Labor markets in a globalizing world: trends, challenges and opportunities

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Chapter 4

The geography of employment polarization, skills mismatch and labor productivity in the Netherlands

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Abstract

Despite their global pervasiveness, employment polarization and skills mismatch are often studied in isolation while their economic effects are mostly indirectly investigated. Using extensive worker-level data from *Statistics Netherlands* between 1999 and 2011, this paper combines quantitative measures of employment polarization and skills mismatch and advances the labor economics literature by investigating their relationship and their economc effects. Our analysis for the Dutch national and local labor markets first uncovers that employment growth is polarizing in a substantial number of regions, while there is also a measurable mismatch between the supply and demand for skills. In our main analysis, the simultaneous equations models provide more robust evidence regarding the relationships and the productivity effects between polarized employment growth and skills mismatch at the regional level. Notably, we conclude that both employment polarization and skills mismatch interact with labor productivity in a non-linear, inverted U-shaped manner. Furthermore, our sensitivity, age-related analysis reveals different non-linear productivity effects from employment polarization and skills mismatch between young and senior workers. Despite our empirical approach's robustness, the investigated relationships merit further attention. In total, our analysis points to active labor market policies to increase the responsiveness of the educational system to the evolving labor market needs due to the joint impact from technology and trade.

Keywords: employment polarization, skills mismatch, regional labor productivity, conditional mixed process

4.1 Introduction

Employment polarization, defined as the clustering of employment growth around the extreme poles of the occupational skill distribution at the expense of middle-skilled jobs (Goos & Manning, 2007) is extensively documented in industrialized labor markets since the early 2000s (Acemoglu & Autor, 2011; Autor, 2010). The main consensus in the literature refers to the asymmetric, occupation-specific impact from automation and the global fragmentation of production as the main mechanisms of polarized employment growth. In particular, labor market and trade economists argue that routine-intensive, medium-skilled occupations are susceptible to be either automated or outsourced away from industrialized labor markets (Autor, Levy & Murnane, 2003; Becker, Ekholm & Muendler, 2013). Technology and trade typically increase the demand for high-skilled jobs, while they have limited effects on low-skilled employment. Polarized employment growth is often the combined outcome of the above disruptive forces (Terzidis & Ortega-Argiles, 2021).

Alongside employment polarization, modern labor markets are increasingly characterized by substantial disparities between the supply and demand for skills. The profound educational expansion of the last decade increased the supply of skills[1] (Hartog & Oosterbeek, 1988) raising valid concerns that the demand for skills cannot keep pace with the increasing supply (Freeman, 1976; Leuven & Oosterbeek, 2011), thus leading to *skills mismatch*. Paralleled by common labor market imperfections (such as incomplete information), rigid employment protection regulations and the recent global economic crisis, skills mismatch is increasingly manifested in modern labor markets (see f.i. Groot and Maasen van den Brink (2000) for a comprehensive overview of the respective literature).

Despite their concurrent proliferation, the literature often studies employment polarization and skills mismatch in isolation. In theory, their relationship is straightforward. Polarized employment growth shifts medium-skilled workers to the tails of the occupational skills distribution. Therefore, in the absence of a supply response, it is expected to increase under-skilling amongst high-skilled jobs and over-skilling amongst low-skilled ones. However, a series of factors render the empirical relationship ambiguous. First, the over-skilling trends in high-skilled occupations are mitigated by the increased supply of high-skilled workers (Kiersztyn, 2013). Secondly, the abovementioned theoretical relationship is based on an

[1] According to the European Commission (2014), the share of tertiary educational attainment amongst the population aged from 30 to 34 in the EU has increased from 34.5 to 36.9 per cent and between 2011 and 2015 and is projected to increase by another 13 per cent by 2020.

initially efficient allocation of skills thus ignoring the pervasiveness of skills mismatch in the industrialized labor markets. As a result, differential conditions might impact the complementarities between employment polarization and skills mismatch. Finally, extensive literature concludes that both employment polarization and skills mismatch are subject to changes in the prevailing economic conditions such as GDP growth, productivity or unemployment (Jaimovich & Siu, 2012; Quintini, 2011) which could shape the outcome of their interaction. Based on the above, the overall relationship between employment polarization and skills mismatch remains an empirical issue.

A central theme in the labor economics literature refers to the productivity effects of employment polarization and skills mismatch. First, employment polarization implies increased employment in high-skill, high-productivity jobs. In contrast, this productivity-augmenting effect from the polarization of employment is mediated by skills mismatch when the latter is reflected by under-skilled workers employed in high-skilled jobs. Furthermore, the largely inconclusive empirical links between employment polarization and the wage premium of high-skilled labor (Antonczyk, DeLeire & Fitzenberger, 2010) indicate a differential relationship between employment polarization and labor productivity where the former implies a larger increase in the productivity of high-skilled workers compared to low- and medium-skilled ones. Therefore, the empirical literature fails to identify a clear causal link between employment polarization and labor productivity.

When invastigating the productivity effects from skills mismatch, the literature differentiates between its two constituent parts; namely *over-* and *under-skilling*. Regarding over-skilling, the wage premium received by over-skilled workers implies an increase in labor productivity (McGuinness, Pouliakas & Redmond, 2018; Leuven & Oosterbeek, 2011). Similarly, Mahy, Rycx and Vermeulen (2015) report that over-skilled workers increase their peers' productivity via substantial spillover effects. The strength of this effect decreases when over-skilled workers remain employed in jobs where they fail to utilize their full potential, undermining the skills allocating efficiency in the entire labor market. Furthermore, under-skilling decreases labor productivity, since it prevents the introduction and utilization of new technologies, thus undermining the economy's innovative capacity. Redding (1996) defines this as the *low-skills, bad jobs, low wages equilibrium trap,* characterised by low productivity, under-investment in human capital and fewer skilled jobs. Within this context, the empirical evidence varies. An important strand of the literature points to adverse effects from skills mismatch on firm-level productivity (Haskel & Martin, 1993; McGowan & Andrews, 2015; Grunau, 2015). In a more detailed approach, Kampelmann and Rycx (2012) and Mahy et al. (2015) conclude that a higher level of over- (under-)education increases (decreases) firm-level productivity.

In light of the above inconclusive empirical findings, the current analysis builds on extensive micro-data for the Netherlands between 1999 and 2011 and advances the debate on the proliferation and the economic effects of employment polarization and skills mismatch in the following ways: First we calculate quantitative indexes of employment polarization and skills mismatch both at the national and regional level. Concerning employment polarization, we utilize the formula proposed by Sparreboom and Tarvid (2016), which considers the imbalanced nature of employment restructuring in the Netherlands, where high-skilled jobs increase more compared to low-skilled ones. Similarly, we measure skills mismatch at the macroeconomic level by calculating the *skills mismatch index* introduced by the International Labor Organization (ILO, 2013a), which compares the educational attainment structure between the 'insiders' and the 'outsiders[2]' of the labor market. Those measures illustrate the pervasiveness of polarized employment growth and skills mismatch across the Dutch local labor markets. Notably, we indicate that their incidence increases between 2006 and 2011, which includes the global economic recession. Our cohort analysis reveals different gender and age patterns in the incidence and trends of employment polarization and skills mismatch. We uncover that employment polarization is mostly a young workers' phenomenon while skills mismatch is increasingly prevalent amongst both young and male workers.

Nevertheless, the current study's predominant contribution lies in the joint investigation of employment polarization, skills mismatch and labor productivity by estimating a simultaneous equations system using the *conditional mixed process* estimator (Roodman, 2011). Following Hartog (2000), we address a significant shortcoming of the empirical literature so far which is based on indirect measures of productivity such as wages (Leuven & Oosterbeek, 2011) or job satisfaction (Quintini, 2011); instead, we measure labor productivity directly using the growth rate of gross value added per worker. Since evidence on the direct productivity effects from employment polarization is missing while the evidence regarding the productivity impact from skills mismatch (Kampelmann & Rycx, 2012; Mahy et al. 2015) encourage additional research focusing on different countries, the current analysis improves our understanding on the productivity nexus of two pervasive labor market phenomena.

[2] In the current analysis, the *outsiders* are defined as workers with weak labor market attachment (part-time contracts, on-calls, substitutes etc.).

Our regression analysis uncovers non-linear, inverted-U shaped relationships between the growth rate of labor productivity and the incidence of both employment polarization and skills mismatch. In essence, we illustrate that high incidence of employment polarization and skills mismatch is correlated with average values of productivity growth. Nevertheless, the above relationships are not uniform, since our cohort analysis concludes on a non-linear, U-shaped relationship between skills mismatch and labor productivity for young workers and a monotone and increasing association between employment polarization and the productivity of senior workers in the Netherlands. Overall, the current analysis addresses a pending question in the literature and indicates the necessity for further research.

From a policy perspective, the current study addresses the relative policy inertia regarding the economic effects from employment polarization and skills mismatch (McGuinness et al. 2018) by suggesting national and regional active labor market policies that will increase the responsiveness of the educational system to the emerging labor market needs (Quintini, 2011). In that, occupational forecasting, career counselling and lifelong learning will promote skills formation and combat skills obsolescence. From the firms' point of view, *High-Performance Work Practices* (Patel & Conklin, 2012) including training activities and challenging tasks for workers will promote skills development and allow for more efficient technological adoption. Furthermore, fostering labor mobility and increasing the information regarding labor supply and demand will improve the matching between firms and workers. Such policy priorities are bound to facilitate the reallocation of the displaced medium-skilled workers due to the polarization of employment growth and the more efficient allocation of skills across occupations with direct (higher productivity) and indirect (higher job satisfaction, lower absenteeism) economic gains.

The remainder of the current chapter is structured as follows. Section 4.2 discusses the theoretical underpinnings of employment polarization and skills mismatch which motivate our analysis. Section 4.3 discusses the data used in our analysis, while Section 4.4 describes the construction of the employment polarization and skills mismatch indexes together with preliminary evidence considering employment trends in the Netherlands. Section 4.5 reports our primary empirical results and Section 4.6 includes the cohort analysis. Finally, Section 4.7 concludes.

4.2 Theoretical considerations

4.2.1 Employment polarization

Extensive literature contends that the asymmetric, occupation-specific impact from automation and the global fragmentation of production are the main forces leading to polarized employment growth. The labor market impact from automation is appropriately encapsulated in the *Routine-Biased Technical Change (RBTC)* or *routinization hypothesis* and argues that the occupational task content is the decisive factor determining the exact impact of both automation and international trade. Specifically, the literature advocates that automation predominantly substitutes employees performing routine tasks while it complements workers performing non-routine, high-skill tasks by increasing their productivity and therefore their labor demand (Autor et al. 2003). The global fragmentation of production also disfavors workers performing routine tasks in industrialized countries, since these are the most vulnerable to be shipped to the developing world (Blinder, 2007; Leamer & Storper, 2001). Taken together, automation and the global fragmentation of production shift employment away from routine-based, medium-skilled occupations, towards non-routine-intensive ones, leading to polarized employment growth.

The literature also offers complementary sources of employment polarization. In that sense, Ottaviano, Peri and Wright (2013) suggest that high wage growth in skilled occupations creates a workforce with an increased opportunity cost of time, which intensifies the demand for low-skilled, non-routine manual jobs (child and elderly care, building maintenance etc.). Such *consumption spillovers* (Mazzolari & Ragusa, 2007), increase the relative demand for low-skill jobs, resulting in employment polarization. Finally, polarized employment growth is also precipitated by supply-side phenomena, such as immigration or labor market frictions including wage rigidities which limit the capacity of wages to absorb macroeconomic shocks.

Employment polarization is empirically documented via the differential movements of employment shares of low-, medium- and high-skilled jobs (Goos et al. 2014; Michaels et al. 2014). More recently, an expanding part of the relevant literature investigates the regional incidence of polarized employment growth (Consoli & Barrioluengo, 2018). Nevertheless, the empirical literature suffers from the absence of a single, uniform and ubiquitous quantitative index of employment polarization. Dauth (2014) and Sparreboom and Tarvid (2016) are notable exceptions since they introduce single, quantitative and meaningful indexes to measure the phenomenon's strength. However, these measures are often based on different assumptions;

they pose computational challenges or are interpreted differently. In this paper, we utilize the index proposed by Sparreboom and Tarvid (2016), mainly because it addresses the asymmetry in the employment change between low- and high-skill jobs (Section 4.1 for the methodological details) which particularly fits the Dutch employment patterns (Terzidis & Ortega-Argiles, 2021).

The absence of a single measure of employment polarization accounts for the limited evidence on its economic effects. The existing evidence exploring the impact of employment polarization on wage inequality is largely inconclusive and country-specific (Hunt & Nunn, 2019; Antonczyk et al. 2010). The evidence on the productivity effects from employment polarization is only indirect, based on imperfect productivity measures, such as wages. Against this background, the current chapter addresses the above shortcomings by investigating the two-way relationship between employment polarization and the growth rate of labor productivity, controlling for skills mismatch and other confounding factors at the regional level.

4.2.2 Skills mismatch

Skills mismatch is defined as the imbalance between the supply and demand for skills and is predominantly explained by the *career mobility theory* (Sicherman & Galor, 1990). The central premise is that workers often start their careers in jobs below their ability level if this is compensated by a higher probability of promotion (Leuven & Oosterbeek, 2011). This is typically due to the workers' lack of experience or the firms' lack of information on the workers' skills (Quintini, 2011). Building on the career mobility theory, the literature documents that both over- and under-skilled workers are more mobile than well-matched ones (Sicherman, 1991; Verhaest & Omey, 2006), a result often attributed to skills mismatch (Allen & van der Velden, 2001). Similarly, several empirical studies validate the career mobility theory in the industrialized countries (Sicherman, 1991 for the US; Alba-Ramirez, 1993 for Spain and Robst, 1995 as well as Wasmer et al. 2007 for several EU countries).

Alternative theoretical explanations build on the assumption that education is merely an imperfect measure of skills. As such, skills mismatch might reflect situations where workers with different educational attainment qualify for similar jobs when tenure and on-the-job training substitute for the lack of formal education, resulting in an almost identical level of human capital (Sloane et al. 1999; Groot & Maasen van den Brink, 2000). Nevertheless, the theories accounting for skills mismatch on the basis of different human capital endowments, worker preferences (Gottschalk & Hansen, 2003) or job competition where high-skilled workers replace low-skilled ones (Gautier et al. 2002) have received little empirical attention.

Relative to its theoretical underpinnings, the literature also discusses whether skills mismatch is a cyclical (transitory) or structural phenomenon. In total, the evidence indicates that although the natural rate of skills mismatch is positive (McGowan & Andrews, 2015), it is also relatively persistent (Mavromaras et al. 2012). Based on the career mobility theory, skills mismatch is considered a transitory trend mainly amongst young workers who are more prone to engage in job shopping at the early stages of their careers. Given its cyclical nature, skills mismatch might occur in periods of rapid economic growth when unemployment is low, which constrains the pool of available workers. In contrast, structural phenomena like automation often require skills that are not directly available in the labor market, resulting in skills mismatch until the educational system adjusts (Quintini, 2011). The discussion is particularly relevant to designing appropriate and situation-based policies to match the supply and demand for skills.

Concerning the empirical measures of skills mismatch at the individual level, the literature distinguishes between three approaches: *the subjective, the realized matches (empirical)* and *the job evaluation method* (McGuinness et al. 2018; Leuven & Oosterbeek, 2011). All three methods compare the worker's skill level (approximated by the educational attainment) and the required level of education to perform a job. Their main difference lies in estimating the occupation-specific educational requirements. In the subjective method, the workers determine the necessary qualifications to do the job, which is then compared to each worker's highest educational level. The realized matches approach estimates a job's educational requirements by calculating the mean (Verdugo & Verdugo, 1989; Bauer, 2002) or modal (Kiker, Santos & De Oliveira, 1997) level of education. Finally, in the job evaluation method professional analysts measure the requirements for successful job performance. The advantages and drawbacks of each method determine its appropriateness for various study designs (see McGuinness et al. 2018 and Dolton & Vignoles, 2000 for a detailed discussion).

