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# Employment Polarization in Local Labor Markets:

# The Dutch Case

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# EMPLOYMENT POLARIZATION IN LOCAL LABOR MARKETS: THE DUTCH CASE[1]

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**Abstract:** Recent literature documents the pervasiveness of job polarization in the labor markets of the developed world. However, relatively little is known about polarization on a sub-national level. We exploit extensive data on both genders from Statistics Netherlands to confirm polarization as an important trend in the Dutch national labor market between 1999 and 2012. Furthermore, our sub-national analysis reveals considerable spatial heterogeneity among local labor markets. The degree of urbanization plays an important role; regions that are initially more urbanized are more likely to exhibit polarization. Finally, using a skill-based approach we report evidence supporting the routinization hypothesis as an important source of polarization.

**Keywords:** job polarization, regional analysis, routine-biased technological change, 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

A vibrant body of empirical literature identifies a job polarization (Goos and Manning, 2007) employment trend in the developed labor markets during the last 25 years. This pattern, characterized by an increase in the employment shares of low- and high-skilled jobs, accompanied by a decrease in middle-skilled occupations. This paper complements the expanding empirical investigations documenting polarization in various developed countries (Autor, Katz & Kearney 2006; 2008 and Autor & Dorn 2013 for the US, Goos & Manning 2007 for the UK, Spitz-Oener 2006 and Dustmann, Ludsteck & Schonberg 2009 for Germany, Green & Sand 2015 for Canada and Adermon & Gustavsson, 2015 for Sweden).

The main theoretical foundation for job polarization is the *Routine Biased Technical Change* (hereafter RBTC) widely known as the *routinization hypothesis.* Based on the *task model* of occupations (Autor, Levy & Murnane 2003 – hereafter ALM), the routinization hypothesis asserts an asymmetric impact of technological development on labor markets. In particular, technological innovations increase labor demand for high-skilled non-routine tasks (e.g. research, medical diagnosis), while they substitute labor in routine tasks (e.g. basic problem solving, machine operation) thus leading to a job polarization pattern. Labor market economics literature also identifies complementary sources of job polarization. Offshoring and outsourcing (Autor & Dorn, 2013), together with wage differential between low and high paying occupations and the subsequent consumption spillovers (Mazzolari & Ragusa 2007), contribute to job polarization dynamics, however, with a weaker overall impact.

Employment 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 have the potential to either increase or dampen the degree of job market polarization. Our main contribution to the international literature is our focus on the regional nature of job polarization. Using extensive data from *Netherlands Statistics* (CBS), we analyze the pervasiveness of employment polarization in Dutch local labor markets, applying two alternative units of spatial analysis (the provincial level (NUTS2) and the level of local labor markets).

We employ two methods to document polarization on a regional level. Firstly, non-parametric analysis indicates employment polarization both in the national and in local labor markets. In our sub-national analysis, we utilize indexes from Eurostat and OECD to identify economic and social characteristics (urbanization, education level of the labor force etc.) that contribute to employment polarization at the regional level. Secondly, by means of regression analysis we offer more systematic evidence of a U-shaped employment curve in the national labor market, indicative of job 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 both cases, the analysis highlight a relationship between urbanization and polarization, where urbanized regions are significantly more likely to exhibit polarization in the subsequent period.

Finally, by means of skill intensity regression analysis we focus on each of the two parts of the U-shaped employment curve individually and link job polarization in the national labor market with its main theoretical foundation, the routinization hypothesis. Based on the diverse monotone relationships between different task measures that we document for low- and high-paying jobs, we argue that the more nuanced impact of task categories causing employment polarization is the result of the above relationships brought together in a unified framework.

In the next section we provide a review of the related literature which motivates our empirical analysis, while in Section 3 discusses the methodological approach. Section 4 contains information on the data and Section 5 presents the results. Finally, in Section 6 summarizes and provides a discussion related to policy implications.

## 2 Relevant Literature

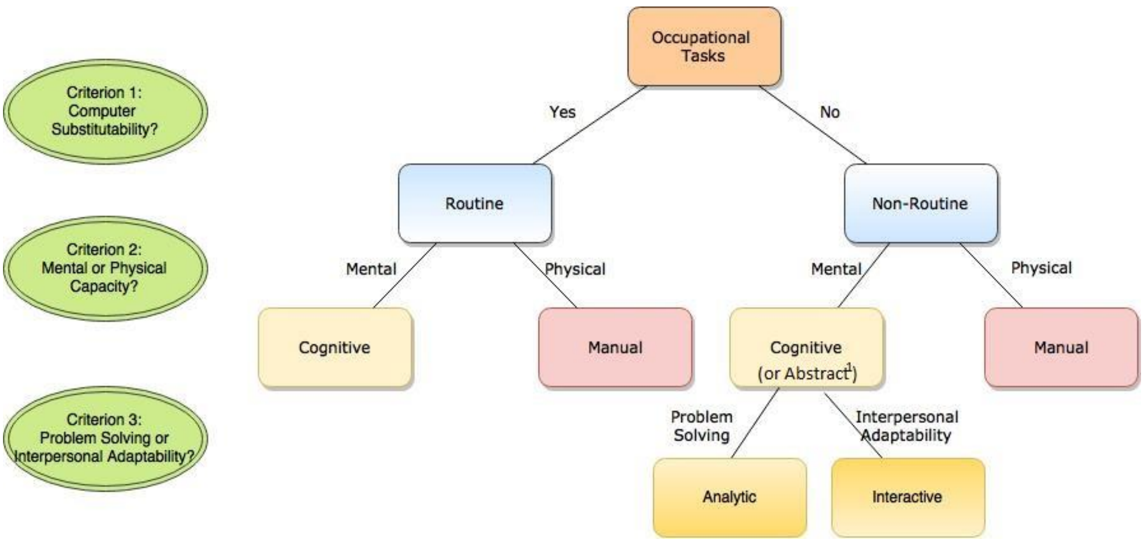
The job polarization debate is currently an ongoing discussion about occupational development. Since the early 1980's, labor market economists accounted for the increased demand for high skilled labor and the subsequent widening of wage inequality (Katz & Autor 1999, Krugman 1995, Bearman, Bound & Machin 1998, Autor, Katz & Krueger 1998) by investigating the impact of technological innovations on employment dynamics and in particular the increased application of ICT in the labor market. The main theory was *Skill Biased Technical Change* (Johnson 1997 – hereafter SBTC) which argued towards a monotone impact of computer technology favoring skilled labor. Specifically, SBTC contended that computer technology complemented skilled employees, thus increasing their productivity and consequently the demand for skilled labor. At the same time Information and Communication Technology (hereafter ICT) substituted tasks performed by unskilled labor, thus lowering the demand for low-skilled workers. Taken together, the above two individual effects constitute the overall monotone impact of technological innovation on employment, increasing the employment shares of skilled occupations and decreasing the ones in low-skilled jobs.

However, a vibrant empirical literature after the mid-1990's pointed towards 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 pervasiveness 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 economies; Michaels, Natraj & van Reenen 2014 for the US, Japan and 9 European economies and Wang et al. 2015 for 31 European countries).

