Employment Polarization in Local Labor Markets: Evidence from the Netherlands

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Abstract: Recent empirical evidence documents the pervasiveness of job polarization in the labor markets of the developed world. Complementing this literature, we confirm job polarization as an important trend in the Dutch national and local labor markets between 1999 and 2012. Using an extensive mixed gender dataset from *Netherlands Statistics* (CBS) in our sub-national analysis we document considerable spatial heterogeneity among local labor markets. However we identify the relative importance of both occupational tasks and the regional social (urbanization status) and labor market (female participation) conditions as significant determinants of regional job polarization. Finally, we find evidence supporting both the routinization hypothesis and international fragmentation of production as important sources of national employment polarization in the Netherlands.

Keywords: job polarization, regional analysis, routine-biased technological change, offshoring, spatial heterogeneity

JEL codes: J21 – Labor Force and Employment, Size and Structure, J24 – Human Capital, Skills, Occupational Choice, Labor Productivity

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1 Introduction

Vibrant empirical literature in the last 25 years identifies the prevalence of employment polarization (Goos and Manning, 2007) in modern labor markets, a trend characterized by employment growth concentrated in relatively high-skilled, high wage and low-skilled, low wage occupations at the expense of middle-skilled and wage jobs. Once unique in the US (Autor, Katz & Kearney 2006; 2008 and Autor & Dorn 2013), employment polarization is currently widespread across industrialized economies. Goos & Manning (2007) document job polarization in the UK, Spitz-Oener (2006) and Dustmann, Ludsteck & Schonberg (2009) in Germany, Green & Sand (2015) in Canada and Adermon & Gustavsson (2015) in Sweden.

The consensus in labor economics literature documents *Routine Biased Technical Change* (hereafter RBTC) as the predominant source of employment polarization, supplemented by the international fragmentation of production (hereafter IFP). RBTC (widely referred to as the *routinization hypothesis*) is founded on the task model of occupations (Autor, Levy & Murnane 2003 – hereafter ALM) and contends on an asymmetric impact of technological development on labor demand. In particular, technological innovations increase labor demand for high-skilled (non-routine) tasks (i.e. research, medical diagnosis), while they substitute labor in routine tasks (i.e. basic problem solving, machine operation).

Labor demand in routine-based occupations is also vulnerable to the increased fragmentation of production especially to the developing labor markets (Becker et al. 2012). Prompted by the cost-cutting imperative and the abundance of mainly unskilled labor in the developing countries, international economic activity is increasingly gaining momentum and affects a larger share of manufacturing and service occupations. IFP predominantly shifts human labor away from middle-skilled and average-waged occupations and thus results in relative employment increase in high-skill jobs. The interplay between technology and global integration contributes to decreasing labor demand in average-skilled, routine-based occupations relative to non-routine ones, either low- or high-skilled.

The present paper offers multiple contributions to the literature. First by utilizing an extensive mixed gender dataset from *Netherlands Statistics* (CBS), we provide a comprehensive empirical investigation of employment polarization in the Netherlands between 1999 and 2012. By means of regression analysis we offer systematic evidence of a U-shaped employment curve in the national labor market, indicative of job polarization.

However job polarization is a more complex issue than most macroeconomic studies suggest (Brakman, Garretsen & Marlet 2015). Variations *inter alia* in the economic structure, labor force composition or trade exposure among different regions can either increase or dampen the degree of job market polarization. Therefore, the main contribution of this paper is to delve into the sub-national nature of job polarization and document its regional pervasiveness. Rather importantly, in our sub-national analysis we utilize indexes from international sources (OECD) to identify locally-specific economic and social characteristics (urbanization status, share of female employment etc.) that contribute to regional employment polarization. Within the same context, we build on Dauth (2014) and construct a polarization index to perform quantitative comparisons between various levels of regional polarization for the first time in the Dutch case.

In addition, since little is known about the behavior of job polarization distinguishing by gender (Cerina, Moro and Rendall, 2017) or by age, we further add to the literature by extending our empirical analysis to include a gender and an age dimension of employment trends for the Dutch national and local labor markets. Finally, this paper complements the job polarization literature by decomposing the relative importance of RBTC and international fragmentation as potential sources of job polarization for the Dutch national labor market. To perform such a task, we separately investigate the impact of RBTC and international fragmentation on low- and high-skilled occupations. Our estimates reveal that both RBTC and trade exposure are important determinants of employment polarization, however we identify different implications between low- and high-skilled jobs.

In the next section we provide a review of the related literature which motivates our empirical analysis, while in Section 3 we present our methodological approach. Section 4 contains information on the data used and Section 5 presents our results. Finally, in Section 6 we summarize our main conclusions and offer insights for potential future labor market policies.

2 Relevant Literature

Till the early 1990's, occupational employment dynamics converged towards increasing demand for high-skill jobs followed by a widening of the wage gap between low- and high-skill occupations. The dominant view among labor economists was that technology favored skilled workers (Katz & Autor 1999, Krugman 1995, Bearman, Bound & Machin 1998, Autor, Katz & Krueger 1998), leading to the principle of *Skill Biased Technical Change*

(Johnson 1997 – hereafter SBTC). SBTC contented that new technologies and in particular the increased application of Information and Communication Technology (hereafter ICT) increased their productivity of skilled labor and consequently their labor demand. At the same time ICT substituted tasks performed by unskilled labor, thus lowering the demand for low-skilled workers. Taken together, the above two individual effects resulted in increasing the employment shares of high-skilled occupations relative to low-skilled ones.

Nevertheless, vibrant empirical literature after the mid-1990's converged on a simultaneous increase in the employment shares of both low-skilled and high-skilled occupations. Goos & Manning (2007) introduced the term *job polarization* to define such employment trends and extensive empirical analyses documented the prevalence of job polarization in the developed world. Autor, Katz & Kearney (2006, 2008) examine job polarization in the US between the 1980's and the 1990's, while Acemoglu & Autor (2011) identify similar trends in the 2000's. Green & Sand (2015) trace job polarization in Canada for the period 1971-2012 and Coelli & Borland (2016) document polarization dynamics in the Australian labor market during the 1980's and 1990's. Similarly, for the European case, Goos & Manning (2007) verify the presence of employment polarization in the UK between 1979 and 1999. Spitz-Oener (2006) and Dustmann, Ludsteck & Schonberg (2009) investigate job polarization in Germany from the 1980's till the 1990's, while Adermon & Gustavsson (2015) find job polarization trends in Sweden between 1975 and 2005.Van den Berge & ter Weel (2015) document labor polarization in the Netherlands, albeit of a more limited degree than in most other European countries. Furthermore, the national pervasiveness of employment polarization is verified by a number of studies utilizing pooled data from various developed economies (Goos, Manning & Salomons 2009 and 2014 for 16 European countries; Michaels, Natraj & van Reenen 2014 for the US, Japan and 9 European economies and Wang et al. 2015 for 31 European labor markets).

Rather importantly, a growing part of the labor economics literature focuses on the sub-national economic, social and demographic heterogeneity and how it affect employment polarization. Empirical work on regional job polarization includes Dauth (2013, 2014), Blien & Dauth (2016) and Senftleben & Wielandt (2014) who confirm the prevalence of employment polarization among German regional labor markets within the last three decades. Similarly, Consoli & Barrioluengo (2016) conclude that employment polarization is the main trend among Spanish local labor markets in that period. In the same respect, Kaplanis (2007) examines the spatial patterns of employment polarization in UK regions between 1991 and 2001 and proves its regional pervasiveness.

To account for employment polarization, the international literature investigates the impact of two iconic manifestations of globalization on occupational employment: technological development and the fragmentation of production chain. However, both of them impose a differential impact, relative to individual occupational characteristics. To appropriately classify occupations based on their inherent attributes, labor economics literature increasingly applies the *task model* (Autor, Levy & Murnane 2003 – hereafter ALM) illustrated in Figure 2.1, which conceptualizes each occupation as a series of tasks[4] performed by employees in their working environment. The task model introduced a two-dimensional typology to classify occupational tasks into two main categories, based on whether they could be performed by computers or not. ALM (2003) firstly distinguish between *Routine* (working on an assembly line, basic machine operation) and *Non-Routine* (management or research) tasks, with the former involving "…methodological repetition of an unwavering procedure" (ALM 2003) and therefore being easily codified and implemented by computers. In contrast, non-routine tasks require interpersonal or situational adaptability and as such, computer technology exhibits limited scope in substituting them. ALM (2003) further divide routine and non-routine tasks into *Cognitive* and *Manual* ones with cognitive tasks requiring greater mental and manual ones higher physical capacity. Finally, non-routine cognitive tasks are further decomposed into *Analytic* (requiring advanced problem solving) and *Interactive* (requiring interpersonal adaptability) ones.

The *task model taxonomy* is extensively applied in the job polarization literature, either unchanged (Coelli & Borland 2016, Goos & Manning 2007, Kampelmann & Rycx, 2011, Spitz-Oener 2006) or with minor variations[5] (Autor et al. 2006 Autor & Handel, 2013, Goos, Manning & Salomons. 2010), thus creating an inconsistency on the task categorization among empirical estimations of job market polarization. However this does not undermine the applicability of the task model as the main task categorization instrument in the international job polarization literature.

[4] Occupational tasks define also the necessary skills possessed by the respective employees. Therefore in what follows the terms "tasks" and "skills" are used interchangeably.

[5] For example, Autor et al. (2006) and Autor and Handel (2013) distinguish between *Abstract*, *Routine* and *Manual* tasks, while Goos et al. (2009) distinguish between *Abstract*, *Routine* and *Service* tasks.

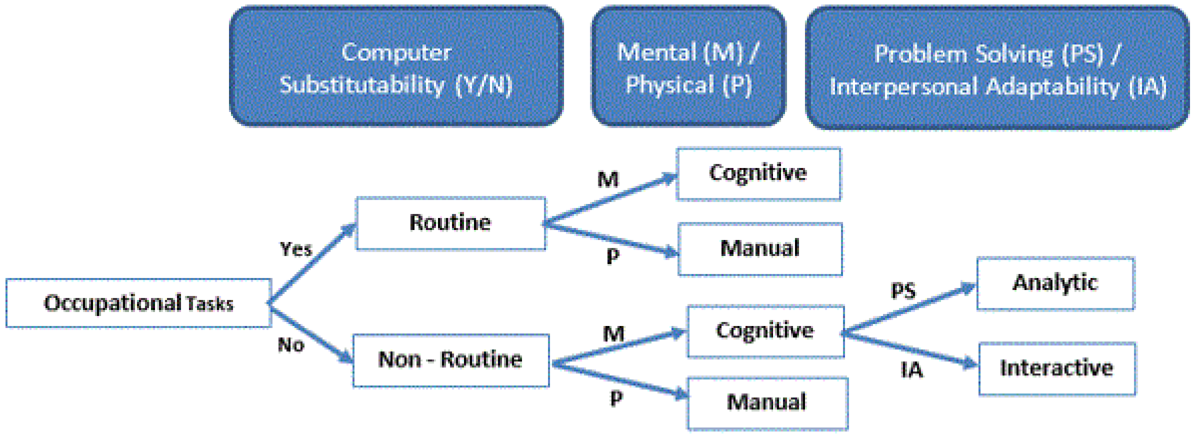

Figure 2.1. The task model (Own elaboration based on ALM 2003)

Following the above division of occupational tasks, after the mid-1990's the international literature on job polarization adopted a more nuanced approach to explain how the technological revolution of ICT changes the composition of human labor. Specifically, the *routinization hypothesis* (ALM – 2003) argued towards a more distinctive impact of ICT[6] on occupational employment, based on each jobs' inherent characteristics. At first, computer capital directly substitutes workers in routine-based occupations, therefore decreasing their labor demand and causing an over-supply of routine labor. Secondly, ICT directly complements workers performing non-routine analytic or interactive tasks, increasing their productivity and subsequently their labor demand. General equilibrium models in labor economics literature (Cortes, 2016) verify that part of the displaced routine workers compensate for the increased labor demand in high-skilled analytic and interactive occupations (direct effect) and a smaller fraction ends up in low-skilled, non-routine manual jobs, for which ICT exhibits limited potential for substitution (indirect effect). The above two effects result in a U-shaped employment change pattern (Figure 2.2), directly indicative of employment polarization.