The current analysis is based on a macro-economic measure of skills mismatch (Section 4.3), which is the most fitting approach to match the employment polarization index and ascertain their combined productivity effects at the regional level. Thus, our comprehensive empirical framework investigates the economic impact of the predominant labor market phenomena across Dutch regions while controlling for confounding factors.

The various skills mismatch measures contribute to the plethora of empirical evidence (see McGuinness et al. 2018; Quintini, 2001 and Groot & Maasen van den Brink, 2000 for comprehensive reviews) confirming its pervasiveness across many industrialized and developing countries. Despite the significant variation across the empirical design, the country and the time, Groot and Maasen van den Brink (2000) systematize the findings from 25 studies and conclude on an overall incidence of over- (under-) qualification equal to 26% (33%). Concerning the Netherlands, van der Velden and van Smoorenburg (1997) find that almost 23% of workers in 1994 report being overqualified. This outcome is higher than Hartog and Oosterbeek (1988), who concluded that in 1974 only 17% of Dutch workers were self-declared as overqualified.

As to the productivity effects of skills mismatch, the empirical literature mainly uncovers negative effects, both on direct (gross value added) and indirect (wages, job satisfaction etc.) measures of productivity. Regarding the former, Kampelmann and Rycx (2012) and Mahy et al. (2015) conclude that over- (under-) education increases (decreases) firm-level productivity in Belgium during the early 2000s. Somewhat differently, Grunau (2016) reports that only under-education decreases productivity in Germany between 2004 and 2010. Similarly, Haskel and Martin (1993) document that skills shortages lower firm-level productivity in the UK during the mid-1980s by 0.7 per cent per annum. Similarly, McGowan and Andrews (2015) find that a higher skills mismatch is associated with lower labor productivity in 19 OECD countries in the 2011-2012 period. Regarding the indirect effects from skills mismatch, a wealth of empirical evidence concludes that over-skilling increases wages while under-skilling entails a wage penalty (McGuinness et al. (2018); Leuven & Oosterbeek, (2011) and Quintini, (2011) for comprehensive reviews).

Additional economic effects from skills mismatch include a negative impact on GDP (Mavromaras et al. 2007), increasing wage inequality (Slonimczyk, 2009; Budria & Egido-Moro, 2008) and unemployment (Jackman et al., 1991; Sneessens, 1995; Manacorda & Petrongolo, 1998; Thissé & Zenou, 2000; Marsden et al. 2002; Skott & Auerbach, 2003). This chapter contributes to the literature investigating the relatively unexplored direct effects of skills mismatch on aggregate labor productivity by enriching the empirical model with employment polarization and performing the analysis at the regional level.

4.3 Data sources

Our analysis combines the highly reliable Dutch Labor Force Survey (Statistics Netherlands) which covers the economically active population between 16 and 64. The labor force survey includes various individual-specific indicators (such as gender, age, occupation, contract type, work location, educational attainment, etc.), allowing us to correct for differences in human capital in constructing our indexes of employment polarization and skills mismatch. Data are consistently available from 1999 till 2011 and standard data cleaning practices (removing incomplete entries and state-sponsored sectors) result in a final database of 719,820 observations. Table 4.1 reports summary statistics for the primary worker and occupational characteristics in our analysis:

Table 4.1 Summary statistics

Variable	Observations	Mean	St. Dev.	Min.	Max.
% Male (53.3%)	383,693				
% Young (47.8%)	343,834				
Age	719,820	38.86	12.30	15	64
Low Skill Occupations (wage)	235,272	17.05	14.10	4.60	368.82
Middle Skill Occupations (wage)	230,702	19.60	13.78	4.61	373.19
High Skill Occupations (wage)	253,842	26.75	17.64	4.63	361.18

Employment information is combined with high-quality administrative data on hourly wages from the Dutch tax authorities. Tax records are available at the job level, resulting in multiple entries per worker. In such cases, we retain the job with the highest wage. In our analysis, we sort occupations according to the *Beroepenindeling ROA-CBS 2014 (BRC)* occupational coding which at the 4-digit level comprises 114 occupations since it features improved occupational coding and job distinction compared to the *International Standardized Classification of Occupations* (ISCO-2008). As we currently lack a consistent international measure of skills reflecting overall job quality, we align with the recent employment polarization literature (Goos & Manning, 2007) and use the start-of-period median hourly wage by occupation as the most meaningful and reliable measure of skill. Based on this, we distinguish between low-skilled jobs (typically including construction, transport and logistics), medium-skilled ones (encompassing social workers and restaurant managers) and high-skilled occupations which incorporate specialized doctors and general managers.

The labor economics literature highlights the importance of an appropriate scale of regional classification, corresponding to the aggregation level where the researched phenomenon is expected to operate with limited spillovers from adjacent areas (Groot, de Groot & Smit, 2014). Therefore, for our time-consistent definition of local labor markets, we rely on the NUTS-3 classification, which separates the Netherlands into 40 local labor markets based on population thresholds and reflecting the national administrative units. NUTS-3 regions are the most extensively used in the regional analyses for European countries since they are considered among labor economics as the most reasonable approximations of local labor markets for economic geographical research (Groot, de Groot & Smit, 2014) and particularly fit our analysis for the following reasons: First, despite being a relatively small territorial unit, they are large enough to cover at least the relatively short-distance commuting to work, which is particularly extensive in the Netherlands. Secondly, the NUTS classification is used by international organizations (such as the OECD) for the harmonized collection of European statistics. Such data allow us to thoroughly capture the local environment and address the impact of confounding factors when estimating the regional employment effects of technology and trade.

4.4 Measurement and preliminary evidence of employment polarization and skills mismatch in the Netherlands

4.4.1 Measuring employment polarization

Due to the lack of a single quantitative measure of employment polarization, our analysis builds on the employment polarization (EP) index proposed by Sparreboom and Tarvid (2016). The index measures the extent of employment polarization at a concrete point in time by comparing the employment changes amongst three occupational skill groups for a given time period, based on the following formula (Eq. 4.1):

$$EP_r = \frac{1}{2} * \left(\overline{\Delta_r l_t} + \overline{\Delta_r h_t}\right) * \left(1 + \left|\overline{\Delta_r h_t} - \overline{\Delta_r l_t}\right|\right) * 100 \tag{4.1}$$

For each region (r) where $|\,.\,|$ denotes the absolute value and the operators $\overline{\Delta_r l_t}$ and $\overline{\Delta_r h_t}$ represent the change in the employment share of low- and high-skilled jobs between the current period (t) and the average value for the earlier r periods. In particular, $\overline{\Delta_r x_t}$ is defined as follows (Eq. 4.2):

$$\overline{\Delta_r x_t} = x_t - \frac{1}{r} * (x_{t-1} + x_{t-2} + \dots + x_{t-r}) \tag{4.2}$$

for each skill-group $x_t \equiv (l_t, h_t)$. We consider the EPI particularly meaningful for two main reasons: First, the sign of the index is determined by the first term of the Eq. 4.1, which is the reverse change of medium-skilled employment. As a result, positive values of the index reflect decreasing employment share of medium-skilled jobs, the first essential condition for polarized employment growth. The second term reflects the sensitivity of the index to the relative employment changes between low- and high-skilled jobs. Specifically, -holding the first term constant- the index increases for larger differences in the change between high- and low-skilled employment. In that respect, the measure is particularly relevant given the asymmetric pattern of polarized employment growth in the Netherlands (Terzidis, van Maarseveen & Ortega-Argiles, 2017).

Based on Eq. 4.1 the EPI varies in the interval [-100, 100]. Since it is composed of employment shares restricted in the [-1, 1] interval, the expression in the first bracket assumes the maximum value of 1. This implies a value of 2 for the second term, which provides the maximum value of 100 for the overall index. Positive index values imply negative employment change for medium-skill jobs, which is the first required condition for polarized employment growth. The main disadvantage of the EPI as proposed by Sparreboom and Tarvid (2016) is that it fails to control for positive employment change in both low- and high-skill jobs, the second essential condition for true polarization. We address this by distinguishing between the following employment patterns, taking into account the employment changes in all occupational groups (Table 4.2). True polarization necessitates positive employment changes in both low- and high-skilled jobs at the expense of medium-skilled ones. Skill-increasing reflects the workers' accession to the occupational skill ladder, while the opposite is true for skill-decreasing trends. Finally, inverse polarization is illustrated by an inverted U-shaped pattern along the occupational skill distribution, comprising growth in medium-skilled jobs accompanied by declining low-and high-skilled employment.

Table 4.2 Employment patterns

Employment pattern	EPI sign	Changes in employment shares
True polarization	+	$\overline{\Delta_r l} > 0$, $\overline{\Delta_r m} < 0$ and $\overline{\Delta_r h} > 0$
Skill-increasing	+	$\overline{\Delta_r l} < 0$, $\overline{\Delta_r m} < 0$ and $\overline{\Delta_r h} > 0$
	-	$\overline{\Delta_r l} < 0$, $\overline{\Delta_r m} > 0$ and $\overline{\Delta_r h} > 0$
Skill-decreasing	+	$\overline{\Delta_r l} > 0$, $\overline{\Delta_r m} < 0$ and $\overline{\Delta_r h} < 0$
	-	$\overline{\Delta_r l} > 0$, $\overline{\Delta_r m} > 0$ and $\overline{\Delta_r h} < 0$
Inverse polarization	-	$\overline{\Delta_r l} < 0$, $\overline{\Delta_r m} > 0$ and $\overline{\Delta_r h} < 0$

Our analysis considers three periods for calculating the EPI. The first exploits the full data span of our dataset by comparing the final (2011) employment shares by skill group with their corresponding averages for the previous 12 years (1999-2010). However, using long periods may involve discrepancies in the employment structures; therefore, we also construct two employment polarization indexes based on 6-year averages for each skill group. The first refers to the 1999-2005 period and the second is based on the years between 2006 and 2011. Finally, to further illuminate the employment patterns, we estimate Eq. 4.1 for each consecutive year, acknowledging the risk that yearly values might be susceptible to business cycle effects (Sparreboom & Tarvid, 2016).

Employment polarization patterns in the Netherlands

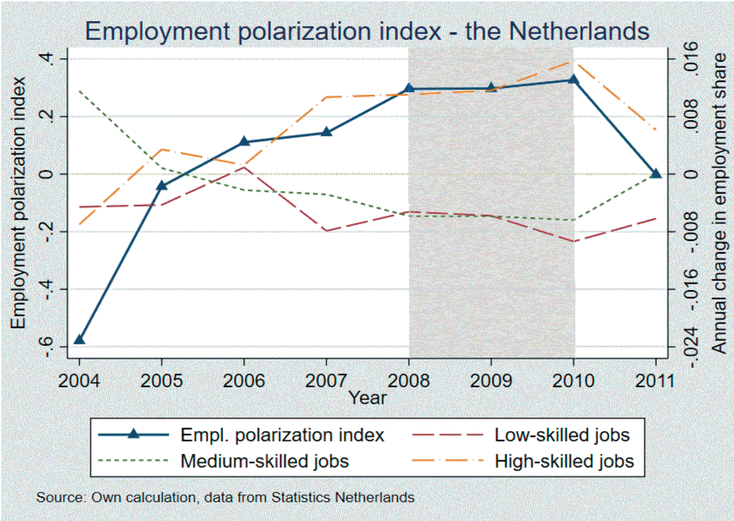
Table 4.3 reports the index values by period for the entire sample of workers. The positive EPI for the entire period of analysis indicates a uniform decrease in medium-skill employment; however, this does not necessarily reflect true polarization. A closer inspection of the employment shares changes by occupational skill group (Columns 2-4) illustrates decreasing low-skilled employment, evidence of upskilling employment patterns.

Table 4.3 Employment polarization index values – vational analysis

	EPI values (1)	% change in employment share Low-skilled jobs (2)	Medium-skilled jobs (3)	High-skilled jobs (4)
Entire period (1999-2011)	0.208	-1.8%	-0.4%	2.2%
First sub-period (1999-2004)	-0.760	-0.6%	1.5%	-0.9%
Second sub-period (2006-2011)	0.476	-1.3%	-0.9%	2.2%

Splitting the analysis into two periods reveals divergent employment dynamics. During the first period (1999 – 2005) employment change in the Netherlands is inversely polarized, as indicated by the negative EPI values. This is further verified by the employment changes across various occupational groups (Columns 2-4), where we document decreasing low- and high-skilled employment shares, while the share of medium-skilled employees is increasing. In contrast, the employment pattern between 2006 and 2011 is similar to the entire period. The positive EPI index translates into a skills-upgrading pattern, where employment gains in high-skilled jobs compensate employment losses in low- and medium-skilled ones.

Figure 4.1 Employment polarization index by year – vational analysis



The analysis so far is based on average values which potentially conceal substantial yearly variation. In the remainder of this section, we discuss the main outcomes from the yearly calculation of the EPI and occupational group employment changes[3]. Figure 4.1 shows that in 2004 and 2005, the EPI was negative and illustrated by the positive change in medium-skilled employment. From 2006 till 2011, the EPI turns positive and assumes its maximum values during the global economic downturn (2008-2010). Nevertheless, positive values of the EPI do not necessarily indicate true polarization. Our more nuanced approach shows that from 2005 till 2011, high-skilled employment is increasing as opposed to negative changes in low- and medium-skilled employment. Taken together, as of 2006, the yearly analysis concludes on a skills-upgrading pattern for the entire labor force. Our sensitivity analysis (Section 4.6) will uncover more subtle employment patterns across various demographic groups.

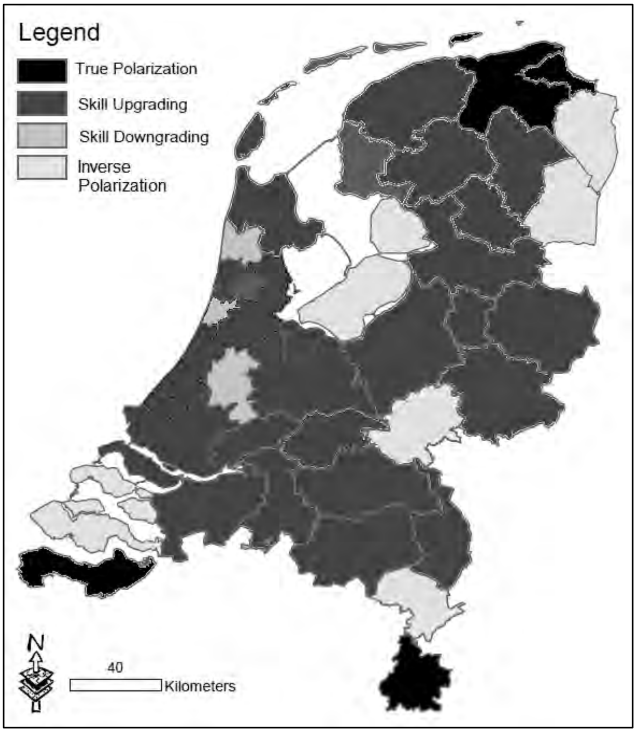
Besides the national-level evidence, we explore regional employment patterns by re-estimating the EPI for each NUTS-3 region, qualifying our conclusions against the employment changes across all occupational skill groups. Table 4.4 reports the frequencies of Dutch local labor markets' employment profiles for all the investigated periods (the detailed regional classifications by period are provided in Figures A1 – A2, Appendix A). The regional

[3] Calculations are performed as follows: The EPI for year 2004 is based on employment changes between 2004 and the average of the period 1999-2003. For each consecutive year, we compare the employment of that year with the average employment in the previous 5 years.

