban workers are more industrious or have a stronger preference for hard work. These are unobservable characteristics that can not be addressed in this cross-sectional setting. However, according to the urban rat race hypothesis, this higher intensity is rewarded

[16] A further comparison was conducted by contrasting the urban–rural estimates with the corresponding gaps across 1-digit industry dummies, using manufacturing as the reference category and retail as the main comparator. These two macro-sectors are among the largest in terms of employment (respectively 15% and 16% of the total according to EWCS 2015 data) and are characterised by well-known differences in wage distributions, unionisation, tradability, and capital-technology intensity, making them useful illustrative benchmarks for interpreting the magnitude of spatial variation in job quality. With respect to work intensity, the manufacturing penalty relative to retail is of a similar magnitude to the urban–rural gap, amounting to around 80% of its size. For job match quality, the retail premium relative to manufacturing is approximately twice as large as the urban advantage. Finally, for job satisfaction, the manufacturing penalty relative to the education sector (no difference is detected with retail) is about four times larger than the urban–rural gap. Overall, these results provide simple and informative benchmarks that help contextualise the urban–rural estimates. They suggest that spatial disparities in job quality are meaningful, particularly in the cases of work intensity and job match quality. The results are available upon request.

Table 2.2: Urban-Rural differentials in job quality

	(1) Intensity	(2) Match	(3) Career	(4) Satisfaction
Urban	2.85***	2.71***	0.16	-1.15***
	(0.52)	(0.57)	(0.54)	(0.36)
Sex	3.36***	-3.38***	-3.69***	-0.73*
	(0.57)	(0.61)	(0.58)	(0.40)
Age	0.04	-0.05	-1.29***	-0.67***
	(0.16)	(0.18)	(0.17)	(0.11)
Age^2	-0.31*	-0.78***	0.91***	0.72***
	(0.19)	(0.21)	(0.20)	(0.13)
Migrant	0.97	-0.80	-1.61*	-2.52***
	(0.92)	(0.98)	(0.94)	(0.65)
Married	0.13	0.80	0.55	0.21
	(0.56)	(0.60)	(0.56)	(0.39)
Have children	0.43	-1.24**	0.30	0.57
	(0.55)	(0.60)	(0.56)	(0.38)
Education	0.36	3.96***	4.95***	2.44***
	(0.62)	(0.69)	(0.64)	(0.44)
Logcom	0.96***	-0.20	-0.54*	-0.96***
	(0.27)	(0.30)	(0.29)	(0.20)
Loghours	11.84***	2.63**	4.01***	-3.90***
	(1.17)	(1.27)	(1.24)	(0.85)
Firm size: 1-9				
10-249	6.69***	0.52	-0.96	-2.93***
	(0.63)	(0.69)	(0.65)	(0.43)
>250	7.39***	-2.03***	-0.28	-3.83***
	(0.71)	(0.78)	(0.74)	(0.50)
Wfh	7.01***	0.19	1.02	0.68
	(0.91)	(1.03)	(0.97)	(0.64)
Constant	-7.75	50.77***	74.94***	103.07***
	(5.20)	(5.68)	(5.44)	(3.70)
Obs.	18,148	17,024	17,428	18,214
Adj. R-sq.	0.13	0.13	0.14	0.07

Notes: OLS regression model with robust standard errors (in parentheses) using EWCS 2015 data. All regressions include occupation, Industry and country dummies controls.***$p < 0.01$,** $p < 0.05$,* $p < 0.1$

through higher wage levels. Drawing on the efficiency wage model (Akerlof, 1984), the elevated work intensity might be driven primarily by higher wages which, in turn, are more likely to be offered in large urban areas where workers exhibit higher productivity. This suggests that wage levels may represent a significant omitted variable in the analysis of the urban-rural gap in work intensity. At the same time, while not directly tackling omitted variable bias, the wage control is expected to strengthen the spatial gaps in term of job matching and satisfaction.

Panel a in Table 2.3 shows the results of analysis after the inclusion of wage. The wage control enters positively and significantly in the first column and the *Urban* coefficient slightly reduces but remains consistent and significant. This result suggests that behind the greater exert of effort supply by urban workers, the monetary consideration is not the only driver of competition and rivalry logic. Potentially, the rat race could arise also for non-wage amenities as well as rewarding only few, possibly the more 'able'. Yet, also controlling for wages, the general level of intensity at work remain higher in urban vs rural areas.

The wage level enters significantly also in the case of job satisfaction while not in the case of job-match. In term of spatial gaps both dimensions remain statistically significant and with the original sign.

In panel b (Table 2.3), sorting concerns are also acknowledged. Knowing all the limitations for the strategy used, on top of wage level which account for productivity mechanisms, a measure that captures 'amenities' consumption is included in the model. The latter is used to account for likely preference of people to sort into urban areas for benefiting from the sharing advantages (Duranton and Puga, 2004) of living in larger urban areas (Glaeser et al., 2001). Panel b shows insignificant changes thus reducing sorting concerns driven by urban amenities.

Moving to the 'better job-match' mechanism, the analysis unveils that job-match represents a fundamental advantage of working in urban areas, allegedly based on the multiple benefits associated to it, such employment and income security and lower psychological cost associated to job search and job loss. Conversely, the non-gap in career questions one of the most recurring benefit linked to agglomeration economies (Rosenthal and Strange, 2008; Kok, 2014*b*,*a*). In this respect, while the

Table 2.3: Controlling for hourly wage and local urban amenities

	(1) Intensity	(2) Match	(3) Career	(4) Satisfaction
Panel a. OVB				
Urban	2.27***	2.92***	-0.51	-1.55***
	(0.57)	(0.62)	(0.57)	(0.39)
Log hour wage	2.18***	0.38	12.88***	6.70***
	(0.68)	(0.75)	(0.73)	(0.49)
Obs.	15,684	14,839	15,126	15,737
Adj. R-sq.	0.13	0.14	0.16	0.09
Panel b. Sorting				
Urban	2.29***	2.90***	-0.51	-1.57***
	(0.57)	(0.62)	(0.57)	(0.39)
Log hour wage	2.20***	0.30	12.90***	6.65***
	(0.68)	(0.75)	(0.73)	(0.49)
Consumption	-0.23	2.86***	0.24	1.31***
	(0.59)	(0.65)	(0.60)	(0.42)
Obs.	15,667	14,825	15,111	15,721
Adj. R-sq.	0.13	0.14	0.16	0.09

Notes: OLS regression model with robust standard errors (in parentheses). All regressions include individual level socio-demographics and other controls, plus occupation, industries and country dummies. $^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$

urban career gap is substantial in the summary statistics (see table 2.A.3), the career premia disappears after socio-demographic controls are included in the regression (See table 2.A.8), suggesting that career prospects are more individual specific rather than connected to labour market spatial characteristics.

Finally, the analysis is robust in rejecting the satisfaction externalities evidence of Dalmazzo and de Blasio (2011). The latter results can be considered as a novel facet of the 'urban paradox' (Sørensen, 2014; Carlsen and Leknes, 2022*b*,*a*): i.e. while urban workers are better off in term of consumption, they are worse-off in term of subjective well-being and job satisfaction.

2.5.2 Further analysis: tasks and different degrees of urbanisation

The baseline results are complemented by two additional investigations. A well-established concern in economics relates to the notion that market size influences the tasks content of same occupations. The underlying idea is that the same occupation involve different tasks depending on whether it is performed in an urban or rural labour market. A recent body of empirical research supports this claim across various national contexts (see Kok (2014*b*) for Germany, Atalay et al. (2024) for the USA, and Rouwendal and Koster (2025) for the Netherlands). These studies consistently find that urban workers engage in more specialized and complex tasks compared to their counterparts in rural areas. For this reason, relying solely on the inclusion of 2-digit occupational dummies in the empirical model is insufficient to fully address these concerns.

To tackle this issue, I construct three additional variables, each capturing a distinct type of task. These measures are derived through a polychoric principal component analysis (PCA) based on a set of questions from the European Working Conditions Survey (EWCS). The PCA yields three components, which are labelled as complex, manual, and social tasks.[17] Table 2.4 confirm that the results remain robust after

[17] The PCA was conducted on a set of survey questions, and three components were extracted, each corresponding to a distinct group of tasks. The list of variables used and the detailed PCA

including these task-related measures.

The second concern relates to a geographical limitation in the current analysis. Specifically, the main independent variable, *Urban*, does not distinguish between different classifications of urban size. As it stands, the variable aggregates large urban, medium and small-sized urban areas under the same category. This lack of differentiation is potentially problematic, as urbanization takes various and markedly different forms—particularly in the European context. Moreover, it is well-established that the most pronounced agglomeration effects are typically concentrated in large metropolitan regions (Duranton and Puga, 2020). As a result, the job quality gaps identified so far may obscure important heterogeneity across different urban contexts.

To address this concern, a refined version of the *Urban* variable is constructed. Although the EWCS does not directly differentiate between various types of urban areas, a new measure is developed by combining regional-level data with the degree of urbanization. Workers are now defined as located in "large urban" areas if (1) they are urban in EWCS and (2) live in a region that includes either the national capital or a city with a population exceeding one million. The identification of latter cities is based on the *Cities and Greater Cities Database* provided by EUROSTAT.[18]

The final result is a newly constructed categorical variable, *Large Urban*, that classifies workers as residing in either large urban, urban, or rural areas. As expected, Table 2.5 confirms that spatial gaps in job quality are primarily driven by larger urban areas. Notably, all the gaps in work intensity, job-match and job satisfaction increase in magnitude. In this context, the widening gaps underscore the strength of agglomeration economies and their externalities as reflected in job quality outcomes. Interestingly, the analysis continues to reveal no evidence of a career premium associated with urban areas, even with the large urban categorisation.

results are available in the appendix, see Table 2.A.9 and Table 2.A.10.

[18]Capital cities included: Tirana, Brussels, Sofia, Bern, Nicosia, Prague, Berlin, Copenhagen, Tallinn, Athens, Madrid, Helsinki, Paris, Zagreb, Budapest, Dublin, Rome, Vilnius, Riga, Podgorica, Skopje, Amsterdam, Oslo, Warsaw, Lisbon, Bucharest, Belgrade, Stockholm, Ljubljana, Bratislava, Ankara, London, and Vienna. Cities with more than one million inhabitants: Milan, Barcelona, Naples, Hamburg, Munich, Valencia, Lyon, Birmingham, Cologne, Istanbul, and Izmir. The capital Luxembourg is excluded. See: `https://ec.europa.eu/eurostat/databrowser/view/URB_CPOP1$DEFAULTVIEW/default/table`.

Table 2.4: Urban-Rural differentials and individual job tasks

	(1) Intensity	(2) Match	(3) Career	(4) Satisfaction
Urban	2.77***	2.81***	0.41	-1.06***
	(0.48)	(0.58)	(0.54)	(0.36)
Complex	5.49***	1.35***	6.54***	2.03***
	(0.26)	(0.30)	(0.28)	(0.19)
Manual	12.03***	-1.58***	-5.08***	-5.22***
	(0.28)	(0.33)	(0.31)	(0.21)
Social	3.83***	0.52*	0.54*	-1.18***
	(0.27)	(0.32)	(0.30)	(0.20)
Obs.	17,479	16,431	16,800	17,525
Adj. R-sq.	0.27	0.13	0.18	0.11

Notes: OLS regression model with robust standard errors (in parentheses) using EWCS 2015 data. All regressions include individual level socio-demographics and other controls, plus occupation, industry and country dummies. The three additional controls (Complex, Manual and Social) are built using a principal component analysis on a series of EWCS questions related to job tasks. For more refer to tables 2.A.9 and 2.A.10 in the Appendix.

Table 2.5: New Urban variable - Large Urban category

	(1) Intensity	(2) Match	(3) Career	(4) Satisfaction
Ref. category: *Rural*				
Urban	1.62***	1.47**	-0.33	-0.91**
	(0.59)	(0.64)	(0.60)	(0.41)
Large Urban	4.56***	4.46***	0.84	-1.49***
	(0.63)	(0.68)	(0.65)	(0.44)
Obs.	18,148	17,024	17,428	18,214
Adj. R-sq.	0.13	0.13	0.14	0.07

Notes: OLS regression model with robust standard errors (in parentheses) using EWCS 2015. The new Urban variable consist now of three categories: large urban, urban and rural. See in text section 5.2. All regressions include individual level socio-demographics and other controls plus occupation, industry and country dummies. $^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$

2.5.3 Robustness checks

This section addresses potential concerns regarding the robustness of the findings (Table 2.A.7), focusing in particular on possible distortions arising from sample selection, survey design, and model specification. The robustness checks begin by re-estimating the main models using the full territorial classification, including the previously excluded intermediate category. In panel a the intermediate category is grouped with the urban one showing stable results, slightly declining in magnitude. Instead, in panel b, the binary *Urban* variable is replaced with the original three-levels classification. The results confirm that the urban–rural job quality gaps remain robust. When examining the intermediate–rural gaps, the results indicate that these persist—though with lower magnitudes—for work intensity and job satisfaction, while the gap for job match disappears. This suggests that, overall, workers in intermediate areas are worse off than their rural counterparts, without benefiting from the job-match advantages that appear to be specific to urban settings. Table 2.A.11 panel a shows the estimates using the original three-levels territorial classification but with the intermediate category as the reference group. The work intensity gap remains marginally significant, the satisfaction gap vanishes, and the job-match premium remains clear and substantial—comparable in magnitude to the urban–rural difference. As anticipated, the coefficients and significance levels for the intermediate category consistently fall between those of the two extremes, suggesting a gradient effect. This gradient pattern lends further support to the main findings by reinforcing the idea that agglomeration effects scale with urban size.

To account for survey sample design parameters, in panel c Table 2.A.7, the baseline model is estimated with the inclusion of the clustered standard errors at the regional level, corresponding to the strata used in the EWCS sample design (Eurofound, 2015). The results remain robust.

In the following panel, a weighted regression is performed using post-stratification weights. These account for non-response rate and adjust for the representativeness of the sample after the sample selection. The results remain stable apart from the job-match gap which disappears. To check further this aspect, I repeat the same analysis, by using the *Large Urban* variable as in Table 2.5. When I use this urban category, the gap re-emerge clear and robust, proving a more robust benefit associated to very large urban areas (see table 2.A.11 panel b). Panel e shows the results of a weighted regression using as weights the inverse of the number of observations per country (Nikolova and Cnossen, 2020). This is performed as a strategy to address concerns surrounding unequal country sample sizes. The results remain aligned.

Lastly, the main analysis is replicated without applying any data cleaning or selection procedures as explained in the data section. The results remain broadly consistent with the baseline specification (Panel f Table 2.A.7).

2.5.4 External validity

In this section I account for the external validity of the results. The baseline results are replicated using data from EWCS 2010 and EWCTS 2021. As discussed above, both survey waves differ from the 2015 version. Specifically, the 2010 wave does not employ the degree of urbanization, while the 2021 wave—conducted during the exceptional circumstances of the COVID-19 pandemic—suffers from extensive missing observations, variables and a different sampling strategy.

The full specified baseline model can largely be replicated using 2010 data. To create the main independent variable *Urban*, an ad-hoc selection of territorial categories is performed for each country. Table 2.A.12 in the appendix illustrates how territorial categories varies considerably across countries. Note that these categories are based on population size rather than a combination of population and density as in the degree of urbanization method. As such, this variable serves primarily to capture a population-size effect.

In the absence of a pre-defined urban–rural classification, two criteria are applied. Workers are categorized as urban if they reside in territorial units with populations exceeding either 50,000 or 100,000 inhabitants.[19] Conversely, rural classification is

[19] The 50,000 threshold is a widely established international standard used to ensure a consistent definition of cities. Note that the same threshold is also applied in the DEGURBA methodology. For more: https://blogs.worldbank.org/en/sustainablecities/how-do-we-define-cities-towns-and-rural-areas

assigned to workers living in areas with fewer than 10,000 inhabitants.[20]

The results, shown in Panel a Table 2.6 , are in line with the previous estimated reinforcing the external validity of the main analysis. The only notable exception refers to job satisfaction, although negative, it is less statistically significant. [21]

Before commenting the results using 2021 data, it is important to note that the scope of the analysis is considerably restricted and cannot be replicated in full. Only two job quality dimensions —work intensity and career prospects— can be analysed in this case, and two key control variables such as migrant status and commuting time are unavailable. Moreover, the 2021 context is highly specific, as the survey was conducted during the height of the global COVID-19 pandemic. It is worth highlighting that the share of workers reporting working from home in the 2021 data exceeds 50%, compared to just above 10% in previous waves.[22] As such, the findings should be interpreted with caution.

Panel b in Table 2.6 indicates that the spatial gap in terms of work intensity is no longer statistically significant, while the urban career premium is, if anything, slightly negative. The lack of significance for intensity stands in contrast to earlier findings that strongly supported the urban rat race theory. One plausible explanation is that the uncertainty surrounding workplace locations and the widespread adoption of remote work diminished face-to-face interactions with peers and superiors, thereby weakening the role of work intensity as a job-signalling strategy.

It is here argued that the non significant gap in intensity at work it is an indirect confirmation that the urban rat race mechanism is primarily active under "normal" conditions—i.e., when mobility is unrestricted and remote work is not widely adopted. Had similar dynamics been observed in the 2021 data, it would have suggested that the pandemic had little to no impacts on workplace functioning. This opens a new set of possible implications that have been rarely taken into consideration in early study on the agglomeration effect of working from home (Behrens et al., 2024; Liu

[20]Clearly there are some exceptions such as in the case of UK where the largest urban category begins at 10 thousand inhabitants. For this reason, the UK is removed from the analysis.

[21]However, the significance re-emerge when the hourly wage is included in the model. Results remain available on request.

[22]Summary statistics available on request.

and Su, 2025).

Finally, the analysis using 2021 data confirms that urban workers are not better-off in term of career prospects, thus supporting even further the previous findings. Clearly, evidence on external validity remains limited due to differences in the institutional and contextual settings across survey waves. In particular, the 2010 wave employs a different measure of agglomeration, while the 2021 wave is affected by the exceptional circumstances associated with the COVID-19 pandemic. As a result, comparability across waves is not fully straightforward.[23]

Table 2.6: External validity using 2010 and 2021 waves

	(1) Intensity	(2) Match	(3) Career	(4) Satisfaction
Panel a - 2010				
Urban	1.83***	3.30***	0.50	-0.58
	(0.55)	(0.52)	(0.48)	(0.39)
Obs.	16,338	15,537	15,930	16,402
Adj. R-sq.	0.15	0.15	0.17	0.11
Panel b - 2021				
Urban	0.47		-0.97*	
	(0.35)		(0.57)	
Obs.	26,960		17,939	
Adj. R-sq.	0.11		0,11	

Notes: OLS regression model with robust standard errors (in parentheses). Panel a. uses data from the EWCS 2010 while Panel b from the EWCTS 2021. All regressions include occupation, industry and country dummies controls. $^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$

[23]In this regard the very recent EWCS 2024 provides an interesting opportunity for future research, and some harmonisation challenges too. To an extent this wave can be deemed more closely comparable with EWCS 2015 than EWCTS 2021, with the latter being carried out in exceptional circumstances due to the pandemic conditions.

2.6 Conclusion

The paper documents the existence of multiple urban-rural gaps in job quality in the European context using individual level data from the EWCS 2015 survey. In doing so, it contributes to the extensive literature on the urban–rural divide and agglomeration economies by providing new empirical evidence on job quality—an aspect that has remained largely under-explored in this field.

Overall, it emerges that the competition and rivalry forces, as predicted by the urban rat race mechanism (Rosenthal and Strange, 2008), explain job quality disadvantages for urban workers in terms of work intensity. An overall higher intensity is a source of work disutility that in the medium-long term may lead to unfavourable socio-health outcomes. Urban workers report also lower job satisfaction which entails multiple costs in term of motivation, life satisfaction and subjective well-being. As expected, urban workers enjoy an advantage in terms of job match possibilities representing a crucial advantage that ensures job and wage security for urban workers, especially in a period marked by significant technological and institutional changes.

A set of policy implications might arise from this work. The first is analytical. Labour and social policies geared toward improving job quality should not rely exclusively on evidence at the individual-firm or national level but, they should adopt a more granular territorial perspective and recognize the role of agglomeration economies as potential contributors to adverse labour market outcomes. Secondly, due to the relevance of job quality for labour supply decisions such as absenteeisms and turnover (Cassar and Meier, 2018; Nikolova and Cnossen, 2020), the work points out to considerable costs associated to pursue further urbanization policies. Both supply decisions have notable impacts on firm revenues and on public welfare expenditure. Possible extensions of this work might think of studying more specifically these supply behaviours along an urban-rural classification. Thirdly, this study unveils new opportunities and advantages associated with job quality in rural areas. Policies might sustain the localization of new firms in rural areas driven by long-term considerations regarding job quality. This point, undoubtedly, warrants further investigation and substantiation through rigorous empirical evidence, beginning with an assessment of the skills supply available in rural areas.

This work has a series of limitations that are worth to underline. The cross-sectional nature of the data used in the work do not allowed to control for worker fixed effects and to support any causal interpretations of the results. At the same time, the number of observations available from the European Working Conditions Survey (EWCS) are particularly low rendering the analysis less robust. The results should be carefully considered.

To conclude, the results of this work seem to suggest, from a very broad perspective, that the job quality disadvantages overcome the advantages underscoring a form of *negative externalities* associated to urbanization.[24] Notably, while the standard urban economics literature highlights the private returns in term of wages and the lower return in public good terms such as pollution, crime and congestion of agglomeration, the job quality diseconomies invite to refocus the attention to the 'private sphere' of the working dimension as well.

Clearly, this represents an initial broad evidence which needs to be complemented further by new empirical and theoretical works.[25] These are needed as we are witnessing an ever-increasing forces toward urban concentration and densification which already characterized the large majority of the European population. These policies hide a job quality side that might lead to remarkable social costs in the medium-long run. These are aspects that warrant consideration while questioning the desirability of agglomeration from a welfare analysis perspective (see for instance Charlot et al., 2006).

[24] This is also supported while using the European Intrinsic Job quality index a la Cascales Mira (2021). This represents a composite indicator that summarize four job quality dimensions: autonomy, interaction, intensity and meaningful work. Results are available on request.

[25] For instance, additional analyses by wage groups show that diseconomies of agglomeration were more pronounced for urban low-wage workers in 2010, who experienced higher work intensity and lower job satisfaction, whereas in 2015 they became more evident among urban high-wage workers, who reported higher work intensity, no job match premia, and lower job satisfaction. Similar trends (exception for job match which always remain more favourable for urban workers) are confirmed when using high vs low skills groups. Future research could further investigate these dynamics and their underlying causes. Overall, the result for work intensity remains consistent across all specifications and survey waves. The results are available upon request.

Declaration of generative AI and AI-assisted technologies in the writing process.

During the preparation of this work the author used ChatGPT in order to check grammar and syntax mistakes. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Appendix 2

A2. Tables

Table 2.A.1: Control variables

Groups	**Variables**	**Description**
Individual	*Sex*	Dummy, female (1)
	Age	Workers between 18 and 70 are included
	Age^2	Age squared to account for non-linearity
	Married	Dummy, being married: yes (1) and no (0)
	Have children	Dummy, have at least one child: yes (1) and no (0)
	Education	Dummy, having a tertiary degree: yes (1) and no (0)
	Migrant	Dummy, the person interviewed and her parents are born in a foreign country*
	Firm size	3 categories: 1 to 9, 10 to 249, more than 250 employees
	Wfh	Dummy variable that takes value 1 when workers work daily or several days a week from home; 0 otherwise
	Loghours	Log weekly work hours. Only workers between 20 and 70 hours
	Logcom	Log of daily commuting time expressed in minutes
	Log hour wage	The original adjusted monthly wage is divided into four (weeks) and then divided by weekly hours worked and transformed in natural log
	Consumption	Dummy variable that takes value 1 when workers daily or several days a week report leisure, sport or cultural consumption; 0 otherwise
Group	*Occupations*	37 occupations based on ISCO-08 classification at the 2-digit level
	Industries	19 economic sectors based on Nace Rev.2 classification at 1-digit level
	Countries	34 Countries, 27 EU (UK included no Malta) and 7 extra EU countries

Table 2.A.2: Urban and Rural observations per country (2015)

	Rural	Urban	Total
Belgium	346	451	797
Bulgaria	169	383	552
Czech Republic	285	263	548
Denmark	301	308	609
Germany	361	616	977
Estonia	265	490	755
Greece	89	486	575
Spain	740	1100	1840
France	307	600	907
Ireland	336	212	548
Italy	248	294	542
Cyprus	113	304	417
Latvia	185	224	409
Lithuania	147	650	797
Luxembourg	361	151	512
Hungary	228	257	485
Netherlands	105	333	438
Austria	281	213	494
Poland	153	416	569
Portugal	131	336	467
Romania	315	299	614
Slovenia	691	203	894
Slovakia	326	226	552
Finland	105	409	514
Sweden	235	323	558
United Kingdom	175	687	862
Croatia	250	255	505
North Macedonia	240	428	668
Turkey	139	659	798
Norway	70	527	597
Albania	166	302	468
Montenegro	169	355	524
Switzerland	177	225	402
Serbia	89	340	429
Total	8298	13325	21623

Table 2.A.3: Job quality averages by urban category

	Urban	Rural	Diff.*
Year: 2010			
Intensity	43.9	40.5	3.4
Match	43.3	37.7	5.6
Career	47.4	42.7	4.7
Satisfaction	67.5	66.2	1.3
Year: 2015			
Intensity	45.1	41.8	3.3
Match	45.8	40.4	5.4
Career	51.9	48.3	3.6
Satisfaction	68.5	69.3	-0.8
Year: 2021			
Intensity	60.1	58.8	2.0
Career	60.3	58.9	1.4

Notes:* T-tests prove all differences are statistically significant in all the cases.

Table 2.A.4: Summary statistics - EWCS 2015

Variable	Obs	Mean	Std. Dev.	Min	Max
Intensity	21466	43.824	33.49	0	100
Match	19985	43.765	35.27	0	100
Career	20466	50.568	33.693	0	100
Satisfaction	19498	65.87	18.978	0	100
Urban	21623	.616	.486	0	1
Sex	21620	.503	.5	0	1
Age	21623	42.587	11.481	18	70
Age2	21623	19.454	9.859	3.24	49
Migrant	20497	.091	.287	0	1
Education	21623	.372	.483	0	1
Married	21623	.663	.473	0	1
Havechildren	21623	.482	.5	0	1
Plant size	20763				
1-9		.303	.46	0	1
10-249		.397	.489	0	1
>249		.299	.458	0	1
Wfh	21501	.102	.302	0	1
Logcom	20176	3.396	.924	0	6.04
Log hours	21623	3.669	.231	2.995	4.094
Hourwage	18502	2.029	.615	.017	4.531
Consumption	21593	.292	.455	0	1
Self	20427	.084	.278	0	1

Table 2.A.5: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) *Intensity*	1.000											
(2) *Match*	0.051	1.000										
	(0.000)											
(3) *Career*	0.006	0.176	1.000									
	(0.310)	(0.000)										
(4) *Satisfaction*	-0.157	0.075	0.366	1.000								
	(0.000)	(0.000)	(0.000)									
(5) *Urban*	0.048	0.075	0.052	-0.015	1.000							
	(0.000)	(0.000)	(0.000)	(0.026)								
(6) *Sex*	-0.036	-0.045	-0.064	0.004	0.001	1.000						
	(0.000)	(0.000)	(0.000)	(0.452)	(0.889)							
(7) *Age*	-0.101	-0.237	-0.177	-0.008	-0.061	-0.004	1.000					
	(0.000)	(0.000)	(0.000)	(0.137)	(0.000)	(0.530)						
(8) *Age2*	-0.104	-0.236	-0.171	-0.003	-0.056	-0.009	0.990	1.000				
	(0.000)	(0.000)	(0.000)	(0.599)	(0.000)	(0.134)	(0.000)					
(9) *Migrant*	0.026	0.019	-0.026	-0.025	0.073	-0.008	-0.028	-0.033	1.000			
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.178)	(0.000)	(0.000)				
(10) *Married*	-0.006	-0.033	-0.009	0.013	-0.073	-0.040	0.157	0.129	0.009	1.000		
	(0.305)	(0.000)	(0.125)	(0.026)	(0.000)	(0.000)	(0.000)	(0.000)	(0.115)			
(11) *Have children*	0.008	-0.026	-0.016	-0.008	-0.072	0.068	0.031	-0.022	0.044	0.403	1.000	
	(0.147)	(0.000)	(0.008)	(0.167)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(12) *Education*	-0.012	0.072	0.181	0.111	0.140	0.090	-0.043	-0.047	0.011	0.008	0.020	1.000
	(0.039)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.055)	(0.137)	(0.001)	

Table 2.A.6: Ordered logistic models

	Intensity 1	Intensity 2	Match	Career	Satisfaction
Panel a. EWCS 2021					
Urban	0.15***	0.15***	0.15***	0.01	-0.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Obs.	18,198	18,186	17,024	17,428	18,214
Pseudo R-sq.	0.040	0.034	0.485	0.051	0.042
Panel b. EWCS 2010					
Urban	0.09***	0.09***	0.22***	0.04	-0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Obs.	16,413	16,388	15,537	15,930	16,402
Pseudo R-sq.	0.047	0.041	0.058	0.062	0.063
Panel c. EWCTS 2021					
Urban	0.03	0.01		-0.05*	
	(0.03)	(0.03)		(0.03)	
Obs.	27,054	27,030		17,939	
Pseudo R-sq.	0.04	0.03		0.3	

Notes: All regressions include individual level socio-demographics and other controls plus occupation, industry and country dummies controls. EWCS 2015 are used. ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$

Table 2.A.7: Robustness checks

	(1) Intensity	(2) Match	(3) Career	(4) Satisfaction
Panel a. Intermediate and Urban				
Urban	2.42***	1.79***	0.30	-0.98**
	(0.46)	(0.50)	(0.47)	(0.31)
Obs.	25,845	24,218	24,858	25,930
Adj. R-sq.	0.12	0.13	0.13	0.07
Panel b. Intermediate				
Rural				
Intermediate	1.93***	0.62	0.33	-0.80**
	(0.54)	(0.58)	(0.55)	(0.37)
Urban	2.82***	2.73***	0.27	-1.13***
	(0.51)	(0.56)	(0.52)	(0.35)
Obs.	25,845	24,218	24,858	25,930
Adj. R-sq.	0.12	0.13	0.13	0.07
Panel c. Cluster standard errors				
Urban	2.85***	2.71***	0.16	-1.15**
	(0.89)	(0.87)	(0.82)	(0.48)
Obs.	18,148	17,024	17,428	18,214
Adj. R-sq.	0.13	0.13	0.14	0.07
Panel d. Post-stratification				
Urban	3.35***	0.86	0.06	-0.82**
	(0.61)	(0.65)	(0.61)	(0.42)
Obs.	18,148	17,024	17,428	18,214
Adj. R-sq.	0.13	0.14	0.14	0.07
Panel e. Country sample size				
Urban	4.12***	2.08***	0.06	-1.25***
	(0.63)	(0.66)	(0.65)	(0.42)
Obs.	18,148	17,024	17,428	18,214
Adj. R-sq.	0.12	0.12	0.13	0.06
Panel f. Full sample				
Urban	2.53***	2.91***	0.06	-1.14***
	(0.46)	(0.51)	(0.48)	(0.33)
Obs.	23,828	22,168	22,474	23,906
Adj. R-sq.	0.14	0.13	0.15	0.09

Notes: OLS regression model with robust standard errors (in parentheses) apart panel c where cluster standard errors are applied. EWCS 2015 are used. All regressions include individual level socio-demographics and other controls plus occupation, industry and country dummies controls. ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$

Table 2.A.8: Urban-Rural differentials in job quality - controls

	(1) Intensity	(2) Match	(3) Career	(4) Satisfaction
Panel a. Group controls				
Urban	3.62***	3.49***	1.13**	-1.80***
	(0.48)	(0.54)	(0.50)	(0.33)
Obs.	21,439	19,961	20,438	21,536
Adj. R-sq.	0.10	0.08	0.11	0.07
Panel b. Socio demographics				
Urban	3.30***	2.38***	0.41	-1.70***
	(0.50)	(0.54)	(0.50)	(0.34)
Sex	2.64***	-3.52***	-4.00***	-0.62*
	(0.54)	(0.58)	(0.55)	(0.37)
Age	0.25*	-0.01	-1.28***	-0.75***
	(0.15)	(0.17)	(0.16)	(0.10)
Age 2	-0.56***	-0.78***	0.90***	0.83***
	(0.17)	(0.19)	(0.18)	(0.12)
Migrant	1.21	-0.95	-1.90**	-2.32***
	(0.87)	(0.93)	(0.88)	(0.61)
Married	0.08	0.83	0.75	0.30
	(0.53)	(0.57)	(0.53)	(0.37)
Have children	0.26	-1.46**	0.06	0.51
	(0.53)	(0.57)	(0.53)	(0.36)
Education	1.09*	3.77***	4.96***	2.24***
	(0.59)	(0.66)	(0.61)	(0.42)
Constant	40.01***	58.58***	87.32***	85.14***
	(3.03)	(3.33)	(3.15)	(2.08)
Obs.	20,322	18,905	19,358	20,410
Adj. R-sq.	0.11	0.13	0.14	0.07

Notes: OLS regression model with robust standard errors (in parentheses) using EWCS 2015 data. Occupation, industry and country controls are always included in the regressions. $^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$

Table 2.A.9: EWCS questions for job tasks

EWCS questions	Answers	Variables
Q30a. Tiring or painful positions	7	Task1
Q30c. Carrying or moving heavy loads	7	Task2
Q30e. Repetitive hand and arm movements	7	Task3
Q30f. Dealing directly with people who are not employees at your workplace	7	Task4
Q30g. Handling angry client, customers, pupils etc	7	Task5
Q30i. Working with computers	7	Task6
Q53a. Meeting precise quality standards	2	Task7
Q53b. Assessing yourself the quality of your own work	2	Task8
Q53c. Solving unforeseen problems on your own	2	Task9
Q53d. Monotonous tasks	2	Task10
Q53e. Complex tasks	2	Task11
Q53f. Learning new things	2	Task12

Notes: These questions are selected from EWCS 2015 (specifically numbers 30 and 53) because they focus directly on what tasks a person actually does at work. Both questions use the same opening phrase: "Does your main job involve...". In our data table, the "Answer" column tracks the number of response options provided for these questions. Seven options correspond to: All the time, almost all the time, around $\frac{3}{4}$ of the time, half time, around $\frac{1}{4}$ of the time, almost never, Never. Two options are Yes or No.

