A new divide? Investigating the effect of hybrid teleworking on socio-spatial job accessibility inequalities among groups in the Dutch workforce

Appendix

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Appendix A. Teleworking in academic literature

Firstly, in most general sense, remote working can be seen as an umbrella term that captures the essence of all other aforementioned terminologies (Figure 1). Remote work refers to working at a different location than the office in the broadest sense (Allen, Golden, & Shockley, 2015) and is defined as the act "where work is fully or partially carried out at an alternative worksite than the default place of work," (Sostero, Milasi, Hurley, Fernandez-Marcias, & Bisello, 2020, p. 8). The location where work is executed is the most dominant factor within the definition of the term. Nevertheless, whether an employee works from home or a mobile location and the use of ICTs is not vastly determined as seen in Garret and Danziger (2007) and Sostero et al. (2020).

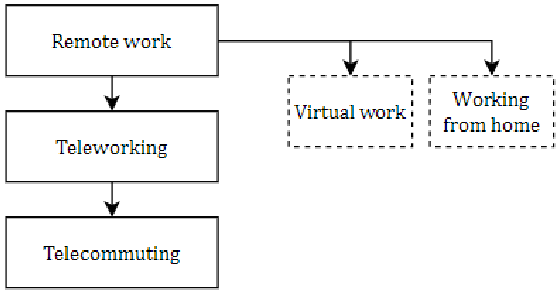


Figure 1: Overview of synonymously used terminologies for teleworking

As part of the definition of remote working belongs teleworking. However, other than the work location, the use of ICTs is a common component within its definition, nevertheless large inconsistencies in academic literature exists. For instance, in academic literature, teleworking is mainly characterized as an arrangement where, by the use of ICTs that facilitate access to digital work opportunities, employees are enabled to perform their work responsibilities at a decentralized location outside the physical boundaries of the organization (Sullivan, 2003; Muhammad, 2007; Ye, 2012). Within this definition, the work location and the use of ICTs are common and essential components (Taskin & Devos, 2005; Garret & Danziger, 2007); Garret and Danziger (2007) address telework generally as "remote work … that involves the use of information and communication technologies (ICTs)," (p. 159) and in the academic work of Taskin and Devos (2005) telework is referred to as "carrying out a professional activity, fully or partly, at distance (i.e. outside the traditional workplace, where the result of this work has to be delivered, and away from any physical capability to monitor the execution of tasks), and requiring information and communication technologies (ICT) use," (p.16). Yet, there are many different operationalizations of teleworking in literature that do not necessarily comply with the aforementioned general understanding of teleworking. The operationalization of Nakrošienė et al. (2018), where teleworkers are addressed as individuals "who have employment contracts with an organization and partly or fully work from home or place other than a traditional working place during traditional or non-traditional working hours," (p. 5), does not include the use of ICTs in their definition. Additionally, Vilhelmson and Thulin (2016) employ teleworking as the act of working partially from any location other than the traditional work place, for regularly contracted employees. Yet, a vast amount of academic works do not disclose their operational definitions of teleworking appropriately (e.g. (Ton, et al., 2022)), leaving uncertainties about the exact work activities studied and therefore inhibits comparability with other academic research on teleworking (Allen, Golden, & Shockley, 2015).

Telecommuting is a concept that is inherent to teleworking, as its definition is a sub-component of the broader term of teleworking (Lindstrom, Moberg, & Rapp, 1997; Allen, Golden, & Shockley, 2015). Thereby, it particularly refers to partial or total avoidance of commuting over space to work locations (Muhammad, 2007; Nilles, 1991), but generally lacks the emphasis on the use of digital technologies to execute work-related activities (Lindstrom, Moberg, & Rapp, 1997; Mokhtarian, Defining telecommuting, 1991) although definitions that include the telecommunication system are not uncommon (Allen, Golden, & Shockley, 2015; Mokhtarian, Defining telecommuting, 1991). Non-digital work activities, such as reading, writing and thinking may also be part of telecommuting (Mokhtarian, Defining telecommuting, 1991). Telecommuting more commonly used in research that aim to assess the impacts of remote working on transportation (Sullivan, 2003; Allen, Golden, & Shockley, 2015) as Allen et al. (2015) define telecommuting as "a work practice that involves members of an organization substituting a portion of their typical work hours (ranging from a few hours per week to nearly full-time) to work away from a central workplace – typically principally from home- using technology to interact with others as needed to conduct work tasks," (p. 44).

Having explored the various terminologies reveals that all three terms share common components; they refer to work that takes place outside of the physical work location and include the use of ICTs to some extent, yet the emphasis on those components is varying within the definitions. Hence, the terms cannot be used reciprocally as is done in much of the available academic literature. To appropriately characterize teleworking to be used within this research, an operationalization is made according to a framework presented in Garret and Danziger (2007) categorized according to four common dimensions: *work location*, *the importance of ICTs*, *locational time distribution* and *contractual relationships* between employer and employee.

The first dimension, *the work location*, refers to the physical location where (digital) work responsibilities are fully or partially actualized, which can be either at a fixed location (e.g. home) or a certain mobile location (e.g. remote) (Garret & Danziger, 2007; Nicklin, Cerasoli, & Dydyn, 2016). Whereas teleworking generally indicates that work is performed outside of the office location, the assumption that work-related activities are performed solely from home does not necessarily hold in all cases (Nicklin, Cerasoli, & Dydyn, 2016). For instance, telework can be performed at a fixed location, where the employee principally works at a (self) established off-site office location, such as home. Further, telework can be performed at multiple non-fixed locations, such as decentralized office locations (e.g. satellite offices) (Nicklin, Cerasoli, & Dydyn, 2016; Garret & Danziger, 2007). As second dimension, *the importance of ICTs* reflects whether ICTs are required to perform the daily work activities of the employee. Whether employees make use of communication technologies is important to distinguish telework and other work at decentralized locations (Sullivan, 2003). After all, not all work opportunities that can be performed outside the physical boundaries of the office location have to be performed via digital communication technologies (e.g. in-situ work and research). Thirdly, the *location time distribution* demonstrates the time that is dedicated to teleworking, i.e. the teleworking intensity (Garret & Danziger, 2007). The teleworking intensity is a common component used in defining teleworking (Sullivan, 2003). Namely, a clear distinction in literature exists where the employed definition of teleworking either considers full-time out of office work or part-time and occasional telework (Muhammad, 2007; Garret & Danziger, 2007). Lastly, the fourth dimension to categorize telework is related to the *contractual relationship* between the workers and the employees. Here, teleworkers can be employed according to a regular contractual agreement or only involve individuals that are self-employed (Garret & Danziger, 2007).

Appendix B. Development and policy of (hybrid) teleworking over the years

The concept of teleworking has increased in popularity fairly recently, where the first conceptualization of working remotely dates back to the 1970's (Garret & Danziger, 2007). Fuelled by the ongoing oil crisis, teleworking was emerging due to concerns about energy consumption, air pollution, traffic congestion, commuting was therefore received with great optimism. The telecommunication system, that consisted of first generation technologies as the telephone and elementary computer-to-computer information transfer, enabled employees of organizations to work at a decentralized location (Nilles, 1975; Messenger & Gschwind, 2016). As consequence of the limited portability of these first generation ICTs, teleworking mainly took place in employee home offices (Messenger & Gschwind, 2016) and homeworking arrangements arose in so-called knowledge intensive white-collar jobs (Allen, Golden, & Shockley, 2015; Smite, Moe, Klotins, & Gonzalez-Huerta, 2021).

As technology progressed over time and computing capacities increased, teleworking became more available for a wider range of job opportunities, increasing the ability of employees to work remotely (Allen, Golden, & Shockley, 2015; Messenger, et al., 2017). Additionally, the development of the second generation of portable ICTs towards the end of the 20th century enabled teleworkers to work flexible in space, where devices as mobile phones and laptops allowed for the creation of more flexible and part-time work arrangements (Messenger & Gschwind, 2016). In the Netherlands, the desire to encourage teleworking was kindled by the increase of women's employment rates, scarcity in the labour market, pressing congestion issues and the globalizing work environment in the 90's. Teleworking was seen as a measure to attract highly educated knowledge workers and to facilitate international business collaborations (Peters, 2020). Around the start of the new century, the Netherlands was frontrunner with regards to teleworking, as 9% of the Dutch employees teleworked for at least one day of the week (Peters & Batenburg, 2004). Positive experiences with teleworking resulted in further motivation of organizations to promote out-of-office work arrangements and further adoption of teleworking led to a transition towards an information based economy in the Netherlands (Muhammad, 2007). To accommodate the fast evolvement of teleworking practices within the Europe Union and to allow telework to be introduced at a large scale, the European Commission set up the Framework Agreement on Telework with its Member States in 2001 (Messenger & Gschwind, 2016; Broughton, 2002). With this agreement, general employment conditions of teleworkers, such as data protection, privacy, equipment, health and safety and training of workers, are defined in order to ensure equal security and fulfilment of needs for teleworkers and employers (Broughton, 2002).

In the years to follow, the feasibility of teleworking ascended further within the Netherlands as result of technological advances such as the introduction of the Internet. In the first half of the 00's, around 21% of the working population had teleworked (Muhammad, 2007). Through access to the internet and communication technologies, information can be gathered instantaneously and freely flow from device to device through cloud and network services (Messenger & Gschwind, 2016). The emergence of work opportunities in virtual space has resulted in the virtualization of aspects of work as the third generation ICTs enable virtual social interaction via social platforms on the internet to share information that diminishes the need for traditional physical communication between individuals (Baane, Houtkamp, & Knotter, 2011). The increasing digitalization is worked in hand due to instant and cheap access to digital connections, where large groups can be connected to online services where people can gather regardless of any (physical) constraints and access to information has increased in importance significantly.

The whitepaper of Microsoft's CEO Bill Gates on the *New world of Work* in 2005 promoted the use of digital technologies to innovate work-related tasks and inspired the movement "Het Nieuwe Werken" (HNW), translated as "the new way of working", in the Netherlands at the end of the decade (Baane, Houtkamp, & Knotter, 2011; Peters, 2020). HNW is employed as a vision to increase the efficiency and effectiveness of work, where the employee acquires more freedom to work when and wherever they want, facilitated by ICTs (Beijer, Van der Voordt, & Hanekamp, 2011). In addition, HNW was seen as a mobility policy to reduce congestion on Dutch roads and CO_2 emissions (CROW, 2009; Van der Loop, 2018). Research shows that the uptake of teleworking after the introduction of HNW has increased around 0,5% between 2014 and 2015, where 35% of the workers in the Netherlands occasionally teleworked during the period (Van der Loop, 2018). Despite that teleworking within the Netherlands was growing continuously (Muhammad, 2007), the pace of teleworking adoption did not follow expectations (Messenger & Gschwind, 2016; PBL, 2021) and the yearly increase in teleworkers was only seen to be small. Yet, the outbreak of COVID-19 and the resulting pandemic and intelligent lockdown in the Netherlands in 2020 instigated a change in uptake of teleworking compared to the past. Whereas the percentage of the working population that teleworked occasionally or fully remained similar before and during the pandemic (37%), the teleworking intensity has increased where more people worked more hours or fully teleworked (PBL, 2021). The prevalence of teleworking in the years before the COVID-19 pandemic, current developments and future expectations are described in more detail in the next section.

B.1. Prevalence of teleworking in the Netherlands before, during and after the pandemic

The extent to which people telework in the Netherlands has been frequently researched in the past. Before the pandemic, the Netherlands had on the European level an above average share of teleworkers, where in 2014 around 30% of the employees engaged in teleworking. Of these employees around 15% teleworked occasionally and 10% teleworked frequently with high mobility and 6% teleworked from home regularly (Figure 2) (Messenger, et al., 2017).

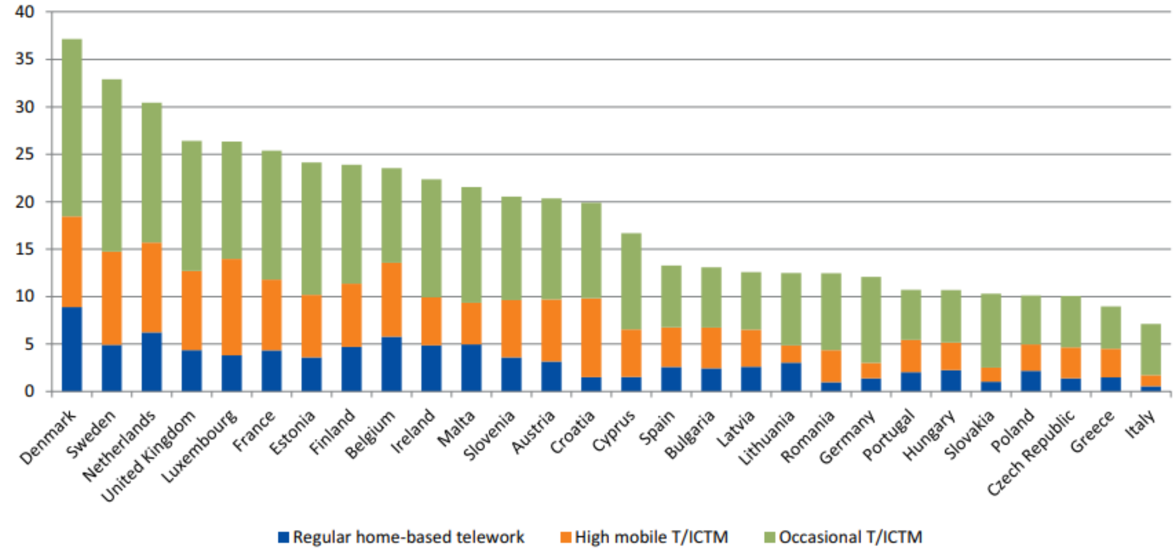


Figure 2: Percentage teleworking within the EU (Messenger, et al., 2017)

From 2014, teleworking within the Netherlands has gradually increased. Although many studies have attempted to determine the degree of teleworking, the results of all studies are slightly varying due to different used operationalizations of teleworking (Hamersma, De Haas, & Faber, 2020) and, consequently, making direct comparisons between dataset may be unfeasible. Hamersma et al. (2020) have provided an extensive overview of the recent representative teleworking values in the period before the pandemic. What can be seen from Table 1, is that the share of teleworking among individuals in the workforce is estimated between 29% and 39%, which leaves some large uncertainties.

Table 1: Prevalence of teleworking in the Netherlands before the pandemic (Hamersma, De Haas, & Faber, 2020)

Source	Time of research	Percentage teleworking	Operationalization
MPN (Mobiliteitspanel Nederland)	Autumn 2019	33%	1 hour/week
LRO (Landelijk reizigersondezoek)	October/November 2019	29%	1 day/week
EBB (Enquete beroepsbevolking)	2019	39%	1 hour/week

Data from CBS (2021a) shows similar values for the percentage of teleworking employees within the Dutch workforce compared to these from the EBB (Figure 3). The figure illustrates a slight increase in teleworking between 2013 and 2019 and presents the teleworking intensity of employees per year. In 2019, 13% of the employees teleworked regularly, while 22% of the employees had occasionally teleworked (CBS, 2021a). On average, 3,8 hours per week were teleworked by employees (Jongen, Verstraten, & Zimpelmann, 2021).

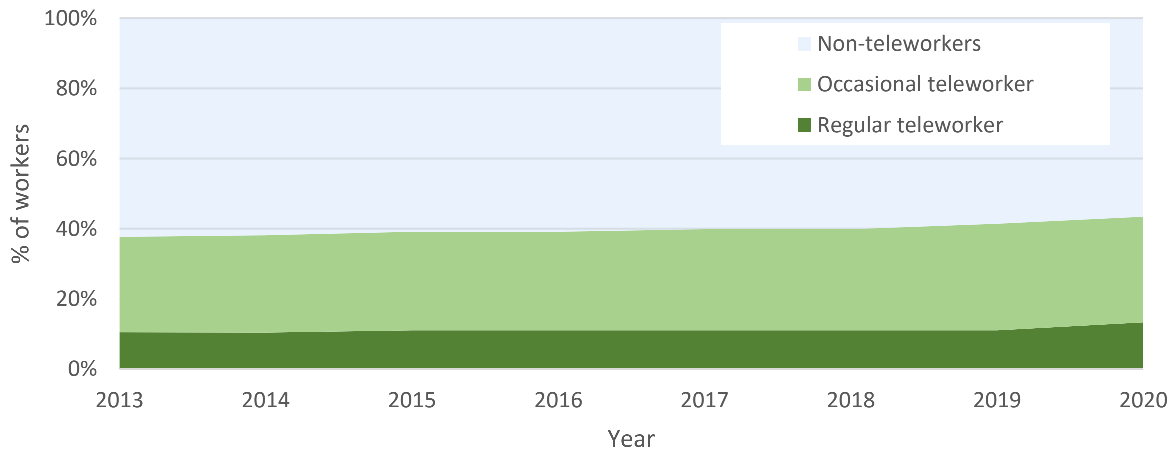


Figure 3: Development of teleworking before the COVID-19 pandemic (CBS, 2021a)

The spread of the COVID-19 virus has significantly influenced the uptake of teleworking in the Netherlands from 2020 and further, where at peak level, 50% of the workforce teleworked for at least one hour per week during the lockdown. Moreover, the weekly average hours teleworked for an employee has increased to 12 hours (De Haas, Hamersma, & Faber, 2022). Thereby, expectations are that teleworking will continue to be popular among employees after the pandemic; around 47% of the employees that teleworked during the pandemic has indicated wanting to continue teleworking in the future. In addition, it is expected that the share of workers that teleworks 2 to 3 days per week will increase the most (De Haas, Hamersma, & Faber, 2021). Despite that the future expected teleworking rates are less than what is observed during the pandemic, a structural increase is expected for the longer time period compared to 2019 due to the outbreak of COVID-19 and positive experiences related to teleworking (De Haas, Hamersma, & Faber, 2022).

However, the prevalence of teleworking, the impacts of the lockdown measures and future teleworking trends are seen to vary largely between sectors, job functions and job responsibilities (Hamersma, De Haas, & Faber, 2020). In literature, the occupations with highest prevalence of teleworking include higher educated, high salary and knowledge intensive jobs (Sostero, Milasi, Hurley, Fernandez-Marcias, & Bisello, 2020). Within the Netherlands, similar patterns are visible. Data from 2019, before the lockdown, displays the distribution of occasional teleworking among 13 occupational classifications within the Netherlands (CBS, 2020a). ICT, managers and creative and linguistic occupations have the highest share of teleworkers, whereas occupations within transport and logistics, service professions and agriculture have the lowest values for teleworking (Figure 4).

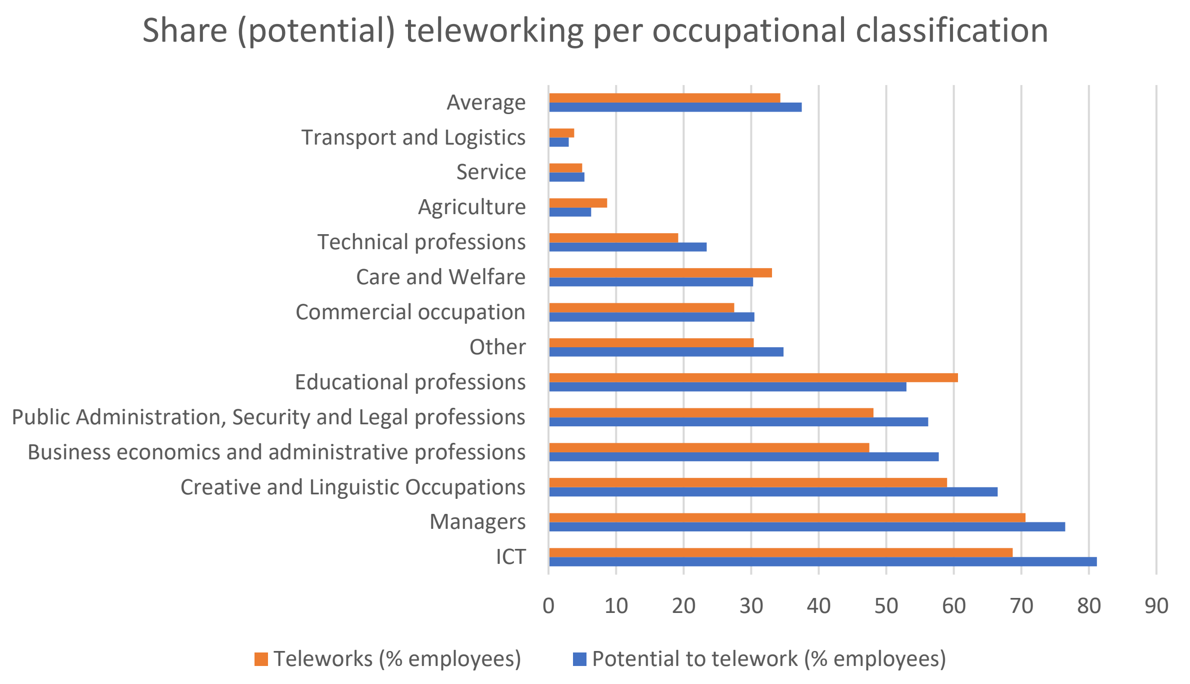


Figure 4: Teleworking and teleworking potential per occupational class – 2019 (CBS, 2020a)

While for the majority of occupational classes there is potential for growth in the degree of teleworking, for Transport and Logistics, Agriculture, Care and Welfare and Educational professions the actual teleworking rates exceeds the teleworking potential. Although the exact cause of these discrepancies are unknown, it stands out that these sectors contain 'vital professions' that are of high importance for the functioning of society. Hence, these occupations may have limited potential for teleworking. Nevertheless, the observed discrepancies do indicate that those individuals have the technical ability to telework, yet may be severely constrained in their job due to the impracticality of teleworking and efficiency losses of communicating digitally. Hence, in spite that those individuals telework, their actual job responsibilities may be suitable for teleworking, which may explain the observed gap in these sectors. The variation in actual teleworking rates and the potential to telework indicates that the adoption of teleworking within the 13 categories of occupations is related to many underlying macro and micro-level factors. While 81,1% of the ICT employees have the potential to telework, only 68,7% actually teleworks occasionally.

Appendix C. Macro-level factors

On the macro level, the extent to which teleworking has developed in Dutch society is generally correlated with five trends and transitions: globalization, digitalization, changing demographics, individualization and urbanization (SER, 2022).

Globalization

Globalization is a process of global economic, political, and cultural integration, where labour is devised on a world wide scale, linked by trade and communication technologies (SER, 2022) and has significantly affected the way people work. Through globalization, companies are getting more and more embedded in a complex network of interconnected business relationships influenced by knowledge and information flows and exchanges, where having access to knowledge has become a competitive advantage against other businesses around the world (Shatrevich & Baranovskis, 2012). As society transforms towards a globalized knowledge economy, new patterns of work emerge; work activities become more complex, computers and robots are seen to both replace and complement existing work activities and through globalization, the organizational boundaries and hierarchical business relationships become less defined. Consequently, globalization requires restructuring of how a business is organized and its culture, hence it is seen that international collaboration and knowledge sharing is accompanied by an increased focus on team-based work, raised time pressure and the need for more flexible work arrangements (Lee, 2016). ICTs can play a large role in the gathering, transfer and creation of knowledge and innovations (Shatrevich & Baranovskis, 2012) and teleworking can facilitate place and time independent work (SER, 2022), grants access to a larger supply of workers and reduces the operational costs of an organization (e.g. energy), saves costs for employees (Nicklin, Cerasoli, & Dydyn, 2016; Ahmad, Ismail, & Jorma, 2021; Babulak, 2009; Smite, Moe, Klotins, & Gonzalez-Huerta, 2021). Hence, it can be seen that the globalization of the work environment positively affects the uptake of teleworking on the macro scale.

Digitalization

Secondly, the rising digitalization of society is one of the fundamental factors that has changed how people work nowadays (Ahmad, Ismail, & Jorma, 2021) and is thereby a driving factor for the development of ICT-based teleworking around the world (Messenger, et al., 2017). The trend of digitalization can be defined as "the use and integration of new technologies into everyday live, across all industries and sectors," (Chopra & Sharma, 2020, p. 3386), which enables employees to have easy access to knowledge and information and can provide service for direct communication (Schwarzmüller, Brosi, Duman, & Welpe, 2018). As described in section 0, the development of digital technologies enables workers to become more location and time independent and an increase in computing power of the technologies allows more individuals to work digitally. Additionally, the extensiveness, coverage and reliability of the ICT infrastructure network (Milasi, González-Vázquez, & Fernández-Macías, 2021) and the availability of teleworking facilities at home (Hamersma, De Haas, & Faber, 2020) also influences the uptake of teleworking. Digitalization therefore is seen to positively influence the degree of teleworking (SER, 2022).

Changing demographics

Whether teleworking is adopted depends not only on the digitalization, but also on the changing demographics within the Netherlands. The Netherlands faces a relative increase in older population, where the share of the working population above 55-years has increased from 6% to 21% between 2011 and 2021 (CBS, 2022a) and is only seen to increase in the future (De Jong, et al., 2022). Additionally, throughout the country, a large divergence with regards to population growth is observed. In general, smaller municipalities in the North and East of the Netherlands expected to experience a decline in population, while larger cities attract more individuals. Expectations are that areas in decline also experience higher rates of aging population up till 2035 (De Jong, et al., 2022). These two trends are affecting telework ability differently within the Netherlands. On the one hand, teleworking requires basic digital skills of the workers (Raišienė, Rapuano, Dőry, & Varkulevičiūtė, 2021) and the degree to which employees are able to use these technologies is therefore an important aspect in the uptake of teleworking. While technological advancements and increasing potential further digitalization of job responsibilities are constantly growing over time, an increasing group of technology-incompetent workers may be faced with inabilities to perform their jobs by teleworking (SER, 2022). Whereas the provision of education on digital skills may alleviate the negative impacts on the degree of teleworking, this trend may potentially inhibit further uptake of teleworking at this point in time. On the other hand, the declining population within the Netherlands requires intensification of work in order to facilitate further economic advancements and the maintenance of the high quality products and services (SER, 2022). Research has shown that teleworking can be used to compensate for the intensification of work, yet can also paradoxically instigate work intensification (Bathini & Kandathill, 2019). For instance, teleworking may offer greater accessibility to work, better self-regulation and time control of employees and may result in less time spent in traffic which may enhance work performance and productivity (Bathini & Kandathill, 2019; Taskin & Devos, 2005). However, the required self-regulation and autonomy to work may increase the mental and physical burden on the employees (Bathini & Kandathill, 2019). Teleworking may conjoin personal and professional life, workers may be more inclined to work during sickness (Taskin & Devos, 2005), thereby intensification may occur as teleworking may result in more work efforts (Bathini & Kandathill, 2019). The teleworker becomes responsible for his or her own management of work responsibilities which is also called the autonomy-control paradox (Taskin & Devos, 2005). Nevertheless, while for an aging population, the ongoing digitalization of work opportunities may counterwork the uptake of teleworking, teleworking, whether it leads to an intensification of work or not, can be a necessary solution for developments in Dutch regions that are faced with decline and aging (Takahashi, 2021). Therefore, the trends of population aging and demographic shifts in the Netherlands acts both as a driver and barrier for teleworking.

Individualization

Over the recent years, developments in Dutch society shown signs of increasing individualization. This individualization is characterized by reduced importance of traditional social institutions such as marriage, more freedom of choice and the creation of social communities and more single-person households (CBS, 2020b). Consequently, a shift in preferences and attitudes towards work is observed (SER, 2022; Commissie Regulering van Werk, 2020). Employees value autonomy, flexibility of contracts and diversification of work responsibilities, where conflicts in private life and the professional life are minimalized (Commissie Regulering van Werk, 2020). For instance, flexibility of work contracts enables individuals to combine work with family life, leisure and is seen to increase the participation rate of workers (Raffaele & Connell, 2016). To facilitate the increasing flexibility in work arrangements, teleworking offers a solution for the employee. For the individual, teleworking provides increased flexibility and autonomy, facilitates working with disabilities and health problems (Raffaele & Connell, 2016) and reduces the costs of daily commute (Smite, Moe, Klotins, & Gonzalez-Huerta, 2021) and facilitates a better balancing of personal and working hours (Messenger, et al., 2017). Hence, the trend towards a more individualized Dutch society may enhance the degree of teleworking in the future.

Urbanization

Trends of urbanization within the Netherlands may affect the degree of teleworking. The Netherlands is faced with a structural deficit on affordable homes for starters, lower- and middle-income groups, which may affect the uptake of teleworking among employees within the country. Developments as a general shortage in housing supply, more single-person households, lack of housing facilities for the elderly population, soaring prices for dwellings in the free sector and restrictions on housing constructions as a result of the nitrogen problems (Boelhouwer & Van der Heijden, 2022; SER, 2022) may impede employees on their choice of living locations. Consequently, as a spatial mismatch between job location and employees may occur, telework offers to be an alternative solution to overcome the commuting distance and accompanying transportation costs between home origins and work destinations (Silva & Melo, 2018). The housing crisis within the Netherlands may further encourage the degree of teleworking among employees.

Appendix D. Conceptual framework

The factors that are of influence on the uptake of teleworking can explain how and why discrepancies in teleworking rates and job accessibility levels among the Dutch workforce occur. What can be seen from literature is that many multi-level variables are at play that have an effect on the individual uptake of teleworking within the Netherlands. The conceptual framework aims to visualize the relationships between the multi-level factors, the uptake of teleworking and job accessibility and depicts the scope within this research (figure 5), where factors at three different scales are presented: macro-scale (global/national level), meso-scale (national level) and micro-scale (individual level). First of all, the aforementioned macro-scale factors are not directly linked to the uptake of teleworking in the model, but indirectly affect teleworking and teleworkability through meso- and micro-level factors. Trends and transitions as globalization, digitalization of society, increasing individualization have firstly resulted in an increasing interests and shift towards teleworking. Policies as the Framework Agreement on Telework and "Het Nieuwe Werken" aimed to manage and enhance the trend through measures that affect the individual work situation. Moreover, the changing demographics observed within the Netherlands affects socio-demographic characteristics such as household composition. Lastly, the urbanization trend within the Netherlands leads and the consequences for the individual may affect (initial) travel behaviour of the individual worker. Whereas the macro- and meso-level factors may have facilitated the adoption of teleworking, factors on the micro-scale are more directly related to actual decision of the individual to (hybrid) telework. The digitalization of society and the element of digital connectivity through the telecommunication system has resulted in a changed understanding of spatial proximity and accessibility as a whole. As consequence of the digitalization, besides physical mobility and spatial proximity, digital connectivity as additional determinant for accessibility has come into existence since recent years (Lyons & Davidson, 2016). Teleworking therefore both replaces and facilitates complementary access to job opportunities through virtual space (Mokhtarian, 2002; Cavallaro & Dianin, 2022; Lyons & Davidson, 2016). The individual-level ability to hybrid teleworking, as determined through the macro-, meso- and micro-level factors, therefore may result in improved access to a greater set of job opportunities as the requirement to commute daily is reduced and physical separation to job opportunities becomes of lesser influence (Muhammad, de Jong, & Ottens, 2008). Workers with favourable individual-level factors may experience an increase in job accessibility. The adoption of hybrid teleworking is therefore directly and positively related to job accessibility levels, but will not be enhanced unless the individual has the opportunity to engage in hybrid teleworking.