Table 4.4 Regional employment profiles

	No of regions			
	True polarization	**Skill-upgrading**	**Skill-downgrading**	**Inverse polarization**
Entire period (1999-2011)	4	27	3	6
First sub-period (1999-2005)	7	19	5	9
Second sub-period (2006-2011)	5	22	7	6

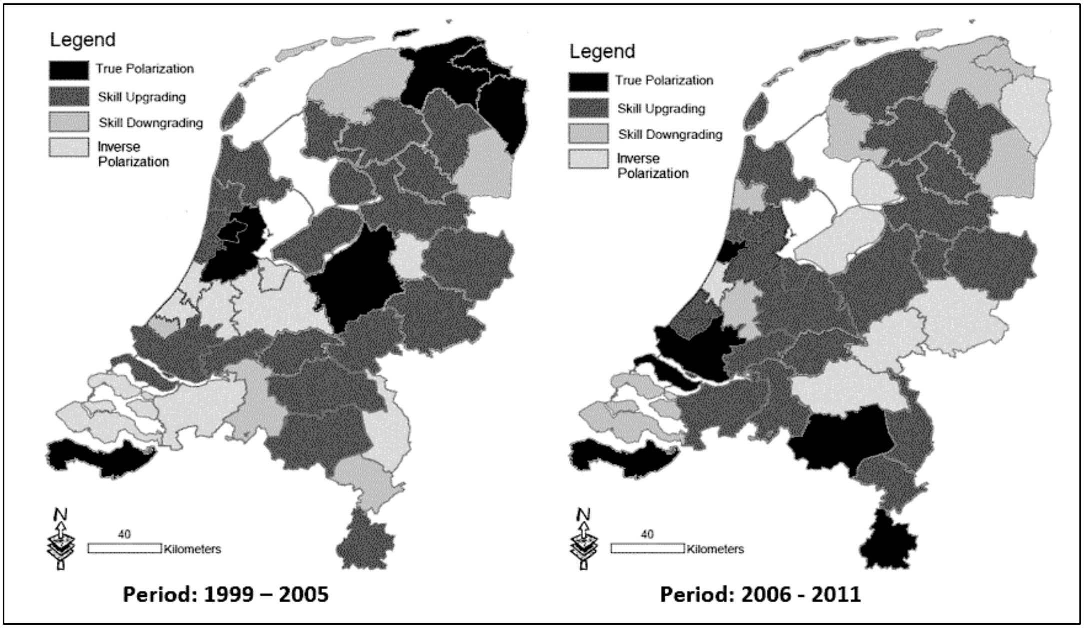
Figure 4.2 Regional employment profiles (1999-2011)



employment profiles are illustrated in Figure 4.2 for the 1999-2011 period, while Figure 4.3 compares the regional employment profiles between the two sub-periods.

Considering the entire period, we document that skills-upgrading is the predominant employment trend in 27 regions, while true polarization is only found in 4 peripheral local labor markets (Delfzijl and surroundings, Overig Groningen, Zeeland Flanders and South Limburg). True polarization and skills-upgrading converge on the increasing share of high-skilled employment. Therefore, the current analysis highlights that regional employment dynamics in the Netherlands between 1999 and 2011 mostly favor high-skilled workers.

Figure 4.3 Regional employment profiles by period



The above pattern seems to be relatively uniform across time. Comparing the two periods, we document that skills upgrading is the main regional employment trend. Together with the regions revealing polarized employment growth, we conclude that employment change in both the two sub-periods favors high-skilled workers. In contrast, skills downgrading and inverse polarization, which reflect negative employment change for high-skilled workers, are represented less frequently across Dutch regions.

Despite the similarities in the frequencies within the employment profiles, Figure 4.3 illustrates considerable within-region variation in the employment trends between the two periods. In particular, we identify two divergent trends. First, local labor markets within or close to the *Randstad* industrial and metropolitan conurbation (such as Utrecht, The Hague Agglomeration) shifted from skills-decreasing trends between 1999 and 2005 to skills-increasing patterns between 2006 and 2011. Together with neighboring regions already favoring high-skilled employment (such as Amsterdam, Rijnmond and Delft and Westland), we safely conclude that more recent employment trends in the Dutch metropolitan regions favor high-skilled workers. In contrast, peripheral regions in the northern part of the country (such as the 3 Groningen regions, SW Friesland, Achterhoek) tend to show decreasing employment shares of high-skilled workers between 2006 and 2011 compared to the first period of our analysis (1999-2005). As a result, the preliminary analysis so far concludes that although skills-upgrading is the main employment trend in Dutch local labor markets, there are substantial disparities between different regions which call for a more nuanced approach to systematize the abovementioned findings.

4.4.2 Measuring skills mismatch

A certain level of skills mismatch, precipitated by labor market frictions and the global economic downturn of 2008-2010 which disrupted the patterns of employment creation and destruction, is omnipresent in the Netherlands. Within this context, skills mismatch has received increased attention, often identified as a major constraint to economic recovery (ILO, 2012). At the macro-level, skills mismatch reflects differences in the supply and the demand for skills, demonstrating the relative inability of the educational system to quickly adjust to the transforming demand for skills due to technology and trade. Data for the Netherlands illustrate a steadily increasing supply of skills across all gender and age groups (Figure B1 - Appendix B). However, it is empirically uncertain whether this increased flow of skilled workers is enough to compensate for the increasing share of high-skilled jobs (from 31% to 35% between 2004 and 2011 – Dutch Labor Force Survey), stimulated by the employment polarization and skills-upgrading trends.

To investigate whether the employment transformation (Section 4.2) might have contributed to increasing skills mismatch when skills are proxied by educational attainment, we estimate the *skills mismatch index (SMI_{rt} – Eq. 4.3)* for the Dutch national and local labor markets, initially introduced by the International Labor Organization (ILO, 2013a).

$$SMI_{rt} = \frac{1}{2}\sum_{i=1}^{3}\left|\frac{E_{it}}{E_t} - \frac{U_{it}}{U_t}\right| \tag{4.3}$$

where $\frac{E_{it}}{E}$ is the proportion of the participants (‘insiders’) in the labor market with educational level i and $\frac{U_{it}}{U}$ is the proportion of the non-participants (‘outsiders’) in the labor market with educational level i for each region r and year t.

The SMI_{rt} is constructed based on the following steps: First, we classify the respondents of the Dutch Labor Force Survey into low-, medium- and high-skilled, based on their educational attainment. Similar to the ISCO occupational-skills classification, low-skilled workers have typically completed primary education and medium-skilled ones have fulfilled secondary education. In contrast, high-skilled ones are matched with tertiary education (Table B1 –

Appendix B reports the detailed correspondence between the educational categories and the workers' skill level). Secondly, we categorize survey respondents into those reporting themselves as *participants (*or *insiders*) and *non-participants* (or *outsiders*) in the labor market. The latter category approximates those only irregularly participating in the labor market as on-calls, substitutes, self-employed, or temporary contracts with non-fixed hours, potentially due to skills obsolescence. Our index primarily reflects that systematic differences in labor market participation by educational level signal that educational attainment is an important determinant of the probability of participating in the labor market. Based on this, the SMI_{rt} becomes particularly relevant for the demographic analysis since it can identify the groups of workers who are most at risk of skills obsolescence.

It is important to emphasize that the skills mismatch index supports a dual interpretation. First, interregional comparisons uncover the local labor markets unable to accommodate their skills base. Thus, it captures the potential inequality of employment opportunities across various educational groups. No mismatch ($SMI_{rt} = 0$) reflects that active participation in the labor market does not depend on the educational skill level, while complete mismatch ($SMI_{rt} = 1$) occurs when all non-participants are sorted into one skills group. Secondly, the yearly fluctuation of the SMI_{rt} by region will determine whether skills mismatch is a structural or cyclical phenomenon which is strongly relevant for policy analysis.

On the downside, the SMI_{rt} only captures the dissimilarities between the insiders and the outsiders in the labor market in terms of educational level; thus, it does not reflect more detailed aspects of skills mismatch as the discrepancies between the skills of the employed and their job requirements. Furthermore, it embodies the typical empirical challenges of skills mismatch indexes at the macroeconomic level including the incomplete measurement of human capital using formal education stemming from the lack of a consistent operationalization of the skills mismatch concept, extensively discussed in the literature (McGuinness et al. 2018; Estevao & Tsounta 2011; Verhaest & Omey 2010).

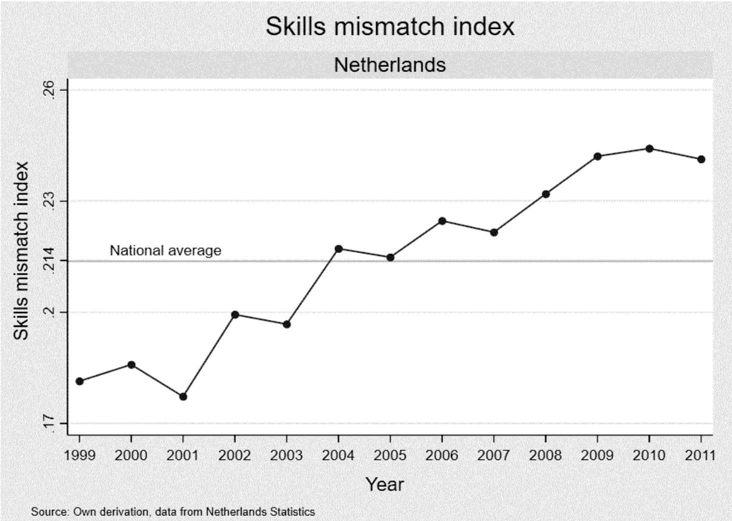
Skills mismatch patterns in the Netherlands

Table 4.5 reports the average values of the skills mismatch for the various periods. The mean value of the SMI_{rt} for the entire period is 0.214, indicating moderate skills mismatch, in line with earlier analyses for the Netherlands (Sparreboom & Tarvid, 2016; McGowan & Andrews, 2015). Comparing earlier and more recent skills mismatch values reveals that between the two periods (1999-2005 and 2006-2011) the skills mismatch index has increased by 20% (from

Table 4.5 Average skill mismatch values - national values

	SM Index
Entire period (1999-2011)	0.214
First sub-period (1999-2004)	0.193
Second sub-period (2006-2011)	0.231

Figure 4.4 Skills mismatch index in the Netherlands



0.193 to 0.231), which contradicts earlier results (ILO, 2013a). Figure 4.4 reports the yearly values of the SMI_{rt} (detailed data in Table B3 – Appendix B) and further illustrates the increasing incidence of skills mismatch in the Netherlands. In particular, the SMI_{rt} follows a robust upward trend with an overall increase of 11% (from 0.217 in 1999 to 0.241 in 2011), assuming its maximum value (0.244) in 2010. The preliminary analysis indicates the increasing incidence of skills mismatch which needs to be addressed in the forthcoming domestic labor market policy agenda.

In what follows, we delve into the regional labor market heterogeneity by reporting the SMI_{rt} values in the first (1999) and the last (2011) years of our analysis for each NUTS-3 region (yearly data are not reported for brevity but available upon request). Average regional skills mismatch between 1999 and 2011 varies from 0.15 (Kop van Noord Holland) to 0.31 (The Hague agglomeration). In line with the descriptive analysis for Finland (Jauhiainen, 2009) we show that skills mismatch assumes its maximum values in large metropolitan regions (such as Greater Amsterdam, Utrecht and The Hague agglomeration) with medium-to-high

Figure 4.5 Skills mismatch index regional analysis – αverage values

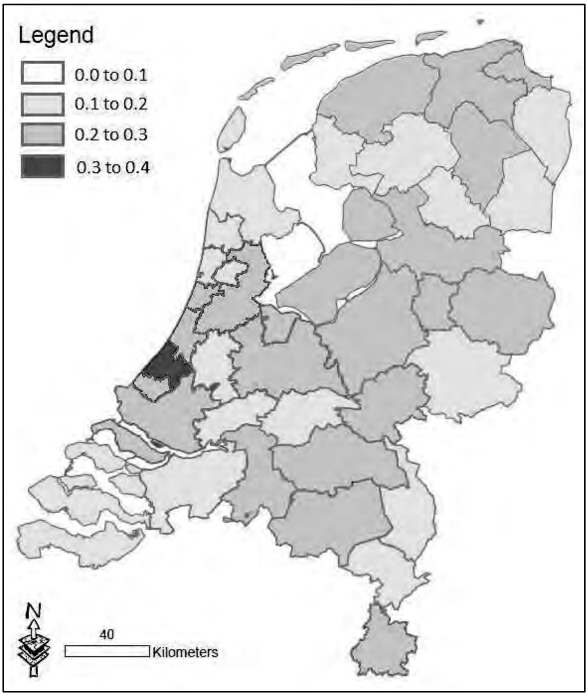
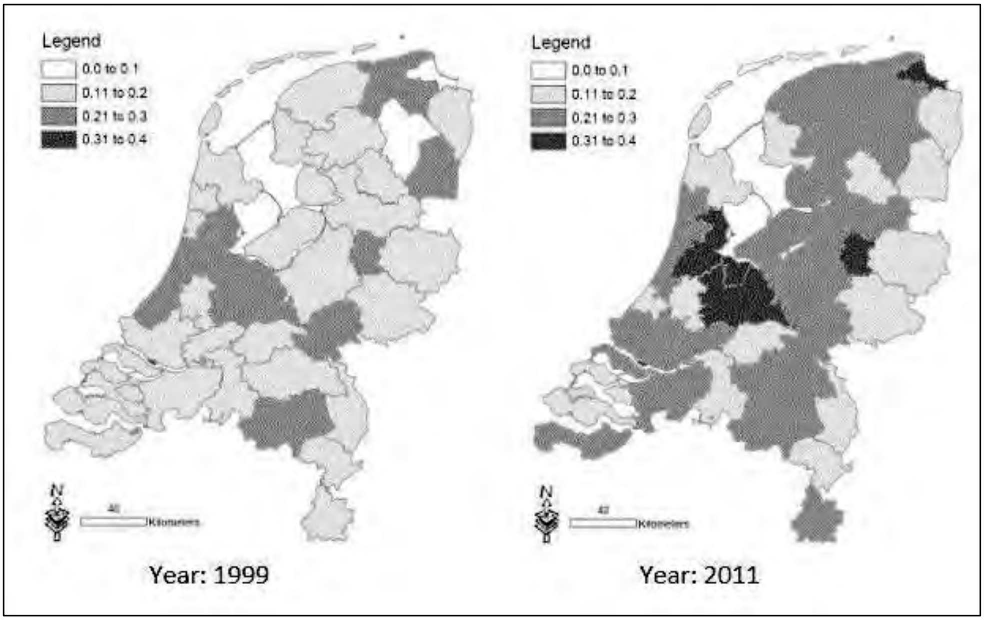


Figure 4.6 Skills mismatch index regional analysis



unemployment levels (OECD Regional Economy data). This reflects that the above regions' substantial unemployment is not uniformly spread across all educational groups and potentially hurts low-skilled workers disproportionately more.

As is often the case, average values conceal considerable yearly variation. To uncover regional trends of skills mismatch, Figure 4.6 compares the regional incidence of skills mismatch between 1999 and 2011. The primary outcome is that the estimated increase in the national level is also reflected in almost all regional labor markets. Despite a few peripheral local labor markets exhibiting decreasing skills mismatch (Southwest Drenthe), regional skills mismatch in the Netherlands is increasing both in central regions (Amsterdam, Utrecht) and in peripheral ones with low initial values (Delfzijl and surroundings, North Drenthe).

It should be emphasized that the skills mismatch index is highly volatile, especially when workers of one category are asymmetrically affected by external demand shocks, such as automation disfavoring low- and medium-skilled workers. Therefore, our analysis so far performs well in highlighting some noteworthy trends; however, it indicates the necessity for a more detailed approach to identify the regional determinants of skills mismatch.