Table 2.A.10: Principal component analysis on job tasks

Variable	Factor1	Factor2	Factor3
Task1		**0.7775**	
Task2		**0.6817**	
Task3		**0.6551**	
Task4			**0.8349**
Task5			**0.8217**
Task6	**0.4099**	-0.3989	0.3329
Task7	**0.5172**	0.2898	
Task8	**0.6201**		
Task9	**0.5944**		
Task10		**0.4768**	
Task11	**0.6858**		
Task12	**0.6974**		

Notes: The table shows the results of the principal component analysis using the set of questions presented in Table 2.A.9. Three latent factors with an eigenvalue higher than 1 are extracted. By observing the set of questions grouped in each factor, I name Factor 1 as "Complex tasks", Factor 2 as "Manual tasks" and Factor 3 as "Social tasks". The three factors respectively explain 17,8%, 16,8% and 13,3% of the total variance.

Table 2.A.11: Further robustness checks

	(1) Intensity	(2) Match	(3) Career	(4) Satisfaction
Panel a. Intermediate as a reference category				
Ref. category: *Intermediate*				
Rural	-1.93***	-0.62	-0.33	0.80**
	(0.54)	(0.58)	(0.55)	(0.37)
Urban	0.89*	2.11***	-0.06	-0.32
	(0.50)	(0.54)	(0.51)	(0.35)
Obs.	25,845	24,218	24,858	25,930
Adj. R-squared	0.12	0.13	0.13	0.07
Panel b. Post-stratification weights - Large Urban				
Ref. category: *Rural*				
Urban	2.41***	-0.10	-0.18	-0.44
	(0.68)	(0.72)	(0.68)	(0.47)
Large Urban	4.62***	2.17***	0.38	-1.35***
	(0.73)	(0.78)	(0.75)	(0.51)
Obs.	18,148	17,024	17,428	18,214
Adj. R-squared	0.13	0.14	0.14	0.07

Notes: OLS regression model with robust standard errors (in parentheses). All regressions included individual level socio-demographics and other controls plus occupation, industry and country dummies controls. ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$

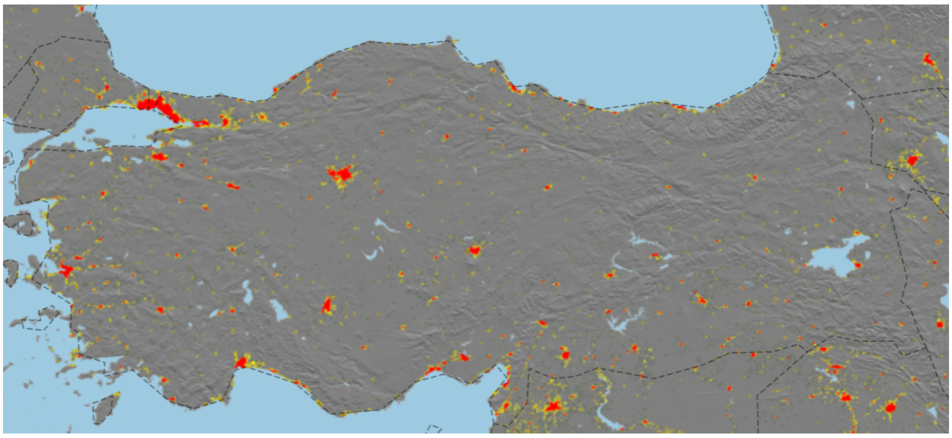
Table 2.A.12: Territorial categories per country - EWCS 2010

Country	Territorial levels*	Country	Territorial levels*
BE	**Cities**	AT	Big cities 5.000 to 50.000
BE	Strongly urbanized areas	AT	**Metro (more than 50.000)**
BE	Somewhat urbanized areas	PL	Village
BE	Rural and less urbanized areas	PL	<20.thous.
BG	Up to 500 inhabitants	PL	20 - 49 thous.
BG	501-9999 inhabitants	PL	**50-99 thous.**
BG	10000-49999 inhabitants	PL	**100-199 thous.**
BG	**Over 50000**	PL	**>200 thous.**
BG	**Capital Sofia City**	PT	<1999
CZ	Up to 4999 inhabitants	PT	2000-4999
CZ	5000 - 19999 inhabitants	PT	5000-9999
CZ	20000 - 99999 inhabitants	PT	10000-19999
CZ	**100000+ inhabitants**	PT	20000-49999
DK	Up to 10000 inhabitants	PT	**50000+**
DK	10000 - 20000 inhabitants	RO	**Capital**
DK	20001 - 50000 inhabitants	RO	**Big city - 200K inhabitants**
DK	**50001 - 500000 inhabitants**	RO	**Big town 100 - 200K inhabitants**
DK	**Over 500000 inhabitants**	RO	Medium town 30-100K
DE	Till under 5.000 inhabitants	RO	Small town - 30K Inhabitants
DE	5.000 till under 20.000	RO	Village
DE	20.000 till under 100.000	SI	Non-urban
DE	**100.000 till under 500.000**	SI	Urban area
DE	**500.000 inhabitants and more**	SI	**Maribor area**
EE	**Capital**	SI	**Ljubljana area**
EE	Other urban	SK	up to 5 thousands
EE	Rural	SK	5-20 thousands
EL	**Urban**	SK	20-50 thousands
El	Rural	SK	**over 100 thousands**
ES	up to 10000 inhabitants	FI	**Metropole-Helsinki area**
ES	10001 - 50000 inhabitants	FI	**Other big city over 50.000**
ES	**50001 - 200000 inhabitants**	FI	Medium size city 10.000-49.999
ES	**over 200000 inhabitants**	FI	Small city/town under 10.000
ES	**Madrid and Barcelona**	SE	**Stockholm/ Goteborg/ Malmo**
FR	**Paris**	SE	**60 000 +**
FR	**Big cities**	SE	25-60 000
FR	Towns	SE	0-25000
FR	Villages	UK	*Urban >10K*
IE	**Urban**	UK	*Town & Fringe*
IE	Rural	UK	*Village*
IT	up to 10000 inhabitants	UK	*Hamlet & Isolated Dwelling*
IT	10001 - 100000 inhabitants	UK	*Scotland Urban Areas*
IT	**100001 - 250000 inhabitants**	UK	*Scotland Rural Areas*
IT	**over 250000 inhabitants**	UK	*Northern Ireland*
CY	**Urban**	HR	**Zagreb**
CY	Rural	HR	**Big cities**
LV	**Capital**	HR	Small towns
LV	Big cities	HR	Villages
LV	Towns	MK	**Skopje**
LV	Village	MK	Urban
LT	**Capital**	MK	Rural
LT	Big cities	TR	up to 2000
LT	Towns	TR	2000 - 20000
LT	Village	TR	20001 - 100000
HU	**Capital**	TR	**100001 - 300000**
HU	Large cities (regional centres)	TR	**300001+**
HU	Towns	NO	Mainly primary industry
HU	Villages	NO	Mainly manufacturing industry
NL	**Very strong urbanisation**	NO	Manufacturing and service industries
	Strong urbanisation	NO	**Large municipalities**
NL	Moderate urbanisation	AL	**Urban**
NL	Little urbanisation	AL	Rural
NL	No urbanisation	KO	**Urban**
AT	Villages - up to 1.999 inhabitants	KO	Rural
AT	Towns 2.000 to 4.999 inhabitants	ME	**Urban**
		ME	Rural

Notes: The territorial categories in bold are those classified as Urban. Those categories underlined are Rural. Not that all the UK categories are in Italics. UK is deleted because of difficulties of identify a reliable urban category.

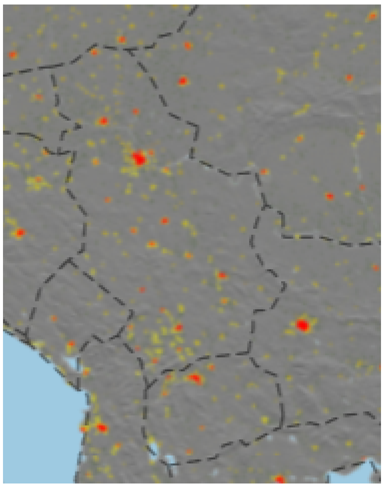
B2. Figures

Figure 2.A.1: Degree of urbanization - Turkey



Notes: Author's own elaboration. The Red characterize urban areas, the yellow intermediate while the grey includes rural areas and non inhabited areas. Turkey data are not available from Eurostat Grid file.
Source: https://human-settlement.emergency.copernicus.eu/index_op.php

Figure 2.A.2: Degree of urbanization - Serbia, Montenegro and North Macedonia



Notes: Author's own elaboration. The Red characterize urban areas, the yellow intermediate while the grey includes rural areas and non inhabited areas. Serbia, Montenegro and North Macedonia data are not available from Eurostat Grid file.
Source: https://human-settlement.emergency.copernicus.eu/index_op.php

3. Green jobs and meaningful work

Fabio Landini[1], Davide Lunardon and Alberto Marzucchi

Abstract

We investigate the perceived meaning of green jobs. Theoretically, we extend the standard meaningful work framework, by introducing a social esteem component, which depends on both the green content of occupations and the socio-political awareness of environmental issues. To identify green jobs, we employ a task-based indicator based on ESCO data, which is then merged with individual-level data from the 2015 and 2021 waves of the European Working Conditions Survey. Moreover, we proxy the degree of environmental consciousness at the country level through the Environmental Policy Stringency index from the OECD. In line with our theoretical framework, we find that workers' perceptions of meaningful work increase with the green content of their occupation and are amplified in countries exhibiting higher levels of environmental consciousness. These results highlight the role of social esteem, derived from the contribution to what is considered a socially valuable objective (i.e. the fight against climate change), in shaping the experience of meaningful work. To allow a more 'causal' interpretation of the results, we employ an instrumental variable approach which corroborates the main findings.

Keywords: Meaningful Work, Green Jobs, Social Esteem, Green Transition, EWCS

JEL Codes: J24, J28, O31, O33, Q20, Q40

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3.1 Introduction

Climate change is one of the greatest threats humanity is facing. Adverse natural phenomena directly linked to it are having enormous impacts on all fronts of the economic, social and political life (Falk et al., 2021). This evidence has raised growing concerns about environmental issues in many segments of the global population (Andre et al., 2024). A recent poll by Eurobarometer (2021), for instance, reports that 93% of the European respondents think that climate change is a serious problem, and 18% view it as the most serious problem facing the world today. While such concerns, and the related emergence of pro-environmental norms and values, are expected to affect economic decisions along many dimensions (often going beyond standard variables such as prices and taxes,(see Besley and Persson, 2023)), the interest of researchers so far has focused primarily on studying these effects on consumption (Nyborg et al., 2006; Kotchen, 2006; Besley and Persson, 2019; Bezin, 2019). Much less attention, instead, has been devoted to investigate how pro-environmental attitudes shape individual orientations toward production activities, including work. For instance, we still know very little about how individuals value their involvement in work activities that can be beneficial to the environment and how such valuations are shaped by cultural and social norms.

This paper starts to fill this gap by studying whether the green content of occupations contributes to the individual perception of meaning at work. The idea that work means something more than the simple provision of labour services in exchange for a wage has a long tradition in political economy and institutional economics thinking. Marx (1967), for instance, originally viewed non-alienated work as a key activity to realize the full potential of human beings. Similarly, Veblen (1898) highlighted the importance of work in the development of human character and well-being.[2] After decades of reduced popularity, the concept of meaningful work has regained centrality in economic research both theoretically (Cassar and Meier, 2018) and empirically (Nikolova and Cnossen, 2020; Nikolova et al., 2024). Under the influence of contributions from social psychologists, most notably self-determination theory (Deci and

[2]For a discussion of the concept of work meaning in classical political economy see Spencer (2015).

Ryan, 1985), a growing number of authors have questioned minimalist views based on the simple trade-off between (disutility of) work and leisure (Spencer, 2015). Rather, it has become common to see humans as having an innate need to make sense of work activity (Chater and Loewenstein, 2016), deriving intrinsic benefits from it (Kaplan and Schulhofer-Wohl, 2018; Akerlof and Kranton, 2005). Although in most of these contributions the sources of meaning are found primarily in specific dimensions of work organizations (Cassar and Meier, 2018), our focus is instead on the content of the occupations and the extent to which the latter receive social recognition for their contribution to fight climate change.

Theoretically, we build our argument by integrating two main streams of literature. We begin with the model proposed by Cassar and Meier (2018), which conceptualizes the meaningfulness of work as a function of various job design characteristics, including competence, relatedness, and autonomy in decision-making. This model has so far guided most empirical economic research on work meaningfulness (Burbano et al., 2024; Nikolova et al., 2024, 2023). To study the role of occupation's green content, we extend this original setting taking advantage of insights from the employment relations literature pointing at the relevance of drivers of work meaning that go beyond the design of individual jobs (Laaser and Karlsson, 2022). In particular, we rely on recognition theory (Honneth, 1995) to emphasize the role played by social esteem, i.e., the intersubjective acknowledgment of one's contribution to a common-valued project, in fostering individual perceptions of meaning at work. In our framework, jobs are viewed as key drivers of workers' experience of social esteem (Dejours et al., 2018; Honneth, 2012), and the fight against climate change constitutes the collectively valued project to which green occupations directly contribute.

More specifically, we put forward two main research hypotheses. First, we suggest that the self-perception of work meaning increases with the green content of occupations. Second, we argue that such a positive relationship varies depending on the green-related social norms that are prevalent in a given social context. In fact, following Honneth (1995), we suggest that what counts as a valuable and esteem-worthy project is the product of ongoing social and political struggles whose scope and results extend beyond the realm of specific organizations. In those contexts in which such struggles lead to the emergence of social orientations valuing the preservation of the environment as a political priority, we expect the green occupational content to exert a stronger influence on work meaning than elsewhere.

We test these predictions by making use of a composite mix of data. In particular, we rely on three main data sources. Firstly, we develop an indicator of green jobs using the green skills information from the European Multilingual Classification of Skills, Competence and Occupation (ESCO). Secondly, we measure the individual perception of work meaning by relying on worker-level data available from the European Working Condition Survey (2015 and 2021) (for a similar approach see Nikolova and Cnossen, 2020). Finally, we use the country-level Environmental Policy Stringency Index from OECD (Kruse et al., 2022) as a proxy of environmental protection being a political priority across countries.

Our results show that an increase in the green content of occupations correlates positively with the perception of meaning at work. Moreover, once investigated in a broader social and political context, such association is in place only in countries with a higher incidence of environmental policy stringency. These results are broadly consistent with the idea that social esteem for green workers is driver of perceived work meaning, particularly in countries where society views the fight against climate change as a valuable social project. To further support our analysis in causal terms, we adopt an instrumental variable approach, using the incidence of tasks related to the evaluation of quality standards as an instrument for whether an occupation qualifies as a green job. The rationale is that green jobs may involve tasks related to implementation of standards directly linked with quality, either coming from regulatory frameworks - e.g. associated with the use of energy and materials - or from the assessment of environmental impact and carbon footprint of products and processes. For an average worker, quality checks should not directly affect the perceived work meaning. The results of our IV estimates confirm our main findings.

The paper contributes to two main streams of literature. First, it contributes to empirical studies on the perception of meaning at work. The literature has shown that perception of doing a meaningful work impacts on several measures of work performance, including effort and productivity (Ariely et al., 2008; Rosso et al., 2010), and is associated with later retirement decision, less absenteeism and increasing likelihood to participate in skill development training (Nikolova and Cnossen, 2020). While previous works have focused primarily on investigating the individual determinants of work meaning (Nikolova and Cnossen, 2020) or, using experimental settings, on how changes in the meaning of work activities affect effort, productivity and labour supply (Ariely et al., 2008), our study focuses instead on the relationship between occupation's green content and meaningful work. As mentioned by Eurofound (2024), this relationship is crucial to understanding the impact of the green transition on the workplace and to capture the motivation of workers in relation to it. Furthermore, by investigating how political factors moderate the individuals' perceptions of work meaning, this paper underpins the importance of taking into consideration the broader societal values when investigating meaningful work. In our setting, these broader societal values are captured by the introduction of explicit public interventions aimed at preserving the quality of the natural environment. From a policy viewpoint, our results are particularly relevant as they suggest that the perceived meaning of green occupations is partly shaped by the social and political contexts in which workers operate, thus opening important avenues for public interventions in this field.

Second, our work contributes to the literature by providing an application of ESCO-derived data to investigate EU(-wide) labour market features and dynamics, more particularly by looking at the distinctive characteristics of green jobs (Dierdorff et al., 2009; Consoli et al., 2016; Vona et al., 2018, 2021). Indeed, while the approach is not totally new but rather based on Vona et al. (2018), it is important to stress that only a few articles have engaged in the development of a green jobs indicator for Europe. Based on cross-referencing classifications at the occupational level, US O*NET data on green jobs have been applied in various contexts beyond the US, including for the Netherlands (Elliott et al., 2024), multiple European countries (Eurofound, 2024), and Latin America (Winkler-Seales et al., 2024). In a recent contribution Maldonado et al. (2024) compare how the classification of green jobs changes using O*NET or ESCO: compared to EU-based data and classification, O*NET over-represents green jobs with a high-skills content. We rely on a finely grained measure of green jobs (4-digit ISCO level), which allows us to provide a detailed analysis of the characteristics and distribution of green employment across Europe, and makes it possible the merger with a reference source of data to investigate the quality of work (i.e. the European Working Condition Survey).

The remainder of the paper is structured as follows. Section 2 develops the conceptual framework. Section 3 discusses the various data sources employed. Section 4 focuses on the construction of the key variables. Section 5 outlines the empirical strategy, while Section 6 presents the main results along with robustness checks. Finally, Section 7 concludes.

3.2 Conceptual Framework

3.2.1 Meaningful work in the social sciences

Over the past decade, scholarly inquiry into the nature, implications, and future trajectories of meaningful work has expanded significantly, giving rise to heterogeneous and vibrant debates across the social sciences (Bailey et al., 2019; Yeoman et al., 2019; Laaser and Karlsson, 2022; Nikolova and Cnossen, 2020). This growing body of work has increasingly informed the agendas of international organizations, as reflected in the many campaigns advocating the creation of decent and purposeful jobs in modern economies (ILO, 2017). Despite such an upsurge in interest, however, the field remains relatively blurred as far as the definition and drivers of work meaning are concerned (Laaser and Karlsson, 2022).

Among economists, the concept of 'meaningful work' is usually associated with how purposeful and worthwhile individuals perceive their working activities (Nikolova and Cnossen, 2020) and how they search for the opportunity for self-development and personal fulfilment (Spencer, 2015). Being partly inspired by concepts originating in the field of organizational psychology (Rosso et al., 2010), this conceptualization represents a clear departure from the most standard economic approaches, which see work activities mainly as a source of dis-utility, valued primarily for its monetary compensation (Spencer, 2015). Against this background, scholars focusing on the meaning of work put forward the idea that humans have an innate need to make sense of the activities they perform (Chater and Loewenstein, 2016) and the output they produce (Besley and Ghatak, 2018; Ariely et al., 2008), with individual jobs that often become an integral part of the workers' own identity (Akerlof and Kranton, 2005). This alternative view is significant not only for offering a more comprehensive framework to analyse individual motivation to work (Chadi et al., 2017), but also for its implications for the design of incentives within organizations (Kosfeld et al., 2017).

In terms of drivers, economic interpretations of meaningful work emphasise the extent to which job designs fulfil the three psychological needs at the basis of individual self-determination, namely autonomy, competence and relatedness (Deci and Ryan, 1985, 2000).

Autonomy highlights the value of having control over tasks and decision-making within one's role. Competence emphasizes the importance of having a job that allows workers to express skills and knowledge. Relatedness underscores the significance of working in a positive environment, fostering strong relationships with peers and superiors (Cassar and Meier, 2018). By focusing on these three characteristics of job designs, Nikolova and Cnossen (2020) conducted an extensive empirical study using worker-level information for a variety of European countries, finding strong support for a positive association between these dimensions and the individual perception of work meaningfulness.

Although self-determination is clearly an important component of life meaning, and work organization has a direct impact on it, economic approaches to work meaning tend to limit the analysis of its determinants primarily to the features of job design. Such an approach contrasts with the views prevailing in other streams of the social sciences, which have emphasized the importance of drivers that extend beyond objective work and job conditions. In the field of humanities, for instance, several contributions highlight the inter-subjective nature of work meaning and the necessary match of workers' interests with broader societal needs that makes work purposeful, worthy and unifying (Laaser and Bolton, 2022). In this framework, the experience of meaningful work is viewed as an 'authentic connection between [...] work and a broader transcendent life purpose beyond the self', which is achieved whenever individuals perceive their work 'invokes the greater good in terms of societal or economic benefits' (Bailey and Madden, 2017, p. 4). Similar views also emerge in sociologically informed industrial relations contributions, which draw attention on enablers of the meaning of work operating at the regulatory and employment levels (Laaser and Bolton, 2022). For instance, Kalleberg and Marsden (2019, p. 45) conceptualize the meaning of work as 'opportunities to exercise autonomy and to help others and society,' emphasizing the objective conditions that make the experience of meaning possible.

One particularly prominent approach linking work meaningfulness to the broader social context in which jobs are carried out is recognition theory. Based on the seminal contribution by Honneth (1995), this theory conceives self-realization, a precondition for a meaningful life, as depending on a set of interrelated patterns of recognition encompassing three domains of social relationships, namely love, respect and social esteem. While the former two pertain to domains of recognition associated with non-economic (e.g., familial) and right-based (e.g. legal) relationships, respectively, social esteem rests on the central role that waged work plays in the industrially organized division of labour, understanding work as one of its key determinants (Fraser and Honneth, 2003). In contrast to job design approaches, views grounded on recognition as social esteem relates work meaningfulness with the inter-subjective acknowledgment of individuals' particular traits, abilities and contributions to commonly valued projects. Which project counts as a valuable one and, as a consequence, which trait is esteem-worthy, is not given, but rather it is a by-product of on-going social and political dynamics within and beyond the specific organizations. In other words, it represents a contested field in which constant struggle for recognition is inherent (Honneth, 1995).

With respect to our analysis, recognition theory offers a valuable framework for understanding how individual involvement in green-related activities contributes to the perception of meaning at work. First, recognition theory enables us to consider the content of individual jobs, along with their design, among the key drivers of work meaningfulness. Indeed, for any given level of autonomy, competence and relatedness, recognition theory postulates that the individual perception of work meaning may vary depending on how the job-specific skills and abilities (i.e., job content) foster recognition as social esteem. Second, this theory links recognition as social esteem to the perceived contribution of individual jobs to what are generally conceived as socially valuable projects. The fight against climate change, along with many others, can be broadly considered as one of them, thus establishing a link between the green content of occupations and the perception of work meaning.

3.2.2 Green jobs, social esteem and work meaning

To further elaborate our argument, we integrate the job-design and the content-based views of work meaning into a single framework through the following function:

$$M = D(\boldsymbol{\alpha}, \mathbf{x}, e) + C(\boldsymbol{\beta}, s(g, p, \mathbf{z}), e), \tag{3.1}$$

where M is the perceived degree of meaning of work, while $D(\boldsymbol{\alpha}, \mathbf{x}, e)$ and $C(\boldsymbol{\beta}, s(g, p, \mathbf{z}), e)$ represent the job design and the job content components, respectively. Based on self-determination theory (Deci and Ryan, 1985) we assume the contribution of job design to depend on the three-dimensional vector $\mathbf{x}$ capturing the characteristics of the job in terms of autonomy, competences and relatedness. In our analysis, the latter are considered exogenously chosen by the employer and affect the perception of the meaning of work through the vector $\boldsymbol{\alpha}$ capturing the weight assigned by each worker to each of the job-design dimensions. Following recognition theory (Honneth, 1995), we assume the content-based component C to be an increasing function of social esteem $s(g, p, \mathbf{z})$ (i.e., $c_s > 0$), where g is the green content of the occupation, p is the incidence of policy measures and social norms fostering the fight against climate change as a socially valuable project and $\mathbf{z}$ is a vector of job-specific characteristics affecting social esteem on top of green-related attributes (e.g. skill level). $\boldsymbol{\beta}$ represents the individual-specific weight through which social esteem affects the meaning of work. Note that both D and C are assumed to depend on work effort e, reflecting the idea that work meaning is an intrinsic aspect of one's job—one that unfolds effectively only when work activities are actively carried out (for a similar approach see Cassar and Meier, 2018).[3]

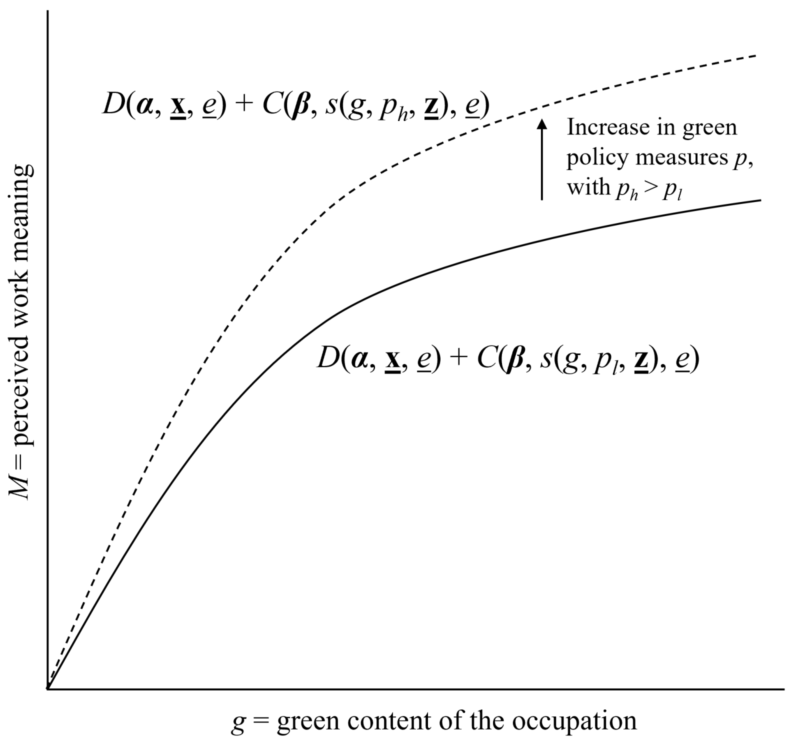
Given this framework, we present a set of theoretical propositions on the relationship between s, g and p (see Figure 3.1). First, we suggest that, everything else equal, social esteem s increases with the green content of occupation g (i.e., $s_g > 0$). A variety of arguments provide support for this prediction. In the framework of recognition theory, for instance, Laaser and Karlsson (2022) highlight the intersubjective admiration and appreciation at the horizontal level of skills and tasks involved in the labour process as key drivers of social esteem and, thus, meaning of work. Although these authors emphasize patterns of recognition occurring primarily among co-workers (as opposed to vertical recognition between supervisors and subordinates), it is reasonable to expect that for some jobs intersubjective admiration and appreciations may extend beyond the organization, involving the society at large. Along these lines, an extended literature in social psychology and behavioural economics has indeed documented that jobs to which society attributes a broadly recognized social mission are more likely to foster individuals' drive for social esteem and meaning of life, framing their actions as part of a bigger social context (see Cassar and Meier, 2018). The model assumes a concave relationship between green job content and perceived work meaning, implying diminishing marginal returns.