Figure 2.2 sorts occupations on the X-axis by means of their mean wage level. The established association in the job polarization literature dictates that employees in routine occupations receive average wages while the workers in non-routine cognitive and interactive jobs are at the top part of the occupational distribution. Finally, non-routine manual occupations receive the lowest wages. Therefore, the middle segment of the occupational distribution consists of routine-based occupations while the tails are occupied by non-routine jobs; however their skill requirements and received wages differ greatly.

[6] Throughout the text, the terms "ICT" and "Computerization" are used interchangeably to stand for technological innovation applied in the labor market.

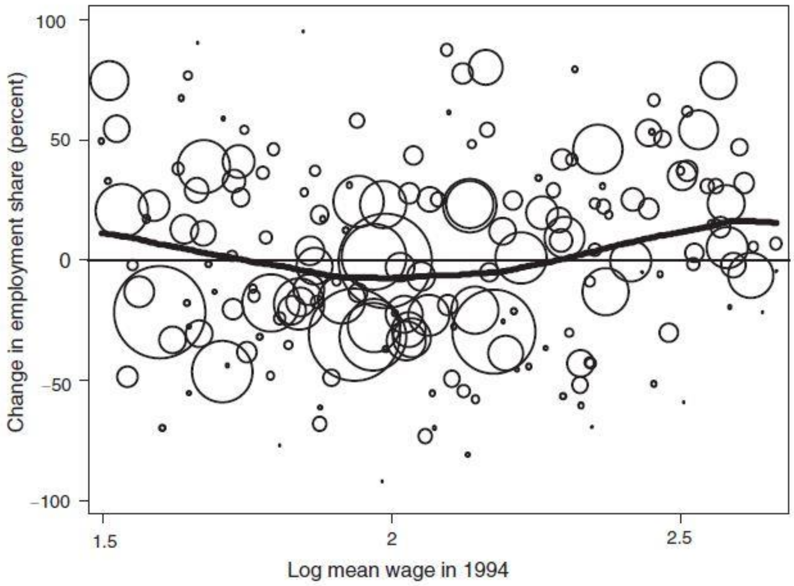

Figure 2.2. Employment curve in the British national labor market (Goos et al. 2009)

Acemoglu and Autor (2010) introduced offshoring as an additional source of job polarization. Although the cost-cutting motivation and the large numbers of cheap labor overseas led western companies to embrace the opportunities of shifting parts of their value chain overseas, the labor market implications are more complex. The fundamental assumption is that offshoring differentially affects low-skilled versus high-skilled occupations. Following the relevant literature, the basic principles that determine a job's propensity to be offshored are: whether the job output is amenable to electronic delivery and if so, how serious is the degradation of its quality (Blinder, 2009). Based on those, the occupational characteristics conducive to offshoring include: no face-to-face service requirement, no physical presence (i.e. working in a fixed location) or cultural sensitivity (i.e. newscaster), low setup barriers and limited social networking, intensive use of ICT and finally high wage differential between the host and the destination country (Bardhan and Kroll, 2003; Blinder and Krueger, 2013; Dossani and Keaney, 2003; Jensen and Kletzer, 2010; van Welsum and Vickery, 2006).

Merging the above occupational characteristics with the task model, Becker et al. (2012), Ekholm and Hakkala (2006), Laemer and Storper (2001) and Oldensky (2012; 2014) conclude that offshoring is related with employment shifting away from routine-based occupations, which involve basic problem solving and repetitive tasks. In contrast, offshoring is inversely related with non-routine manual and abstract tasks, which involve decision-making, creativity and interpersonal adaptability. Therefore offshoring considerably redistributes the structure of employment both in the domestic and the receiving labor markets. As a result it receives increased attention as a potential source of employment polarization.

Although RBTC and offshoring impose a similar qualitative impact in the relative demand for routine and non-routine occupations, disentangling their exact implications poses an empirical challenge, which is intensified by the lack of trade data at the occupational level. These conditions result in a relative scarcity of empirical estimations of RBTC and offshoring as simultaneous sources of employment polarization. Goos et al. (2014) regress routine intensity and offshorability indicators on hours worked per occupation only to determine that routine intensity is a more important determinant of employment polarization in 16 Western European countries between 1993 and 2010. In a similar manner, Oldenski (2014) uses US wage and employment data to verify Autor et al. (2010) in that increased offshoring in routine-based occupations is a significant source of polarization both at the industry and occupational level.

Finally, labor economics literature also proposes a complementary source of employment polarization, however with weaker overall impact. Goos, Manning & Salomons (2014) and Manning (2004) suggest that the wage growth in the top part of the occupational distribution also increases employment in low-skilled, non-tradable sectors, resulting in job polarization. The mechanism is straightforward. Employment growth in high-paying jobs creates a workforce with increased opportunity cost of time which in turn intensifies the demand for low-skilled, non-tradable occupations (child or elderly care, retail salespersons, janitors etc.). Mazzolari and Ragusa (2007) define this employment trend as *consumption spillovers*, however its potential of causing employment polarization is rather limited.

3 Methodology

Instead of establishing the presence of polarization only on figures, such as Figure 2.2, we rely on regression analysis to provide more systematic evidence regarding the occurrence of job polarization in the Dutch national and local labor markets. Based on the fact that job polarization is illustrated by a parabola (Figure 2.2), we add a quadratic term in the regression analysis to identify the (possible) presence of a parabola. Furthermore, the national-based regression provides us with a Polarization Index (Dauth 2014): the t-value of the quadratic term. The higher the t-value, the stronger the polarization effect. The main advantage of the t-value being used as a quantitative measure of polarization is the fact that it is not susceptible to outliers that could determine the shape of the parabola. In turn, this follows from the robust standard errors on which our regression analysis is based. In contrast, such a quantitative index is by principle an imperfect qualitative measure of employment polarization. In our case, the index we apply does not allow us to identify the exact shape of the parabola and distinguish between wider, U-shaped curves (potentially with more than one inflexion points) from more narrow, V-shaped curves (one inflexion point and lower representation of routine-based occupations).

Finally, in order to trace the exact impact of the two main sources of job polarization (SBTC and offshoring) we perform weighted regressions of occupational employment on appropriate indicators of each theoretical concept. However the above regressions are carried out only in the national labor market. Lack of sufficient regional data on skill utilization and offshoring per occupation especially in densely employed local labor markets prevent us from applying this method in the sub-national level as well.

3.1 Regression Analysis

3.1.1 National labor market - Determining a U-shaped employment curve

The standard approach in empirical economics to identify U-shaped curves (Aghion et al. 2005, Grossman & Krueger 1995) is to include a quadratic term that captures the non-linear effect identified as a parabola. In our case, we regress employment share percentage changes per occupation on a ranking variable and it's squared term. We consider employment shares rather that wage differentials. The obvious critique is that Netherlands, as a typical continental Europe country, consists of sufficiently institutionalized labor markets and therefore labor market shocks are transmitted through employment levels, rather than wages (Davis, 1998). We sort occupations according to their median initial (1999) wage and divide them into percentiles based on their initial employment share. As a result, large occupations can expand over multiple percentiles, whereas small ones are normally included into a single one. Thus, we avoid that our results are being driven by compositional effects[7]. Then we estimate the following quadratic model:

$$\Delta s_{i,1999-2012} = a_0 + a_1 rank + a_2 rank^2 + \varepsilon_\iota \quad (1)$$

[7] In our case, the c*ompositional effect* refers to our results being driven by potentially large employment share changes in the case of just a few very small occupations.

Where: $\Delta s_{i,1999-2012}$ is the change in employment share between 1999 and 2012 of each percentile while $rank$ and $rank^2$ are the ranking variables and ε_t is the error term[8]. The above model is used to test whether the relationship between initial wage and subsequent change in employment share is indeed described by a U–shaped pattern[9].

In our regression model (Eq. 1), a_1 and a_2 are the parameters of interest, where a_2 identifies a parabola. The necessary criterion for U-shaped relationships within a given interval requires a statistically significant negative slope at the low interval values and a significant positive one at higher ones, so $a_1 < 0$ and $a_2 > 0$.

However the empirical application of the above criterion although intuitively sound, is potentially misleading in establishing a parabola. A quadratic specification might conclude towards a parabola even in cases when the true relationship is convex but monotone within relevant data values. Instead of a 'true' parabola, an L-shaped curve or 'half 'a parabola can also occur. Therefore we need to test whether the relationship is decreasing among low values of the interval of interest and increasing in high values within this interval. To properly test for a parabola within a specific interval of values, following Lind & Mehlum (2010) and Sasabuchi (1980) we add the following condition:

$$a_1 + a_2 f^{'}(rank_l^2) < 0 < a_1 + a_2 f^{'}(rank_h^2) \quad (2)$$

Where: $f^{'}(rank_l^2)$ and $f^{'}(rank_h^2)$ are the first derivatives of the non-linear term estimated at the lowest *(l=1)* and highest *(h=100)* values of the data range.

In sum, a robust non-monotone, U-shaped relationship on some values interval requires a negative and significant linear term in all the usual statistical levels (α=10%, 5% and 1%), a positive and significant squared term as well as validity of inequality (2). Those conditions ensure decreasing relationship at low values of the interval turning to an increasing at higher interval values (Lind and Mehlum, 2010).

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[8] The employment share of percentiles are calculated as the weighted average of the employment change of every occupation included in the percentile.

[9] Standard algebra dictates that the mathematical identification of a parabola occurs through a quadratic equation. Specifically, a U-shaped parabola in the economic sensible part of the quadrant requires that α_1<0 and α_2>0.

3.1.2 A regional polarization Index

We repeat the analysis of equation (1) for each region, using the national occupation-to-percentile correspondence for each region.[10] Using the estimates of Eq. (1) and following Dauth (2014), the following adjusted t-value[11] of the squared term (Eq. 3) is an index for job polarization, and can be used to compare the magnitude between different local labor markets:

$$t_{rank^2} = \frac{\hat{a}_2}{\hat{\sigma}} c = PI \qquad (3)$$

Based on Eq. (3), the t-ratio of the squared term takes into account the curvature of the regression ($\hat{a}_2$) as well as how close the regression curve fits to the data ($\hat{\sigma}$). As discussed in Dauth (2014) the use of robust standard errors makes the adjusted t-value also insensitive to outliers.

The t-ratio of the non-linear term is therefore used as a *Polarization Index* (PI) since it allows comparisons between (regional) levels of job polarization. As such, it is increasingly applied in the job polarization literature, especially in regional approaches (Blien & Dauth 2016; Dauth 2014). Technical details on the derivation of Eq. (3) and the suitability of the t-value as a polarization index are provided in the Appendix A1. A disadvantage of the measure is that different U-shapes could have the same t-value. However to the best of our knowledge identifying different types of U-shaped curves is not still addressed in the job market polarization literature.

3.2 Sources of job polarization

A simple OLS regression investigates the impact of the independent variables to the mean value of the response variable, therefore it is an appropriate instrument for capturing linear relationships. However we intend to establish a non-monotone (U-shaped) employment change pattern, therefore we divide the occupational percentile distribution based on the

[10] An alternative is to calculate new occupation-wage percentile relationships for each region. However, comparisons between regions become extremely difficult in that case. For instance, in the province of Utrecht in the year 2003 (earlier year for which data is available) 30,5% of the population was considered to be higher educated, whereas this was only 16,5% in Drenthe (CBS, 2017). As a result, the same occupational percentile will contain very different jobs in Utrecht compared to Drenthe when using local percentile-occupation linkages, which will highly complicate any region comparison. To prevent this, we use the national occupation-percentile linkage for all regions.