4.4.3 Employment polarization, skills mismatch and productivity

This section reports preliminary evidence on the relationship between employment polarization, skills mismatch and labor productivity, the latter measured by the growth rate of gross value added (GVA) per worker. Figure 4.7 illustrates the EP_r (Eq. 4.1), the SMI_{rt} (Eq. 4.3) and the growth rate of GVA per worker for the Netherlands between 2004 (the first year for which the EPI can be calculated) and 2011.

Preliminary comparisons of the EP_r, the $SMI_{rt}$and labor productivity are mostly inconclusive. Besides the peak of the global economic crisis (2009), the growth rate of labor productivity in the Netherlands is always positive; however, this coincides both with years with negative EP_r values (such as 2004) and the year when the EP_r assumes its' maximum value (2010). As to the relationship between the SMI_{rt} and labor productivity, preliminary evidence is also unclear, mainly due to the relatively low variation in skills mismatch. This is illustrated in Figure 4.7, where we come across years when the SMI_{rt} coincides both with increasing (such as the years between 2004 and 2008) labor productivity and the peak of the global economic crisis where positive SMI_{rt} values are associated with decreasing labor productivity. Therefore, the

Figure 4.7 Employment polarization, skills mismatch and productivity

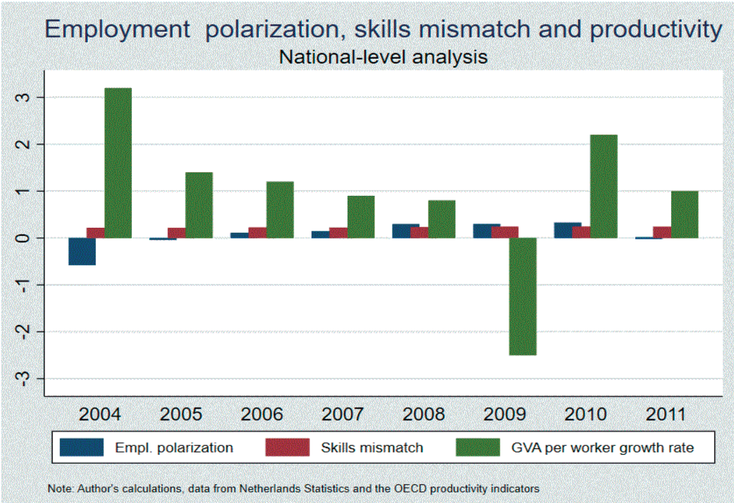


Table 4.6 Correlation matrix

Variables	Employment Polarization Index	Skills Mismatch Index	GVA per worker (growth)
Panel A – National analysis			
Employment Polarization Index	1.000		
Skills mismatch Index	0.623*	1.000	
GVA per worker (growth)	-0.590	-0.179	1.000
Panel B – Regional values			
Employment Polarization Index	1.000		
Skills mismatch Index	0.200*	1.000	
GVA per worker (growth)	-0.059	0.010	1.000

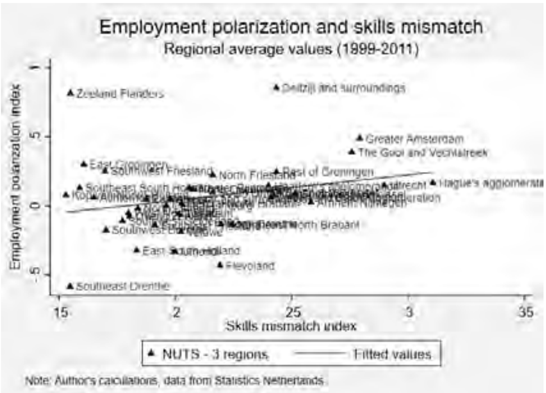
Note: Panel A reports correlations based on N=8 observations (1 region x 8 years) while *Panel B* reports correlations based on N=320 observations (40 regions x 8 years) * shows significance at the 0.1 level,

preliminary correlations between skills mismatch and labor productivity contrast earlier empirical findings (Kampelmann & Rycx, 2012; Mahy et al. 2015; Grunau, 2016) and illustrate that the relationship between skills mismatch and labor productivity is mainly subject to the cyclical nature of the latter.

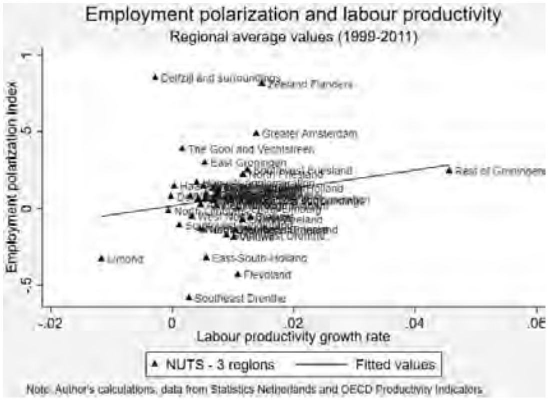
This lack of significant associations is also confirmed in the correlation matrix (Table 4.6) where both national (Panel A) and regional values (Panel B) point to only one significant positive relationship between the employment polarization and the skills mismatch indexes. Interestingly, the growth rate of labor productivity is negative –albeit insignificantly- associated with the EPI at the national and regional level, thus implying potential productivity disruptive effects from polarized employment growth. Finally, the relationship between skills mismatch and labor productivity is very small and insignificant.

Figure 4.8 further elaborates on the above relationships by plotting the average values of the EP_r, the SMI_{rt} and the growth rate of labor productivity for all local labor markets in the Netherlands. Panel A illustrates the positive association between the $EP_r$and SMI_{rt} reported in Table 4.6. In contrast, Panel b indicates that employment polarization is positively associated with regional productivity, as opposed to the correlation matrix, while Panel c verifies the inconclusive evidence regarding the association between skills mismatch and labor productivity. Our preliminary analysis so far points to some general trends which call for more robust evidence provided in our subsequent regression analysis (Section 4.5).

Figure 4.8 Regional relationships between the EPI, the SMI and labor productivity



(a) EP_r and SMI_{rt}



(b) EP_r and labor productivity

(c) SMI_{rt} and labor productivity

4.5 Employment polarization, skills mismatch and regional productivity at the macro-level – main regression analysis.

4.5.1 Empirical strategy

To systematize the relationships between the regional employment polarization, skills mismatch and labor productivity we estimate a system of three equations (Eq. 4.4 to 4.6) where the dependent variables are the yearly-regional values of the employment polarization index (EP_{rt}), the skills mismatch index (SMI_{rt}) and the growth rate of gross value added per worker ($gvapwgr_{rt}$), which is our direct labor productivity measure.

$$\begin{cases} EP_{rt} = \alpha_0 + \alpha_1 SMI_{rt-1} + \alpha_2 gvapwgr_{rt-1} + \alpha_3 x_{rt-1} + d_t + \mu_r + \varepsilon_{rt} & (4.4) \\ SMI_{rt} = \gamma_0 + \gamma_1 EP_{rt-1} + \gamma_2 gvapwgr_{rt-1} + \gamma_3 x_{rt-1} + d_t + \mu_r + \eta_{rt} & (4.5) \\ gvapwgr_{rt} = \lambda_0 + \lambda_1 EPI_{rt-1} + \lambda_2 SMI_{rt-1} + \lambda_3 x_{rt-1} + d_t + \mu_r + \upsilon_{rt} & (4.6) \end{cases}$$

where r stands for each NUTS-3 region and t for each year between 2004 and 2011. The estimated equations also include a set of control variables (x_{rt-1}), appropriately describing the regional socio-economic and demographic conditions (sources and summary statistics are provided in Tables D1 and D2 - Appendix D) while d_t are the year and μ_r the region fixed effects. The error terms ($\varepsilon_{rt}, \eta_{rt}$ and υ_{rt}) are assumed to be serially independent with zero means.

Single equation models are potentially biased since they do not account for the possible relationship between the error terms of the three equations; therefore, we simultaneously estimate the above system of three equations adopting a *conditional mixed process (cmp)* framework (Roodman, 2011). The cmp approach is fundamentally a seemingly unrelated regressions method; nevertheless it offers much broader empirical options. First, it allows for the error terms to be correlated, thus correcting for endogeneity in the modelled equations. Secondly, the estimated equations can have different samples, overlapping or not. As such, the estimations are *conditional* on the data. Finally, cmp allows for truncated dependent variables by equation (*mixed process*) which increases the estimation efficiency and is particularly important for our analysis, since our measures of employment polarization and skills mismatch are calculated within relevant intervals.

4.5.2 Empirical results

Table 4.7 reports the results from estimating the system of equations 4.4 - 4.6 employing *conditional mixed process (cmp)* estimators. According to the χ^2 statistic and the *Bayesian Information Criterion,* the equations system is well-specified, except for Eq. 4.6 which, when individually estimated, fails the F-test of overall significance (individual estimations are not reported for brevity). This might reflect that a different set of independent variables is necessary to predict employment polarization; nevertheless, the system of equations has a strong predictive power. To allow for the economic effects of labor market trends to materialize, we capitalize on our dataset's panel structure and use lagged values of the independent variables by one period.

The estimation results indicate the following: First, Column 1 shows that the employment polarization index is negatively and significantly affected by skills mismatch. The effect is large and equal to 4.8. The same equation indicates a positive relationship between polarized employment growth and labor productivity; the effect is close to 4 and signals that the sorting of workers at the tails of the skill distribution is positively related with the growth rate of labor productivity. Regarding the determinants of skills mismatch, Column 2 reveals that it is positively affected by both the employment polarization index and the growth rate of labor productivity. Regional productivity imposes the largest effect (0.15) while the impact from the employment polarization index is substantially smaller (0.005). Finally, Column 3 fails to identify significant linear relationships from either the skills mismatch or the employment polarization index to labor productivity, indicating the necessity for a more nuanced approach.

In Columns 4-6 we investigate non-linear relationships by including squared terms of the employment polarization, the skills mismatch index and the growth rate of labor productivity when they are used as independent regressors. The specification tests (F-test and the BIC) are relatively improved compared to the linear specifications (Columns 1-3), which validates the quadratic approach.

Besides verifying the negative linear relationship between the employment polarization and skills mismatch indexes indicated in Column 1, Column 4 also uncovers a non-linear (inverted U-shaped) relationship between regional productivity and polarized employment growth. Similarly, Column 5 corroborates the linear and positive relationship between employment polarization and skills mismatch. Furthermore, it points to a non-linear (inverted U-shape)

Table 4.7 Employment polarization, skills mismatch and regional productivity – conditional mixed process estimation results
Dependent variables: EP_{rt} , SMI_{rt} and $gvapwGR_{rt}$
Independent variables: EP_{rt-1}, EP^2_{rt-1}, SMI_{rt-1}, SMI^2_{rt-1}, $gvapwGR_{rt-1}$, $gvapwGR^2_{rt-1}$

	Linear models			Quadratic models		
	EPI_{rt} (1)	**SMI_{rt} (2)**	**$GVApwgr_{rt}$ (3)**	**EP_{rt} (4)**	**SMI_{rt} (5)**	**$GVApwgr_{rt}$ (6)**
SMI_{rt-1}	-4.830** [2.206]		0.002 [0.063]	-11.434* [6.814]		-0.091 [0.178]
SMI^2_{rt-1}				14.186 [17.464]		0.306 [0.441]
EP_{rt-1}		0.005** [0.003]	0.031 [0.062]		0.004** [0.002]	0.003 [0.003]
EP^2_{rt-1}					0.001 [0.001]	0.003 [0.002]
$GVApwgr_{rt-1}$	3.999** [1.991]	0.149* [0.089]		5.478** [1.665]	0.155** [0.079]	
$GVApwgr^2_{rt-1}$				-67.024** [22.567]	-1.378** [0.792]	
constant	-248.98 [175.79]	2.339 [8.118]	2.909 [5.171]	-185.76 [165.01]	3.000 [5.621]	5.861 [3.338]
Control variables	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
Observations	320	320	320	320	320	320
χ^2 - stat (p-value)		$4.98*10^9$***			$1.54*10^{11}$***	
BIC		-1129.54			-1155.18	

Note: Robust st. errors, clustered by region. The detailed specifications include the following control variables (lagged one period): fixed capital formation, population density, dependency ratio (demographic), male to female ratio, labor utilization, total employment and net migration. */**/*** denote significance to the 10% / 5% and 1% level.

relationship between labor productivity and skills mismatch. Finally, similar to the log-linear analysis, Column 6 demonstrates that both employment polarization and skills mismatch are insignificant predictors of labor productivity. The two non-linear relationships uncovered in Columns 4 and 5 reveal that an increase in the growth rate of labor productivity is associated with an increase in the EP_{rt} (Column 4) and the SMI_{rt} (Column 5) at relatively low productivity growth levels; nevertheless, the associations turn negative at high levels of productivity growth rates.

In sum, our regression analysis so far establishes the following: First, higher levels of the EP_{rt} are associated with higher incidence of skills mismatch. This potentially reflects that the restructuring of employment due to the polarization trends might jeopardize the active labor market participation amongst low- or medium-skilled workers disproportionately more, which is captured by our SMI_{rt}. Secondly, we uncovered similar composite relationships between labor productivity on one side and employment polarization and skills mismatch on the other. Finally, our analysis documents that the reverse effects are insignificant. The latter reveals that despite our robust methodology, further analysis is necessary to shed more light into the current findings.

4.6 Sensitivity analysis

In this section, we proceed beyond the average evidence presented so far and investigate how the incidence and the economic effects from employment polarization and skills mismatch vary across demographic characteristics, such as gender and age. Section 4.6.1 repeats the analysis separately for male and female workers, while section 4.6.2 reports the findings from our age-related analysis.

4.6.1 Gender analysis

Gender-specific evidence of employment polarization in the Netherlands

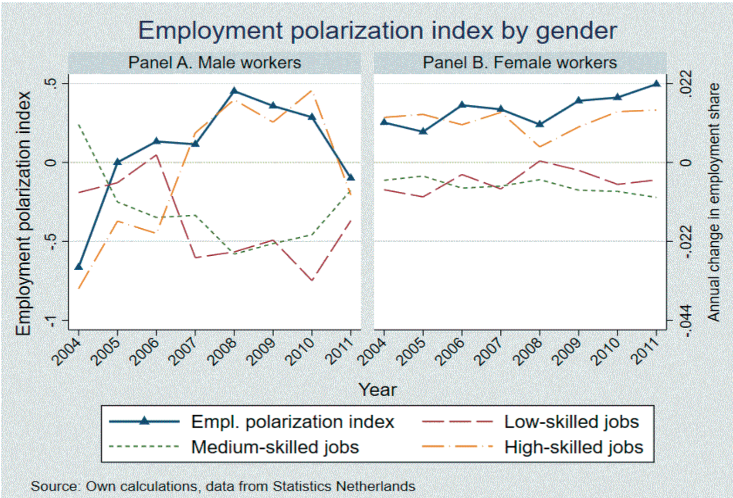
Gender-specific employment patterns are particularly relevant for the Netherlands, where both genders almost equally participate in the labor market. Table 4.8 contrasts the various EP_r values for multiple time periods between male and female workers. Regarding the entire period (1999-2011), the EP_r is substantially larger for women (1.202) compared to men (0.169). Nevertheless, the positive index values should not be interpreted as true polarization; instead, they both reveal skill upgrading patterns. For men, we indicate that the share of high- and medium-skilled jobs increase, at the expense of low-skilled ones. Similarly, female high-skilled employment increases as opposed to negative changes in the employment shares of medium- and low-skilled jobs. The greater asymmetry in the employment changes between high- and low-skilled jobs (in absolute values) accounts for female workers' larger EP_r value.