Based on these insights, we expect the individual involvement in occupations characterized by some positive degree of green content to be the source of admiration and appreciation by the society for their contribution in preserving the natural environment, which in turn fosters social esteem and thus the perception of work meaning. Also, we expect this positive association to hold regardless of the skill level of the occupation (i.e., controlling for $\mathbf{z}$). While this prediction may seem straightforward for certain jobs —for instance, high-skilled intellectual occupations such as environmental engineers involved in designing large-scale, high-visibility green projects (e.g., renewable energy farms, industrial recycling plants)— it may be less obvious for others. Indeed, a broad range of low-skilled manual occupations is characterized by

[3]For the sake of simplicity we decided to model work meaning as an additive function of D and C. However, a more general model could obviously take a different approach, without gaining much in terms of our empirical analysis, which essentially aimed to estimate the contribution of g and p to the meaning of work.

direct involvement in green-related activities. However, these occupations are usually granted with a lower degree of social visibility, which may reduce the chances to receive direct acknowledgment for their contribution to the greening of the economy.

Figure 3.1: Meaningful work, green occupational content and climate-mitigation policy



Notes: The figure shows the hypothesized relationship between perceived work meaning (M), social esteem (s), occupation's green content (g) and intensity of green policy measures, for any given level (lower bar) of the other variables ($\mathbf{x}$, e, $\mathbf{z}$, e). The larger the green content of the occupation, the higher the recognized social esteem ($s_g > 0$) and thus the greater the perceived work meaning. Moreover, we suggest the increase in social esteem and work meaning associated with a marginal increase in green content is larger, the higher the incidence of green policy measures (i.e., when p increases from p_l to p_h.

On this respect, however, some evidence from qualitative case studies helps to support our proposition also for low-skilled green jobs. In a recent study of a group of English refuse collectors, for instance, Bailey and Madden (2017) show that awareness of their occupation's contribution to the preservation of the natural environment plays a key role in shaping workers' perceptions of social esteem and the meaningfulness of their work. Although they perform largely unskilled manual labour, with job design features such as lack of competence and autonomy in decision making, refuse collectors do report a sense of pride in performing a job that is perceived as contributing to the common good (for example, one worker is reported to say 'I'm actually doing something for the public and for the environment', p. 8). Moreover, they place particular emphasis on recognition patterns that go beyond the workplace, ultimately extending across multiple generations of society.[4] These insights point to the green content of the occupation as a factor that is perceived as shaping social esteem and work meaning *per se*, over and above the contribution stemming from the skill level and job design characteristics of the profession.

At the same time, however, the extent to which being involved in a green job is worthy of social esteem does not depend only on the perceptions of the individual workers. Rather, it depends on the recognition of his/her job as contributing to a project that is considered valuable also by the rest of the society. Far from being granted, such recognition is often the result of political and social processes through which green-related interventions manage to achieve a sufficient degree of public legitimacy. For this reason, the second proposition that we put forward is that the positive contribution of occupation's green content to social esteem and work meaning varies depending on the context. More specifically, we expect it to be more relevant in those contexts in which the high incidence of green-related policy measures promotes the fight against climate change as a commonly valued social project (i.e., $s_{gp} > 0$).

Once again, we ground this proposition on a set of theoretical considerations. First, as emphasized by a long tradition of research in electoral competition and political economics (Persson and Tabellini, 2002), there exists a link between the adoption of specific policy measures at the country level and the importance that specific issues have for the underlying population of voters. In these views, the emergence of a political commitment toward the pursuing of a specific policy agenda is often considered an indication that the underlying policy issue ranks high among the set of social priorities. With reference to climate mitigation policies, for instance, Brennan et al.

[4] For instance, when asked about the meaningfulness of his work one refuse collector is reported to say: 'Every day you are doing something for the environment ... I still feel it's important that I contribute [by recycling] because I've got grandchildren who are going to have grandchildren. It affects [the] next generation coming up.' (Bailey and Madden, 2017, p. 11).

(2020) establish an explicit link between their introduction at the macro level and a set of pro-environmental pressures and actions operating at the micro level, which ultimately contribute to shape the commitment of national authorities to address climate change. On this basis, it is reasonable to expect that where environmental policies are more stringent, the social recognition of climate mitigation as a valuable social endeavour is stronger. Consequently, also individual participation in green jobs is more likely to be regarded as worthy of social esteem, thus fostering its association with work meaning.

Second, it is important to acknowledge that the positive association between the commitment of policy makers to green policy interventions and the perceived contribution of green occupations to social esteem and work meaning can be further reinforced by the gradual adaptation of social norms and individual preferences to emerging policy frameworks. Indeed, a growing number of recent studies explicitly account for the processes through which pro-environmental norms and values consolidate in populations that are recurrently exposed to changes in climate-related policy regimes. In a dynamic model of cultural evolution, for instance, Besley and Persson (2023) relate the acquisition of green attitudes and values in a population of consumers to the economic incentives introduced by green policy initiatives and the firm choices implemented within the economy. Mattauch et al. (2018) takes a similar approach in examining the impact of climate policy-induced changes on consumers' values. More generally, Besley and Persson (2019) model environmentalism as a cultural phenomenon that co-evolves with policies aimed at protecting society from the climate risks. Based on these contributions, it is reasonable to expect that not only green attitudes and social norms may influence pro-environmental policymaking, but also the reverse may hold. Namely, increasing political commitment to environmental protection may foster the spread of green values across society, reinforcing the recognition of green jobs as worthy of social esteem. This may ultimately strengthen the related perception of work meaning.

3.3 Data

3.3.1 Overview

To test our theoretical predictions we rely on three main data sources. The first is the European Working Condition Survey (EWCS), which provides comprehensive worker-level information and a detailed occupational classification at the ISCO 4-digit level[5]. The latter is used to build an indicator of green jobs relying on the European multilingual classification on Skills, Competence, and Occupation (hereafter ESCO), which contains information about green skills at the occupation level. Lastly, to investigate the role of the policy context, we use the Environmental Policy Stringency Index (hereafter EPS), a country-level indicator, produced by the OECD. In the following subsections, we provide some further details for each of these sources.

3.3.2 EWCS

The EWCS is a well-known database for studying working conditions and job quality in Europe (see, for example, Aleksynska, 2018; Nikolova and Cnossen, 2020; Belloc et al., 2022; Nikolova et al., 2024). Conducted every five years since 1990, the EWCS is an interview-based survey that covers a representative sample of workers, comprising roughly 44,000 observations per wave. One of its key advantages is that it provides harmonized cross-country information on working conditions, individual attributes, task environment and occupational codes. This allows us to compute individual-level indexes of job meaning and relate them to occupation-specific measures of green content.[6]

In this study, we consider only the last two waves of the EWCS, namely 2015 and 2021. This choice is motivated by the need to minimize the time gap between the classification of green jobs based on ESCO (see below) and the measurement of work

[5] We are grateful to Eurofound for granting access to a secure version of the survey including the 4-digits ISCO codes.

[6] To ensure the representativeness of the working population, EWCS uses complex sample strategy for the selection of workers which ensure the randomness of the selection. Each individual has the same non-zero probability to be selected (Eurofound, 2016, 2022*b*).

meaning. While the previous editions (including the 2015) were carried out through face-to-face interviews, the 2021 survey, due to COVID-19, was conducted via the telephone.[7] This implies that caution is needed when combining data from these two waves. Following Nikolova et al. (2024), we address potential distortions arising from differences in survey methods by including year fixed effects. Moreover, we account for differences in sample size across waves and countries by including post-stratification weights as well as country sample size weights in some of our regressions (see below).

To enhance the reliability of our results, we conduct data cleaning and apply sample restrictions based on sectoral and occupational criteria prior to empirical analysis. More precisely, we exclude the agriculture and public administration sectors, along with their related occupational categories (Consoli et al., 2016), as well as the sector of extra-territorial activities and defence-related occupations. Moreover, we refine the sample by focusing only on an age range that better includes the active population: from 18 to 70 year old people. Finally, we focus on countries surveyed in both waves. The final sample amounts to roughly 75,000 individual level observations distributed among 34 countries, all the EU-27 countries plus the UK, Norway, Switzerland, Albania, Serbia, North Macedonia and Montenegro. Table 3.A.1 shows the number of observations per country and year.

3.3.3 ESCO - Green Skills

ESCO works as a dictionary to describe, identify and classify professional occupations and skills that are relevant for the EU labour market (ESCO, 2019). It provides very detailed information on about 3,000 occupations, which are defined as sets of "jobs whose main tasks and duties are characterized by a high degree of similarity". ESCO occupations are organized hierarchically based on the International Standard Classification of Occupations (ISCO) and they are subdivided into several levels from five to eight digits. Each occupation is characterized by an extremely rich set of skills, representing abilities "to apply knowledge and know-how to complete tasks and solve

[7] For more details see Eurofound (2022*a*).

problems".[8]

In this study, we use two versions of ESCO, specifically the first version launched in April 2018 (v1.0.3) and the latest version launched in the early 2022 (v1.1.0).[9] The latter provides a list of skills labelled as "green" aligning with the necessity for the EU Commission to map the presence of green jobs within the EU area following the launch of the European Green Deal Plan in 2019 (ESCO, 2022).[10] To classify skills as green, ESCO followed a multiple-steps procedures starting from the 'operationalization' of the Cedefop (2012) definition of green skill as "the knowledge, abilities, values and attitudes needed to live in, develop and support a society which reduces the impact of human activity on the environment" (ESCO, 2022). Overall, in the 2022 ESCO version, 384 skills are labelled green, representing approximately 3,5% of the total. When we apply the same definition of green skills to the 2018 ESCO version, we are able to identify 269 skills amounting to 2.5%. Table 3.A.2 in the Appendix shows a list of the most frequently occurring green skills across occupations.

3.3.4 Environmental Policy Stringency Index

The final data source that we use is the Environmental Policy Stringency Index (EPS), which provides a proxy for the incidence of policy measures that promote the fight against climate change as a socially valuable project in countries. EPS is produced by OECD to facilitate cross-country comparisons while considering the multifaceted aspects related to environmental policies. It is a unique composite indicator that combines market, non-market, and policy-based aspects related to environmental protection (Kruse et al., 2022).[11] Since its creation, it has been used in several

[8]ESCO includes another construct, i.e. "knowledge", which is defined as "the body of facts, principles, theories and practices that is related to a field of work and study". We exclude knowledge from the analysis because it does not capture any effective tasks. Indeed, while every occupation might require knowledge that can be considered "green", this does not imply that such green competences are then also applied.

[9]https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/esco-v1

[10]https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/esco-v11

[11]Taxes and trading schemes systems on pollution are example of market-based instruments. Emissions limits and standards on nitrogen, sulphur and particulate are examples of non-market measures. Finally, public expenditure in R&D and support for renewable energy such as solar and

empirical studies (Martinez-Fernandez et al., 2010; Marin and Vona, 2019; Benatti et al., 2024; Hassan et al., 2024). Figure 3.2 shows the evolution from 1990 to 2020 of the indicator using a restricted group of countries. Interestingly, the graph shows how EPS has increased during the last decades, particularly between 2000 and 2010, confirming the growing concerns of governments within the OECD area for environmental issues. Also, starting from 2010, there emerges a stable heterogeneity across countries in terms of environmental policy stringency, which can supposedly reflect different attitudes toward environmental protection in these countries. We exploit this heterogeneity to investigate the role of the policy context in shaping the relationship between green jobs and work meaning.

3.4 Variables

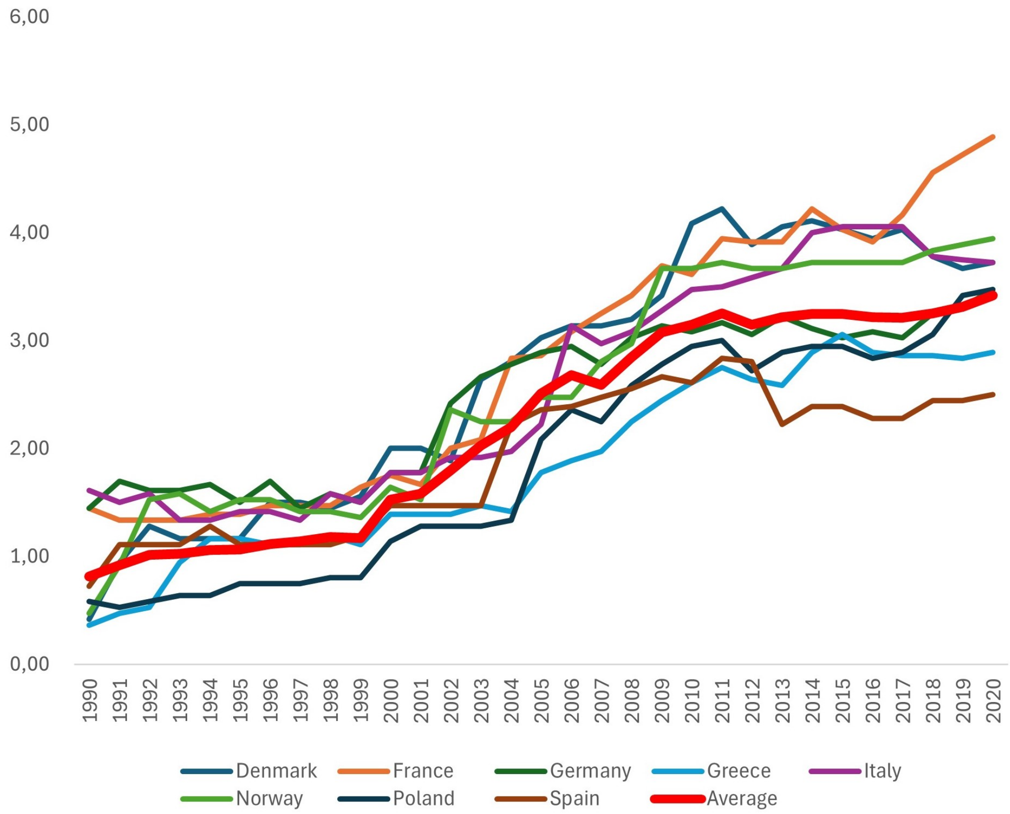
3.4.1 Occupation's green content

Our first variable of interest is the green content of occupations, which we measure following a task-model approach à la Vona et al. (2018). In this approach, occupations are conceptualized as a "bundle of tasks" and serve as a primary unit of analysis to identify what workers do in their job. Green jobs are identified by measuring the 'greenness' of the occupation, which is expressed as the ratio of green skills to the total skills. We begin by computing this indicator at the 5-digit ESCO level. This gives us a highly detailed classification that covers a total of 1,682 and 1,761 occupations in 2018 and 2022, respectively.[12] To enable a merge with EWCS data, we then aggregate this indicator at the 4-digit ISCO level, exploiting the direct correspondence between the ESCO and ISCO classifications. More specifically, for any given set of 5-digit occupations within a 4-digit ISCO group, we compute the average greenness (g) as follows:

wind, in clean technologies and their adoption are examples of policy-based dimensions.

[12]For comparison, the O*NET database, one of the most commonly used sources to compute task-based metrics in the US, includes around 1,000 occupations at its most detailed 8-digit level.

Figure 3.2: Evolution of EPS across countries, 1990-2020



Notes: Own elaboration on OECD data. The EPS index captures a composite set of interventions combining market, non-market and policy based aspects related to environmental protection. For more detail see Kruse et al. (2022). For the sake of clarity, the analysis is restricted to a selected gorup of countries.

$$g_{i_{(4dig)}} = \frac{1}{n} \sum_{i_{(5dig)}=0}^{n} g_{i_{(5dig)}} \tag{3.2}$$

where n is the number of 5-digit occupations included in the higher order 4-digit group.

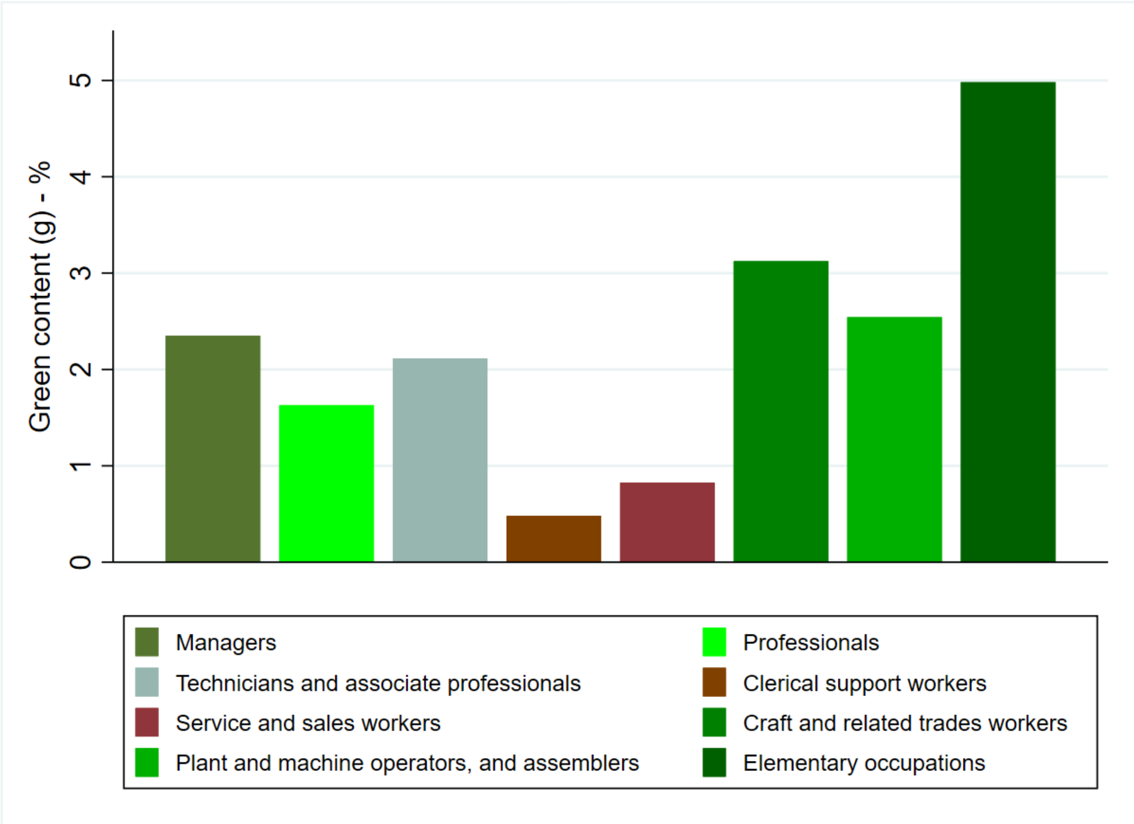
Our final indicator captures the average green content of the ISCO 4-digit occupations. Following Vona et al. (2018), we interpret these metrics as a proxy for the relevance of job-related activities that reduce the impact of human activity on the environment. While we acknowledge the limitations of this approach, particularly the aggregation from 5- to 4-digit classifications, we contend that it delivers one of the most detailed green job indicators currently available for the European context. In this regard, a study we are aware of that uses a measure of greenness at the 4-digit level is Elliott et al. (2024). However, the latter study identifies green jobs relying on the O*NET classification, raising concerns about the validity of using green metrics computed on US data to study the European context Maldonado et al. (2024). The existence of institutional differences between the US and Europe undermines the possibility of directly inferring occupational content based on data collected in another country.

Table 3.A.3 in the Appendix shows the 20 occupations with the highest green score. Overall, out of the total of 426 occupations, 215 have at least one green skill. Among the occupations with the highest green score we have 'elementary' occupations such as waste sorters and collectors, 'professionals' such environmental engineers; 'technicians and associated professionals' such as incinerator and water treatment plant operators, as well as manufacturing managers; and 'craft and related trade workers' such as building structure cleaners. Figure 3.3 reports the distribution of the green score across macro occupational groups.

3.4.2 Work meaning and additional controls

Our main empirical goal is to relate occupation's green content (g) to the perception of work meaning (m). To measure the latter, we follow Nikolova and Cnossen (2020)

Figure 3.3: Incidence of green content across occupational groups



Notes: Owns elaboration on EWCS and ESCO data. Grenness is measured as the share of green skills over the total number of skills associated with the occupation. This measure is first computed at the 5-digit ESCO level and then aggregated at the 4-digit ESCO and ISCO level. The praph reports the mean value of this greenness indicator across macro (1 digit) occupational groups.

and perform a polychoric principal component analysis (PCA) on two questions of the EWCS asking respondents to state whether the following two statements best describe their work: a) your job gives you the feeling of work well done and b) you have the feeling of doing useful work. The first statement captures the individual source of fulfillment with the working activity, while the second one is a proxy of the social 'utility' perspective. After the PCA, we extract the first component that accounts for more than the 80 % of the variation and, for easing the interpretation, we rescale it from 0 (low) to 100 (high).[13]

In addition to the green content of the occupation, the perception of the meaning of work is affected by the characteristics of job design (D), which can be broadly associated with the features emphasized by self-determination theory (x). To account for the latter, we refer again to Nikolova and Cnossen (2020) and build a set of metrics capturing the dimensions of autonomy, competence and relatedness. While we are able to follow integrally the approach used in the original paper using EWCS 2015 data, we need to adopt some adjustments for the EWCTS 2021 version. All details of the changes are explained in Table 3.A.4.

A series of other controls, summarized in Table 3.A.5, complement the analysis. In line with the model developed in Cassar and Meier (2018), which postulates that the meaning of work depends on effort (e), we include the log of weekly hours worked as a proxy for labour supply. Subsequently, we control for the extrinsic rewards of work, including career perspective, individual recognition and the monetary compensation.[14] With respect to our main regressor, these controls help to attenuate concerns regarding the sorting of workers into green jobs. For instance, being in high demand, green jobs might offer greater career prospects as well as wage premia.[15] Both aspects could also be correlated with the perception of the meaning of work. Finally, the inclusion of a variable capturing individual recognition—constructed from

[13]In the Appendix C and D sections are shown more details with respect to the output of the PCA and some descriptive statistics about meaningful work by occupational groups (ISCO 1-digits) and by country-years levels.

[14]Unfortunately, the latter is available only for EWCS 2015.

[15]Some descriptive evidence from US suggest a wage premium (Vona et al., 2019). A more recent paper finds a green wage premium for Japan (Kuai et al., 2025).

the survey question "I receive the recognition that I deserve from my work"—allows us to control for one's preference for being recognized in the workplace.

A set of standard worker-level controls is also included, capturing key sociodemographic characteristics such as age, biological sex, tertiary education achievement, and work tenure. These variables have been widely used in prior studies on meaningful work (Nikolova and Cnossen, 2020; Burbano et al., 2024), and are essential in this context for several reasons. First, green jobs are held predominantly by men; second, younger generations tend to show greater environmental awareness (see, e.g., Eurofound, 2024; Maldonado et al., 2024); and third, green jobs typically demand higher levels of human capital, both in terms of formal education and work experience (Consoli et al., 2016).

In addition, we include controls for firm size and private ownership. The former acknowledges potential concerns that environmental regulations tend to be more stringent for larger companies (Calel and Dechezleprêtre, 2016; Borghesi et al., 2020), while the latter rule out the possibility that individuals who are more environmentally conscious are disproportionately employed in the non-private sector, such as public and non-profit organizations (Besley and Ghatak, 2018). Finally, we include occupations (ISCO 1-digit level), industry (NACE rev2.2 at 2-digit), country and year fixed effects. We use occupation at 1-digit to remove the common broader occupational characteristic, allowing to have a cleaner green skills - work meaning relationships, while avoiding the risk that a more detailed classification could result in numerous groups with either no or only green occupations. Industry controls are crucial to capture the differences in environmental regulations, which are often specific to the industrial sectors and the output produced (Brennan et al., 2020; Eurofound, 2024). Finally, countries dummies help to rule out any potential aspect related to differences in broader labour market institutions. Table 3.A.6 presents the summary statistics.

3.5 Empirical strategy

The empirical analysis consists of two main parts. First, we explore whether our theoretical prediction on the existence of a positive association between occupation's green content and the perception of work meaning is supported by the data. Second, we investigate the extent to which such an association gets comparatively stronger in contexts characterized by higher incidence of policy measures promoting the protection of the environment as a valuable social goal. In both cases, we rely on standard linear models with clustered standard errors at the occupation 4-digit level.

More precisely, we begin by estimating the following model:

$$M_{izjct} = \gamma + X_i'\alpha_1 + \alpha_2 e_i + \beta_1 g_{occ} + Z_i'\beta_2 + \phi_z + \lambda_j + \sigma_c + \varphi_t + \varepsilon_{occ} \tag{3.3}$$

where subscripts i, z, j, c and t denote the individual, industry, country and time, respectively; M_{izjct} is the measure of work meaning; X_{izjct} is a vector capturing the features of job design in terms of autonomy, competences and relatedness; e_{izjct} is the work effort; g_{occ} (4-digits occupation) is the occupation's green content; Z_{izjct} is a vector accounting for extrinsic rewards (career perspective, individual recognition, monetary compensation), individual-level socio-demographics and firm-level characteristics, $\phi_z, \lambda_j, \sigma_c, \varphi_t$ refer respectively to occupation, industry, country and time dummies, and ε_{occ} is the error term clustered at the occupation 4-digit level.

In the second part of the analysis, we explore the heterogeneity of the effect associated with g_{occ} across countries with varying incidence of green-related policy measures. We begin by splitting the countries into two groups depending on the value of the EPS index (p). EPS is high (low) when the mean value of the country for the three years before the EWCS wave is higher (lower) than the sample mean. We decided to make the average over multiple years because we acknowledge that environmental regulations might take years to implement. [16] Figure 3.A.1 shows a map of the coun-

[16] All the split-sample estimations (High vs Low EPS) are repeated using the median value instead of the mean value of EPS. The results remain coherent across all specifications.

tries based on the high vs. low EPS split. To investigate the heterogeneous effect of g_{occ} we re-estimate model (1) on the two country groups separately. Since EPS data are not available for all the countries included in the EWCS, in running these estimates we experience a slight reduction in the number of observations compared to the baseline.

Notwithstanding the inclusion of a set of controls drastically reduces the sorting concerns, some endogeneity concerns still remain. These relate to unobservable characteristics that drive sorting as well as some potential measurement errors, which may derive from the aggregation from 5 to 4 digit occupations when creating a green score that is amenable for EWCS data (see Section 4.1). To mitigate these issues, we conclude the analysis by resorting to an instrumental variable approach. We build an occupation-level (4-digit ISCO) instrument that captures the probability for an occupation to follow precise quality standards. Quality standards find application across sectors, occupations, and objectives (e.g., security and safety, product certification). In recent years, multiple environmental management schemes and connected certification have also become more common. See, for instance, European Management and Auditing Schemes or ISO 14001 (Jiang and Bansal, 2003; Rennings et al., 2006; Iraldo et al., 2009) whose general scope is to improve the firm environmental performance and monitoring into the organization and operations of firms. We contend that, ceteris paribus, in light of the aforementioned management practices and due to regulatory push/pull effects (Rennings, 2000), green-oriented workers are more engaged in quality checks, being associated with the use of materials and energy, or considerations on the environmental impact and footprint of products and processes. For an average worker, quality checks should not be directly associated with meaningfulness gains, unless sector and occupation specificities (which we partially account for) command higher esteem for workers that are directly engaged in quality controls; see, for instance, the case of luxury brands or goods.

3.6 Results

3.6.1 Baseline

Table 3.1 reports the results of the baseline estimation, employing pooled data from the two waves of the EWCS survey, that is, 2015 and 2021. We progressively include controls in the different specifications. Aligned with the conceptual framework, we first assess whether an occupation's green content exerts an effect on work meaning on top of the standard components of self-determination theory, namely autonomy, competence and relatedness. In this specification, we also control for a proxy of work effort through weakly hours worked. We find that greenness has a positive and significant effect. Columns 2 and 3 proceed by adding further controls, that is, those associated with external rewards (i.e. career opportunities and individual recognition) and individual and firm-level controls (see Section 4.2), respectively. In both cases, the association between greenness and the meaning of work remains positive and significant. All control estimates are aligned with expectations and with previous findings such as those of Nikolova and Cnossen (2020). In particular, we document a meaning premium for women, older and tenured workers. The negative association for tertiary education and firm size is also consistent as well as the extrinsic rewards associated with meaningful work—such as working hours, career prospects, and individual recognition. Finally, in line with expectations, public sector workers report higher levels of meaningful work compared to private sector workers (Dur and Van Lent, 2019).[17]

We test the robustness of these baseline results in different ways. First, we make sure that the findings remain valid when employing weights in our regressions. Specifically, we re-estimate the most complete specification reported in Table 3.1 using post-stratification weights to account for the nonresponse rate and different probabil-

[17] To assess the robustness of the results to potential omitted variable bias, we perform the Oster (2019) test. The analysis yields an implied value of $\delta = 4.65$, indicating that selection on unobservables would need to be more than four times stronger than selection on observables in order to fully eliminate the estimated effect. This evidence therefore suggests that the estimated relationship is relatively robust to omitted variable bias. Results are available on request.

ity selection (Eurofound, 2016, 2022*b*). Moreover, we repeat the same exercise using the inverse of the country size as weight to remove the concern that the results are driven by sample size differences (see Nikolova and Cnossen, 2020). The results are reported in Table 3.A.8 (columns 1 and 2, respectively). Once again, we find a positive and statistically significant association between the green content of the occupation and the perceived meaning at work. The magnitude of this effect is consistent with that observed in the baseline estimates.

Another potential issue in the baseline specification is the omission of information on individual wage, which may introduce bias due to its correlation with both perceived meaning of work (Kesternich et al., 2021) and, potentially, the green content of occupations (Vona et al., 2019; Kuai et al., 2025). Unfortunately, data on hourly wages are not available for the 2021 wave of the EWCS. As a result, the most feasible approach is to replicate the analysis using the 2015 wave alone, incorporating hourly wages as an additional control. The results of this empirical exercise are reported in Table 3.2. Following the same step-wise strategy as before, we introduce control variables sequentially. Across all specifications, the coefficient associated with the green content of the occupation remains positive and statistically significant, reinforcing our confidence in the positive relationship between greenness and perceived work meaning. In line with some extant evidence (Ariely et al., 2008), and the notion that workers may accept a lower wage to carry out meaningful jobs (Cassar and Meier, 2018), wage level becomes negatively associated with the meaning of work in the fully specified model (column 4).

3.6.2 Heterogeneity across green policy regimes

As argued above, our theoretical framework postulates that the positive association between occupation's green content and work meaning is driven by social esteem and that the latter tends to be stronger in contexts characterized by the recognition of the fight against climate change as an important social goal. To test for this mechanism, we conduct a heterogeneity analysis that takes advantage of the cross-country variation in green policy regimes. Our underlying assumption is that stronger policy interventions in this field reflect the presence of greater pro-environmental social norms and attitudes within the population. These, in turn, are likely to enhance the social esteem of individuals employed in green occupations, thereby increasing their sense of the meaning of work. In more detail, we proceed by splitting the sample into two subsets according to the incidence of EPS, as explained above (Section 3.5). In our theoretical framework, this policy difference captures parameter p (see Figure 3.1). Then, we re-estimate the full model specification separately for each country group under three different scenarios: a) using pooled data from the 2015 and 2021 waves, without controlling for individual wages; b) using only the 2015 wave, again without wage controls; and c) using only the 2015 wave, this time including controls for individual wages.