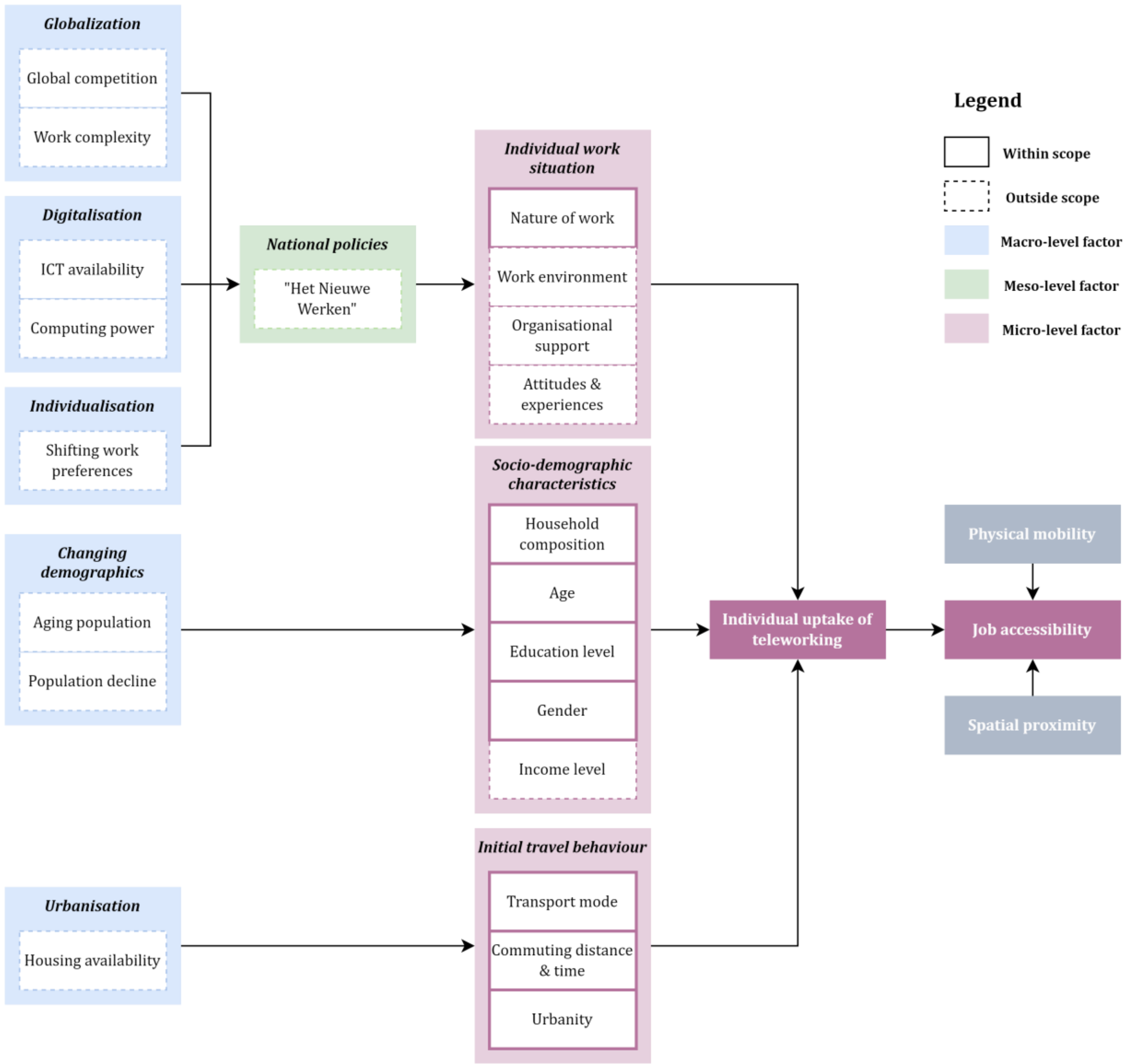


Figure 5: Conceptual framework on factors influencing the uptake of teleworking and individual-level job accessibility in the Netherlands

Appendix E. Job accessibility model components

Conventional accessibility modelling methods often lack the consideration of varying behaviours of individuals within the general population due to high aggregation level of the measures (Geurs, Krizek, & Reggiani, 2012). Hence, accessibility measures can be further supplemented by considering segmentation of the population under study, job matching and job competition to yield more accurate and disaggregated accessibility approximations for different socio-economic groups (Pan, Jin, & Liu, 2020) and improve understanding of the job accessibility levels of these groups (Neutens, 2015). Two common perspectives in job accessibility modelling are person-based measures and location-based measures (Lui, Kwan, & Kan, 2022). Whereas person-based accessibility measures have the advantage to be highly disaggregate in nature, are able to account for all four components (Geurs & Van Wee, 2004) and hence suitable for personalized accessibility calculations, main challenge of the more disaggregate approaches is the high data intensity (e.g. home-work locations, individual travel patterns) (Geurs & Van Wee, 2004; Huang, 2020), hence not often considered in accessibility studies. Location-based measures, on the other hand, are more aggregated and consider the ease of reaching opportunities from a specific location, but even so lack the comprehensiveness in the accessibility calculations. Nonetheless, having insights about the inherent individual attributes and their accessibility scores is a valuable component in assessing job accessibility equity in both physical and hybrid space.

The various strengths and limitations of accessibility measures have led to a diverse range of proposed methods for measuring accessibility. Accordingly, Páez et al. (2010) and (2013) aimed to address the limitations of the individual-based and location-based perspectives by the development of a compromised model (Deboosere & El-Geneidy, 2018). Their measure contains both socio-demographic characteristics of individuals and their residential locations (Páez, Mercado, Farber, Morency, & Roorda, 2010), and data is thus not as aggregated as the location-based measures, but do not require same high resolution of data as the person-based measures (Deboosere & El-Geneidy, 2018). In addition, Pan et al. (2020) have explored physical job accessibility considering spatial and non-spatial constraining effects as job proximity, one-sided competition effects, multi-modal transportation and job matching based on socio-economic backgrounds. Simultaneous consideration these factors are often not included in job accessibility studies due to the intensified data requirements and increased complexity with regards to the interpretation of results (Pan, Jin, & Liu, 2020). Yet, integration of the job matching and competition in accessibility modelling results in a more precise depiction of accessibility in the spatial and social dimension (Pan, Jin, & Liu, 2020; Dixon & Johnson, 2019; Cheng & Bertolini, 2013). Cheng and Bertolini (2013) have proposed a comprehensive modelling approach where spatial proximity, job competition and job matching is included, but given the article's focus on physical job accessibility, access through virtual space is not included. Previous research that does incorporate access through opportunities in virtual space have included spatial proximity and job competition effects in the accessibility measure without job matching (Shen, 2000; Muhammad, 2007) or do not consider these factors at all (Cavallaro & Dianin, 2022).

Appendix F. Accessibility measures

Physical job accessibility studies aim to analyse the ease to which individuals can access a set of employment opportunities stratified over space by using the available transportation networks. Individuals who obtain higher accessibility scores are more advantaged in job accessibility compared to those with lower scores (Grengs, 2012). In conceptual form, location-based job accessibility can be quantitatively expressed as the sum of job opportunities (O) in neighbouring zones (j) which an individual is able to reach from its residential location (i). Yet, realistically, it is assumed that the number of job opportunities which an individual can reach is constrained by the transport component; job opportunities that require high travel budgets may be less attractive than opportunities which require low travel expenditures. Hence, the incorporation of the costs of commuting is essential.

Various location-based accessibility measures have been developed that aim to approximate the level of job accessibility with variations in modelling complexity to appropriately capture accessibility levels (Geurs & Van Wee, 2004). Location-based accessibility studies mostly employ a set of two accessibility measures: cumulative accessibility and gravity-based, potential accessibility measures (Geurs, 2018). Cumulative accessibility measures, or contour measure, operationalize accessibility as the sum of reachable job opportunities within a pre-established transport impedance threshold value (e.g. travel time or travel distance) (Geurs & Van Wee, 2004). While cumulative accessibility measures are advantageous due to the high interpretability and communicability of results, the measures are methodologically weak for job accessibility modelling due to its dichotomous nature by the exclusion of opportunities that lay outside the arbitrarily defined threshold value (Geurs & Van Wee, 2004; Karou & Hull, 2014; Bertolini, le Clercq, & Kapoen, 2005). In addition, the cumulative measure thereby ignores variation in travel time budgets among individuals with different socio-economic backgrounds (Bertolini, le Clercq, & Kapoen, 2005).

Hansen's (1959) gravity-based accessibility measure can be employed to overcome the limitations of the cumulative measure as the measure incorporates the separation of space to job opportunities by applying a distance or travel-time decay function that weights the attractiveness of job opportunities based on travel distance to those locations (Geurs, 2018; Karou & Hull, 2014; Bertolini, le Clercq, & Kapoen, 2005). It corrects the available job opportunities by the travel costs resistance of the individual (Pan, Jin, & Liu, 2020), by considering the theoretical 'willingness' of the individual or socio-economic group to travel a given amount of time, distance or generalized costs commuting by car, public transport or bike. The distance decay function is based on the analogy to the Newton's gravity theory that the degree of interaction between two locations, i.e. the accessibility, is directly proportional to the 'mass' of the locations, i.e. number of job opportunities, and inversely proportional to distance between the locations. Potential job opportunities that are along the boundaries or beyond the individual's job search space are considered to a lesser extent or none at all to the total set of accessible job opportunities. The latter results in a more gradual decrease of access the more distant the opportunity is (Bertolini, le Clercq, & Kapoen, 2005). The comprehensiveness of the gravity-based measure is expected to enhance the validity of the model results and is therefore chosen as fundament for accessibility analyses within this study.

Appendix G. Job matching

Personal attributes can create barriers or opportunities for individuals to job opportunities and are a source for inequalities with regards to available jobs across different socio-economic and demographic groups within society, thereby highlighting its importance as constraining component in job accessibility modelling. In addition, further substantiation for incorporating job matching is especially relevant when considering teleworking, given that the afore-explored individual characteristics such as the nature of work and education level are few of the many factors influencing the degree of teleworking and hence also affect the set of available job opportunities. Accounting for group-based constraints that influences job accessibility alike in a real-world situation requires matching individuals with a potential set of job opportunities that are available for them based on the individual's social-economic characteristics as educational background, occupation, wages, experience or a combination of said characteristics (Cheng & Bertolini, 2013; Pan, Jin, & Liu, 2020; Cervero, Timothy, & Bruce, 1995; Geurs & Ritsema van Eck, 2003).

G.1. Occupational classes

A common job matching approach is considering the type of work opportunities within the study area, as seen in Cheng and Bertolini (2013), Geurs and Eck (2003), Cervero et al. (1999) and Gioanotti et al. (2022). Whereas more recent research of Cheng and Bertolini (2013) classify employees and employment opportunities according to 9 economic sectors as offices, education, health, industry, transport, retail (daily-goods), retail (non-daily goods), restaurants and agriculture, it is found that a sectoral classification results in increased heterogeneity of the population within the group and lesser between group differences with regards to characteristics as a variety of incomes and job activities, responsibilities and types of workers and qualifications are present within the same sector (Deitz, 1998). Consequently, to enhance the understanding of potential job accessibility inequalities among the Dutch workforce, it is crucial to approach the classification of groups of workers accordingly that emphasizes between-group differences. Hence, it is more preferable to use a classification system that highlights the differences between groups of workers, and minimizes the differences within those groups. This will help to establish a clearer understanding of how socio-economic characteristics impact job accessibility, particularly in relation to teleworking. By using the Dutch Occupational Classification (BRC2014) (ROA-CBS, 2014) system instead of a sectoral one, how job opportunities are distributed among different socio-economic and demographic groups in the Dutch workforce can more accurately identified.

The Dutch Occupational Classification system (BRC2014) is a standardized classification system where occupations with similar requirements on knowledge, skills, responsibilities and tasks are identified and combined. Division of occupations is made on several hierarchical levels, ranging from most detailed classifications according to occupational groups (n=114) and segments (n=42), to more general classification according to occupational classes (n=13) (ROA-CBS, 2014). Within this study, the method of classifying workers and job according to 12 classes of occupations is employed, excluding the thirteenth occupational class 'Other' as no description on this class is available. The following occupational classes are identified: 1. Educational professions, 2. Creative & Linguistic occupations, 3. Commercial occupations, 4. Business economics & administrative professions, 5. Managers, 6. Public administration, security & legal professions, 7. Technical professions, 8. ICT, 9. Agriculture, 10. Care & Welfare professions, 11. Service professions, and 12. Transport & Logistics.

G.2. Education levels

Incorporating education levels in accessibility modelling leads to more accurate predictions of job accessibility (Geurs & Ritsema van Eck, 2003), hence education is widely regarded as a vital factor in studies that incorporate job matching (Pan, Jin, & Liu, 2020). For instance, individuals with lower educational attainment are potentially less likely to qualify for higher-skilled job opportunities, while conversely those with higher levels of educational attainment are potentially over-qualified for lower skilled jobs. Individuals who do not match the required job-specific qualifications may therefore not have these employment opportunities available for them. In addition, various studies have highlighted the relationship between education levels and teleworking patterns (Shabanpour, Golshani, Tayarani, Auld, & Mohammadian, 2018; Hamersma, De Haas, & Faber, 2020; Olde Kalter, Geurs, & Wismans, 2021; Sostero, Milasi, Hurley, Fernandez-Marcias, & Bisello, 2020), thus including education levels may capture the varying sensitivities to hybrid teleworking in the hybrid job accessibility measurements more accurately.

On the worker's side, education levels are assigned based on the highest level of achieved education. The classification of jobs per education level is based on the combination of required competencies and skills that reflect the complexity of tasks associated with a given occupation. The tasks are thereby assessed based on the nature of the work, the requisite level of formal education for job entry and the significance of training and work experience in ensuring proficient job performance (ROA-CBS, 2014). More advanced tasks and job responsibilities necessitate higher levels of educational attainment and vice versa. The education-based classification is structured into three tiers: low, middle and high education (table 2).

Table 2: Education level classification descriptions

Education level	Educational levels	Level description
Low	· No education · Primary education · Lbo · Vmbo	Primary and lower-secondary level of education
Middle	· Havo · Vwo · Mbo (level 1,2,3 & 4)	Upper-secondary and lower-tertiary education
High	· Hbo (associate degree, bachelor) · Wo (bachelor, master) · PhD	Higher-tertiary education

In summary, combining both occupational class (n=12) and education level (n=3) matching, results in the identification of 36 different worker and job opportunity groups, from here denoted as c, to be used in the job matching approach. An overview of occupations per occupational class and education level is provided in appendix H.

Appendix H. Jobs per occupational class and education level

Table 3: Description of jobs (ROA-CBS, 2014; CBS, 2021b)

Occupational class	Education level	Occupations
1. Educational professions	*Low*	Childcare workers and teaching assistants
	Middle	Sports instructors
	High	Primary school teachers
		Secondary school teachers for general subjects
		Secondary school teachers for vocational subjects
		Lecturers in higher education and professors.
2. Creative & Linguistic occupations	*Low*	Performing artists
		Visual artists
	Middle	Photographers and interior designers
	High	Authors and linguists
3. Commercial occupations	*Low*	Retail salespersons
		Retailers and team leaders in retail
		Cashiers
		Outbound call centre employees and other salespersons
	Middle	Sales representatives and buyers
	High	Marketing, public relations, and sales advisors
4. Business Economics & Administrative professions	*Low*	Administrative employees
		Secretaries
		Receptionists and telephone operators
		Transport planners and logistics workers
	Middle	Accountants
		Business service providers
		Executive secretaries
	High	Financial specialists and economists
		Business and organizational advisors
		Policy advisors
		Specialists in personnel and career development
5. Managers	*Low*	Managers other
	Middle	Hospitality managers
		Retail and wholesale managers
		Commercial and personal services managers
	High	CEOs
		Business and administrative service managers
		Sales and marketing managers
		Production managers
		Logistics managers
		ICT managers
6. Public Administration, Security & Legal professions	*Low*	Security personnel
		Military professions
	Middle	Government officials
		Police inspectors
	High	Government leaders
		Lawyers
		Military professions
7. Technical professions	*Low*	Construction workers for rough work
		Carpenters
		Construction workers for finishing work
		Plumbers and pipefitters
		Painters and metal spray painters
		Metal workers and construction workers
	Middle	Technical workers in construction and nature
		Industrial and construction production leaders
		Process operators
	High	Biologists and natural scientists
		Engineers (excluding electrical engineering)
		Electrical engineers
		Architects
8. ICT	*Low*	ICT user support
		Radio and television technicians
	Middle	Software and application developers
		Database and network specialists
	High	Software and application developers
		Database and network specialists
9. Agriculture	*Low*	Farmers and foresters
		Gardeners, horticulturists, and cultivators
		Animal breeders
		Agricultural laborers
	Middle	Farmers and foresters
		Agricultural laborers
	High	Agricultural laborers
10. Care & Welfare	*Low*	Caregivers
	Middle	Laboratory assistants
		Pharmacy assistants
		Nurses (vocational)
		Medical practice assistants
		Medical specialists
		Social workers, group and residential care counsellors
	High	Doctors
		Specialized nurses
11. Service	*Low*	Tour guides
		Cooks
		Waiters and bartenders
		Hairdressers and beauticians
		Caretakers and cleaning team leaders
		Providers of other personal services
	Middle	Cooks
		Kitchen assistants

		Cleaners
	High	Kitchen assistants
		Cleaners
12. Transport & Logistics	*Low*	Drivers of cars, taxis, and vans
		Bus drivers and tram operators
		Truck drivers
		Mobile machine operators
		Loaders, unloaders, and stockers
		Garbage collectors and newspaper deliverers
	Middle	Loaders, unloaders, and stockers
	High	Deck officers and pilots

Appendix I. Job synthesis

Job synthesis involves the process of disaggregating national data on jobs per municipality and characterizing these jobs according to the employed occupational and educational class groups to account for job matching. Both aggregate and disaggregated data sources are combined to obtain the job data in the preferred categorization and resolution scale.

The following data manipulation techniques are used in the job synthesis: dasymetric mapping and Iterative Proportional Fitting (IPF). The general land-use coverage of employment is provided by the Spectrum dataset, where job densities per building function type (BAG functions) are calculated for every zone within the Netherlands. To obtain the number of jobs per zone, dasymetric mapping is applied to disaggregate and stratify the CBS dataset (CBS, 2021c) that proves the number of jobs per sector (SBI2008) on the municipal level over the employed zonal level. For dasymetric mapping, a relationship matrix between every BAG function type land-use coverage and sector of employment is estimated based on the sector descriptions and job activities described in Kruiskamp (2022). This relationship matrix is used to link jobs per sector to the spatial coverage seen in the Spectrum dataset. Finally, jobs per sector (SBI2008) in every zone in the Netherlands are translated to the Dutch occupational classification system (BRC2014) using the EBB (CBS, 2021b) dataset (Dutch: Enquête BeroepsBevolking), that describes the workforce of the Netherlands. The IPF algorithm is applied to minimize deviations between the number of jobs per zone as provided in the Spectrum dataset and the number of jobs per occupational class on the national level from the EBB. Lastly, education level requirements are added to the jobs, which are similarly derived from the EBB. This last step finalizes the job synthesis and provides a comprehensive dataset of the spatial location of 8,5 job opportunities, categorized by occupational class and education level.

Dasymetric mapping

Dasymetric mapping is a technique used to display spatially aggregated data over smaller areas to obtain a better representation of the spatial variation of the data (Mennis, 2009; Mennis, 2015). This technique is particularly useful in addressing spatial incongruity of data which is often encountered in geographical studies where often various administrative boundaries are employed (Zandbergen & Ignizio, 2010). For instance, large scale population count datasets are often specified according to highly aggregated administrative zones (e.g. provinces or neighbourhoods) to preserve privacy of the individuals, yet lacks the true spatial variation of the population on a finer scale (Mennis, 2015). Dasymetric mapping can aid in the disaggregation of low resolution data to more fine grained high-resolution datasets. In the dasymetric mapping procedure, two data inputs are required: the spatial land use pattern of the jobs and aggregated data on the number of jobs within an administrative boundary.

To estimate the number of jobs for each occupational class, firstly the OminTRANS Spectrum dataset is used to display the job data spatially; the dataset provides information about the number of jobs in each zone within the study area. While the Spectrum dataset provides a fine-grained perspective on the distribution of jobs within the Netherlands, main limitation of the dataset is that it does not deliver the number of jobs according to the preferred occupational classification system (BRC2014), but provides the number of jobs per BAG (Dutch: Basisregistratie Adressen en Gebouwen) building function type.

Especially, in order to obtain the spatial location of jobs per occupational class within the Netherlands, it is difficult to derive what occupations resides within each building without making many unsupported assumptions due to the lack of data. Besides, it is easier to assign building functions to the economic activities/sector of job locations since jobs within a sector (and thereby the various occupations within the sector) are accumulated within the same building. Moreover, information about the occupations within each sector is available which allows finally for the translations of jobs per sector to jobs per occupational class. Hence, it is chosen to convert the number of jobs per BAG function type to the number of jobs per sector (SBI2008 classification) by determining the relationship between each sector and BAG building function type.

Relationship BAG function and sectors (SBI2008)

The determination of the relationships between the function of buildings and the sector that may reside in such building involves many arbitrary assumptions which makes the exact relations highly uncertain. Yet, the lack of available data on job types per building function, including the necessity to obtain an accurate display of the distribution of jobs per zone within the study area as provided in the Spectrum dataset, presents the ultimate reasoning behind the choice for this approach. The paper of Kruiskamp (2022) sheds some lights on the nature of the jobs within each sector. Along with the function type descriptions as seen in figure 6, both descriptions provide some insights on the sectors and building function to be able to make some assumptions on the relationships that may occur between the two. As result, the following sector-land use relationship matrix is derived.

SBI 2008 classification		Cell	Education	Industry	Office	Shopping: other	Food store: other	Food store: supermarket	Healthcare	Sport	Meeting	Accommodation	Farm	Terminal	Distribution center	Other	Combined
Agriculture, forestry and fishing	A												1				
Mining and quarrying	B			1													
Industry and manufacturing	C			1													
Electricity, gas, steam and air conditioning supply	D			1													
Water supply; sewerage, waste management and remediation activities	E			1													
Construction	F			1													
Wholesale and retail trade; repair of motor vehicles and motorcycles	G					1											
Transportation and storage	H													0.5	0.5		
Accommodation and food service activities	I						0.4	0.2				0.3					0.1
Information and communication	J				1												
Financial institutions	K				0.8											0.2	
Renting, buying and selling of real estate	L				0.5											0.25	0.25
Consultancy, research and other specialized business services	M				1												
Renting and leasing of tangible goods and other business support services	N			0.3	0.3	0.4											
Public administration, public services and compulsory social security	O	0.2														0.4	0.4
Education	P		1														
Human health and social work activities	Q								1								
Culture, sports and recreation	R									0.3	0.6					0.1	
Other service activities	S										0.5					0.5	

Figure 6: Sector – land-use relationship matrix

From the relationship matrix, it can be seen that sector K Financial Institutions are potentially residing in buildings with an office function (80%) and buildings with 'other' function (20%), such as a governmental buildings. The purpose of the relationship matrix is to assign the number of jobs per sector, from the CBS dataset, to the underlying spatial pattern/distribution of jobs per function type over all zones within the Netherlands as observed within the Spectrum dataset. For instance, the sector K Financial institution, 80% of the jobs should follow the spatial distribution of office functions, while the other 20% of the jobs follows the spatial distribution of 'other' function. To obtain the spatial distributions of the building function types, the Spectrum dataset is used to determine the areal weighting of jobs within the Netherlands.

Areal weighting by BAG function

Second input of the dasymetric mapping approach is to obtain the spatial land coverage of the jobs per function type within each zone. Land cover types are frequently used in dasymetric mapping (Zandbergen & Ignizio, 2010). The spatial land coverage is determined with the use of areal weighting. Areal weighting here implies the density ratio of jobs per function type within a zone compared to the sum of jobs per function type for all zones within the municipality expressed by formula 1.

$$w_{fi} = \frac{J_{fi}}{\sum_{i=1}^{M} J_{fi}} \qquad (1)$$

Where:

- w_{fi} equals the weight factor for jobs of function type f within zone i
- J_{fi} represents the number of jobs belonging to function type f within zone i.

Dasymetric mapping procedure

The number of jobs per sector (SBI2008) in every municipality (first input), their relationship with building types and the corresponding spatial land cover in every zone (second input) enables to disaggregate the data from a municipal level to the zonal level using dasymetric mapping. Employment of the procedure within this research is demonstrated in figure 7 with a hypothetical scenario.

Consider a hypothetical scenario where municipality A contains 400 jobs of sector K Financial institutions. The municipality can be subdivided into two zones of dissimilar size. Objective of the procedure is to subdivide the 400 jobs of the SBI2008 classification over the two zones (zone 1 and zone 2) according to the underlying spatial coverage of jobs in both zones. This example shows the procedure only for zone 1. Firstly, the jobs per sector are ascribed to the relating BAG function type, using the BAG-SBI2008 relationship matrix. According to the matrix, in the whole municipality 320 jobs belong to buildings with an office function (400*0.8 = 320) and 80 jobs belong to buildings categorized as other (400*0.2 = 80). Secondly, knowing the spatial coverage of office buildings and other buildings in zone 1, the number of jobs for SBI2008 K Financial institutions within zone 1 can be calculated. Assume that the within municipality A, 70% of the buildings with offices (w_{of1}=0.7) and 60% of other buildings are located in zone 1 (w_{ot1}=0.6). The total number of jobs belonging to K Financial institutions is then (320*0.7) + (80*0.6) = 224+48 = 272 jobs for the respective sector. Repeating this process for every zone within every municipality and every sector results in the number of jobs per sector in each zone within the Netherlands.

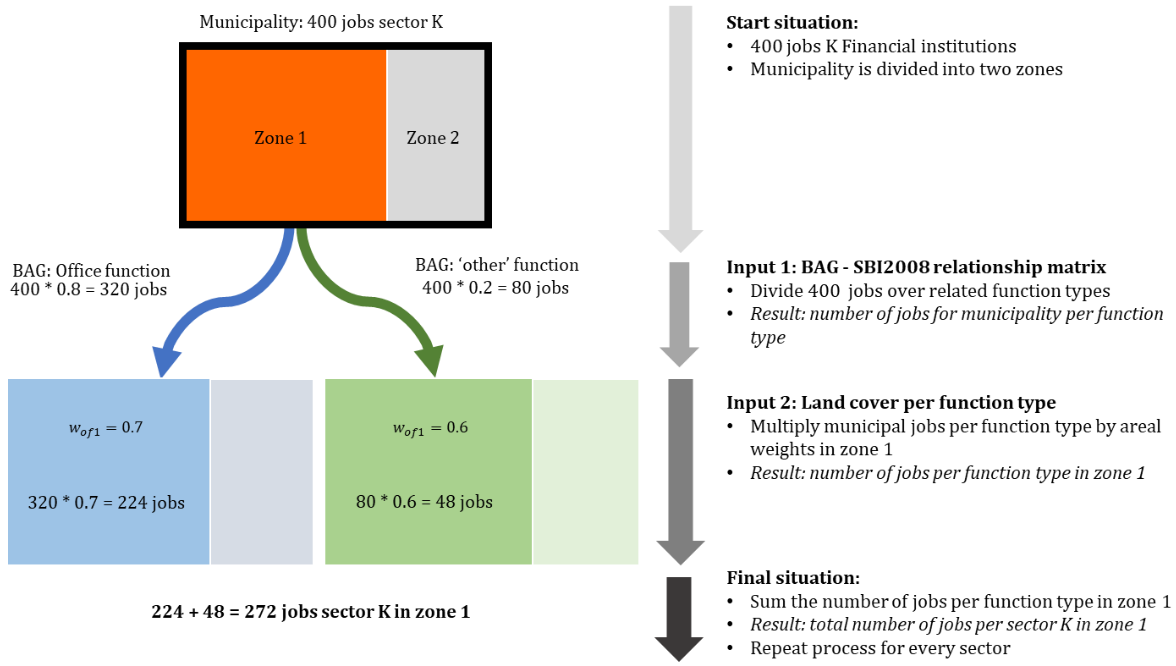


Figure 7: Dasymetric mapping procedure to determine the number of jobs per sector in every zone in the study area

Determining jobs per occupational class

Based on the number of jobs per sector in every zone, the number of jobs per occupational class can be empirically derived from the EBB dataset. The EBB dataset is a survey dataset that sampled information about individuals between 15 and 90 years old (CBS, 2021b) and thereby provides information about the workforce in the Netherlands. Within the EBB is the distribution of occupations (BRC2014) within sectors or economic business activities of workplaces (SBI2008). This dataset therefore provides valuable information about the occupations within each sector, which allows for the translation of jobs per sector to jobs per occupational class, thereby maintaining the job counts from the CBS dataset. For the majority of the sectors. Since sector A and B are merged in the EBB dataset, these sectors have a similar distribution for occupations. In addition, due to the absence of sector D and E in the EBB dataset, both sectors have been linked to the category 'industry other' as described by the EBB and therefore follow similar distributions for occupations. Analysis of the distribution of occupations per job sector reveals the following distribution table:

SBI 2008 classification		Occupational classification (BRC2014)												
		1	2	3	4	5	6	7	8	9	10	11	12	13
Agriculture, forestry and fishing	A	0	0	0.026	0.053	0.02	0	0.086	0	0.678	0.013	0.033	0.086	0.007
Mining and quarrying	B	0	0	0.026	0.053	0.02	0	0.086	0	0.678	0.013	0.033	0.086	0.007
Industry and manufacturing	C	0.002	0.01	0.084	0.176	0.072	0.007	0.47	0.036	0.02	0.017	0.03	0.063	0.012
Electricity, gas, steam and air conditioning supply	D	0.007	0.007	0.071	0.181	0.046	0.014	0.404	0.032	0.057	0.025	0.057	0.082	0.018
Water supply; sewerage, waste management and remediation activities	E	0.007	0.007	0.071	0.181	0.046	0.014	0.404	0.032	0.057	0.025	0.057	0.082	0.018
Construction	F	0.003	0.003	0.021	0.147	0.064	0.003	0.671	0.008	0.003	0.005	0.01	0.057	0.008
Wholesale and retail trade; repair of motor vehicles and motorcycles	G	0.001	0.01	0.44	0.126	0.07	0.002	0.099	0.018	0.004	0.027	0.023	0.176	0.005
Transportation and storage	H	0	0	0.025	0.305	0.042	0.014	0.042	0.02	0	0.003	0.05	0.496	0.003
Accommodation and food service activities	I	0.008	0.003	0.113	0.063	0.069	0.003	0.008	0	0.003	0.003	0.672	0.052	0.003
Information and communication	J	0.01	0.111	0.104	0.155	0.084	0.01	0.03	0.481	0	0	0.007	0.007	0
Financial institutions	K	0	0.004	0.146	0.553	0.106	0.035	0.013	0.119	0	0.013	0.009	0	0
Renting, buying and selling of real estate	L	0.01	0.073	0.094	0.383	0.067	0.063	0.161	0.051	0.002	0.05	0.019	0.023	0.002
Consultancy, research and other specialized business services	M	0.01	0.073	0.094	0.383	0.067	0.063	0.161	0.051	0.002	0.05	0.019	0.023	0.002
Renting and leasing of tangible goods and other business support services	N	0.013	0.054	0.083	0.337	0.061	0.052	0.141	0.042	0.028	0.046	0.106	0.032	0.003
Public administration, public services and compulsory social security	O	0.01	0.008	0.028	0.337	0.026	0.335	0.069	0.073	0.012	0.073	0.018	0.01	0.002
Education	P	0.687	0.016	0.019	0.111	0.04	0.007	0.019	0.019	0	0.037	0.043	0.002	0
Human health and social work activities	Q	0.073	0.001	0.01	0.097	0.023	0.004	0.007	0.011	0.001	0.701	0.068	0.002	0
Culture, sports and recreation	R	0.169	0.32	0.07	0.157	0.047	0.017	0.023	0.023	0.017	0.035	0.11	0.012	0
Other service activities	S	0.041	0.023	0.047	0.157	0.012	0.017	0.058	0.023	0	0.151	0.465	0	0.006

Figure 8: Distribution of jobs per sector (SBI2008) within each occupational class (BRC2014) (CBS, 2021b)

Figure 8 displays the loads of the sectors for each occupational class where the column-wise sum is equal to 1. A load of 0 indicates that zero percent of the jobs within this sector belong to that corresponding occupational class. What can be observed is that within each sector, a large variety of occupations is present. This further substantiates the choice for an occupational classification compared to sectoral one. For instance, within sector K Financial institutions, around 55% of the jobs belong to occupational class 4: 4. Business Economics & Administrative professions, 14% to occupational class 3: 3. Commercial occupations and more jobs scattered over other occupational classes. Interestingly, there is no one-on-one relationship present for sectors and occupations that initially seem to have a similar focus, e.g. a mere 68% of the jobs in sector P Education belongs to individuals who actually have an occupation related to education (OC 1). A similar pattern is visible for both the healthcare sector (sector Q) and healthcare occupations (OC 10). Applying the distributions to the job counts in every zone, yields the number of jobs per occupational class within the zone. In order to make sure that the absolute number of jobs complies with the pattern in the Spectrum dataset, Iterative Proportional Fitting (IPF) is applied.

Iterative Proportional fitting & education level assignment

Next step in the job synthesis is ensuring that the generated job dataset is compliant with national and zonal statistics. Namely, while the general distribution of jobs per occupational class over all zones within the Netherlands is known, there are inconsistencies with regards to the total number of jobs in the Netherlands between the used datasets. While for 2021 the Spectrum considers 8.8 million jobs in the Netherlands, the CBS considers a total of 7.9 million jobs, data on national statistics of jobs in 2021 reveals a total of 8.5 million jobs (CBS, 2022a). Potential cause for the large inconsistencies in job counts could be due to differences in operationalization of jobs. For instance, whether part-time, full-time jobs and unfulfilled jobs (vacancies) are counted is unknown and whether exclusive financial compensation and agreement with a formal party is required is not specified. Yet, CBS (2022a) provides a most detailed operationalization for jobs that fits within the scope of this research and distinguishes between employees with a contractual agreement and self-employed individuals and consists of the average number of jobs that are enlisted within economic institutions within the Netherlands.

Hence, the reference number of jobs for the dataset is set to 8.579.000. As consequence, a correction of the job values is necessary for best representation of jobs within the Netherlands. This can be done with Iterative Proportional Fitting (IPF) procedure. IPF is a statistical optimization algorithm used to adjust the cell values (seed cells) of an existing dataset so that the sum of both the column and row values are equal to known marginal totals of a reference source (Pritchard & Miller, 2012; Hunsigner, 2008). Most common application practices are demographic studies for estimating total population for a study area where often only national census data is known and regional sample data, but exact relationships between the two data components for subnational scales (seed cells) is uncertain (Choupani & Mamdoohi, 2016; Simpson & Tranmer, 2005). With IPF, values of the seed cells are iteratively adjusted until the data matches the marginal totals both row-wise as well as column-wise (Hunsigner, 2008). Primary objective for the IPF algorithm application within the job synthesis is to adjust the number of jobs per occupation level to known reference national statistics, while maintaining the initial distribution of the jobs over the zones, aiming to maintain integrity of the original dataset. This results in a more representative and corrected pattern for the number of jobs on the national and zonal level.