[11] The value in formula 3 is based on Dauth (2014). Correlation between this value and the standard t-values of the squared term are 0.995.

occupational wages and initial employment into two segments[12] (percentiles 1-49 and 50-100 respectively). The first segment corresponds to low-paying, low-skilled jobs, while the second one includes high-paying and skill ones. We document the relationship between each one of the tasks included in the task model as well as our measure of international economic activity (offshoring) on each of the two parts of the occupational distribution.

Considering the applicability of RBTC in the Dutch labor market, we expect a differential impact from each task measure between low- and high-paying (and skill) jobs, based on the relative task content of each occupation.

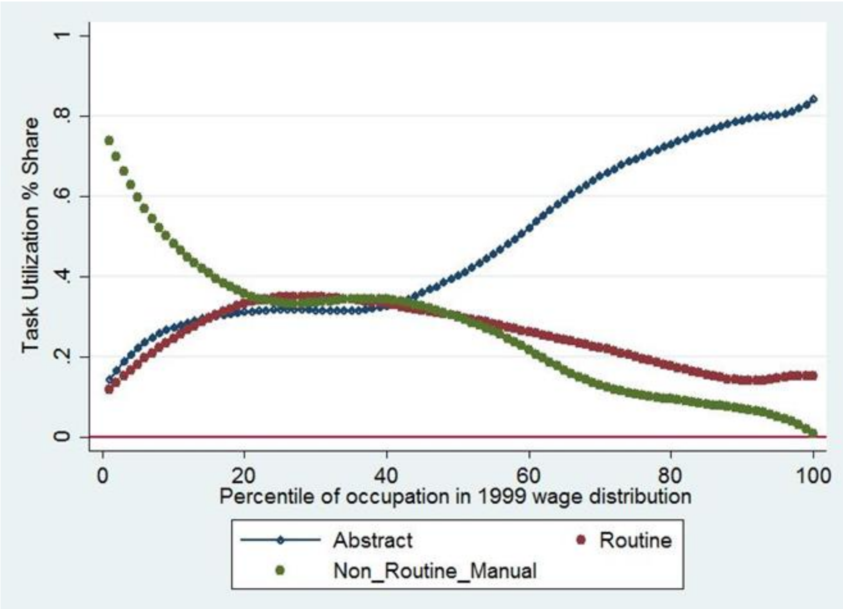

Figure 3.1. Task Utilization per Occupational Percentile

Figure 3.1 arranges occupations into wage percentiles and plots the smoothed task input per occupation. To simplify the illustration, we follow a common practice in the job market polarization literature (Goos and Manning, 2007) and merge the non-routine analytic and non-routine interactive tasks into the *Abstract* task category (Figure 2.1). We provide a more detailed decomposition into all 5 categories, in Appendix A2.1. Evidently the task composition of jobs varies considerably along the occupational distribution. In compliance with the literature (ALM - 2003), our data verifies that the share of non–routine manual tasks is generally higher in the low - paying occupations and decreases monotonically with the occupational wage. In contrast, the share of abstract tasks is rather low in low paying jobs and increases monotonically with occupational wage, while the share of routine tasks follows a

[12] Our preferred methodology would be to distinguish between three occupational segments, corresponding to low-, medium- and high-paying occupations. However we only have data for 108 occupations, which is too small to allow such a detailed division.

non-monotone inverted-U curve, reaching its maximum point in middle paying occupations. Table A2.3 (Appendix) presents the mean wages per task category only to verify the above conclusion.

To properly decompose the impact from RBTC and international economic activity on employment dynamics, we regress appropriate measures of the various task contents together with our indicator of offshorability in the employment change per occupation between 1999 and 2012. Furthermore, we estimate separate equations for low- and high-paying (and skill) jobs, to identify different employment trends. Equation (4) provides our general estimation model:

$$\Delta s_{i,1999-2012} = a_0 + a_1 TaskInt_i + a_2 Offsh_i + a_3 WageDif_i + \varepsilon_\iota \qquad (4)$$

Where: $\Delta s_{i,1999-2012}$ is the percentage difference in employment share per occupation *i* between 1999 and 2012, $TaskInt_i$ is the intensity of each task measure, $Offsh_i$ is our occupational-based index on offshoring, $WageDif_i$ is the wage difference between 1999 and 2012 per occupation and ε_ι is the error term.

Based on the *task model* (Figure 2.1), we create a consistent taxonomy for our analysis. Specifically the task model offers the chance to follow either a condensed taxonomy of the three broad categories presented in Figure 3.1 (*Abstract*, *Routine* and *Non-Routine Manual*), or a more disaggregated categorization of five task categories. In the latter case, we divide abstract tasks into Non-Routine Analytic (those involving higher complexity problem solving) and Non-Routine Interactive (requiring interpersonal skills) ones and *Routine* tasks into *Routine Cognitive* (requiring greater mental capacity) and *Routine Manual* (those demanding greater physical strength). Avoiding to make our analysis too complex, our main regressions utilize the 3-category (broad) typology. However to provide better insight on task utilization in the Dutch national labor market, we also report results for the detailed taxonomy. Table 1 reports the association between the two taxonomies and some representative task examples.

Table 1: Task Taxonomy

3 – Category Typology	5 – Category Typology	Examples of Tasks
Abstract (or: Non-Routine Cognitive)	Analytic	Medical diagnosis, research
	Interactive	Work delegation, persuading / selling
Routine	Cognitive	Bookkeeping, calculation
	Manual	Machine operation, repetitive assembly
Non-Routine Manual		Housekeeping, janitorial services

We test the impact of each task measure individually as well as in combinations and we are interested in systematic differences in the coefficient a_1 (Eq. 4) across the two different parts of the occupational distribution. Such differences reveal a non-monotone impact of each task measure in occupational employment dynamics, dependent on the exact segment of the occupational distribution.

4 Data

Employment:

We utilize extensive data on the Dutch labor market provided by the National Agency for Statistics (Netherlands Statistics). Our main data source is the quarterly labor market questionnaire (Enquete Beroepsbevolking - EBB), which accounts for 0.25% of the total population[13]. The questionnaire includes extensive information related to occupation, contract type, hours worked and a large number of demographic and socio-economic household characteristics (age, marital status, number and age of children etc.). The information from the EBB is merged with administrative data on income and work location.

The data cleaning process (excluding agricultural employment in line with job polarization literature, removing incomplete entries etc.) resulted in a dataset of 750,969 observations for both genders, available in a consistent time-series from the first quarter of 1999 until the third quarter of 2012[14]. Table 2 provides mean values of our main data characteristics. We classify occupations by means of the *Beroepenindeling ROA-CBS 2014* (BRC) and the *International Standardized Classification of Occupations* (ISCO-2008). BRC is based on the ISCO taxonomy, however CBS appropriately modified job aggregation and occupational coding, which improved the occupational distinction. Furthermore, it is directly compatible with the EBB questionnaire and therefore our Dutch labor market data. Based on these advantages, our main analysis disaggregates between 114 occupations, according to the BRC 4-digit pattern.

[13] The individuals participating in the questionnaire change on a quarterly basis. Every month a random selection of addresses is drawn for each of the 400 Dutch municipalities, proportional to their size. Participation is weighted to ensure normal representation of the overall Dutch labor market and the weights are corrected for non-response amongst groups based on age, gender and nationality. Each participant is provided with a questionnaire for five consecutive quarters. Only the information from the first questionnaire is used, since this is the only one that contains information related to occupation and hours worked

[14] An inconsistency in the data collection process after the third quarter of 2012 prevents us from using more recent data available.

Table 2 – Summary Statistics

Variable	
Average hours worked	31.4
% Female	46.1%
Age	38.9
Mean hourly wage (in year 2000 euro's)	18.85
No of workers	750969

Occupational Task Content and Offshorability

Data on the task content of occupations were adapted from Spitz-Oener[15] (2006), who directly measures occupational requirements for the German labor market based on the employees' responses on the activities they perform at their workplace. Each task weight is the ratio of the actual tasks the worker actually performs divided by the total number of tasks per category. Assuming comparable task structure between Germany and Netherlands, we cluster tasks according to the 5-category typology (Table 1), and –when necessary- into the 3-Category as well. Therefore, the task content of each occupation consists of five individual task measures, allowing for the possibility that some of them are zero.

Table 3 adopts the 3-category task typology to report task utilization levels for the first and last year of our analysis. Dutch labor market is predominantly abstract – intensive, since on average almost 50% of the tasks performed nationally require abstract skills. Simultaneously, routine and non-routine manual tasks are almost equally represented. The Dutch labor market differs from the more routine –based German labor market (Senftleben and Wielandt, 2014).

A more detailed decomposition of the Dutch labor market into the two types of routine and abstract tasks (Appendix A2 - Table A2.1) highlights the importance of the routine cognitive tasks as well as non-routine interactive ones. Furthermore, we decompose skill utilization per province (Appendix A2 – Table A2.2) and identify Z. Holland, Flevoland and Utrecht as the most abstract-based sub-national labor markets and Overijssel, N. Brabant, Zeeland and Limburg as the most routine-intensive ones.

[15] The task measures are based on the Qualification and Career Survey, which includes four cross-sections, launched in 1979. 1985/86. 1991/92 and 1998/99. Spitz – Oener (2006) classifies employees in a wide range of industries, including manufacturing, services and public institutions. Later, den Butter en Mihaylov (2013) adapted those weights according to the SBC 1992 occupational coding. We adapt those task weights to also correspond to the BRC 4-Digit and ISCO 4 – digit occupational sorting.

Table 3 – Task Intensity

	Non - Routine Manual	Routine	Abstract
Initial (1999)	25.14%	26.32%	48.53%
Final (2012)	24.69%	23.80%	51.49%

Occupations are based on the BRC4 digit occupational sorting

Labor economics literature exhibits considerable scarcity in measures of offshoring potential per occupation. We apply a measure of offshorability adapted from Blinder (2009). Utilizing extensive data on US occupations (O*NET), Blinder (2009) sorts occupations into four categories (*Highly Offshorable, Offshorable, Hard to Offshore, Not Offshorable*) based on their propensity to be offshored. In a second step, based on how personal and how closely tied to a particular location a service is, Blinder assigns an occupational-specific value [1-100] to measure a job's potential to be offshored. Our measure is primarily based on this continuous index by Blinder (2009), however we perform a series of adjustments.

At first, based on the same principles with Blinder (2009), we assign index values [1-25] to the *Non-Offshorable* category, which is out of the analytical scope of Blinder (2009). Secondly, we transform the index from SOC occupational coding first to ISCO – 2008 and then to BRC 4-digit to match our analysis. In the few cases that a BRC occupation consists of multiple ISCO jobs with different offshorability values, our index is the weighted average of those values, with the weights being the occupational shares of each ISCO occupation in our dataset. In addition, we normalize the index to have zero mean and unit standard deviation. Table 4 lists the index values for the five occupations most and least prone to be offshored.

Table 4 - Offshorability Potential per Occupation

High Offshorability Potential			Low Offshorability Potential		
BRC2014 Code	Description	Index Value	BRC2014 Code	Description	Index Value
811	Software Developers	2.270	733	Construction Workers	-1.259
423	Executive Secretaries	2.124	731	Structural Construction Workers	-1.222
213	Journalists	2.051	734	Plumbers and Pipe Fitters	-1.186
212	Authors and Linguists	2.051	632	Police and Fire Department	-1.150
214	Visual Artists	1.905	633	Security Staff	-1.150

The correlation matrix (Table 5) reveals positive and significant correlations between our offshoring index and the *Routine* and *Non-Routine Manual* task measures, while the correlation with the *Abstract* task intensity is insignificant. Significant correlations point towards related and overlapping impacts from our measures of task intensity and offshoring. This complies with comparable offshoring indexes and alternative task measures applied in the literature (Blinder and Krueger, 2013; Goos et al., 2014), however it warns for additional caution in the exact decomposition between RBTC and offshoring in causing job polarization.