Rather importantly, a growing part of the job polarization literature focuses on the sub-national economic, social and demographic heterogeneity and how these factors increase or dampen job market 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) analyze regional polarization for the period 1981-2011 and find that job polarization is the main employment trend among Spanish regions 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 adopts a more nuanced approach of the technological effect on the task composition of human employment. Specifically, the *routinization hypothesis* (Autor, Levy & Murnane 2003 – hereafter ALM) argued towards a more distinctive impact of ICT[5], based on the task content of each occupation. In their *task model* illustrated in Figure 2.1, ALM (2003) conceptualized each occupation as a series of tasks[6] performed by employees and introduce a two dimensional typology in classifying them into categories. Based on whether occupational tasks can be performed by computers, ALM (2003) distinguish at first between *Routine* (working on an assembly line, basic machine operation) and *Non-Routine* (management or research) tasks. Routine tasks involve "…methodological repetition of an unwavering procedure" (ALM 2003) and therefore are 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 the former requiring greater mental and the latter higher physical capacity. Finally, non-routine cognitive tasks are further decomposed into Analytic (requiring advanced problem solving) and Interactive (requiring interpersonal adaptability) tasks.

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




[5] Throughout the text, the terms "Information and Communication Technology - ICT" and "Computerization" are used interchangeably to stand for technological innovation applied in the labor market.
[6] In turn, those tasks define the necessary skills possessed by the employees, therefore in what follows, the terms "Tasks" (for occupations) and "Skills" (for employees) are used interchangeably.

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[7] (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.

Following the above division of occupational tasks, the *routinization hypothesis* explains how the advent of computer technology changes the composition of human labor. According to its main theoretical principle, ICT substitutes human labor performing routine tasks, therefore decreasing employment in routine-based occupations (both cognitive and manual). In addition, computer capital complements human capacity in performing non-routine cognitive tasks, thus increasing their productivity and the employment shares in non-routine cognitive-intensive occupations. Finally, ICT shows limited potential in affecting labor performing non-routine manual tasks; therefore it offers no clear theoretical prediction as to the exact effect of ICT in non-routine manual intensive occupations.

ALM (2003) argues that employees in routine occupations receive average wages while the workers in non-routine cognitive jobs are at the top part of the occupational distribution and non-routine manual ones at the bottom. Therefore, the middle segment of the occupational distribution consists of routine-based occupations. On the other hand, the tails are occupied by non-routine occupations, although the skill requirements and received wages differ greatly.

Employment polarization is the main theoretical prediction of the routinization hypothesis. This is graphically illustrated by a U-shaped employment curve when occupations are arranged into percentiles based on their median wages. Figure 2.2 (Goos et al. 2009) plots such employment change and clearly illustrates such a U-shaped employment curve for the British national labor market between 1993 and 2006.

[7] 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.

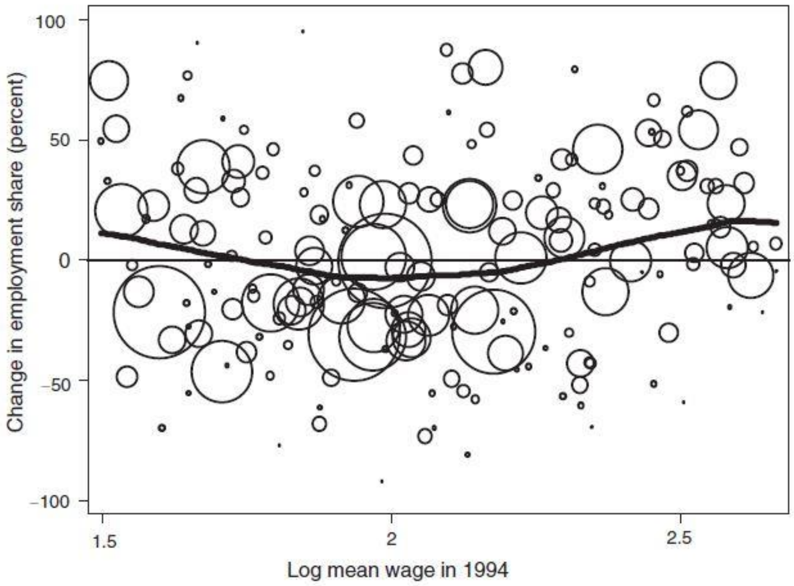



**Figure 2.2. Employment curve in the British national labor market (Goos et al. 2009)**

Besides the routinization hypothesis, the theoretical literature on job polarization offers additional mechanisms leading to polarization, however of weaker explanatory power. Globalization and in particular offshoring and outsourcing (Autor, Dorn & Hanson 2013; Blinder 2007) are found to contribute to polarized employment dynamics. Finally, Goos, Manning & Salomons (2014); Manning (2004) and Mazzolari & Ragusa (2007) propose wage inequality as a potential source of polarization. They argue that wage growth in the top part of the occupational distribution increases the opportunity cost of time for top-payed employees. In turn, a demand is created towards low-skilled occupations (housekeeping services, children and elderly care etc.) ultimately leading to an employment polarization pattern.

# 3 Methodology

Instead of establishing the presence of polarization only based on figures, such as Figure 2.2, we identify polarization using non-parametric analyses as well as statistical analyses. We provide a small overview of our methods, before discussing them in greater detail. The non-parametric analyses are rather straightforward, and only analyze whether the employment share of occupations in the low, middle and high-end of the labor market are respectively increasing, decreasing and increasing for the various regions. The regression analysis offers more systematic evidence regarding the occurrence of job polarization in the Dutch national and local labor markets. The idea is simple. Polarization is visible as a parabola (see for instance Figure 2.2). Therefore, we add a quadratic term in the regression analysis to identify the (possible) presence of a parabola. Furthermore, this regression analysis provides us with a

Polarization Index (Dauth 2014): the t-value of the quadratic term in the regression analysis. The higher the t-value, the stronger the polarization effect. In addition, our regression analysis is based on robust standard errors, therefore the t-value of the quadratic term is not susceptible to outliers that could determine the shape of the parabola; this constitutes the main advantage of the t-value used as a polarization index.

Finally, by means of skill-intensity regression analysis, we individually investigate the theoretical predictions of the routinization hypothesis in occupational employment changes in the Dutch national labor market. Skill-intensity regression analysis is carried out only in the national labor market. Lack of sufficient regional data on skill utilization and in particular the insufficient representation of specific task categories especially in densely employed local labor markets prevent us from applying this method at the sub-national level as well.

## 3.1 Non-parametric analysis

In the non-parametric analysis, we identify the major trends in the Dutch labor market dynamics between 1999 and 2012. First we classify occupations according to their median wage in 1999 and ascribe each one a percentile value (between 1 and 100) based on their initial employment share. Occupations that are larger in terms of their initial employment occupy a greater number of percentiles. Then we divide the occupational distribution in five quintiles and calculate employment share percentage changes within the lowest (0-20), the middle (40-60) and the highest (80-100) occupational quintile. Increasing employment shares in the tails of the occupational distribution, accompanied by a hollowing out of employment in the middle segment indicate a job polarization pattern. For the regional non-parametric analysis we retain the national linkage between percentiles and occupations, in order to prevent compositional differences in occupations from driving the results.

## 3.2 Regression Analysis

### 3.2.1 National labor market - Determining a U-shaped employment curve

The standard approach in empirical economics to identify U-shaped curves is to include a quadratic term that captures the non-linear effect identified as a parabola (Aghion et al. 2005, Grossman & Krueger 1995). In our case, we regress employment share changes on a ranking variable and its squared term. We once again 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 percentile. Thus, we avoid that our results are being driven by compositional effects[8]. We then estimate the following quadratic model:

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

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 (from 1 to 100) and $\varepsilon_t$ is the error term[9]. 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[10].

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:

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

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

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[8] 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.

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

[10] 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 $\alpha_1$<0 and $\alpha_2$>0.

ensure decreasing relationship at low values of the interval turning to an increasing at higher interval values (Lind and Mehlum, 2010).