In the jobs dataset, every row represents a zone within the Netherlands. For every zone, the total number of jobs are known from the Spectrum dataset. Every column represents the occupational class of the jobs on the national level. Column totals are described in the CBS (2021b) dataset. Every cell within the dataset is the relationship between a zone and the occupational class, depicting the number of jobs per occupational class within every zone. Since row and column totals of the two datasets are not equal, due to potential different operationalization of jobs, a scaling constant is applied to firstly correct these values to the previously determined reference value (8.579.000 jobs), similar to the approach adopted in Horner and Mefford (2007).

IPF can be performed using the IPFN package in Python (PYPI, 2021). For each iteration, firstly the seed cells are adjusted to match the row totals. Secondly, the cells are adjusted to match the column totals. This process is performed iteratively where for each iteration, the estimated cell values become closer to the true value. The more reliable the cell value is, the less adjustment is necessary and vice versa. The procedure is iterated until the dataset is converged, meaning that the adjustments for the estimated values are small indicating approaching an optimal solution (Hunsigner, 2008). Result of the IPF procedure is an updated dataset where the number of jobs per occupational class and zone is correctly adjusted to the national statistics, while the initial relationships between the two variables is maintained.

Lastly, the number of jobs are subdivided per education level in order to facilitate job matching. Alongside the distributions of occupations per sector, the EBB (Dutch: Enquete BeroepsBevolking) from the CBS (2021b) classifies the occupations according to their required skill levels for these occupations, which can be used to derive the education level requirements of jobs (low, middle, high). The description of the levels as seen in (ILO, 2012) and the classification to education level is as follows:

- Level 1: primary education (low education)
- Level 2: secondary education (low education)
- Level 3: completion of secondary education + higher education between 1-3 years (middle education)
- Level 4: completion of study at higher educational institution (high education)

Appendix J. Worker synthesis

The job accessibility calculations require information on the number of workers per occupational class and their socio-demographic and spatial characteristics as age, gender, income level, household composition, zone of residence and urbanity. Available (public) data sources, however, do not provide fine-grained data of individual socio-demographic characteristics, occupation and residential locations due to privacy concerns, and often solely provide information on national or municipal level. Hence, due to the high abstraction level the available data, large uncertainties exist with regards to the population characteristics and their occupations on lower aggregation levels. The Population Synthesizer, developed by Goudappel and Dat.mobility, provides a synthetic population at the lower aggregation levels, thereby including every individual within the Netherlands and their personal characteristics. However, information about the occupations of these individuals is unknown. As requirement for the adopted job-matching approach and classification of groups within the workforce, it is necessary to assign occupations to individuals based on their individual characteristics. Hence, to generate a dataset of workers per occupational class, worker synthesis is required. The purpose of the workers synthesis is therefore to further enrich the existing Population Synthesizer with occupations of individuals. Only the workforce is selected for the worker synthesis, therefore only employed individuals between the age of 15 and 75 are selected.

The first step in the worker synthesis is assigning one of the twelve occupational classes to individuals based on the gender, age category and education level of the individual. The CBS (2022a) provides insights on these three characteristics per occupational class and is used to generate simple discrete probability mass distributions that are related to each occupational class. Occupations are assigned based on the observed chance that an individual with a certain combination of gender (male/female), age (15-24, 25-34, 35-44, 45-54, 55-64, 65-75) and education level (low, middle, high) is employed within one of the thirteen occupational classes. This thus results in a unique discrete probability mass distribution for every combination of attribute levels for the three characteristics. Using the derived probabilities as weights, an occupational class is assigned to every individual using a discrete random classifier function in Python. This approach of directly deriving a discrete probability mass distribution from the dataset is chosen over using statistical modelling techniques such as Multinominal Logistic regression, since the former method preserves the initial distribution of the population over all thirteen occupational classes as observed in the CBS dataset (2022a). The resulting approach yields a population dataset with the characteristics, residential location and occupations of every individual in the Dutch workforce.

Secondly, as workers in agriculture may often live at the farm or close to their work locations in the less dense residential areas within the country, the residential location of agriculture workers are remodelled to better comply to the spatial location of agriculture jobs. The remodelling of residential locations both involves applying a worker redistribution algorithm, that redistributes agricultural workers closer to potential jobs, and IPF to make sure that agricultural workers are moved to habitable zones and that the total number of residents in each zone is not exceeded.

Occupational classification

For the occupational classification of individuals, and thereby enabling distinction between socio-economic groups within the population dataset, the CBS dataset on the working population (CBS, 2022b) characterizes the workers per occupational class on three characteristics: age, gender and education level. This data, containing individual-level characteristics, aids in a more accurate assignment of occupations to individuals.

In order to assign an occupation to an individual, the age categorization between the two datasets must be identical. Therefore, the adopted categorization of ages in the Population Synthesiser (A: 0-17, B: 18-29, C: 30-44, D: 45-65, 65+) are recoded to comply with the age classes in the CBS used dataset (15-24, 25-34, 35-44, 45-54, 55-64, 65-75). Taking the age distribution of the male and female population in the Netherlands separately, probability values that an individual of the male or female gender is categorized as age-category A, B, C or D falls within the overlapping age ranges of the CBS dataset are determined (figure 9 - left). Subsequently, every individual of the same gender and original age category group in the population dataset is randomly assigned the CBS age categorization depending on the likelihood this individual may belong to one of the overlapping CBS categories. Individuals categorized either as 0-14 or 75+ are finally omitted from the population dataset as these individuals are not part of the workforce as defined by the CBS, hence are out of scope for this research. The recoding of the age categories for the population now allows for assigning occupations to individuals based on their age, gender and education level.

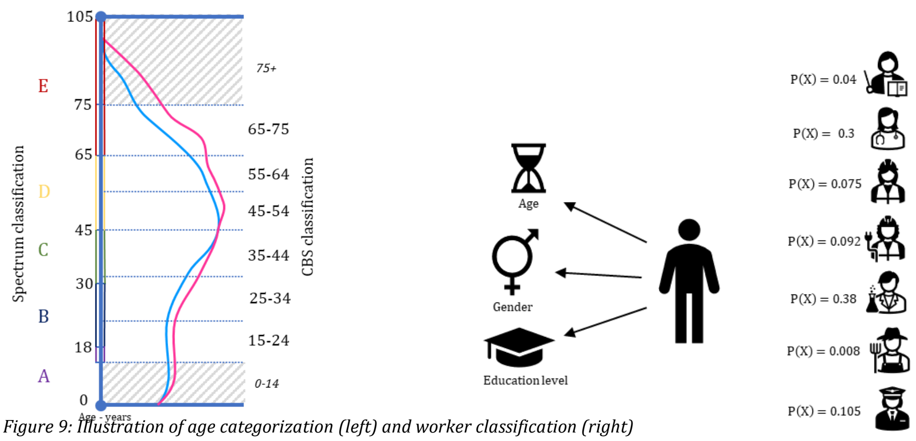


Figure 9: Illustration of age categorization (left) and worker classification (right)

Occupations are assigned to individuals in a similar probabilistic way and are based on the observed probability that an individual with a certain combination of age category, gender and education level belongs to one of the thirteen occupational classes (figure 9 - right). For the occupational classification, only individuals that are employed are considered. Other individuals are removed from the population dataset.

The probabilities have been derived from the CBS (2022b) dataset by determining the share of every occupational class per combination of the three individual-based variables, creating a probability mass function that describes the probability that an individual with this combination of characteristics is assigned to an occupational class. Again, using the probabilities as weights, an occupational class (1 to 13) is assigned to individuals using a discrete random classifier function in Python. The resulting approach yields a population dataset with the characteristics, residential location and occupations of every individual in the Dutch workforce (figure 10).

Individual	Residential zone	No. Adults	No. Cars	Household size	Household composition	Driver's license	Migration background	Social participation	Gender	Age category	Education	Occupational class	Occupation
1	32	2	1	2	No children	Yes	Dutch	Employed	Male	55	High	4. Business Economics & Administrative professions	Specialists in business management
2	13	2	2	2	No children	Yes	Dutch	Employed	Male	15	Middle	11. Service	Employees personal service
3	12	1	0	1	Single	Yes	Dutch	Employed	Female	45	Middle	10. Care & Welfare	Health care specialists
4	693	1	3	1	Single	Yes	Dutch	Employed	Male	15	Middle	8. ICT	Specialists IT
5	67	3	2	3	Children	Yes	Dutch	Employed	Female	45	Low	4. Business Economics & Administrative professions	Administrative staff
6	78	1	1	1	Single	Yes	Dutch	Employed	Male	55	Middle	5. Managers	Production and specialization managers
7	46	3	2	4	Children	Yes	Non-Western	Employed	Female	35	Middle	4. Business Economics & Administrative professions	Administrative staff
8	93	3	2	3	Children	Yes	Dutch	Employed	Male	55	Low	7. Technical professions	Construction workers
9	34	2	2	4	Children	Yes	Dutch	Employed	Female	35	Middle	1. Educational professions	Sports instructors
10	877	2	0	3	Children	No	Dutch	Employed	Female	45	High	4. Business Economics & Administrative professions	Business management specialists
11	87	2	1	2	No children	Yes	Dutch	Employed	Male	45	High	7. Technical professions	Engineers and researchers
12	4564	3	2	4	Children	Yes	Dutch	Employed	Male	25	High	7. Technical professions	Engineers and researchers

Figure 10: Example of the synthesised population dataset

Remodelling residential locations

The classification of occupations to individuals based on three socio-demographic characteristics, thereby ignoring any spatial aspects, poses a major limitation in the classification approach. Yet, due to the lack of publicly available micro-data on living locations of individuals per occupational class, the modelled residential locations of individuals belonging to a particular occupational class may not be fully accurate. Hence, the generated population dataset may not have an appropriate spatial representation of these individuals, which may be particularly apparent for agricultural workers.

Core to land-use and transportation models is the supposed interrelationship between transportation and land use and economic activities in a region (Ibeas, Cordera, dell'Olio, & Coppola, 2013) which creates the assumption that residential locations are correlated with work locations. Interdependence of work locations and residential locations must therefore not be forgotten. Yet, accurate remodelling of resident locations is highly complex in nature due to heterogeneity of households and employment opportunities that may impact the strength of locational choice factors that influences residential choices as income level, household composition and various other factors (Deitz, 1998). While for the large majority of the occupations the rather random stratification of individuals and their respective occupational class over the zones may not be a large issue, due to the fact that their work opportunities may be more evenly scattered over all urbanity levels, work opportunities for agriculture may be more likely to be situated in rural areas. Hence, to account for the interdependence of residential and work locations, the residential locations of agricultural workers are remodelled closer to the already determined work locations to more accurately reflect their spatial residential pattern.

While residential relocation modelling can be considered as a study in itself, such applying utility-maximization models as seen in Frenkel et al. (2013) and Bayer et al. (2016), this study considers a simpler ratioing approach involving IPF and a redistribution algorithm is applied to redistribute agricultural workers over space, without altering the absolute number of workers per occupational class and by solely considering the habitable zones in the Netherlands without exceeding the pre-established population counts per zone in the Spectrum dataset.

The ratioing approach that has been adopted is as follows. Firstly, the relative importance or attractiveness of a zone for agricultural workers is determined by considering the number of agricultural jobs in the zone compared to the average number of agricultural jobs of all zones within the Netherlands. A value above 1 indicates more than average number of jobs in the zone, hence relatively more workers are expected to live in this zone, compared to zones that have below average number of jobs. To obtain a dataset with reference value that display the desired number of agricultural workers per education level in each zone, the ratio value is multiplied with the overall mean number of workers per education level per zone in the entire study area. However, this method does not take into account the population counts per zone and thereby potentially incorrectly assigns more residents in zones than allowed, such as inhabitable zones as industrial zones, whereas other zones may contain less residents than the actual values.

To resolve this issue, IPF is applied to the dataset with reference values, given that per occupational class and education level (columns) and per zone (rows) the marginal totals are known. The IPF algorithm harmonizes the reference values with the residential land use pattern found in the Spectrum dataset, while simultaneously preserving the original residential location data within the population dataset to largest extent.

The updated reference values for every zone within the Netherlands are subsequently applied in the redistribution algorithm. The redistribution algorithm makes permutations in the population dataset where agricultural workers are moved from one residential location to another residential location if necessary. The pseudocode is presented in table 4. Per zone, the observed values (number of workers) for agriculture are compared to the reference value for agriculture. If there is a difference observed, the algorithm has two tasks: if the zone contains less agriculture workers than the reference value (e.g. in rural areas where there are relatively more jobs for agriculture), it randomly takes an agriculture worker from another zone that has a surplus to this zone. It continues this approach until the difference is 0. On the other hand, if the zone contains more agriculture workers than the reference value (e.g. in urban inner cities), the algorithm randomly takes an agricultural worker from the initial zone and places it in a zone with a deficit until there are no workers left to redistribute. Finally, a population dataset where agricultural workers are better adjusted towards their potential work locations is synthesized.

Table 4: pseudocode residential redistribution algorithm

Pseudocode redistribution algorithm		
Input: P_x population dataset of agricultural workers with education level x		
Input: R_x reference values for agricultural workers with education level x for every zone		
Initialization		
$\delta = P_x - R_x$	❖	Difference per zone between actual and reference population
for *zone* in Netherlands **do**:		
if $\delta > 0$:	❖	Too many agricultural workers
K = no. individuals available to redistribute	❖	Amount of individuals in zone that can be redistributed
while $K > 0$:		
Target zone = random zone where $\delta < 0$	❖	Relocate to zone with too few individuals
P_x['*residential location*'] = Target zone	❖	Set residential location to target zone
$\delta = \delta - 1$		
$K = K - 1$		
if $\delta < 0$:	❖	Too few agricultural workers
K = no. individuals available to redistribute		
while $K > 0$:		
Target zone = random zone where $\delta > 0$	❖	Relocate from zone with too many individuals
P_x['*residential location'] = zone*	❖	Set residential location of individual in target zone to current zone
$\delta = \delta - 1$		
$K = K - 1$		
else:	❖	Exactly enough agricultural workers
pass	❖	Skip zone and move to next

Appendix K. Teleworking behaviour

The extent to which individuals in the Dutch workforce are teleworking is observable through empirical data of the LRO dataset (Taale, Olde Kalter, Haaijer, & Damen, 2022; MuConsult, 2022). The number of days that an individual is teleworking (t) is derived per occupational class and education level group c. The data is based on actual observed teleworking patterns of both part-time and full-time workers, whereby individuals that have potential to telework but are currently not teleworking are not considered in the analysis. In addition, to ensure that the analysis specifically targets hybrid workers, individuals who exclusively work from home for the entirety of their workweek (full-time teleworkers) are not included. For simplification purposes, it is assumed that the observed teleworking behaviours are determined by the nature of work and are not resultant of other factors such as personal preferences and abilities. The obtained data regarding the distribution of teleworking per day t for every occupational class and education level group c has two main purposes: (1) to identify the set of jobs that are available per day teleworking in the hybrid job accessibility model (O_{jc}^{t}) by multiplying the total set of jobs (O_{jc}) with the proportion of observed teleworking behaviour per day (t) (see appendix L.3), and (2) to construct the distance decay functions $f_c(c_{ij}^{v})$ and $f_c^{t}(c_{ij}^{v})$ for the physical and hybrid job accessibility model.

K.1. Deriving decay functions

For both the physical and hybrid job accessibility models, travel costs are defined on the basis of physical proximity to employment locations expressed as travel time in minutes (c_{ij}) by car, public transportation and bike. In the physical job accessibility model, travel impedances per mode vary according to the occupational classes, whereas in the weighted hybrid job accessibility model, travel impedances per mode depend on the number of days hybrid teleworking (t=0 to t=4), where the 0-day teleworking decay function is equal to the physical decay function of the corresponding occupational class c.

The decay function can be expressed in various forms, e.g. (negative) exponential-decay functions (Cheng & Bertolini, 2013; Muhammad, de Jong, & Ottens, 2008), log-logistic functions (Palacios & El-Geneidy, 2022), log-normal decay functions (Östh, Lyhagen, & Reggiani, 2016) and power functions (Luo, 2014). The power $f(c_{ij}) = -\alpha * c_{ij}^{\beta}$, log-logistic $f(c_{ij}) = \frac{1}{1+e^{\alpha} * c_{ij}^{\beta}}$, and the log-normal decay functions $f(c_{ij}) = \alpha * \exp(-\beta * \ln^2(c_{ij}+1))$, are better seen to conform to the spatial interaction measurements (Östh, Lyhagen, & Reggiani, 2016; Palacios & El-Geneidy, 2022). The choice of the function (log-logistic, log-normal or power function) and estimation of its parameters α and β for every function is determined based on a best-fit to the empirical travel-to-work flows in the LRO dataset. In the data, home and work locations of the individuals are collected at PC4 level and travel times between these locations are used for modelling the spatial interaction to these work locations. Travel time data is derived from a travel time matrix from the OmniTRANS Spectrum dataset and contains travel times from and to every Spectrum zone in the Netherlands for all three modes. To match with the zonal configuration of the travel time matrix, PC4 home and work locations of the LRO are disaggregated to the zonal level. This process involves assigning PC4 locations to a specific zone in the Spectrum configuration, based on spatial intersection of the PC4 and Spectrum vector layers. Given the higher aggregation level of PC4 zones, each PC4 zone is randomly assigned to a single intersecting Spectrum zone. For the calculation of the interzonal travel times, travel times from both peak (morning and evening) and off-peak hours have been averaged to represent an average day of the week. Travel times in minutes from and to every zone in the Netherlands are depicted for car, multi-modal commutes by public transport (including feeder modes, train and other public transport modes) and bike. Since the data of the LRO is collected though a survey, there is a significant likelihood of inaccurate or unreliable postal-codes being provided for home and work locations; respondents may feel uncomfortable disclosing the locations of their home and work, or might lack knowledge regarding the postal codes. Consequently, in some cases, the PC4 location may contain randomly chosen number (e.g. 9999) which can potentially result in outliers that affect the slope of the decay function. Outliers, origin-destination pairs that contains longer travel times than 1.5 times the interquartile range (IQR) have been filtered from the dataset.

The three proposed functions, log-logistic, log-normal and power, are calibrated to the empirical observations and tested on their fit using the AIC (Akaike Information Criterion). Their performance is compared per mode of transport for every occupational class or t-days teleworking, where the lower the AIC, the better the performance. AIC is therefore used to compare and select models based on their quality of fit. The AIC Least-Squares Case is calculated according to equation 2 (Hu, 2007):

$$AIC = \begin{cases} N \ln\left(\frac{RSS}{N}\right) + 2K, & \frac{N}{K} \geq 40 \\ N \ln\left(\frac{RSS}{N}\right) + 2K + \frac{2K(K+1)}{N-K-1}, & \frac{N}{K} < 40 \end{cases} \tag{2}$$

Where:

- $RSS = (Y_{obs} - Y_{est})^2$
- N is the number of observations
- K is the number of parameters in the used function

While the size of the AIC is dependent on the number of observations used within the model, indicating that the AIC cannot be compared across every impedance function (per mode and occupational class or per mode and days teleworking) and can only be used to compare the performance of the power, log-logistic and log-normal models, the grand average of the AIC score is presented to give a general indication of the overall performance of the models (table 5). The results indicate an overall resolute best-fit for the power function for both the physical and hybrid job accessibility, meaning that this function generally conforms best to the empirical observations. Hence, the decay functions for both the physical and hybrid job accessibility model are both expressed by the power function.

Table 5: AIC grand average and model rank

Impedance	***Power***	***Log-logistic***	***Log-normal***
Physical AIC	-2891	-2657	-2191
Hybrid AIC	-6417	-5644	-4893
Rank score	**1**	**2**	**3**

Appendix L. Jobs within the Netherlands

Through the integration of multiple data sources, an overview of the synthesized employment landscape of the Netherlands in 2021 has been created. Over 8,5 million job opportunities have been identified that require a formal contractual agreement with a Dutch economic institution and the employee, excluding jobs for self-employed individuals. A complete overview of the occupations and required education levels, derived from the EBB dataset, can be found in appendix O.

L.1. Characterization of jobs

Data on the absolute number of jobs presents the fourth occupational class Business economics and administrative professions as the most prominent occupational class (figure 11). Of all job opportunities, 1.559.069 jobs belong to this category, followed by 1.230.981 jobs for technical professions and 1.170.201 for care and welfare occupations. Least amount of jobs are categorized as Other (165142 jobs), agriculture (195150) and creative and linguistic occupations (206567).

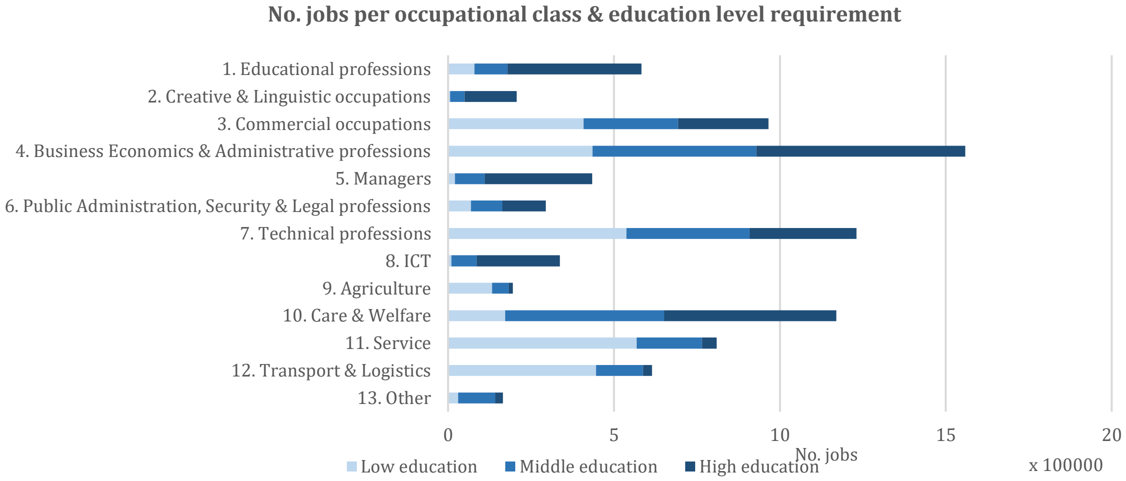


Figure 11: Distribution of jobs per occupational class and education level

With regards to the required educational attainment, there are large deviations between the education requirements for the occupational classes within the Netherlands (figure 11). Generally seen, around 36% of the available job opportunities require a Dutch degree in higher education, such as Hbo bachelor, university bachelor or master and PhD, 30% of the jobs require upper-secondary or lower-tertiary education, while the remaining 34% of jobs require up to lower-secondary education levels and below.

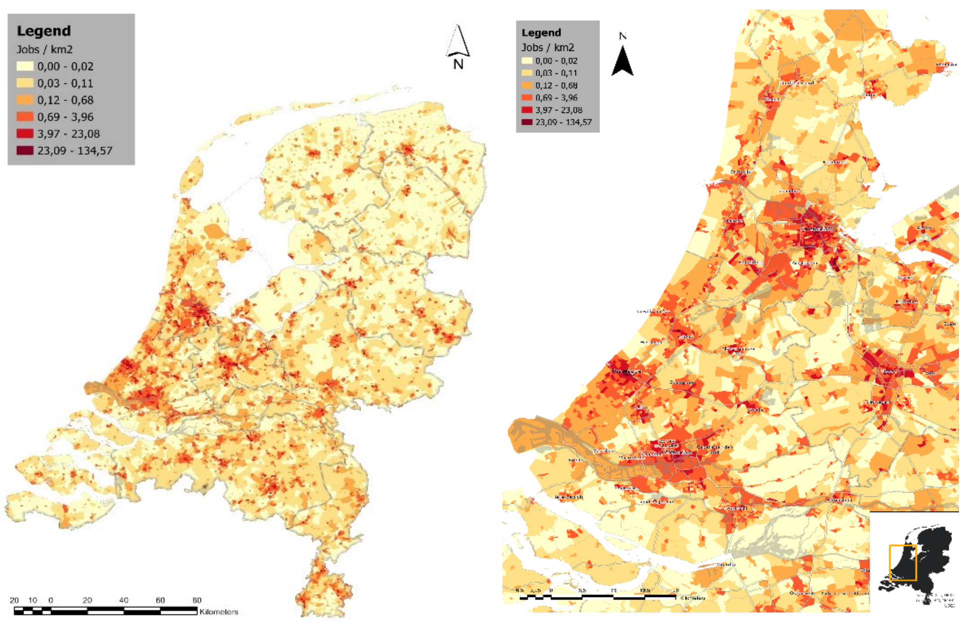


Figure 12: Spatial distribution of jobs (jobs/km²)

A spatially diverse pattern of job opportunities can be found within the Netherlands as seen in figure 12. The map on job densities reveals large regional segregation with regards to job densities. The majority of jobs are more closely concentrated in urban cores, especially the Randstad area as highlighted in figure 12 (left), while the more northern parts of the Netherlands experience overall lower concentration of jobs. Part of the Randstad are large urban agglomerations in the west of the Netherlands as Amsterdam, Rotterdam, Utrecht and The Hague, accounting for 47% of the total job opportunities (4.000.014 jobs).

In addition, appendix M.2. displays the spatial distribution of job opportunities for every occupational class within the Netherlands. While spatially large concentrations are consistently observed within the Randstad, some minor differences can be observed which are most apparent in the more rural regions in the Netherlands. For instance, care and welfare, transport and logistics professions and 'other' occupations appear more spatially scattered compared to most other occupational classes. Jobs per level of urbanization is presented in table 6.

Table 6: Overview of jobs per urbanization level

		Highly urbanized	**Strongly urbanized**	**Moderately urbanized**	**Slightly urbanized**	**Non-urbanized**
1. Educational professions	**n**	157754	131059	74562	78223	141276
	%	27%	22%	13%	13%	24%
2. Creative & Linguistic occupations	**n**	54258	35422	27118	40088	49680
	%	26%	17%	13%	19%	24%
3. Commercial occupations	**n**	257090	178614	144052	187242	198360
	%	27%	19%	15%	19%	21%
4. Business Economics & Administrative professions	**n**	382415	263657	209176	308840	394981
	%	25%	17%	13%	20%	25%
5. Managers	**n**	102450	74476	60509	87420	109659
	%	24%	17%	14%	20%	25%
6. Public Administration Security & Legal professions	**n**	86122	48622	35134	50770	73704
	%	29%	17%	12%	17%	25%
7. Technical professions	**n**	196133	162325	162992	286036	423496
	%	16%	13%	13%	23%	34%
8. ICT	**n**	91103	60793	43921	63704	77742
	%	27%	18%	13%	19%	23%
9. Agriculture	**n**	28833	20732	19745	34794	91045
	%	15%	11%	10%	18%	47%
10. Care & Welfare	**n**	297214	276645	211528	220045	164769
	%	25%	24%	18%	19%	14%
11. Service	**n**	198816	141165	113466	148310	207952
	%	25%	17%	14%	18%	26%
12. Transport & Logistics	**n**	136318	100282	86487	125642	165781
	%	22%	16%	14%	20%	27%
13. Other	**n**	57397	22349	20677	19450	45269
	%	35%	14%	13%	12%	27%
Total jobs	**n**	2045903	1516141	1209366	1650563	2143713
	%	24%	18%	14%	19%	25%

L.2. Spatial distribution of jobs

Figure 13: Spatial distribution of jobs (jobs/worker) per occupational class

L.3. Teleworkability of jobs

From the LRO dataset on teleworking behaviour, the number of days individuals per occupational class can teleworking is derived. From this information, the teleworkability of jobs per occupational class and education level requirement is determined. Figure 14 shows the observed patterns with regards to teleworking. What stands out is that higher educated individuals are generally more likely to work more days from home. This is potentially due to the fact that their work may be more suitable for teleworking compared to jobs requiring lower educational attainment. This trend is persistent throughout all occupational classes.

Nevertheless, some variations can be observed with regards to the teleworkability of jobs. For instance, individuals within public administration professions (e.g. government leaders, lawyers, government officials), ICT (e.g. user support and software developers) and business economics (e.g. secretaries, accountants and policy advisors) are observed to have a large share of teleworking ability. Contrastingly, job opportunities within transport and logistics (e.g. divers of cars, taxis and vans), service professions (e.g. waiters, hairdressers and cleaners) and care and welfare occupations (e.g. nurses, medical specialists and doctors) are faced with lower rates of teleworking compared to the other occupations. The absolute number of jobs per day teleworking can be found in the appendix. This data is used in the weighted hybrid job accessibility model to depict the job opportunities O_j^t per day (t) teleworking for every occupational and educational group within the workforce.

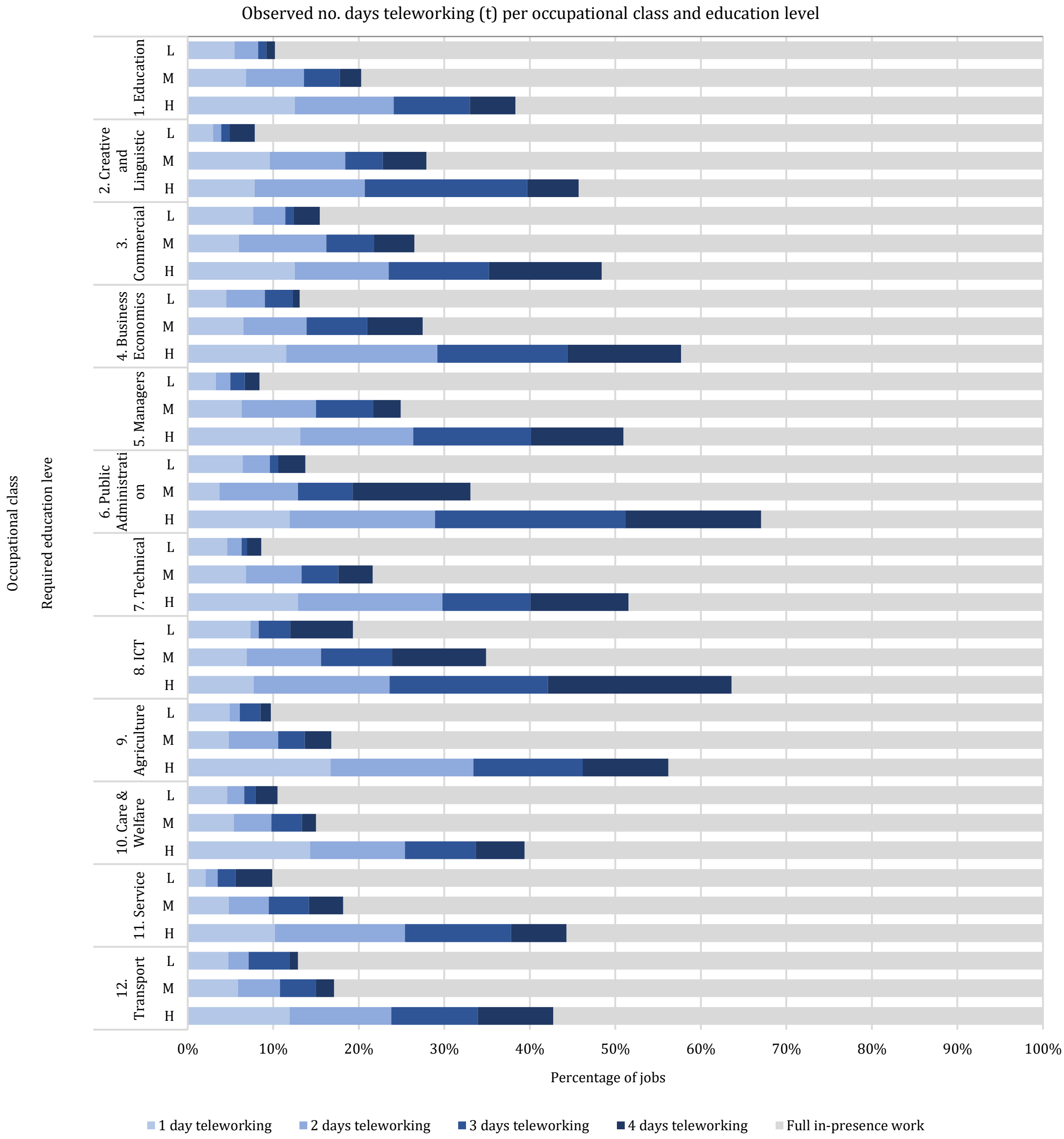


Figure 14: Teleworking rates per occupational class and education level

Appendix M. Workers within the Netherlands

The enrichment of the population synthesizer data with information about occupations of individuals generated a large dataset where every individual within the working population is included. In accordance with the national statistics of the CBS (2022a), the total number of individuals within the population dataset is 8.075.000 million employees. Individuals belonging to the workforce are characterized as individuals between the age of 15 and 75, who are currently employed within a non-self-employed job position.

M.1. Characterization of workers

To characterize the population of the Netherlands, firstly a general overview of individuals over each occupational class and education level is given. The distribution of the population over the occupational classes and education levels can be seen in figure 15. A detailed overview of all workers and characteristics can be found in appendix N.3.