Table 5 - Correlation Matrix Between Offshoring Index and Task Measures

	Offshoring	Abstract	Routine	Non Routine Manual
Offshoring	1.000			
Abstract	0.0816 (0.405)	1.000		
Routine	0.1757 (0.071)	-0.5599 (0.000)	1.000	
Non Routine Manual	-0.2328 (0.016)	-0.8249 (0.000)	-0.0066 (0.9452)	1.000

Finally, there is increasing concern of potential endogeneity between Dutch wages and offshoring by Dutch firms. Although firms consider several conditions before deciding on offshoring (tax policy, institutions, technological feasibility, trade agreements etc.) wages might also play a role (Oldensky, 2014). We deal with this issue in two ways: First by using the occupational wage difference as an additional control variable in our regression analysis and secondly by basing our offshoring index on US data. As discussed in Oldenski (2014) when US firms decide on offshoring, they are considering wages in their own labor markets, relative to wages in the rest of the world. Although a series of offshoring determinants (such as an exogenous shock that might change the cost of offshoring) might be the same for US and European firms, the decision of US firms to offshore is not based on the fluctuation of wages in Europe.

5 Results

Our results section fully corresponds with our methodological approach. Section 5.1 reports our regression analysis results divided between Section 5.1.1 where we systematically determine the U-shaped national employment curve and Section 5.1.2 where we apply the polarization index in Dutch local labor markets. Finally, in Section 5.2 we perform individual regressions for the downward and upward sloping parts of the occupational curve to empirically investigate the applicability of the routinization hypothesis as a potential source of job polarization in the Dutch national labor market.

5.1 Occupational Ranking Regression Analysis

5.1.1 National Labor Market – Determining a U-shaped employment curve

Building on Dauth (2014) we investigate the composite relationship between wages and employment change per occupation, by estimating Eq. (1) for the Dutch labor market. Adding the additional conditions for the proper estimation of a U-shaped curve (Lind and Mehlum, 2011), we provide systematic evidence of one extreme point falling at the economic sensible part of the quadrant (turning point is estimated at the 40th occupational percentile).

$$\Delta s_{i,1999-2012} = \underset{(0.054994)}{0.041135} + \underset{(0.002747)}{0.005101}\,rank + \underset{(0.000026)}{0.000064}\,rank^2 \quad (5)$$

The empirical estimation for the quadratic regression (Eq. 5 - robust standard errors in parentheses) clearly points to a U-shaped employment pattern. The model is significant in all usual levels ($F_{2,97} = 5.47$) and the R^2 coefficient ($R^2 = 0.08$) falls within the range of values in the job polarization literature applying similar methodology[16]. The graphical illustration of the fitted regression line (Figure 5.1) verifies the asymmetric pattern of employment polarization

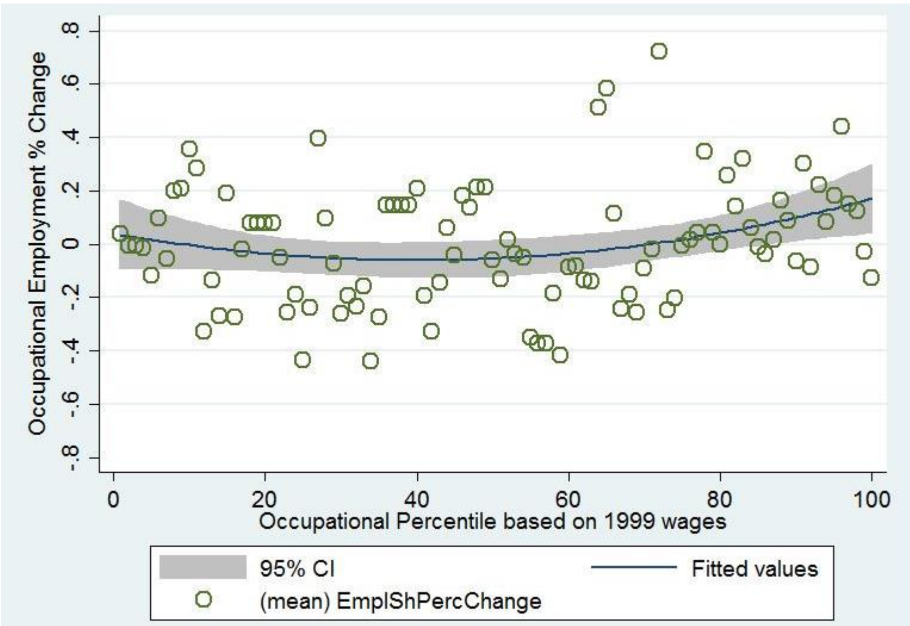

Figure 5.1. Occupational Employment Change Curve in the Netherlands (1999-2012)

indicated by our non-parametric analysis. The percentage point increase in the employment share of the top quintile considerably exceeds the respective increase in the lowest

[16] The R^2 coefficients reported by Dauth (2013, 2014) for the German labor market are 13% and 12% respectively, while Lago (2016) applies the same regression analysis and reports an adjusted R^2 equal to 7%.

occupational quintile. In that respect, our econometric specification is in line with empirical findings from the international literature (Blien and Dauth 2016, Dauth 2013, 2014).

5.1.2 A regional Polarization Index

The sub-national context of our occupational ranking regression analysis consists of utilizing the t-value of the squared term from Eq. (3) as an appropriate *Polarization Index* and performing quantitative comparisons between the degrees of polarization among Dutch local labor markets (arbeidsmarktregios).

Based on the *Polarization Index* value (PI = 2.19) from Eq. (5), we classify the regional regression results (Figure 5.1) into four categories, depending on their degree of polarization (Analytical results are provided in Table A5.1 – Appendix) . Polarized local labor markets (t-value > 1.65 for the 10% significance level) are divided between *Strongly* (PI > 2.19) and *Significantly Polarized* (1.65 < PI < 2.19) ones, with the former showing a stronger U-shaped relationship compared to the national labor market. In contrast, *Not polarized* local labor markets exhibit insignificant PI values (PI < 1.65) while *Negatively Polarized* ones exhibit an inverted U-shape employment pattern (PI < - 1.65). Finally, we classify a region as not polarized if equation 2 fails to hold or if the F-statistic of the regression is below the critical value for significance at least at the 10% level, which means that all the independent variables are jointly equal to zero.

Based on our arbeidsmarktregio results (Figure 5.3 - Analytical results in Table A5.2) Dutch local labor markets exhibit substantial disparities in employment dynamics. Only eight out of the thirty-five local labor markets exhibit U-shaped employment patterns, however in all of them the degree of polarization is stronger than the aggregate Dutch labor market (PI > 2.19). The regional regression analysis indicates measurable employment polarization dynamics both in the cases of central labor markets (such as Amsterdam or Rijnmond) and also some peripheral ones (such as Groningen or Zuid Limburg).

Although Netherlands is a relatively small country and therefore regional disparities are not as pronounced as in bigger countries, we contribute to the regional polarization literature by identifying structural economic and labor market attributes consistently leading to or discouraging regional employment polarization. In order to identify such underlying regional characteristics, we employ probit analysis and regress the probability of a local labor market exhibiting job polarization (based on our PI regional outcomes) on a vector of regional labor market and demographic variables (Eq. 6).

$$polDum_i = a_0 + a_1 Rout\_Cog + a_2 Rout\_Man + a_3 NonRout\_An + a_4 NonRout\_Int + \\ + a_5 NonRout\_Man + a_6 Urb + a_7 ShareFem + \varepsilon_i \qquad (6)$$

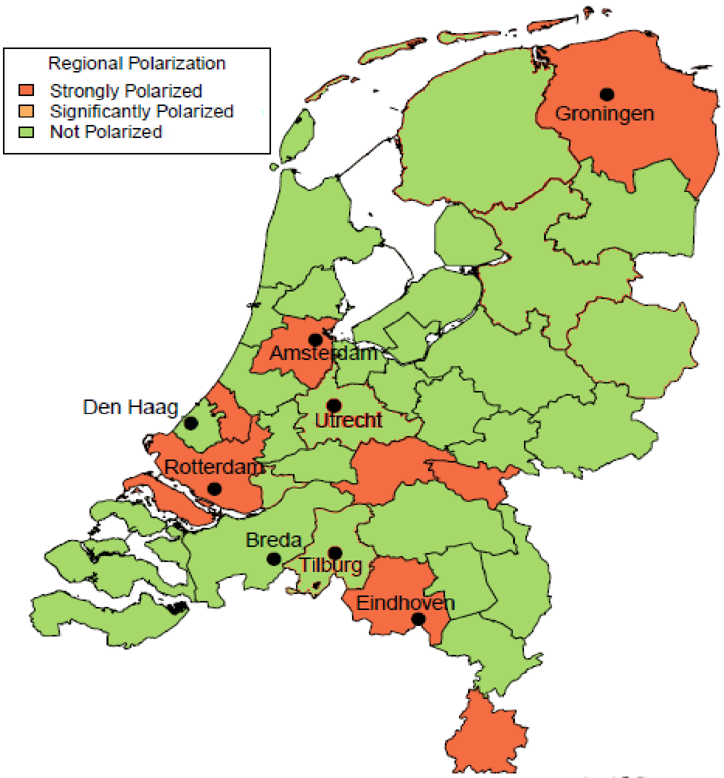

Figure 5.2. Occupational Ranking Regression Analysis Arbeidsmarktregio Results

The dependent variable ($polDum_i$) is a dummy variable controlling for *Strong* or *Significant* polarization, based on the proceeding analysis (Table A5.2). Following the literature (Goos et al., 2014) we include all occupational task measures at their most disaggregated level (5 category taxonomy), as indicated by the model with the lowest *Akaike Information Criterion (AIK)*. In addition, to account for demographic and labor market conditions, we add an urbanization dummy based on the OECD rural / urban typology and the share of women in the total regional labor force.

The estimated marginal effects (Table A5.1-panel B) indicate the significance of both labor market and demographic conditions. Routine cognitive task intensity imposes a negative effect on a region's probability to exhibit employment polarization, however it is partially superseded by the positive impact from non-routine interactive task intensity. The estimated marginal effect for the routine manual tasks intensity is significant at the 5% level and points towards an enormous increase in the probability of the arbeidsmarktregio exhibiting job polarization by 603.03 per one s.d. increase in the regional routine task intensity. Similarly, the marginal effect from interactive task intensity increases the probability of a local labor market exhibiting job polarization by 410.55 units per 1 s.d. increase in the interactive task intensity. Finally, the marginal effect of the urbanization dummy is significant at the 5% level and predicts a 0.2617 increase in the probability of a local labor market exhibiting job polarization when an arbeidsmarktregio is urban.

5.1.3 Sensitivity analyses

To provide further insight of employment trends in the Dutch national and local labor markets we reiterate the above analysis dividing between young and old employees (age differentiation) as well as between males and females (gender differentiation).