### 3.2.2 A polarization Index

We repeat the analysis of equation (1) for each region, using the national occupation-to-percentile correspondence for each region.[11] Using the estimates of Eq. (1) and following Dauth (2014), the following adjusted t-value[12] of the squared term can form 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 a method to properly identify different types of U-shaped curves is not yet developed in the job market polarization literature.

## 3.3 Skill Intensity Regression Analysis

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, as we intend to establish a non-monotone (U-shaped) employment

[11] 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.

[12] 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.

change pattern we divide the occupational percentile distribution based on wages and initial employment per occupation into two segments[13] (percentiles 1-49 and 50-100 respectively). The first segment corresponds to low-paying occupations, while the second one includes mainly high-paying jobs. The non-monotone relationship is the outcome of two opposing linear relationships (a negative one for low-paying occupations and a positive one for high-paying ones).

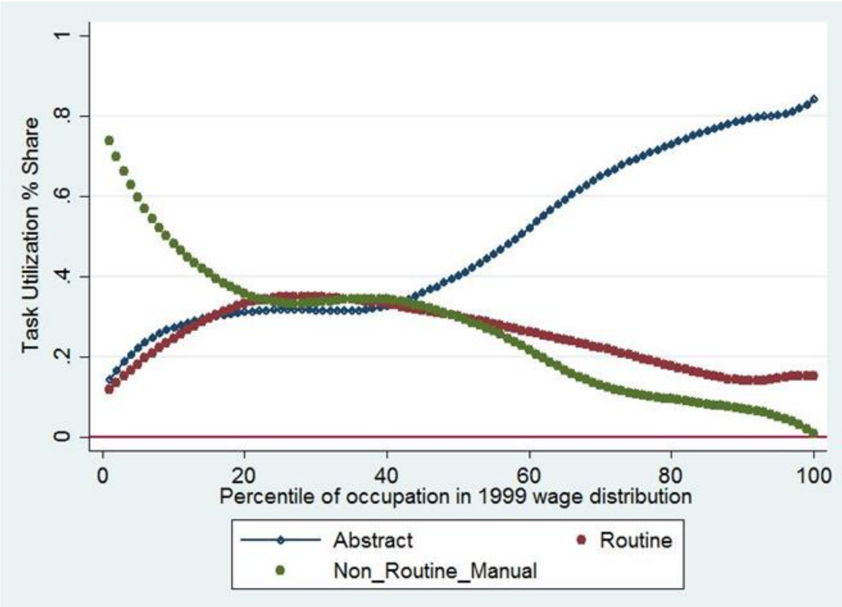


**Figure 3.1. Task Utilization per Occupational Percentile**

Figure 3.1 plots the smoothed task input per occupation, when occupations are sorted by their 1999 wages and arranged into percentiles by their 1999 employment share. 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). For a more detailed decomposition into all 5 categories, see Appendix A2.1. It is evident that the task composition of jobs varies considerably along the occupational distribution. Although not unanimous, 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 non-monotone inverted-U curve, reaching its maximum point in middle paying occupations.

[13] 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.

In the skill intensity regression analysis, we identify the differential impact of each task category on both the downward (percentiles 1-49) and upward (percentiles 50-100) sloping parts of the employment curve, corresponding to low- and high-paying occupations respectively.

$$\Delta s_{i,1999-2012} = a_0 + a_1 TaskInt_i + \varepsilon_i \quad (4)$$

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 and $\varepsilon_i$ 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 we also used 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 the Non-Routine Analytic (those involving higher complexity problem solving) and Non-Routine Interactive (requiring interpersonal skills) and *Routine* tasks into *Routine Cognitive* (requiring greater mental capacity) and *Routine Manual* (demanding 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 local labor markets, we also report results for the five task categories. 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<br>Interactive | Medical diagnosis, research<br>Work delegation, persuading / selling |
| Routine | Cognitive<br>Manual | Bookkeeping, calculation<br>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.

A limitation of this analysis rests in the investigation of only the routinization hypothesis as the source of job polarization. However there are no objective indexes on a job level related to offshoring which can be used to properly disentangle the effect from the task-content of occupations and offshoring as potential sources of job polarization.

## 4 Data Description

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 Labour Force Survey (Enquête Beroepsbevolking - EBB), which accounts for 0.25% of the total population[14]. 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 civil servants and 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[15]. Table 2 provides mean values of the main variables used in our analysis. 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 3 and 4-digit taxonomy, where Netherlands Statistics 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.

[14] 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

[15] An inconsistency in the data collection process after the third quarter of 2012 prevents us from using data from Q4 2012 onwards.

Table 2 – Sample Characteristics

| 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 |

Data on the task content of occupations were adapted from Spitz-Oener[16] (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 cognitive part of routine tasks and the interactive part of the abstract tasks. 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.

[16] 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

We further examine the association between skill and wage distributions. Table 4 reports average hourly wages in 1999 and 2012 for *Non-Routine Manual*, *Routine* and *Abstract* intensive occupations. In compliance with a basic assumption in the job polarization literature (Autor, Levy & Murnane, 2003), our data verify that non-routine manual-intensive occupations are at the bottom of the wage distribution, routine-intensive occupations are in the middle while abstract–intensive jobs are the highest paid both in the beginning (1999) and the final (2012) year of our analysis.

Table 4 - 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.

# 5 Results

Our results section fully corresponds with our methodological approach. In Section 5.1, we present the non-parametric results, where we obtain an indication of the national and regional pervasiveness of job polarization. Section 5.2 reports our regression analysis results divided between Section 5.2.1 where we systematically determine the U-shaped national employment curve and Section 5.2.2 where we apply the polarization index in Dutch local labor markets. Finally, in Section 5.3 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 Non – parametric results

### 5.1.1 National Labor Market

Table 5 reports the changes in employment share for the lowest-, middle- and highest-paying occupational quintile, based on occupational median wages in 1999. The results clearly point to a job polarization pattern. Employment growth is concentrated to the tails of the occupational distribution, while middle paying jobs exhibit negative growth. Such a polarization pattern follows the unified international evidence of employment trends, both in European advanced (Goos, Manning & Salomons 2009) or developing economies (Kupets 2016) and North American labor markets (Green & Sand 2015). A more complete illustration of employment change per occupation is given by Figure 5.1, where we detect that occupations in the second quintile also decrease in employment, while occupations in the fourth quintile experience an increase in employment share.

Table 5 – Non-parametric Analysis

| | Employment Share % Change (1999-2012) |
|---|---|
| Low-paying 20% | 1.94% |
| Middle-paying 20% | -9.72% |
| High-paying 20% | 11.08% |

Occupations are classified using the BRC 4-digit occupational sorting

Interestingly, our results indicate an asymmetric pattern of employment polarization, with a greater employment increase in the top quintile relative to the bottom quintile. This is a common trend in the job polarization international literature (Autor, Katz & Kearney 2006 for the US and Goos and Manning 2007 for the UK) and is partially attributed to episodic supply-sided shocks and mainly to the labor market institutional environment (minimum wage, health and safety state regulations, employment protection schemes etc.) which dampen employment growth in low paying occupations (Dustmann, Ludsteck & Schonberg 2009). The Dutch labor market is highly institutionalized and unionized (OECD 2013, OECD Employment Protection database 2012), which might partially explain the asymmetric polarization evident in Table 5.