The economic expansion period (1999-2005) uncovers different employment dynamics by gender. As indicated by the negative EP_r value (-0.822) male employment follows a skills-downgrading pattern where the increasing shares of low- and medium-skilled jobs compensate for the decrease in high-skilled employment. In contrast, female employment transformation in the same period favors high-skilled workers. The positive EP_r value (0.282) reflects a skills upgrading pattern that comprises increasing high-skilled employment as opposed to negative changes in low- and medium-skilled jobs. During the 2006-2011 period, employment restructuring is relatively similar across the two genders. The positive indexes (0.431 for men

Table 4.8 Employment polarization index values – national analysis

	EP_r values (1)	% change in employment share Low-skilled jobs (2)	Medium-skilled jobs (3)	High-skilled jobs (4)
Panel A – Male workers				
Entire period (1999-2011)	0.169	-1.2%	0.3%	1.5%
First sub-period (1999-2005)	-0.822	0.2%	1.6%	-1.8%
Second sub-period (2006-2011)	0.431	-1.8%	-0.8%	2.6%
Panel B – Female workers				
Entire period (1999-2011)	1.202	-1.5%	-2.3%	3.8%
First sub-period (1999-2005)	0.282	-0.9%	-0.5%	1.4%
Second sub-period (2006-2011)	0.618	-0.8%	-1.2%	2.0%

Figure 4.9 Employment polarization index by gender and year



and 0.618 for women) reveal skill upgrading patterns where male and female workers are displaced from low- and medium-skilled jobs and sort into high-skilled ones.

However, illustrating the EP_r yearly values by gender (Figure 4.9) reveals substantial differences between the two genders. Panel A illustrates both negative (2004 and 2011) and positive (from 2005 till 2010) values of the EP_r for men. The different signs reflect divergent employment trends, varying from inverse polarization (2004) to skills upgrading (from 2007 till 2010). Considering female workers (Panel B), the yearly patterns are more uniform. In particular, the –always- positive EP_r is associated with skills upgrading employment transformation, where each year female workers shift out of low- and medium-skilled jobs and sort into high-skilled ones.

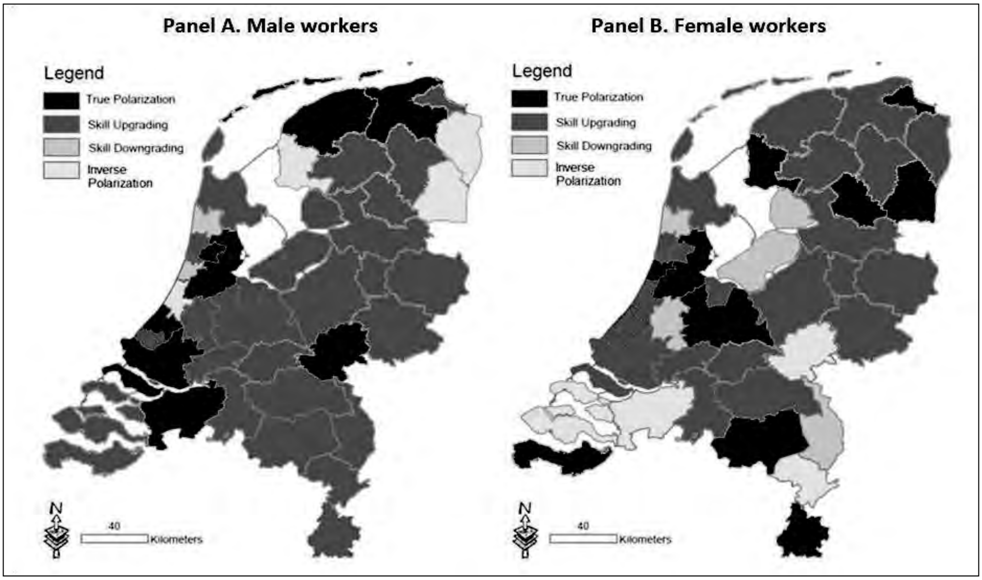
Table 4.9 reports the regional employment patterns separated by period and gender. Several outcomes stand out based on the reported frequencies: First, both genders principally follow a skills upgrading employment change pattern between 1999 and 2011. Together with the substantial representation of true polarization dynamics (10 regions in the case of men and 8 for women), the evidence so far indicates that regional employment growth in the Netherlands between 1999 and 2011 favors high-skilled male and female workers. As illustrated in Figure 4.10, both genders' employment growth is polarizing in regions with contrasting geographical and economic characteristics. In that, male employment (Panel A) is polarizing in central metropolitan regions (such as Amsterdam or Rijnmond) and peripheral ones such as North Friesland. Similarly, true polarization for female workers (Panel B) is evident in the central regions of Amsterdam or Utrecht and more peripheral ones like Delfzijl or Southwest Friesland.

Table 4.9 Regional employment profiles by gender

	Number of regions			
	True polarization	**Skills-upgrading**	**Skills-downgrading**	**Inverse polarization**
Panel A – Male workers				
Entire period (1999-2011)	10	22	4	4
First sub-period (1999-2005)	2	13	16	9
Second sub-period (2006-2011)	8	26	4	2
Panel B – Female workers				
Entire period (1999-2011)	8	26	2	4
First sub-period (1999-2005)	11	22	6	1
Second sub-period (2006-2011)	10	17	8	5

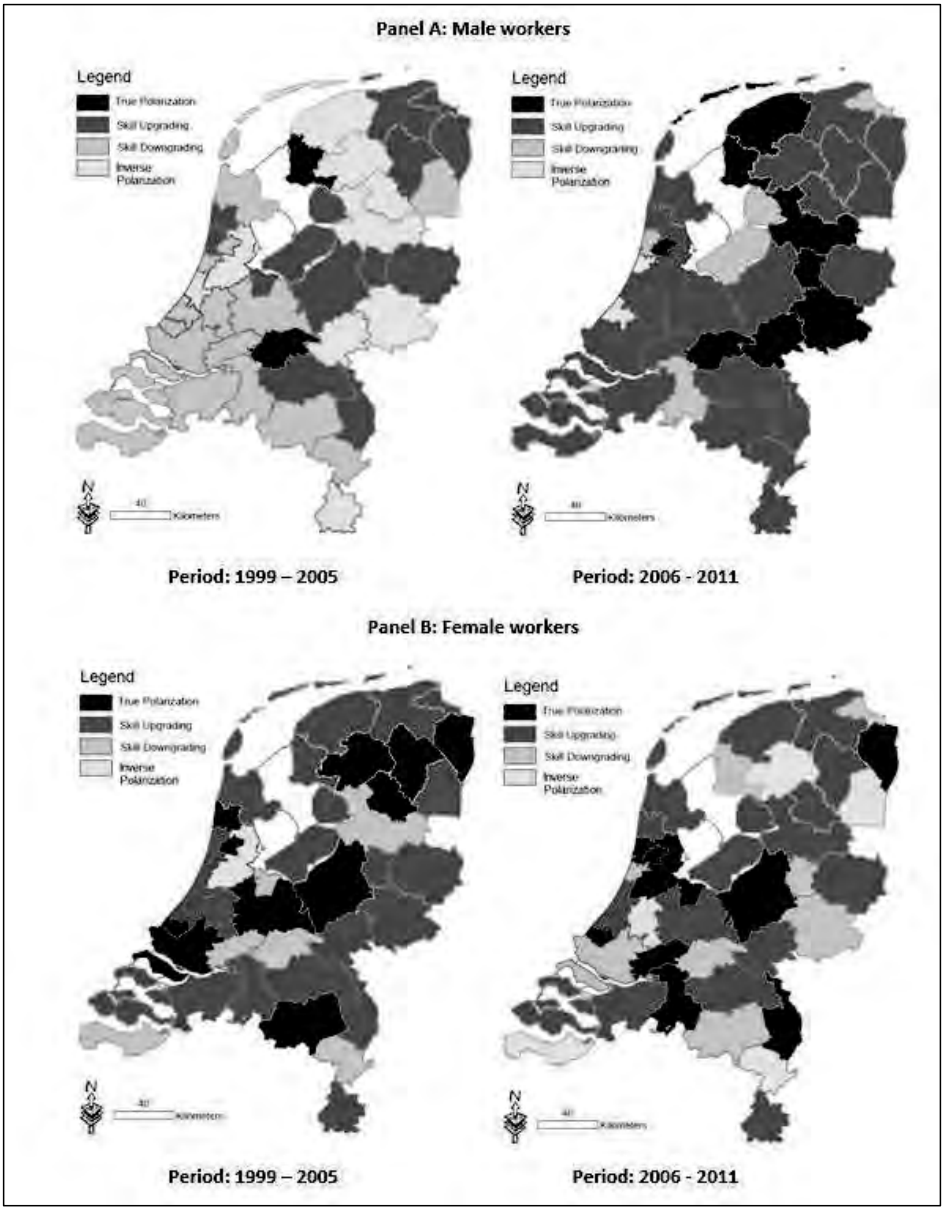
Regarding the years of economic expansion (1999-2005) the evidence is somewhat differentiated. The central premise is that regional employment polarization between 1999 and 2005 is a female workers' phenomenon since it is the prevailing trend in 11 local labor markets instead of only 2 in the case of male workers. Along similar lines, female employment mostly features a skills upgrading pattern (22 regions) while skills downgrading (6 regions) or inverse polarization (1 region) are much less represented. In contrast, male employment in the same period is relatively more balanced between skills upgrading (13 regions) and skills downgrading (16 regions). Given that the nine inversely polarized local labor markets also reflect decreasing high-skilled employment, we conclude that male employment transformation between 1999 and 2005 disfavors high-skilled workers.

Figure 4.10 Regional employment profiles by gender (1999-2011)



The above discussion is also verified in Figure 4.11. Vertical comparison of the maps in the first column indicates the greater pervasiveness of polarizing employment growth for women (Panel B) in the 1999-2005 period. However, the above simple illustration offers no conclusive evidence as to the regional characteristics that favor employment polarization, as polarizing regions are spread in the entire country and vary from central, metropolitan ones (such as Rijnmond or Utrecht) to more peripheral and less populated ones (such as East Groningen or North Drenthe). In contrast, regional employment restructuring for the same period regarding male workers (Panel A) is either inversely polarized or skills downgrading. The common element between the two trends is decreasing high-skilled employment, which clearly illustrates that regional employment changes between 1999 and 2005 mostly favor low- or medium-skilled male workers.

Figure 4.11 Regional employment profiles by period and gender



Gender-specific employment patterns between 2006 and 2011 are relatively similar. Table 4.9 shows that employment growth is polarizing in many local labor markets for men (8 in total) and women (10 in total). Once again, comparing the maps in the right column of Figure 4.11 we uncover substantial dispersion of the polarized regions which prevents solid insight regarding the regional determinants of employment polarization. Nevertheless, skills upgrading is the single predominant trend, although it is relatively more evident for men (26 regions) than women (17 regions). The above two findings highlight a consistent trend across genders; namely, regional employment changes in the Netherlands between 2006 and 2011 mostly favor high-skilled workers.

Horizontal comparison of the two panels in Figure 4.11 uncovers gender-specific regional employment dynamics. The main difference lies in Panel A where we show that male employment restructuring in the first period (1999-2005) benefits low-skilled workers as opposed to the second period where –despite the increase in regional employment polarization- employment change is mainly biased towards high-skilled workers. In contrast, employment patterns are more uniform in female workers; Panel B reveals that high-skill biased regional employment transformation is the main trend in both periods of analysis. Interestingly, our preliminary analysis reveals substantial regional disparities in the employment profiles between the two periods. Notably, Amsterdams' female employment growth is polarizing between 1999 and 2005 while it follows a pattern of inverse polarization between 2006 and 2011. The reverse is true for Southeast Friesland. Only a small number of regions (Overig Groningen, Zaanstreek, Achterhoek) follow consistent true polarization patterns across both periods. Since the regions where employment growth is polarizing exhibit different socio-economic characteristics, a more nuanced approach to uncover the determinants of employment polarization is necessary; however, this is beyond the scope of the current analysis.

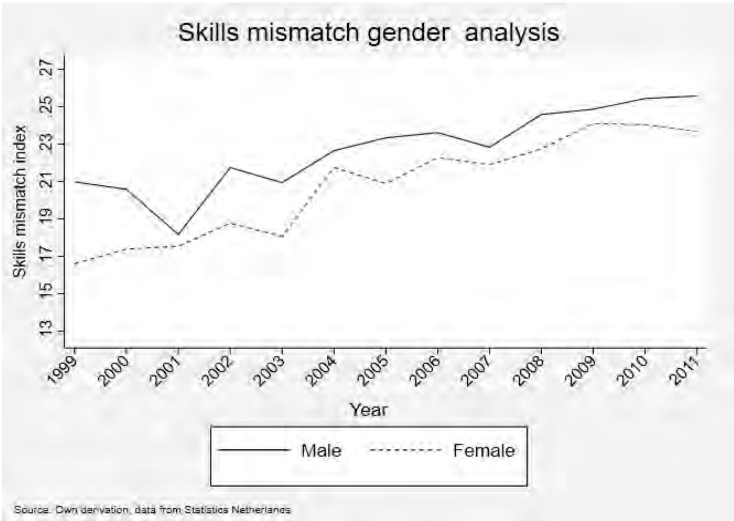
Gender-specific evidence of skills mismatch in the Netherlands

This section contributes to the open debate regarding the gender-specific incidence of skills mismatch. The theoretical discussion predicts different outcomes. On the one hand, job search spatial models often conclude that the misalignment between the workers' skills and the job requirements is more frequent amongst women who are considered to be 'tied-movers' or 'tied-stayers' to the job search of their spouses (Quintini, 2011). Additional family constraints such as child-rearing might increase skills mismatch for female workers. Such spatial models of job search are expected to be less valid for the Netherlands where each household typically consists of two relatively equal wage earners. Therefore, we do not expect radical differences in the incidence of skills mismatch across genders, as predicted by the 'dual job search' argument (Leuven & Oosterbeek, 2011).

Table 4.10 Regional sill mismatch indexes by gender

	SM Index (Men)	SM Index (Women)
Entire period (1999-2011)	0.227	0.207
First sub-period (1999-2005)	0.212	0.187
Second sub-period (2006-2011)	0.245	0.231

Figure 4.12 Skills mismatch index – gender analysis



Within the above context, the gender-specific incidence of skills mismatch is mostly considered an empirical issue depending on the applied measures and the country or period of analysis. Given those shortcomings, Groot and Maasen van den Brink (2000) systematize 50 estimates of over-education and 36 estimates of under-education and conclude that over- (under-) education is more (less) frequent amongst female workers. In contrast, Leuven and Oosterbeek (2011) bring together evidence from 42 studies since the 1970s and report no systematic differences in the incidence of skills mismatch by gender.

Table 4.10 reports the average yearly values of the skills mismatch index for the Netherlands by gender and period of analysis. The main outcome is that skills mismatch is more frequent amongst male workers both in the entire period of analysis (1999-2011) and in each of the two subperiods. Given the macro-economic nature of our skills mismatch index, this finding reflects that female labor market 'outsiders' in the Netherlands are more unevenly distributed across the various educational groups.

The yearly analysis (Figure 4.12 - detailed data are reported in Table D1 - Appendix D) reveals that skills mismatch between 1999 and 2011 increases for both genders; albeit the increase is more pronounced for women (24% compared to 17% for men). Splitting between the two periods (1999-2005 and 2006-2011) further indicates the convergence in skills mismatch between men and women. Although we consistently trace higher incidence of skills mismatch for men, the difference is smaller in the second sub-period than the earlier years of our analysis.