A) Age differentiation

National labor market:

Different labor market dynamics between younger and older employees are particularly important, especially in the Netherlands which is faced with an ageing population and higher life expectancy (Bosch and ter Weel, 2013). Within this context, we investigate the predominance of labor market polarization between younger (less than 35 years) and older (equal or more than 35 years) employees in the national and local labor markets.

$$\Delta s_{i,1999-2012} = \underset{(0.8840)}{0.24218} - \underset{(0.0041)}{0.01459} * rank + \underset{(0.00004)}{0.00015} * rank^2 \qquad (7)$$

$$\Delta s_{i,1999-2012} = -\underset{(0.50518)}{0.06314} + \underset{(0.00262)}{0.00113} * rank + \underset{(0.00002)}{0.000002} * rank^2 \qquad (8)$$

Our comparative analysis of job polarization between younger and older employees (Eq. 7 and 8) reveals remarkably different trends. The estimated equation for young workers (Eq. 7) is overall significant in all usual levels ($F_{2,97}$ = 6.35) and the negative (positive) and significant level (squared) term clearly determine a U-shaped employment pattern, indicative of employment polarization. Younger employees are drawn away from middle-waged, routine jobs and seek employment in non-routine occupations, both high- and low-skilled. In contrast, Eq. 8 is unable to capture a job polarization trend among older employees. The estimated model is insignificant ($F_{2,97}$ = 1.58) and so are the independent variables when individually tested.

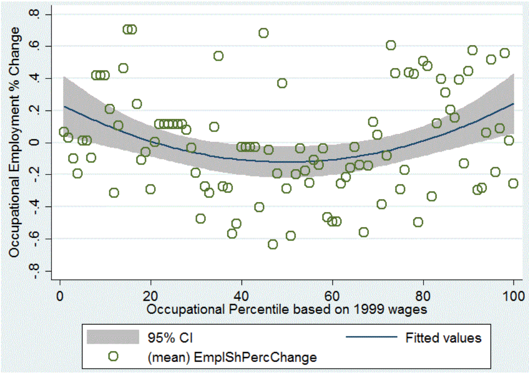

Figure 5.3. National Employment Trends (young workers)

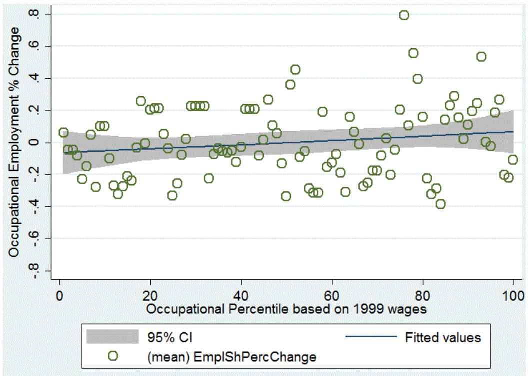

Figure 5.4. National Employment Trends (old workers)

Figures 5.3 and 5.4 provide visual confirmation of the abovementioned divergent trends. In the case of young workers (Figure 5.3) the regression line from Eq. 7 verifies the U-shaped employment curve, as opposed to older employees (Figure 5.4) who exhibit a rather stable employment trend. Such discernible differences in employment dynamics re-invigorate the debate considering labor market opportunities of old workers. Rapid technological developments alter the tasks performed especially in high-skilled jobs, however the occupational-specific human capital acquired by old employees within their working spell is nowadays obsolete, leading them out of the labor force. Moreover, old labor force faces additional restrictions (mobility becomes costly with age) that further confine their potential to find employment. In contrast, young workers adjust more easily to technological advances, advancing their human capital thus increasing their labor market efficiency.

A regional polarization index:

Our sub-national analysis separated between young (Figure 5.5) and old (Figure 5.6) employees reveals striking differences. Job polarization dominates employment dynamics among employees at the first stages of their working life in fifteen out of the thirty-five local labor markets (Figure 5.5 – Analytic results in Table A4.2 - Appendix) while it is barely evident in labor markets of older employees (Figure 5.6 - Analytic results in Table A4.3 - Appendix). Job polarization among young workers is evident in arbeidsmarktregios extending in all the country and exhibiting different demographic and labor market characteristics (for instance job polarization is traced in highly rural areas such as Drenthe and in highly urban ones, such as Amsterdam). Under such patterns, it is not possible to define a socio-economic environment conducive to employment polarization. We can unambiguously determine however that job polarization dominates labor markets consisting of young employees, making it a labor market phenomenon bound to increase in importance in the coming years.

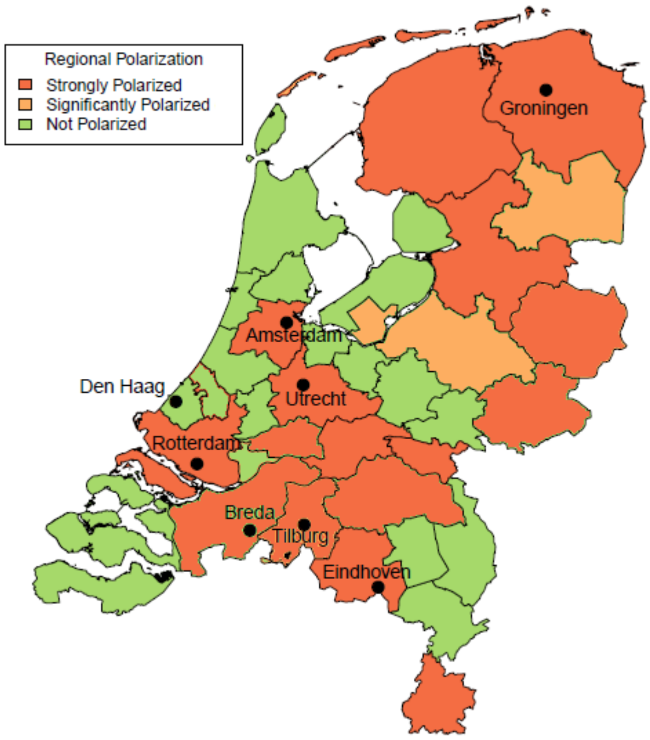

Figure 5.5. Sub-national analysis (young workers)

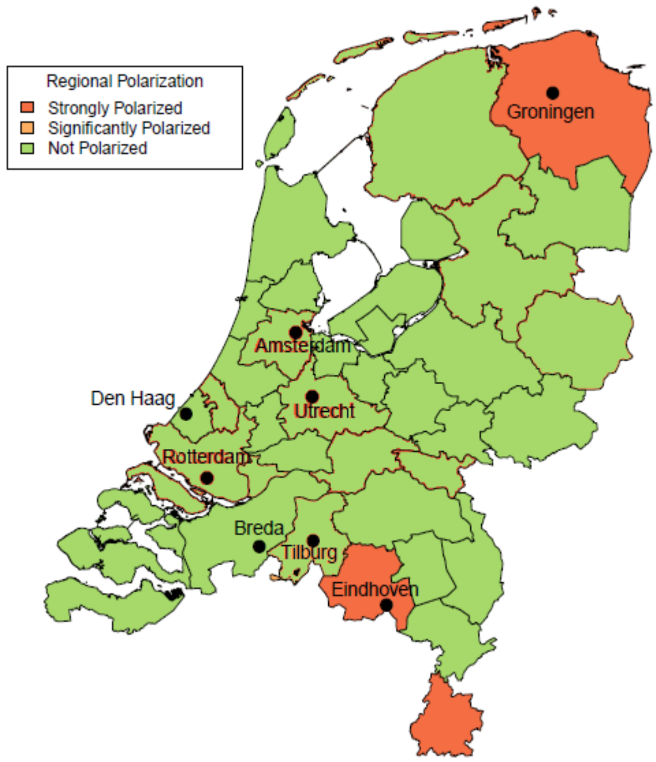

Figure 5.3. Sub-national analysis (young workers)

B) Gender Differentiation

Equations 9 and 10 decompose our analysis by gender, documenting diverse employment trends for men and women in the Dutch national labor market. Eq. 9 is overall significant ($F_{2,97}$ = 2.99) and fulfills all the required conditions for a U-shaped regression curve. Therefore it provides evidence for the prevalence of job polarization in the male national labor market. Men are hollowing out of middle-skilled occupations but succeed in obtaining both low- and high-skilled non-routine jobs, thus giving rise to an employment polarization pattern.

$$\Delta s_{i,1999-2012} = \underset{(0.06224)}{0.09656} - \underset{(0.00278)}{0.00619}\, rank + \underset{(0.00002)}{0.00006}\, rank^2 \qquad (9)$$

$$\Delta s_{i,1999-2012} = \underset{(0.06543)}{-0.07465} - \underset{(0.00341)}{0.00233}\, rank + \underset{(0.00003)}{0.00006}\, rank^2 \qquad (10)$$

In contrast, the female national labor market exhibits an upgrading trend. The estimated equation (Eq. 10) is overall significant ($F_{2,97}$ = 11.18), however we cannot verify positive employment with negative slope in low-paying jobs. Female workers are pulling out of low-and middle-skilled employment in the favor of high-skilled occupations. The divergence between male and female employment trends is further shown in Figures 5.7 and 5.8, where employment dynamics for men (Figure 5.7) follow a U-shaped pattern, while for women the pattern is monotonous with a positive slope. In sum, our gender analysis follows the scarce empirical literature (Coelli and Borland, 2016) and verifies that employment polarization in the Dutch national labor market is largely a male phenomenon.

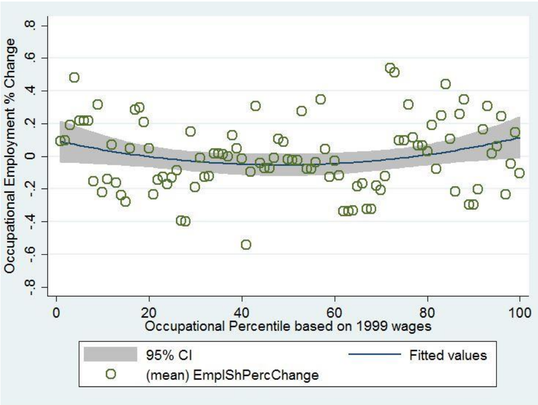

Figure 5.7. National Employment Trends (male workers)

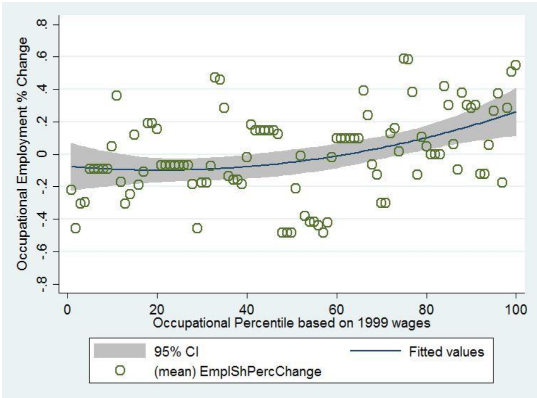

Figure 5.8. National Employment Trends (female workers)

To account for these divergent trends, we disembark from the stylized fact that employment polarization is predominantly a demand-driven phenomenon. Instead, we account for the upgrading employment trend for women by means of two explanations. Changes in the occupational distribution within each gender are decomposed into i) changes in the overall employment distribution and ii) changes in the gender-specific occupational distribution. Our gender-invariant analysis so far has shown that overall employment changes in the Netherlands follow a job polarization pattern, therefore we need to account for our result by changes in occupational employment within women.

A potential solution would be the *composition effect.* In case women were concentrated in low-paying jobs, even an evenly spread employment growth would point towards greater growth in high-paying jobs. However the distribution of female employment in occupations sorted by their initial wage is skewed to the right (Sk = 2.94). As a result, women are initially greater represented in high-paying occupations, therefore the composition effect is not a valid explanation. An alternative explanation rests in the non-economic reasons that influence female labor force participation. Women often enter and exit the labor market based on social (i.e. childbirth) rather than economic criteria. Such irregularities render the female labor force more heterogeneous than the male one and consequently more different to model. For instance, Cerina et al. (2017) show that the non-economic criteria influencing female participation in the labor market differ between married and single women. As a result, gender-specific labor market investigations need to be very detailed. Since then, it is important to be cautious of any gender-specific result interpretation.