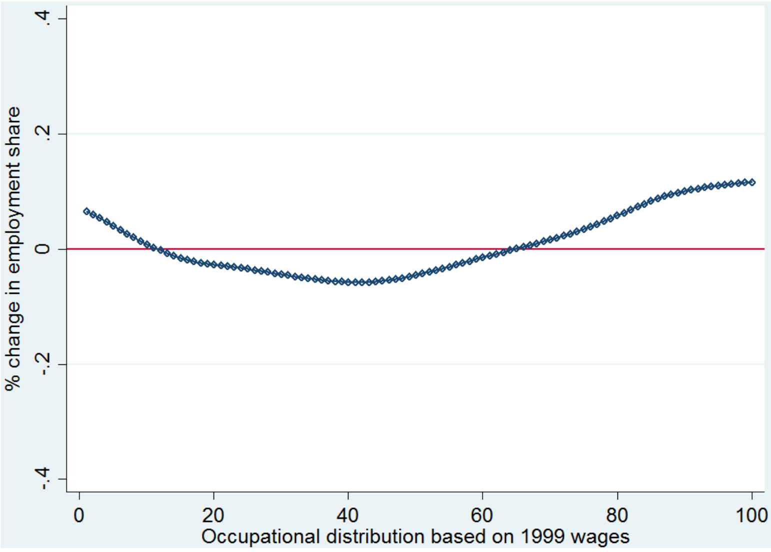


**Figure 5.1. Employment % Change per Occupational Wage Percentile**

### 5.1.2 Sub-National Labor Markets

Employment polarization is subject to the local social, economic and demographic environment (job and workforce composition, education level etc.), therefore it is not uniformly present in the sub-national labor markets (Autor et al., 2013). We operationalize our concept of sub-national labor markets for the Netherlands in terms of the NUTS 2 provinces and local labor market regions (so called arbeidsmarktregio's)[17]. Throughout this section we conduct our non-parametric analysis for each local labor market and identify local conditions either favorable or unfavorable to employment polarization. Associating our results with the international literature on job polarization, we provide evidence that the Dutch sub-national labor markets largely follow internationally established employment patterns.

[17] Arbeidsmarktregio's were introduced in 2012 by the municipalities and the Dutch Unemployment Agency and are by now an important administrative unit for local labor market policies.

**Provincial Analysis**

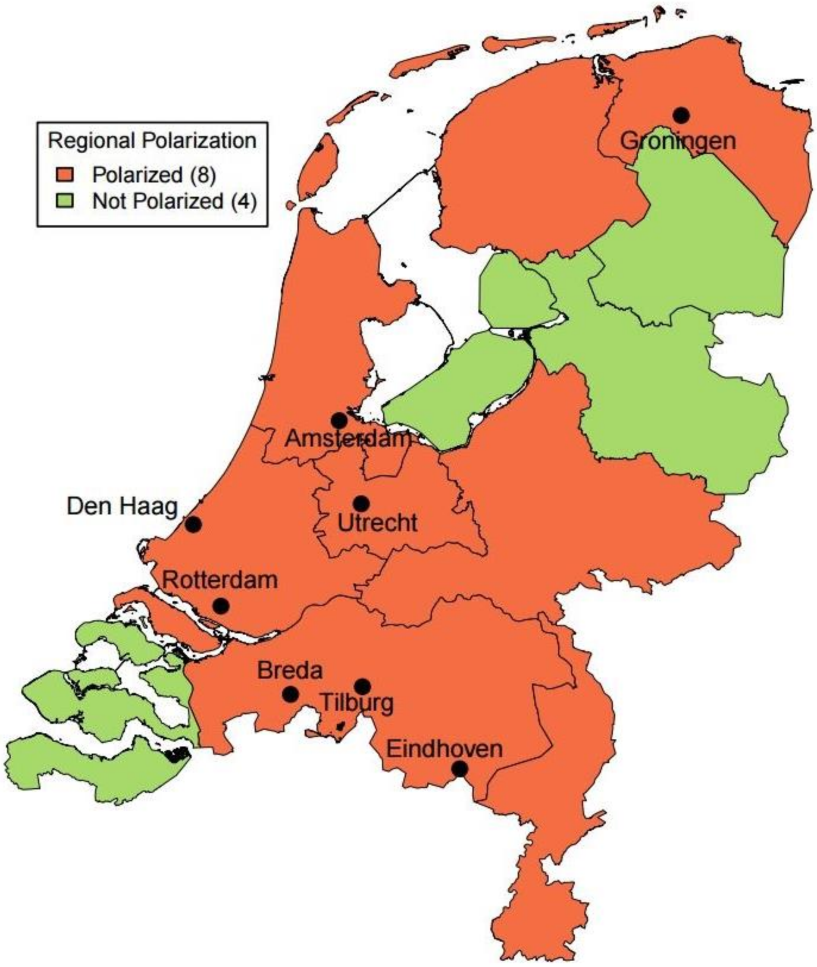


**Figure 5.2. Job Polarization among Dutch Provinces**

Figure 5.2 documents the prevalence of job market polarization among Dutch provinces between 1999 and 2012 (for underlying results, see Table A5.1 in the Appendix). Eight out of the twelve provinces follow employment polarization dynamics[18], while there are four exceptions (Drenthe, Flevoland, Overijssel and Zeeland) where decreasing employment in the lowest quintile prevents employment polarization.

Figures 5.3 and 5.4 illustrate two representative cases of the employment trends outlined above, by plotting employment share percentage change per occupation between 1999 and 2012 for Groningen and Zeeland respectively. Groningen shows a clear job polarization pattern with increasing employment at both tails of the occupational distribution and

[18] As before defined as an increase in employment share of the lowest paying and highest paying 20% occupations and a decrease in the middle 20% occupations (based on their employment shares in 1999).

hollowing out of employment in the middle segment, giving rise to a U-shaped curve. Conversely, middle- and high-paying occupations in Zeeland increase in employment at the expense of low-paying ones, as evident in Figure 5.4. Our results are consistent with the international literature documenting the regional pervasiveness of job polarization. Autor and Dorn (2013) and Autor, Dorn and Hanson (2013) confirm the prevalence of job polarization in local US Commuting Zones since the beginning of the 1980's, while Senftleben and Wielandt (2014) and Dauth (2014) report similar results for German local labor markets for the same period and Consoli and Sanchez-Barrioluengo (2016) report evidence of job polarization for Spanish NUTS 3 regions between 1981 and 2011.

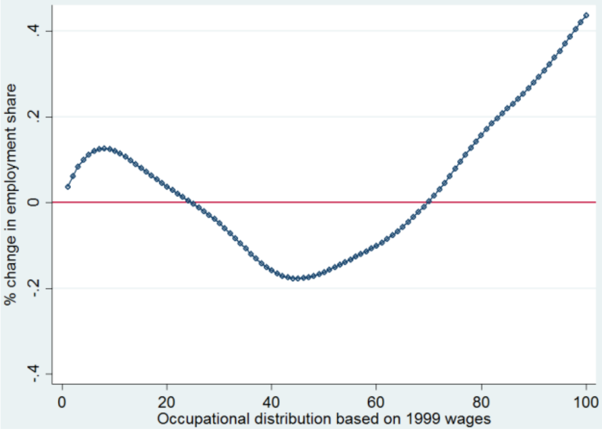


**Figure 5.3. Groningen**

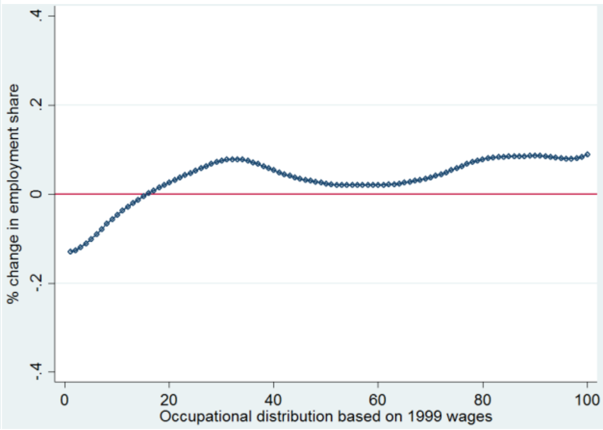


**Figure 5.4. Zeeland**

Although the Netherlands is a relatively small country and therefore regional disparities are not as pronounced as in larger countries, we contribute to the regional polarization literature by identifying structural economic and labor market attributes consistently leading to or prohibiting regional employment polarization. Prompted by the fact that 73% of the Dutch population resides in job-polarized provinces[19] we first link sub-national employment polarization with regional urbanization.