Table 3.1: Occupation's green content and meaningful work, 2015-2021

	(1)	(2)	(3)
Autonomy	0.1880***	0.1635***	0.1632***
	(0.0066)	(0.0064)	(0.0060)
Competence	0.1507***	0.1269***	0.1340***
	(0.0048)	(0.0047)	(0.0046)
Relatedness	0.2351***	0.1954***	0.1996***
	(0.0062)	(0.0053)	(0.0054)
Loghours	-1.9793***	-1.4215***	-1.4445***
	(0.2590)	(0.2677)	(0.2800)
Green content (g)	0.0698***	0.0671***	0.0606***
	(0.0248)	(0.0244)	(0.0220)
Career		2.4968***	3.5342***
		(0.2124)	(0.2255)
Individual recognition		7.6301***	7.1823***
		(0.2722)	(0.2703)
Biological sex: Ref. Men			
Woman			1.6763***
			(0.2300)
Age: Ref. 18-34			
35-45			2.4456***
			(0.2669)
46-60			5.3753***
			(0.2526)
>60			9.0677***
			(0.5250)
Education: Ref. No tertiary			
Tertiary			-2.9670***
			(0.2648)
Work tenure: <1			
1-5 years			0.3088
			(0.3035)
>5 years			0.6802**
			(0.3391)
Firm size: Ref. <250 employees			
>250			-1.0784***
			(0.2677)
Ownership: Ref. Public			
Private			-1.0471***
			(0.3333)
Group controls	Yes	Yes	Yes
Constant	36.2407***	34.1645***	31.8657***
	(4.1026)	(4.5455)	(5.3962)
Obs.	61,249	59,857	55,721
R-squared	0.2162	0.2420	0.2603

Notes: Own elaborations on ESCO and EWCS data. Estimates obtained from OLS models with clustered standard errors in parentheses. Group controls include occupation, industries, countries and year dummies. *** p<0.01, ** p<0.05, * p<0.1

Table 3.2: Controlling for hourly wage, 2015

	(1)	(2)	(3)	(4)
Autonomy	0.1654***	0.1617***	0.1353***	0.1323***
	(0.0095)	(0.0091)	(0.0089)	(0.0089)
Competence	0.0385***	0.0370***	0.0354***	0.0433***
	(0.0064)	(0.0074)	(0.0073)	(0.0073)
Relatedness	0.2871***	0.2800***	0.2271***	0.2324***
	(0.0087)	(0.0088)	(0.0082)	(0.0082)
Loghours	-1.4313***	-1.2426***	-1.0731**	-1.7498***
	(0.3766)	(0.4396)	(0.4434)	(0.5019)
Green content (g)	0.1006***	0.1097***	0.1085***	0.1023***
	(0.0359)	(0.0380)	(0.0385)	(0.0370)
Hourly wage		0.5648	-0.1698	-0.8893**
		(0.3529)	(0.3608)	(0.3999)
Career			2.4794***	3.3596***
			(0.3471)	(0.3909)
Individual recognition			8.2516***	7.8699***
			(0.3864)	(0.4048)
Individual and firm controls	No	No	No	Yes
Group controls	Yes	Yes	Yes	Yes
Constant	41.0739***	40.4041***	40.6808***	42.3279***
	(3.8150)	(4.6351)	(5.1539)	(6.1888)
Obs.	27,114	23,766	23,138	20,869
R-squared	0.2224	0.2166	0.2465	0.2575

Notes: Own elaborations on ESCO and EWCS data. Estimates obtained from OLS models with clustered standard errors in parentheses. Individual and firm controls account for age, biological sex, tertiary education, work experience intervals, firm sizes, private vs other ownership forms. Group controls include occupation, industries, countries and year dummies. *** p<0.01, ** p<0.05, * p<0.1.

The corresponding results are presented in Table 3.3, Columns 1–2, 3–4, and 5–6, respectively. These, in turn, are likely to enhance the social esteem of individuals employed in green occupations, thereby increasing their sense of the meaning of work. In more detail, we proceed by splitting the sample into two subsets according to the incidence of EPS, as explained above (Section 3.5). In our theoretical framework, this policy difference captures parameter p (see Figure 3.1). Then, we re-estimate the full model specification separately for each country group under three different scenarios: a) using pooled data from the 2015 and 2021 waves, without controlling for individual wages; b) using only the 2015 wave, again without wage controls; and c) using only the 2015 wave, this time including controls for individual wages. In line with our theoretical framework, we find that the association between occupation's green content and perceived work meaning is not uniform across countries. Specifically, in countries with high EPS, the relationship remains positive and statistically significant across all specifications, regardless of the dataset used or the inclusion of wage controls. In contrast, in countries with low EPS, the association is consistently null. Although all specifications include country fixed effects and a rich set of individual-level controls, the high versus low EPS analysis still reflects differences across broader policy environments that may also correlate with other country level factors such as labour market institutions or sectoral composition. Therefore, the results are intended to capture how environmental policy contexts condition the relationship between green job content and meaningful work, rather than to provide a strict causal comparison across countries.[18]

[18] One potential limitation of the above analysis is that all the estimated models rely on partially distinct survey questions to measure the components of self-determination theory. Since these components are major drivers of the meaning of work, their mismeasurement can bias the results. To further substantiate our findings, we carry out an additional robustness check addressing this issue. Specifically, we generate three variables that capture the main components of self-determination theory (i.e., autonomy, competence and relatedness), using only the same questions available in both waves of the EWCS (for details, see Table 3.A.10 in the Appendix). To ensure consistency, the responses to these questions are transformed into dummy variables. Then, we re-estimate all the models of interest using these variables as controls. Results are reported in Table A5, in the Appendix. Our main findings are confirmed across the board.

Table 3.3: Heterogeneity across countries: high and low EPS (p)

Waves	2015-2021		2015		2015	
	(1) High (p)	(2) Low (p)	(3) High (p)	(4) Low (p)	(5) High (p)	(6) Low (p)
Green content	0.1007***	0.0516	0.1766***	0.0606	0.1910***	0.0510
	(0.0373)	(0.0327)	(0.0628)	(0.0485)	(0.0622)	(0.0546)
Self-determination theory	Yes	Yes	Yes	Yes	Yes	Yes
Weakly hours worked	Yes	Yes	Yes	Yes	Yes	Yes
Hourly wage	No	No	No	No	Yes	Yes
Other external rewards	Yes	Yes	Yes	Yes	Yes	Yes
Individual and firms controls	Yes	Yes	Yes	Yes	Yes	Yes
Group controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18,896	21,241	6,293	10,144	5,864	8,579
R-squared	0.2577	0.2687	0.2487	0.2766	0.2432	0.2676

Notes: Own elaborations on ESCO, EWCS and OECD data. Estimates obtained from OLS models with clustered standard errors in parentheses. In columns 1, 3 and 5 the analysis is restricted to countries with EPL index higher than the sample mean. In columns 2, 4 and 6 the analysis is restricted to countries with EPL index lower than the sample mean. Self-determination theory refers to job design controls (autonomy, competence and relatedness). Other external rewards accounts for career prospects and individual recognition. Individual and firm controls account for age, biological sex, tertiary education, work experience intervals, firm sizes, private vs other ownership forms. Group controls include occupation, industries, countries and year dummies. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.6.3 Endogeneity

Given that the exogeneity of occupation's green content in our baseline specifications may be compromised by sorting on unobservables and measurement error, we now turn to the results of our instrumental variable (IV) estimation strategy. To do so, we use the EWCS question "Does your job involve to follow quality standards" and we further aggregate it at the occupation 4 digit ISCO level. In the appendix, we show the distribution of the variable by occupational levels (Figure 3.A.2). Our instrument exploits variation in the incidence of quality standards across occupations. These standards reflect external regulatory and organizational constraints that shape how work is performed—through procedures and compliance—rather than why it is performed. Since environmentally oriented occupations are more likely to be subject to such standards, their incidence should predicts an higher green content of jobs.[19] At the same time, quality standards are not inherently linked to workers' perceived purpose or societal contribution.

Clearly some concerns would emerge if the instrument directly affects meaningfulness. Nevertheless, to the extent to which the execution of quality checks leads to higher meaning via higher autonomy, better relations in the workplace or better use of extant competences, no particular issues emerge, as these are the self-determination theory elements we control for. What is more, performing quality checks can be considered a work task that is specific to the individual work context. In this sense, we can argue that whenever performing quality standard checks relate to recognition this is mostly happening in the locus where quality checks occur, that is the workplace. This is controlled for in our specification, which includes a measure of individual perceived recognition (i.e., whether the worker feels adequately recognised at work).[20]

[19]This is clearly illustrated in Table 3.A.2, which reports the most frequently used green skills, and is further confirmed by ESCO (2022), showing that the majority of green skills fall within the information and communication broad skill categories.

[20]Quality standards that generate individual recognition should not be problematic insofar as they reflect work practices that produce recognition within the workplace, for which we already include a specific control. This assumption is overly optimistic in case quality checks tie to intrinsic features of products and services that are highly valued or recognized in the market and thus can provide a sense

Table 3.4 reports the results of regressions in which we use the incidence of tasks related to meeting quality standards across occupations as an instrument for occupation's green content. In all estimated models, we consider the full set of control variables including the individual wage, thus limiting the analysis to the 2015 wave, to avoid incurring in omitted variable bias. Column 1 shows the IV results for the whole sample, while in Columns 2 and 3 we split the countries between high and low EPS, as discussed above. In line with our priors, in the first-stage regressions we find a positive association between quality standards and occupation's green content. Moreover, we note the relevance of the instrument: indeed, across all specifications, the F statistics is well above conventional values. Regarding the second-stage results, we find that, when considering the whole sample, the green content of the occupation positively affects the perception of the meaning of work. While the IV specification is primarily introduced to address potential sorting issues, the substantially larger estimates suggest that the baseline OLS estimates were likely affected by attenuation bias arising from measurement error. Such a concern is plausible in this setting, given that the green content of occupations is captured through an indirect proxy rather than a direct measure.

An intuition on the magnitude of the effect is the following: An increase of one standard deviation in the green content leads to a 6 percentage points higher meaningfulness. To put this into perspective, this effect is comparable in size to that of relatedness and twice as large as the effect of autonomy. Finally, when we repeat the IV analysis by splitting the sample between high- and low-EPS countries, we obtain further evidence corroborating our theoretical framework. The results are supported also when using the median value to split EPS in High vs Low (See Table 3.A.11).

of meaning and achievement to the worker. One can think of high-quality products and services, like sports cars, customised experiences in hospitality, or high-precision/performance machinery. To account for the competitive pressure and strategic relevance associated to meaning-rewarding quality standards in producing high-quality products and services, we control for the relevance of reputational assets at the sector level. To this aim, we calculate the sectoral intensity of brand investment at 2-digit industry and country level using the EUKLEMS data (Bontadini et al., 2022; Corrado et al., 2022). We take the intensity of the brand investment (calculated as in Bontadini et al. (2022), dividing by the total sectoral value added. We then add the new indicator in our specification. The results, presented in Table 3.A.12 in the Appendix, remain stable and consistent with our main findings.

Specifically, in countries with a high incidence of pro-environmental policy, occupation's green content has a positive and statistically significant effect on perceived work meaning. In contrast, in countries where such policy interventions are less prominent, the effect is not statistically different from zero. These patterns are broadly consistent with the idea that the social context matters in shaping the relationship between green jobs and the meaning of work. Whenever the defence of the environment is perceived as a relevant social goal, as proxied by the presence of dedicated policy effort, workers in green occupations are more likely to be seen as worth of social esteem, thereby enhancing their perception of work meaning.

3.7 Conclusion

This paper set out to investigate whether workers intrinsically value their involvement in occupations that promote the protection of the natural environment, using the lens of meaningful work. The literature on the engagement of individuals in the green transition and their reaction to norms and values has heavily emphasized the role played by consumption-side behaviour (Besley and Persson, 2019). Instead, the production side, and specifically the motivational dimensions of workers engaged in green jobs, has received comparatively little attention. Building on the foundational framework developed by Cassar and Meier (2018), we extend the concept of meaningful work by incorporating a social esteem component, drawing from recognition theory (Honneth, 1995). This expanded model enables us to link the green content of occupations, measured by the incidence of green skills, with broader contextual factors that shape the social recognition of green jobs, such as the implementation of pro-environmental policy initiatives and the emergence of societal norms and attitudes related to it. Together, these elements reinforce the social esteem attached to green occupations, thereby enhancing the perceived meaningfulness of work for those employed in them.

Our empirical findings support the proposed theoretical framework. Drawing on individual-level data from the European Working Conditions Survey (EWCS) and the

Table 3.4: IV specification: full sample and high vs. low EPS (p) split, 2015

	(1) All	(2) High (p)	(3) Low (p)
First stage: green content (g)			
Quality standards	0.0384***	0.04434***	0.0324***
	(0.0031)	(0.00599	(0.0051)
F	153.74	54.76	39.53
	(1, 20726)	(1, 5748)	(1, 8459)
R-Squared	0.2834	0.3655	0.2861
Second stage: work meaning			
Green content (g)	1.3367***	1.6702**	0.4330
	(0.4440)	(0.6854)	(0.8251)
Self-determination theory	Yes	Yes	Yes
Loghours	Yes	Yes	Yes
Hourly wage	Yes	Yes	Yes
Other external rewards	Yes	Yes	Yes
Individual and firm controls	Yes	Yes	Yes
Group controls	Yes	Yes	Yes
Obs.	20,867	5,863	8,578
R-squared	0.2182	0.1736	0.2637

Notes: Own elaborations on ESCO, EWCS and OECD data. Estimates obtained from Instrumental Variable (IV) models with clustered standard errors in parentheses. In column 1 the analysis considers the whole sample of countries. In columns 2 the analysis is restricted to countries with EPL index higher than the sample mean. In columns 3 the analysis is restricted to countries with EPL index lower than the sample mean. Self-determination theory refers to job design controls (autonomy, competence and relatedness). Other external rewards accounts for career prospects and individual recognition. Individual and firm controls account for age, biological sex, tertiary education, work experience intervals, firm sizes, private vs other ownership forms. Group controls include occupation, industries, countries and year dummies. All the controls are included in the first stage. *** p<0.01, ** p<0.05, * p<0.1.

country-level Environmental Policy Stringency (EPS) index, we find that the occupation's green content is positively associated with the perception of work meaning. However, this effect is not uniform across countries. In particular, it is higher in magnitude and statistically significant only in countries that attribute more value to the fight against climate change as a valuable social goal, proxied by the adoption of more stringent environmental policies. To reinforce the causal interpretation of our results, we perform an instrumental variable approach, which delivers consistent results.

We acknowledge some limitations of our study. First, the lack of longitudinal data prevents us from exploiting time variations to identify the effect of occupation's green content on the perception of work meaning. Although the use of an IV approach helps mitigate this issue, causal inferences would be strengthened if this method was combined with the use of panel data. Second, the lack of information about the distribution of finely grained occupational groups partially undermines the aggregation process that we used to obtain green scores to be merged across different data sources. Once again, the IV strategy helps mitigate some of the bias arising from such measurement errors. However, future research could integrate our results by leveraging more granular occupational data and improving linkage across datasets.

Our findings have important implications for both academic research and policy design. From a research perspective, the expanded framework that we propose for analysing the drivers of meaningful work, by integrating occupational content with contextual dimensions such as social norms and public policy, offers a valuable foundation for future empirical and theoretical research in this field. Whereas much of the existing economic literature tends to focus on individual job characteristics or intrinsic task features when assessing work meaningfulness, our study demonstrates that the broader societal context also plays a crucial role. Exploring how different institutional settings, policy regimes, or public narratives shape the meaning individuals attach to their work represents a promising direction for future research.

In terms of policy design, our findings underscore the potential for mutually reinforcing synergies between environmental goals and labour market strategies. Green jobs not only contribute to environmental sustainability but also generate social value by enhancing the meaningfulness of work. This occurs when workers perceive their roles as contributing to widely recognized societal objectives, such as addressing climate change. Policymakers should therefore recognize that ambitious environmental regulations can yield important co-benefits for worker motivation, especially when such policies help reinforce pro-environmental social norms. However, these synergies are not automatic. They rely on the degree of social esteem attributed to green occupations, which itself can be shaped through targeted policy efforts. Public awareness campaigns, sustainability education programs, and employer branding initiatives that highlight the social relevance of environmental commitments can all help cultivate a narrative in which green jobs are seen as socially valuable and purpose-driven. Such interventions may be especially effective in fostering greater commitment to green employment among the workforce, facilitating the recruitment of younger workers and individuals seeking careers that align with their values.

Declaration of generative AI and AI-assisted technologies in the writing process.

During the preparation of this work the author used ChatGPT in order to check grammar and syntax mistakes. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

Authorship contribution statement

Fabio Landini - Conceptualization, Investigation, Methodology, Writing - Original Draft, Supervision. **Davide Lunardon** - Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing - Original Draft, Project administration. **Alberto Marzucchi** - Conceptualization, Methodology, Formal Analysis, Investigation, Writing - Original Draft, Supervision.

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Appendix 3

A3. Tables

Table 3.A.1: Country sample size

	2015	2021
Belgium	2207	2500
Bulgaria	906	1046
Czech Republic	885	1177
Denmark	867	1098
Germany	1806	2458
Estonia	839	1042
Greece	856	1076
Spain	2849	1745
France	1300	1865
Ireland	864	1052
Italy	1190	1887
Cyprus	870	825
Latvia	767	1018
Lithuania	837	1128
Luxembourg	878	751
Hungary	831	1056
Malta	908	932
Netherlands	890	1039
Austria	890	1067
Poland	940	1729
Portugal	790	1145
Romania	841	1085
Slovenia	1383	1617
Slovakia	881	1090
Finland	831	1088
Sweden	848	1005
United Kingdom	1414	1249
Croatia	756	1056
fyrom	756	663
Norway	895	1864
Albania	750	569
Montenegro	729	699
Switzerland	871	749
Serbia	738	720
Total	34863	41090

Table 3.A.2: List of Green Skills (ESCO)

Green Skills	2015
Ensure compliance with environmental legislation	63
Follow health and safety procedures in construction	62
Ensure compliance with environmental legislation in food production	59
Dispose of hazardous waste	47
Dispose food waste	40
Dispose of non-hazardous waste	30
Replace defect components	30
Dispose waste	28
Report pollution incidents	27
Monitor the welfare of animals	26
Advise on animal welfare	23
Assess environmental impact	23
Promote environmental awareness	23
Manage waste	22
Analyse environmental data	21
Follow procedures to control substances hazardous to health	21
Monitor water quality	19
Ensure correct goods labelling	18
Execute disease and pest control activities	17
Advise on pollution prevention	16
Green Skills	2021
Ensure compliance with environmental legislation	68
Follow health and safety procedures in construction	65
Ensure compliance with environmental legislation in food production	61
Dispose of hazardous waste	51
Dispose food waste	40
Dispose of non-hazardous waste	31
Replace defect components	31
Dispose waste	28
Report pollution incidents	27
Promote environmental awareness	27
Monitor the welfare of animals	26
Assess environmental impact	25
Advise on animal welfare	23
Follow procedures to control substances hazardous to health	22
Manage waste	22
Analyse environmental data	22
Monitor water quality	19
Ensure correct goods labelling	18
Execute disease and pest control activities	17
Educate on sustainable tourism	16

Notes: The table presents the most commonly used green skills, with the reported figures indicating the total number of occupations in which each skill is applied.

Table 3.A.3: Greeness - ISCO 4 digit

ISCO 1 digit (2015)	ISCO 4 digit	Occupations	Greenness	Tot-Skills
Elementary occupations	9612	Refuse Sorters	61,1	23,5
Elementary occupations	9611	Garbage and Recycling Collectors	57,9	19,0
Professionals	2143	Environmental Engineers	54,4	28,0
Professionals	2133	Environmental Protection Professionals	47,5	28,3
Technicians and associated	3132	Incinerator and Water Treatment Plant Operators	37,8	28,3
Elementary occupations	9215	Forestry Labourers	30,0	30,0
Managers	1311	Agricultural and Forestry Production Managers	26,7	30,0
Craft and related trade workers	7133	Building Structure Cleaners	26,4	23,4
Technicians and associated	3112	Civil Engineering Technicians	24,9	23,1
Professionals	2142	Civil Engineers	21,5	172,0
Professionals	2132	Farming, Forestry and Fisheries Advisers	21,4	29,5
Elementary occupations	9214	Garden and Horticultural Labourers	19,4	36,0
Technicians and associated	3143	Forestry Technicians	16,7	30,0
Professionals	2263	Environmental and Occupational Health and Hygiene	16,4	21,5
Managers	1321	Manufacturing Managers	16,3	196,0
Service and sales workers	5411	Firefighters	14,6	48,0
Technicians and associated	3257	Environmental and Occupational Health Inspectors	14,0	29,7
Technicians and associated	3113	Electrical Engineering Technicians	13,5	34,5
Craft and related trade workers	7544	Fumigators and Other Pest and Weed Controllers	12,5	16,0
2021				
Elementary occupations	9612	Refuse Sorters	61,1	23,5
Elementary occupations	9611	Garbage and Recycling Collectors	57,9	19,0
Professionals	2143	Environmental Engineers	55,0	28,5
Professionals	2133	Environmental Protection Professionals	43,9	37,1
Technicians and associated	3132	Incinerator and Water Treatment Plant Operators	37,8	28,3
Elementary occupations	9215	Forestry Labourers	31,0	29,0
Managers	1311	Agricultural and Forestry Production Managers	27,6	29,0
Craft and related trades workers	7133	Building Structure Cleaners	26,4	23,4
Technicians and associated	3112	Civil Engineering Technicians	23,3	23,8
Professionals	2142	Civil Engineers	20,9	206,0
Professionals	2132	Farming, Forestry and Fisheries Advisers	19,3	34,2
Elementary occupations	9214	Garden and Horticultural Labourers	17,7	37,0
Technicians and associated	3143	Forestry Technicians	17,2	29,0
Professionals	2151	Electrical Engineers	16,7	66,0
Professionals	2263	Environmental and Occupational Health and Hygiene	16,3	24,6
Professionals	2144	Mechanical Engineers	15,4	208,0
Professionals	2161	Building Architects	15,3	59,0
Technicians and associated	3257	Environmental and Occupational Health Inspectors	15,0	30,0
Service and sales workers	5411	Firefighters	14,6	48,0
Elementary occupations	9213	Mixed Crop and Livestock Farm Labourers	14,3	21,0

Notes: The table lists the occupation with the highest green score for both years 2015 and 2021.

Table 3.A.4: Self-determination theory (SDT)

SDT	EWCS questions	Methods
Autonomy		
2015	(1) Are you able to choose order to tasks? (1 = Yes, 0 =No), (2) Are able to chose or change methods? (1 = Yes, 0 =No); (3) Are able to choose or change speed? (1 = Yes, 0 =No); 4) Assessing yourself quality? (1 = Yes, 0 =No); 5) You can take a break when you wish? (from never to always 1 - 5); 6) Are you able to apply your own ideas in your work? (from never to always 1 - 5).	PCA
2021	(1) "Are able to choose methods?" (from strongly disagree to strongly agree 1 - 5) and 2) Are you able to influence decision that are important for you? (from strongly disagree to strongly agree 1 - 5).	PCA
Competence		
2015	1) Does the respondent have the appropriate skills to handle current or more demanding duties? The answer are rescale 1 = Yes, and have more than required skills; 0 = No) 2) Does your main job involve: "Solving unforeseen problems on your own? (1 = Yes; 0 = No) 3) Learning new things? (1 = Yes; 0 = No).	PCA
2021	1) Does the respondent's job involve learning new things? From strongly disagree to strongly agree 1-5; 2) Do you have enough opportunity to use their knowledge and skills in their current job? From strongly disagree to strongly 1-5).	PCA
Relatedness		
2015	1) Your colleagues support you (from strongly disagree to strongly agree 1-5) 2) Your manager support you (from strongly disagree to strongly agree 1-5)	PCA
2021	1) Your colleagues support you. The answer is rescaled from 0 (strongly disagree) to 100 (strongly agree)	

Notes: All the index are rescaled from 0 to 100. Given the categorical nature of the underlying variables, the estimation applies Polychoric Principal Component Analysis (PCA). For a similar approach, see Nikolova and Cnossen (2020).

Table 3.A.5: Variables

Variables	Description
Loghours	Natural log of worked hours per week
External rewards	
Career	My job offers goof prospects for career advancement (1 - Strongly agree and agree; 0 = remaining options
Individual recognition	I receive the recognition I deserve from my work (1 - Strongly agree and agree; 0 = remaining options
Hourly wage	We divide the adjusted net monthly salary per 4 (weeks). We further divide by hour worked per week. We use only workers with a minimum hour of 20 and a maxium of 70 per week. We take the natual log. Available only for 2015.
Individual and firm controls	
Age intervals	Age groups: 1 = 18-35; 2= 36-45; 3) 45-60; 4) 60 - 70
Biological sex	1= Female; 2= Male; 3= other and missing information
Human capital	1 = Having a tertiary degree (ISCED 6, 7, 8), 0 = No Tertiary degree (ISCED 0, 1, 2, 3, 4, 5)
Tenure interval	Number of years in the same company/organization. Tenure interval; 1= less than one year; 2 = from 1 to 5; 3 = more than 5 years
Firm size	Company size indicator (1 = <= 250 employees; 0 = >= 250 employees
Private ownership	1 = Firm is private; 0 = Firm is public or other ownership forms
Group controls	
Occupation	ISCO 08 1-digit
Industry	NACE rev 2.2 2-digit
Country	34 European country
Year	Survey waves (2015, 2021)

Table 3.A.6: Summary statistics

	Obs	Mean	Std. Dev.	Min	Max
Meaningful work	74842	75.656	23.687	0	100
Autonomy	73210	61.659	26.249	0	100
Competence	74128	63.705	24.956	0	100
Relatedness	62992	74.483	25.958	0	100
Loghours	74839	3.583	.448	-1.469	4.248
Green content (g)	74842	1.974	4.535	0	61.09
Hourly wage	39975	2.076	.641	0.203	4.535
Career	71757	.49	.5	0	1
Individual recognition	73775	.689	.463	0	1
Sex	74836	.496	.5	0	1
Age intervals	74842				
18-34		.3	.458	0	1
35-45		.265	.441	0	1
46-60		.376	.484	0	1
More than 60		.059	.236	0	1
Tertiary education	74562	.497	.5	0	1
Tenure intervals	74272				
Less than 1 year		.122	.328	0	1
1 to 5		.368	.482	0	1
More than 5		.509	.5	0	1
Firm size	72227	.218	.413	0	1
Private	71882	.731	.444	0	1
Years	74842				
2015		.471	.499	0	1
2021		.529	.499	0	1

Notes: Own elaborations on ESCO and EWCS data. For all the variables except *hourly wage*, the reported statistics refer to pooled data from the 2015 and the 2021 waves of the EWCS. For *hourly wage*, due to information unavailability, the statistics refers to EWCS 2015 only.

Table 3.A.7: Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) *Meaning*	1.00													
(2) *Autonomy*	0.29	1.00												
	(0.00)													
(3) *Competence*	0.23	0.28	1.00											
	(0.00)	(0.00)												
(4) *Relatedness*	0.30	0.17	0.23	1.00										
	(0.00)	(0.00)	(0.00)											
(5) *Loghours*	-0.02	0.01	0.10	0.03	1.00									
	(0.00)	(0.01)	(0.00)	(0.00)										
(6) *Green content*	0.01	0.00	-0.02	-0.02	0.03	1.00								
	(0.20)	(0.40)	(0.00)	(0.00)	(0.00)									
(7) *Career*	0.19	0.18	0.29	0.25	0.09	0.01	1.00							
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)								
(8) *Recognition*	0.27	0.23	0.20	0.29	-0.02	0.00	0.33	1.00						
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.71)	(0.00)							
(9) *Sex*	0.03	-0.05	-0.03	0.01	-0.17	-0.15	-0.08	-0.02	1.00					
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)						
(10) *Age intervals*	0.10	0.06	-0.03	-0.07	-0.02	0.02	-0.16	0.00	0.02	1.00				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.25)	(0.00)					
(11) *Tertiary degree*	-0.03	0.12	0.20	0.09	0.05	-0.07	0.13	0.08	0.10	-0.03	1.00			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
(12) *Work tenure*	0.06	0.09	0.02	-0.04	0.10	0.00	-0.08	-0.02	-0.01	0.42	0.03	1.00		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.39)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
(13) *Firm size*	-0.06	-0.04	0.02	-0.05	0.05	-0.01	0.03	-0.03	-0.02	0.01	0.06	0.09	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
(14) Private ownership	-0.05	0.03	-0.08	-0.04	0.05	0.05	0.02	0.02	-0.17	-0.10	-0.17	-0.11	-0.09	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 3.A.8: Weighted regressions, 2015-2021

	(1) Post-stratification	(2) Country sample size
Green content (g)	0.0777***	0.0740***
	(0.0274)	(0.0246)
Self-determination theory	Yes	Yes
Loghours	Yes	Yes
External rewards	Yes	Yes
Individual and firm controls	Yes	Yes
Group controls	Yes	Yes
Constant	29.3744***	33.4382***
	(5.3057)	(5.0452)
Obs.	55,721	55,721
R-squared	0.2571	0.2574

Notes: Own elaborations on ESCO and EWCS data. Estimates obtained from weighted OLS models with clustered standard errors in parentheses. Self-Determination Theory refers to job design controls (autonomy, competence and relatedness), external rewards account for career prospects and individual recognition. Group controls include occupation, industries, countries and year dummies. Individual and firms controls account for age, biological sex, tertiary education, work experience intervals, firm sizes, private vs other ownership forms. *** p<0.01, ** p<0.05, * p<0.1

Table 3.A.9: Variables SDT reduced

Variables	Description
Autonomy	"Are you able to choose or change methods of work?" In 2015 EWCS surveys, this question has two possible responses: yes or no. Differently, in the 2021 survey, there are five response options: always, often, sometimes, rarely, and never. To maintain consistency, we group always, often, and sometimes as yes and categorized rarely and never as no (where 1 = Yes, 0 = No).
Competence	"Learning new things". In 2015 EWCS surveys, this question has only two possible responses: yes or no. Differently, in the 2021 survey, there are five response options: from strongly disagree to strongly agree. To maintain consistency, we group strongly agree and agree as 1 and the rest as 0. For survey waves 2010 and 2015, this indicator is calculated by extracting the first component after a PCA on the following questions: 1) respondent has the appropriate skills to cope with current or more demanding duties; 2) main jobs involves "solving unforeseen problems on your own"; 3) main paid jobs involves "learning new things". For survey 2021, a PCA is performed on two questions: 1) learning new things and 2) I have enough opportunities to use my knowledge and skills in my current job
Relatedness	"Do your colleagues help and support you?" The question are rescaled to 1 (strongly agree and agree) and 0 (the remaining options)

Notes: Own elaboration based on EWCS 2015 and EWCTS 2021 survey data.