A regional polarization index:

\Investigating employment polarization by gender in Dutch local labor markets (Figures 5.9 and 5.10) mainly verifies our results on the national labor market. Job polarization is more pronounced in male labor markets (12 job polarized arbeidsmarktregios compared to only 6 for women). Although there are some local labor markets for which job polarization is evident both for men and women (Groningen, Rivierenland, Rijk van Nijmegen) sample restrictions and the very low prevalence of employment polarization in the case of women prevent us from proceeding to any meaningful comparisons.

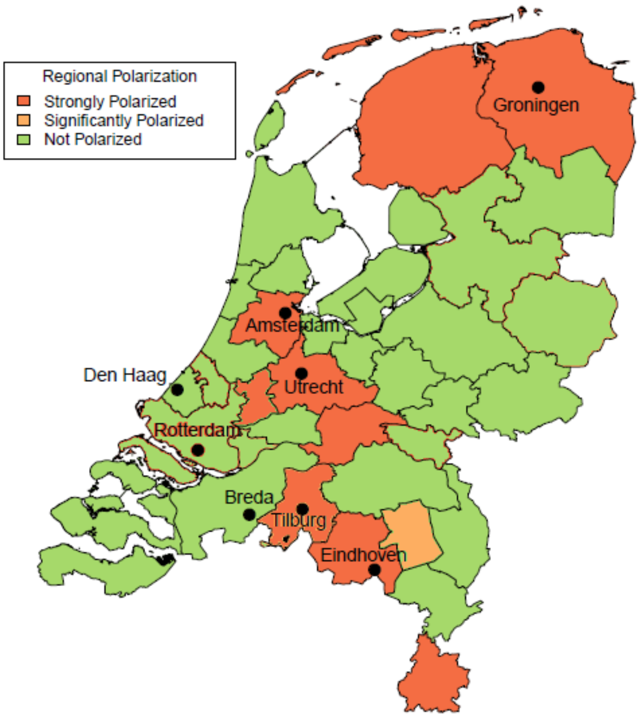

Figure 5.9. Sub-national analysis (male workers)

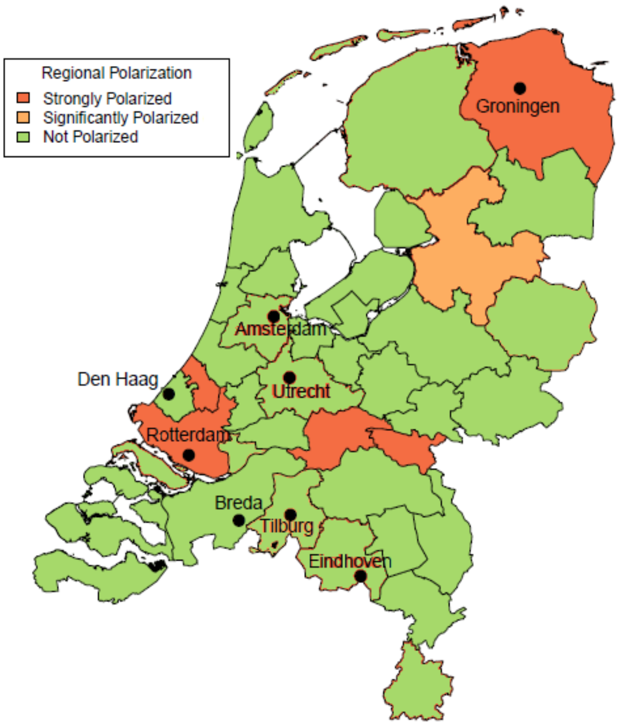

Figure 5.10. Sub-national analysis (female workers)

5.2 Sources of job polarization

Tables 6 and 7 report our regression results investigating the potential sources of job polarization for the Dutch national labor market. Our empirical estimates are robust to alternative sets of independent variables (different aggregation of task measures) and

Table 6 – Regression Analysis – Sources of Job Polarization – Low-paying occupations **(perc < 50)**
Dependent Variable: Employment Share Change (%) per occupation between 1999 and 2012 (Q3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Routine	- 0.8142 [0.1777]***		- 0.4882 [0.2268]**				
Abstract	- 0.4321 [0.3668]			0.0082 [0.2395]			
Non Routine Manual	- 0.2964 [0.2496]				0.3574 [0.1624]**		
Routine Cognitive						- 0.2892 [0.2558]	
Routine Manual						- 0.7864 [0.1730]***	
Non Routine Analytic							- 1.3001 [1.2281]
Non Routine Interactive							0.0060 [0.2360]
Offshoring	- 0.0929 [0.0349]**	-0.1221 [0.03814]***	-0.0833 [0.0337]**	-0.1220 [0.0190]***	-0.1160 [0.0301]***	-0.0687 [0.0315]**	-0.1211 [0.0403]***
Wage Difference	2.5796 [1.4277]*	1.7224 [1.4366]	2.2895 [1.2852]*	2.1898 [1.6648]	3.0189 [1.2747]**	1.2525 [1.2922]	1.6178 [1.8428]
Constant		-0.3281 [0.2384]	-0.2957 [0.2449]	-0.4318 [0.2417]*	-0.7135 [0.2148]***	-0.1180 [0.2352]	-0.3064 [0.2969]
Observations	42	44	42	42	42	42	42
F-stat	7.79	5.34	11.13	3.49	10.29	16.80	3.75
R^2	0.40	0.22	0.38	0.26	0.35	0.44	0.28

Occupations are sorted according to the BRC 4-digit pattern. */**/*** denote significance in the 10%/5%/1% respectively. Robust standard Errors are reported in the parentheses

estimation techniques (occupations weighted by their initial employment). The estimation results confirm the routinization hypothesis and the predicted effect of offshoring in the labor economics literature, both for low- and high-paying (and skill) occupations.

Focusing on low-paying jobs (Table 6), our models argue towards a consistent negative effect from offshoring on occupational employment. The fragmentation of production is significantly associated with decreasing employment in low-paying (and skill) jobs. The effect varies from 12% average decrease in employment per 1 s.d. increase in offshoring when offshoring is modelled alone (Spec.: 2) or when it is the only significant predictor (Spec.: 4 and 7) to a 6.96% when offshoring is modelled together with the two constituents of Routine task intensity. In our general model (Spec.: 1) 1 s.d. increase in the potential to offshore results in 9.5% decrease in average employment for the Dutch national labor market.

Furthermore, our regression results verify the theoretical predictions of RBTC. In particular, model 1, documents the negative impact from routine task intensity on the employment shares of low-paying jobs. The negative effect persists even when routine task intensity is the only task measure used as a predictor (Spec.: 3), although with considerably decreased magnitude. Disaggregating between cognitive and manual routine tasks, we prove the relative importance of routine manual tasks. Our result supports the routinization principle, since manual tasks are more easily codified and implemented by computer capital compared to cognitive ones..

Abstract task intensity imposes no significant impact on employment dynamics of low-paying jobs, as pointed both by our general (Spec. 1) and individual (Spec. 3) models. We mainly attribute this on the low representation of Abstract tasks in such jobs (Figure 3.1). Furthermore, neither of the two constituents of abstract tasks (analytic and interactive) impose a significant impact on occupational employment (Spec. 7). Finally, Specification 5 reveals a positive employment effect in low-skilled occupations stemming from non-routine manual task intensity. Although our estimate is not verified by our general model (Spec.: 1), it captures the employment transition from routine occupations to low-paying jobs, exhibiting high non-routine manual task intensity, as indirectly predicted by the routinization hypothesis.

Table 7 – Regression Analysis – Sources of Job Polarization – High-paying occupations (**perc >= 50**)
Dependent Variable: Employment Share Change (%) per occupation between 1999 and 2012 (Q3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Routine	- 0.0179 [0.2957]		- 0.5115 [0.2025]**				
Abstract	0.3549 [0.1617]***			0.4054 [0.1037]***			
Non Routine Manual	- 0.0796 [0.1539]				- 0.5377 [0.1499]***		
Routine Cognitive						- 0.4523 [0.2068]**	
Routine Manual						- 0.9134 [0.5511]	
Non Routine Analytic							0.4165 [0.1637]**
Non Routine Interactive							0.3998 [0.1471]***
Offshoring	- 0.0658 [0.0298]**	- 0.0695 [0.0312]**	-0.0508 [0.0275]*	-0.0634 [0.0279]**	-0.0811 [0.0309]**	-0.0509 [0.0278]*	-0.0642 [0.0295]**
Wage Difference	-1.2020 [1.0939]	-0.6825 [1.0859]	- 0.2996 [1.0413]	- 1.1241 [0.9367]	- 1.6708 [1.0469]	- 0.5573 [0.9897]]	- 1.1071 [0.9106]

Constant		0.1409 [0.1624]	0.1849 [0.1491]	-0.0598 [0.1454]	0.3662 [0.1633]**	0.2304 [0.1420]	-0.0610 [0.1429]
Observations	64	64	64	64	64	64	64
F-stat	3.86	2.55	4.08	6.43	5.02	2.90	4.94
R^2	0.22	0.08	0.16	0.21	0.18	0.17	0.21

Occupations are sorted according to the BRC 4-digit pattern. */**/*** denote significance in the 10%/5%/1% respectively. Robust standard Errors are reported in the parentheses

Considering high-paying jobs (Table 7) once again we detect a negative employment effect from the potential to offshore. However in this case the impact is considerably smaller, since it varies from 5% average employment decrease from 1 unit increase in the offshoring potential (Spec.: 3 and 6) to 8% (Spec.: 5). The estimate from the general model (Spec.: 1) predicts a 6.5% decrease on average employment due to a 1 s.d. increase in the offshoring potential.

Our estimation results considering high-skilled jobs confirm a set of significant monotone effects from the available task measures. In particular, Abstract task intensity significantly impacts average employment positively, an effect similar in magnitude between the general (Spec.: 1) and the individual model (Spec.: 4). Disentangling among its two constituents (Spec.: 7), we determine that both non-routine analytic and interactive tasks impose a positive and similar in magnitude (40% increase in average employment by 1 unit increase in analytic or interactive task intensity) effect on employment. Routine task intensity causes a decrease in average employment equal to 30% on average due to a 1 unit increase in routine task intensity (Spec.: 3), however this impact is not significant in the general specification. Separating between routine cognitive and manual tasks (Spec.: 6), we conclude that the cognitive part is the only one to impose a significant negative effect on employment. Finally, our model (Spec.: 5) captures a negative employment effect from the non-routine manual task intensity, although it is not verified by our general specification.

Taken together, offshoring is associated with a contraction of employment throughout the occupational distribution. Compared to the impact from offshoring predicted by Goos et al. (2014) for 16 Western European economies, our significant offshoring coefficients in document that employment in the Netherlands is more vulnerable to international fragmentation than the rest of the European countries. In particular, low-paying (and skill) jobs are more prone to be internationally fragmented. We attribute this difference to our more disaggregated offshorability index. We assign offshorability values to 106 BRC 4 digit occupations, while the one utilized by Goos et al. (2014) provides values for 22 ISCO 2-digit occupations. However low-skilled occupations in the Netherlands suffer a greater negative effect due to international fragmentation of production compared to high-skilled ones. In addition, our predictions confirm the theoretical standpoints of RBTC as a potential source of job polarization. We were able to trace a monotone negative effect from Routine and a positive from Abstract tasks in low- and high-paying occupations respectively. These monotone effects, brought together in a unified framework verify the occupational transition dynamics predicted by the routinization hypothesis.