Our provincial analysis indicates the prevalence of job polarization in the highly urbanized and agglomerated 'Randstad' area in the south-western part of the country, which includes the agglomerations of Amsterdam, Den Haag, Rotterdam and Utrecht, together with the most urbanized parts of the Brabant province. Conversely, polarization is less pronounced in peripheral provinces, such as Drenthe, Flevoland, Overijssel and Zeeland with the exceptions of Groningen and Limburg which –although peripheral provinces- exhibit clear job polarization patterns.

[19] Own calculations, based on the Dutch Population Census 2011 (Source: *Statistics Netherlands*)

To identify demographic characteristics conducive to job polarization in a more formal sense, we divide the NUTS2 regions and arbeidsmarktregio's according to their population densities in 1999. Appendix A3 explains the classification procedure in more detail. As table 6 shows, all 6 regions classified as *Urbanized* or *Relatively urbanized* exhibit polarization, whereas only 2 of the 6 *relatively rural* and *rural* NUTS2 regions exhibit polarization.

Table 6: Polarization in the NUTS2 regions

| | | Change in employment share (1999-2012) | | |
|---|---|---|---|---|
| Province | Urbanization status | Lowest 20% | Middling 20% | Highest 20% |
| **Noord Holland** | Urbanized | 4.98% | -12.93% | 9.44% |
| **Utrecht** | Urbanized | 4.57% | -14.40% | 9.36% |
| **Zuid Holland** | Urbanized | 4.86% | -9.74% | 5.86% |
| **Gelderland** | Relatively urbanized | 2.66% | -1.54% | 10.64% |
| **Limburg** | Relatively urbanized | 5.84% | -8.73% | 16.01% |
| **Noord Brabant** | Relatively urbanized | 1.70% | -7.75% | 17.50% |
| Flevoland | Relatively rural | -5.87% | -5.74% | 6.98% |
| **Groningen** | Relatively rural | 11.84% | -22.47% | 22.55% |
| Overijssel | Relatively rural | -1.06% | -7.83% | 21.23% |
| Drenthe | Rural | -0.99% | -2.58% | 22.39% |
| **Friesland** | Rural | 5.05% | -13.22% | 12.75% |
| Zeeland | Rural | -5.08% | -2.32% | 2.25% |

**Arbeidsmarktregio Analysis**

Utilizing a finer spatial unit of analysis, Figure 5.5 (underlying results in Appendix A5) further verifies the prevalence of employment polarization in Dutch local labor markets. Nearly all local labor markets exhibit increasing employment shares in the highest quintile of occupations, together with decreasing employment in the middle quintile. In the lowest occupational quintile, the evidence is mixed with both positive and negative employment trends. This results in twenty-one out of the thirty-five Dutch arbeidsmarktregio's exhibiting job polarization, adding the Netherlands to the international literature on regional employment polarization (Autor and Dorn 2013, Autor et. al. 2013, Blien and Dauth 2016, Dauth 2014, Senftleben and Wielandt, 2014).

We once again observe that polarization mainly emerges in the urban agglomerations of the central and southern part of the country. Job polarization is an important employment trend in Groot Amsterdam, Midden Brabant, Midden Holland, Midden Utrecht and Gooi, Rijnmond, West Brabant and Zuidoost Brabant. On the other hand, peripheral arbeidsmarktregio's such as Zeeland or Drenthe follow non-polarized employment patterns.

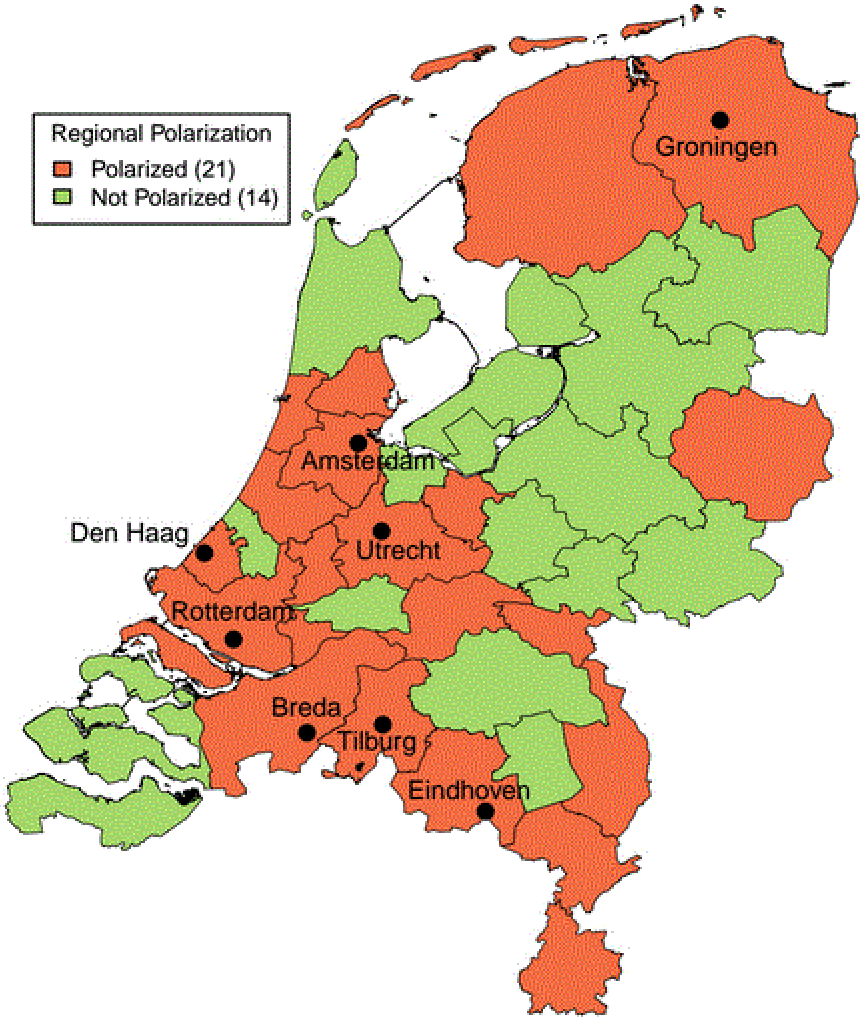


**Figure 5.5. Job Polarization among Dutch Arbeidsmarktregio's**

In order to analyze the relationship between urbanization and polarization more structurally, we also classify the arbeidsmarktregio's according to the degree of urbanization (again see Appendix A3 for the details). The full table with results are provided in Appendix A6. Again a relationship is visible between urbanization and polarization. Out of the 18 arbeidsmarktregio's classified as *urban* or *relatively urban*, 14 exhibit polarization (78%). Out of the 17 arbeidsmarktregio's classified as *rural* or *relatively rural*, only 7 exhibit polarization (41%).