Table 3.A.10: Baseline 2015-2021 - Reduced SDT indicators

	(1)	(2)	(3)	(4)	(5)
		Rob checks		EPS	
Meaningful work	Baseline	Post-strat.	Country size	High	Low
Autonomy (d)	3.9789***	3.9485***	4.0102***	4.0714***	4.5085***
	(0.2115)	(0.2660)	(0.2273)	(0.3383)	(0.3671)
Competence (d)	5.0051***	4.8902***	5.0271***	5.1845***	4.9476***
	(0.2401)	(0.2749)	(0.2647)	(0.3959)	(0.3821)
Relatedness (d)	6.9129***	7.2850***	6.7688***	5.4862***	7.7560***
	(0.2798)	(0.3175)	(0.2967)	(0.4542)	(0.4452)
Loghours	-1.2044***	-1.0940***	-1.1976***	-0.9382*	-1.2554**
	(0.2948)	(0.3341)	(0.3242)	(0.4783)	(0.5011)
Green content (g)	0.0622***	0.0711**	0.0814***	0.1091***	0.0568*
	(0.0226)	(0.0280)	(0.0243)	(0.0370)	(0.0336)
Career	5.5965***	5.2385***	5.1532***	5.0593***	5.3468***
	(0.2384)	(0.2775)	(0.2798)	(0.3485)	(0.3872)
Individual rec.	10.4196***	10.4718***	10.5806***	10.7610***	10.8590***
	(0.2973)	(0.3319)	(0.3152)	(0.4490)	(0.3836)
Ind&Firm cont.	Yes	Yes	Yes	Yes	Yes
Group controls	Yes	Yes	Yes	Yes	Yes
Constant	49.0973***	46.0417***	50.9643***	46.7843***	50.2706***
	(5.5085)	(5.4575)	(5.1226)	(8.3660)	(6.0405)
Obs.	58,807	58,807	58,807	19,654	22,494
R-squared	0.1898	0.1885	0.1843	0.1813	0.1964

Notes: Own elaborations on ESCO, EWCS and OECD data. Estimates obtained from OLS models with clustered standard errors in parentheses. Columns 1 reports estimate for the baseline specification. Columns 2 and 3 shows the results of weighted regressions. Columns 4 and 5 reports the results when distinguishing countries depending of the incidence of ESP. Individual and firm controls account for age, biological sex, tertiary education, work experience intervals, firm sizes, private vs other ownership forms. Group controls include occupation, industries, countries and year dummies. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.A.11: IV Robustness checks - EPS median value

	(1) High (p)	(2) Low (p)
First stage: green content (g)		
Quality standards	0.0443***	0.0339***
	(0.0060)	(0.0056)
F	56.23	36.79
	(1, 6788)	(1, 7419)
Second stage: work meaning		
Green content (g)	1.5400**	0.3289
	(0.6866)	(0.8410)
Self-determination theory	Yes	Yes
Loghours	Yes	Yes
Hourly wage	Yes	Yes
Other external rewards	Yes	Yes
Individual and firm controls	Yes	Yes
Group controls	Yes	Yes
Obs.	6,904	7,537
R-squared	0.1817	0.2693

Notes: Own elaborations on ESCO, EWCS and OECD data. Estimates obtained from Instrumental Variable (IV) models with clustered standard errors in parentheses. The table shows only the estimates of second stage. The first stage estimates and parameters are in line with the main analysis. In columns 1 the analysis is restricted to countries with EPL index higher than the sample mean. In columns 2 the analysis is restricted to countries with EPL index lower than the sample mean. Self-determination theory refers to job design controls (autonomy, competence and relatedness). Other external rewards accounts for career prospects and individual recognition. Individual and firm controls account for age, biological sex, tertiary education, work experience intervals, firm sizes, private vs other ownership forms. Group controls include occupation, industries, countries and year dummies. Table shows only the estimates of second stage. The first stage estimates are also aligned with the main analysis. *** p<0.01, ** p<0.05, * p<0.1..

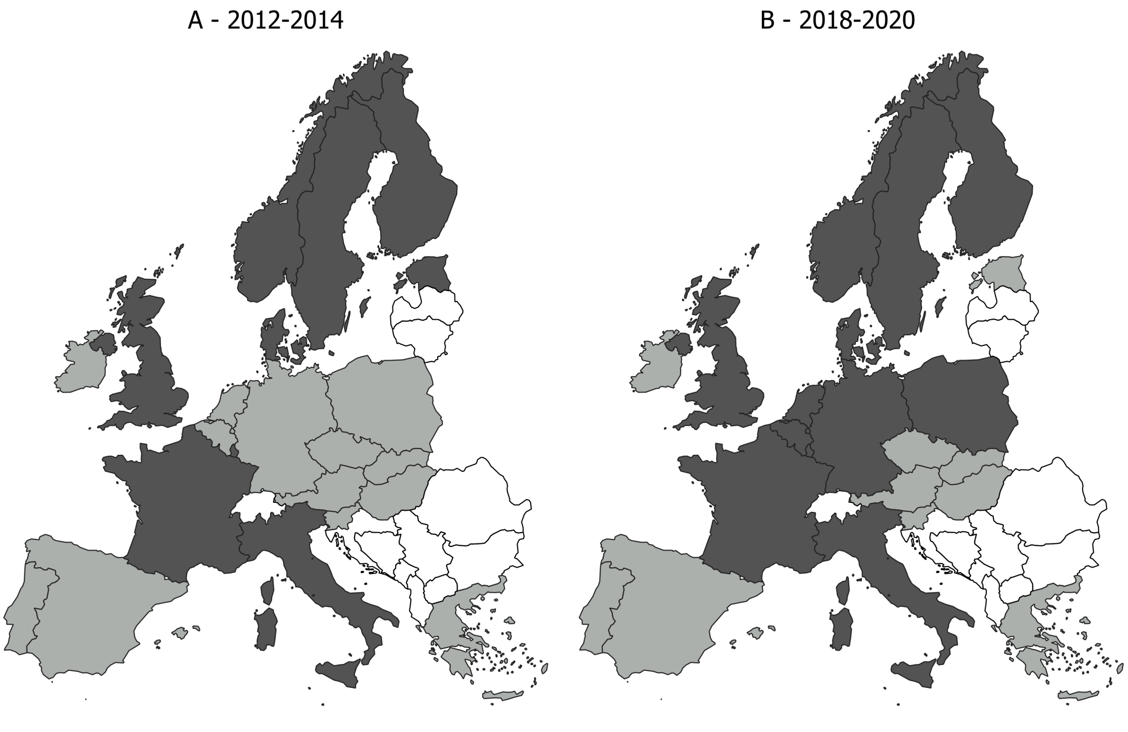
Table 3.A.12: IV Robustness checks

	(1)	(2)	(3)
First stage: green content	All	High (p)	Low (p)
Quality standards	0.0362***	0.0473***	0.0331***
	(0.0035)	(0.0063)	(0.0053)
F	105.69	56.04	39.99
	(1, 16804)	(1, 4964)	(1, 8281)
P>F	0.0000	0.0000	0.0000
Second stage: work meaning			
Green content (g)	1.3707***	1.5328**	0.1106
	(0.5102)	(0.6766)	(0.7982)
Brand intensity	0.0374	-0.3143	0.1104
	(0.1360)	(0.2966)	(0.2174)
Obs.	16,894	5,034	8,356
R-squared	0.2068	0.1755	0.2659

Notes: Own elaborations on ESCO, EWCS and OECD data. Estimates obtained from Instrumental Variable (IV) models with clustered standard errors in parentheses. The table shows only the estimates of second stage. The first stage estimates and parameters are in line with the main analysis. In column 1 the analysis considers the whole sample of countries. In columns 2 the analysis is restricted to countries with EPS index higher than the sample mean. In columns 3 the analysis is restricted to countries with EPS index lower than the sample mean. Self-determination theory refers to job design controls (autonomy, competence and relatedness). Other external rewards accounts for career prospects and individual recognition. Individual and firm controls account for age, biological sex, tertiary education, work experience intervals, firm sizes, private vs other ownership forms. Group controls include occupation, industries, countries and year dummies. Table shows only the estimates of second stage. The first stage estimates are also aligned with the main analysis. *** p<0.01, ** p<0.05, * p<0.1..

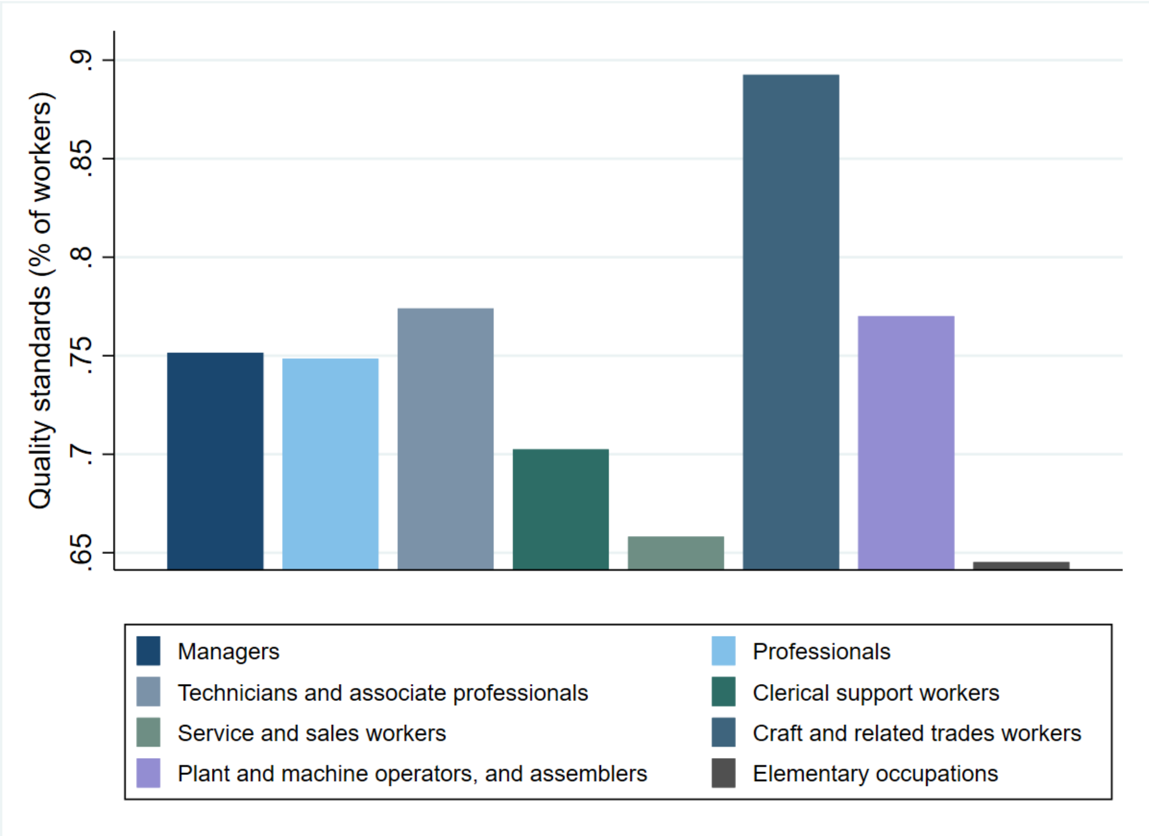
B3. Figures

Figure 3.A.1: Heterogeneity of EPS: high vs. low incidence across countries



Notes: Own elaboration based on OECD data. High EPS countries (dark grey) are those with mean value for the three years before the survey larger than the sample mean. Conversely, low EPS country (light grey) are those with mean value lower than the sample mean. Panel A reports the country classification for the period 2012-2014 (i.e., prior EWCS 2015). Panel A reports the country classification for the period 2018-2020 (i.e., prior EWCS 2021). Grey areas refers to country with no available information.

Figure 3.A.2: Quality standards by ISCO 1-digit (% of workers)



Notes: Own elaboration based on EWCS 2015 data.

C3. Tables & Figures - Meaningful work

Table 3.C.1: Meaningful work by country-years

Countries	2015	2021	Diff. 21-15
Malta	87,9	84,8	-3,0
Romania	73,3	84,4	11,1
Slovenia	82,8	83,2	0,4
North Macedonia	82,7	82,9	0,2
Bulgaria	83,1	82,4	-0,7
Estonia	74,5	81,8	7,3
Spain	78,5	81,5	3,0
Montenegro	75,3	81,4	6,1
Albania	70,4	81,1	10,7
Portugal	81,9	81,1	-0,8
Austria	78,1	79,0	0,8
Cyprus	76,6	78,7	2,1
Hungary	71,8	78,3	6,5
Serbia	75,9	77,6	1,7
Netherlands	79,2	75,7	-3,6
Switzerland	74,5	75,4	0,9
Croatia	73,6	75,4	1,8
Slovakia	67,7	74,7	7,0
Italy	74,9	74,7	-0,3
Germany	72,7	74,6	2,0
Luxembourg	81,6	74,5	-7,0
Latvia	72,8	74,4	1,6
Poland	70,2	73,5	3,3
Denmark	76,5	73,3	-3,3
Greece	71,7	73,2	1,6
Lithuania	69,7	73,1	3,4
Belgium	76,5	72,7	-3,8
Czech Republic	73,5	71,4	-2,1
France	75,5	71,2	-4,3
Norway	76,0	71,2	-4,8
Sweden	71,6	70,5	-1,1
Ireland	77,6	70,0	-7,7
United Kingdom	70,4	68,7	-1,7
Finland	69,3	65,2	-4,0

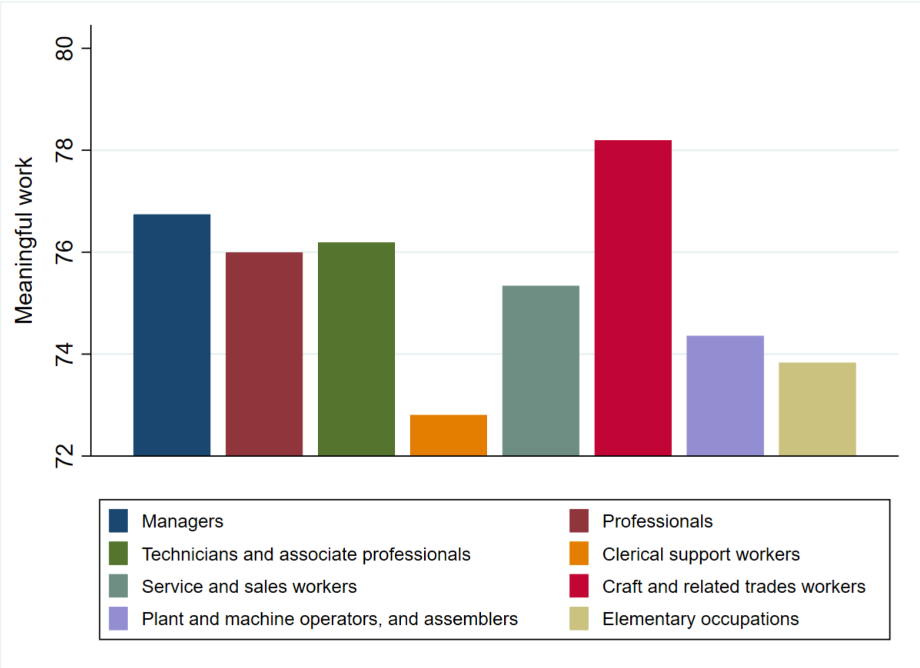
Notes: Own elaboration on EWCS 2015 and 2021 data. Averages meaningful work by countries. Here are reported only the countries that are surveyed in both surveys.

Table 3.C.2: PCA results for meaningful work indicators

Variable	2015 Comp. 1	2021 Comp. 1
Feeling of work well done	0.707	0.707
Feeling of doing useful work	0.707	0.707
Component statistics		
Eigenvalue	1.693	1.637
Explained variance	84.6%	81.9%
Sample size	42,942	48,047

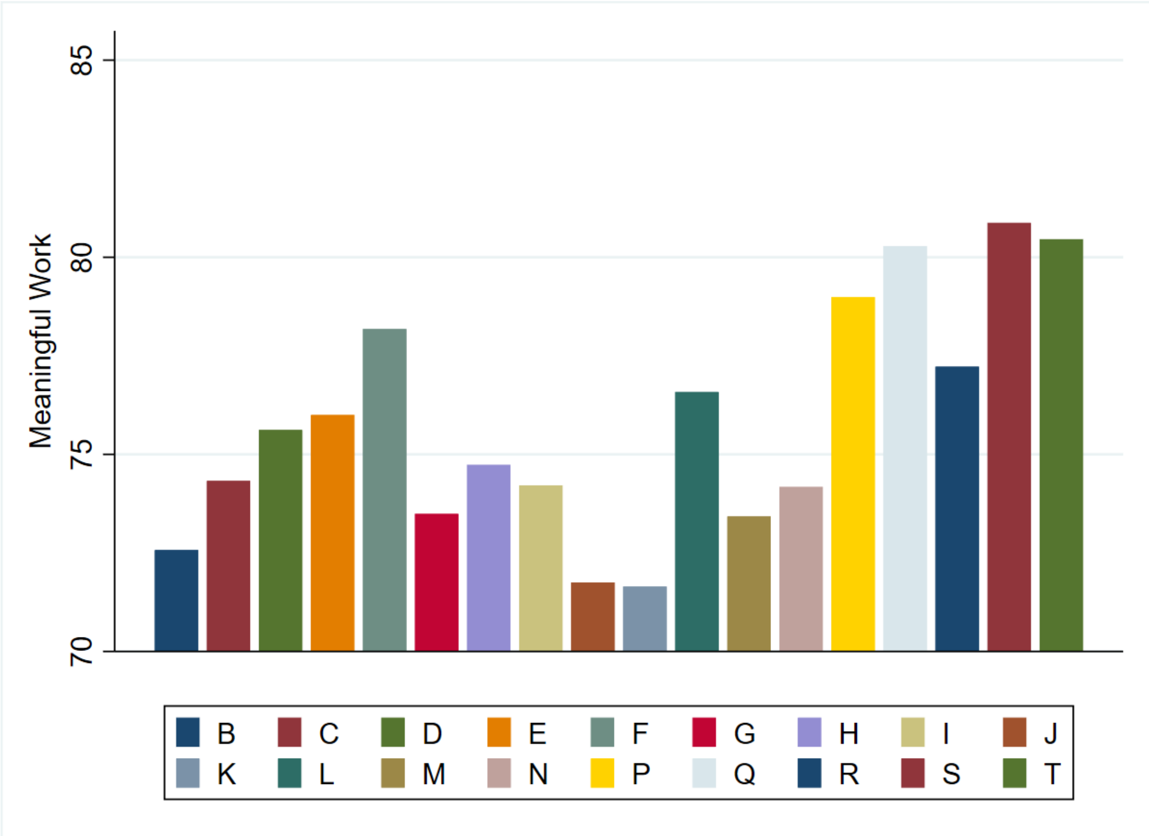
Notes: The table reports results from a polychoric principal component analysis based on two ordinal indicators of meaningful work. The first principal component is used to construct the index in both years.

Figure 3.C.1: Meaningful work by occupation groups (ISCO 1-Digits)



Notes: Own elaboration on EWCS 2015 and 2021 data

Figure 3.C.2: Meaningful work by NACE 1-digit sectors



Notes: Own elaboration on EWCS 2015 and 2021 data. B= Mining, C=Manufacturing, D=Energy supply, E=Water supply and others, F=Construction, G=Retail sectors, H=Logistics, I=Food and accommodation, J=ICT activities, K=Financial activities, L=Real estates, M=Scientific and other professions, N=Travel and business agencies, P=Education, Q=Health, R=Art, sport and cultural activities and T=Households activities.

4. Job Attributes and Turnover

Femke Cnossen[1] and Davide Lunardon

Abstract

We show how dissatisfaction with different job attributes relates to workers' job mobility. We distinguish between salary, tangible and intangible job attributes, using ten waves of the Dutch Working Conditions Survey (2014-2023) linked to administrative records covering over 400.000 workers. We find that dissatisfaction with intangible attributes -interesting work, learning opportunities and supervisors- is the strongest and most robust predictor of job separation, associated with a rise in the separation rate of three to five percentage points on a mean of 20.5%. Different sources of dissatisfaction are associated with different mobility behaviours: salary dissatisfaction predicts job-to-job transitions, dissatisfaction with interesting work predicts exits into unemployment, and dissatisfaction with supervisors predicts transitions from wage employment into self-employment. The availability of external opportunities, captured using a local labour markets tightness indicator— is relevant for the learning opportunities attribute in predicting separation. Overall, we show that the type of job attributes a worker is dissatisfied with matters both for the likelihood of leaving and for the kind of labour market transition that follows. Policy implications are highlighted in the conclusion.

Keywords: Non-wage job attributes; Job mobility; Labour supply; Local labour market tightness; Job quality

JEL Codes: J28; J22; E32

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4.1 Introduction

Labour turnover is a defining feature of modern labour markets (Lee et al., 2023; Nikolova, 2024), especially in relatively flexible ones like the Netherlands (Bekker and Mailand, 2019; Scheer et al., 2022; Patra et al., 2025). While worker mobility is an important driver in reallocating productive factors (Engbom, 2022; Faberman et al., 2022), it also entails substantial costs: firms bear hiring and training costs equivalent to multiple months of pay (Eeckhout, 2018) while workers incur in search costs (Miano, 2023), foregone learning-by-doing (Burdett et al., 2020), and significant psychological burdens when transitions involve job loss or illness (Knabe and Rätzel, 2011). Understanding the mechanisms underlying worker exits, either into new jobs or out of employment, therefore remains a central question in labour economics.

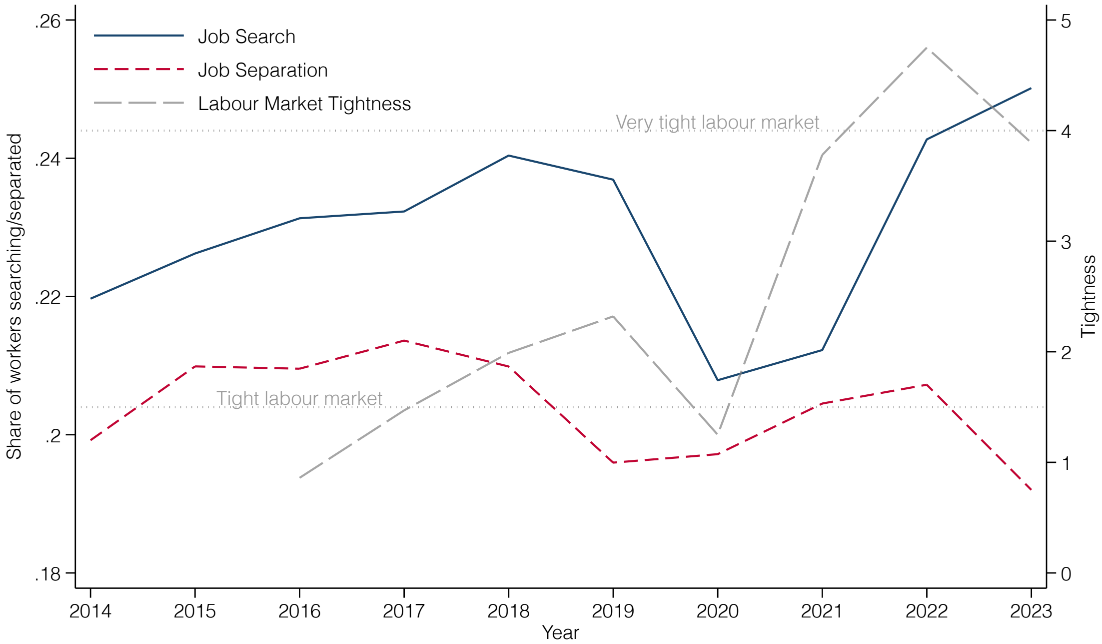
In this paper, we provide new evidence on the relationship between job attributes and labour turnover, taking into consideration also the role play by local labour market and in particular the availability of outside options, using a tightness indicator measure. Furthermore, we study how dissatisfaction with nine job attributes relates not only to job separation, but also to the destination of the exit: job-to-job moves, unemployment, self-employment, or education. We exploit a rich dataset combining large-scale administrative mobility records and survey data on job attribute satisfaction, using ten waves of the Dutch Working Conditions Survey (2014–2023) covering over 400,000 workers. We group attributes into three categories: monetary, tangible (contract type, job security, part-time options, control over hours, and working from home), and intangible job attributes (interesting work, learning opportunities, and supervisor quality). Using a simple search-theoretical framework that links dissatisfaction with monetary, tangible, and intangible attributes to separation decisions, we show how different attribute types are associated with distinct separation and exit destination patterns.

While the canonical labour supply model emphasizes monetary compensation (Burdett, 1978; Burdett et al., 2020; Faberman et al., 2022), a growing literature shows that workers value a broad set of non-wage job attributes. Our analysis fits in two related but distinct literatures. The first examines how workers value job amenities and how these enter search and self-selection decisions, using stated-preference methods and revealed-preference or structural search models that embed amenities in match surplus (e.g. Mas, 2025; Bagga et al., 2025; Humlum et al., 2025; Wiswall and Zafar, 2018; Maestas et al., 2023; Van Landeghem et al., 2024; De Schouwer and Kesternich, 2024; Sullivan and To, 2014). The second uses job satisfaction measures as reduced-form summaries of job quality to predict quitting and mobility (e.g. Freeman, 1978; Clark, 2001; Böckerman and Ilmakunnas, 2009; Lévy-Garboua et al., 2007). Job satisfaction research demonstrates that evaluations of the combined wage and non-wage bundle predict job search and separations (Clark, 2001; Lévy-Garboua et al., 2007; Böckerman and Ilmakunnas, 2009; Pelly, 2023). While the amenities literature focuses on valuation and trade-offs, the job-satisfaction literature documents predictive links between satisfaction, as proxy for utility, and turnover (intentions). We contribute to both by applying a job satisfaction approach to a series of (non-)wage attributes, combining detailed dissatisfaction measures with linked administrative data on subsequent mobility in the Netherlands.

The Dutch institutional context is well suited to studying these mechanisms. The labour market is characterised by high turnover (Gonne, 2023) and flexible working-time arrangements (Scheer et al., 2022). Consistent with this, our data show that roughly one in five workers separates in a given year (Figure 4.1). Outside options are both heterogeneous and salient: workers have access to generous unemployment benefits, widespread part-time work opportunities, and well-developed (adult-)education pathways (Bekker and Mailand, 2019; Patra et al., 2025). Moreover, labour-market tightness increased substantially over the study period, as evidenced by the long-dashed line in Figure 4.1, with substantial within-occupation variation. Tightness essentially raises the relative value of outside options and thus makes job separation potentially more interesting from the worker perspective. This combination of high mobility, flexible work arrangements, and across-time variation provides a rich environment for examining how dissatisfaction with different job attributes relates to labour turnover.

Existing job satisfaction contributions underpin the importance of using a satisfaction framework to predict job mobility, though overall satisfaction aggregates

Figure 4.1: Labour market dynamics in the Netherlands, 2014-2023



Notes: Job search: share of respondents indicating they have actively searched for a new job in the past year, reported in the 4th quarter of each year. Source: Dutch Working Conditions Survey (NEA). Job separation: share of workers no longer working for the same employer in december of the year following the survey. Source: Non-public register data from Netherlands Statistics. Labour market tightness is measured using the UWV Spanningsindicator, which calculates the ratio of job vacancies to unemployed individuals receiving benefits for less than six months, in the fourth quarter of each year. Values above 1.5 indicate a tight labour market, and values above 4 indicate a very tight labour market. Source: Dutch Unemployment Agency (UWV).

across all job components and obscures which specific attributes drive quitting (Pelly, 2023). Clark (2001) for the UK and Faberman et al. (2022) for the US emphasise dissatisfaction with pay and job security as the most salient predictors of quits and on-the-job search, though they also document the important roles of job amenities such task content, under-utilised skills, and unstable job duties. Using linked Finnish survey–administrative data, Böckerman and Ilmakunnas (2009) show that a broad set of job disamenities, such as hazards, insecurity, lack of supervisor support, mentally demanding tasks, limited promotion prospects and discrimination, lowers satisfaction and thereby increases job search and through search, job separation. Lévy-Garboua et al. (2007) argue that the difference between the job satisfaction in the current job and the expectation of job satisfaction in other jobs best predicts quits, suggesting the relative importance of outside options. Finally, related work from the Netherlands by Delfgaauw (2007) highlights that dissatisfaction with specific attributes predicts not only the search but also the direction of search: dissatisfaction with management predicts employer changes; high valuation of autonomy predicts internal mobility; dissatisfaction with task duties predicts search outside the industry.

Compared with the existing literature, our study offers several conceptual and empirical advances. Conceptually, we embed job attributes into a simple search-theoretic framework in which workers derive utility from three additive components: wages, non-wage tangible amenities, and non-wage intangible attributes (Mas, 2025). The probability of separation increases when the utility from any of these components falls, or when the value of the outside option rises, which we model empirically using differences in occupational tightness. A key implication of our framework is that dissatisfaction with intangible job attributes should be especially predictive of job separation, through the channel of decreased motivation (Gagné and Deci, 2005). Unlike wages or contractual features, intangible aspects of work are largely experienced goods: their true quality is learned only after entering the job. Dissatisfaction with leadership, task interestingness, or workplace relationships with the supervisors therefore reflects negative realised match quality. This prediction is consistent with extensive evidence showing that intangible aspects such as competence, recognition, meaningfulness, task variety, and psychological safety matter substantially for workers' motivation, well-being, effort and retention (Deci et al., 2017; Nikolova and Cnossen, 2020*a*; Ashraf et al., 2025; Asuyama, 2021; Collis and Van Effenterre, 2025; Cnossen and Nikolova, 2025).[2]

We test the predictions from our model in a descriptive, revealed-preference way, contributing to the extant literature on revealed-preferences and non-wage amenities. Existing work such as Bagga et al. (2025) focuses on the valuation of working-from-home arrangements, while Humlum et al. (2025) analyse amenity-driven job-to-job mobility. Like Humlum et al. (2025), we incorporate a broad set of job-utility components but we study these components not only in the context of job-to-job transitions but also for non-employment exits (unemployment, education, and self-employment). Our focus is not on estimating willingness-to-pay for amenities (Mas, 2025; Humlum et al., 2025), but on understanding their role in labour mobility. We use job dissatisfaction as an empirically observable proxy for on-the-job utility, without claiming causal inference. The linked survey-administrative data provide rich descriptive evidence on how different dimensions of job dissatisfaction relate to realised mobility.

Empirically, our main contribution is to show that different dimensions of job dissatisfaction predict not only whether workers separate from their jobs, but also how and when they do so. First, we show that dissatisfaction with non-monetary job attributes is strongly associated with subsequent job separation. For instance, dissatisfaction with interesting work and supervisors is linked to a five percentage point increase in the probability of leaving a job, on a sample mean of 20.5%. Next, we demonstrate that different forms of dissatisfaction predict distinct exit destinations: while dissatisfaction with salary and learning opportunities is associated with job-to-job mobility, dissatisfaction with other attributes is more likely to be followed by non-wage employment outcomes. For example, dissatisfaction with leadership predicts transitions into self-employment and unemployment and dissatisfaction with

[2]These attributes capture the psychological dimensions of work that drive intrinsic motivation, which is increasingly used in economics (Deci et al., 2017; Cassar and Meier, 2018). Self-determination theory (SDT) (Gagné and Deci, 2005; Deci et al., 2017) identifies three basic needs (autonomy, competence, and relatedness) that drive intrinsic motivation. In our coding scheme, opportunities to apply skills and supportive peer/supervisor relationships are treated as intangible work attributes, while control over one's schedule is classified as a tangible work arrangement. Survey-based dissatisfaction measures are assumed to reflect shortfalls in these needs.

interesting work predicts entry into unemployment or education. Finally, for interesting work and learning opportunities, the relationship with job separation is stronger when outside options improve, as captured by higher local labour market tightness. While no moderation effect is documented for salary and the other tangible work arrangements. The findings on learning opportunities are especially noteworthy, as local labour market tightness act as the channel sustaining the robustness of the relationship. This represents a further contribution that highlights the spatial nature of learning beyond the more common investigated learning benefits due to proximity and agglomeration economies (Duranton and Puga, 2004) and opens to further analysis in this direction.