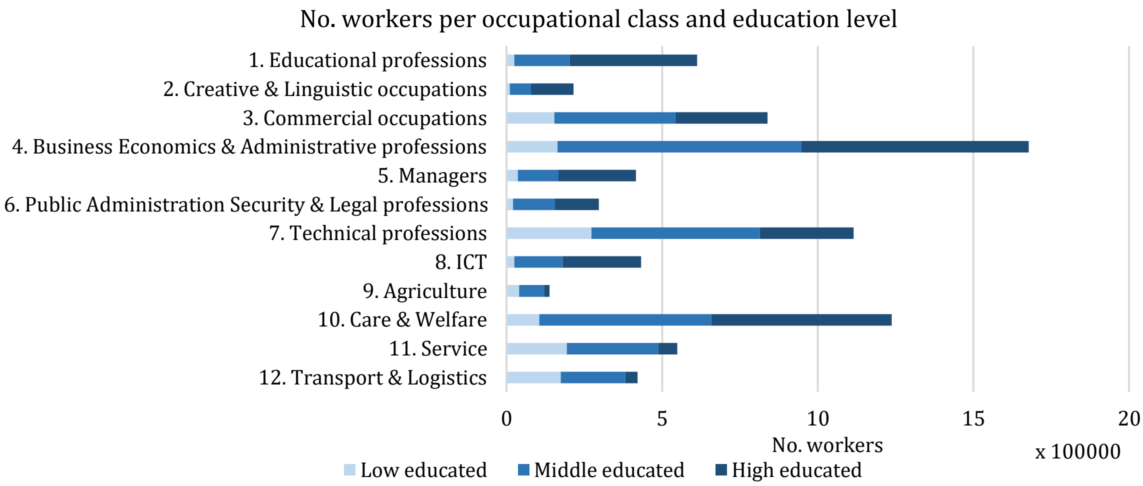


Figure 15: Distribution of workers per occupational class and education level

Characteristics assigned to individuals varies largely per occupational class. Figure 16 shows the gender distribution for every occupation. Women are most dominantly present within the educational occupations, creative and linguistic occupations, commercial occupations, business economics and administrative professions, care and welfare professions and service professions.

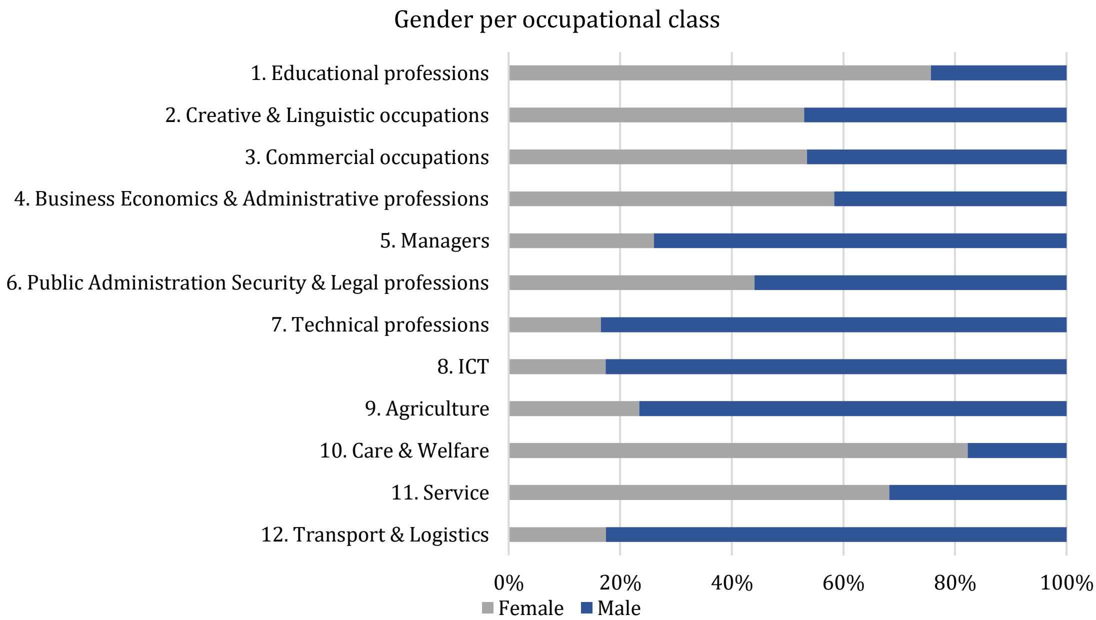


Figure 16: Distribution of gender per occupational class

Lastly, the age distribution of individuals per occupational class is shown in figure 17.

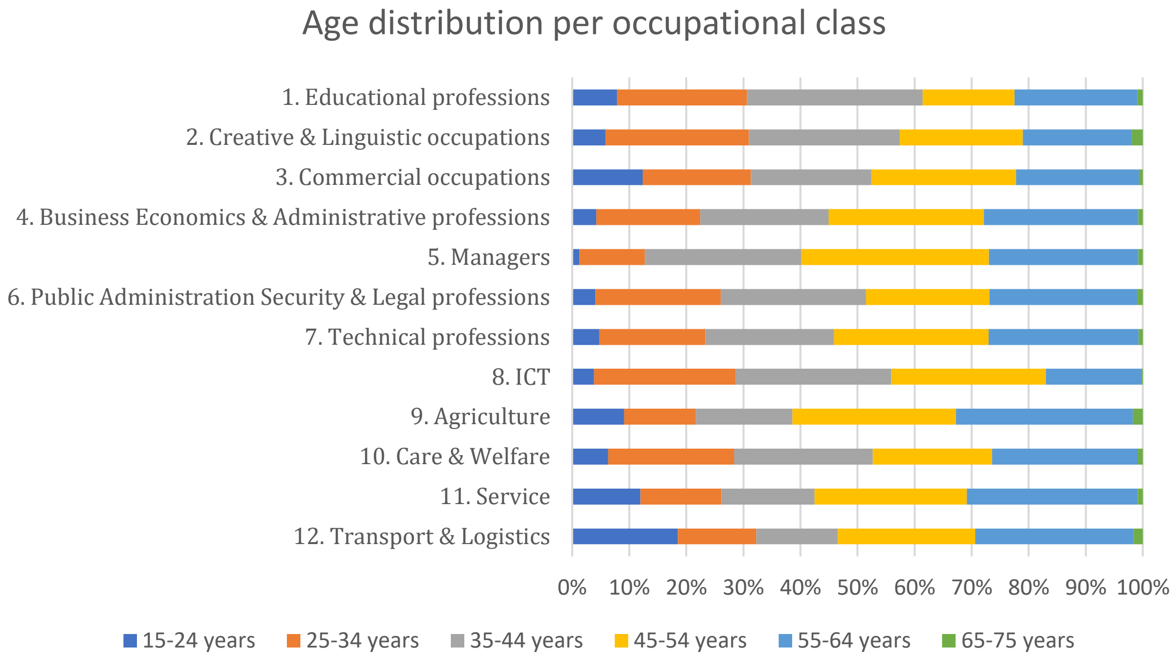


Figure 17: Distribution of age per occupational class

Appendix N.4. is supplemented with a comparison table that shows the deviations in the distribution of gender, age and education level with the CBS dataset used in the synthesis (CBS, 2022a). The table gives insights in the representativeness of the synthesized data compared to the national statistics. Based on the latter, some deviations with the reference dataset are observed, but overall the synthesized data occurs to be compliant.

With regards to the spatial distribution of individuals, a similar pattern to the jobs dataset can be observed: high concentrations of workers are observed within the urban core of the Netherlands (figure 18). The zoomed map in the figure shows the agglomeration of Dutch inhabitants within and around major cities, where stark contract between habitable areas (residential neighbourhoods) and non-habitable areas (e.g. industrial zones, Natura2000 areas) can be observed.

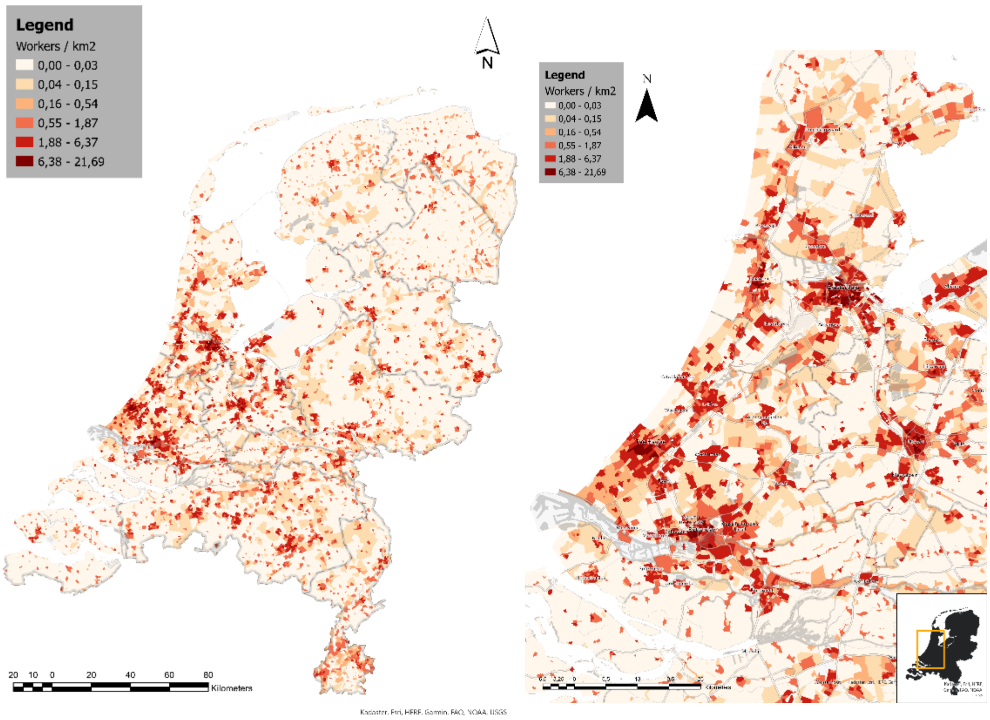


Figure 18: Spatial distribution of workers (worker/km²)

The spatial distribution of individuals within each occupational class is shown in Appendix N.2.. What can be observed is that for all occupations, density of inhabitants is largest in the west of the country. Yet, individuals working in agriculture are more evenly dispersed throughout the country, which is the result of the spatial relocation that has been employed in the workers synthesis. Additionally, table 7 gives insights on the distribution of individuals over multiple levels of urbanization.

Table 7: Overview of workers per urbanization level

		Highly urbanized	Strongly urbanized	Moderately urbanized	Slightly urbanized	Non-urbanized
1. Educational professions	**n**	168966	149523	107227	94853	92063
	%	28%	24%	18%	15%	15%
2. Creative & Linguistic occupations	**n**	57792	52592	38311	33703	33446
	%	27%	24%	18%	16%	15%
3. Commercial occupations	**n**	198655	206865	151491	136676	145320
	%	24%	25%	18%	16%	17%
4. Business Economics & Administrative professions	**n**	398619	415588	305519	273844	283860
	%	24%	25%	18%	16%	17%
5. Managers	**n**	103873	101672	74343	67217	68554
	%	25%	24%	18%	16%	16%
6. Public Administration Security & Legal professions	**n**	72748	72601	53639	48353	49698
	%	24%	24%	18%	16%	17%
7. Technical professions	**n**	246216	277570	205593	184714	201429
	%	22%	25%	18%	17%	18%
8. ICT	**n**	112462	104865	77198	68488	69799
	%	26%	24%	18%	16%	16%
9. Agriculture	**n**	27979	34367	26169	23448	26246
	%	20%	25%	19%	17%	19%
10. Care & Welfare	**n**	307036	306575	222595	198740	202635
	%	25%	25%	18%	16%	16%
11. Service	**n**	112599	138495	102763	92744	102497
	%	21%	25%	19%	17%	19%
12. Transport & Logistics	**n**	88823	104943	77267	70263	79636
	%	21%	25%	18%	17%	19%
13. Other	**n**	27351	30537	22635	20677	22037
	%	22%	25%	18%	17%	18%
Total employed labour force	**n**	1923119	1996193	1464750	1313720	1377220
	%	24%	25%	18%	16%	17%

M.2. Spatial distribution of workers

Figure 19: Spatial distribution of workers (workers per occupational class/jobs per occupational class)

M.3. Characteristics of the worker population

Table 8: General characteristics of the Dutch workforce

	1. Educational professions		2. Creative & Linguistic occupations		3. Commercial occupations		4. Business Economics & Administrative professions		5. Managers		6. Public Administration Security & Legal professions		7. Technical professions		8. ICT		9. Agriculture		10. Care & Welfare		11. Service		12. Transport & Logistics		13. Other		Total employed labour force	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Number of workers	612,632		215,844		839,007		1,677,430		415,659		297,039		1,115,521		432,812		138,209		1,237,580		549,098		420,932		123,237		8,075,000	
Gender																												
Female	463824	76%	114376	53%	448785	53%	979451	58%	108238	26%	130964	44%	184284	17%	75266	17%	32396	23%	1018652	82%	374814	68%	73411	17%	41592	34%	4,046,053	50%
Male	148808	24%	101468	47%	390222	47%	697979	42%	307421	74%	166075	56%	931237	83%	357546	83%	105813	77%	218928	18%	174284	32%	347521	83%	81645	66%	4,028,947	50%
Age category																												
15-24 years	48214	8%	12627	6%	103701	12%	71291	4%	5237	1%	12000	4%	52653	5%	16533	4%	12591	9%	78091	6%	65837	12%	77999	19%	9452	8%	566,227	7%
25-34 years	139374	23%	54285	25%	159160	19%	305460	18%	47884	12%	65289	22%	207710	19%	107208	25%	17359	13%	273258	22%	77752	14%	57920	14%	18214	15%	1,530,872	19%
35-44 years	188752	31%	56940	26%	177450	21%	377254	22%	113724	27%	75626	25%	251327	23%	118374	27%	23413	17%	300856	24%	89503	16%	60025	14%	23144	19%	1,856,387	23%
45-54 years	98695	16%	46644	22%	212353	25%	455590	27%	136835	33%	64309	22%	302306	27%	117162	27%	39583	29%	258778	21%	146774	27%	101234	24%	36897	30%	2,017,160	25%
55-64 years	131900	22%	41291	19%	180890	22%	454584	27%	108778	26%	76814	26%	293270	26%	72583	17%	42831	31%	316573	26%	164235	30%	117230	28%	34371	28%	2,035,349	25%
65-75 years	5697	1%	4079	2%	5454	1%	13252	1%	3201	1%	3030	1%	8255	1%	952	0%	2446	2%	9777	1%	5052	1%	6567	2%	1158	1%	68,919	1%
Education level																												
High education	409912	67%	137083	64%	296673	35%	730353	44%	248730	60%	141569	48%	301637	27%	252892	58%	17456	13%	579559	47%	61609	11%	39105	9%	32855	27%	3,249,431	40%
Low education	24873	4%	10857	5%	153622	18%	163885	10%	36329	9%	21238	7%	272856	24%	25363	6%	40993	30%	105566	9%	194051	35%	174350	41%	41457	34%	1,265,440	16%
Middle education	177908	29%	67905	31%	388712	46%	783192	47%	130600	31%	134232	45%	541028	49%	154557	36%	79760	58%	552456	45%	293383	53%	207477	49%	48925	40%	3,560,135	44%
Migration background																												
Dutch	405991	66%	146191	68%	597373	71%	1176717	70%	293829	71%	206591	70%	809534	73%	304483	70%	102745	74%	847619	68%	403148	73%	311995	74%	89495	73%	5,695,710	71%
Not western	127795	21%	43320	20%	149175	18%	309654	18%	74819	18%	57002	19%	198228	18%	81282	19%	22639	16%	238110	19%	88624	16%	71053	17%	21074	17%	1,482,775	18%
Western	78846	13%	26333	12%	92542	11%	191227	11%	47011	11%	33447	11%	107648	10%	47047	11%	12826	9%	151851	12%	57326	10%	37884	9%	12669	10%	896,656	11%
Household size																												
1	121546	20%	43449	20%	146323	17%	305628	18%	79308	19%	56794	19%	208491	19%	80936	19%	24864	18%	227096	18%	86099	16%	72990	17%	22762	18%	1,476,284	18%
2	141824	23%	50378	23%	215625	26%	446364	27%	104372	25%	70576	24%	259916	23%	102317	24%	34027	25%	326474	26%	155175	28%	97446	23%	30156	24%	2,034,650	25%
3	122404	20%	40665	19%	166543	20%	321731	19%	75941	18%	56734	19%	219758	20%	76564	18%	28319	20%	244051	20%	118331	22%	93279	22%	25966	21%	1,590,285	20%
4	155425	25%	56206	26%	217387	26%	428583	26%	109194	26%	78478	26%	295502	26%	118850	27%	35672	26%	311251	25%	137220	25%	107253	25%	30785	25%	2,081,804	26%
5	53605	9%	18886	9%	69554	8%	131678	8%	34500	8%	26169	9%	99058	9%	41074	9%	11623	8%	96903	8%	38217	7%	38010	9%	9871	8%	669,149	8%
6	17828	3%	6281	3%	23492	3%	43445	3%	12304	3%	8258	3%	32796	3%	13028	3%	3690	3%	31682	3%	14057	3%	11954	3%	3697	3%	222,512	3%
Household composition																												
Children	354040	58%	121758	56%	480667	57%	939193	56%	228612	55%	167946	57%	629489	56%	242937	56%	77853	56%	706287	57%	317873	58%	244604	58%	69789	57%	4,581,048	57%
No children	137597	22%	50788	24%	212688	25%	434454	26%	107822	26%	72507	24%	277876	25%	109069	25%	35534	26%	305806	25%	145731	27%	103465	25%	30735	25%	2,024,073	25%
Single	120995	20%	43298	20%	145652	17%	303783	18%	79183	19%	56616	19%	208156	19%	80849	19%	24822	18%	225487	18%	85495	16%	72863	17%	22713	18%	1,469,911	18%
Urbanity																												
Highly urbanized	168966	28%	57792	27%	198655	24%	398619	24%	103873	25%	72748	24%	246216	22%	112462	26%	27979	20%	307036	25%	112599	21%	88823	21%	27351	22%	1,923,119	24%
Strongly urbanized	149523	24%	52592	24%	206865	25%	415588	25%	101672	24%	72601	24%	277570	25%	104865	24%	34367	25%	306575	25%	138495	25%	104943	25%	30537	25%	1,996,193	25%
Moderately urbanized	107227	18%	38311	18%	151491	18%	305519	18%	74343	18%	53639	18%	205593	18%	77198	18%	26169	19%	222595	18%	102763	19%	77267	18%	22635	18%	1,464,750	18%
Slightly urbanized	94853	15%	33703	16%	136676	16%	273844	16%	67217	16%	48353	16%	184714	17%	68488	16%	23448	17%	198740	16%	92744	17%	70263	17%	20677	17%	1,313,720	16%
Non-urbanized	92063	15%	33446	15%	145320	17%	283860	17%	68554	16%	49698	17%	201429	18%	69799	16%	26246	19%	202635	16%	102497	19%	79636	19%	22037	18%	1,377,220	17%

M.4. Worker characteristics validation table

Based on the validation table (table 9), it can be seen that some substantial deviations in distributions occur within the service and transport and logistics occupational classes. For instance, the results indicate a large systematic overrepresentation of individuals within the age range of 55-64 and a substantial underrepresentation of the youngest age category (15-24). Additionally, an overall overrepresentation of the middle educated individuals is visible.

While some substantial deviation are visible, the synthesised population dataset does not deviate more than 9,4% on average from the reference data. For instance, there might be no perfect conformity between the sample population from the CBS dataset and the population synthesizer. For instance, the sample population from the CBS might deviate from the total population, hence there is uncertainty whether the distribution of characteristics per occupational class displays the actual picture. Besides, over- or underrepresentation of certain individual characteristics might be already present within the population synthesizer, resulting in an inherent over- or underrepresentation of these characteristics.

Table 9: Deviation of synthesized dataset from CBS dataset (2022a)

	1. Educational professions	2. Creative and Linguistic occupations	3. Commercial occupations	4. Business Economics & Administrative professions	5. Managers	6. Public Administration, Security & Legal professions	7. Technical professions	8. ICT	9. Agriculture	10. Care & Welfare	11. Service	12. Transport & Logistics	13. Other	Average deviation from CBS dataset
Gender														
Female	4.5%	2.4%	0.2%	4.2%	0.7%	2.6%	0.9%	1.8%	1.1%	2.6%	3.3%	-3.0%	1.1%	1.7%
Male	-4.5%	-2.4%	-0.2%	-4.2%	-0.7%	-2.6%	-0.9%	-1.8%	-1.1%	-2.6%	-3.3%	3.0%	-1.1%	-1.7%
Age category														
15.0	-6.6%	-4.3%	-15.4%	-5.1%	-1.2%	-4.3%	-7.2%	-4.2%	-15.0%	-6.3%	-18.0%	-24.5%	-9.7%	-9.4%
25.0	-2.0%	-2.4%	-0.2%	-3.1%	-3.2%	-3.1%	-3.6%	-5.1%	-1.0%	-2.3%	-0.5%	0.9%	-2.6%	-2.2%
35.0	7.4%	5.7%	4.5%	3.0%	1.5%	4.1%	1.7%	3.1%	2.2%	4.4%	2.3%	3.7%	1.4%	3.5%
45.0	-0.7%	1.0%	5.5%	1.3%	0.0%	0.9%	4.5%	2.8%	7.5%	0.5%	7.6%	9.8%	5.6%	3.6%
55.0	4.1%	4.2%	7.3%	6.0%	4.6%	5.1%	6.7%	3.7%	9.8%	5.8%	11.2%	12.8%	8.4%	6.9%
65.0	-2.0%	-4.2%	-1.7%	-2.0%	-1.9%	-2.7%	-2.1%	-0.6%	-4.1%	-2.1%	-2.6%	-2.8%	-2.5%	-2.4%
Education level														
High education	-0.3%	-2.1%	1.7%	-3.8%	-3.6%	-2.8%	-1.8%	-3.5%	0.3%	-2.4%	0.4%	0.8%	-1.1%	-1.4%
Low education	-1.4%	-1.0%	-5.6%	-1.6%	-0.8%	-1.2%	-2.5%	-0.4%	-5.6%	-1.9%	-5.6%	-7.9%	-3.2%	-3.0%
Middle education	2.0%	3.5%	4.3%	5.6%	4.5%	4.3%	5.3%	4.8%	6.5%	4.5%	6.8%	8.2%	5.7%	5.1%

Appendix N. Summary of workers and jobs per occupational class and education level group *c*

Table 10 shows the characteristics of the Dutch working population and jobs per t-day teleworking within the entire study area in 2021. The employed Dutch workforce compromises over 8 million workers, with approximately 40% having a high level of education, 44% with a middle level of education, and the remaining 16% possessing a low level of education. Per occupational class, the education levels of workers largely varies. With regards to job opportunities, more than 8,5 million (full-time) jobs are observed, of which 36% require higher education levels, 30% middle education levels and 34% lower education levels. From this set of jobs, approximately 71% require full in-presence work (t=0), whereas the resultant 29% of jobs allow 1 or more days teleworking per week. In general, the most teleworkable occupational classes are 8. ICT (56%, t>0) and 6. Public Administration, Security & Legal professions (44%, t>0) and jobs that require higher education are structurally more teleworkable compared to other education levels (appendix M.3.) such as database and network specialists and lawyers (high educated) compared to security personnel (low educated). Conversely, least teleworkable jobs are found within 9. Agriculture and 11. Service occupations (86% t=0) which include jobs as farmers and foresters, waiters, bartenders and cleaners. The job to worker (J/W) ratio suggests an overall surplus of job opportunities (>1) when considering the entire workforce and supply of jobs. Among the three education levels and occupational classes, individuals with lower education often have greater set of job opportunities per person compared to those with middle or high levels of education, ignoring downward educational matching.

*Table 10: General worker and job characteristics per occupational class and education level group (c), *total includes 13. Other*

Occupational class and education level (*c*)		Workers Total		Jobs Total		Jobs t=0		Jobs t=1		Jobs t=2		Jobs t=3		Jobs t=4		J/W ratio Total
		N	%	N	%	N	%	N	%	N	%	N	%	N	%	
1. Educational professions	*High*	409,912	67%	404,121	69%	249,336	43%	50,502	9%	46,875	8%	35,964	6%	21,405	4%	0.99
	Middle	177,908	29%	99,567	17%	79,377	14%	6,734	1%	6,734	1%	4,150	1%	2,429	0%	0.56
	Low	24,873	4%	79,185	14%	50,502	9%	4,305	1%	2,083	0%	683	0%	683	0%	3.18
	Total	612,632	100%	582,873	100%	379,215	65%	61,541	11%	55,692	10%	40,797	7%	24,517	4%	0.95
2. Creative & Linguistic occupations	*High*	137083	64%	156,781	76%	85,164	41%	12,192	6%	20,220	10%	29,794	14%	9,375	5%	1.14
	Middle	67905	31%	43,632	21%	31,443	15%	4,115	2%	3,780	2%	1,830	1%	2,151	1%	0.64
	Low	10857	5%	6,154	3%	5,748	3%	114	0%	23	0%	23	0%	114	0%	0.57
	Total	215,844	100%	206,567	100%	122,355	59%	16,421	8%	24,023	12%	31,647	15%	11,640	6%	0.96
3. Commercial occupations	*High*	296673	35%	272,226	28%	140,533	15%	33,994	4%	29,929	3%	31,815	3%	35,931	4%	0.92
	Middle	388712	46%	284,782	30%	209,302	22%	17,056	2%	29,035	3%	15,928	2%	13,346	1%	0.73
	Low	153622	18%	408,350	42%	345,068	36%	31,013	3%	15,475	2%	4,032	0%	12,609	1%	2.66
	Total	839,007	100%	965,358	100%	694,903	72%	82,063	9%	74,439	8%	51,775	5%	61,886	6%	1.15
4. Business Economics & Administrative professions	*High*	730353	44%	629,865	40%	266,418	17%	72,429	5%	111,484	7%	95,737	6%	83,771	5%	0.86
	Middle	783192	47%	494,225	32%	358,307	23%	32,118	2%	36,563	2%	35,072	2%	32,118	2%	0.63
	Low	163885	10%	434,979	28%	378,003	24%	19,548	1%	19,548	1%	14,332	1%	3,421	0%	2.65
	Total	1,677,430	100%	1,559,069	100%	1,002,728	64%	124,095	8%	167,595	11%	145,141	9%	119,310	8%	0.93
5. Managers	*High*	248730	60%	324,167	75%	159,116	37%	42,791	10%	42,791	10%	44,728	10%	35,008	8%	1.30
	Middle	130600	31%	89,511	21%	67,339	15%	5,606	1%	7,762	2%	5,949	1%	2,806	1%	0.69
	Low	36329	9%	20,837	5%	19,137	4%	592	0%	270	0%	270	0%	270	0%	0.57
	Total	415,659	100%	434,515	100%	245,592	57%	48,989	11%	50,823	12%	50,947	12%	38,084	9%	1.05
6. Public Administration, Security & Legal professions	*High*	141569	48%	130,992	45%	43,113	15%	15,534	5%	22,284	8%	29,064	10%	20,780	7%	0.93
	Middle	134232	45%	94,488	32%	63,199	21%	3,425	1%	8,640	3%	5,998	2%	13,009	4%	0.70
	Low	21238	7%	68,872	23%	59,399	20%	4,352	1%	2,127	1%	600	0%	2,127	1%	3.24
	Total	297,039	100%	294,352	100%	165,711	56%	23,311	8%	33,051	11%	35,662	12%	35,916	12%	0.99
7. Technical professions	*High*	301637	27%	322,516	26%	156,373	13%	41,605	3%	54,519	4%	33,209	3%	37,069	3%	1.07
	Middle	541028	49%	370,525	30%	290,495	24%	25,170	2%	24,069	2%	15,908	1%	14,795	1%	0.68
	Low	272856	24%	537,940	44%	491,691	40%	24,728	2%	9,105	1%	3,162	0%	9,105	1%	1.97
	Total	1,115,521	100%	1,230,981	100%	938,559	76%	91,503	7%	87,693	7%	52,279	4%	60,969	5%	1.10
8. ICT	*High*	252892	58%	251,207	74%	91,414	27%	19,319	6%	39,916	12%	46,465	14%	54,012	16%	0.99
	Middle	154557	36%	75,625	22%	49,278	15%	5,157	2%	6,536	2%	6,196	2%	8,289	2%	0.49
	Low	25363	6%	10,430	3%	8,476	3%	687	0%	53	0%	308	0%	687	0%	0.41
	Total	432,812	100%	337,262	100%	149,168	44%	25,163	7%	46,505	14%	52,969	16%	62,988	19%	0.78
9. Agriculture	*High*	17456	13%	12,256	6%	5,283	3%	2,057	1%	2,057	1%	1,527	1%	1,127	1%	0.70
	Middle	79760	58%	50,496	26%	41,989	22%	2,350	1%	2,869	1%	1,483	1%	1,483	1%	0.63
	Low	40993	30%	132,397	68%	119,598	61%	6,443	3%	1,510	1%	3,119	2%	1,510	1%	3.23
	Total	138,209	100%	195,149	100%	166,870	86%	10,850	6%	6,436	3%	6,129	3%	4,120	2%	1.41
10. Care & Welfare	*High*	579559	47%	519,051	44%	314,543	27%	74,201	6%	57,603	5%	43,039	4%	29,553	3%	0.90
	Middle	552456	45%	479,305	41%	407,421	35%	25,841	2%	21,041	2%	17,209	1%	7,608	1%	0.87
	Low	105566	9%	171,846	15%	153,841	13%	7,858	1%	3,383	0%	2,191	0%	4,412	0%	1.63
	Total	1,237,580	100%	1,170,202	100%	875,805	75%	107,900	9%	82,027	7%	62,439	5%	41,573	4%	0.95
11. Service	*High*	61609	11%	44,521	5%	24,833	3%	4,519	1%	6,719	1%	5,438	1%	2,837	0%	0.72
	Middle	293383	53%	196,758	24%	160,961	20%	9,406	1%	9,218	1%	9,218	1%	7,831	1%	0.67
	Low	194051	35%	568,428	70%	512,174	63%	11,909	1%	7,919	1%	11,909	1%	24,431	3%	2.93
	Total	549,098	100%	809,707	100%	697,968	86%	25,834	3%	23,856	3%	26,565	3%	35,099	4%	1.47
12. Transport & Logistics	*High*	39105	9%	26,403	4%	15,186	2%	3,065	0%	3,065	0%	2,634	0%	2,260	0%	0.68
	Middle	207477	49%	142,566	23%	118,188	19%	8,367	1%	6,936	1%	5,946	1%	2,936	0%	0.69
	Low	174350	41%	445,541	73%	388,071	63%	21,363	3%	10,656	2%	21,363	3%	4,407	1%	2.56
	Total	420,932	100%	614,510	100%	521,445	85%	32,795	5%	20,657	3%	29,943	5%	9,603	2%	1.46
Total*	*High*	3,249,431	40%	3117367	36%	1,557,611	18%	380,548	4%	441,642	5%	403,594	5%	333,286	4%	0.96
	Middle	3,560,135	44%	2,532,514	30%	1,951,276	23%	159,206	2%	177,044	2%	129,533	2%	113,447	1%	0.71
	Low	1,265,440	16%	2,915,805	34%	2,554,156	30%	140,346	2%	72,386	1%	62,226	1%	64,010	1%	2.30
	Total	8,075,000	100%	8,565,686	100%	6,063,043	71%	680,100	8%	691,072	8%	595,353	7%	510,743	6%	1.06

Appendix O. Decay functions per occupational class

The physical decay functions per occupational class separately, are presented in figure 20. In general, longest commutes are observed by public transport (± 120 minutes), followed by car and bike (± 60 minutes). Per mode, some variations in decay functions are found per occupational class are visible. By car, teachers and other educational professions (1. Educational professions) are overall least willing to commute long periods of time by car, whereas farmers (9. Agriculture) and ICT professionals (8. ICT) are more likely to travel to more distant work opportunities compared to other occupational classes. For commuting by public transport, larger variations in physical decay can be found. Waiters, bartenders, cooks, hairdressers and other service professions (11. Service) spent least commuting time in public transport, as opposite to bus and truck drivers (12. Transport & Logistics). Lastly, occupations such as security personnel, policy officers, government leaders and layers (6. Public Administration, Security & Legal professions) tend to have the shortest bike commutes. On the contrary, workers in agricultural occupations (9. Agriculture) experience the longest commutes by bike.

Important to note is that these decays may not only reflect the 'willingness' but also forced or mandatory travel, so called 'coerced mobilities' (Giannotti, Tomasiello, & Bittencourt, 2022) if individuals are required to longer commutes in case job opportunities may be more distant from their residence location; the spatial location of job opportunities can therefore significantly impact the commute lengths. For instance, teachers may have shorter car commutes since schools are often located close to residential areas. On the other hand, individuals employed in ICT and agriculture occupations might not have job opportunities in their immediate residential vicinity, thereby imposing longer commutes to reach their places of work.