The sub-national job market polarization literature offers potential explanations for the above urban nature of job polarization. In particular, the geographic distribution of higher-skilled workers and jobs is changing, with these workers and jobs becoming increasingly concentrated in certain local areas (European Commission, 2016). The presence of higher education institutions and demand for highly skilled labor make cities and especially metropolitan areas an ideal place for highly educated population (OECD, 2014b; Eurostat, 2015). In turn, the presence of high-skilled labor with increased opportunity cost of time is among the causes of job market polarization, due to the consumption spillovers effect (Mazzolari and Ragusa, 2007). Therefore the presence of high skilled labor is a plausible reason for the prevalence of job market polarization in metro areas.

## 5.2 Occupational Ranking Regression Analysis

### 5.2.1 National Labor Market – Determining a U-shaped employment curve

Following Dauth (2014) we investigate the composite relationship between wages and employment change per occupation, by estimating Eq. (1) for the Dutch labor market. At the same time, by testing the validity of the sufficient condition (Proof of Eq. (2)), we ensure that the extreme point falls within the economic sensible part of the quadrant, namely the one defined by the lower and upper limit of our ranking variable.

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

The empirical estimation for the quadratic regression (robust standard errors in parentheses) (Eq. 5) 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[20]. The graphical illustration of the fitted regression line (Figure 5.6) verifies the asymmetric pattern of employment polarization 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 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).

[20] 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%.

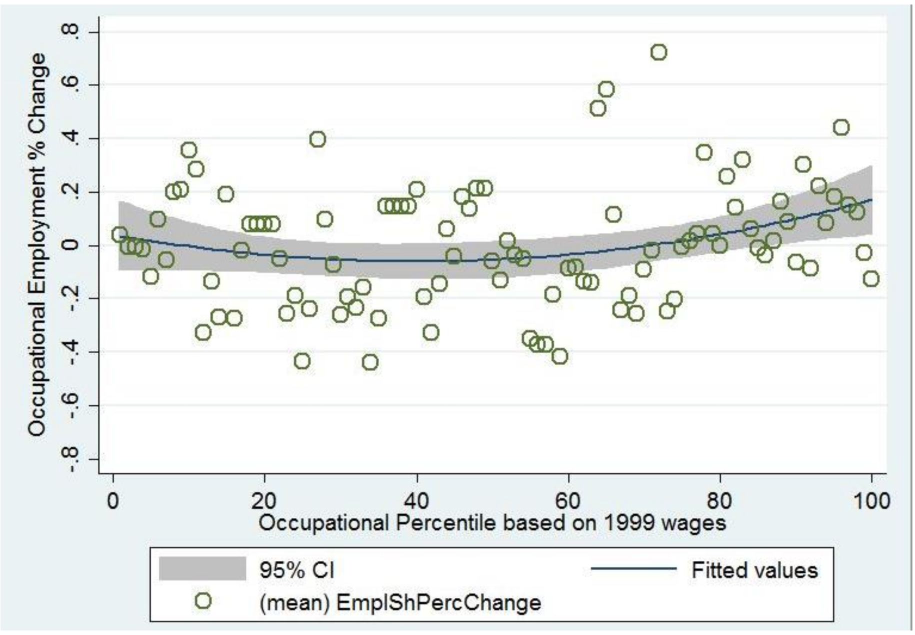


**Figure 5.6. Occupational Employment Change Curve in the Netherlands (1999-2012)**

### 5.2.2 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 perform quantitative comparisons between the degrees of polarization among various spatial analytical units (NUTS 2 provinces and arbeidsmarktregio's).

**Provincial Analysis**

Based on the *Polarization Index* value (PI = 2.19) from Eq. (5), we classify the regression results based on provinces into four categories, depending on their degree of polarization. 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. The results are shown in figure 5.7 (Analytical results are provided in Appendix 6).

The estimated results point out job polarization as the prevalent employment trend among Dutch provinces between 1999 and 2012. Specifically, 9 out of the 12 provinces follow a U-shaped employment curve with 8 of them showing stronger job polarization than the aggregate country. The international literature lacks empirical evidence on regional polarization based on NUTS 2 regions. The closest spatial counterfactual (NUTS 1 regions) is applied by Lago (2016) which traces significant employment polarization in 10 out of the 17 Spanish regions between 1994 and 2008. In that respect, the above results converge with our own in documenting the regional pervasiveness of job polarization.

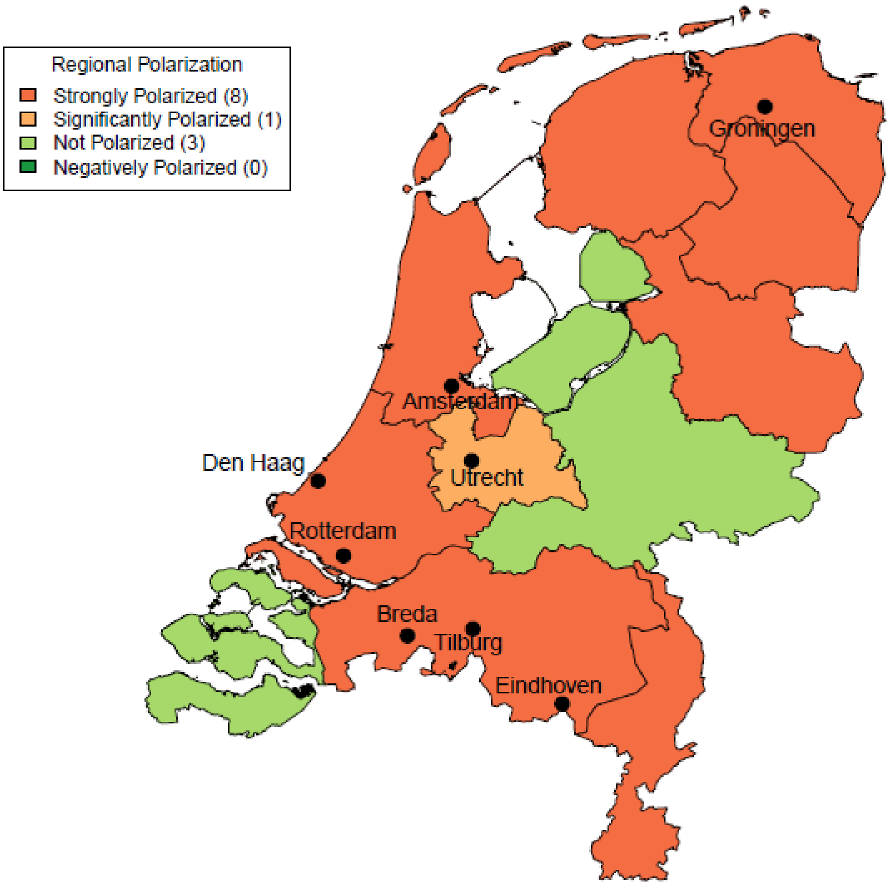


**Figure 5.7. Occupational Ranking Regression Analysis Provincial Results**

Our provincial PI results (Figure 5.7) predominantly verify the employment dynamics outlined by our non-parametric analysis. Employment polarization is the main trend in Dutch NUTS 2 provinces, especially in the Randstad area (N. Holland, Z. Holland, N. Brabant, and to a lesser degree Utrecht). In addition, we trace similar job polarization pattern also in peripheral regions, such as Groningen and Friesland. Identical to the non-parametric analysis, job polarization cannot be traced either in Zeeland or Flevoland.