6 Conclusions and discussion

In the last years, a number of studies have shown that in industrialized countries employment growth is "polarizing": most employment growth has concentrated in high-skill and high-paid and low-skill and low-paid work, with the hollowing out of jobs in the middle of the wage distribution. Empirical literature predominantly focuses on "demand-side" explanations for job market polarization, such as technological advancements or trade and offshoring. In that respect, changes in educational attainment or shifts in workers' potential to participate in the labor market will in turn change the employers' demands for skills, not only the available supply of skills. Potential contributors to the polarization of employment of primal importance in industrialized economies are the routinization hypothesis (Baumol, 1976; ALM, 2003), the international trade and offshoring of goods and services (Blinder, 2009; Blinder and Krueger, 2013; Goos, Manning and Salomons, 2014) and the falling of real value of the minimum wage (Lee, 1999). While job polarization has been occurring in countries such as the United States, Canada and Australia, trends have been mixed within Europe at national and sub-national geographical levels (Goos, Manning and Salomons, 2009, 2014; OECD, 2016).

The premise of this paper is that Netherlands follows the international pattern of asymmetric employment polarization between 1999 and 2012. By means of regression analysis, we verify earlier empirical results (OECD, 2016) that Dutch national labor market shows greater employment growth in high-skilled and wage occupations, compared to low-skilled ones.

At the regional level, we confirm the spatial heterogeneity both in the occurrence and the degree of job market polarization. In that sense, we compare the degree of job polarization both between regions and between regions and the national labor market. Our results indicate that the majority of the provinces and almost half of the Dutch local labor markets (arbeidsmarktregio's) experience polarization. Furthermore, our analysis provides some evidence that polarization is linked to regionally-specific economic conditions: predominantly polarized local labor markets also exhibit considerable urbanization and employment in Science and Technology sector in the beginning of our time period (1999).

Investigating the potential sources of job polarization, our regression estimates confirm both the routinization hypothesis and offshoring as sources of employment polarization in the Dutch national labor market. Our results on the task content of occupations verify the negative impact to occupational employment imposed by the routine intensity of the job, especially in low-paying jobs. In addition, we documented a positive impact to occupational employment due to the degree of the abstract-intensity of the occupation. In addition, we trace a differential impact from the non-routine manual task intensity, which increases employment in low-paying occupations and decreases employment in high-paying ones. Given that abstract task intensity is mostly pronounced in high-skilled jobs, routine intensity is the main task intensity in average skilled jobs and non-routine manual in low-paying occupations, the above three effects contribute to U-shaped employment polarization dynamics. Similarly, our conclusions are in line with previous empirical literature (Autor, 2010; Goos, Manning and Salomons, 2009, 2014; Ceda, 2015) and support the *routinization hypothesis* as the main source of employment polarization in the Netherlands.

International fragmentation of production is an additional source of job polarization in the Netherlands. In compliance with the literature, the potential to offshore imposes a negative impact on occupational employment, especially in low-skilled jobs. Employment is shifting away from low-skilled and routine-based occupations in greater degree than high-skilled ones, further contributing to employment polarization. Unfortunately, lack of regional data on offshoring prevents us from disentangling the exact complementarities between the routinization hypothesis and offshoring at the sub-national level.

Policy implications

The results show that although polarization is present on an aggregate level, many regions do not exhibit any polarization, either due to decline of the high-paying jobs, an increase of middle paying jobs, a decline in job paying jobs or a combination of these three. As a result, should a policy response to polarization be deemed necessary, that this would be best provided on a local level. Furthermore, substantial work remains for future scholars. Although we establish a link between urbanization and polarization, this relationship is far from perfect and is hard to prove definitive given the small number of Dutch regions. Some peripheral regions such as Groningen and Friesland exhibit consistent polarization, which suggests that urbanization cannot fully explain the regional heterogeneity.

Finally, our analysis comes with a few caveats. First of all, we ignore any changes that may have occurred within jobs, as we use the 1999 wage as indicator for the skill level. Spitz-Oener (2006) and Akcomak et al. (2012) show that the changes in task composition within jobs are substantial, and in magnitude comparable to the effect of changes in job-composition. Second, we have ignored any changes in the labour force composition. It is well known that the supply of university graduates has been increasing over the last decades, both in absolute numbers as well as in a relative sense. Thus, it might well be that polarization is less of a ‘problem’ than a suitable adaption to the skill upgrading of the workforce. For instance, van den Berge en Ter Weel (2015) show that a significant amount of the polarisation in the Netherlands can be explained by changes in labour supply. However, constructing a regional labour supply is extremely difficult in the Netherlands, given the high degree of commuting between regions (f.i. 30% of the population works in a different NUTS3-region than they live). Therefore, we cannot make any inferences about the degree to which polarization is ‘a problem’ that might require a solution or policy intervention.

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Appendix

Appendix A1 – A Job Polarization Index

Based on Eq. (1) in the main text, the formula for the squared term is the following:

$$t_{rank^2} = \frac{\hat{a}_2}{\dfrac{\hat{\sigma}}{\sqrt{[SST_{rank^2}(1-\rho_{rank:rank^2})]^2}}} \qquad (1)$$

the t-value depends on: the estimated parameter (a_2), the standard error of the regression ($\hat{\sigma}$), the total sum of squares (SST_{rank^2}) and the correlation coefficient between the linear and the non-linear term, therefore capturing the magnitude as well as the variation of the effect. However –to ensure regional comparability- we apply the same occupational ranking in all local labor markets, therefore the coefficient $\rho_{rank:rank^2}$ remains constant. Due to this, the whole term $SST_{rank^2}(1-\rho_{rank:rank^2})$ is represented by a constant c. As a result, Eq. (3) is now reduced to:

$$t_{rank^2} = \frac{\hat{a}_2}{\hat{\sigma}} c = PI$$

Where $c = \sqrt{[SST_{rank^2}(1-\rho_{rank:rank^2})]^2}$

Appendix A2

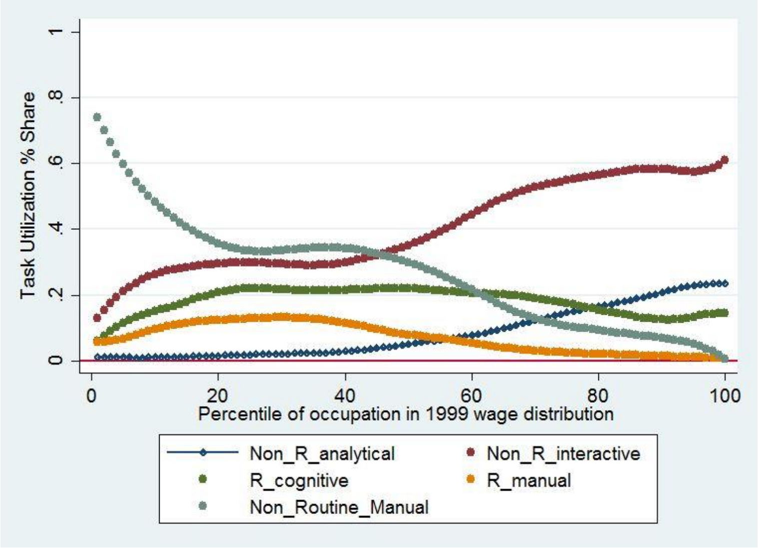

Figure A2.1. Task Utilization per Occupational Percentile (5 – Category Taxonomy)

Table A2.1 – Task Intensity (5 Categories)

	Non - Routine Manual	Routine Cognitive	Routine Manual	Non Routine Analytic	Non Routine Interactive
Initial (1999)	25.14%	18.95%	7.36 %	8.26%	40.26%
Final (2012)	24.69%	17.27%	5.52%	8.76%	42.72%

Occupations are classified according to the BRC 4-Digit Occupational Classification

Table A2.2 – Initial and Final Skill Utilization per Province

Province	Year	Non - Routine Manual	Routine Cognitive	Routine Manual	Non Routine Analytic	Non Routine Interactive
Drenthe	1999	30.17%	16.96%	9.18%	6.19%	37.48%
	2012	31.35%	16.83%	6.94%	6.61%	38.25%
Flevoland	1999	24.26%	18.17%	7.17%	7.55%	42.86%
	2012	23.87%	17.42%	4.88%	8.62%	45.20%
Friesland	1999	28.94%	18.40%	8.19%	6.24%	38.22%
	2012	26.75%	17.75%	6.59%	7.11%	41.75%
Gelderland	1999	26.80%	18.01%	8.31%	7.81%	39.06%
	2012	26.11%	17.53%	5.87%	8.60%	41.88%
Groningen	1999	28.49%	16.76%	8.63%	7.71%	38.41%
	2012	25.35%	18.15%	6.10%	9.00%	41.40%
Limburg	1999	26.96%	17.72%	9.45%	6.75%	39.09%
	2012	27.43%	17.62%	6.66%	7.66%	40.63%
Noord Brabant	1999	26.58%	18.07%	9.33%	7.56%	38.48%
	2012	26.08%	17.81%	6.40%	8.32%	41.39%
Noord Holland	1999	22.19%	20.73%	5.14%	9.03%	42.91%
	2012	22.75%	19.30%	4.32%	8.98%	44.64%
Overijssel	1999	28.15%	17.62%	9.70%	6.39%	37.58%
	2012	26.31%	17.74%	6.95%	7.56%	41.43%
Zuid Holland	1999	23.62%	19.84%	6.17%	8.93%	41.42%
	2012	23.09%	18.76%	4.89%	9.55%	43.70%
Utrecht	1999	21.25%	19.75%	5.37%	11.34%	42.28%
	2012	21.04%	18.85%	4.01%	10.96%	45.13%
Zeeland	1999	31.71%	18.01%	9.08%	5.36%	35.83%
	2012	30.13%	17.01%	9.21%	5.93%	37.71%

Occupations are classified according to the BRC 4-Digit Occupational Classification

Table A2.3 - Mean hourly Wages per Occupational Type in 1999 and 2012

	Non - Routine Manual	Routine	Abstract	Overall
Initial (1999)	13.98	14.07	20.13	15.66
Final (2012)	21.82	22.68	30.77	25.17

Source: Netherlands Statistics. Wages are based on gross income, excluding pension payments.

Appendix A3 –Urbanization index by region

We construct a two – dimensional *Urbanization Index* taking into account regional population density and the presence of a large (greater than 200.000 inhabitants) urban center. At first (Criterion 1), we sort local labor markets according to their population density and split their distribution into four equal parts: *Urbanized*, *relatively urbanized*, *relatively Rural* and *Rural.* At a second stage (Criterion 2), following Davis and Dingel (2013) and Hu et al. (2014) in their argument that large cities attract high – skilled workers occupied in skill-intensive sectors, we incorporate the presence of a large urban center in our urbanization index by moving one category higher all the local labor markets that incorporate one or more of the four largest Dutch cities with population exceeding 200.000 inhabitants in the year 1999 (Amsterdam, Rotterdam, the Hague, Utrecht– Source *Statistics Netherlands 2016*). In that sense, our index adopts the construction principle of the *new typology on rural / urban regions* (Eurostat).