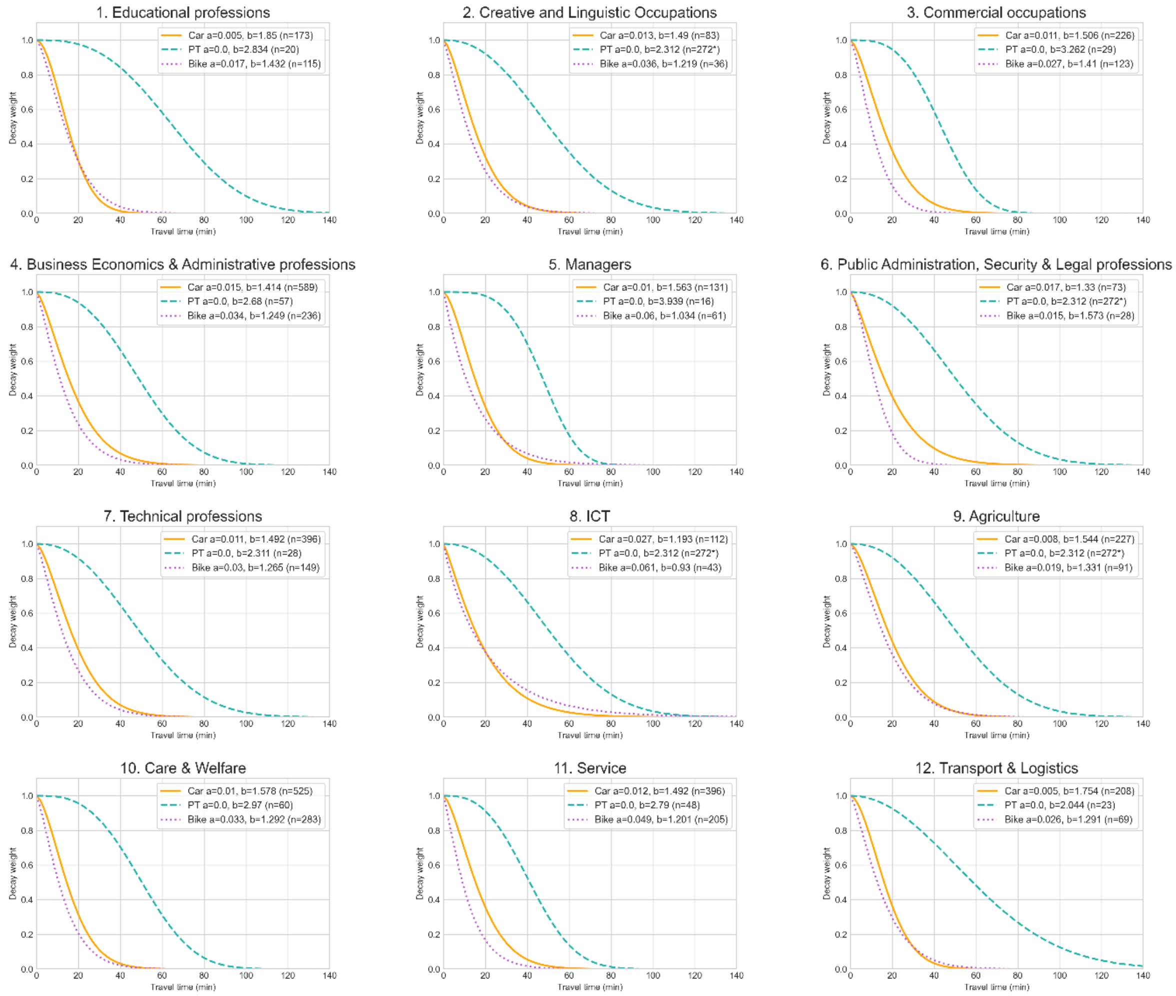


Figure 20: Physical decay functions per occupational class

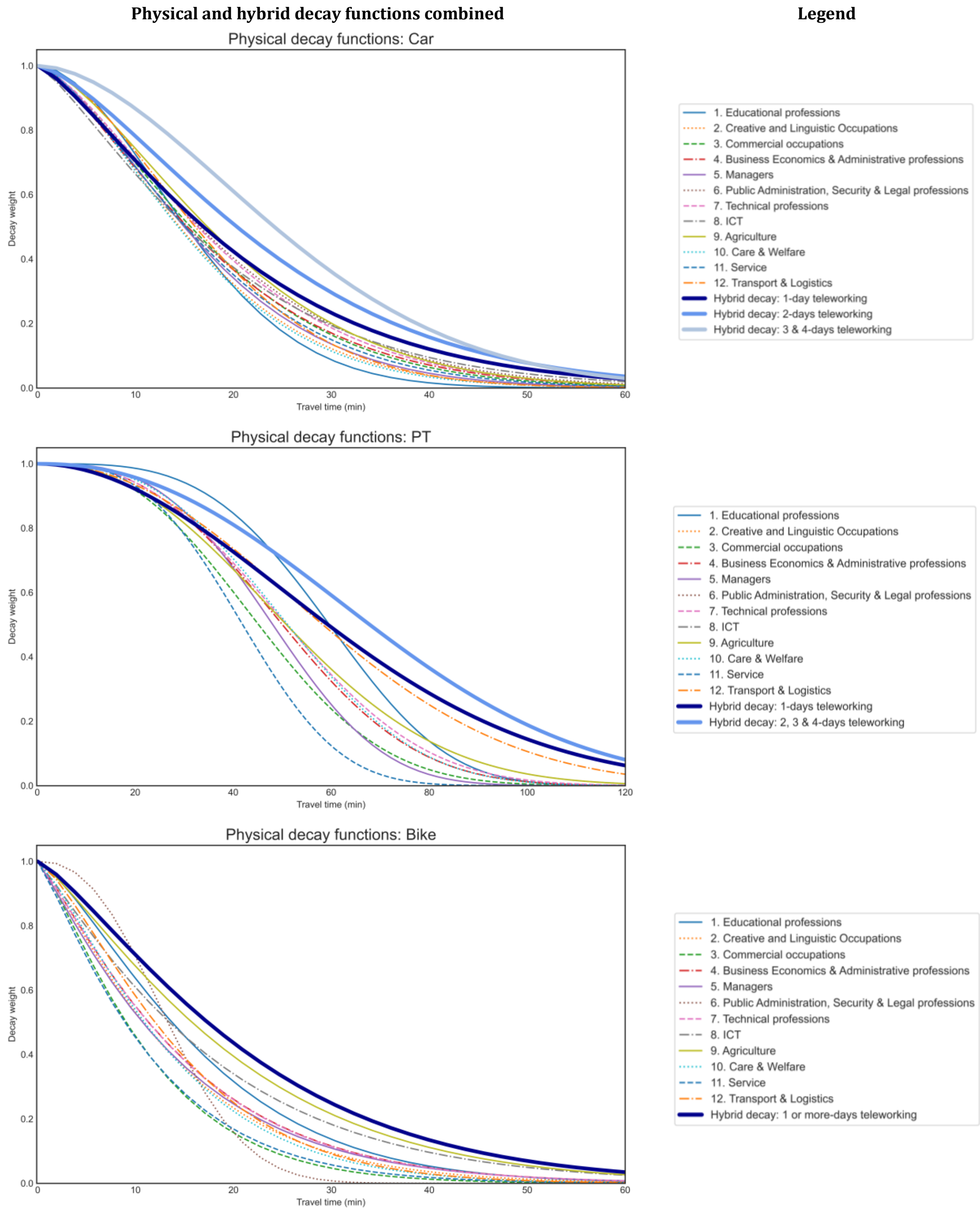


Figure 21: Physical and hybrid decay functions combined for every mode of transport

Appendix P. Correlation matrix

Multicollinearity can be checked in various ways. A common method for detecting multicollinearity is Pearson's correlation coefficient, where a 0 indicates no correlation and 1 indicates perfect correlation. Generally seen, correlations above 0.8 indicate high likeliness of multicollinearity between predictor variables in the regression analysis (Shrestha, 2020). Given that the observed correlations per mode in the Hansen- and Shen-based models are very similar, it is chosen to only display the correlation matrix of the Hansen-based generalized model (table 11).

Table 11: Correlation matrix between independent variables of the multiple linear regression model

	Gender - Male	Age category 15-24	Age category 25-34	Age category 35-44	Age category 45-54	Age category 55-64	Age category 65-75	Education level - Low education	Education level - Middle education	Education level - High education	Occupational class 1. Educational professions	Occupational class 2. Creative and Linguistic occupations	Occupational class 3. Commercial occupations	Occupational class 4. Business Economics & Administrative professions	Occupational class 5. Managers	Occupational class 6. Public Administration, Security & Legal professions	Occupational class 7. Technical professions	Occupational class 8. ICT	Occupational class 9. Agriculture	Occupational class 10. Care & Welfare	Occupational class 11. Service	Occupational class 12. Transport & Logistics	Household composition - Single	Household composition - With children	Household composition - No children	Household size	Migration background - Dutch	Migration background - Western	Migration background - not Western	Urbanity - Highly urbanized	Urbanity - Strongly urbanized	Urbanity - Moderately urbanized	Urbanity - Slightly urbanized	Urbanity - Non-urbanized	Physical accessibility score
Gender - Male	1																																	
Age category 15-24	-0.04	1																																
Age category 25-34	-0.04	-0.13	1																															
Age category 35-44	-0.03	-0.15	-0.26	1																														
Age category 45-54	0.04	-0.16	-0.28	-0.32	1																													
Age category 55-64	0.04	-0.16	-0.28	-0.32	-0.33	1																												
Age category 65-75	0.03	-0.03	-0.04	-0.05	-0.05	-0.05	1																											
Education level - Low education	0.07	0.00	-0.06	-0.10	0.07	0.07	0.00	1																										
Education level - Middle education	0.01	0.00	-0.02	-0.02	0.02	0.02	-0.01	-0.38	1																									
Education level - High education	-0.06	0.00	0.06	0.09	-0.08	-0.08	0.01	-0.35	-0.73	1																								
Occupational class 1. Educational professions	-0.15	0.01	0.03	0.05	-0.06	-0.02	0.00	-0.09	-0.09	0.16	1																							
Occupational class 2. Creative and Linguistic occupations	-0.01	-0.01	0.03	0.01	-0.01	-0.02	0.02	-0.05	-0.04	0.08	-0.05	1																						
Occupational class 3. Commercial occupations	-0.02	0.07	0.00	-0.01	0.00	-0.03	-0.01	0.02	0.02	-0.03	-0.10	-0.06	1																					
Occupational class 4. Business Economics & Administrative professions	-0.08	-0.06	-0.01	-0.01	0.03	0.02	0.00	-0.08	0.03	0.03	-0.15	-0.08	-0.17	1																				
Occupational class 5. Managers	0.11	-0.05	-0.04	0.02	0.04	0.01	0.00	-0.04	-0.06	0.09	-0.07	-0.04	-0.08	-0.12	1																			
Occupational class 6. Public Administration, Security & Legal professions	0.02	-0.02	0.02	0.01	-0.02	0.00	0.00	-0.05	0.00	0.03	-0.06	-0.03	-0.07	-0.10	-0.05	1																		
Occupational class 7. Technical professions	0.27	-0.04	0.00	0.00	0.02	0.01	0.00	0.10	0.04	-0.11	-0.11	-0.07	-0.14	-0.21	-0.09	-0.08	1																	
Occupational class 8. ICT	0.16	-0.03	0.04	0.02	0.01	-0.05	-0.02	-0.06	-0.04	0.09	-0.07	-0.04	-0.08	-0.12	-0.06	-0.05	-0.10	1																
Occupational class 9. Agriculture	0.07	0.01	-0.02	-0.02	0.01	0.02	0.01	0.05	0.04	-0.07	-0.04	-0.02	-0.04	-0.07	-0.03	-0.03	-0.05	-0.03	1															
Occupational class 10. Care & Welfare	-0.27	-0.01	0.03	0.01	-0.04	0.00	0.00	-0.08	0.00	0.06	-0.12	-0.07	-0.14	-0.22	-0.10	-0.08	-0.17	-0.10	-0.06	1														
Occupational class 11. Service	-0.10	0.05	-0.03	-0.04	0.01	0.03	0.00	0.15	0.05	-0.16	-0.08	-0.04	-0.09	-0.14	-0.06	-0.05	-0.11	-0.06	-0.04	-0.11	1													
Occupational class 12. Transport & Logistics	0.15	0.11	-0.03	-0.05	-0.01	0.01	0.02	0.17	0.02	-0.15	-0.07	-0.04	-0.08	-0.12	-0.05	-0.05	-0.09	-0.06	-0.03	-0.10	-0.06	1												
Household composition - Single	0.01	-0.02	-0.01	-0.01	0.01	0.01	0.04	-0.02	-0.05	0.07	0.01	0.01	-0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	-0.02	-0.01	1											
Household composition - With children	-0.03	0.00	0.07	0.11	-0.08	-0.08	-0.07	0.05	-0.01	-0.03	0.01	0.00	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	-0.54	1										
Household composition - No children	0.02	0.02	-0.07	-0.12	0.08	0.08	0.04	-0.03	0.05	-0.03	-0.02	-0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	-0.27	-0.66	1									
Household size	0.03	0.01	0.08	0.12	-0.09	-0.09	-0.07	0.01	0.01	-0.02	0.00	0.00	0.00	-0.01	0.00	0.00	0.01	0.01	0.00	-0.01	0.00	0.01	-0.66	0.78	-0.30	1								
Migration background - Dutch	0.05	0.00	-0.04	-0.07	0.05	0.05	0.01	0.05	0.06	-0.09	-0.03	-0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.01	-0.02	0.02	0.02	-0.28	0.16	0.07	0.23	1							
Migration background - Western	-0.05	0.02	0.00	-0.02	0.00	0.00	0.02	-0.02	-0.06	0.08	0.02	0.01	0.00	0.00	0.00	0.00	-0.02	0.00	-0.01	0.02	-0.01	-0.02	0.12	-0.12	0.03	-0.12	-0.55	1						
Migration background - not Western	-0.02	-0.02	0.05	0.10	-0.06	-0.06	-0.02	-0.04	-0.02	0.05	0.02	0.01	-0.01	0.00	0.00	0.00	-0.01	0.00	-0.01	0.01	-0.02	-0.01	0.24	-0.09	-0.11	-0.17	-0.73	-0.17	1					
Urbanity - Highly urbanized	-0.01	0.05	0.05	0.04	-0.05	-0.06	-0.01	-0.04	-0.11	0.14	0.03	0.01	0.00	0.00	0.01	0.00	-0.02	0.01	-0.01	0.01	-0.02	-0.01	0.24	-0.18	-0.01	-0.20	-0.25	0.09	0.22	1				
Urbanity - Strongly urbanized	0.00	-0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.01	-0.02	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	0.02	-0.03	0.00	-0.07	0.01	0.07	-0.32	1			
Urbanity - Moderately urbanized	0.00	-0.02	-0.01	0.00	0.01	0.01	0.00	0.01	0.02	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.07	0.05	0.00	0.05	0.05	-0.02	-0.05	-0.26	-0.27	1		
Urbanity - Slightly urbanized	0.00	-0.02	-0.01	-0.01	0.02	0.02	0.00	0.01	0.03	-0.03	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.10	0.06	0.02	0.08	0.13	-0.04	-0.12	-0.25	-0.25	-0.21	1	
Urbanity - Non-urbanized	0.02	0.00	-0.03	-0.04	0.03	0.03	0.01	0.02	0.06	-0.08	-0.02	-0.01	0.00	0.00	0.00	0.00	0.01	-0.01	0.01	-0.01	0.01	0.01	-0.11	0.06	0.03	0.10	0.19	-0.06	-0.17	-0.25	-0.26	-0.21	-0.20	1	
Physical accessibility score	-0.02	-0.02	0.02	0.03	-0.01	-0.02	-0.01	0.02	-0.22	0.21	-0.14	-0.11	-0.07	0.40	-0.10	-0.11	0.08	0.00	-0.11	0.00	-0.09	-0.09	0.11	-0.06	-0.03	-0.09	-0.20	0.07	0.18	0.39	0.05	-0.09	-0.16	-0.24	1

Appendix Q. Job accessibility per urbanity level

How generalized job accessibility is distributed over all levels of urbanity is illustrated in figure 22. Outliers, values that lie beyond 1.5 times the Inter Quartile Range (IQR), have been removed from the figure for clarity. Descriptive statistics of job accessibility per level of urbanity can be found in table 12. The downward trend of the boxplots that are visible in both figures indicate that physical and hybrid job accessibility of individuals is consistently lower in less urbanized zones. Additionally, the Mann-Whitney U test reveals significant differences (p-value <0.001) between the distribution of physical and hybrid job accessibility across all urbanization levels and for both the Hansen and Shen model.

As can be seen from the boxplots, most spatial variability in job accessibility levels is observed in the Hansen model (left). While overall job accessibility is increasing due to hybrid teleworking, relatively large differences between the highly urbanized and non-urbanized zones are visible. Thereby, dense urban areas are concomitant with higher variations of job accessibility among individuals; some individuals may have a high score, while other are observed to have lower scores. Contrarily, in the less dense urbanized areas, not only the absolute level of job accessibility is lower, also these individual-level variations, thus differences between individuals, become smaller. The results of the Hansen-based model suggest that a lower number of jobs in the vicinity also result in less extreme potential variations in accessibility scores.

Differences in physical and hybrid job accessibility between the levels of urbanity are less apparent in the Shen-based model (right). While overall job accessibility over the levels of urbanity still decreases in both scenarios, the variation in accessibility scores remain similar. The high number of jobs available, as seen in the Hansen model, are now less accessible due to potential competition from other zones, which reduces the contrast between highly dense and non-urbanized zones. The competition also explains the similar shape of the boxplots in the Shen-model, which reveals a proportionate spatial distribution of both jobs and workers over space.

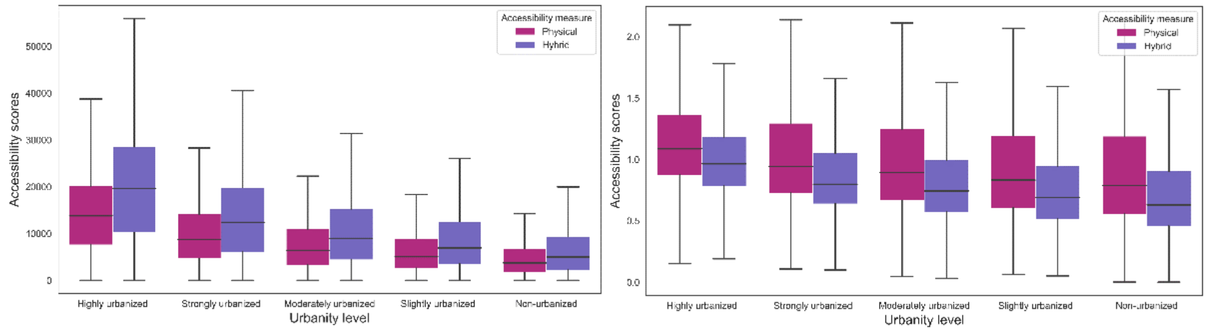


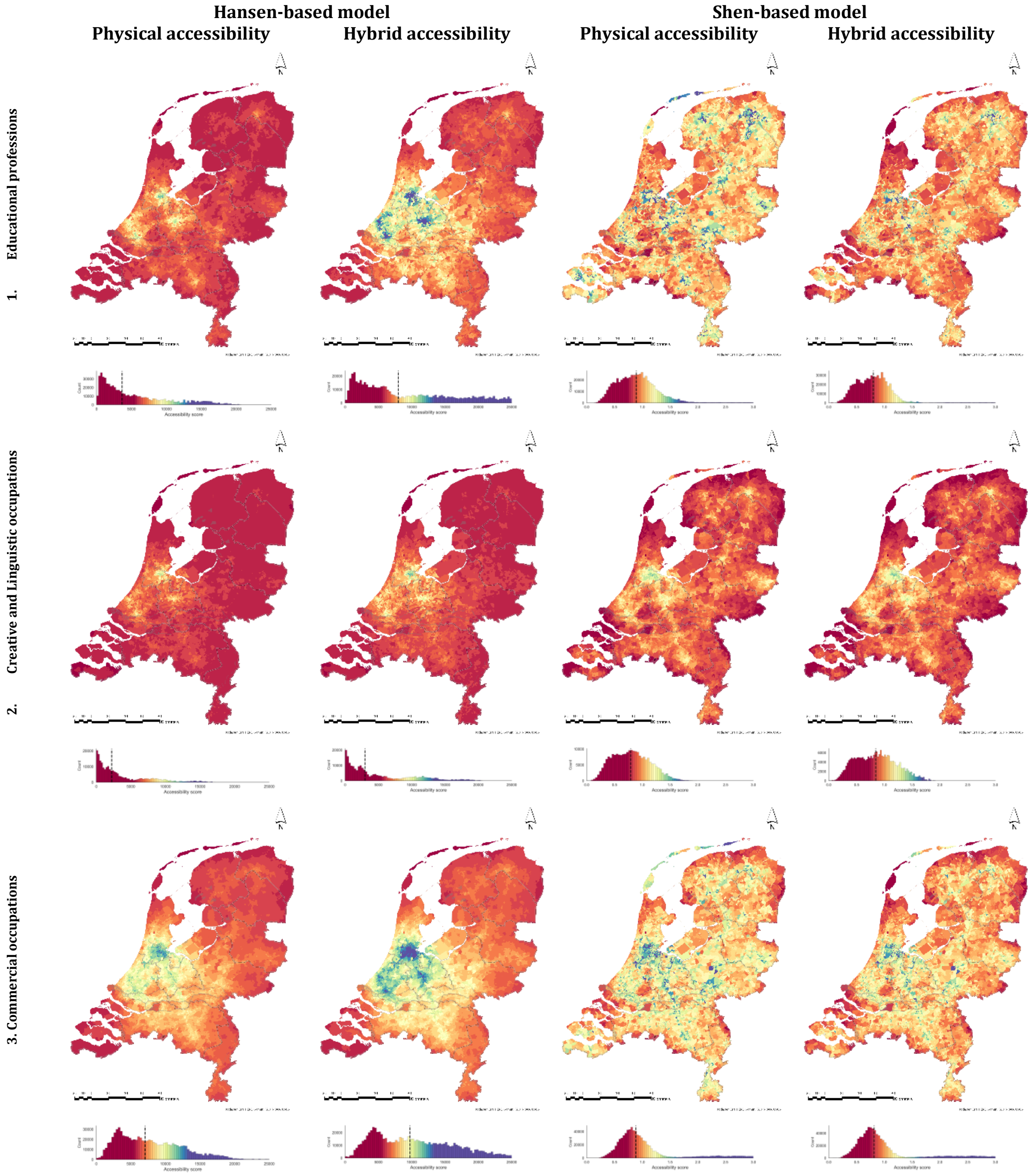
Figure 22: Distribution of generalized job accessibility per urbanity level Hansen-based (left) and Shen-based (right)

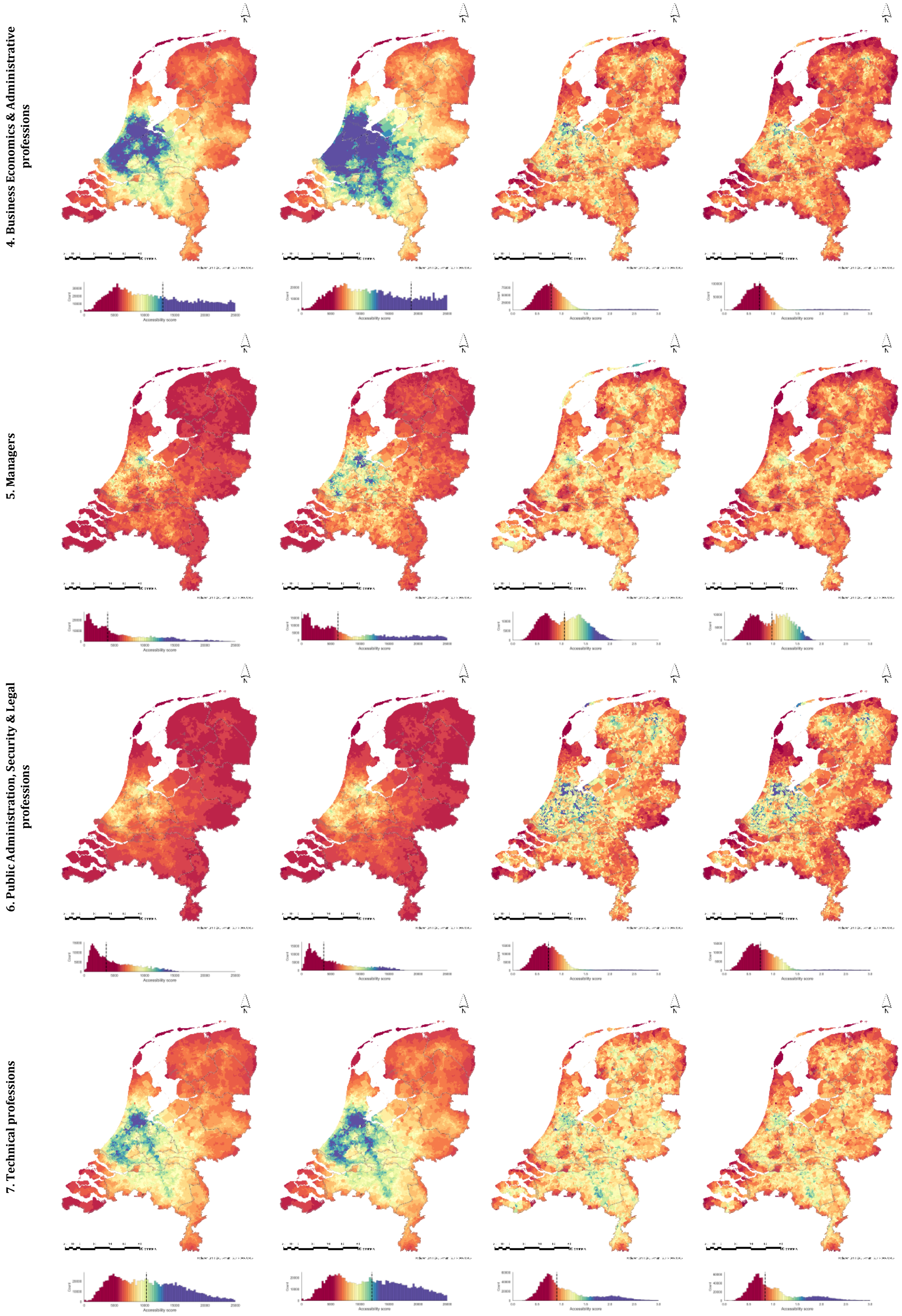
Table 12: Descriptive statistics of generalized job accessibility per urbanity level

		Physical accessibility								Hybrid accessibility								Mann-Whitney U test	
		Median	**S.D.**	**Min**	**25%**	**75%**	**Max**	**SK.**	**KU.**	**Median**	**S.D.**	**Min**	**25%**	**75%**	**Max**	**SK.**	**KU.**	**U**	**p-value**
Hansen	**Highly urbanized**	13788	9846	5	7633	20104	55819	0.918	0.811	19595	14621	4	10223	28486	81014	1.060	1.254	186743	<0.001
	Strongly urbanized	8722	7265	6	4669	14108	53072	1.087	1.341	12384	10735	6	6012	19805	77243	1.316	2.365	145623	<0.001
	Moderately urbanized	6398	6360	4	3287	10872	52529	1.481	2.872	8951	9309	4	4463	15227	74980	1.694	4.131	90683	<0.001
	Slightly urbanized	5031	5606	6	2586	8887	48384	1.733	4.192	6912	8162	6	3533	12545	69703	1.931	5.566	75908	<0.001
	Non-urbanized	3913	4742	0	1938	6902	47836	1.934	5.271	5304	6682	0	2590	9650	69308	2.189	7.467	64961	<0.001
Shen	**Highly urbanized**	1.034	0.798	0.119	0.854	1.303	8.909	2.759	8.921	0.965	0.773	0.104	0.786	1.184	7.982	2.814	8.913	135469	<0.001
	Strongly urbanized	0.917	0.764	0.112	0.741	1.216	8.674	2.319	6.162	0.798	0.700	0.099	0.641	1.049	7.558	2.248	5.188	833	<0.001
	Moderately urbanized	0.859	0.710	0.023	0.682	1.146	7.942	2.325	6.393	0.744	0.643	0.032	0.573	0.995	7.456	2.218	5.386	1883	<0.001
	Slightly urbanized	0.809	0.662	0.089	0.625	1.094	7.950	2.329	6.698	0.690	0.594	0.051	0.515	0.947	6.493	2.240	5.910	17393	<0.001
	Non-urbanized	0.765	0.725	0.000	0.577	1.079	9.279	2.423	7.844	0.629	0.634	0.000	0.459	0.904	9.913	2.400	8.098	57162	<0.001

Appendix R. Job accessibility per occupational class

The spatial distribution of generalized physical and hybrid job accessibility of both the Hansen- and Shen-based models per occupational class is presented in figure 23. Every map has been mean-normalized on the generalized physical job accessibility score of the corresponding model and the colours within each model type are comparable. The applied symbology therefore displays the extent to which the observed job accessibility scores per occupational class are below of above the generalized physical average job accessibility score of the Hansen-based model or Shen-based model. The scores per occupational class can be found in appendix V.



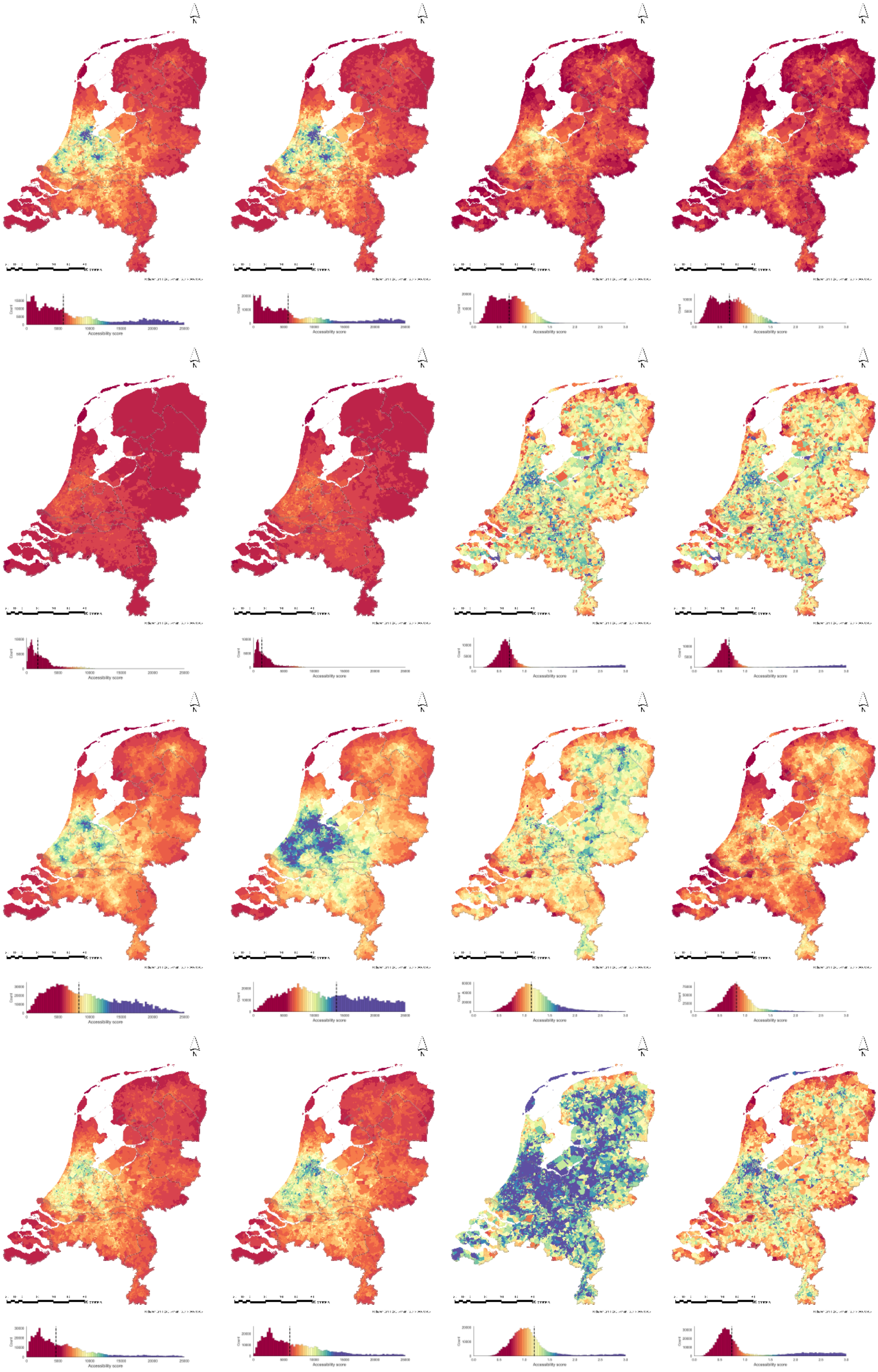

4. Business Economics & Administrative professions
5. Managers
6. Public Administration, Security & Legal professions
7. Technical professions
Accessibility score

8. ICT

9. Agriculture

10. Care & Welfare

11. Service



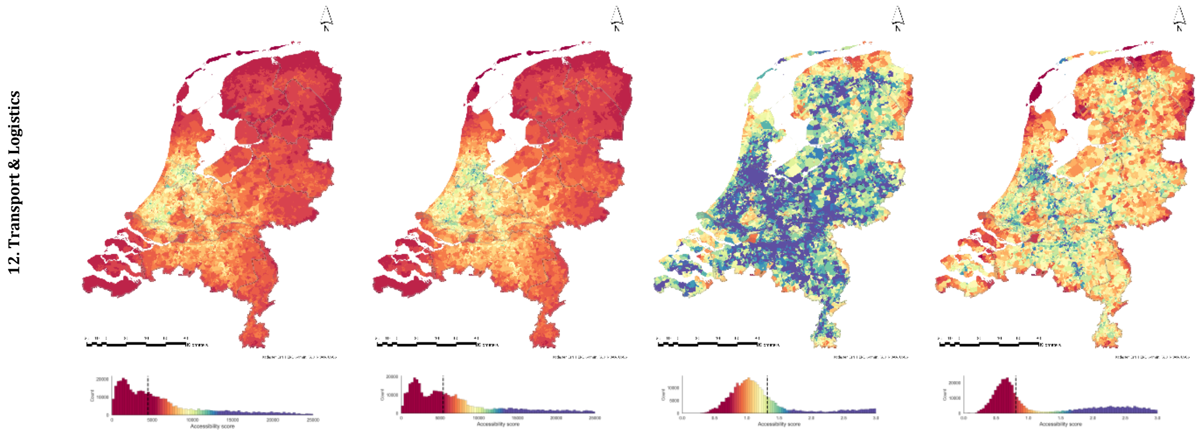


Figure 23: Spatial distribution of generalized physical and hybrid job accessibility per occupational class

Appendix S. Spatial clustering

Besides visual comparison of job accessibility distribution, a bivariate local Moran's I analysis is performed on the absolute physical and hybrid accessibility scores of the zones within the Netherlands per mode (generalized, car, public transport and bike). The analysis generates an understanding of existing relationships between the spatial distribution of physical and hybrid job accessibility and provides statistical evidence whether and which zones exhibit similar accessibility scores. Figure 24 and 25 present the results of the spatial autocorrelation analysis for the generalized Hansen-based and Shen-based accessibility scores and per mode and shows how there are statistically significant clusters of mostly High-High values (high physical and hybrid accessibility) and Low-Low values (low physical and hybrid accessibility) throughout the study area and per mode of transport. Additionally, table 13 and table 14 give an overview of the cluster types per urbanity level.