However our non-parametric and PI results point to different employment dynamics in three regions. Contrary to the non-parametric analysis, our regression results identify employment polarization in Drenthe and Overijssel. Similarly, the PI analysis fails to verify the indication of employment polarization in Gelderland, originating from the non-parametric analysis. Some degree of discrepancy is expected since there are different types of analysis, however in such cases of conflicting results we emphasize more on the more systematic evidence provided by the regression analysis for a variety of reasons. The regression analysis not only considers the complete occupational distribution, but also tests for the statistical significance of the terms which define the U-shaped employment curve. In contrast, the non-parametric results are based on simple calculations of employment changes in only three ($1^{st}$, $3^{rd}$ and $5^{th}$) out of the five available quintiles, therefore it is used to provide mere indications of employment polarization.

Associating the provincial percentile regression outcomes with the underlying economic and demographic regional structure returns mixed evidence. Out of the 4 provinces which are not Strongly polarized, one is *urban* (Utrecht), one *relatively urban* (Gelderland), one *relatively rural* (Flevoland) and one *rural* (Zeeland).

Utilizing the *Science and Technology* (S&T) employment indicator also yields non-definite results (polarized provinces predominantly score high on the S&T index, however non-polarized local labor markets such as Gelderland (S&T=29.8) considerably outperform some polarized ones, such as Limburg (S&T=25.7). The above inconclusiveness is expected in highly aggregated spatial units (provinces), due to their considerable socioeconomic heterogeneity they involve, therefore we apply the same analysis to more disaggregated units of local labor markets (arbeidsmarktregio's).

**Arbeidsmarktregio Analysis**

Based on our arbeidsmarktregio results (Figure 5.8 - Analytical results in Table A6.2) Dutch local labor markets exhibit substantial disparities in employment dynamics. Fourteen out of the thirty-five local labor markets exhibit U-shaped employment patterns, while in eleven of them the degree of polarization is stronger than the aggregate Dutch labor market (PI > 2.19). In contrast, twenty-one local labor markets show no evidence of job polarization. The regression analysis on arbeidsmarktregio's managed to confirm the polarization dynamics indicated by the non-parametric analysis, both in the cases of central labor markets (such as Amsterdam, Rijnmond, Midden Brabant, Zuidoost Brabant) and also some peripheral regions (Groningen, Friesland, Zuid Limburg). However due to the additional criteria included in the regression analysis, it failed to verify the employment polarization pattern indicated by the non-parametric analysis in a number of local labor markets (such as Noord and Midden

Limburg, Haaglanden, Zuidwest Brabant). Although such cases call for further investigation, in general we rely more on the regression analysis results.

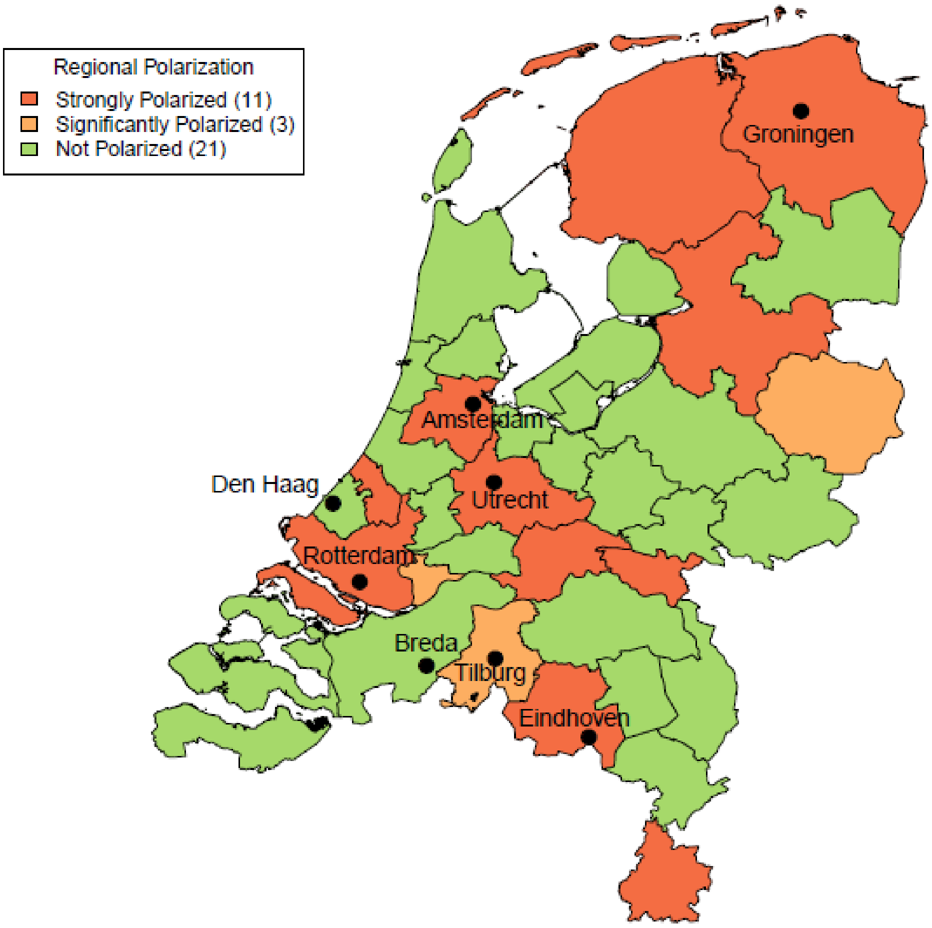


**Figure 5.8. Occupational Ranking Regression Analysis Arbeidsmarktregio Results**

Once again we can compare the degree of polarization with the urbanization classification as described in appendix A4. The results of table A6.2 indicate that 9 out of the 18 arbeidsmarktregio's classified as *urban* or *relatively urban* exhibit polarization (50%), whereas 5 out of the 17 *relatively rural* and *rural* arbeidsmarktregio's exhibit polarization (29%), providing some weak evidence that polarization is related to urbanization.

## 5.3 Skill Intensity Regression Results

Tables 7 and 8 report the skill intensity regression results for each of the task weights separated between the downward and upward sloping part of the occupational employment change curve, which control for low- and high-paying occupations respectively. Our empirical estimates support the theoretical predictions of the routinization hypothesis as to the impact of each task category in occupational employment dynamics, leading to job market polarization.

Considering low-paying occupations (Table 7), in column 1 we simultaneously investigate the impact on occupational employment from the three main task categories in the 3-category taxonomy (Table 1). In line with the routinization hypothesis, we trace a negative relationship between the routine content of a job and its employment dynamics. Neither the abstract, nor the non-routine manual weights show a significant effect, which is in line with the job polarization theory. Specifically, the routinization hypothesis makes no prediction on the impact of computer technology on non-routine manual tasks, while the complementary impact of ICT on abstract tasks is mainly pronounced in the high-paying occupational segment.

Columns 2, 3 and 4 report the impact from each of the above categories individually. In accordance with the general specification (Column 1), we trace a negative relationship between routine task intensity and employment change in low-paying jobs. Furthermore, the magnitude of the impact increases from 0.41% to 0.61% decrease in employment share per percentage point increase in the routine task intensity (Column 2). Abstract (Column 3) as well as non-routine manual (Column 4) tasks again fail to establish a significant effect on the subsequent change in employment share. Moreover, the respective specifications are insignificant ($F_{(1,41)} < F_{crit}$) at every usual statistical level. This constitutes an additional indication of the low explanatory power of the above task categories in the employment dynamics of low-paying jobs. Additionally, it can be attributed to the unequal number of observations per segment (the 50$^{th}$ percentile which is our demarcation line splits between 42 low- and 64 high paying occupations).