Urbanization Index for Arbeidsmarktregios:

Table A.3.2: Urbanization Index of arbeidsmarktregio's

Region	**Pop. Density**	**Urbanization Index**
Haaglanden	2926	Urbanized
Groot Amsterdam	1843	Urbanized
Drechtsteden	1797	Urbanized
Zuid-Kennemerland	1520	Urbanized
Zuid-Holland Centraal	1283	Urbanized
Rijnmond	1128	Urbanized
Gooi en Vechtstreek	1091	Urbanized
Holland Rijnland	1058	Urbanized
Zuid-Limburg	977	Urbanized
Midden-Utrecht	801	Urbanized
Zaanstreek/Waterland	851	Relatively urbanized
Amersfoort	849	Relatively urbanized
Rijk van Nijmegen	831	Relatively urbanized
Midden-Holland	685	Relatively urbanized
Midden-Gelderland	675	Relatively urbanized
Midden-Brabant	549	Relatively urbanized
Zuidoost-Brabant	519	Relatively urbanized
Food Valley	457	Relatively urbanized
West-Brabant	446	Relatively rural
Noordoost-Brabant	443	Relatively rural
Helmond-De Peel	436	Relatively rural
Noord-Holland Noord	428	Relatively rural
Twente	404	Relatively rural
Gorinchem	370	Relatively rural
Midden-Limburg	343	Relatively rural
Rivierenland	322	Relatively rural
Noord-Limburg	320	Relatively rural
Stedendriehoek en NW Veluwe	304	Rural
Flevoland	247	Rural
Achterhoek	244	Rural

Groningen	231	Rural
IJsselvechtstreek	217	Rural
Zeeland	207	Rural
Friesland	185	Rural
Drenthe	171	Rural

Appendix A4 –Regional Regression Results

Table A4.1 - Arbeidsmarktregio Results

	Urbanization status	PI-value	U/ Test	Extreme Point (Percentile)	F-statistic	Polarization status
Drechtsteden	Urban	1.67	No	-	1.91	None
Gooi en Vechtstreek	Urban	0.35	No	-	3.59	None
Groot Amsterdam	Urban	2.58	Yes	48.62	3.48	Strong
Haaglanden	Urban	1.15	No	-	0.93	None
Holland Rijnland	Urban	0.49	No	-	1.11	None
Midden Utrecht en Gooi	Urban	1.84	No	-	2.30	None
Rijnmond	Urban	2.48	Yes	41.95	3.80	Strong
Zuid Holland Centraal	Urban	2.78	Yes	59.16	4.42	Strong
Zuid Kennemerland en Ijmond	Urban	1.08	No	-	0.58	None
Zuid Limburg	Urban	3.48	Yes	44.77	6.06	Strong
Amersfoort	Relatively urban	-0.15	No	-	0.52	None
Food Valley	Relatively urban	-0.35	No	-	1.80	None
Midden Brabant	Relatively urban	1.82	No	-	4.05	None
Midden Gelderland	Relatively urban	-0.31	No	-	0.92	None
Midden Holland	Relatively urban	0.80	No	-	6.58	None
Rijk van Nijmegen	Relatively urban	3.04	Yes	45.75	5.15	Strong
Zaanstreek Waterland	Relatively urban	0.53	No	-	0.53	None
Zuidoost Brabant	Relatively urban	4.48	Yes	45.89	10.98	Strong
Gorinchem	Relatively rural	-0.31	No	-	2.83	None
Helmond - De Peel	Relatively rural	0.70	No	-	0.34	None
Midden Limburg	Relatively rural	1.36	No	-	1.79	None
Noord Holland	Relatively rural	-0.22	No	-	0.25	None
Noord Limburg	Relatively rural	1.01	No	-	1.00	None
Noordoost Brabant	Relatively rural	2.01	No	-	4.55	None
Rivierenland	Relatively rural	2.95	Yes	48.23	6.28	None
Twente	Relatively rural	1.60	No	-	1.73	None

West Brabant	Relatively rural	0.33	No	-	0.95	None
Achterhoek	Rural	-0.19	No	-	0.06	None
Drenthe	Rural	0.11	No	-	0.04	None
Flevoland	Rural	0.07	No	-	0.74	None
Friesland	Rural	1.50	No	-	2.11	None
Groningen	Rural	3.86	Yes	44.30	7.53	Strong
Ijsselvechtstreek	Rural	1.97	No	-	3.83	None
Stedendriehoek B.V.	Rural	1.24	No	-	2.18	None
Zeeland	Rural	-0.24	No	-	0.68	None

Table A4.2 - Age-Specific Regression Results

	Young Employees					Old Employees				
	PI-value	U-Test	Extreme Point	F-statistic	Polarization status	PI-value	U-Test	Extreme Point	F-statistic	Polariza
Drechtsteden	1.85	No	-	1.78	None	0.98	No	-	0.49	None
Gooi en Vechtstreek	0.48	No	-	1.44	None	0.25	No	-	1.47	None
Groot Amsterdam	3.59	Yes	52.23	5.44	Strong	1.22	No	-	0.80	None
Haaglanden	1.81	No	-	2.27	None	-0.18	No	-	0.80	None
Holland Rijnland	1.28	No	-	2.39	None	0.77	No	-	0.38	None
Midden Utrecht en Gooi	3.78	Yes	53.56	7.25	Strong	0.25	No	-	1.47	None
Rijnmond	3.75	Yes	50.60	7.70	Strong	-0.53	No	-	2.97	Nome
Zuid Holland Centraal	1.33	No	-	2.03	None	-0.26	No	-	1.56	None
Zuid Kennemerland en Ijmond	0.95	No	-	0.45	None	1.30	No	-	0.94	None
Zuid Limburg	4.65	Yes	53.18	11.42	Strong	2.91	Yes	35.35	7.21	Strong
Amersfoort	0.09	No	-	1.13	None	1.00	No	-	0.97	None
Food Valley	-0.80	No	-	2.10	None	0.73	No	-	1.10	None
Midden Brabant	3.01	Yes	43.95	4.86	Strong	-0.14	No	-	0.29	None
Midden Gelderland	1.61	No	-	2.13	None	-1.13	No	-	5.77	None
Midden Holland	0.02	No	-	1.36	None	-0.53	No	-	2.97	None
Rijk van Nijmegen	3.06	Yes	44.21	4.70	Strong	0.01	No	-	0.00	None
Zaanstreek Waterland	1.44	No	-	1.34	None	1.05	No	-	0.96	None
Zuidoost Brabant	3.98	Yes	47.16	8.08	Strong	3.75	Yes	46.72	7.03	Strong
Gorinchem	2.67	Yes	39.15	2.67	Strong	-1.96	No	-	2.26	None
Helmond - De Peel	0.85	No	-	0.51	None	-1.37	No	-	2.73	None

Midden Limburg	1.34	No	-	1.48	None	1.21	No	-	0.93	None
Noord Holland	1.46	No	-	1.45	None	0.58	No	-	0.28	None
Noord Limburg	0.05	No	-	1.93	None	0.90	No	-	0.83	None
Noordoost Brabant	2.42	Yes	40.93	3.09	Strong	0.75	No	-	1.62	None
Rivierenland	2.29	Yes	63.48	2.83	Strong	1.36	No	-	1.07	None
Twente	3.54	Yes	51.00	6.40	Strong	0.12	No	-	0.47	None
West Brabant	3.54	Yes	46.88	6.38	Strong	-0.49	No	-	0.17	None
Achterhoek	2.72	Yes	40.17	4.07	Strong	-0.85	No	-	0.99	None
Drenthe	2.07	Yes	45.90	2.24	Significant	-0.88	No	-	0.47	None
Flevoland	2.05	No	-	2.10	None	-1.01	No	-	0.68	None
Friesland	2.79	Yes	44.62	4.61	Strong	-0.79	No	-	0.35	None
Groningen	3.88	Yes	47.92	7.57	Strong	2.94	Yes	40.56	5.70	Strong
Ijsselvechtstreek	2.97	Yes	42.98	4.54	Strong	0.44	No	-	2.60	None
Stedendriehoek B.V.	1.88	Yes	51.64	2.17	Significant	1.66	No	-	1.38	None
Zeeland	-0.26	No	-	0.50	None	-0.46	No	-	0.19	None

Table A4.3 - Gender – specific Regression Results

	Male Employees					Female Employees				
	PI-value	U-Test	Extreme Point	F-statistic	Polarization status	PI-value	U-Test	Extreme Point	F-statistic	Pola s
Drechtsteden	0.53	No	-	0.56	None	0.63	No	-	1.19	None
Gooi en Vechtstreek	-0.02	No	-	0.82	None	1.44	No	-	2.25	None
Groot Amsterdam	3.73	Yes	48.86	7.02	Strong	0.67	No	-	1.52	None
Haaglanden	0.79	No	-	0.66	None	0.67	No	-	0.32	None
Holland Rijnland	0.17	No	-	0.30	None	0.23	No	-	0.91	None
Midden Utrecht en Gooi	3.16	Yes	57.43	5.43	Strong	1.38	No	-	14.82	None
Rijnmond	1.32	No	-	2.26	None	3.554	Yες	44.70	6.29	Strong
Zuid Holland Centraal	-0.13	No	-	0.87	None	2.58	Yες	48.94	4.24	Strong
Zuid Kennemerland en Ijmond	0.54	No	-	0.44	None	0.81	No	-	0.34	None
Zuid Limburg	3.85	Yes	46.74	7.41	Strong	1.64	No	-	4.09	None
Amersfoort	1.27	No	-	1.24	None	-1.57	No	-	2.08	None
Food Valley	2.36	No	-	5.90	None	-1.74	No	-	7.67	None
Midden Brabant	2.36	Yes	51.36	2.81	Strong	1.79	No	-	9.48	None
Midden Gelderland	-0.54	No	-	0.29	None	-0.77	No	-	0.54	None
Midden Holland	2.21	Yes	57.83	4.46	Strong	1.19	No	-	1.25	None
Rijk van Nijmegen	1.47	No	-	1.70	None	3.20	Yες	47.34	5.25	Strong

Zaanstreek/Waterland	0.82	No	-	0.27	None	0.27	No	-	1.90	None
Zuidoost Brabant	3.56	Yes	45.70	6.42	Strong	2.25	No	-	5.47	None
Gorinchem	1.76	No	-	1.57	None	0.46	No	-	5.56	None
Helmond - De Peel	1.91	Yes	47.90	3.37	Significant	0.39	No	-	0.32	None
Midden Limburg	1.66	No	-	1.37	None	0.65	No	-	0.63	None
Noord Holland	1.20	No	-	1.13	None	-1.07	No	-	0.59	None
Noord Limburg	0.90	No	-	0.86	None	0.01	No	-	4.72	None
Noordoost Brabant	1.63	No	-	3.17	None	1.18	No	-	10.54	None
Rivierenland	2.00	Yes	47.13	2.44	Significant	2.60	Yες	37.42	5.36	Strong
Twente	1.58	No	-	1.38	None	0.62	No	-	2.63	None
West Brabant	0.09	No	-	0.34	None	0.82	No	-	3.24	None
Achterhoek	0.12	No	-	0.01	None	-0.75	No	-	0.83	None
Drenthe	1.52	No	-	2.29	None	0.69	No	-	3.58	None
Flevoland	-0.70	No	-	0.31	None	1.63	No	-	10.58	None
Friesland	2.56	Yes	38.55	4.07	Strong	1.28	No	-	4.77	None
Groningen	3.29	Yes	44.82	6.83	Strong	3.12	Yες	41.92	5.94	Strong
Ijsselvechtstreek	1.34	No	-	3.38	None	2.40	Yες	37.11	4.43	Strong
Stedendriehoek B.V.	1.35	No	-	3.55	None	0.51	No	-	2.09	None
Zeeland	0.64	No	-	0.38	None	0.10	No	-	0.13	None

Table A5.1 – Probit Regression

Panel A – Regression Results	
	Coefficient
Routine Cognitive	-2913.91
	(1477.40)*
Routine Manual	1436.295
	(1086.65)
Non Routine Analytic	-1207.80
	(894.22)
Non Routine Interactive	1983.82
	(885.89)**
Non Routine Manual	-799.90
	[310.32]
Urbanization Dummy	1.2648
	(0.7392)*
Female Share	-24.4612
	(8.0773)
Obs	35
LR χ^2 (3)	17.35
Pseudo – R^2	0.32
Panel B – Estimated Marginal Effects	
Routine Cognitive	-603.03
	(278.21)**

Routine Manual	297.24
	(218.22)
Non Routine Analytic	-249.95
	(176.77)
Non Routine Interactive	410.54
	(165.34)**
Non Routine Manual	-165.54
	(167.80)
Urbanization Dummy	0.2617
	(0.1248)**
Female Share	-5.0622
	(3.5776)