The results of the bivariate Moran's I for the Hansen models are displayed in figure 24. From this figure, the overall high physical and hybrid job accessibility levels are visibly clustered in the Randstad area, whereas the outer regions of the Netherlands both face low physical and hybrid job accessibility levels. Thereby, 20% of the zones within highly urbanized areas are categorized as High-High clusters (Table 13). This pattern is similarly observed for accessibility by car, public transport and bike. Nevertheless, with regards to generalized job accessibility, almost no High-Low and Low-High clusters are found, indicating that physical and hybrid job accessibility follow similar spatial patterns.

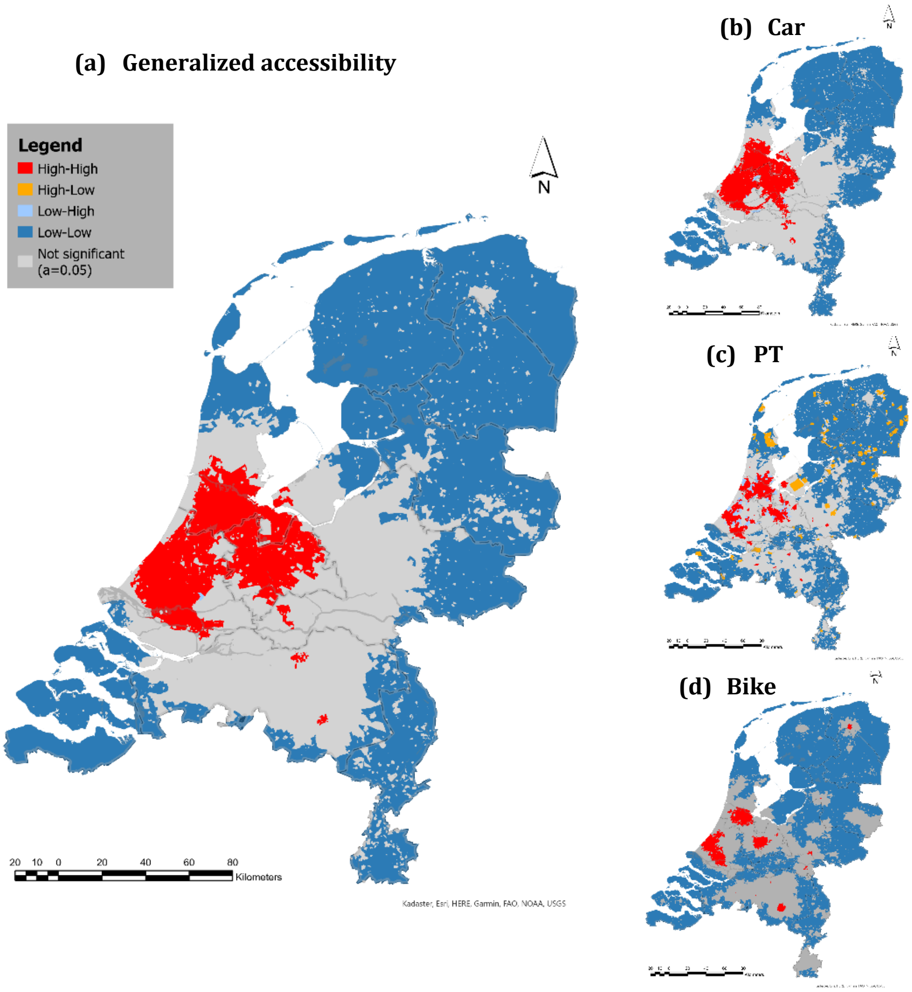


Figure 24: Bivariate Moran's I Hansen-based models

Table 13: Cluster types of generalized job accessibility per urbanity level (Hansen-based model)

Cluster type	High-High		High-Low		Low-High		Low-Low		Not significant		Total
Urbanization level	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**
Highly urbanized	1152	37.44%	0	0.00%	0	0.00%	80	2.60%	510	16.57%	1742
Strongly urbanized	801	26.03%	0	0.00%	0	0.00%	291	9.46%	1167	37.93%	2259
Moderately urbanized	372	12.09%	0	0.00%	0	0.00%	396	12.87%	981	31.88%	1749
Slightly urbanized	337	10.95%	0	0.00%	0	0.00%	610	19.82%	1145	37.21%	2092
Non-urbanized	415	13.49%	1	0.03%	1	0.03%	2711	88.11%	2839	92.27%	5967
Total	**3077**	**22.28%**	**1**	**0.01%**	**1**	**0.01%**	**4088**	**29.60%**	6642	**48.10%**	**13809**
Spatial coverage (km²)	3338	7.98%	<0.1	<0.1%	6	0.01%	19710	47.10%	18796	44.91%	41850
Number of workers	2688007	33.29%	0	<0.1%	758	0.01%	1598038	19.79%	3788197	46.91%	8075000

For the Shen-based generalized accessibility and accessibility by car and public transport (figure 25), the larger metropolitan areas (e.g. Amsterdam, Utrecht, Rotterdam, The Hague) and some smaller regions in each cardinal direction (e.g. Groningen, Enschede, Eindhoven, Maastricht) are visibly clustered with both high scores in physical accessibility and hybrid accessibility. The outer regions of the Netherlands contain a large share of Low-Low clusters.

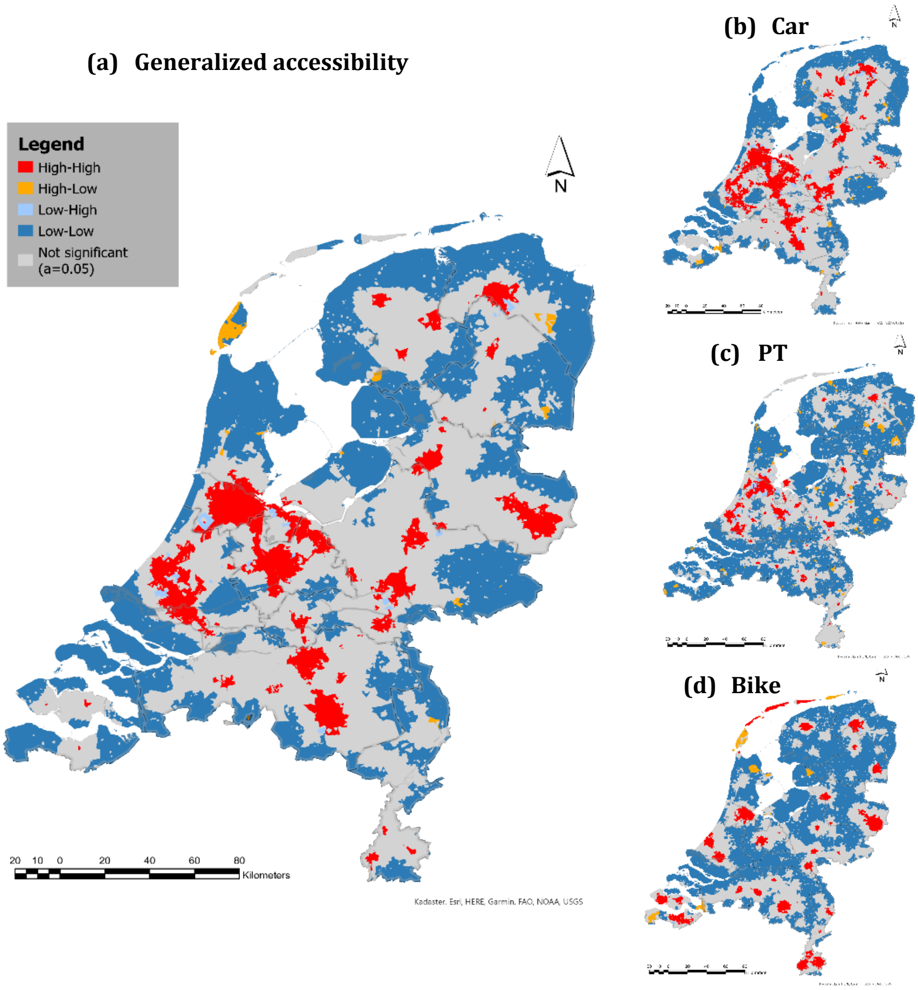


Figure 25: Bivariate Moran's I Shen-based models

Among all zones within the study area, 20% of the zones are High-High clusters, whereas another 20% of the identified clusters are categorized as Low-Low, remaining clusters are either categorized as High-Low (0,1%) and Low-High (0,2%) clusters (table 14). The High-high clusters cover an approximate area of 3000 km² and are predominantly found in urban areas, with 66,1% of the these clusters located in the most urbanized zones within the Netherlands. In these areas, a combination of high physical accessibility and high hybrid accessibility are seen.

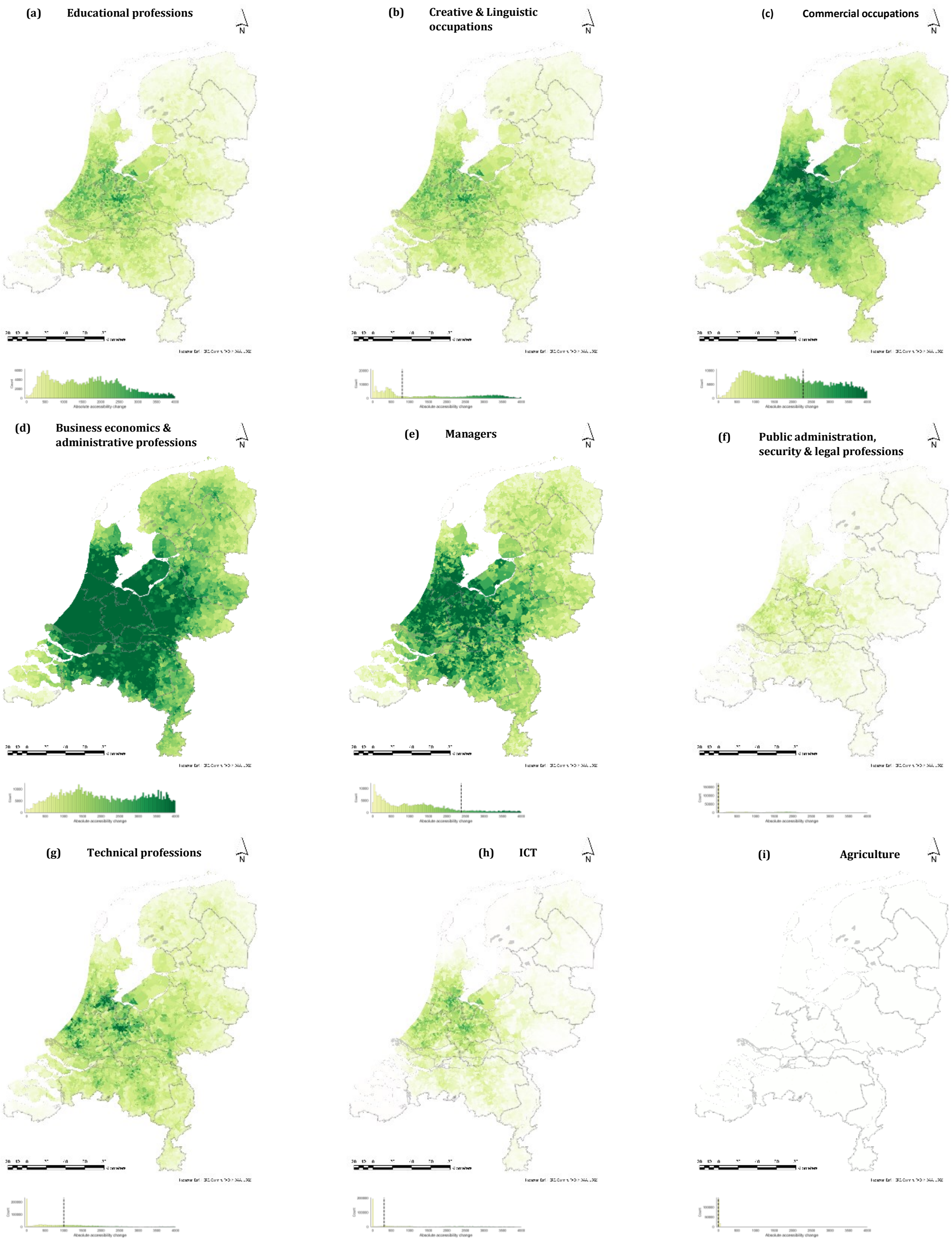
On the contrary, the Low-Low clusters are primarily observed in the outer regions and have the largest spatial coverage, spanning over 14000 km^2. Individuals living within these clusters experience both low physical and hybrid job accessibility. Thereby, 30,9% of the clusters are located in non-urbanized areas. There are several High-Low clusters where physical accessibility is high but hybrid accessibility is low. These clusters can be found on Texel (Wadden Island) and sparsely stratified through low urbanized regions within the Netherlands. Lastly, Low-High clusters are predominantly located adjacent to the High-High clusters and represent areas where physical job accessibility is low but the job accessibility levels are faced with significant improvement due to hybrid teleworking.

The presented results from the Hansen-based and Shen-based models demonstrate evidence of an inverse relationship between the presence of High-High and Low-Low clusters and the level of urbanity: individuals in highly urbanized areas face simultaneously high physical and hybrid job accessibility levels, while contrastingly individuals in low urbanized regions are often not only disadvantaged on their physical accessibility to jobs, but also experience no additional job accessibility benefit from hybrid teleworking. This divide significantly impacts a substantial portion of the Dutch working population, with approximately 32% residing in High-High clusters and 24% in Low-Low clusters when competition effects are considered. In addition, locations where hybrid teleworking does improve the accessibility scores of individuals (Low-High clusters) are mostly unobserved. These findings indicate that hybrid teleworking is seen to perpetuate the already existing spatial inequalities between urbanized and non-urbanized regions in the Netherlands, but also that more than half of the working population is involved in this divide.

Table 14: Clusters descriptive statistics generalized job accessibility (Shen)

Cluster type	**High-High**		**High-Low**		**Low-High**		**Low-Low**		**Not significant**		**Total**
Urbanization level	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**
Highly urbanized	1151	66.1%	0	0.0%	1	0.1%	35	2.0%	555	31.9%	1742
Strongly urbanized	698	30.9%	0	0.0%	6	0.3%	186	8.2%	1369	60.6%	2259
Moderately urbanized	362	20.7%	2	0.1%	0	0.0%	250	14.3%	1135	64.9%	1749
Slightly urbanized	289	13.8%	1	0.0%	4	0.2%	415	19.8%	1383	66.1%	2092
Non-urbanized	390	6.5%	14	0.2%	17	0.3%	1846	30.9%	3700	62.0%	5967
Total	**2890**	**20.9%**	**17**	**0.1%**	**28**	**0.2%**	**2732**	**19.8%**	**8142**	**59.0%**	**13809**
Spatial coverage (km^2)	3060	7.3%	201	0.5%	142	0.3%	14616	34.9%	23831	56.9%	41850
Number of workers	2588432	32.1%	2896	<0.1%	6503	0.1%	1928048	23.9%	3549121	44.0%	8075000

Appendix T. Spatial differences per occupational class



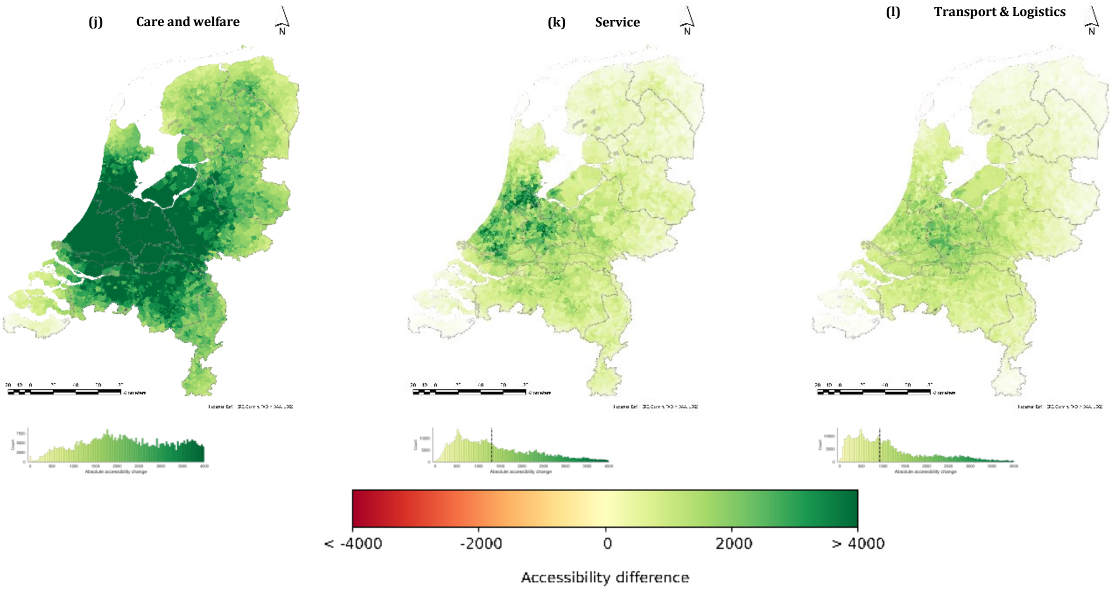
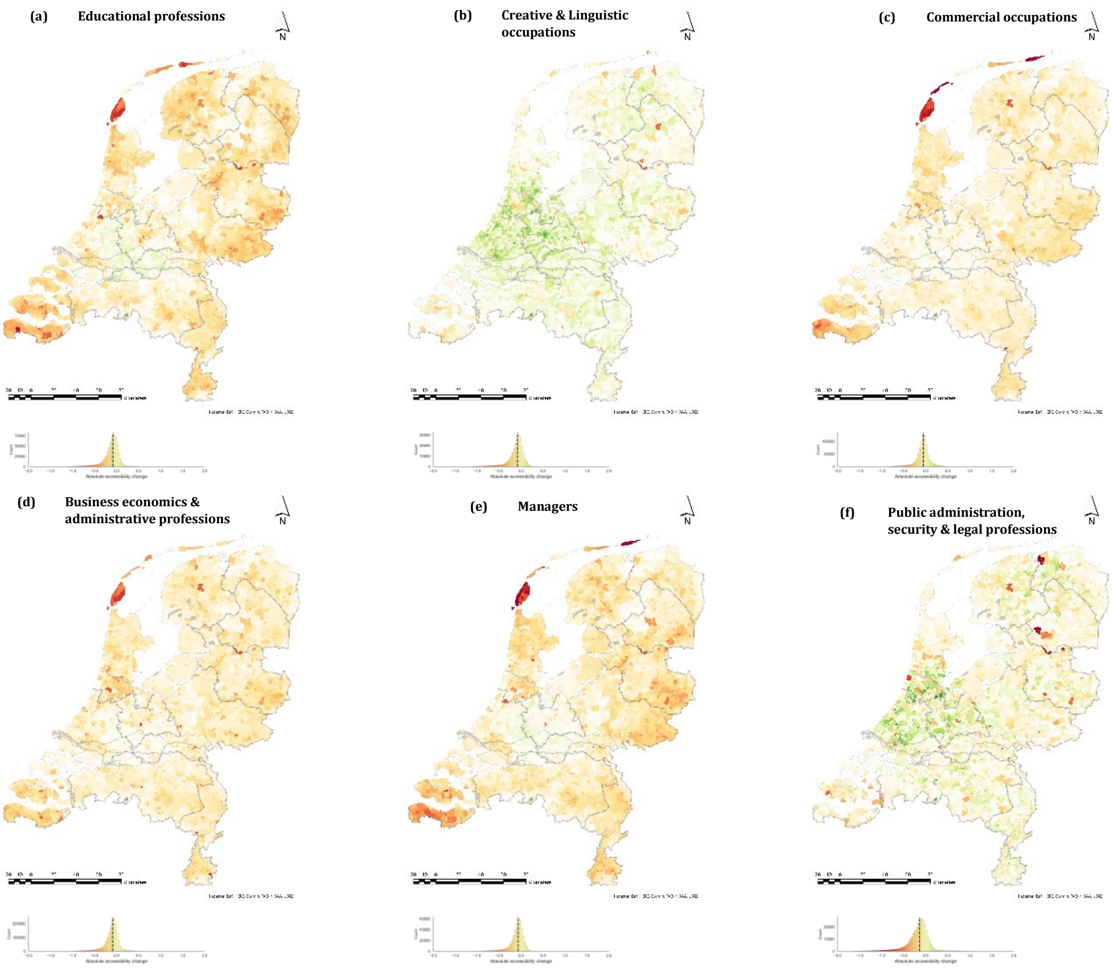


Figure 26: Spatial distribution of generalized job accessibility differences per occupational class – Hansen



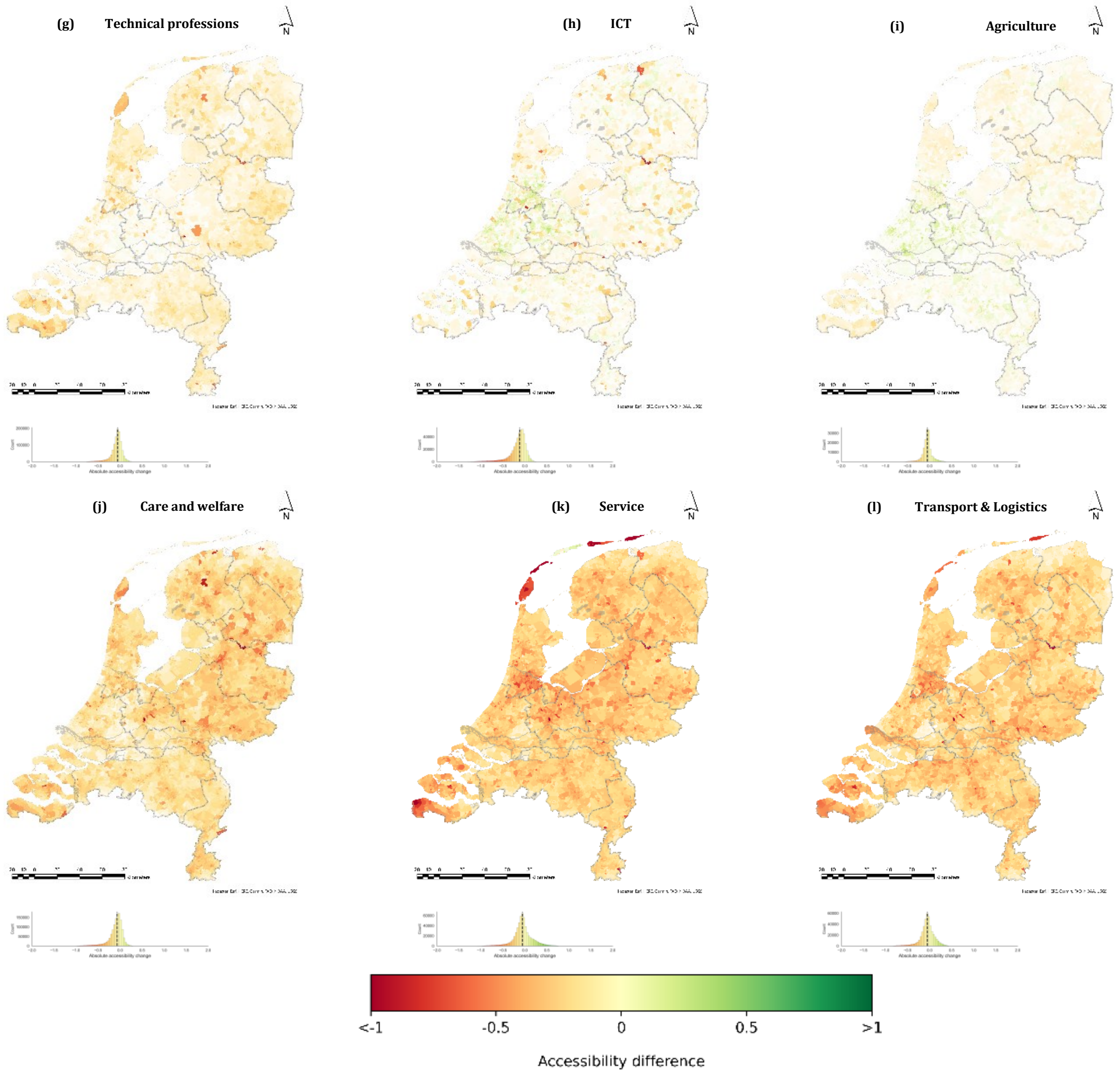


Figure 27: Spatial distribution of generalized job accessibility differences per occupational class, with competition (Shen-based)

Appendix U. Job competition effects

Figure 29 shows the development of job competition over space, including all occupational classes, derived through the cross-modal demand component $D^x_{jc(t)}$. Whereas in physical space, an average competition of 14000 individuals is observed, this number increases by 1144% up to 166 thousand workers competing for jobs within every zone of the Netherlands with hybrid teleworking. Besides, the data reveals how competition relatively increases the most for more rural regions (table 15). This implies that individual living in these regions now face a larger influx of potential competing individuals for jobs in areas that are already economically marginalized due to a low supply of jobs.

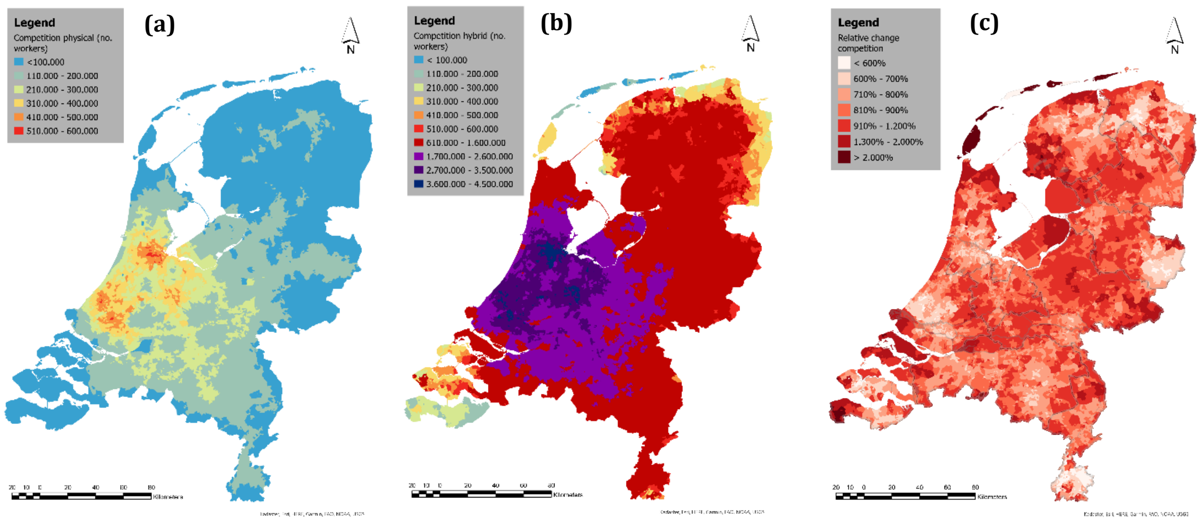


Figure 28: (a) competition physical (b) competition hybrid, (c) relative change competition of generalized accessibility (Shen)

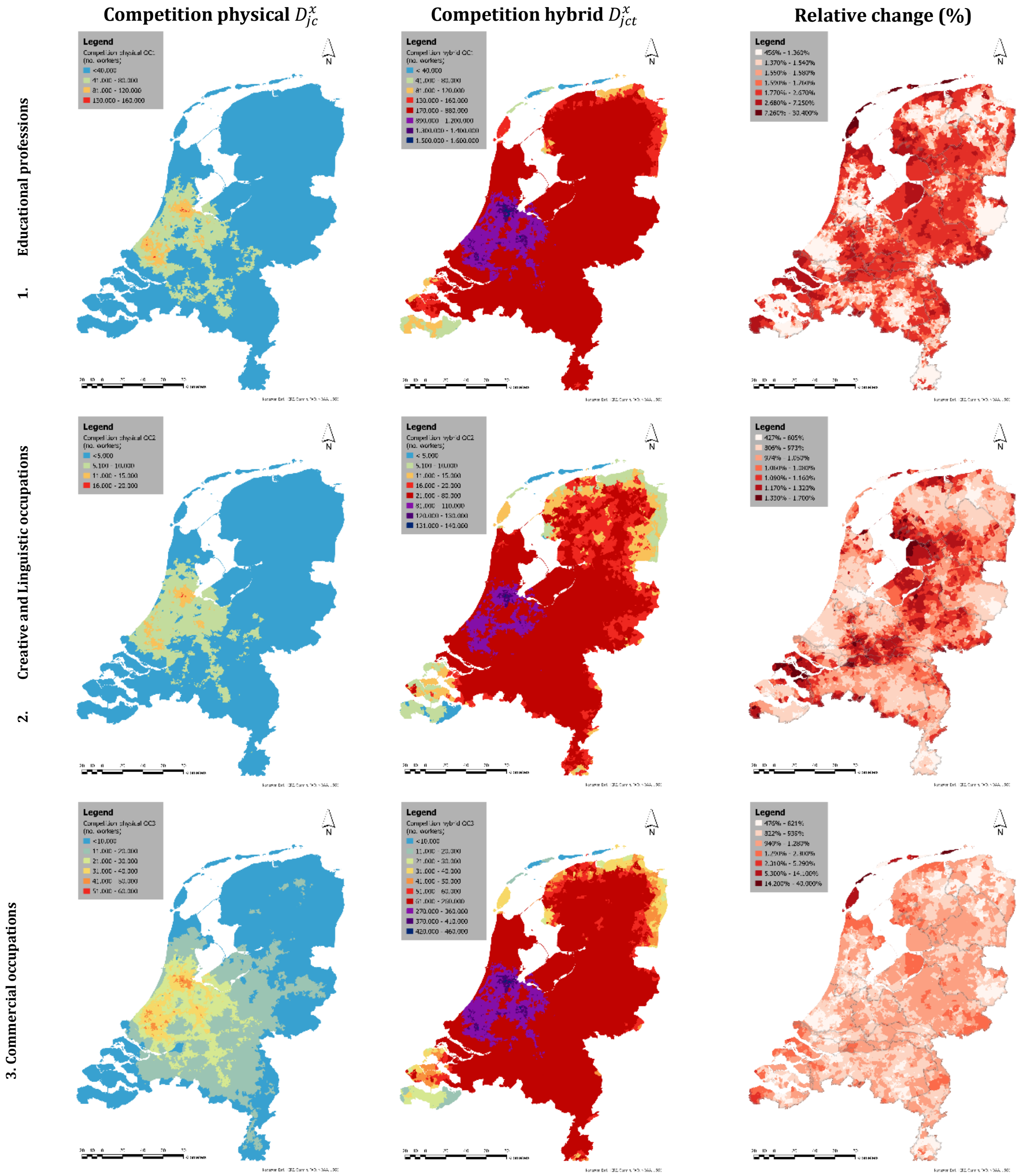
Table 15: Average total competition (no. individuals) and rel. change (%) per urbanity level

Urbanity	Physical competition D^x_{jc}	Hybrid competition D^x_{jct}	Relative change (%)
Highly urbanized	24968	266418	960%
Strongly urbanized	17990	205173	1053%
Moderately urbanized	15005	174111	1098%
Slightly urbanized	13428	159330	1137%
Non-urbanized	9908	123556	1247%
Total	14309	166753	1144%

Mostly in the dense urban regions, such as the Randstad area, the relative competition increases are lower, however the actual number of individuals competing for jobs in the area reaches up to 4.5 million in the most extreme case (figure 29). However, as these number seem extreme, the actual competition effects in the Shen-based models are more nuanced as they are considered per occupational class, as shown in figure 30 and table 16. Strongest average competition increases due to hybrid teleworking are observed for workers in 10. Care & Welfare professions, whereas least increases can be found for workers in 9. Agriculture.