The remainder of the paper is organized as follows. The next section presents a stylized version of a search model and explicitly derives the job mobility choice as a function of a worker's satisfaction with the three job value components. Section 3 presents the data source and variable construction. Section 4 present the empirical strategy. Section 5 discusses the results and section 6 concludes.

4.2 Theoretical framework

Worker (i) derives utility from three additive components of their job (j): wage, tangible and intangible job attributes (Mas, 2025). During each period (t)(year, by convention), the worker decides whether to remain or separate from their job. A separation occurs when the value of the outside option (V_{it}^{out} plus a separation shock ν_{it}) exceeds the current realized utility ($U_{ij,t}$) and the expected continuation value:

$$V_{it}^{\text{out}} + \nu_{it} > U_{ij,t} + \delta \mathbb{E}[V_{ij,t+1}^{\text{stay}} \mid \mathcal{F}_{it}], \tag{4.1}$$

where δ is the discount factor and $\mathcal{F}_{it}$ denotes available information. Outside options depend on local labour market cyclicality and institutional features (e.g., unemployment benefits, education subsidies), all of which raise the value of the outside option V_{it}^{out}. Importantly, the utility from different components can be negative, for instance when poor amenities lead to stress or burn-out, implying that the value of the outside option does not need to be high.

Because V_{it}^{out} and continuation values are unobserved, we estimate a reduced-form hazard model:

$$\Pr(\text{Separate}_{ijt} = 1 \mid \mathcal{F}_{it}) = \Lambda\big(\alpha_t + U_{ij,t}^w + U_{ij,t}^a + U_{ij,t}^z + X_{ijt}'\beta\big)\,, \tag{4.2}$$

where, for ease of notation, U^w, U^a, and U^z denote experienced utility from wage, tangible and intangible amenities, and their coefficients capture how each component predicts mobility in a revealed-preference sense, where utility is expected to relate negatively to separation risk.

Upon separating workers choose among multiple destinations d (job-to-job, unemployment, education and self-employment). Each destination has a latent value:

$$V_{it}^d = \alpha_d + \theta_d U_{ij,t}^w + \psi_d U_{ij,t}^a + \phi_d U_{ij,t}^z + X_{it}'\gamma_d + \eta_{it}^d, \tag{4.3}$$

with η_{it}^d i.i.d. extreme-value. The chosen destination maximizes V_{it}^d . The probability of choosing destination d depends on the latent value of that option, versus all other options:

$$P_{it}^d = \frac{\exp\left(V_{it}^d\right)}{\sum \exp\left(V_{it}^{d'}\right)} \tag{4.4}$$

In this way, disutility from work components reduces the value of current jobs as well as the expected value of other jobs. This implicitly raises the value of non-wage-employment outside options.

4.2.1 Empirical implementation

We link survey-based satisfaction measures on salary, tangible work arrangements, and intangible job attributes to administrative records on wages, hours, contract type, and firm characteristics. Satisfaction serves as a proxy for the evaluative component of realized on-the-job utility. The register data provide independent measures of objective job attributes.

For satisfaction to capture job utility, identification relies on a few conditions.

First, reported satisfaction should be monotonically related to underlying utility, so that higher dissatisfaction corresponds to higher disutility of work. Second, conditional on observed job characteristics, dissatisfaction should not be driven entirely by anticipating a move for reasons unrelated to job attributes.[3] Third, reporting noise should be random on average, so that measurement error does not systematically bias the results. Under these conditions, coefficients on satisfaction variables can be interpreted as reduced-form links between experienced utility and separation or exit outcomes, consistent with a revealed-preference interpretation.

One consideration is that workers may sort into jobs, either based on contractible, observable characteristics such as salary or tangible work arrangements, or based on expectation about work context, climate or culture. To account for the former, we control for objective job characteristics including hourly wages, contract type, working hours, and the option to work from home. Even after accepting a job with full knowledge of these features, workers may still be dissatisfied with some attributes. Including these controls therefore helps to isolate dissatisfaction that arises from the realised job rather than from baseline contract differences. To account for sorting based on preferences for job content or expectations regarding industry or occupational work culture and values (Burbano et al., 2024; Kesternich et al., 2021; De Schouwer and Kesternich, 2024), we include detailed industry and occupation fixed effects. In addition, we conduct an analysis using survey measures of the relative importance of each job attribute to account for individual preferences.

4.2.2 Theoretical predictions

The framework and the extant literature yield several predictions. First, dissatisfaction with any attribute should relate to higher job separation rates, but we expect differences by type of job attribute.

Dissatisfaction with intangible attributes, such as leadership, learning opportunities, and task content, should increase the likelihood of separation through lower work

[3]To address potential anticipatory behaviour, we provide an analysis where we split the sample between workers actively searching on the job and those who are not.

motivation. Following the motivation literature, workers require an environment that allows them to flourish, satisfying basic psychological needs such as engaging in interesting work that matters, feeling valued and recognized by supervisors, and having opportunities for learning and autonomy (Gagné and Deci, 2005; Deci et al., 2017). When these needs are not met, motivation and effort can decline, which may lead to contracts not being renewed or to voluntary quits (Ashraf et al., 2025; Cnossen and Nikolova, 2025; Lazear et al., 2015). Exits may take multiple forms: workers could move to another job, or leave employment temporarily through unemployment, self-employment, or education to avoid poor working conditions or to acquire new skills. Because these motivational needs are broadly relevant across workers, we expect the effects of dissatisfaction with intangibles to be relatively uniform across the population.

Consistent with the canonical labour supply model, dissatisfaction with salary is primarily driven by comparisons to alternative job opportunities. We therefore expect it to be most strongly related to job-to-job mobility, or potentially self-employment as a way to obtain higher earnings, rather than to unemployment or education, which involve higher costs (e.g., Burdett, 1978; Faberman et al., 2022).

Dissatisfaction with tangible work arrangements, such as job security, contract type, working hours, and flexibility, can make it difficult for workers to balance work and personal life. A long line of literature shows that these attributes influence both sorting into a new job and leaving the current one (e.g., Böckerman and Ilmakunnas, 2009; Lévy-Garboua et al., 2007; Sullivan and To, 2014; Bagga et al., 2025). Even when these features are known at hiring, experience on the job may reveal incompatibilities that increase stress or burnout, which can trigger employment exits. In the Dutch context, widespread part-time work, high flexibility, and available education pathways provide many alternatives to one's current employment (Bekker and Mailand, 2019; Scheer et al., 2022; Patra et al., 2025), so dissatisfaction with tangibles may lead not only to job-to-job mobility in search of better arrangements, but also to non-employment spells such as unemployment or education as a temporary break form employment. Because these incompatibilities may differ across workers and life circumstances, we expect the effects of dissatisfaction with tangibles to vary rather than be uniform.

These predictions guide the interpretation of the empirical associations documented below: intangible dissatisfaction as a match-quality signal, salary dissatisfaction primarily as an outside-option mechanism, and work arrangement dissatisfaction as reflecting constraints or incompatibility with life circumstances.

4.3 Institutional context: The Netherlands

The Dutch labour market is characterized by high levels of flexibility and job-to-job mobility (Gonne, 2023). Apart from relatively high mobility between employers, institutional features support transitions into unemployment or education/training via generous benefits (Salverda, 2025). These pathways imply that different forms of dissatisfaction may lead to different exit destinations.

Unemployment benefits in the Netherlands are relatively generous and can be received for up to 24 months, conditional on employment history. These benefits are only accessible following separations that involve dismissal, the end of a fixed-term contract, or a mutually agreed termination[4], but not after voluntary quits.[5]

These institutional arrangements imply that transitions into unemployment primarily occur through contract expiration, dismissal, or mutually agreed separation rather than voluntary quitting. Our analysis therefore does not interpret such transitions as evidence of workers voluntarily opting for unemployment. Rather, we show that individuals who are more dissatisfied with specific amenities are more likely to experience these forms of job separation. Because the distinction between permanent and temporary contracts is central for determining eligibility for unemployment, and because contract type shapes the likelihood of involuntary separation, we include contract type as a key control in our empirical analysis to account for this institutional structure.

Part-time employment and flexible scheduling are widespread: almost half of

[4]A so-called *vaststellingsovereenkomst* or settlement agreement.

[5]See the Dutch Unemployment Agency for more information: `https://www.uwv.nl/en/individuals/unemployment-benefit/about`.

Dutch employees work under 35 hours per week and working-time arrangements are often negotiable (Gonne, 2023). This makes flexibility and work-life balance salient and heterogeneous amenities across jobs, and dissatisfaction with these potentially strongly related with turnover.

Since 1 January 2020, the Balanced Labour market Law (Wet Arbeidsmarkt in Balans - WAB) adjusted labour-market rules affecting flexible versus permanent contracts. Employers face lower unemployment-insurance premiums for permanent hires, temporary contracts can now last longer before converting automatically, on-call contracts have stricter minimum requirements, and severance pay is owed from day one, making flexible contracts relatively unattractive to employers (Patra et al., 2025).[6] Furthermore, the study period (2014-2024) is characterized by increasing labour market tightness as shown in Figure 4.1, particularly after 2020.[7] These trends motivate splitting the analysis by year and by pre- versus post-2020, capturing both COVID-19 and WAB effects.

Figure 4.2 show the tightness at the local labour market level in 2016 (on the left) and the growth till 2023 (on the right), expressed as a simple difference between 2023 and 2016 levels. While the right side of the figure points to the exceptional increase in tightness of the labour market in the period under-observation, in particular in the north-eastern side of the country, overall, almost every regional markets in the Netherlands have gone through a consistent increase (higher than 3). The Netherlands have one of lowest spatial heterogeneity of labour markets in EU. The NUTS-2 disparities are very low and the country is characterised by high regional employment rates (between 80% and 85% in 2024).[8] Despite this picture would point to a rather homogenous tightness of local labour markets, an element of heterogeneity that will

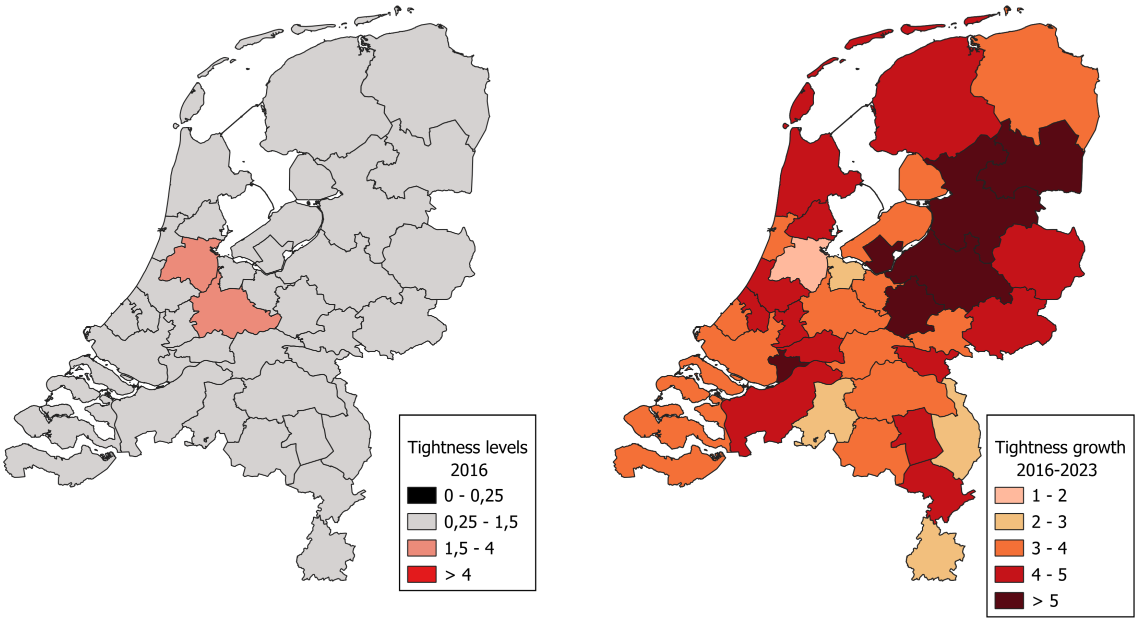
[6] While the WAB aimed to increase job security, early evidence suggests effects have been mixed, with some flexible contracts terminated but not always replaced by permanent ones (Patra et al., 2025).

[7] However, because the COVID-19 pandemic coincided with the policy change, our empirical setting does not allow for a clear distinction between the effects of the policy reform and those of the pandemic shock. Consequently, we cannot draw firm conclusions about the magnitude of the policy's impact.

[8] According to EUROSTAT data, the Netherlands have the lowest employment rate differences in EU as well. For both see: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Labour_market_statistics_at_regional_level

also be exploited in our empirical application (Section 4.1.3) concern the variation across occupations.

Figure 4.2: Local Labour Markets Tightness 2016 levels and growth 2016-2023



Notes: Own elaboration using QGIS. On the left, the tightness level from 2016 is shown. The tightness indicator measures the ratio of job vacancies to unemployed individuals receiving benefits for less than six months, in the fourth quarter of each year. Values below 0.25 indicate a slack labour market, values between 0.25 and 1.5 reflect average tightness, and values above 1.5 indicate a tight labour market. Values above 4, very tight labour markets. On the right of the figure, it is shown map of the tightness growth in between 2016 and 2023. The latter is measured as a difference between 2023 and 2016 levels.
Source: Dutch Unemployment Agency (UWV).

4.4 Data and Descriptives

4.4.1 Data sources

This paper uses data from the Dutch Working Conditions Survey (*Nederlandse Enquête Arbeidsomstandigheden*, or NEA), an annual, nationally representative cross-sectional survey conducted in the Netherlands. Each wave includes approximately 50,000 respondents and is administered in the fourth quarter of the year. For our analysis, we use ten pooled survey waves from 2014 through 2023.

The NEA collects detailed information on working conditions, job characteristics, and worker attitudes. Importantly, respondents can be linked at the individual level through pseudonymized personal identifiers to administrative data from the Social Statistical Database (SSB) of Statistics Netherlands (CBS). This allows us to combine rich survey responses with objective data on wages and employer characteristics.

Main independent variables

All respondents are asked to report their satisfaction with various aspects of their job, with answer options very satisfied, satisfied or not satisfied. In our main specifications, we group satisfied and very satisfied together to understand the differential effect of dissatisfied workers. Full questions and answer phrasing is provided in appendix 4B.

We divide these aspects into three conceptual categories.

The first category is intangible attributes. It contains variables on satisfaction with interesting work, learning opportunities, and supervisors.[9] These attributes capture the intrinsic qualities of a job that are not or poorly understood before entering a job. Their satisfaction reflects the quality of the match between the worker preferences and the employer, on job characteristics that are not part of the employment contract.[10]

To capture monetary job attributes we use the item on satisfaction with salary, so the entire income associated with the job. The third category is that of tangible non-monetary work arrangements (Mas and Pallais, 2020), which captures how work is organized and how well it fits into workers' personal lives. This includes two variables

[9]These attributes also tangentially relate to self-determination theory (Deci et al., 2017), which predicts that workers whose psychological needs for competence, autonomy and relatedness are met are more motivated at work (Gagné and Deci, 2005).

[10]The attribute "learning opportunities" (*mogelijkheid om te leren*) is somewhat ambiguous here. Though we mainly interpret it as informal, on-the-job learning in our categorization, it could also reflect formal training offered by the employer, which contributes to skill accumulation and human capital. In the survey, this item appears immediately after interesting work and before pleasant atmosphere (some years) and good supervisors (all years), suggesting that respondents primarily interpret it as part of the work culture, and thus as an intangible attribute. Still, some ambiguity remains. Importantly, this distinction does not affect the main outcomes of our model. It only concerns the conceptual grouping of variables, as we do not add the variables into one index of intangible attributes.

related to job future and stability: job security and contract type (tenured or flexible). It also contains two variables on working time, namely the ability to work part-time and to determine one's own working hours. And lastly, it contains the amenity of remote work possibilities.

Dependent variables

Our main dependent variable is whether workers are separating from their employer in the year after the survey. Job separation is measured by linking NEA respondents to administrative employer–employee data. We identify each respondent's employer at the time of the survey and verify whether the individual is still employed at the same firm in December of the following year. If the individual is no longer employed at that firm, we code them as having separated. To avoid misclassifying separations due to firm closures, we check whether the original employer still exists in the firm registry in the subsequent year.

To measure destinations after separation, we use Statistics Netherlands' socio-economic status (SECM) measure for the survey year and the year after. SECM is constructed by integrating multiple administrative sources, including tax and social security records, unemployment and disability benefit registers, pension data, and education enrollment. Each indvidual is assigned to mutually exclusive main socio-economic categories. The main-status assignment follows a fixed Statistics Netherlands priority hierarchy across income and benefit sources rather than hours worked, so the category reflects an individual's dominant administrative signal rather than their full allocation of time. We observe SECM status in December of the year after the survey (approximately $t + 12$ months), ensuring that it primarily captures the post-separation state.

We focus on four categories within the SECM.[11] Employment captures whether a

[11] CBS defines the following detailed main-status categories: 11 Employee; 12 Director-major shareholder; 13 Self-employed entrepreneur; 14 Other self-employed; 15 Contributing family worker; 21 Unemployment benefit recipient; 22 Social assistance benefit recipient; 23 Other social security benefit recipient; 24 Sickness/disability benefit recipient; 25 Pension benefit recipient; 26 Not yet in school/pupil/student with income; 31 Not yet in school/pupil/student without income; 32 Other without income. In the analysis, we group these into: (1) Employee (11); (2) Unemployed (21); (3)

person's main status is working for a firm. Unemployment reflects receipt of statutory unemployment benefits. Third, self-employment reflect an individual registered as self-employment entrepreneur or other self-employed type. Fourth, student status indicates that an individual is registered as enrolled in education during the reference month, regardless of whether they also work or receive other income.

Additional covariates

We include a rich set of control variables from the NEA. For individual characteristics, we include gender, age, highest level of education, age of the youngest child (if applicable), and household position. Job characteristics included are contract type (permanent or flexible), part-time status, number of working days per week, self-employment besides current job, working from home, multiple job holding, supervisory role, tenure at the current firm, firm size, and urbanity. Lastly, the NEA collects variables on occupation (ISCO 2008), industry (SBI 2008[12]) and local labour market region (*arbeidsmarktregio*).

We further augment the data set with two external data sources. First, respondents are linked to administrative wage data from December of the survey year, enabling us to calculate their hourly wage (contractual base wage divided by contractual hours), which we log-transform.

Second, we include labour market tightness indicators of the Dutch Unemployment Agency (UWV), which measures the ratio of job vacancies to unemployed individuals receiving benefits for less than six months, in the fourth quarter of each year. Values below 0.25 indicate a slack labour market, values between 0.25 and 1.5 reflect average tightness, and values above 1.5 indicate a tight labour market. Values above 4, which are increasingly common, especially after 2020, indicate a very tight labour market. This measure is available from Q4 2016 onward, at the occupation-by-local labour

Self-employed (13, 14); (4) Student (26, 31); and (7) Other (12, 15, 22, 23, 25, 24, 32). Note that, with respect to self-employed workers, we are not able to identify whether workers who transition into self-employment continue to work for the same firm as external suppliers.

[12] This is a Dutch industry classification. The first digits are in line with international NACE industry codes.

market level.[13] We opt for this more refined version that combines occupation-by-local labour market tightness measure in order to explain a larger variation than a tightness measure captured only at the LLM level. Figure 4.2 clearly shows that tightness levels are pretty homogenous in 2016 and at the same time that the growth in the period under analysis is pretty high in any of the LLM. The tightness thresholds are provided by the Dutch national institute of statistics.

Sample cleaning

As final cleaning steps, we exclude respondents in the armed forces. We drop individuals without valid information on job separation, those who cannot be matched to an employer in the registry at the time of the survey, and workers employed at firms that exited the market within a year after the survey, to ensure that observed job separations are not driven by firm closures.

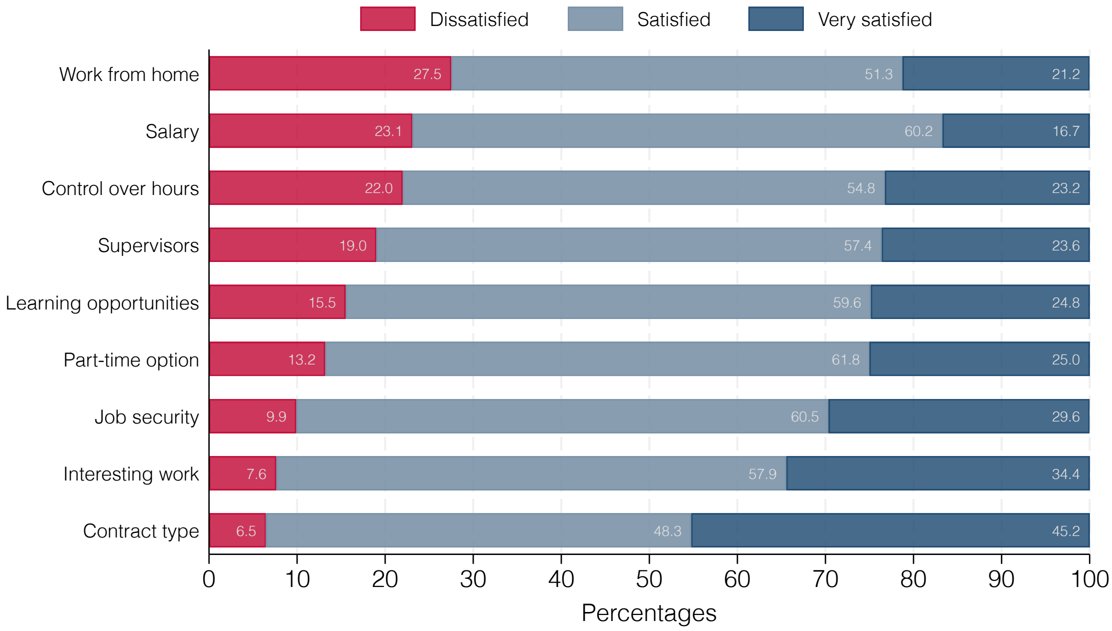
For all categorical dependent variables, we include a 'missing' category to retain respondents who skipped one or more survey items, to remove bias from selection into item non-response (Nikolova and Cnossen, 2020*b*; Nikolova et al., 2024). These categories are included in the regressions, but not reported in the tables. After all cleaning steps, the final sample includes 429,627 individuals. The population weights provided by the NEA make the results representative of the Dutch population.

4.4.2 Descriptive statistics

Table 4.A.1 reports the means and standard deviations of our main variables. In our sample, job separation occurs for 20.4%. Roughly one in five workers (21.7%) of our sample is in an open-ended flexible contract. Slightly over half of our sample workers 32 hours or less, and so is in a part-time contract. Our sample is predominantly higher educated, followed by middle and low education.[14]

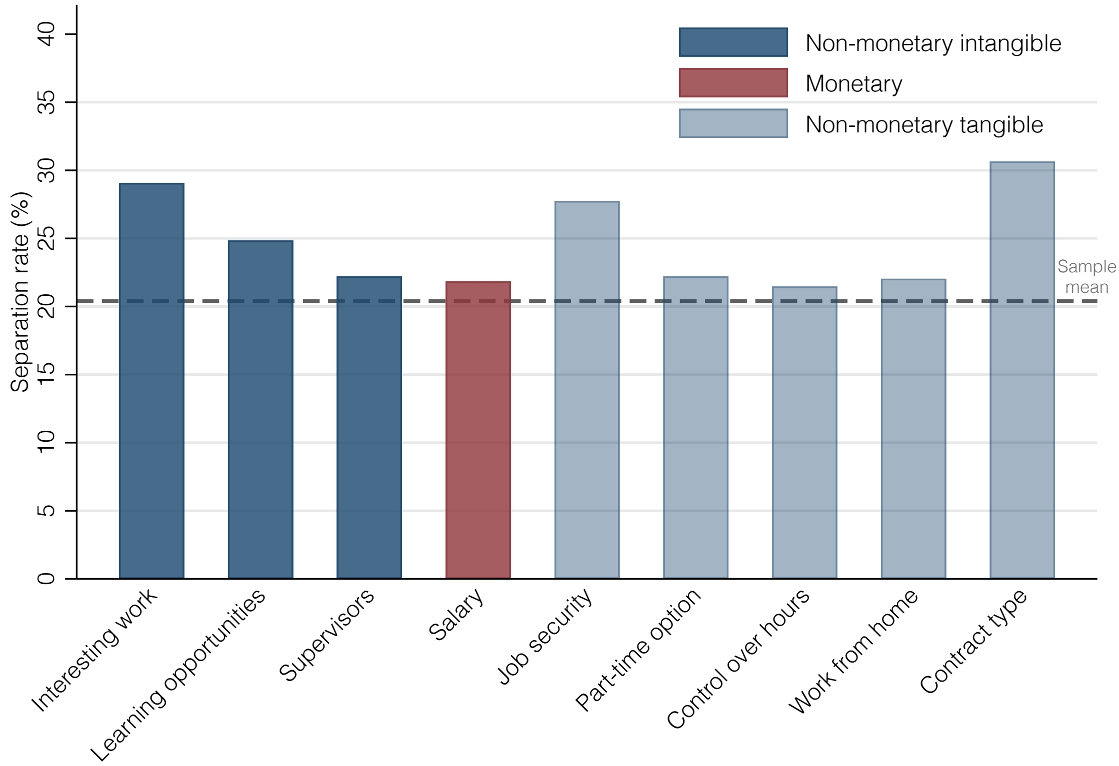
[13]The occupations roughly correspond to ISCO 3 digit, with some exceptions. The authors created a crosswalk to match the UWV data to ISCO data, which is available on request. The local labour market level ("arbeidsmarktregio") is a functional area where local municipalities, the national social security agency (UWV), and social partners work together to align job supply and demand within

Figure 4.3: Satisfaction with job attributes in the Netherlands, in percentages (2014–2023)



Notes: Frequencies of respondents' answers to the question: How satisfied are you with the following aspects of your current job? Data covers 2014–2023. Source: Dutch Working Conditions Survey (NEA).

Figure 4.4: Job separation rates for workers dissatisfied with different job attributes (compared to sample mean)



Notes: Job separation: share of workers no longer working for the same employer in December of the year following the survey. Dissatisfied: Respondents indicating they are dissatisfied with job attribute. Data covers 2014-2023. *Source:* Dutch Working Conditions Survey (NEA) and non-public register data from Netherlands Statistics.

Satisfaction with attributes Figure 4.3 presents the satisfaction with job attributes for the entire sample, in percentages. Across all categories, the majority of respondents report being at least satisfied with most aspects of their job.[15] Attributes related to the work intangible show particularly high satisfaction levels: for example, nearly 93% are satisfied or very satisfied with having interesting work, and almost 85% express satisfaction with learning opportunities and supervisors. In contrast, monetary satisfaction is notably lower. About 23% of respondents report being dissatisfied with their salary. Satisfaction with work arrangements shows more variation. While most workers report relatively high satisfaction with job security (84.5% satisfied or very satisfied), attributes such as control over working hours and the ability to work from home show higher dissatisfaction: 22% and 27,5% of respondents are dissatisfied with these aspects, respectively.

Job separation and attribute satisfaction

Figure 4.4 presents job separation rates for dissatisfied workers by various job attributes. Across all attributes, dissatisfied workers are consistently more likely to separate from their job compared to the mean level. However, the magnitude of these differences varies by attribute. The largest gaps are observed for interesting work, learning opportunities, job security, and contract type, where dissatisfied workers are substantially more likely to separate from their jobs. The difference between workers satisfied and dissatisfied with monetary attributes is relatively small.

4.5 Empirical strategy

Our main empirical approach uses logistic regressions, in which we regress job separation as a binary outcome variable on a set of satisfaction measures, controlling for

a specific region.

[14] We use sample weights provided by TNO and Netherlands Statistics to correct for this.

[15] Some amenity satisfaction variables are moderately correlated (see Table 4.A.2). For instance, control over hours dissatisfaction correlates with working from home dissatisfaction (0.53). This implies that coefficients should be interpreted as conditional associations rather than fully independent effects.

a rich set of individual and job characteristics.

Job separation is constructed from administrative records, and equals one if the respondent no longer works for the same employer in the December following the survey wave. This definition captures both voluntary and involuntary job separations.

Our key independent variables are a set of satisfaction indicators with job attributes, drawn from the NEA survey. All satisfaction measures are included as dummies. In our main analyses, we group satisfied and very satisfied into one category, which serves as the reference category. We include dummies for missing responses to avoid selection bias due to item non-response.[16]

We estimate the following baseline model:

$$\Pr(y_i = 1) = \alpha + \beta'\mathbf{S}_i + \gamma'\mathbf{X}_i + \delta_{o(i)} + \theta_{r(i)} + \zeta_{k(i)} + \lambda_t, \tag{4.5}$$

where y_i denotes the binary outcome (either job search or separation) for individual i, $\mathbf{S}_i$ is a vector of satisfaction indicators, and $\mathbf{X}_i$ includes personal characteristics (gender, age, education, household position, presence and age of children) and job characteristics (contract type, tenure, firm size, supervisory status, weekly hours, multiple job-holding, urbanity). We additionally control for the respondent's log hourly wage, constructed from administrative data as the ratio of contracted base wage to contracted hours in December of the survey year. We include 3 digit ISCO occupation ($\delta_{o(i)}$), local labour market ($\theta_{r(i)}$), 2 digit SBI industry ($\zeta_{k(i)}$) and survey-year fixed effects (λ_t). Standard errors are clustered at the occupation $\times$ industry $\times$ local labor market level.

[16]We run additional specifications without the missing response categories. Results do not change and are available on request. These coefficients have no economically meaningful interpretation, and are therefore not reported in the main text.

4.6 Results

4.6.1 Baseline regressions

Table 4.1 presents the results of the baseline cross-sectional logistic regressions, where the dependent variable is job separation. The main independent variables capture worker dissatisfaction across three groups of job attributes: work intangibles, monetary rewards, and work arrangements.

Column (1) includes controls for survey mode and year, Column (2) adds demographic controls, and Column (3) presents the full set of covariates, including objective measures of work arrangements (part-time status, working days, tenure, contract type, and working from home), 3-digit ISCO occupation, 2-digit SBI industry, local labour market dummies, log hourly wage and socio-economic status at the time of the survey.[17] Figure 4.5 reports marginal effects from the full specification, showing that the coefficients correspond to economically significant differences between the probability of job separation for different satisfaction levels. In the full model, dissatisfaction with all intangible work attributes is associated with a higher likelihood of job separation. For example, workers dissatisfied with interesting work have a predicted probability of separation from their job that is roughly 5 percentage points higher than those who are satisfied (26.3 versus 21%), equivalent to about a quarter of the national mean separation rate (21%) (see Figure 4.5). As intangibles are only partly observed before entering a job, we treat these associations as evidence of a poor match quality between the worker and the work environment, pushing workers out of their current job.