Figure 4.13 illustrates the regional average values of the SMI be gender. Simply comparing the two panels reveals greater variation in the SMI values for male workers. Specifically, Panel A uncovers higher incidence of skills mismatch in male employment in 5 local labor markets (The Hague Agglomeration, Delft and Westland, Gooi and Vechstreek, Utrecht and Delfzijl and surroundings). Except for the last region, all the rest are central labor markets in the Randstad industrial and metropolitan area. In contrast, female labor employment exhibits a more balanced regional distribution of skills mismatch, with high index values in central regions (Amsterdam, Utrecht) and more peripheral ones (North Friesland, North Drenthe). As such, more robust analysis is necessary to uncover the determinants of skills mismatch at the regional level.

Figure 4.13 Skills mismatch index. Regional gender analysis

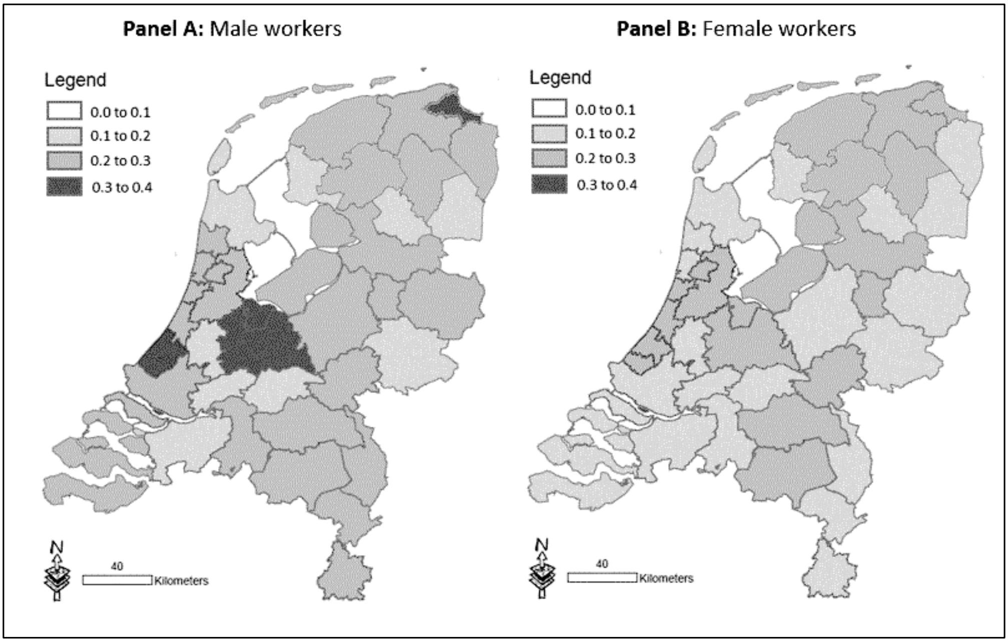
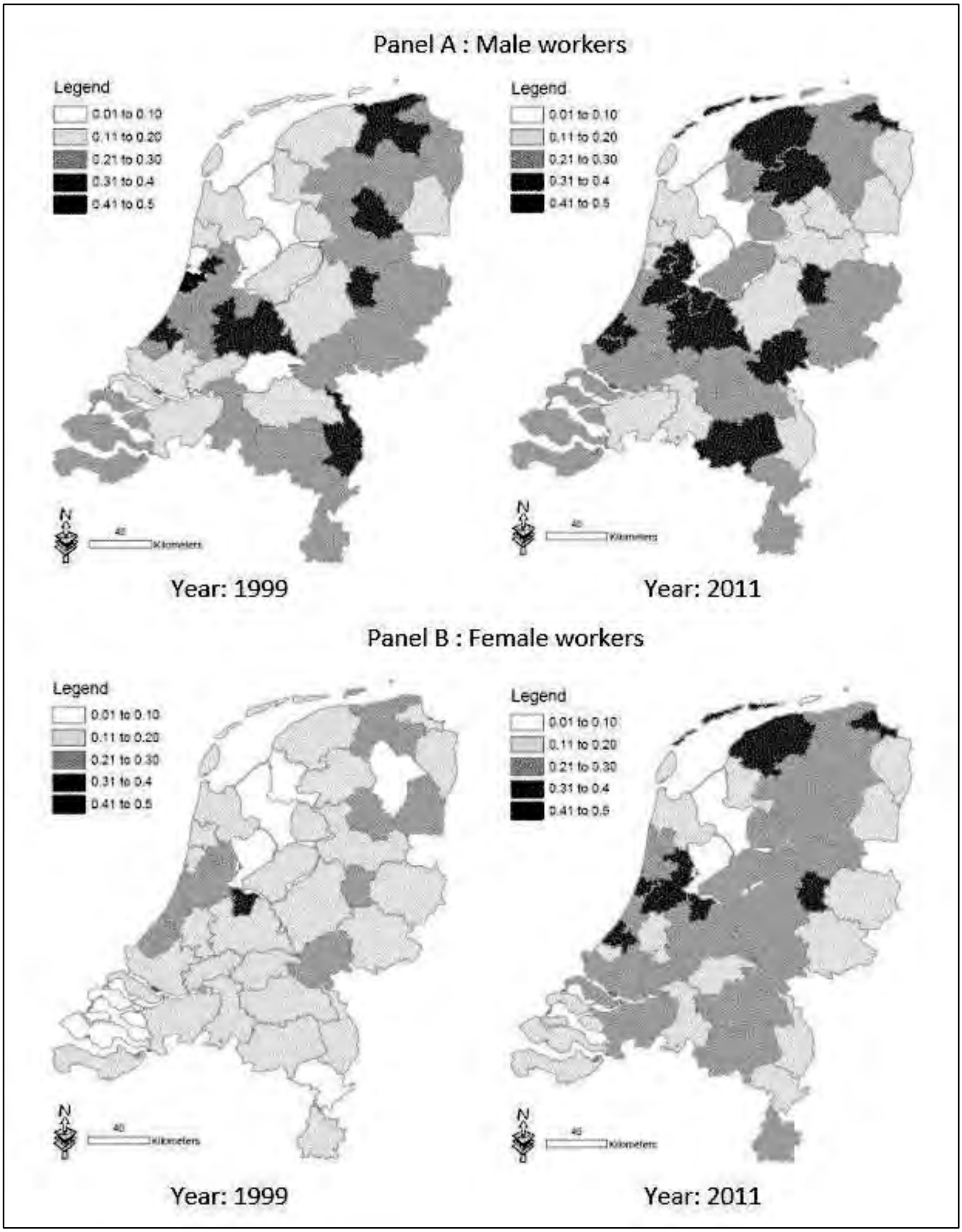


Figure 4.14 Skills mismatch index. Regional gender analysis



Nevertheless, an average analysis conceals significant yearly variation. To uncover the regional trends regarding the incidence of skills mismatch, Figure 4.14 illustrates the regional, gender-specific distributions of the skills mismatch index for the first (1999) and the last (2011) years of the analysis. Comparing panels A (for men) and B (for women), we first indicate that the higher national values of skills mismatch for male workers are also represented in most local labor markets. This result holds both for central regions (Utrecht) and ones in the periphery (Overig Groningen). Nevertheless, we also come across a few exceptions where skills mismatch is higher for women, such as Gooi and Vechstreek in 1999 and Delft and Westland in 2011. Unfortunately, the current analysis offers little insight as to the regional labor market conditions that contribute to a higher incidence of skills mismatch, since the regions with increased skills mismatch index are spread in the entire country and vary from central, urbanized ones (Amsterdam or The Hague Agglomeration) to more peripheral local labor markets (Arnhem-Nijmegen or North Friesland).

Secondly, the increasing trends in the incidence of national-level skills mismatch (Table 4.10) are also reflected in the regional results. Horizontal comparison reveals that between 1999 and 2011, the skills mismatch index increases in most local labor markets for both genders (prominent examples include Amsterdam and North Friesland). However, this trend is not uniform, since we also come across a small number of local labor markets with decreasing incidence of skills mismatch (such as Southwest Drenthe for men and Southeast Drenthe for women). The current analysis verifies both the higher incidence of skills mismatch for male workers in the Netherlands and its increasing trend in the majority of the local labor markets for both genders. However, a more detailed approach is bound to reveal the labor market characteristics which shape the regional incidence of skills mismatch at the local level.

The relationship between employment polarization, skills mismatch and labor productivity—gender-specific evidence.

This section systematizes the gender-specific relationships between employment polarization, skills mismatch, and labor productivity by estimating the system of equations 4.4-4.6 using a conditional mixed process estimator separately by gender. Table 4.11 reports the estimation results (Panel A for men and panel B for women). Like the primary analysis (Section 4.5), the equations system is well-specified and has significant predictive power.

Concerning male workers (Panel A), four main outcomes stand out: First, Column 2 uncovers a positive and significant linear relationship between the employment polarization and skills mismatch indexes. The effect magnitude is similar to the one in the main analysis (Table 4.7) and equal to 0.004. Secondly, the same regression indicates a significantly positive relationship between labor productivity and skills mismatch. The estimated term indicates an effect equal

Table 4.11 Employment polarization, skills mismatch and regional productivity by gender group – conditional mixed process estimation results
Dependent variables: EP_{rt} , SMI_{rt} and $gvapwGR_{rt}$
Independent variables: EP_{rt-1}, EP^2_{rt-1}, SMI_{rt-1}, SMI^2_{rt-1}, $gvapwGR_{rt-1}$, $gvapwGR^2_{rt-1}$

	Linear models			**Quadratic models**		
	EP$_{rt}$ (1)	**SMI$_{rt}$ (2)**	**GVApwgr$_{rt}$ (3)**	**EP$_{rt}$ (4)**	**SMI$_{rt}$ (5)**	**GVApwgr$_{rt}$ (6)**
Panel A – Male workers						
SMI_{rt-1}	0.805 [1.720]		-0.003 [0.002]	4.030 [6.897]		0.062 [0.169]
SMI^2_{rt-1}				-7.499 [13.025]		-0.135 [0.324]
EP_{rt-1}		0.004** [0.002]	0.002 [0.002]		0.005** [0.002]	0.002 [0.002]
EP^2_{rt-1}					-0.0003 [0.0007]	-0.136 [0.324]
$GVApwgr_{rt-1}$	1.307 [2.339]	0.231** [0.095]		2.087 [2.766]	0.264** [0.122]	
$GVApwgr^2_{rt-1}$				-41.307** [27.507]	-1.618** [0.765]	
constant	-208.49 [187.68]	9.543 [10.569]	3.777 [2.931]	-189.06 [190.39]	11.908 [10.659]	4.299 [3.031]
Control variables	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
Observations	320	320	320	320	320	320
χ^2 - stat (p-value)		9.38*10^8***			7.05*10^8***	
BIC		-744.94			-738.21	
Panel B – Female workers						
SMI_{rt-1}	0.793 [1.845]		0.004 [0.031]	-2.446 [7.653]		0.002 [0.163]
SMI^2_{rt-1}				7.219 [17.907]		0.003 [0.381]
EP_{rt-1}		0.003 [0.002]	-0.001 [0.001]		0.003 [0.003]	-0.001 [0.001]
EP^2_{rt-1}					-0.0050 [0.001]	0.0003 [0.0007]
$GVApwgr_{rt-1}$	-1.010 [3.156]	0.095 [0.091]		-0.700 [3.498]	0.138 [0.091]	
$GVApwgr^2_{rt-1}$				-18.380 [27.916]	-2.017** [0.323]	
constant	125.70 [208.91]	2.475 [7.011]	1.983 [3.413]	-143.96 [198.21]	4.654 [7.256]	1.767 [3.516]
Control variables	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes

Region fixed effects	yes	yes	yes	yes	yes	yes
Observations	320	320	320	320	320	320
χ^2 - stat (p-value)		$4.92*10^9$***			629664.06***	
BIC		-858.29			-857.68	

Note: Robust st. errors, clustered by region. The detailed specifications include the following control variables (lagged one period): fixed capital formation, population density, dependency ratio (demographic), male to female ratio, labor utilization, total employment and net migration. */**/*** denote significance to the 10% / 5% and 1% level.

to 0.23. The respective quadratic model (Column 5) further clarifies the above relationships. Besides verifying the linear relationship between employment polarization and skills mismatch, we also document an inverted-U relationship between skills mismatch and labor productivity growth. As such, skills mismatch amongst male workers is positively associated with labor productivity at low levels of productivity growth while the relationship turns negative for high levels of the regional labor productivity growth rate.

Interestingly, the significant squared productivity term in Column 4 implies a non-linear, downward-sloping relationship between regional labor productivity growth and male employment polarization. If causally interpreted, this outcome indicates that employment polarization is a decreasing function of labor productivity growth; however, at an increasing rate. Similarly, as the growth rate of labor productivity increases, the negative effects on our employment polarization index increase as well.

Regarding female workers (Panel B), our analysis concludes only on a significant non-linear, downward-sloping relationship between the growth rate of labor productivity and the skills mismatch index (Column 5). In particular, we show that our skills mismatch index for female workers decreases as the growth rate of labor productivity increases, with the effect becoming larger for higher values of the labor productivity growth rate.

The current analysis uncovers gender-specific evidence on the relationships connecting employment polarization, skills mismatch and labor productivity. First, we show that the primary analysis results (Table 4.7) are mainly replicated for male workers since our female workers' analysis yields mostly inconclusive evidence. Secondly, we advance the debate on the economic determinants of skills mismatch by concluding on a non-linear (inverted-U shaped) relationship between the growth rate of labor productivity and skills mismatch amongst male workers in the Netherlands.

4.6.2 Age-related analysis

Age-specific evidence of employment polarization in the Netherlands

The age-related analysis of national employment patterns (Table 4.12) reveals important differences between young and senior workers. In the 1999-2011 period, the employment polarization index is positive for both young (1.894) and senior (0.026) workers. Considering also the employment change by occupational group, we conclude on a uniform skills upgrading pattern with growing high-skilled employment at the expense of low- and medium-skilled jobs. The greater asymmetry in the employment change between high- and low-skilled jobs for young workers accounts for the larger value of the employment polarization index.

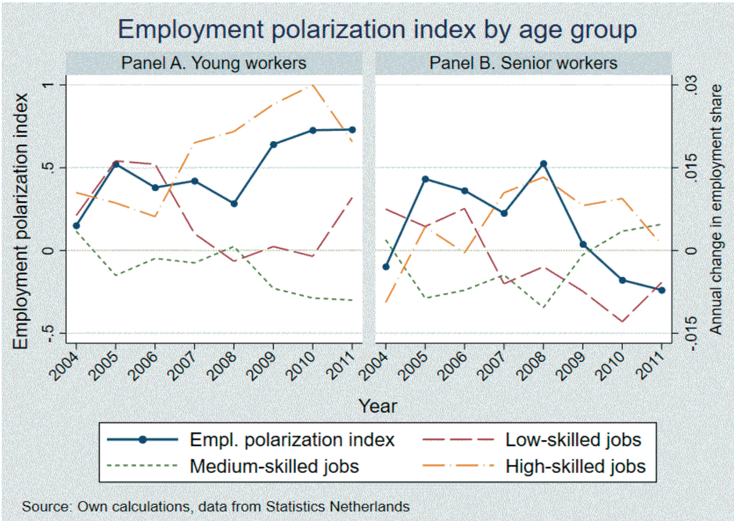
The economic expansion (1999-2005) is characterized by substantial differences in the employment trends between young and senior workers. In particular, young workers sort out of low- and medium-skilled jobs and into high-skilled ones. The resulting skills upgrading pattern is also reflected by the positive employment polarization index (0.422). In contrast, senior workers during the same period sort out of high-skilled jobs and into low- and medium-skilled ones. The above changes comprise a skills downgrading employment pattern, as indicated by the negative employment polarization index (-0.211). Skills upgrading is the predominant employment trend for both age groups between 2006 and 2011. Nevertheless, the trends are not entirely uniform, since medium-skilled employment decreases for young workers, while it increases for senior ones. As a result, the employment polarization index between 2006 and 2011 is positive (negative) for young (senior) workers.