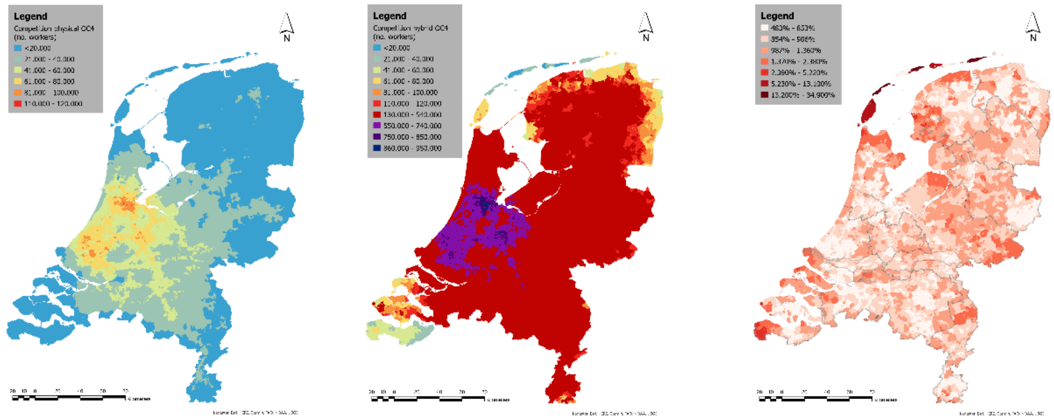
Table 16: Job competition effects per occupational class

Occupational class	Physical competition D^x_{jc}	Hybrid competition D^x_{jct}	Rel. change (%)
1. Educational professions	37143	600479	1719%
2. Creative & Linguistic occupations	4530	46218	966%
3. Commercial occupations	17277	173696	973%
4. Business Economics & Administrative professions	35017	353787	981%
5. Managers	7965	92027	1168%
6. Public Administration, Security & Legal professions	8945	65005	636%
7. Technical professions	25972	233851	843%
8. ICT	15347	99013	547%
9. Agriculture	4203	28115	580%
10. Care & Welfare	15546	252865	1754%
11. Service	6552	107451	1699%
12. Transport & Logistics	5714	90532	1625%

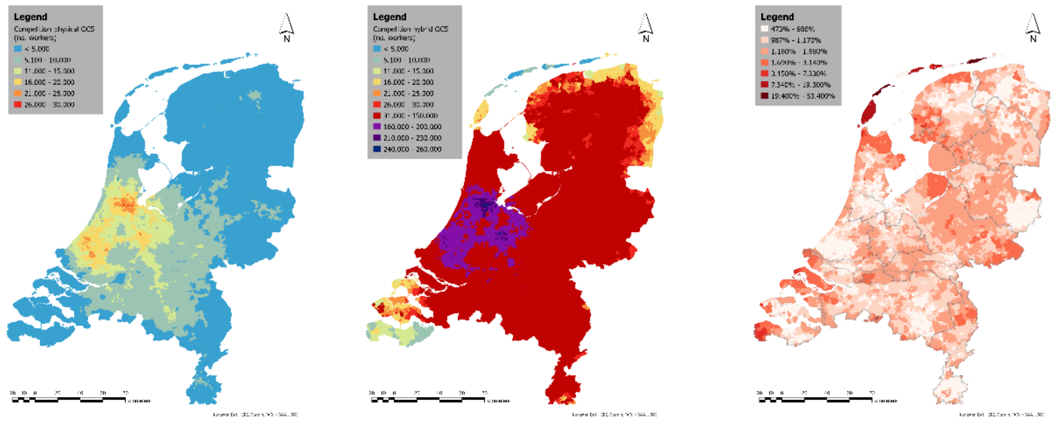


Competition physical D_{jc}^{x}
Competition hybrid D_{jct}^{x}
Relative change (%)
1. Educational professions
2. Creative and Linguistic occupations
3. Commercial occupations
Legend

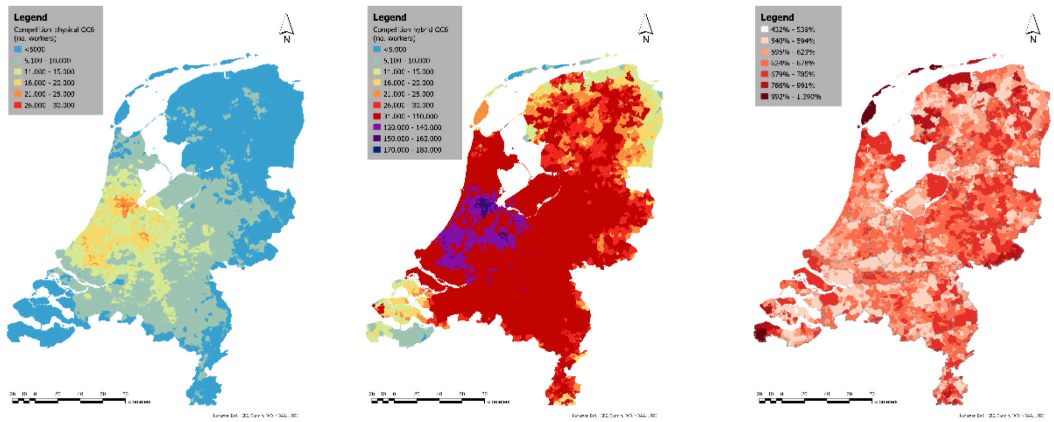
4. Business Economics & Administrative professions



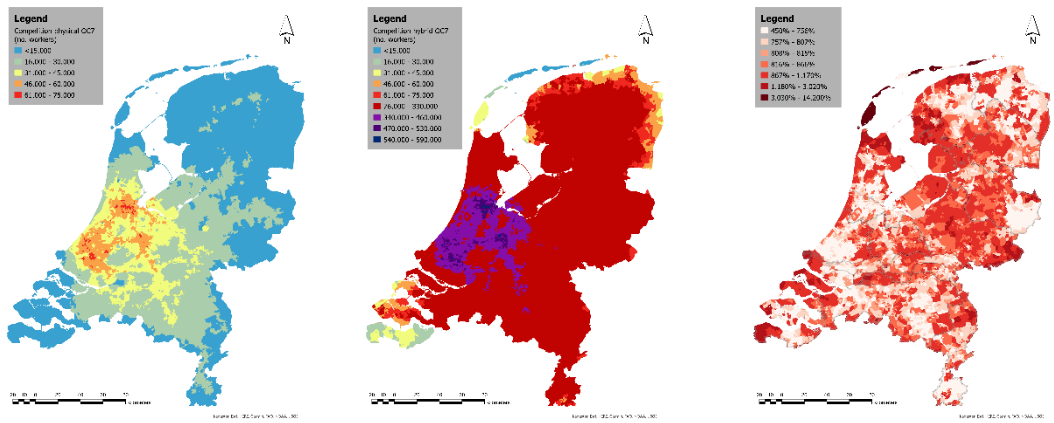
5. Managers



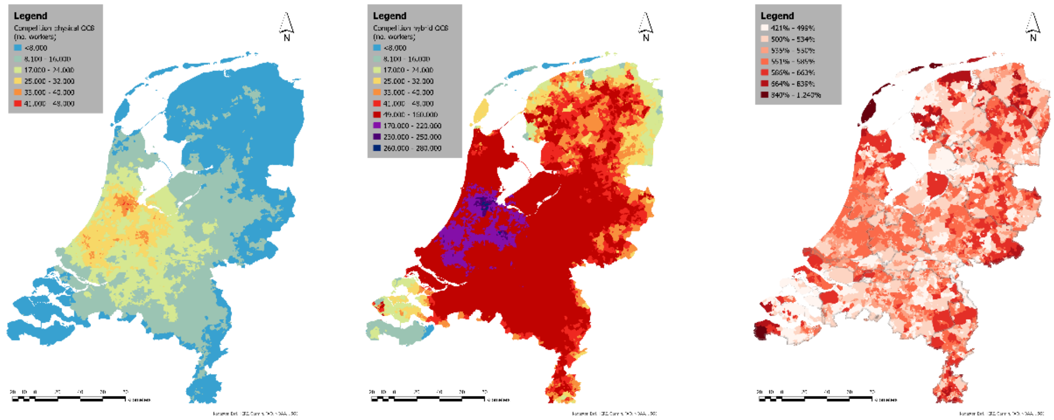
6. Public Administration, Security & Legal professions



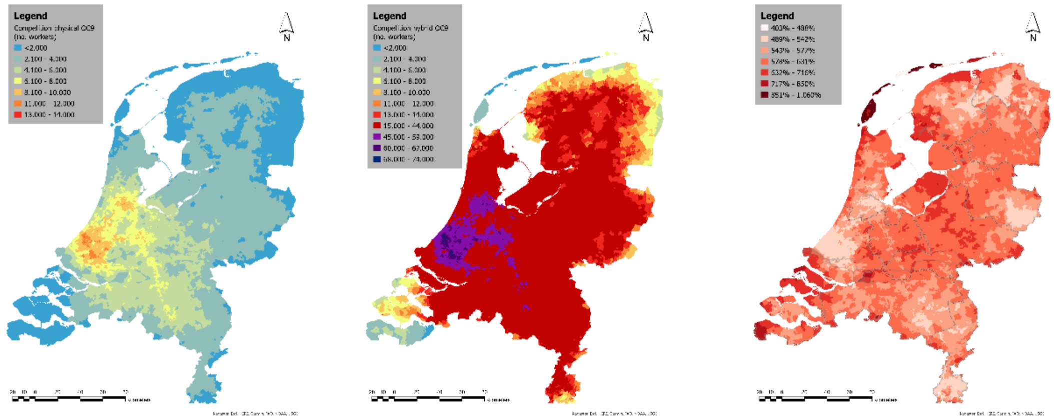
7. Technical professions



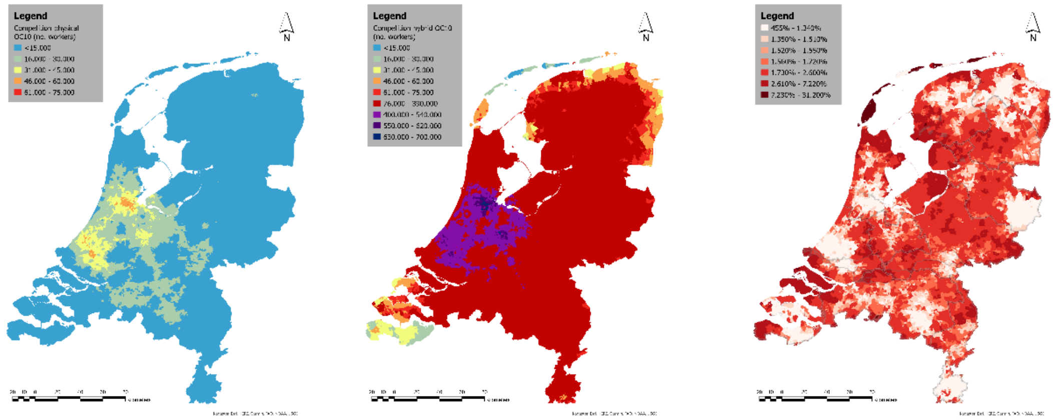
8. ICT



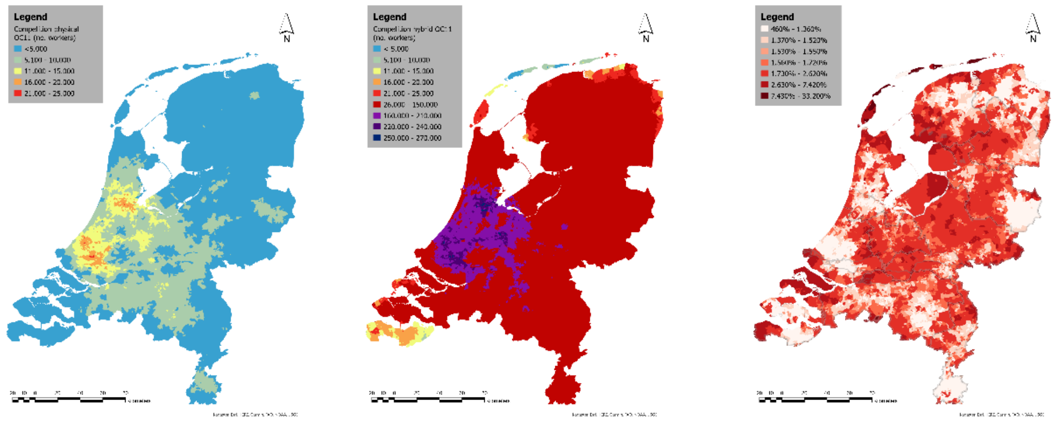
9. Agriculture



10. Care & Welfare



11. Service



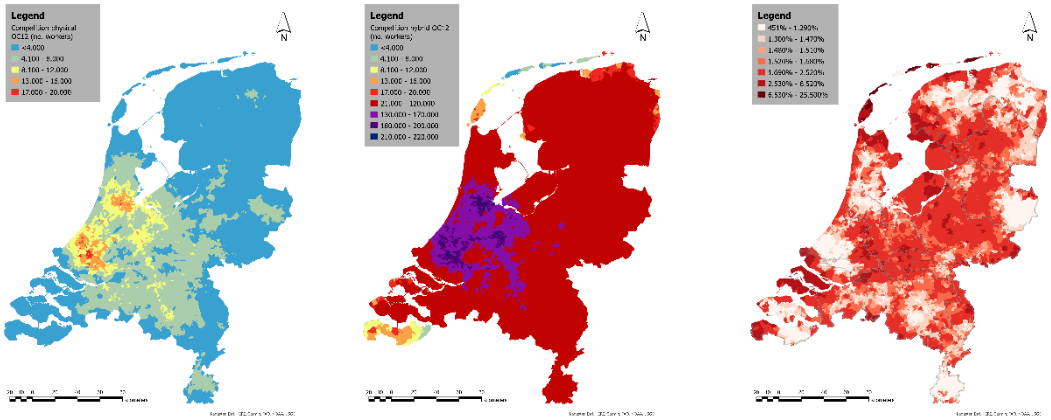


Figure 29: Cross-modal competition effects in the physical scenario, hybrid scenario and relative spatial change per occupational class

Appendix V. Generalized job accessibility per socio-demographic characteristic

Descriptive statistics of the generalized physical and hybrid job accessibility and the differences in job accessibility for the Hansen- and Shen-based models are presented per socio-demographic characteristic of the population (n=8075000) in table 17. Descriptive statistics, Gini-indices and Mann-Whitney U test results per occupational class are presented in table 28.

Table 17: Generalized job accessibility per socio-demographic characteristic

		Hansen-based job accessibility									Shen-based job accessibility								
		Median	**%**	**S.D.**	**Min**	**25%**	**75%**	**Max**	**SK.**	**KU.**	**Median**	**%**	**S.D.**	**Min**	**25%**	**75%**	**Max**	**SK.**	**KU.**
Gender																			
	Physical	7065		8034	0	3306	13375	55819	1.439	2.466	0.906		1.002	0.000	0.672	1.287	15.131	2.823	10.575
Male	Hybrid	9290		11358	0	4253	17671	81014	1.771	4.234	0.869		0.956	0.000	0.654	1.209	14.740	2.694	8.886
	Difference	1473	31%	4252	0	406	3928	28061	2.266	5.501	-0.023	-4%	0.139	-3.325	-0.077	0.001	2.904	-2.936	38.084
	Physical	7367		8059	0	3628	13453	55819	1.517	2.872	0.961		0.914	0.000	0.720	1.270	15.413	3.155	13.452
Female	Hybrid	10936		12102	0	5263	20190	81014	1.550	3.015	0.903		0.875	0.000	0.690	1.169	14.740	3.131	12.550
	Difference	2961	48%	4692	0	1237	6670	28061	1.534	2.147	-0.043	-6%	0.124	-3.943	-0.098	-0.011	2.290	-3.180	35.581
Age category																			
	Physical	6660		7758	0	3098	12448	55819	1.607	3.382	0.996		1.100	0.000	0.756	1.330	15.124	2.689	8.719
15-24 years	Hybrid	9300		11346	0	4242	17586	81014	1.774	4.296	0.930		1.055	0.000	0.720	1.216	13.943	2.637	7.826
	Difference	2038	40%	4344	0	788	4800	28061	2.002	4.232	-0.049	-7%	0.134	-3.218	-0.111	-0.011	1.845	-3.306	34.603
	Physical	7653		8270	0	3683	13939	55819	1.465	2.630	0.929		0.851	0.000	0.699	1.217	15.100	3.508	17.530
25-34 years	Hybrid	10942		12229	0	5073	20064	81014	1.584	3.198	0.885		0.811	0.000	0.678	1.137	14.740	3.429	15.644
	Difference	2497	43%	4776	0	878	6117	28061	1.650	2.527	-0.033	-5%	0.135	-3.325	-0.087	-0.002	2.904	-2.638	36.689
	Physical	7618		8267	0	3653	13906	55819	1.471	2.645	0.920		0.790	0.000	0.696	1.200	15.072	3.797	21.150
35-44 years	Hybrid	11095		12271	0	5116	20239	81014	1.570	3.127	0.877		0.746	0.000	0.674	1.122	14.740	3.696	18.748
	Difference	2586	46%	4829	0	924	6430	28061	1.576	2.225	-0.032	-5%	0.132	-3.087	-0.086	-0.003	2.904	-3.145	36.143
	Physical	7017		7922	0	3376	13173	55819	1.453	2.519	0.927		1.029	0.000	0.680	1.348	15.131	2.637	9.099
45-54 years	Hybrid	9556		11377	0	4504	18002	81014	1.703	3.823	0.881		0.985	0.000	0.656	1.257	14.740	2.547	7.930
	Difference	1847	36%	4271	0	618	4658	28061	2.060	4.526	-0.030	-5%	0.130	-3.943	-0.082	-0.004	2.315	-3.195	38.651
	Physical	6963		7856	0	3370	13088	55819	1.468	2.607	0.944		1.043	0.000	0.691	1.371	15.413	2.596	8.700
55-64 years	Hybrid	9589		11364	0	4556	18086	81014	1.689	3.751	0.892		1.001	0.000	0.666	1.269	14.740	2.514	7.601
	Difference	1918	38%	4328	0	667	4921	28061	1.963	4.010	-0.034	-6%	0.131	-3.792	-0.088	-0.006	2.904	-2.961	38.553
	Physical	6416		7712	0	2954	12115	55819	1.602	3.198	0.949		1.007	0.000	0.705	1.298	11.526	2.725	9.145
65-75 years	Hybrid	9116		11397	0	4102	17487	81014	1.719	3.815	0.896		0.970	0.000	0.679	1.205	9.547	2.686	8.398
	Difference	2013	42%	4488	0	636	5225	26084	1.789	3.066	-0.039	-6%	0.138	-2.959	-0.099	-0.004	1.781	-2.469	32.073
Education level																			
	Physical	7339		7777	0	3149	14635	41517	0.848	-0.066	2.474		1.375	0.000	1.811	3.466	15.413	0.780	1.296
Low educated	Hybrid	8308		8638	0	3777	16258	51677	0.864	0.093	2.430		1.330	0.000	1.773	3.392	14.740	0.715	1.092
	Difference	714	13%	1472	0	0	1921	13589	1.723	3.760	-0.041	-2%	0.139	-2.531	-0.124	-0.008	2.904	1.873	32.599
	Physical	5575		6427	0	2661	10549	43798	1.418	2.112	0.736		0.613	0.000	0.562	0.968	13.203	6.955	72.720
Middle educated	Hybrid	6990		8331	0	3402	13645	55831	1.450	2.176	0.710		0.512	0.000	0.547	0.917	10.673	6.341	63.553
	Difference	1392	25%	2195	0	552	2943	14611	1.464	1.666	-0.022	-4%	0.131	-3.359	-0.057	-0.005	0.550	-6.203	58.678
	Physical	9202		9164	0	4667	15499	55819	1.418	2.205	0.988		0.300	0.000	0.811	1.184	8.731	0.771	2.259
High educated	Hybrid	14921		14074	0	7749	24713	81014	1.300	1.742	0.933		0.257	0.000	0.774	1.103	5.178	0.459	0.713
	Difference	5308	62%	5528	0	2352	10238	28061	0.950	0.237	-0.051	-5%	0.134	-3.943	-0.117	0.000	0.675	-2.324	19.265
Migration background																			
	Physical	6363		7250	0	3123	11743	55819	1.587	3.312	0.903		0.955	0.000	0.665	1.270	15.413	2.832	10.753
Dutch	Hybrid	8818		10568	0	4243	16407	81014	1.795	4.467	0.856		0.913	0.000	0.642	1.176	14.740	2.754	9.465
	Difference	1839	39%	4112	0	643	4542	28061	2.039	4.535	-0.032	-5%	0.128	-3.943	-0.086	-0.004	2.904	-3.210	37.621
	Physical	8795		9151	0	4104	15738	55819	1.358	2.067	0.984		0.930	0.000	0.753	1.277	14.527	3.287	14.384
Western	Hybrid	12596		13570	0	5645	22756	81014	1.452	2.456	0.933		0.892	0.000	0.724	1.189	13.943	3.227	13.185
	Difference	2908	43%	5233	0	1020	7147	28061	1.458	1.640	-0.039	-5%	0.135	-3.359	-0.095	-0.006	2.291	-2.509	34.160
	Physical	9946		9299	0	4390	17096	55819	1.076	1.121	1.005		1.053	0.000	0.764	1.331	14.619	3.027	11.869
Not Western	Hybrid	14028		13572	0	5826	23987	81014	1.239	1.790	0.954		1.002	0.000	0.736	1.240	14.002	2.903	10.176
	Difference	2833	41%	5202	0	920	7167	28061	1.429	1.580	-0.035	-5%	0.152	-3.744	-0.089	-0.006	2.904	-3.072	33.773
Urbanity																			
	Physical	13788		9846	5	7633	20104	55819	0.918	0.811	1.087		1.065	0.107	0.876	1.364	12.651	3.352	13.795
Highly urbanized	Hybrid	19619		14598	5	10240	28488	81014	1.065	1.265	1.041		1.020	0.115	0.850	1.291	10.219	3.253	12.281
	Difference	4313	42%	5810	0	1764	9572	28061	1.120	0.550	-0.040	-4%	0.157	-3.359	-0.094	-0.005	2.904	-2.110	33.157
	Physical	8722		7265	6	4669	14108	53072	1.087	1.341	0.944		0.994	0.107	0.730	1.293	12.266	2.773	9.518
Strongly urbanized	Hybrid	12396		10716	6	6071	19833	77243	1.320	2.378	0.899		0.949	0.114	0.710	1.192	9.894	2.676	8.065
	Difference	2536	42%	4424	0	1018	5894	24649	1.589	2.326	-0.032	-5%	0.136	-3.310	-0.088	-0.002	1.821	-3.191	35.740
	Physical	6398		6360	4	3287	10872	52529	1.481	2.872	0.892		0.918	0.046	0.667	1.246	11.055	2.749	9.624
Moderately urbanized	Hybrid	8968		9298	4	4509	15258	74980	1.696	4.137	0.844		0.875	0.043	0.644	1.143	9.305	2.670	8.313
	Difference	1868	40%	3756	0	713	4454	25184	1.929	4.084	-0.033	-5%	0.124	-3.325	-0.087	-0.005	1.643	-3.559	35.485
	Physical	5031		5606	6	2586	8887	48384	1.733	4.192	0.832		0.849	0.064	0.608	1.192	11.130	2.727	9.919
Slightly urbanized	Hybrid	6943		8156	6	3573	12557	69703	1.932	5.562	0.790		0.810	0.062	0.584	1.096	9.065	2.675	8.764
	Difference	1508	38%	3276	0	554	3606	22503	2.195	5.725	-0.031	-5%	0.115	-3.050	-0.085	-0.005	1.807	-3.500	33.657
	Physical	3717		4785	0	1697	6704	52460	1.973	5.471	0.797		0.952	0.000	0.558	1.222	15.413	2.685	10.467
Non-urbanized	Hybrid	5020		6697	0	2273	9336	76856	2.195	7.451	0.745		0.904	0.000	0.534	1.103	14.740	2.586	8.941
	Difference	950	35%	2557	0	296	2401	24823	2.726	9.640	-0.031	-7%	0.123	-3.943	-0.084	-0.008	1.998	-4.507	38.981

Table 18: Generalized job accessibility per occupational class

Hansen-based job accessibility

Occupational class		Median	%	S.D.	Min	25%	75%	Max	SK.	KU.	Gini G_i	Mann-Whitney U: U	Mann-Whitney U: p-value
	Physical	3737		4886	1	1541	8179	22082	1.048	0.109	0.48		
1. Educational professions	Hybrid	8238		9155	1	3333	18473	36740	0.674	-0.784	0.45	132123	<0.001
	Difference	4604	120%	4532	0	1711	10176	18352	0.407	-1.299	-		
	Physical	2403		3906	0	944	6309	18407	1.262	0.804	0.52		
2. Creative and Linguistic occupations	Hybrid	3257		5067	0	1344	9189	21960	0.995	-0.052	0.51	7207	<0.001
	Difference	1018	36%	1275	0	344	2733	4378	0.470	-1.306	-		
	Physical	7062		4724	28	3923	11044	31800	0.766	0.231	0.34		
3. Commercial occupations	Hybrid	9732		6216	28	5225	15054	37383	0.588	-0.365	0.33	81891	<0.001
	Difference	2286	38%	1934	0	1211	3783	9954	0.910	0.045	-		
	Physical	13020		10672	10	6936	22611	55819	0.886	0.161	0.37		
4. Business Economics & Administrative professions	Hybrid	18824		16489	10	9707	32312	81014	0.929	0.108	0.39	154307	<0.001
	Difference	5041	45%	6338	0	2301	10274	28061	1.001	-0.149	-		
	Physical	3974		5573	1	1610	9507	26212	1.084	0.325	0.49		
5. Managers	Hybrid	6429		9247	1	2514	17357	38711	0.814	-0.516	0.49	35396	<0.001
	Difference	2558	62%	3811	0	851	7820	14905	0.559	-1.153	-		
	Physical	3759		3708	0	1880	7429	16876	0.863	-0.267	0.41		
6. Public Administration, Security & Legal professions	Hybrid	4130		4276	0	2044	7993	19009	0.941	-0.136	0.44	298	<0.001
	Difference	0	10%	710	0	0	974	2332	1.007	-0.526	-		
	Physical	10314		6236	6	5979	15200	40159	0.716	0.236	0.31		
7. Technical professions	Hybrid	12114		6819	7	6865	17659	41217	0.446	-0.512	0.3	28493	<0.001
	Difference	1003	17%	1826	0	266	2098	8754	1.333	0.728	-		
	Physical	5956		8788	0	2708	15460	38632	1.050	0.072	0.5		
8. ICT	Hybrid	6144		9939	0	2752	17371	42819	1.054	0.015	0.52	70	<0.001
	Difference	328	3%	1183	0	0	1880	4201	1.048	-0.309	-		
	Physical	1866		2202	1	895	3235	11396	1.560	2.041	0.45		
9. Agriculture	Hybrid	1866		2199	1	899	3235	11396	1.566	2.057	0.43	4001	<0.001
	Difference	0	0%	12	0	0	0	70	2.993	8.250	-		
	Physical	8324		5840	1	4845	13814	28884	0.590	-0.573	0.35		
10. Care & Welfare	Hybrid	13717		9536	1	7520	22272	44881	0.570	-0.617	0.35	241787	<0.001
	Difference	5030	65%	3980	0	2525	8486	20570	0.655	-0.563	-		
	Physical	4714		6393	12	2181	8538	39806	1.744	3.031	0.48		
11. Service	Hybrid	6050		7890	13	2911	10928	49318	1.749	3.127	0.46	19125	<0.001
	Difference	1321	28%	1568	0	724	2382	13589	1.844	3.996	-		
	Physical	4533		6175	3	2014	8569	35349	1.504	1.804	0.48		
12. Transport & Logistics	Hybrid	5493		7002	3	2448	10251	38503	1.383	1.284	0.47	7729	<0.001
	Difference	932	21%	967	0	488	1673	7595	1.208	1.097	-		

Shen-based job accessibility

Occupational class		Median	%	S.D.	Min	25%	75%	Max	SK.	KU.	Gini G_i	Mann-Whitney U: U	Mann-Whitney U: p-value
	Physical	0.890		0.613	0.058	0.641	1.132	9.213	3.901	24.275	0.29		
1. Educational professions	Hybrid	0.848		0.585	0.044	0.617	1.054	8.814	4.238	26.897	0.26	2805	<0.001
	Difference	-0.026	-5%	0.104	-2.693	-0.086	0.000	0.122	-4.606	45.198	-		
	Physical	0.805		0.334	0.003	0.559	1.052	3.725	0.394	0.238	0.23		
2. Creative and Linguistic occupations	Hybrid	0.928		0.378	0.003	0.636	1.198	2.121	0.209	-0.592	0.23	18294	<0.001
	Difference	0.113	15%	0.122	-2.632	0.056	0.188	0.675	-2.739	28.686	-		
	Physical	0.884		0.816	0.150	0.709	1.159	8.834	2.075	4.260	0.37		
3. Commercial occupations	Hybrid	0.849		0.806	0.151	0.683	1.087	7.387	2.086	4.129	0.34	47717	<0.001
	Difference	-0.023	-4%	0.073	-1.875	-0.053	-0.007	0.086	-5.851	65.666	-		
	Physical	0.790		0.677	0.120	0.609	1.004	7.234	3.071	11.521	0.34		
4. Business Economics & Administrative professions	Hybrid	0.749		0.664	0.121	0.577	0.935	6.465	3.154	11.742	0.31	138055	<0.001
	Difference	-0.026	-5%	0.085	-3.265	-0.063	-0.010	0.071	-6.384	76.175	-		
	Physical	1.072		0.417	0.112	0.708	1.392	3.632	0.157	-0.795	0.25		
5. Managers	Hybrid	1.038		0.379	0.110	0.679	1.318	1.993	0.008	-1.063	0.23	19883	<0.001
	Difference	-0.030	-3%	0.098	-2.166	-0.088	-0.007	0.141	-3.905	34.112	-		
	Physical	0.725		0.643	0.001	0.539	0.940	7.619	3.476	14.716	0.31		
6. Public Administration, Security & Legal professions	Hybrid	0.786		0.785	0.001	0.582	1.057	8.055	3.818	17.663	0.32	43315	<0.001
	Difference	0.078	8%	0.211	-3.325	0.033	0.150	2.904	0.684	25.782	-		
	Physical	0.904		0.597	0.080	0.694	1.393	4.793	1.189	0.780	0.31		
7. Technical professions	Hybrid	0.876		0.592	0.064	0.675	1.302	3.833	1.243	0.857	0.29	46901	<0.001
	Difference	-0.012	-3%	0.066	-1.803	-0.036	-0.002	0.098	-5.572	60.404	-		
	Physical	0.708		0.321	0.002	0.453	0.941	3.787	0.521	0.679	0.25		
8. ICT	Hybrid	0.732		0.336	0.002	0.466	0.990	1.757	0.316	-0.661	0.27	42535	<0.001
	Difference	0.039	3%	0.107	-2.604	0.012	0.079	0.363	-5.931	70.761	-		
	Physical	0.696		1.180	0.009	0.574	2.450	5.180	1.111	-0.387	0.43		
9. Agriculture	Hybrid	0.703		1.239	0.007	0.579	2.516	5.403	1.134	-0.312	0.44	3854	<0.001
	Difference	0.018	1%	0.085	-1.011	0.003	0.053	0.612	0.768	8.354	-		
	Physical	1.139		0.446	0.053	0.934	1.394	5.698	1.747	5.702	0.2		
10. Care & Welfare	Hybrid	1.036		0.419	0.044	0.856	1.254	5.157	2.005	6.927	0.19	27762	<0.001
	Difference	-0.075	-9%	0.099	-2.297	-0.138	-0.044	0.028	-4.278	39.973	-		
	Physical	1.197		1.782	0.218	0.927	3.554	15.413	1.241	0.792	0.46		
11. Service	Hybrid	1.059		1.734	0.208	0.829	3.411	14.740	1.220	0.651	0.45	59494	<0.001
	Difference	-0.109	-12%	0.103	-3.943	-0.172	-0.067	0.252	-4.250	45.230	-		
	Physical	1.325		1.538	0.208	0.981	3.518	8.679	0.850	-0.450	0.42		
12. Transport & Logistics	Hybrid	1.210		1.500	0.199	0.894	3.393	7.982	0.841	-0.500	0.39	49989	<0.001
	Difference	-0.087	-9%	0.087	-2.126	-0.148	-0.054	0.183	-3.709	34.038	-		

Appendix W. Regression analysis output

Table 19: Generalised Hansen- and Shen-based job accessibility differences regression output