We find heterogeneous results for tangible work arrangements: whereas workers dissatisfied with job security and contract type show substantially higher separation

[17]We perform the Oster (2019) for reducing concerns related to omitted variable bias. The results indicate that, across job attributes, selection on unobservables would need to be substantially stronger than selection on observables to fully explain away the estimated effects, with δ ranging from 1.45 for contract type to almost 11 for job security. These results suggest that the set of controls employed captures a substantial portion of the relevant selection, and that the estimated relationships are relatively robust to omitted variable bias.Results are not presented in the appendix but are available on request.

Table 4.1: Logistic regressions of job separation on dissatisfaction with attributes

	(1)	(2)	(3)
Dissatisfaction with:			
Intangible job attributes			
Interesting work	0.640***	0.366***	0.344***
	(0.017)	(0.017)	(0.017)
Learning opportunities	0.289***	0.206***	0.194***
	(0.013)	(0.014)	(0.014)
Supervisors	0.026**	0.334***	0.358***
	(0.012)	(0.012)	(0.012)
Monetary attributes			
Salary	0.042***	0.037***	-0.004
	(0.011)	(0.011)	(0.012)
Tangible work arrangements			
Job security	0.505***	0.439***	0.414***
	(0.014)	(0.015)	(0.015)
Part-time option	-0.044***	0.107***	0.090***
	(0.015)	(0.015)	(0.015)
Control over hours	-0.169***	0.018	0.045***
	(0.014)	(0.014)	(0.014)
Work from home	0.262***	0.016	0.020
	(0.013)	(0.013)	(0.013)
Contract type	0.776***	0.275***	0.297***
	(0.018)	(0.018)	(0.018)
Constant	-2.047***	-0.842***	-0.153
	(0.051)	(0.187)	(0.226)
Obs.	429,647	429,647	429,647
Pseudo R-squared	0.0375	0.116	0.126
Survey-year	X	X	X
Demographics		X	X
Job characteristics			X
Ind, region, occ dummies			X

Notes: Standard errors are reported in parentheses and are clustered at the occupation × industry × local labour market level. All regressions are weighted using population-based probability weights. The reference category for all dissatisfaction variables is "satisfied." Survey year covariates in include survey mode and survey year. Demographics contain gender, age, education level, household position, age of the youngest child (if applicable). Job characteristics include a log hourly wage, contract type dummy, tenure at the current firm, a part-time status dummy, firm size, a supervisory role dummy, number of working days multiple job holding, and urbanity. Columns (3) and (4) include fixed effects for industry (SBI 2-digit), region (*arbeidsmarktregio*), and occupation (ISCO 3-digit).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

rates (with differences of approximately 6.5 and 4.5 percentage points as shown in Figure 4.5), we observe smaller differences between workers dissatisfied with working time components, such as part-time options and control over hours. We find no significant effect for dissatisfaction with working from home. The association with working time dissatisfaction and separation rates may reflect incompatibilities between home and working life, whereas the association for the job stability related amenities are more likely to reflect longer-run preferences for security. In contrast dissatisfaction with salary does not significantly predict job separation for the full sample.

To evaluate the relative importance of different groups of variables in explaining job separation rates, we apply a Shapley decomposition of the model's pseudo R-squared. The results are shown in Appendix Table 4.2. Non-monetary components together explain over 20%, of which intangibles account for roughly half (10.3%) and tangibles the other half (11.1%). Dissatisfaction with salary only explains 0.6% of total explained variation. Objective job characteristics, including hourly wage, contract type, tenure, and part-time status, together explain a greater share of the variation than the satisfaction-based measures.

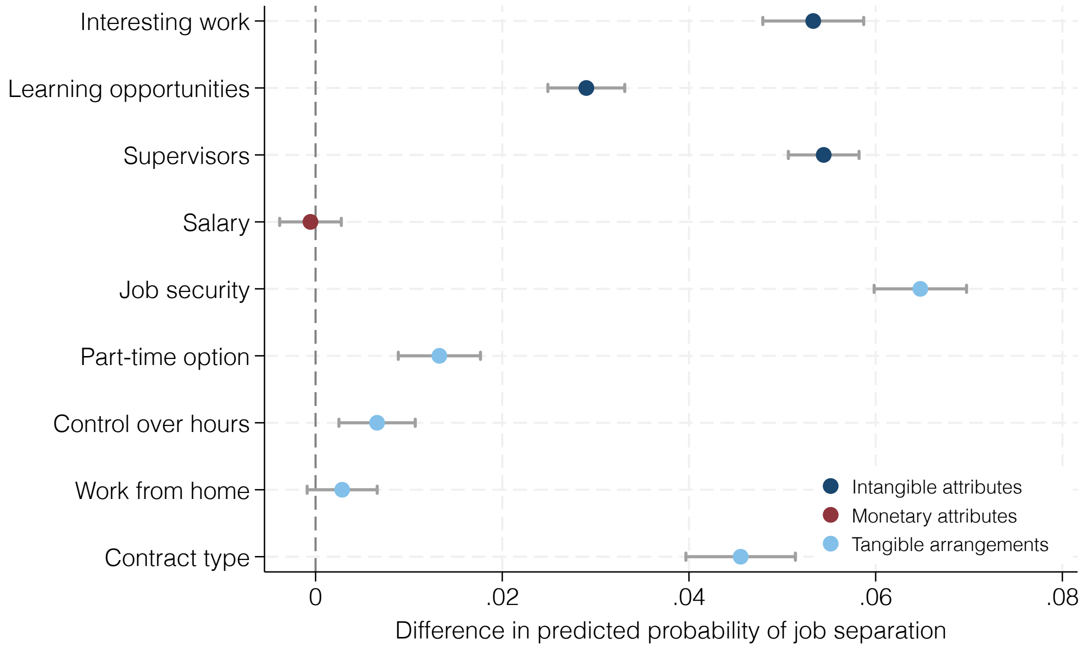
To shed light on the mechanisms through which dissatisfaction with job amenities may translate into turnover, we next examine heterogeneity in these associations across worker and job characteristics.

4.6.2 Heterogeneity analysis

We assess the heterogeneity of our findings by conducting a set of stratified analyses across key demographic and employment contexts (as in Clark (2001)). In Table 4.3 we show the results based on: (i) gender, (ii) contract type (permanent vs. flexible), (iii) tenure levels (categorized as $<$ 2 years, 2–5 years, and $>$ 5 years) and (iv) based on job search activity. We further complement this by specifying analyses by educational levels, supervisory role, age groups, public versus private sector[18], pre- and post-COVID-19 periods, and by survey years (see Appendix Tables 4.A.4 and

[18]For public sector we select public administration (O), as well as education (P) and health (Q) sectors, even though some companies within health and education may be private.

Figure 4.5: Marginal effects of job attribute (dis)satisfaction on probability of leaving job in the year after survey



Notes: Here are plotted the differences between the marginal effects of dissatisfied vs satisfied workers. Marginal effects are presented in Appendix Table 4.A.3. Non-public register data from Netherlands Statistics. Dissatisfied: Respondents indicating they are dissatisfied with job attribute. Satisfied: Respondents indicating they are either satisfied or very satisfied with job attribute (aggregated). Data covers 2014-2023. Source: Dutch Working Conditions Survey (NEA)

Table 4.2: Shapley value decomposition by variable group

Dependent variable: Job separation			
Group of Variables	Subgroup	Shapley value	Percent
Satisfaction	Intangible Work attributes	0.0116	10.3%
	Monetary rewards	0.0007	0.6%
	Tangible Work arrangements	0.0125	11.1%
Job attributes	Wage	0.0183	16.2%
	Contract type	0.0331	29.4%
	Part-time	0.0032	2.8%
	Tenure	0.0120	10.7%
Other	Demographic variables	0.0125	11.1%
	Remaining covariates	0.0221	7.7%
	Total pseudo R-squared	0.1240	100%

Notes: Intangible work attributes includes satisfaction with interesting work, learning opportunities, and leadership. Monetary rewards: satisfaction with salary. Tangible work arrangements: satisfaction with job security, part-time option, control over hours, work from home, and contract type. Wage: log hourly wage in December of the survey year. Contract type: fixed or permanent. Part-time and tenure are listed separately as non-monetary job attributes. Demographic variables include age, gender, and highest attained level of education. Remaining covariates (not shown here) include position in the household, age of youngest child, self-employment, multiple jobs, number of working days, firm size, supervisory role, urbanity, industry (SBI 2-digit), region (local labour market), and occupation (ISCO 3-digit) fixed effects.

4.A.5).

Firstly, to address the concern that job separations for workers on flexible contracts may reflect contract expiration rather than voluntary worker decisions, columns 3 and 4 of Table 4.3 split the sample into permanent and flexible contracts. The results alleviate this concern, showing no substantial differences across contract types, with the exception of the experience of part-time work attribute.

Overall, the results clearly support that all intangible work attributes demonstrate high consistency in both sign and statistical significance across all subgroups. The same holds for the tangible attributes of job security and contract type. Instead, we observe little heterogeneity for the attribute control over hours which vary based on gender and tenure (Table 4.3). The former finding aligns with the notion that women have a greater imperative for flexible scheduling to accommodate family care responsibilities (De Schouwer and Kesternich, 2024) and, at the same time, that work arrangements are still insufficient to meet these needs. The latter suggests that workers with less than two years of tenure are initially more controlled, as their productivity is still not fully known, as well as their knowledge about the organization routines are not yet at the level of more experienced workers.

Arguably, reported job dissatisfaction may partly reflect forward-looking behaviour: workers who are already searching for alternative jobs may retrospectively report dissatisfaction with job attributes. To assess this possibility, we split the sample by on-the-job search behaviour using a survey question that asks whether respondents actively searched for other work in the past year.[19] The results are reported in Columns 8 and 9 in Table 4.3. For non-monetary job attributes, we observe some differences in coefficient magnitudes, but no substantial changes in signs or statistical significance. Overall, these findings indicate that our results for non-monetary job attributes are not (fully) driven by anticipatory job search or planned job quits.

The heterogeneity of dissatisfaction with the salary component deserves a separate analysis. This may explain why the monetary dimension is insignificant in the full specified baseline model. A breakdown by tenure intervals reveals counteracting forces

[19] We use the following survey item: *"In the past 12 months, have you actually taken any action to find another job?"* which can be answered with either yes or no.

at play. Dissatisfaction with salary predicts separation for workers with short tenure (< 5 years), but has a negative association for those with tenure over 5 years (Table 4.3). At the same time, we find that dissatisfaction with salary is negative associated with separation as well as the sign flip between pre- and post-COVID-19 (Table 4.A.4), changing from negative to positive. [20] Finally, dissatisfaction with salary is negatively associated with job separation among workers who engage in on-the-job search.

These results indicate that unobservable factors may play an important role. Still, any interpretation of these findings seems to point towards a complex combination of salary levels and bargaining considerations. In fact, it is noteworthy that these heterogeneous patterns are observed among longer-tenure and public-sector workers, who typically earn higher wages (Topel, 1991; Parsons, 1972; Postel-Vinay, 2015), as well as among workers who report on-the-job search activity, which is often associated with greater bargaining power and increased inter-firm competition (Cahuc et al., 2006). Given the cross-sectional nature of the analysis, it is not possible to investigate these mechanisms further, as doing so lies beyond the scope of this paper. Nevertheless, these patterns warrant further investigation in future extensions of this work.

[20]Looking at the annual data, we generally see an overall non-significant and negative association between salary dissatisfaction and the likely to separate in the 2014-2020 interval which explain the slight negative sign before 2020. For the period after COVID-19, the annual data points to 2021 as a significant anomaly, with salary positively and significantly predicting separation (Appendix Table 4.A.5), driving the post-pandemic results.

Table 4.3: Subsample analysis: regression on job separation, by categories

	Gender		Contract type		Tenure			On-job-search	
	Men	Women	Permanent	Flexible	<2 years	2-5 years	5 + years	Searched	Did not
Dissatisfaction with:									
Intangible attributes									
Interesting work	0.322***	0.364***	0.399***	0.276***	0.361***	0.311***	0.336***	0.220***	0.277***
	(0.024)	(0.023)	(0.022)	(0.027)	(0.028)	(0.034)	(0.027)	(0.023)	(0.024)
Learning opportunities	0.183***	0.210***	0.227***	0.159***	0.246***	0.254***	0.210***	0.152***	0.089***
	(0.019)	(0.019)	(0.017)	(0.023)	(0.025)	(0.027)	(0.021)	(0.021)	(0.018)
Supervisors	0.318***	0.401***	0.381***	0.325***	0.446***	0.455***	0.341***	0.322***	0.209***
	(0.017)	(0.017)	(0.014)	(0.024)	(0.024)	(0.026)	(0.017)	(0.018)	(0.016)
Monetary attributes									
Salary	-0.008	-0.005	-0.003	0.028	0.076***	0.075***	-0.061***	-0.090***	-0.013
	(0.016)	(0.016)	(0.014)	(0.019)	(0.020)	(0.024)	(0.018)	(0.019)	(0.015)
Tangible attributes									
Job security	0.397***	0.427***	0.437***	0.343***	0.369***	0.391***	0.453***	0.370***	0.375***
	(0.022)	(0.021)	(0.020)	(0.023)	(0.025)	(0.034)	(0.023)	(0.022)	(0.021)
Part-time option	0.102***	0.103***	0.117***	0.032	0.136***	0.084***	0.057***	0.059**	0.068***
	(0.020)	(0.024)	(0.018)	(0.027)	(0.026)	(0.032)	(0.024)	(0.024)	(0.020)
Control over hours	-0.001	0.087***	0.035**	0.065***	0.080***	0.009	0.040*	0.022	0.032*
	(0.020)	(0.020)	(0.018)	(0.023)	(0.024)	(0.030)	(0.022)	(0.023)	(0.019)
Work from home	0.003	0.033*	0.030*	0.019	0.018	0.046	0.016	0.009	0.004
	(0.019)	(0.018)	(0.017)	(0.021)	(0.021)	(0.028)	(0.021)	(0.022)	(0.016)
Contract type	0.351***	0.248***	0.302***	0.225***	0.202***	0.282***	0.300***	0.197***	0.322***
	(0.027)	(0.026)	(0.035)	(0.023)	(0.025)	(0.042)	(0.043)	(0.027)	(0.026)
Constant	-0.400	0.276	-0.341	0.720**	0.982*	0.443	-1.357*	0492	-0.352***
	(0.301)	(0.350)	(0.419)	(0.349)	(0.382)	(0.496)	(0.379)	(0.432)	(0.270)
Obs.	216,614	212,993	336,517	93,075	102,579	81,508	245,473	98,348	331,272
Pseudo R-squared	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.105	0.123

Notes: Coefficients from separate regressions for each subgroup. All set of controls are included. Standard errors are reported in parentheses and are clustered at the occupation × industry × local labour market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.6.3 Where do job separators go to?

Having established that dissatisfaction with specific job attributes is associated with job separation, either consistently or heterogeneously across subsamples, we now turn to the question of where workers go after leaving their employer. To shed light on the underlying mechanisms, we exploit the linked survey–administrative structure of our data, which allows us to observe not only whether individuals separate from their job, but also their subsequent labour market destination. We distinguish four post-separation states[21]: two employment outcomes (moving to a new employer (wage employment) or becoming self-employed) and two non-employment outcomes (unemployment or (re-)entry into education). The employment outcomes capture situations in which workers leave their employer while remaining attached to the labour market, potentially seeking a different type of job. These analyses provide new insights into the pathways through which job-attribute dissatisfaction translates into turnover. To the best of our knowledge, this is the first study to document these pathways in such detail for a sample of this size.

Table 4.4 reports multinomial logit estimates for the employment status of workers one year after they leave their employer (81,083 individuals). Because separation is not randomly assigned and the analysis relies on cross-sectional data, the estimates should be interpreted as conditional on separation. Although we control for a rich set of observable characteristics, the possibility of bias due to unobserved heterogeneity cannot be fully ruled out in this setting.

Dissatisfaction with task interestingness is associated with exits into education, consistent with workers seeking to retrain or acquire new skills to move into jobs that better match their interests (Delfgaauw, 2007). It is also linked to unemployment, potentially reflecting temporary disengagement through the channel of reduced motivation (Deci et al., 2017) or even boredom (Spanouli et al., 2023), resulting in counterproductive work behaviour.

On the other hand, dissatisfaction with supervision increases the likelihood of

[21] See the Data section for a detailed description of these outcomes and how they are measured and Appendix Table 4.A.6 for descriptive statistics for separated and non-separated workers.

entering unemployment but also appears to push workers toward self-employment. These patterns are consistent with evidence showing that supervisors can play a significant role in pushing workers out of jobs, while high-quality supervision is associated with lower turnover (Lazear et al., 2015; Hoffman and Tadelis, 2021). Some workers may temporarily exit employment to avoid unsatisfactory supervision (Hommelhoff et al., 2025), whereas poor supervision can also serve as intrinsic motivation to start a business to increase autonomy (Douglas and Shepherd, 2000; Lange, 2012).

Dissatisfaction with learning opportunities shows not significant difference associated with transitions into non-employment states, while it is associated to wage employment rather than self-employment. Conceptually, dissatisfaction with learning opportunities may reflect concerns about future skill accumulation, which workers may address by changing employers in the hopes of finding better learning environments.

Overall, we find contrasting patterns within the intangible variables. One interpretation is that dissatisfaction with supervision and task content directly undermines motivation and well-being (Gagné and Deci, 2005; Deci et al., 2017; Lazear et al., 2015; Hommelhoff et al., 2025), which reduces not only one's motivation to work for the current employer, but also for future employers (Elliot, 2006). This may push workers into non-employment or self-employment states (Henley, 2021). Dissatisfaction with learning opportunities, by contrast, is primarily forward-looking and potentially less immediately detrimental to work motivation. As a result, the former is more likely to induce exits into non-employment, while the latter leads to reallocation within wage employment (see Table 4.A.7).

Next, we examine tangible work arrangements. Dissatisfaction with job security follows the expected pattern: it predicts shifts into unemployment but reduces transitions into self-employment, consistent with a preference for stability among those concerned about security (Delfgaauw and Dur, 2008). This may partly reflect the sorting of risk-averse workers into stable jobs, such that dissatisfaction leads primarily to unemployment or job-to-job mobility, but not self-employment, which is negatively related to security concerns (Bonin et al., 2007).

Dissatisfaction with part-time options is positively related to exits into unemployment, but not to job-to-job mobility. This pattern may reflect a poor match between work and home responsibilities: workers who cannot obtain satisfactory part-time arrangements may leave employment altogether rather than transition directly to another job. The high prevalence of part-time work in the Netherlands, particularly among women, and the limited flexibility or career prospects associated with part-time roles make such mismatches more likely (Gonne, 2023).

Although dissatisfaction with salary is not associated with higher separation overall, it is predictive of job-to-job mobility (see Table 4.A.7) rather than transitions into non-employment. This is consistent with standard job-search theory and evidence that monetary dissatisfaction drives workers to seek better-paid opportunities rather than exit the labour force. Dissatisfaction with intangible attributes, by contrast, is more strongly linked to exits into non-employment states, though we cannot determine whether these separations are voluntary or involuntary, the results nevertheless show that different types of dissatisfaction are associated with distinct exit pathways.

These results can also be interpreted in light of the broader institutional context. The Dutch labour market is characterised by high flexibility, with large shares of part-time and other non-standard work arrangements. While this flexibility can facilitate labour market matching, it has also been linked to deteriorating protection for more vulnerable workers as risk is shifted onto employees (Salverda, 2025). Flexible arrangements and self-employment opportunities may help workers dissatisfied with salary to optimize their income, but for those dissatisfied with non-monetary outcomes, such arrangements can increase the likelihood of separations not immediately followed by a new job.

Table 4.4: Multinomial regression: employment status one year after survey on sample of separated workers

	Employment status (base: employed)		
	Unemployed	Self-employed	Student
Dissatisfaction with:			
Intangible job attributes			
Interesting work	0.331***	0.060	0.261***
	(0.054)	(0.073)	(0.050)
Learning opportunities	0.002	-0.124**	0.073
	(0.047)	(0.062)	(0.047)
Supervisors	0.269***	0.187***	0.019
	(0.041)	(0.058)	(0.052)
Monetary attributes			
Salary	-0.159***	0.071	-0.159***
	(0.043)	(0.057)	(0.041)
Tangible work arrangements			
Job security	0.529***	-0.177**	-0.039
	(0.045)	(0.069)	(0.053)
Part-time option	0.105**	-0.068	-0.084
	(0.053)	(0.078)	(0.064)
Control over hours	0.014	0.053	-0.155***
	(0.051)	(0.072)	(0.049)
Work from home	0.028	-0.029	0.024
	(0.051)	(0.068)	(0.041)
Contract type	-0.049	-0.257***	-0.229***
	(0.060)	(0.090)	(0.063)
Constant	-2.823***	0.218	9.687***
	(0.750)	(1.116)	(0.701)
Obs.		81,083	
Pseudo R-squared		0.411	

Notes: Multinomial logit coefficients on dissatisfaction measures for individuals who separated from their employer at the time of the survey. Base category is employed (but at another firm than during the survey). All sets of controls are included. Standard errors are reported in parentheses and are clustered at the occupation × industry × local labour market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.6.4 Local Labour market tightness: raising the value of outside options

To assess how external conditions shape job separations, we test whether labour market tightness moderates the link between the various job-attribute dissatisfaction and mobility. In our framework, tighter labour markets raise the value of the outside option, for instance by improving expected job offers or by increasing workers' bargaining power. This implies that dissatisfaction should be more strongly associated with separation when tightness is high.

To study this, we use region-by-occupation-level tightness at the 3-digit level (*UWV Spanningsindicator*) for 2016–2023[22], grouped into slack (baseline), average, and tight conditions. As shown in Figure 4.2, the Dutch labour market are not much heterogeneous in term of tightness, for this reason we use the more granular occupation-by-region form which increases the heterogeneity. Table 4.5 reports selected interaction estimates for work-intangible attributes and satisfaction with salary.[23]

Column (1) shows the baseline specification with tightness dummies included; column (2) adds interactions with dissatisfaction. The results show that association between dissatisfaction with intangibles -interesting work and learning opportunity and separation is affected by local labour market tightness. While for the interesting work, the interaction with tightness increases further the likelihood of dissatisfied individuals to separate, for the case of learning opportunities, the tightness indicator entirely moderates the association with job separation. The latter represents the more important result of this section.

The divergent patterns observed between intangibles attributes may be due to their distinct nature. Specifically, while dissatisfaction with supervision is an organizational specific issue which is contingent on individual personal characteristics

[22] This period is shorter than our main analysis. To ensure that the results are not driven by sample selection, we reran the analyses for the 2016–2023 subgroup. The results are consistent with the baseline findings for 2014–2023. Table available on request.

[23] The job attributes, apart salary, are displayed based on significance. For the rest of dimension, no interaction effect is found. Full results are available on request.

and thus largely independent of tightness; dissatisfaction with the lack of interesting work implies an occupational mismatch. This mismatch becomes more relevant when there are available outside options, as reflected by the interaction with the tightness indicator, but it adds an additional effect rather than moderating the full relationships. Instead, learning job amenity differs from the other intangibles because it does not occur in isolation but it inherently requires interaction Duranton and Puga (2004). In the context of predicting labour turnover, learning appears to depend on workers' comparative assessment of superior alternatives within the immediate local labour market. This interpretation is also supported by the fact that, among intangible job attributes, learning is the only one more strongly associated with job-to-job transitions rather than exits from the labour force (see Table 4.A.7). The evidence underscores the importance of the spatial context for learning and in particular the opportunities arising in the same labour market, extending our understanding of the spatial dimension of learning deriving mostly from the agglomeration literature (Duranton and Puga, 2004). Note that we control for a measure of urbanity which allow, for the time being, to reduce the concern that this result is mainly driven by urban workers. Further investigation should clarify further this interesting result which for the moment is beyond the scope of this paper.

Furthermore, salary dissatisfaction shows no significant moderation - contrary to theoretical formulation-, and dissatisfaction with tangible work arrangements is likewise unaffected by tightness. To examine whether these null effects reflect the coarse measure of job separation, which includes exits to non-employment states, we reran the tightness analyses using the specific post-separation states as dependent variables. Even in these models, we find no evidence that salary dissatisfaction is associated with higher job-to-job mobility in tight local labour markets.

The fact that this relationship is not moderated by labour market tightness may reflect two distinct aspects. On the one hand, more conjectural, there may be an individual-level component related to belief updating, whereby workers implicitly incorporate their outside options when evaluating their wage satisfaction. On the other hand, the salary dissatisfaction turnover relationship may be driven by within-firm relative pay comparisons, an interpretation more directly supported by the empirical

Table 4.5: Full logit regressions with interaction terms between dissatisfaction domains and labour market tightness

	(1)	(2)
Dissatisfaction with:		
Intangible Work attributes		
Interesting work	0.400***	0.271***
	(0.022)	(0.056)
Learning opportunities	0.204***	0.053
	(0.018)	(0.046)
Supervisors	0.370***	0.379***
	(0.015)	(0.045)
Monetary attributes		
Salary	0.006	0.042
	(0.015)	(0.041)
Tangible Work arrangements		
Job security	0.421***	0.384***
	(0.020)	(0.050)
Part-time option	0.116***	0.037
	(0.019)	(0.057)
Control over hours	0.041**	0.018
	(0.018)	(0.064)
Work from home	-0.008	0.063
	(0.016)	(0.045)
Contract type	0.296***	0.380***
	(0.023)	(0.057)
Labour market tightness (ref: slack)		
Average	0.052**	0.054*
	(0.023)	(0.032)
Tight	0.089***	0.031
	(0.022)	(0.029)
Interactions		
Interesting work × Average		0.104
		(0.072)
Interesting work × Tight		0.179***
		(0.062)
Learning opportunities × Average		0.175***
		(0.061)
Learning opportunities × Tight		0.180***
		(0.050)
Supervisors × Average		-0.102*
		(0.055)
Supervisors × Tight		0.013
		(0.049)
Salary × Average		-0.065
		(0.051)
Salary × Tight		-0.033
		(0.044)
Obs.	264,854	264,854
Pseudo R-squared	0.107	0.107

Notes: Logistic regressions weighted using population-based survey weights. Standard errors are clustered at the occupation × industry × local labour market level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The reference category is "satisfied". Columns (1)–(2) use occupation-level tightness measures from UWV, while columns (3)–(4) incorporate tightness indicators at both the occupation and local labour market (*arbeidsmarktregio*) level. The number of observations is slightly lower in the latter due to data availability constraints in some region-occupation combinations of the UWV data. Results using tightness indicators on the LLM-level or on the occupation-province level are available on request.

evidence in Card et al. (2012).[24]

4.7 Conclusion

This paper has examined how dissatisfaction with different job attributes -monetary, tangible and intangibles- relates to workers' job separation and quit using rich survey and administrative data from the Netherlands. We propose a multidimensional approach to job value which allows to differentiate between the different job components. Using a satisfaction approach, we document that dissatisfaction with intangibles job attributes are robustly associated to job separation across different specifications. In contrast, dissatisfaction with monetary rewards and work arrangements, apart the dimension of job security and contract type, show more heterogeneous and context-dependent associations.

The role of outside options, captured using a local labour market tightness indicators, matter only for intangibles job attributes and in particular for the learning dimension. This finding adds a further evidence on the spatial nature of learning, beyond the common literature on the learning benefits of agglomeration economies (Duranton and Puga, 2004).

Our analysis of post-separation destinations further examines the role of non-monetary attributes and in particular of intangibles attributes. Workers dissatisfied with intangibles are more likely to exit into unemployment or other non-employment statuses, suggesting that poor work intangibles may push workers out of employment altogether, not just from one employer to another. Conversely, wage dissatisfaction primarily drives job-to-job transitions, highlighting its role in matching processes rather than pushing workers out of the labour force.

While these findings provide robust evidence for the role of (non-)monetary job attributes in shaping mobility, a potential limitation is self-selection into job attributes based on worker preferences, particularly for intangible features. We partly address this by controlling for objective job characteristics, and exploratory checks including

[24]Results not reported here, but available on request.

perceived importance of job attributes in some survey years do not materially change the results (Burbano et al., 2024; Kesternich et al., 2021; De Schouwer and Kesternich, 2024) (see Appendix Table 4.A.8). Another limitation is the cross-sectional nature of our main models, which limits causal interpretation. Finally, several features of the Dutch institutional context may limit the generalisability of the results to settings with different labour market institutions. The Dutch labour market combines relatively flexible employment relationships with strong employment protection and generous social insurance provisions. In this context, the relationship between dissatisfaction and exit into unemployment may be shaped by the accessibility of these benefits. Overall, whether the multidimensional approach to job value and its association with job separation can be replicated in other institutional contexts, such as other EU countries, remains an open question and an important avenue for future research for assessing the external validity of the findings.

Beyond the afro-mentioned limitations, our findings still carry important implications for employers and policymakers. Amid growing labour supply shortages in the Netherlands (Gonne, 2023) and across other European countries, labour turnover is likely to become an increasingly pressing and debated policy issue. Overall, the results highlight the importance of investing in non-monetary dimensions of job quality—particularly intangible job attributes—as an effective strategy to retain employees and reduce the risk of undesired turnover.

Policymakers may act along two margins. First, at a broader level, they should: emphasize the strategic role of leadership quality (Hoffman and Tadelis, 2021; Hommelhoff et al., 2025; Lazear et al., 2015), ensure better matching between workers and jobs in terms of intrinsic work motivation (Deci et al., 2017; Asuyama, 2021) and recognize the importance of learning opportunities in tight labour markets to reduce overall turnover. Although work-related intangibles are largely organization-specific and therefore strongly shaped by employer decisions, policymakers may still have room to intervene. For instance, they could promote awareness campaigns and specialized training programs targeting managerial and organizational competencies as a mean to improve retention.

Second, they may consider designing measures that facilitate and support "good" turnover—such as transitions into entrepreneurial self-employment or further skill development—since the results indicate that different intangible job attributes are associated with different forms of job separation. Such measures could help reallocate resources away from unemployment toward potentially more productive activities.

Declaration of generative AI and AI-assisted technologies in the writing process.

During the preparation of this work the author used ChatGPT in order to check grammar and syntax mistakes. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

Authorship contribution statement

Femke Cnossen - Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing - Original Draft.

Davide Lunardon - Conceptualization, Methodology, Formal analysis, Writing - Original Draft.

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Appendix 4

A4. Tables

Table 4.A.1: Descriptive statistics

	Mean	SD
Job separation	0.204	0.403
Log hourly wage	2.913	0.543
Flexible contract	0.217	0.412
Part-time	0.524	0.499
WFH	0.369	0.482
Tenure	10.75	10.76
Age	42.80	14.15
Female	0.496	0.500
Low education	0.168	0.374
Mid education	0.395	0.489
High education	0.428	0.495
Job search	0.229	0.420
N	429,647	

Notes: Table reports sample means and standard deviations. Flexible contract, part-time, work from home (WFH), female, and education indicators are dummy variables (1 = yes, 0 = no). *Source:* Authors' calculations using NEA survey data and non-public register data from Statistics Netherlands.