Despite the relative prevalence of skills upgrading employment trends, the yearly comparison (Figure 4.15) reveals a significant difference. In particular, medium (high-)skilled employment always decreases (increasing) for young workers, resulting in positive employment polarization index values. In contrast, the yearly employment changes by skill group are less uniform for senior workers, which results in both positive (2006-2009) and negative (2010-2011) values of the employment polarization index.

Table 4.12 Employment polarization index values – age analysis

	EPI values (1)	% change in employment share Low-skilled jobs (2)	Medium-skilled jobs (3)	High-skilled jobs (4)
Panel A – Young workers				
Entire period (1999-2011)	1.894	-0.04%	-3.5%	3.5%
First sub-period (1999-2004)	0.422	-0.1%	-0.4%	0.5%
Second sub-period (2006-2010)	0.998	-1.1%	-1.9%	3.0%
Panel B – Senior workers				
Entire period (1999-2011)	0.026	-1.2%	-0..05%	1.25%
First sub-period (1999-2004)	-0.211	0.9%	0.4%	-1.3%
Second sub-period (2006-2010)	-0.189	-1.7%	0.4%	1.3%

Figure 4.15 Employment polarization index by age and year



The regional employment profiles by age group (Table 4.13) reveals strikingly different employment trends between young and senior workers in the Netherlands. Between 1999 and 2011, we indicate polarizing employment growth amongst young employees in most local labor markets (21 in total). Together with the 17 regions with skill-increasing employment pattern, regional employment change amongst young workers in the Netherlands is strongly high-skill-favoring. For the same period, employment patterns amongst senior workers are more balanced. Skills upgrading is still the main trend; however, employment growth in 11 regions dis-favors high-skilled workers while employment restructuring in 8 local labor markets is inversely polarized. Finally, employment polarization is evident only in 4 regions.

Table 4.13 Regional employment profiles by age group

	No of regions			
	True polarization	**Skill-upgrading**	**Skill-downgrading**	**Inverse polarization**
Panel A – Young workers				
Entire period (1999-2011)	21	17	2	0
First sub-period (1999-2005)	10	16	10	4
Second sub-period (2006-2011)	11	21	6	2
Panel B – Senior workers				
Entire period (1999-2011)	4	17	11	8
First sub-period (1999-2005)	7	8	23	2
Second sub-period (2006-2011)	1	22	9	8

Figure 4.16 Regional employment profiles by age group (1999-2011)

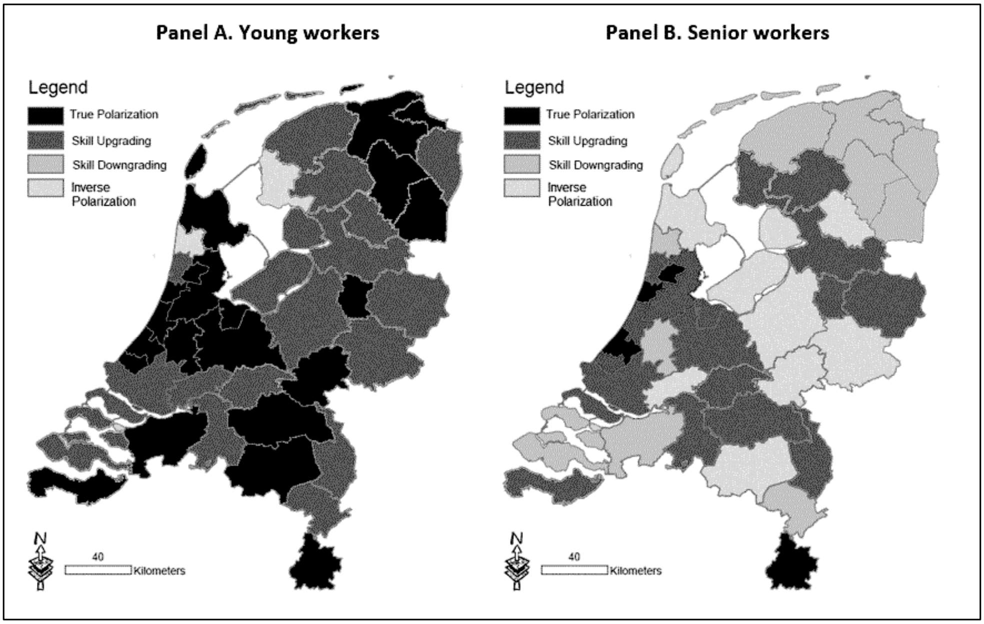


Figure 4.16 further verifies the pervasiveness of regional employment polarization amongst young workers. A closer inspection of Panel A reveals that employment is polarizing in local labor markets with different characteristics, such as the metropolitan regions of Amsterdam or Utrecht as opposed to the rural region of Zeeland Flanders. Concerning senior workers, Panel B illustrates the more balanced distribution of regional employment patterns where employment restructuring in some regions favors high-skilled workers, while in many others, it favors low-skilled ones.

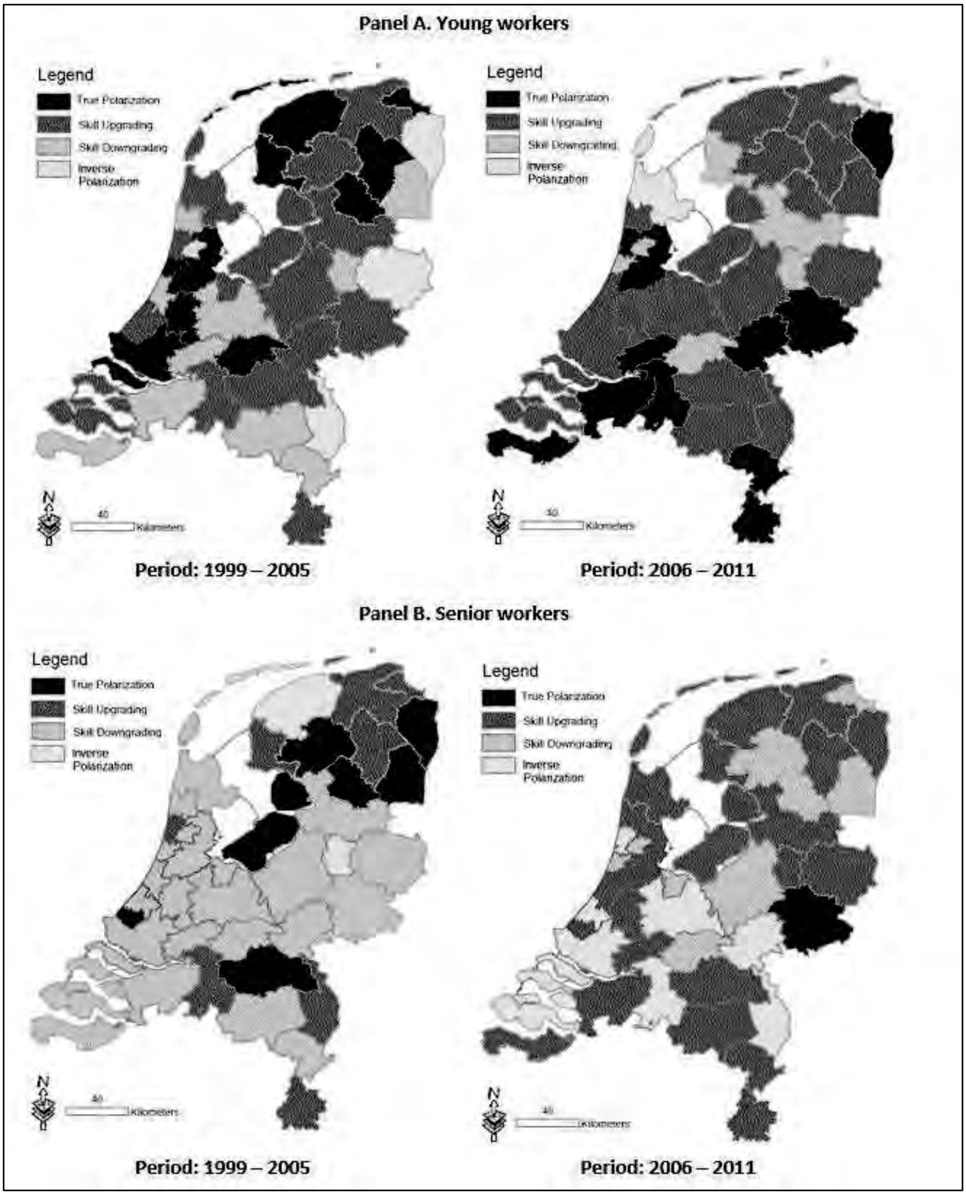
In the early years of our analysis (1999-2005) we indicate remarkable differences in the regional employment patterns between the two age groups. Employment growth concerning young workers is relatively balanced. First, we identify 10 regions where employment growth is polarizing and 16 more with skill upgrading employment patters. The findings indicate that young workers in Dutch regions between 1999 and 2005 are more likely to sort into high-skilled jobs. Nevertheless, this is not entirely uniform, since we also uncover a substantial number of local labor markets where employment restructuring follows either a skills downgrading pattern (10 regions) or is inversely polarized (4 regions). In contrast, senior workers mostly sort into low-skilled jobs in the same period, resulting in the pervasiveness of skills downgrading regional employment trend. Simultaneously, only a small number of local labor markets exhibit skills upgrading or polarized employment growth (8 and 7 regions, respectively).

The divergent employment trends across the two age groups are also illustrated in Figure 4.17, which illustrates the employment patterns by age group and period. Simply eyeballing the maps in the first column, we notice that employment growth amongst young workers (Panel A) is relatively balanced across all categories, besides inverse polarization. In contrast, Panel B shows that between 1999 and 2005, regional employment transformation amongst senior workers mostly favors low-skilled ones.

The regional employment profiles in the period between 2006 and 2011 are more homogeneous across the two age groups favoring high-skilled young and senior workers (in 21 and 22 local labor markets respectively). Notably, regional employment polarization is also substantially represented in young workers (11 regions) but not in senior ones (1 region). The above differences are also evident in the second column of Figure 4.17. The bottom map illustrates the lack of employment polarization for senior workers between 2006 and 2011, substituted by employment restructuring that disfavours high-skilled workers (either skill downgrading or inversely polarized).

Horizontal comparison of the two panels in Figure 4.17 advances our insight on the dynamics of regional employment patterns by age group. We first indicate that young workers (Panel A) mostly sort into high-skilled jobs with employment also polarizing in a substantial number of local labor markets. Notably, those trends are consistent across the two periods. In contrast, employment growth amongst senior workers shows greater disparity. Between 1999 and 2005 skills downgrading is the most prominent trend, as opposed to the second period of our analysis

Figure 4.17 Regional employment profiles by age group and period



where senior workers mostly sort into high-skilled jobs. Finally, employment polarization is less pronounced between 2006 and 2011. In total, the age-related analysis so far documents that employment polarization in the Netherlands is mostly a young workers' phenomenon while its importance regarding senior workers is decreasing in the more recent period.

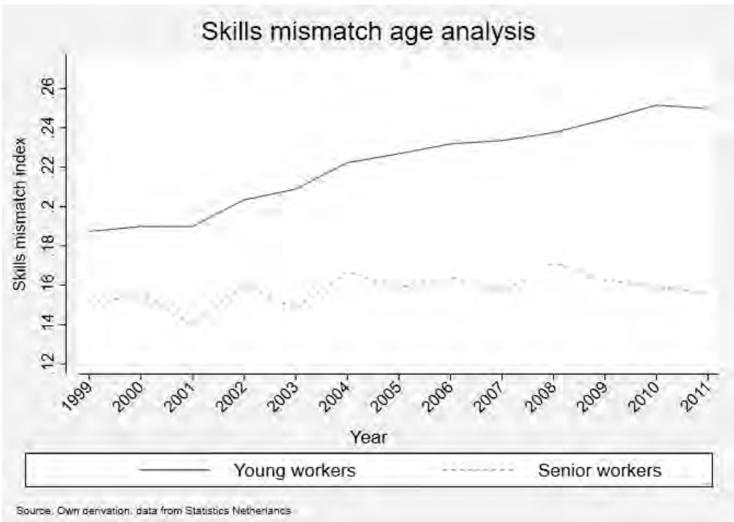
Age-specific evidence of skills mismatch in the Netherlands

Investigating the incidence of skills mismatch across different generations of workers is particularly relevant since it addresses the skill depreciation (Mahy et al. 2015; Kampelmann & Rycx, 2012). The average values of the SMI_{rt} for both age groups between different time periods (Table 4.14) first indicate that between 1999 and 2011 skills mismatch is a greater concern for young workers in the Netherlands (0.220) than their senior counterparts (0.188). The macroeconomic nature of the SMI_{rt} reflects that active participation in the labor market is more asymmetrically distributed across the various skill groups for young workers compared to a more even distribution for senior ones.

Table 4.14 Regional sill mismatch indexes by gender

	SM Index (Young)	**SM Index (Senior)**
Entire period (1999-2011)	0.220	0.188
First sub-period (1999-2005)	0.202	0.182
Second sub-period (2006-2011)	0.241	0.196

Figure 4.18 Skills mismatch index – age analysis



Splitting the analysis into two sub-periods, we point that skills mismatch is increasing for both young and senior workers; albeit the increase is more considerable for the former (19.3% than a 7.7% increase for senior ones). Figure 4.18 also illustrates the more pronounced yearly increase in the skills mismatch index for young workers (detailed data are reported in Table E1 – Appendix E). Contrary to European values of similar skills mismatch indexes (Sparreboom

& Tarvid, 2016) which conclude on decreasing trends during the economic crisis, our analysis reveals an opposite trend in the Netherlands where the period between 2006 and 2011 is characterized by increasing skills mismatch especially for young workers.

The greater incidence of skills mismatch at the national level is also evident in the regional analysis (Figure 4.19). Notably, skills mismatch amongst young workers is substantially higher in central local labor markets, such as Amsterdam, Utrecht or The Hague Agglomeration. In contrast, only the peripheral region of Delfzijl and surroundings exhibits a relatively high SMI value (above 0.3) in senior workers. The above preliminary analysis shows that young labor market 'outsiders' are more unevenly distributed across the various skill groups compared to a more equal distribution of senior labor market 'outsiders'.