	Hansen (r-squared = 8.830)						Shen (r-squared = 0.797)					
	β	S.E.	t-statistic	P-value	[0.025	0.975]	β	S.E.	t-statistic	P-value	[0.025	0.975]
Intercept	-263.577	2.509	-105.032	<0.001	-268.495	-258.658	-0.168	0.023	-7.407	<0.001	-0.213	-0.123
Gender (ref = Female)												
Male	121.164	1.508	80.338	<0.001	118.208	124.119	0.000	0.012	0.010	0.992	-0.024	0.024
Age category												
15-24 years	-66.606	2.479	-26.868	<0.001	-71.465	-61.748	-0.031	0.020	-1.579	0.116	-0.070	0.008
25-34 years	21.365	1.853	11.532	<0.001	17.733	24.996	-0.031	0.011	-2.819	0.005	-0.053	-0.009
35-44 years	4.621	1.790	2.581	<0.001	1.112	8.130	-0.035	0.012	-2.835	0.005	-0.059	-0.011
45-54 years	-36.894	1.712	-21.550	<0.001	-40.250	-33.539	-0.027	0.010	-2.563	0.011	-0.047	-0.006
55-64 years	-53.686	1.709	-31.413	<0.001	-57.035	-50.336	-0.044	0.010	-4.207	<0.001	-0.065	-0.023
65-75 years	-132.377	6.088	-21.743	<0.001	-144.309	-120.444	0.009	0.033	0.280	0.780	-0.056	0.074
Education level												
Low educated	-1992.265	1.537	-1296.565	<0.001	-1995.276	-1989.253	0.027	0.016	1.721	0.087	-0.004	0.059
Middle educated	-612.335	1.266	-483.674	<0.001	-614.816	-609.854	-0.091	0.008	-11.004	<0.001	-0.107	-0.075
High educated	2341.023	1.355	1727.321	<0.001	2338.367	2343.679	-0.105	0.011	-9.799	<0.001	-0.126	-0.083
Occupational class												
1. Educational professions	2985.266	5.925	503.802	<0.001	2973.653	2996.880	0.399	0.047	8.429	<0.001	0.305	0.492
2. Creative and Linguistic occupations	-701.941	6.723	-104.402	<0.001	-715.119	-688.763	0.661	0.051	12.859	<0.001	0.560	0.763
3. Commercial occupations	173.590	5.761	30.134	<0.001	162.300	184.881	0.428	0.045	9.588	<0.001	0.339	0.515
4. Business Economics & Administrative professions	1447.624	5.757	251.445	<0.001	1436.340	1458.907	0.433	0.045	9.615	<0.001	0.344	0.522
5. Managers	1393.800	6.114	227.972	<0.001	1381.817	1405.783	0.465	0.048	9.578	<0.001	0.369	0.560
6. Public Administration, Security & Legal professions	-1517.871	6.373	-238.170	<0.001	-1530.362	-1505.380	0.530	0.050	10.596	<0.001	0.431	0.629
7. Technical professions	-1903.234	5.720	-332.745	<0.001	-1914.444	-1892.023	0.434	0.043	9.997	<0.001	0.349	0.520
8. ICT	-3167.738	6.128	-516.936	<0.001	-3179.748	-3155.728	0.478	0.047	10.108	<0.001	0.384	0.571
9. Agriculture	180.849	7.339	24.643	<0.001	166.465	195.233	0.431	0.081	5.332	<0.001	0.271	0.590
10. Care & Welfare	2240.581	5.716	391.959	<0.001	2229.377	2251.785	0.405	0.044	9.256	<0.001	0.319	0.491
11. Service	614.074	5.955	103.119	<0.001	602.402	625.745	0.430	0.043	9.996	<0.001	0.345	0.515
12. Transport & Logistics	161.856	6.103	26.519	<0.001	149.894	173.818	0.427	0.043	9.871	<0.001	0.342	0.513
Household composition												
Single	-22.232	1.715	-12.961	<0.001	-25.594	-18.870	-0.062	0.014	-4.373	<0.001	-0.090	-0.034
With children	-128.989	1.986	-64.954	<0.001	-132.881	-125.097	-0.069	0.017	-4.153	<0.001	-0.102	-0.036
No children	-112.356	1.357	-82.786	<0.001	-115.016	-109.696	-0.036	0.011	-3.342	0.001	-0.058	-0.015
Household size	-16.017	0.901	-17.772	<0.001	-17.783	-14.250	0.011	0.007	1.506	0.134	-0.003	0.025
Migration background												
Dutch	-21.850	1.302	-16.777	<0.001	-24.403	-19.297	-0.043	0.011	-4.077	<0.001	-0.064	-0.022
Western	-110.757	1.713	-64.658	<0.001	-114.115	-107.400	-0.077	0.014	-5.318	<0.001	-0.105	-0.048
Not Western	-130.969	1.545	-84.756	<0.001	-133.998	-127.941	-0.048	0.013	-3.767	<0.001	-0.073	-0.023
Urbanity												

Highly urbanized	-167.761	1.539	-109.034	<0.001	-170.776	-164.745	0.012	0.011	1.086	0.279	-0.010	0.034
Strongly urbanized	33.705	1.325	25.445	<0.001	31.109	36.301	-0.034	0.012	-2.957	0.004	-0.057	-0.011
Moderately urbanized	-13.238	1.469	-9.010	<0.001	-16.117	-10.358	-0.020	0.012	-1.691	0.093	-0.044	0.003
Slightly urbanized	-26.769	1.558	-17.183	<0.001	-29.822	-23.716	-0.054	0.011	-4.996	<0.001	-0.075	-0.033
Non-urbanized	-89.515	1.581	-56.634	<0.001	-92.613	-86.417	-0.072	0.011	-6.239	<0.001	-0.094	-0.049
Accessibility												
Physical accessibility	0.369	0.000	3298.489	<0.001	0.369	0.369	-0.081	0.008	-9.864	<0.001	-0.098	-0.065

Table 20: Mode-specific Hansen-based regression output

	Car (r^2= 0.845)				PT (r^2= 0.808)				Bike (r^2= 0.733)			
	β	**S.E.**	**t-statistic**	**P-value**	**β**	**S.E.**	**t-statistic**	**P-value**	**β**	**S.E.**	**t-statistic**	**P-value**
Intercept	<0.001	0.033	<0.001	<0.001	<0.001	0.034	<0.001	<0.001	<0.001	0.040	<0.001	<0.001
Gender (ref = Female)												
Male	-0.041	0.044	-0.926	0.356	0.000	0.043	0.004	0.997	-0.018	0.050	-0.357	0.721
Age category												
15-24 years	0.013	0.033	0.393	0.695	0.017	0.033	0.515	0.607	0.037	0.040	0.926	0.356
25-34 years	-0.014	0.030	-0.451	0.652	0.017	0.029	0.579	0.564	-0.040	0.034	-1.166	0.245
35-44 years	0.043	0.028	1.509	0.133	-0.007	0.030	-0.238	0.812	0.000	0.034	-0.012	0.990
45-54 years	0.003	0.026	0.119	0.905	-0.033	0.028	-1.149	0.252	0.038	0.032	1.189	0.236
55-64 years	-0.045	0.030	-1.519	0.131	0.020	0.029	0.669	0.504	-0.020	0.032	-0.627	0.532
65-75 years	0.005	0.036	0.133	0.894	-0.019	0.036	-0.526	0.600	-0.008	0.041	-0.192	0.848
Education level												
Low educated	-0.222	0.029	-7.642	<0.001	-0.059	0.031	-1.908	0.058	-0.080	0.037	-2.138	0.034
Middle educated	-0.165	0.023	-7.328	<0.001	0.008	0.024	0.321	0.749	-0.041	0.027	-1.531	0.128
High educated	0.360	0.024	14.685	<0.001	0.037	0.024	1.531	0.128	0.096	0.029	3.263	0.001
Occupational class												
1. Educational professions	0.236	0.069	3.436	0.001	0.258	0.098	2.631	0.009	0.003	0.039	0.087	0.931
2. Creative and Linguistic occupations	-0.021	0.049	-0.435	0.664	-0.059	0.063	-0.937	0.350	0.007	0.043	0.174	0.862
3. Commercial occupations	0.032	0.077	0.413	0.680	0.203	0.106	1.918	0.057	0.115	0.036	3.188	0.002
4. Business Economics & Administrative professions	0.085	0.111	0.769	0.443	0.298	0.155	1.921	0.056	-0.005	0.039	-0.129	0.897
5. Managers	0.013	0.052	0.261	0.795	0.176	0.087	2.028	0.044	-0.010	0.041	-0.249	0.804
6. Public Administration, Security & Legal professions	-0.111	0.062	-1.780	0.077	0.063	0.074	0.849	0.397	0.026	0.040	0.649	0.517
7. Technical professions	-0.131	0.091	-1.435	0.153	0.096	0.123	0.776	0.439	-0.162	0.038	-4.284	<0.001
8. ICT	0.017	0.050	0.346	0.730	-0.104	0.098	-1.064	0.289	-0.137	0.040	-3.440	0.001
9. Agriculture	0.027	0.052	0.517	0.606	0.041	0.043	0.967	0.335	-0.012	0.042	-0.293	0.770
10. Care & Welfare	0.236	0.111	2.129	0.035	0.327	0.150	2.179	0.031	0.114	0.037	3.075	0.002
11. Service	0.039	0.078	0.494	0.622	0.222	0.110	2.021	0.045	0.074	0.039	1.883	0.061
12. Transport & Logistics	0.021	0.067	0.311	0.756	0.082	0.072	1.129	0.261	-0.032	0.043	-0.750	0.454
Household composition												
Single	0.042	0.042	1.007	0.315	0.008	0.040	0.199	0.843	0.020	0.054	0.379	0.705
With children	-0.005	0.035	-0.151	0.880	-0.039	0.035	-1.116	0.266	-0.012	0.051	-0.238	0.812
No children	-0.030	0.025	-1.198	0.232	0.038	0.026	1.433	0.154	-0.007	0.032	-0.217	0.829
Household size	0.039	0.063	0.612	0.541	0.061	0.065	0.930	0.353	-0.012	0.086	-0.142	0.887
Migration background												
Dutch	0.024	0.022	1.084	0.280	-0.012	0.022	-0.535	0.593	-0.001	0.027	-0.028	0.978
Western	-0.073	0.029	-2.563	0.011	-0.009	0.030	-0.280	0.780	-0.040	0.036	-1.114	0.267
Not Western	0.027	0.026	1.073	0.285	0.022	0.027	0.794	0.428	0.035	0.033	1.061	0.290
Urbanity												
Highly urbanized	-0.132	0.034	-3.924	<0.001	0.146	0.031	4.767	<0.001	0.064	0.042	1.530	0.128
Strongly urbanized	0.003	0.028	0.114	0.910	0.001	0.028	0.020	0.984	-0.048	0.031	-1.535	0.127
Moderately urbanized	0.095	0.029	3.209	0.002	-0.019	0.029	-0.638	0.524	0.003	0.036	0.069	0.945
Slightly urbanized	0.032	0.028	1.112	0.268	-0.052	0.031	-1.685	0.094	-0.020	0.037	-0.550	0.583
Non-urbanized	0.016	0.030	0.539	0.591	-0.100	0.030	-3.297	0.001	0.005	0.036	0.129	0.898
Accessibility												
Physical accessibility	0.577	0.049	11.822	<0.001	0.727	0.044	16.519	<0.001	0.706	0.059	11.967	<0.001

Table 21: Mode-specific Shen-based regression output

	Car (r^2= 0.850)				PT (r^2= 0.707)				Bike (r^2= 0.639)			
	β	**S.E.**	**t-statistic**	**P-value**	**β**	**S.E.**	**t-statistic**	**P-value**	**β**	**S.E.**	**t-statistic**	**P-value**
Intercept	<0.001	0.030	<0.001	<0.001	<0.001	0.042	<0.001	<0.001	<0.001	0.046	<0.001	<0.001
Gender (ref = Female)												
Male	-0.049	0.036	-1.371	0.172	-0.020	0.052	-0.391	0.697	-0.024	0.054	-0.453	0.651
Age category												
15-24 years	-0.063	0.029	-2.144	0.033	-0.013	0.039	-0.325	0.745	0.030	0.050	0.593	0.554
25-34 years	-0.008	0.026	-0.302	0.763	-0.014	0.036	-0.399	0.690	0.063	0.039	1.630	0.105
35-44 years	0.009	0.026	0.365	0.715	0.012	0.035	0.348	0.728	-0.063	0.040	-1.573	0.117
45-54 years	-0.001	0.023	-0.026	0.979	-0.040	0.034	-1.148	0.252	-0.018	0.036	-0.491	0.624
55-64 years	0.016	0.024	0.659	0.511	0.039	0.035	1.117	0.266	0.035	0.037	0.948	0.344
65-75 years	0.057	0.031	1.857	0.065	0.033	0.045	0.747	0.456	-0.120	0.048	-2.498	0.013
Education level												
Low educated	0.313	0.038	8.238	<0.001	-0.084	0.053	-1.597	0.112	0.196	0.056	3.512	0.001
Middle educated	0.051	0.025	2.069	0.040	-0.039	0.032	-1.230	0.220	0.004	0.035	0.125	0.901
High educated	-0.289	0.022	-13.406	<0.001	0.101	0.032	3.175	0.002	-0.143	0.034	-4.254	<0.001
Occupational class												
1. Educational professions	1.205	0.084	14.315	<0.001	-1.361	0.121	-11.247	<0.001	-0.056	0.109	-0.516	0.607
2. Creative and Linguistic occupations	1.028	0.065	15.909	<0.001	-0.636	0.076	-8.333	<0.001	0.083	0.088	0.944	0.346
3. Commercial occupations	1.351	0.091	14.883	<0.001	-1.405	0.129	-10.864	<0.001	0.608	0.172	3.535	0.001
4. Business Economics & Administrative professions	1.715	0.117	14.658	<0.001	-1.800	0.168	-10.733	<0.001	0.432	0.194	2.230	0.027
5. Managers	0.981	0.070	13.955	<0.001	-0.898	0.095	-9.437	<0.001	0.047	0.146	0.322	0.748
6. Public Administration, Security & Legal professions	0.977	0.071	13.761	<0.001	-0.910	0.105	-8.654	<0.001	0.490	0.101	4.877	<0.001
7. Technical professions	1.727	0.113	15.253	<0.001	-1.607	0.147	-10.940	<0.001	0.392	0.175	2.241	0.026
8. ICT	1.281	0.083	15.391	<0.001	-0.890	0.101	-8.775	<0.001	0.017	0.123	0.140	0.889
9. Agriculture	0.613	0.048	12.761	<0.001	-0.201	0.052	-3.897	<0.001	0.120	0.067	1.796	0.074
10. Care & Welfare	1.696	0.127	13.398	<0.001	-1.823	0.158	-11.537	<0.001	0.235	0.162	1.445	0.150
11. Service	0.992	0.086	11.568	<0.001	-1.051	0.093	-11.279	<0.001	0.354	0.127	2.786	0.006
12. Transport & Logistics	0.917	0.073	12.544	<0.001	-0.853	0.085	-10.052	<0.001	0.085	0.110	0.771	0.442
Household composition												
Single	-0.024	0.038	-0.626	0.532	-0.014	0.048	-0.286	0.775	0.004	0.053	0.077	0.939
With children	0.002	0.035	0.044	0.965	0.000	0.041	0.009	0.993	0.001	0.048	0.010	0.992
No children	0.019	0.023	0.798	0.426	0.012	0.033	0.364	0.716	-0.005	0.039	-0.115	0.909
Household size	-0.025	0.063	-0.394	0.694	-0.085	0.077	-1.104	0.271	0.085	0.083	1.023	0.308
Migration background												
Dutch	-0.004	0.018	-0.237	0.813	-0.027	0.027	-0.985	0.326	-0.025	0.031	-0.785	0.434
Western	-0.007	0.026	-0.285	0.776	0.002	0.037	0.048	0.962	-0.017	0.040	-0.411	0.681
Not Western	0.010	0.022	0.462	0.645	0.030	0.032	0.929	0.354	0.041	0.038	1.072	0.285
Urbanity												
Highly urbanized	-0.015	0.027	-0.568	0.571	0.016	0.039	0.408	0.684	-0.125	0.043	-2.942	0.004
Strongly urbanized	0.066	0.025	2.602	0.010	-0.032	0.033	-0.945	0.346	-0.052	0.039	-1.328	0.186
Moderately urbanized	-0.011	0.025	-0.442	0.659	-0.046	0.038	-1.233	0.219	0.040	0.042	0.968	0.335
Slightly urbanized	0.002	0.027	0.085	0.932	0.075	0.039	1.918	0.057	0.083	0.043	1.923	0.056
Non-urbanized	-0.051	0.027	-1.860	0.065	-0.013	0.038	-0.330	0.742	0.063	0.041	1.563	0.120
Accessibility												
Physical accessibility	-0.602	0.055	-10.971	<0.001	0.099	0.082	1.216	0.226	-0.311	0.081	-3.826	<0.001

Appendix X. Extension of comparative analysis

The spatial distribution of physical and hybrid job accessibility, as calculated through the aggregate measure, is presented in figure 31 for the Hansen-based model and figure 32 for the Shen-based model. Overall, a similar spatial pattern of job accessibility is visible when comparing to the disaggregated measures. Nevertheless, visual comparison to the disaggregated measure also shows that the spatial distribution of both physical and hybrid job accessibility appear more heavily concentrated in the physical scenario, indicating less extreme values between zones within the Netherlands.

The impact of hybrid teleworking for the Hansen- and Shen-based models is visualized using mean normalization based on the physical job accessibility variants. What can be observed is that job accessibility for both models improves to such extent due to hybrid teleworking, that the scores for the majority of zones the country become indiscernible as result of to the applied symbology and normalization. Notably, despite this substantial enhancement of job accessibility, both models highlight evident lower scores in the northern and southern outer regions and the Wadden Islands. This is especially more pronounced in the Hansen-based model.

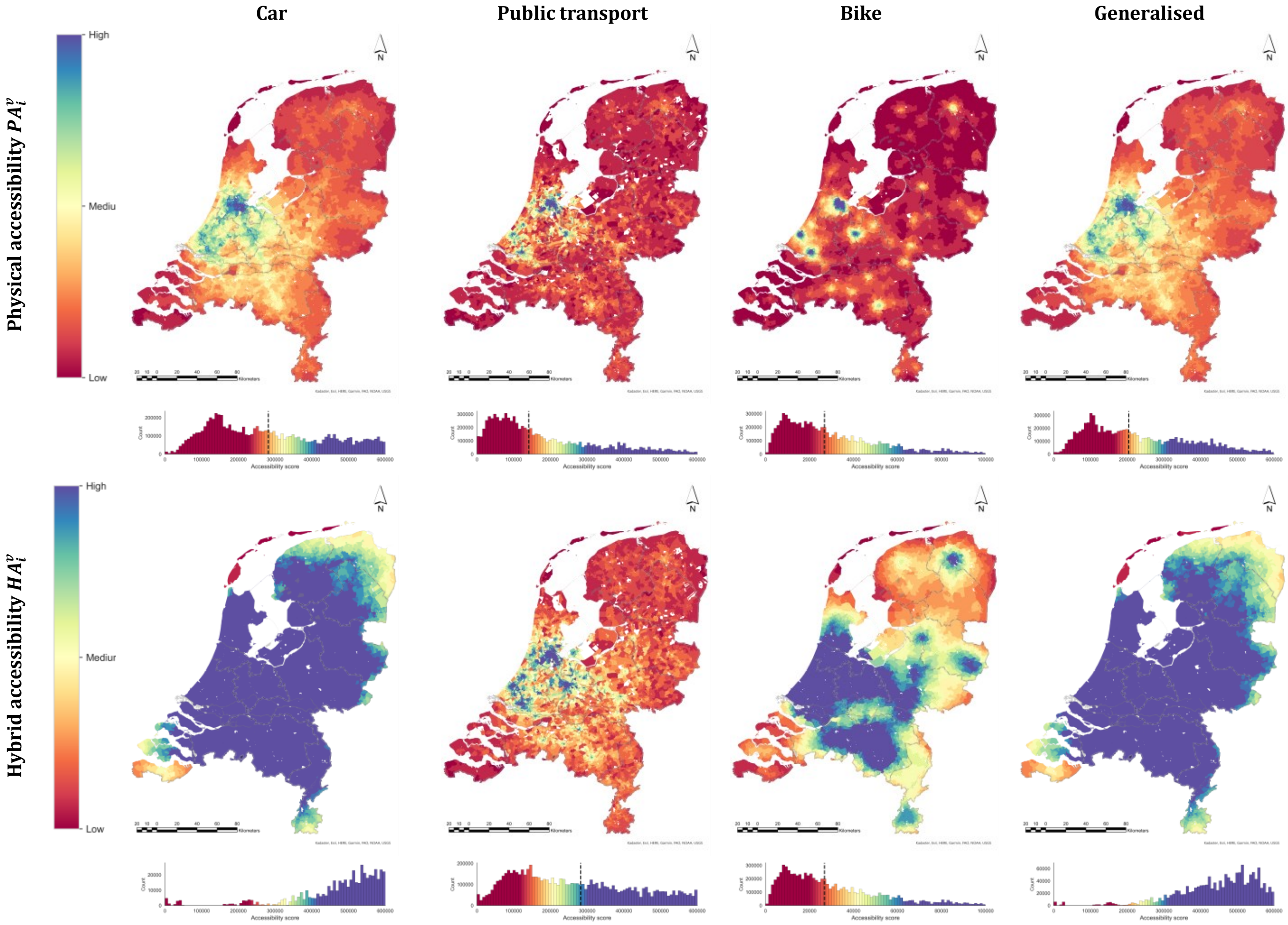


Figure 30: Spatial distribution of physical and hybrid job accessibility, without competition (Hansen-based)

Table 22: Descriptive statistics of physical and hybrid job accessibility, without competition (Hansen-based)

Model											*Global Moran's I*		*Mann-Whitney U*	
	Mode		Median	S.D.	Min	25%	75%	Max	SK.	KU.	I	p-value	U	p-value
Hansen	Car	*Physical*	283523	191969	552	156818	469896	943575	0.564	-0.621	0.972	<0.001	217055	<0.001
		Hybrid	1810241	652853	687	1145073	2232898	3067579	-0.355	-0.987	0.971	<0.001		
	PT	*Physical*	142878	187338	0	72801	305027	1265539	1.313	1.214	0.822	<0.001	9369436	<0.001
		Hybrid	286310	229534	28	144828	489884	1417410	0.777	-0.138	0.919	<0.001		
	Bike	*Physical*	26980	44316	459	13924	51697	243697	2.126	4.666	0.979	<0.001	229638	<0.001
		Hybrid	159022	148617	713	90652	286440	656687	1.103	0.549	0.980	<0.001		
	Generalised	*Physical*	205542	148957	496	114378	345443	748871	0.703	-0.333	0.980	<0.001	399204	<0.001
		Hybrid	1244054	471026	658	775788	1581590	2163638	-0.272	-1.043	0.986	<0.001		

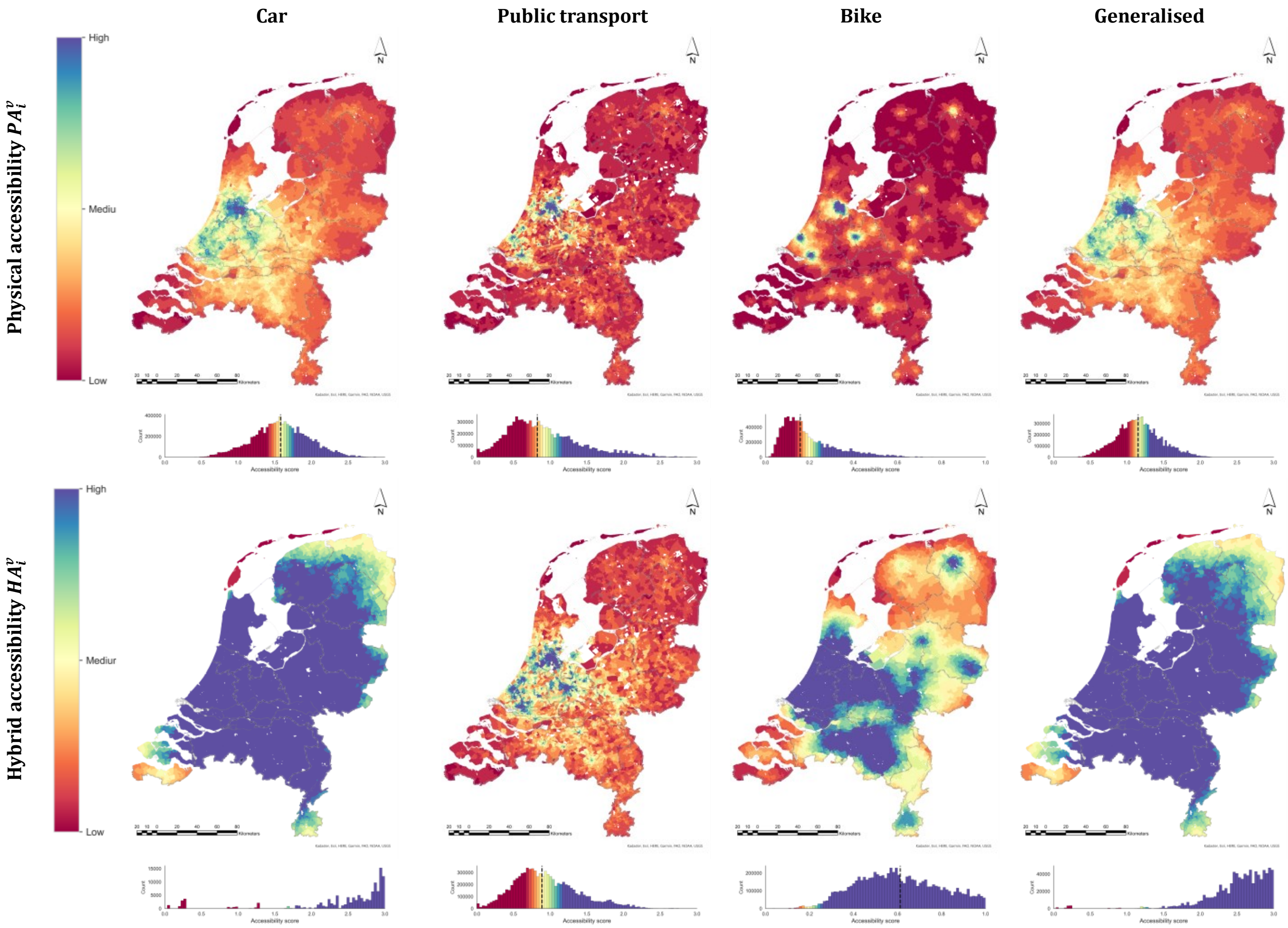


Figure 31: Spatial distribution of physical and hybrid job accessibility, with competition (Shen-based)

Table 23: Descriptive statistics of physical and hybrid job accessibility, with competition (Shen-based)

Model											***Global Moran's I***		***Mann-Whitney U***	
Mode			**Median**	**S.D.**	**Min**	**25%**	**75%**	**Max**	**SK.**	**KU.**	**I**	**p-value**	**U**	**p-value**
Shen	Car	*Physical*	1.579	0.384	0.191	1.334	1.839	2.983	0.035	-0.020	0.358	<0.001	4895	<0.001
		Hybrid	6.451	1.417	0.032	5.284	7.245	10.007	-0.390	-0.082	0.355	<0.001		
	PT	*Physical*	0.830	0.514	0.000	0.551	1.204	4.504	0.990	1.232	0.485	<0.001	94328	<0.001
		Hybrid	0.896	0.440	0.000	0.641	1.214	3.722	0.709	0.550	0.479	<0.001		
	Bike	*Physical*	0.159	0.127	0.008	0.107	0.255	0.953	1.336	1.647	0.449	<0.001	3875	<0.001
		Hybrid	0.615	0.230	0.032	0.477	0.799	1.264	0.471	-0.292	0.470	<0.001		
	Generalised	*Physical*	1.153	0.305	0.172	0.961	1.355	2.322	0.234	0.037	0.797	<0.001	1050969	<0.001
		Hybrid	4.467	0.958	0.030	3.669	4.995	6.899	-0.405	-0.108	0.612	<0.001		

Spatial differences in job accessibility are visualized in figure 33 for the Hansen-based model variants Shen-based models. Similar to the spatial distribution, the differences of job accessibility are fairly large, but mostly evenly distributed throughout the country. For both models, largest accessibility increases are observed by car. Job accessibility by public transport reveals a more localized picture, where largest increases are mostly visible in centrally located regions. Moreover, decreases in job accessibility by public transport are visibly clustered in some locations. These not only include rural locations, but also the highly urbanized regions in Amsterdam and Groningen experience this decrease in job accessibility. Potentially, strong competition effects over other modes of transport (car and bike) are the cause of this decrease. Job accessibility changes by bike appears to be more evenly distributed throughout the country in both models.

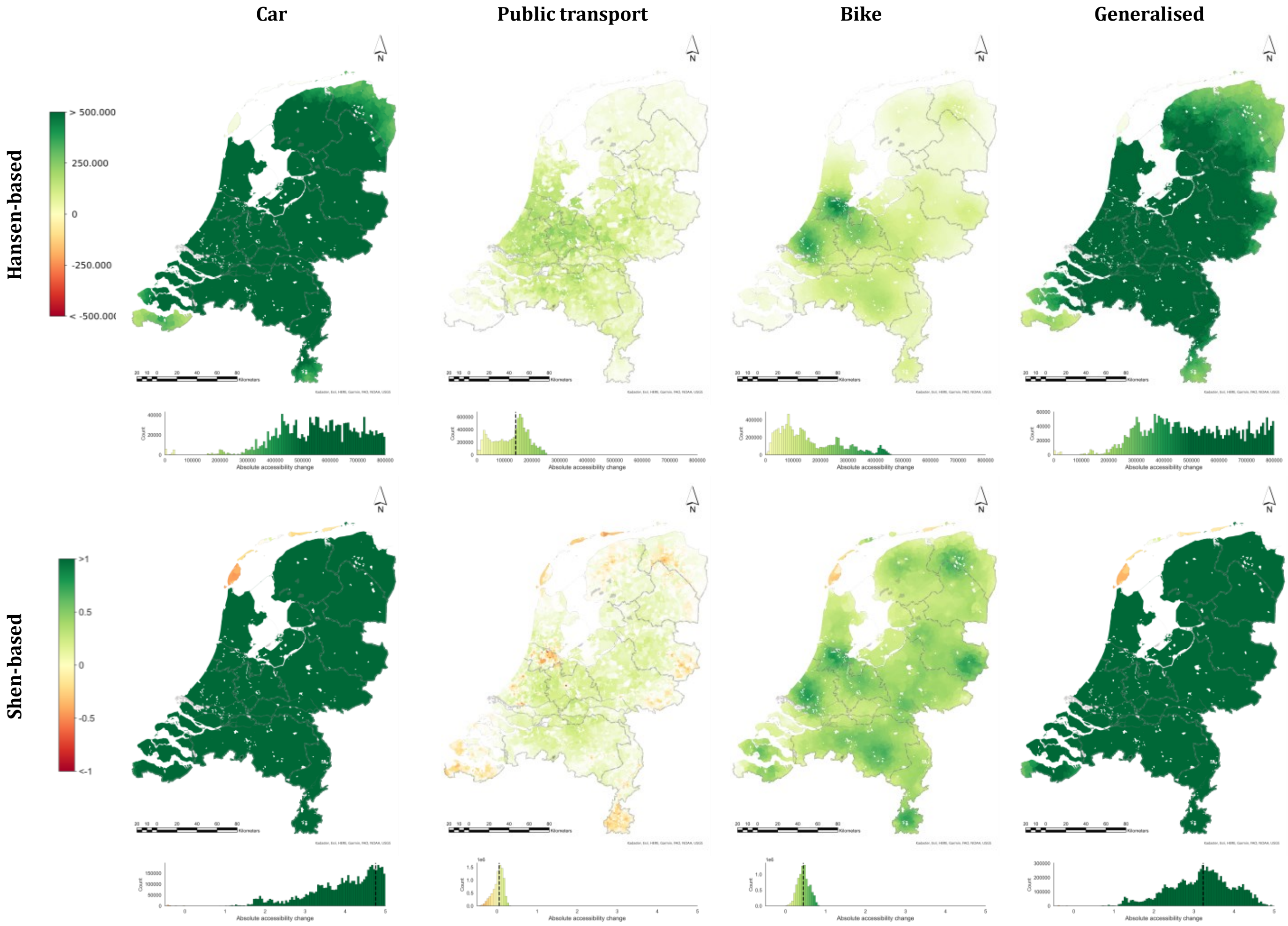


Figure 32: Spatial distribution of job accessibility differences, Hansen-based and Shen-based models

Table 24: Descriptive statistics job accessibility differences

Model											*Global Moran's I*	
	Mode	**Median**	**(%)**	**S.D.**	**Min**	**25%**	**75%**	**Max**	**SK.**	**KU.**	**I**	**p-value**
Hansen	***Car***	1507585	538%	490805	20	1003772	1733434	2312929	-0.523	-0.719	0.815	<0.001
	PT	141799	100%	60878	0	73971	169682	253830	-0.256	-0.955	0.829	<0.001
	Bike	128451	489%	111277	37	74739	243030	455750	0.827	-0.303	0.912	<0.001
	Generalised	1031981	505%	344058	77	675518	1210560	1590845	-0.505	-0.817	0.818	<0.001
Shen	***Car***	4.759	309%	1.205	-0.455	3.92	5.505	7.475	-0.408	0.051	0.708	<0.001
	PT	0.055	8%	0.133	-0.781	-0.044	0.127	0.367	-0.863	0.805	0.805	<0.001
	Bike	0.447	287%	0.146	-0.304	0.348	0.548	0.819	-0.014	-0.025	0.765	<0.001
	Generalised	3.233	287%	0.796	-0.376	2.644	3.701	4.953	-0.447	0.084	0.701	<0.001

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