Table 4.A.2: Correlation matrix of job separation, and dissatisfaction with job attributes

	Job separation	Interesting work	Learning opp.	Supervisors	Salary	Job security	Part-time	Control over hours	Work from home	Contract type	Hourly wage
Job separation	1.00										
Interesting work	0.14	1.00									
Learning opportunities	0.12	0.40	1.00								
Supervisors	0.06	0.18	0.29	1.00							
Salary	0.05	0.13	0.19	0.17	1.00						
Job security	0.13	0.16	0.19	0.18	0.17	1.00					
Part-time option	0.04	0.10	0.17	0.16	0.12	0.15	1.00				
Control over hours	0.03	0.13	0.19	0.19	0.21	0.12	0.39	1.00			
Work from home	0.07	0.17	0.23	0.15	0.20	0.12	0.31	0.53	1.00		
Contract type (perm/flex)	0.14	0.11	0.12	0.07	0.14	0.35	0.11	0.11	0.11	1.00	
Hourly wage	-0.23	-0.16	-0.14	0.05	-0.18	-0.06	-0.01	-0.06	-0.19	-0.10	1.00

Notes: Interesting work to contract type are dissatisfaction dummies.
Source: Authors' calculations using NEA data and non-public microdata from Statistics Netherlands.

Table 4.A.3: Marginal Effects of Job Satisfaction on Job Separation

Dissatisfaction with:	Job Separation
Interesting work	
Dissatisfied	0.263***
	(0.00261)
Satisfied	0.210***
	(0.00074)
Learning opportunities	
Dissatisfied	0.239***
	(0.00184)
Satisfied	0.210***
	(0.00080)
Supervisors	
Dissatisfied	0.259***
	(0.00175)
Satisfied	0.205***
	(0.00077)
Salary	
Dissatisfied	0.215***
	(0.00142)
Satisfied	0.215***
	(0.00083)
Job security	
Dissatisfied	0.272***
	(0.00237)
Satisfied	0.207***
	(0.00076)
Part-time option	
Dissatisfied	0.227***
	(0.00204)
Satisfied	0.214***
	(0.00078)
Control over hours	
Dissatisfied	0.220***
	(0.00178)
Satisfied	0.214***
	(0.00084)
Work from home	
Dissatisfied	0.219***
	(0.00151)
Satisfied	0.216***
	(0.00095)
Contract type	
Dissatisfied	0.256***
	(0.00291)
Satisfied	0.210***
	(0.00099)
Obs.	429,647

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.A.4: Subsample analysis: regression on job separation, alternative categories

	Education			Supervisory role		Age Groups		Sector		Covid-19 (2020)	
	Low	Middle	High	Yes	No	25-35	35-50	Public	Private	Pre	Post
Dissatisfaction with:											
Intangible attributes											
Interesting work	0.237***	0.360***	0.441***	0.416***	0.329***	0.411***	0.331***	0.508***	0.307***	0.313***	0.405***
	(0.036)	(0.026)	(0.028)	(0.038)	(0.019)	(0.027)	(0.034)	(0.039)	(0.018)	(0.021)	(0.028)
Learning opportunities	0.148***	0.165***	0.264***	0.185***	0.200***	0.318***	0.261***	0.249***	0.178***	0.201***	0.185***
	(0.031)	(0.021)	(0.022)	(0.029)	(0.016)	(0.031)	(0.026)	(0.029)	(0.015)	(0.017)	(0.023)
Supervisors	0.240***	0.349***	0.420***	0.436***	0.328***	0.430***	0.498***	0.362***	0.357***	0.323***	0.431***
	(0.032)	(0.019)	(0.018)	(0.024)	(0.014)	(0.027)	(0.022)	(0.022)	(0.015)	(0.015)	(0.021)
Monetary attributes											
Salary	0.048*	-0.028*	0.006	-0.025	0.006	0.064**	-0.042*	-0.058**	0.019	-0.031**	0.040**
	(0.025)	(0.017)	(0.019)	(0.025)	(0.013)	(0.025)	(0.023)	(0.023)	(0.013)	(0.015)	(0.019)
Tangible attributes											
Job security	0.392***	0.415***	0.445***	0.513***	0.388***	0.366***	0.530***	0.396***	0.420***	0.434***	0.368***
	(0.037)	(0.023)	(0.024)	(0.032)	(0.017)	(0.035)	(0.028)	(0.031)	(0.017)	(0.018)	(0.029)
Part-time option	0.023	0.090***	0.155***	0.089***	0.087***	0.091***	0.106***	0.156***	0.075***	0.084***	0.112***
	(0.036)	(0.023)	(0.024)	(0.028)	(0.018)	(0.031)	(0.029)	(0.034)	(0.017)	(0.019)	(0.026)
Control over hours	0.065**	0.044**	0.064***	0.021	0.053***	0.058*	0.053*	0.092***	0.035**	0.038**	0.056**
	(0.033)	(0.020)	(0.024)	(0.030)	(0.016)	(0.031)	(0.028)	(0.025)	(0.017)	(0.018)	(0.024)
Work from home	-0.013	0.045**	0.023	0.036	0.016	0.030	0.045	0.039	0.017	0.017	0.026
	(0.028)	(0.019)	(0.023)	(0.028)	(0.015)	(0.031)	(0.027)	(0.026)	(0.015)	(0.016)	(0.023)
Contract type	0.323***	0.301***	0.300***	0.322***	0.292***	0.271***	0.308***	0.255***	0.310***	0.299***	0.298***
	(0.044)	(0.028)	(0.030)	(0.043)	(0.021)	(0.039)	(0.037)	(0.035)	(0.022)	(0.023)	(0.033)
Constant	0.129	0.241	-0.368	-0.724	-0.324	0.153	-0.646	0.102	-0.192	-0.282	0.432
	(0.562)	(0.380)	(0.471)	(0.532)	(0.368)	(0.796)	(0.531)	(0.461)	(0.260)	(0.266)	(0.424)
Obs.	72,248	169,571	183,782	108,243	314,911	69,283	129,093	153,094	276,469	269,024	160,561
Pseudo R-squared	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.130	0.123

Notes: Coefficients from separate regressions for each subgroup. All set of controls are included. Standard errors are reported in parentheses and are clustered at the occupation × industry × local labour market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.A.5: Regressions on job separation, by year and pre-and post-covid.

		By survey year									
	Pooled	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Intangible attributes											
Interesting work	0.344***	0.204***	0.315***	0.310***	0.350***	0.384***	0.317***	0.434***	0.449***	0.316***	0.392***
	(0.017)	(0.062)	(0.052)	(0.056)	(0.051)	(0.043)	(0.047)	(0.049)	(0.051)	(0.068)	(0.065)
Learning opportunities	0.194***	0.214***	0.177***	0.160***	0.227***	0.215***	0.236***	0.188***	0.154***	0.271***	0.153***
	(0.014)	(0.047)	(0.041)	(0.041)	(0.041)	(0.036)	(0.038)	(0.039)	(0.042)	(0.056)	(0.058)
Supervisors	0.358***	0.287***	0.284***	0.289***	0.351***	0.407***	0.321***	0.414***	0.482***	0.359***	0.462***
	(0.012)	(0.043)	(0.038)	(0.037)	(0.038)	(0.032)	(0.034)	(0.036)	(0.037)	(0.051)	(0.050)
Monetary attributes											
Salary	-0.004	-0.078*	-0.015	0.006	-0.002	-0.033	-0.064**	0.031	0.089***	0.057	-0.069
	(0.012)	(0.044)	(0.038)	(0.039)	(0.037)	(0.029)	(0.031)	(0.033)	(0.034)	(0.043)	(0.045)
Tangible attributes											
Job security	0.414***	0.525***	0.492***	0.343***	0.401***	0.394***	0.473***	0.402***	0.280***	0.318***	0.530***
	(0.015)	(0.046)	(0.043)	(0.043)	(0.048)	(0.040)	(0.043)	(0.045)	(0.054)	(0.072)	(0.072)
Part-time option	0.090***	0.065	0.081	0.061	0.077	0.110***	0.107***	0.084**	0.064	0.112*	0.301***
	(0.015)	(0.060)	(0.050)	(0.051)	(0.049)	(0.037)	(0.040)	(0.042)	(0.045)	(0.064)	(0.066)
Control over hours	0.045***	0.134**	0.030	0.033	-0.040	0.031	0.056	0.071*	0.072*	-0.015	0.065
	(0.014)	(0.056)	(0.047)	(0.046)	(0.047)	(0.034)	(0.037)	(0.038)	(0.040)	(0.058)	(0.061)
Work from home	0.020	-0.056	0.069*	-0.001	0.030	0.043	0.021	0.030	0.006	0.124*	-0.028
	(0.013)	(0.051)	(0.040)	(0.041)	(0.042)	(0.031)	(0.033)	(0.037)	(0.039)	(0.065)	(0.066)
Contract type	0.297***		0.328***	0.321***	0.240***	0.284***	0.384***	0.366***	0.354***	0.238***	0.072
	(0.018)		(0.054)	(0.056)	(0.057)	(0.046)	(0.049)	(0.053)	(0.058)	(0.077)	(0.079)
Constant	-0.153	0.468	-0.780	-0.776	-0.792	0.648	0.808	1.195*	-1.265	2.030	-0.667
	(0.226)	(0.664)	(0.641)	(0.613)	(0.687)	(0.682)	(0.671)	(0.652)	(0.786)	(1.489)	(0.974)
Obs.	429,647	35,473	39,745	40,184	39,050	59,108	55,215	54,663	47,132	29,015	29,619
Pseudo R-squared	0.126	0.142	0.158	0.137	0.134	0.132	0.152	0.133	0.127	0.132	0.136

Notes: All controls are included. Standard errors are reported in parentheses and are clustered at the occupation × industry × local labour market level *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Missing cells indicate unavailable estimates or dropped variables.

Table 4.A.6: Assigned socio-economic status based on register data, for A. workers in the same employer, and B. separated workers

	Socio-economic status					
Year	Employed	Unemp	Self-emp	Student	Others*	N
Panel A: Did not separate						
2014	91.4%	0.1%	0.5%	4.2%	3.8%	28,473
2015	90.9%	0.1%	0.5%	5.0%	3.5%	31,440
2016	90.9%	0.2%	0.5%	4.9%	3.5%	31,783
2017	90.8%	0.2%	0.5%	5.1%	3.4%	30,730
2018	90.6%	0.1%	0.4%	4.9%	4.0%	46,741
2019	91.0%	0.2%	0.4%	4.9%	3.4%	44,437
2020	90.8%	0.1%	0.5%	4.6%	3.9%	43,899
2021	91.4%	0.1%	0.5%	3.9%	4.0%	37,518
2022	91.0%	0.1%	0.6%	3.9%	4.3%	23,048
Panel B: Separated						
2014	53.7%	8.1%	3.3%	16.8%	16.8%	7,083
2015	54.8%	6.5%	2.8%	19.6%	15.4%	8,352
2016	58.1%	6.3%	3.2%	17.8%	13.6%	8,426
2017	58.3%	5.5%	2.7%	17.9%	14.7%	8,348
2018	58.8%	5.4%	3.0%	17.4%	14.5%	12,418
2019	50.4%	6.5%	2.9%	20.6%	18.6%	10,832
2020	56.4%	4.7%	2.8%	18.1%	16.9%	10,784
2021	59.4%	3.0%	3.6%	16.0%	16.9%	9,647
2022	58.3%	3.7%	3.3%	15.6%	17.7%	6,027

Notes: Authors' calculations using SECMBUS data on NEA respondents. Statistics Netherlands (CBS) constructs this variable by integrating multiple administrative sources (e.g., tax, social security, unemployment/disability benefits, pensions, education enrollment) to assign individuals to mutually exclusive categories such as employed, unemployed, self-employed, student, or others, based on their most important status at each time. This means that even when workers did not separate from their employer (Panel A), their dominant state may be different from 'employed' as they are for instance student for the majority of the time. *Others group contains: Director-major shareholder; Contributing family worker; Social assistance benefit recipient; Other social security benefit recipient; Sickness/disability benefit recipient; Pension benefit recipient; Other without income.

Table 4.A.7: Logistic regression of dissatisfaction with job attributes on socio-economic status

	Employed (1)	Unemployed (2)	Self-employed (3)	Student (4)
Dissatisfaction with:				
Intangible jork attributes				
Interesting work	-0.245***	0.251***	0.117	0.194***
	(0.030)	(0.054)	(0.080)	(0.052)
Learning opportunities	0.082***	0.024	-0.135**	0.056
	(0.025)	(0.047)	(0.067)	(0.049)
Supervisors	-0.061**	0.283***	0.221***	-0.003
	(0.024)	(0.040)	(0.060)	(0.054)
Monetary attributes				
Salary	0.196***	-0.133***	0.088	-0.119***
	(0.023)	(0.044)	(0.061)	(0.043)
Tangible work arrangements				
Job security	-0.015	0.583***	-0.151**	-0.009
	(0.028)	(0.045)	(0.075)	(0.056)
Part-time option	-0.040	0.044	-0.086	-0.101
	(0.032)	(0.053)	(0.081)	(0.067)
Control over hours	0.008	0.023	0.016	-0.081
	(0.028)	(0.052)	(0.077)	(0.052)
Work from home	-0.018	0.054	-0.022	0.021
	(0.026)	(0.051)	(0.072)	(0.043)
Contract type	0.199***	-0.035	-0.144	-0.163**
	(0.034)	(0.060)	(0.097)	(0.067)
Obs.	81,881	81,788	81,137	81,185
Pseudo R-squared	0.253	0.157	0.247	0.679

Notes: Standard errors are reported in parentheses and are clustered at the occupation × industry × local labour market level. All regressions are weighted using population-based probability weights. The reference category for all dissatisfaction variables is "satisfied". Covariates included: survey mode, survey year, gender, age, log hourly wage, education level, household position, age of the youngest child (if applicable), contract type, tenure at the current firm, part-time, firm size, supervisory role, number of working days, multiple job holding, and urbanity, and fixed effects for industry (SBI 2-digit), region (*arbeidsmarktregio*), and occupation (ISCO 3-digit).
Source Authors' calculations using NEA data and SECMBUS data on the sample of NEA respondents. Statistics Netherlands (CBS) constructs this variable by integrating multiple administrative sources, including tax and social security records, unemployment and disability benefits registers, pension data, and education enrollment, to assign individuals to mutually exclusive socio-economic categories such as employed, unemployed, self-employed, or student based on the most important status at each moment in time.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.A.8: Logit regressions: Dissatisfaction with job attributes and job separation (including preferences for job attributes)

	Job Separation
Dissatisfaction with:	
Intangible job attributes	
Interesting work	0.332***
	(0.021)
Learning opportunities	0.197***
	(0.017)
Supervisors	0.355***
	(0.015)
Monetary attributes	
Salary	0.000
	(0.015)
Tangible work arrangements	
Job security	0.412***
	(0.019)
Part-time option	0.077***
	(0.019)
Control over hours	0.035*
	(0.019)
Work from home	0.029*
	(0.017)
Contract type	0.344***
	(0.023)
Constant	-0.639**
	(0.299)
Obs.	261,816
Pseudo R-squared	0.134

Notes: Logit regression with population-based weights. Standard errors clustered at the occupation × industry × local labour market level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Column includes controls for job attribute importance.

4B Questions from NEA

For the job attribute satisfaction variables, we use the Employment Conditions (*arbeidsvoorwaarden*) section of the NEA survey. This section follows the general job satisfaction questions and asks workers to specify their satisfaction with particular aspects of their job. It begins with: "How satisfied are you with the following aspects of your current job:" (*Hoe tevreden bent u over uw huidige baan als het gaat om:*)[25].

Respondents rate fourteen attributes on a three-point scale: 1. not satisfied, 2. satisfied, or 3. very satisfied. Below we list these fourteen attributes, showing both the English translation and the original Dutch text. In brackets, we indicate the assigned category used in our analysis:

[label=h]

1. Interesting work (*Interessant werk*) [Intangible]
2. Opportunities to learn (*Mogelijkheid om te leren*) [Intangible]
3. Pleasant atmosphere at work (*Prettige sfeer op het werk*) [Not included[26]]
4. Good supervisors (*Goede leidinggevenden*) [Intangible]
5. Good salary (*Goed salaris*) [Monetary Attributes]
6. Good job security (*Goede werkzekerheid*) [Tangible Work Arrangements]
7. Possibility of working part-time (*Mogelijkheid om in deeltijd te werken*) [Tangible Work Arrangements]
8. Possibility of determining my own working hours (*Mogelijkheid om zelf uw werktijden te bepalen*) [Tangible Work Arrangements]
9. Possibility of working from home (*Mogelijkheid om thuis te werken*) [Tangible Work Arrangements]
10. Commuting time/distance to work (*Reistijd/afstand naar het werk*) [Not included[27]]
11. Healthy work (small chance of becoming sick at work) (*Gezond werk (kleine kans op ziek worden door het werk)*) [Not included[28]]

[25]Exact phrasing, including underlined text.
[26]This variable was discontinued and excluded from the NEA dataset.
[27]This is not strictly a characteristic of the job itself, but rather influenced by personal and contextual factors such as housing location or partner's job.
[28]This variable was discontinued and excluded from the NEA dataset.

12. Your employment/type of contract (e.g. permanent, temporary, temp) (*Uw dienstverband/contractvorm (vast, tijdelijk, uitzendkracht, e.d.)*) [Tangible Work Arrangements]

13. Representation of your interests by trade unions (*Vertegenwoordiging van uw belangen door vakbonden*) [Not included[29]]

14. The collective labour agreement for your company (CAO) (*De cao (collectieve arbeidsovereenkomst) voor uw bedrijf*) [Not included[30]]

15. Representation of your interests by personnel representative bodies (e.g. works council (OR) or employee participation council (MR)) (*Vertegenwoordiging van uw belangen door personeelsvertegenwoordiging (zoals ondernemingsraad (OR) of medezeggenschapsraad (MR))*) [Not included[31]]

16. Your pension scheme (*Uw pensioenregeling*) [Not included[32]]

[29] This variable reflects institutional representation rather than an individual-level job attribute.

[30] This item captures institutional arrangements that vary at the firm or sector level, not necessarily at the individual level.

[31] Similar to union representation, this item relates to institutional governance rather than individual job attributes, and is therefore outside the scope of the current analysis.

[32] This variable reflects institutional arrangements rather than an individual-level job attribute. Pension schemes in the Netherlands are typically determined at the sectoral or national level and are not directly influenced by individual employer practices or negotiable within the employment relationship.

5. Conclusions

This thesis contributes to the empirical literature on job quality highlighting its relevance for the study of labour markets. Conventional approaches, which rely exclusively on wage levels, tend to reduce the complexity of labour markets to a mere market transaction. Against this backdrop, research on job quality represents a significant advancement from three main perspectives: first, it focusses on production rather than consumption; second, it places at the centre workers rather than markets; and finally, it embraces a multidimensional approach to job value rather than using only the monetary compensation. Built around these three perspectives, the adoption of a job quality approach uncovers new evidence on a range of broad socio-economic challenges.

Chapter two examines the phenomenon of urbanisation, adopting an urban–rural lens on four job quality indicators: work intensity, job match, career prospects, and job satisfaction. The results suggest that urban workers report lower average job quality in two out of the four dimensions, namely work intensity and job satisfaction, while simultaneously benefiting from greater job-match opportunities. The absence of a consistent urban–rural gap in career prospects is also a notable result, as it runs counter to the conventional wisdom that is often implicitly associated with urban employment.

The chapter advances the literature from two main perspectives. First, it provides a framework for incorporating a spatial approach to job quality. Second, it partially challenges the conventional view of the multiple advantages of working in urban areas, as established in the extensive literature in urban economics and economic geography (Ahlfeldt and Pietrostefani, 2019; Donovan et al., 2024).

An extension of this work could aim to provide a more comprehensive evaluation of the multiple trade-offs arising from the combination of the advantages and disadvantages of job quality. On the one hand, higher work intensity and lower job satisfaction are typically regarded in the job quality literature as negative outcomes, with potential medium- to long-term implications for health and labour supply (Fischer and Sousa-Poza, 2009; Hunt and Pickard, 2022; Fur and Trannoy, 2024). On the other hand, the job quality advantages associated with job match represent a source of job security and bargaining power. A possible approach would be to more directly investigate the physical and mental health consequences of denser urban environments, as well as specific labour market outcomes such as turnover and absenteeism.

Further research on the urbanisation–job quality nexus could also examine the role of remote working practices, including whether they constitute an alternative to the ongoing trend of urban concentration or instead reflect a renewed strategy of firm localisation (Gokan et al., 2022; Liu and Su, 2025). In general, further empirical research on the topic is needed to develop new analytical lenses and tools for assessing the welfare implications of agglomeration processes, as well as for informing place-based and territorial policies (Eurofound, 2023).

The third chapter investigates the relationship between green jobs and meaningful work. The contribution is empirical but theoretically grounded in an extended version of the standard meaningful work function (Cassar and Meier, 2018), enriched with a content-based component that incorporates a self-esteem term borrowed from recognition theory (Honneth, 1995). The empirical analysis supports the theoretical predictions. Using an instrumental variable approach, the chapter provides robust evidence that workers value green jobs in terms of meaning, and that this association is stronger in contexts characterised by higher environmental policy stringency.

The chapter makes several contributions to the literature. First, by extending the theoretical framework of Cassar and Meier (2018), it offers a potentially useful structure for further empirical research on green tasks. Second, the application of an ESCO-based green job indicator constitutes a substantive methodological contribution, which could help consolidate the evidence base in the European context. Finally, the results provide compelling empirical evidence on the importance of the meaningful work dimension, reinforcing and extending a growing body of literature (Nikolova et al., 2024; Ashraf et al., 2025) while also highlighting the relevance of the social-policy context.

Significant scope remains for extending the analysis using more detailed individual-level microdata. Building on the data used in the fourth chapter of this dissertation, a detailed case study could represent a valuable extension of this work by exploiting richer information. A more context-specific approach would allow for a finer-grained territorial perspective, which is needed to understand how local social capital, exposure to climate change risks, and local production structures shape workers' perceptions of meaningful work in relation to the green transition. A major challenge for the transition remains concentrated in regions whose economic base is rooted in more polluting sectors, where the green transition may lead to unemployment and lower economic living standards (Vandeplas et al., 2022). Finally, the importance of meaningful work also rests on its multiple labour supply implications (Nikolova and Cnossen, 2020). A more direct analysis of the relationship between green tasks and labour supply outcomes—such as absenteeism, job separation, or willingness to undertake training—could enrich and strengthen the job quality approach to the green transition by offering more concrete evidence on the associated labour supply channels and potential benefits.

The fourth and final chapter presents a series of results on the job satisfaction–labour turnover nexus. First, dissatisfaction with intangible aspects of work—such as interesting work, learning opportunities, and supervisory relations—is more consistently and ubiquitously associated with job separation than monetary and tangible job attributes across all specifications. Second, conditional on separation, intangible attributes such as interesting work and supervision are associated with exits from the labour force, including transitions into unemployment, education, and self-employment. Finally, the chapter highlights the role of local labour market conditions, proxied by a tightness indicator, in shaping the relationship between learning opportunities and job separation.

The empirical analysis offers several novel contributions. First, the data used and the time span covered represent a unique contribution in the literature, and this approach appears particularly promising for future research. Second, the analysis finds that dissatisfaction with intangible attributes plays a strong role in predicting turnover, and in particular exits from the labour force. This represents a novelty in the literature beyond the typical focus on pay or job security (Clark, 2001), as well as on job-to-job transitions. Finally, the role of local labour market conditions in shaping the effect of learning opportunities supports further the intuition that a geographical lens on job quality is particularly valuable.

Future studies could investigate more in detail the transition from waged employment to unemployment, education, or self-employment while looking at intangibles job attributes. This represents a relatively unexplored channel for active labour market policies, with potential implications for improving occupational matching, fostering entrepreneurial activity, and reducing the burden of unemployment. Future works should aim to replicate the analysis in other countries, possibly applying the same multidimensional approach (Mas, 2025) and directing a particular focus on intangible job attributes. Although the Netherlands has a highly specific labour market setting, a useful starting point could be a comparison with closely related contexts such as Denmark. Finally, given that quits and unemployment rates are key macroeconomic labour market indicators, future research adopting a job satisfaction framework should aim to develop a broader macro perspective, assessing the potential contribution of low job quality evaluations and their impact on wages, in the case of job-to-job transitions, or on public expenditure, when they lead to exits from the labour force. Accounting for the aggregate implications of job quality remains a central challenge in the literature.

Despite the results are specific to each chapter, their complementarity implications should not be underestimated. For instance, the finding that local labour market tightness moderates the relationship between learning opportunities and turnover, in the forth chapter, is particularly relevant in the context of urban agglomeration. The second chapter highlights how urban workers benefit from higher job opportunities and report lower job satisfaction, simultaneously. Anecdotally, this may suggest that in urban areas, firms face stronger competition for retaining workers who value learning opportunities. According to Jovanovic (1995), modern economies devote more than 20% of their resources to learning in the form of education, research, learning-by-doing, and training. These costs may therefore be substantially higher in urban areas. These aspects might benefit from a more in depth exploration of the learning mechanisms using a urban-rural lens, exploring the different learning categories.

Furthermore, the use of intangible job attributes in the fourth chapter is consistent with the self-determination components discussed in the third chapter. The two sets of findings highlight the importance of these factors both for increasing the perception of meaning at work and for predicting job separation and exits from the labour market. This helps clarify that, in the context of the green transition, it is not sufficient to simply place workers and green task at the centre of policy design; it is also necessary to consider the psychological needs emphasised by self-determination theory. Failing to recognise the importance of these aspects may offset the potential job quality benefits of green tasks by increasing the probability of job separation which implies raising hiring costs for firms (Eeckhout, 2018) and job search costs for workers (Miano, 2025).

A final consideration concerns the extent to which agglomeration externalities in job quality may affect the positive benefits associated with performing green jobs. In the context analysed -Europe-, the green transition is largely an urban phenomenon, as most population and economic activity are concentrated in urban areas. It is therefore relevant to question whether agglomeration externalities may reduce the intrinsic values associated to green jobs. At the same time, the agglomeration side of green job can be particularly valuable while considering the potential role of societal norm and the policy context. While urban environments are associated with environmental degradation and unsustainable patterns of production and consumption (UN, 2019), cities are also at the forefront of addressing the challenges of climate change across different domains, including mitigation and adaptation policies (UN-HABITAT, 2024). Understanding how these two opposite forces interact using an intrinsic value approach may represent a valuable combination of both chapters.

The dissertation is subject to a set of relevant limitations. First, in none of the chapters could a strong causal relationship be established, largely due to constraints related to job quality data. The dissertation, as in most existing studies (Green and

McIntosh, 2001; Nikolova and Cnossen, 2020; Adăscăliței et al., 2022; Nikolova et al., 2024), relies on cross-sectional surveys such as the European Working Conditions Survey (EWCS), which do not follow individuals over time. This limits the use of more advanced econometric techniques that would have strengthened the robustness of the results. Future research will therefore benefit from access to more reliable longitudinal data.

Second, in line with the multidimensional approach to job quality, the thesis adopts different dimensions across chapters. While this represents a strength insofar, as it reflects the complexity and adaptability of job quality analysis, it also results in a somewhat heterogeneous and potentially fragmented picture. The results are difficult to compare across chapters and remain largely stand-alone pieces of evidence. This is despite the availability of composite job quality indicators for the context under analysis (see for instance, Eurofound, 2016; Cascales Mira, 2021), which might have been used to ensure greater comparability across chapters. This therefore represents a limitation of the thesis.

Finally, the analysis adopts primarily a European perspective and is therefore limited to a specific geographical context. This is despite the fact that surveys similar to the EWCS are also available in other contexts, such as the United States, Canada, and South Korea. An extension of the analysis to other settings would likely have strengthened the overall contribution of the thesis.

Several questions remain unresolved and merit further exploration within the job quality literature. Overall, job quality research still needs to clarify the relationship between job quality, labour market institutions, and public policy. At present, job quality is largely treated as a matter of social policy, given that its effects spillover into domains such as health, education, and retirement. However, as illustrated by the cases of urbanisation and the green transition, job quality also clearly intersects with industrial and place-based policies, suggesting a broader and still underdeveloped policy relevance. This ambiguity is partly rooted in the way the concept has evolved over time. Despite being discussed for several decades, job quality remains a relatively vague and only partially operationalised concept at the policy level. Notwithstanding the growing prominence of job quality in international and European policy debates over recent decades—most notably through the International Labour Organization's Decent Work Agenda, the United Nations 2030 Agenda, and the European Union's "More and Better Jobs" agenda—the concept remains difficult to operationalise in a way that meaningfully informs labour market policy (for the European case, see Bothfeld and Leschke, 2012). This persistent gap between normative ambition and practical implementation underscores the need for further conceptual and empirical work.

The contribution of the dissertation goes in the direction of highlighting how job quality is linked to significant externalities that can generate hidden costs and benefits (Holman and McClelland, 2011), ultimately influencing policy effectiveness. The findings of Lugova et al. (2026) point in this direction. While investigating the impact of delayed retirement age policies across a set of European countries, between 2011 and 2015, the authors robustly show that the negative impacts of delayed retirement age on mental health tend to be less severe—and in some cases even positive—for individuals in high-quality jobs, whereas those in more precarious jobs with lower career prospects and autonomy tend to suffer more severe health problems. This study represents a tangible example of the substantial social and material costs associated with lower job quality.

This line of reasoning is relevant across a wide range of policy domains. One particularly contemporary issue is the rapid expansion of artificial intelligence. As highlighted by Korinek and Stiglitz (2018), technological unemployment may involve not only monetary losses for workers but also the potential erosion of the meaning derived from work. This consideration may therefore represent a relevant policy concern when reflecting on whether universal basic income schemes or job subsidies could constitute appropriate responses for supporting a welfare-enhancing adoption of artificial intelligence.

Early evidence on robotisation (Nikolova et al., 2024) suggests that workers face costs in term of reduced meaning and autonomy. These points already to a set of hidden social costs, for instance Lopes et al. (2014) find that lower work autonomy decrease the civic participation engagement. It therefore appears that whether job quality is incorporated into overall welfare assessments may substantially affect how the costs and benefits of complex policies are evaluated. This suggests a potential need for further empirical research on job quality, alongside the development of more explicit normative frameworks for interpreting empirical findings. At present, the literature provides only limited guidance in this respect.

That said, notwithstanding the strong emphasis placed on the public policy side of job quality, this should not diminish the central importance of employers. Employers are, in fact, the actors who hold the greatest day-to-day leverage in shaping and improving working conditions (Osterman, 2013). Job quality is experienced through everyday work activities. Therefore, those with the authority to address concerns related to working life—namely employers and managers—remain central actors in determining workers' job quality. Employers who fail to organise work schedules and routines with attention to job quality may face competitive disadvantages, significant organisational costs stemming from higher turnover, lower productivity, and reduced employee motivation. The broader social costs associated with job quality, as illustrated by the findings of Lugova et al. (2026), suggest that employers may play an important role in shaping outcomes relevant to social welfare and public expenditure.

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