Figure 4.19 Skills mismatch index. Regional age-specific analysis (average values)

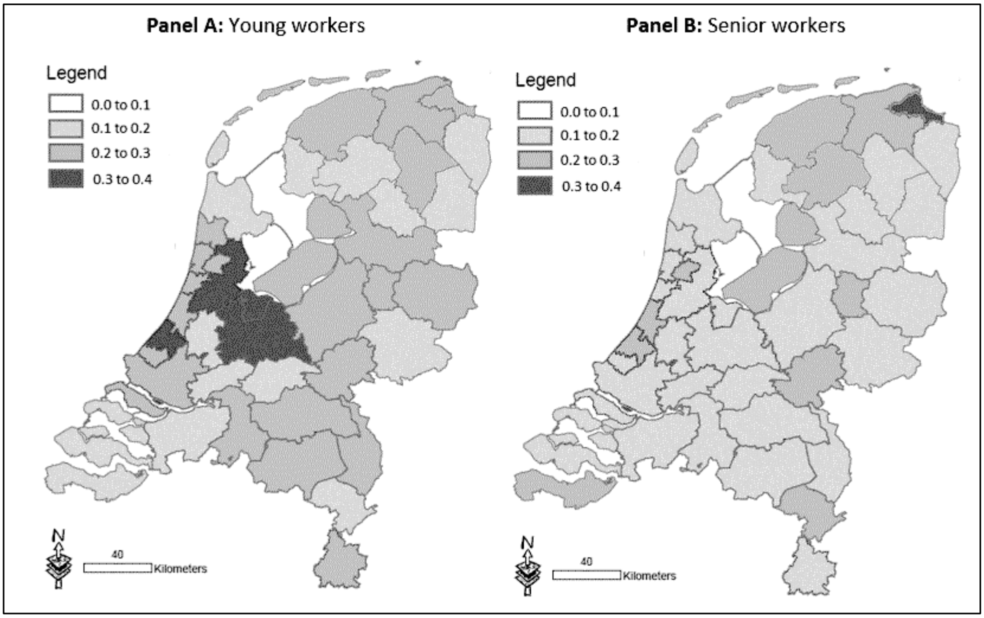
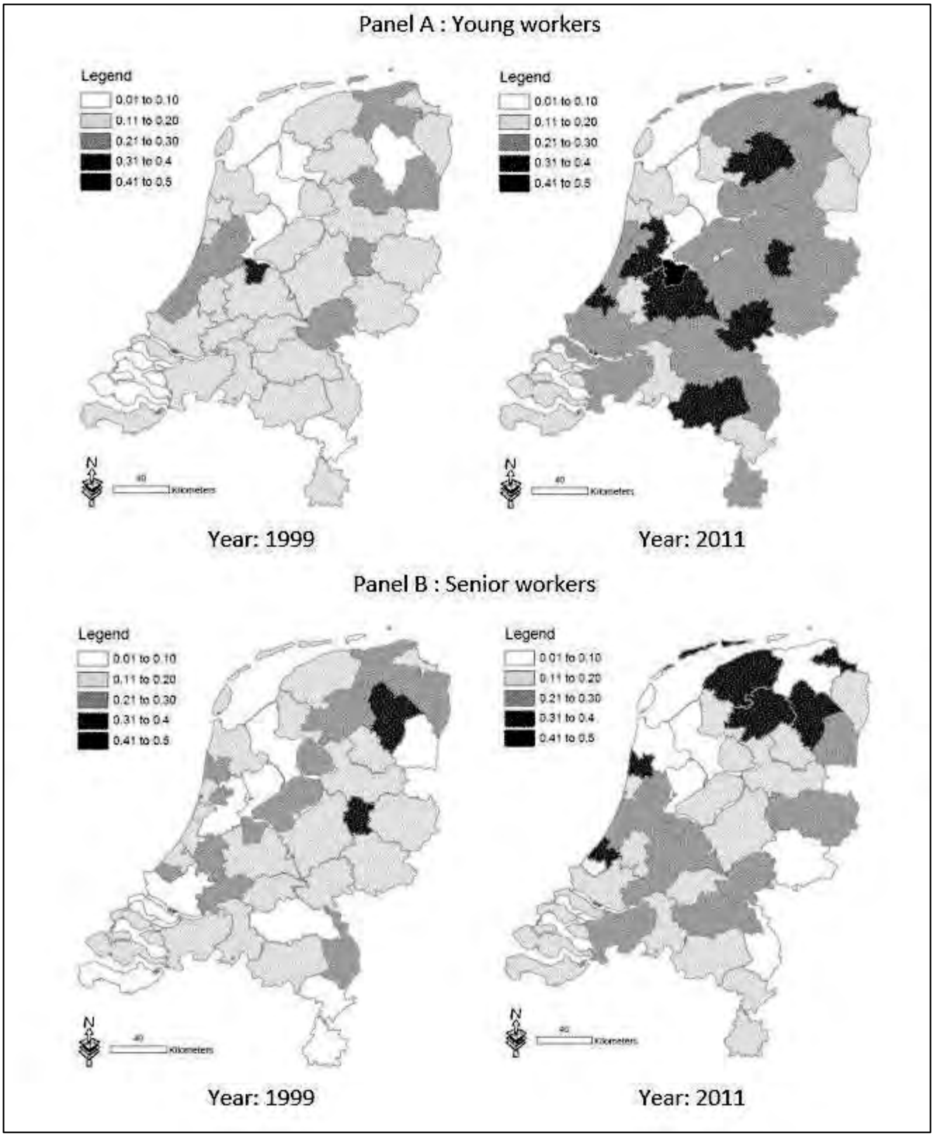


Figure 4.20 Skills mismatch index. Regional age analysis (two periods)



The abovementioned average analysis masks potentially different trends in the incidence of skills mismatch by age group. Based on the age-specific regional distribution of the skills mismatch index for the first (1999) and the last (2011) year of our analysis (Figure 4.20), we conclude the following. First, the initial dispersion of skills mismatch is greater for senior workers (Panel B) than a more even regional dispersion for young ones (Panel A). The two maps in the first column illustrate that the skills mismatch index for young workers varies between 0.11 and 0.2 for most local labor markets, as opposed to senior employment where we encounter more regions with relatively high (such as North Drenthe or Southwest Overijssel) or very low (such as Amsterdam or Rijnmond) incidence of skills mismatch. Notably, the metropolitan regions of Amsterdam and Rijnmond are typical examples of considerable differences on the incidence of skills mismatch across age groups since they exhibit high (low) values of the skills mismatch index for young (senior) workers.

Furthermore, the regional analysis by age group indicates that skills mismatch increases substantially more for young workers. Panel A uncovers increasing trends of skills mismatch for young workers in almost all regions between 1999 and 2011. Those increasing trends are less pronounced for senior workers (Panel B) where we also uncover several local labor markets in the periphery with decreasing incidence of skills mismatch (such as Overig Groningen or Achterhoek). Interestingly, our regional analysis documents a substantial increase in the skills mismatch for both age groups in the Dutch central metropolitan regions, such as Amsterdam, Rijnmond, Utrecht or The Hague. This finding illustrates that the distribution of 'mon-partivipants' in those labor markets becomes more uneven, disproportionately affecting specific skill groups. Further research will uncover the most severely affected workforce by the misalignment in the demand and the supply of skills and suggest evidence-based policy measures to alleviate the harmful effects of skills mismatch.

The relationship between employment polarization, skills mismatch and labor productivity. Age-related evidence.

Table 4.15 reports the conditional mixed process results from estimating the system of equations 4.4-4.6 for young (Panel A) and senior (Panel B) workers in the Netherlands. The reported standard econometric tests (χ^2 test and Bayesian Information Criterion) verify the validity and the significant predictive power of the estimated models.

Concerning young workers (Panel A), the regression analysis indicates the following. First, similar to the main analysis, Column 1 reveals a negative linear relationship between the skills mismatch and the employment polarization indexes. The size of the effect is equal to -4.33 and implies that higher regional incidence of skills mismatch is associated with lower values of the employment polarization index. Furthermore, Column 3 points to a significantly positive linear association between employment polarization and labor productivity. The estimated term (0.003) illustrates that larger values of the employment polarization index are associated with

Table 4.15 Employment polarization, skills mismatch and regional productivity by age group – conditional mixed process estimation results
Dependent variables: EP_{rt} , SMI_{rt} and $gvapwGR_{rt}$
Independent variables: EP_{rt-1} , : EP^2_{rt-1}, SMI_{rt-1}, SMI^2_{rt-1}, $gvapwGR_{rt-1}$, $gvapwGR^2_{rt-1}$

	Linear models			**Quadratic models**		
	EPI$_{rt}$ (1)	**SMI$_{rt}$ (2)**	**GVApwgr$_{rt}$ (3)**	**EPI$_{rt}$ (4)**	**SMI$_{rt}$ (5)**	**GVApwgr$_{rt}$ (6)**
Panel A – Young workers						
SMI_{rt-1}	-4.331* [2.605]		-0.063 [0.046]	-2.034 [9.882]		-0.283* [0.159]
SMI^2_{rt-1}				-6.677 [20.367]		0.489* [0.292]
EP_{rt-1}		0.001 [0.002]	0.003* [0.002]		0.003* [0.002]	0.002 [0.002]
EP^2_{rt-1}					-0.001 [0.0006]	0.0004 [0.0004]
$GVApwgr_{rt-1}$	2.168 [2.944]	0.145 [0.106]		3.178 [3.137]	0.134 [0.093]	
$GVApwgr^2_{rt-1}$				-57.801 [39.439]	-0.903 [0.584]	
constant	-36.945 [237.68]	2.794 [5.874]	3.287 [2.910]	12.918 [243.32]	4.562 [5.553]	2.603 [2.867]
Control variables	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
Observations	320	320	320	320	320	320
χ^2 - stat (p-value)	2778062.77***			11254.41***		
BIC	-899.70			-922.46		
Panel B – Senior workers						
SMI_{rt-1}	-1.428 [1.216]		0.042 [0.027]	-6.204** [2.902]		-0.046 [0.090]
SMI^2_{rt-1}				12.176** [6.560]		0.192 [0.251]
EP_{rt-1}		0.005** [0.003]	-0.0004 [0.012]		0.006* [0.003]	-0.0006 [0.001]
EP^2_{rt-1}					-0.001 [0.002]	0.002*** [0.0004]
$GVApwgr_{rt-1}$	0.642 [3.659]	0.056 [0.219]		1.432 [3.879]	0.031 [0.217]	
$GVApwgr^2_{rt-1}$				-42.194 [52.405]	0.380** [2.268]	
constant	-555.56 [213.11]	-22.066* [12.607]	1.751 [3.529]	-526.92 [191.57]	-22.053 [12.541]	1.439 [3.626]
Control variables	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes

Region fixed effects	yes	yes	yes	yes	yes	yes
Observations	320	320	320	320	320	320
χ^2 - stat (p-value)		520717.01***			2.59*10^8***	
BIC		-614.47			-633.86	

Note: Robust st. errors, clustered by region. The detailed specifications include the following control variables (lagged one period): fixed capital formation, population density, dependency ratio (demographic), male to female ratio, labor utilization, total employment and net migration. */**/*** denote significance to the 10% / 5% and 1% level.

higher subsequent growth rate of labor productivity. Nevertheless, higher values of the employment polarization index do not necessarily reflect true polarization. Since they can also be associated with skills upgrading, the above finding should be interpreted with a grain of salt.

Our analysis also contributes to the literature on the economic effects of skills mismatch (Kampelmann & Rycx, 2012) by uncovering a significant non-linear, U-shaped relationship between skills mismatch and labor productivity (Column 6). This finding suggests that an increase in the skills mismatch index is initially adversely related to labor productivity; however, the relationship turns positive for high values of the skills mismatch index. This potentially reflects that a natural level of skills mismatch should be expected and –especially when it reflects overskilling- is often beneficial to productivity. Finally, the quadratic model in Column 5 indicates a significantly positive linear relationship between employment polarization and skills mismatch. However, we consider this only as weak evidence since it is not verified by the respective linear model (Column 2).

Regarding senior workers in the Netherlands, three main conclusions stand out. First, we provide further evidence of a significantly positive linear relationship between employment polarization and skills mismatch, as indicated in the primary analysis. This relationship is verified by both the linear (Column 2) and the quadratic (Column 5) models and implies that higher regional values of the employment polarization index are associated with higher incidence of skills mismatch amongst senior workers in the Netherlands. Secondly, Column 4 indicates that the regional skills mismatch and the employment polarization indexes are linked in a non-linear, U-shaped pattern. An increase in the skills mismatch index is initially associated with lower values of the employment polarization index; however, the relationship turns positive at higher skills mismatch levels.

Finally, the current analysis also highlights two monotonic non-linear relationships. Specifically, Column 5 indicates a non-linear, increasing relationship between labor productivity and skills mismatch. This suggests that skills mismatch is positively linked with the growth rate of labor productivity with the association becoming stronger at higher levels of labor productivity growth. Similarly, Column 6 traces a monotone non-linear relationship between the employment polarization index and labor productivity. In particular, we show that higher values of the employment polarization index are associated with higher labor productivity growth at an increasing rate. This finding might reflect that the skills upgrading employment patterns which increase the employment polarization index also involve significant productivity gains due to workers sorting in high-skilled, high-productivity jobs.

Our age-specific regression analysis sheds further light to the outcomes of the main analysis by uncovering different, age-specific patterns of association between employment polarization, skills mismatch and labor productivity across Dutch local labor markets. In turn, those relationships suggest different policy initiatives that will alleviate the negative and maximise the positive economic impact from current labor market developments.

4.7 Conclusions and policy implications

This study introduces a comprehensive empirical framework to advance the current knowledge regarding the relationships and the productivity effects from employment polarization and skills mismatch, which are often considered in isolation. Based on reliable micro-data for individual workers in the Netherlands, combined with a comprehensive set of economic and demographic indicators, we adopt a dual empirical approach: First, we construct meaningful quantitative indexes of employment polarization (Sparreboom & Tarvid, 2016) and skills mismatch (ILO, 2013a) and thoroughly describe the incidence and trends of polarized employment growth and skills mismatch in the Netherlands between 1999 and 2011 both at the national and regional level. Secondly, we estimate a simultaneous equations framework utilizing a conditional mixed process estimator (Roodman, 2011) to systematize the relationships and investigate the productivity effects from employment polarization and skills mismatch. Notably, we use a direct measure of labor productivity instead of relying on indirect ones like wages or job satisfaction.

The current analysis has culminated into several noteworthy outcomes: First, despite the prevailing employment trend in the Netherlands favoring high-skilled workers, we document that employment polarization is represented in a substantial number of regions, especially amongst young workers. Similarly, although the imbalance between the supply and the demand for skills has not yet reached an alarming level, our cohort analysis reveals increased skills mismatch amongst male and young workers. Notably, both employment polarization and skills mismatch increase in the more recent years, including the global economic recession; however, no causal link is established.

Furthermore, in the current study's primary contribution, we systematize the relationships between employment polarization, skills mismatch and labor productivity. Controlling for simultaneity, time- and region-specific characteristics, cohort effects and dynamics in the adjustment process of labor market phenomena, we first indicate non-monotonic, inverted U-shape relationships between labor productivity growth and the incidence of both employment polarization and skills mismatch. Interestingly, our cohort analysis by age groups advances the current debate on the productivity effects of employment polarization and skills mismatch (Mahy et al. 2015; Kampelmann & Rycx, 2012). In particular, we uncover that the relationship between skills mismatch and the growth rate of young workers' productivity follows a non-linear, U-shaped pattern. Besides, we document a monotonic and increasing relationship between employment polarization and senior workers' productivity growth rate.

From a policy perspective, our findings underscore the urgency for region-specific and evidence-based active labor market policies to improve the adjustment of the educational system to the transforming demand for skills (Quintini, 2011). Lifelong learning programmes that will equip workers with the required job skills for more efficient sorting into the labor market vacancies are bound to decrease skills mismatch, thus benefiting overall productivity. Besides, given that the Dutch labor markets mostly follow a skills upgrading pattern, improved career forecasting and dissemination of information across firms and workers will decrease labor market frictions and promote the reallocation of the displaced low- and medium-skilled workers. In that sense, subsidies conditional on hiring the longer-term unemployed could facilitate workers sorting into high-skilled jobs and further advance the productivity benefits of high-skilled employment.

The above results notwithstanding, the current analysis involves a number of limitations. Although the applied macroeconomic measure of skills mismatch does not lack content and prediction validity, it does not differentiate between over- and under-skilling. It is thus inappropriate for revealing different productivity implications from over- or under-skilled workers. Secondly, our regional approach combined with the lack of diversity in the regional labor market regulations prevents us from investigating how the institutional factors such as wage bargaining or firing and hiring practices mediate the productivity effects from employment polarization and skills mismatch. Finally, given the gradual development of the investigated employment trends, a more extended multinational dataset is probably required to pin down their economic impact securely. Despite the above caveats that merit further attention, our approach's comprehensiveness and robustness highlight many of the economic implications of the prevalent labor market phenomena that are bound to advance the relevant academic and policy debate.