Column 5 disaggregates between the two routine constituent categories (routine cognitive and routine manual). In line with the routinization hypothesis, the results highlight the relatively greater importance of the routine manual part, since manual tasks are more easily codified and substituted by computer capital than cognitive ones. Finally, our specification in Column 6 verifies the relatively low importance of abstract tasks for employment dynamics of low-paying occupations, since both two parts of the abstract task intensity (non-routine analytic and non-routine interactive) fail to impose a significant impact on occupational employment change.

Table 7 – Skill Intensity Weighted Regressions – Low-paying occupations (**perc < 50**)
Dependent Variable: Employment Share Change (%) per occupation between 1999 and 2012 (Q3)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Routine Task Intensity | - 0.4811<br>[0.1899]** | - 0.6116<br>[0.2484]** | | | | |
| Abstract Task Intensity | 0.2312<br>[0.1806] | | 0.3015<br>[0.2438] | | | |
| Non Routine Manual Task Intensity | 0.0972<br>[0.1156] | | | 0.2599<br>[0.2066] | | |
| Routine Cognitive Task Intensity | | | | | - 0.3115<br>[0.2739] | |
| Routine Manual Task Intensity | | | | | - 0.9978<br>[0.1574]*** | |
| Non Routine Analytic Task Intensity | | | | | | - 1.4293<br>[1.0292] |
| Non Routine Interactive Task Intensity | | | | | | 0.2461<br>[0.2496] |
| No of Observations | 42 | 42 | 42 | 42 | 42 | 42 |
| F-statistic | 2.32 | 6.06 | 1.53 | 1.58 | 24.64 | 2.75 |
| $R^2$ | 0.24 | 0.21 | 0.04 | 0.05 | 0.38 | 0.08 |

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

In Table 8 on the next page, we instead focus on high paying occupations, represented in the upward sloping part of the employment change curve. Our general specification (Column 1) supports the routinization hypothesis in three ways. At first, although routine tasks are relatively less pronounced in high-paying jobs (Figure 3.1), they still impose a negative impact to occupational employment. Secondly, the effect of abstract task is now positive, as would be expected. Finally, non-routine manual tasks fail to impose a significant effect on occupational employment, similar to the results obtained in table 7.

Columns 2 to 4 report individual results for the three main task categories. Specification (2) establishes the negative association between routine tasks and employment change in high-paying jobs. Once again, the individual effect is greater in magnitude than in the general model (-0.62% compared to -0.41% change in employment per percentage point change in routine task intensity). In Column 3 we trace a significant positive effect from abstract task intensity to employment change in high-paying jobs, highlighting the relative importance of abstract tasks for such occupations. Finally, column 4 shows a negative effect of the non-routine manual task intensity on employment changes.

Table 8 – Skill Intensity Weighted Regressions - High-paying occupations (**perc >= 50**)
Dependent Variable: Employment Share Change (%) per occupation between 1999 and 2012 (Q3)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Routine Task Intensity | - 0.4141<br>[0.2068]** | - 0.6188<br>[0.2195]*** | | | | |
| Abstract Task Intensity | 0.1702<br>[0.0683]*** | | 0.3886<br>[0.1229]*** | | | |
| Non Routine Manual Task Intensity | - 0.0581<br>[0.1384] | | | - 0.2988<br>[0.1470]** | | |
| Routine Cognitive Task Intensity | | | | | - 0.5969<br>[0.2333]** | |
| Routine Manual Task Intensity | | | | | - 0.9000<br>[0.5906] | |
| Non Routine Analytic Task Intensity | | | | | | 0.3405<br>[0.1857]* |
| Non Routine Interactive Task Intensity | | | | | | 0.4101<br>[0.1528]** |
| No of Observations | 64 | 64 | 64 | 64 | 64 | 64 |
| F-statistic | 3.89 | 7.95 | 9.99 | 4.13 | 3.79 | 4.89 |
| R2 | 0.15 | 0.12 | 0.12 | 0.03 | 0.13 | 0.12 |

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

In column 5 we disaggregate between the two routine categories only to find that the routine cognitive has a significant effect on employment change in high-paying jobs. Comparing the results from columns 2 and 5, we conclude that the whole impact of routine task intensity we found in column 2 is nearly perfectly attributed to the routine cognitive part as far as high-paying jobs are concerned. Finally column 6 show that in the upward sloping part of the employment curve both the non-routine analytic and the non-routine interactive tasks are positively associated with occupational employment changes.

To sum up our findings, our skill-intensity regression analysis establishes a monotonic impact of each task category on occupational employment, in accordance with the routinization hypothesis. The negative effect of routine intensity is evident for both low and high paying occupations, with striking similarity in the magnitude of the impact. However this negative effect can be attributed mainly to routine manual tasks in the case of low-paying jobs, whereas for high-paying occupations the routine cognitive tasks appear to drive the result. Furthermore, the positive effect of abstract task intensity is significant only in the high-paying segment of the occupational distribution, where abstract tasks are most pronounced. This positive effect can be attributed to both subcategories: analytical and interactive non-routine tasks. Taken together, these monotonic effects result in the ‘nuanced’ impact of technology in occupational employment based on the task content of jobs, as dictated by the routinization hypothesis theoretical principles, illustrated by the U-shaped employment pattern (Figure 2.2).

# 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’ willingness to participate in the labor market will in turn change the employers’ demands for skills, not only the available supply for skills. Several potential contributors to the polarization of employment in industrialized economies are the routinization hypothesis (Baumol, 1976; ALM, 2003), the international trade and offshoring of goods and services (Blinder, 2007; 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).

This paper provides robust evidence that Netherlands follows the international employment trends and exhibits a pattern of asymmetric employment polarization between 1999 and 2012. The non-parametric analysis shows that employment in middle paid occupations is declining, while high-skill jobs exhibit greater employment increase than low-skill occupations. The results support previous empirical evidence that Dutch labor market shows faster growth in more skilled jobs (OECD, 2016).

Our regional regression results confirm the spatial heterogeneity both in the existence and the degree of job market polarization. In that sense, we compare the degree of job polarization both among regions and between regions and the national labor market. Our results indicate that the majority of the provinces and about half of the Dutch local labor markets (arbeidsmarktregio’s) experiences polarization. Furthermore, our analysis provides some evidence that polarization is linked to urbanization: regions that are more urbanized in the beginning of our time period (1999) are more likely to exhibit polarization between 1999 and 2012.

In addition, our skill-regression analysis verifies the association between tasks performed within jobs and occupational wages reported in the literature (ALM 2003). As such, non-routine manual tasks are mostly pronounced in low-paying occupations in the Netherlands, with their share decreasing monotonically with 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 non-monotone inverted-U curve, reaching its maximum point in middle paying occupations.

Rather importantly, we explicitly test the relationship between tasks and occupational employment share changes. Our results verify the negative impact to occupational employment share imposed by the routineness of the occupation, especially in low-paying jobs. In addition, we document a positive impact to occupational employment due to the degree of the abstract-intensity of the occupation. Taken together, 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.

***Policy implications***

The results show that although polarization is present on an aggregate level, many regions do not exhibit any polarization, either due to a decline of 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, then 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 definitively 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 labor 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 relative terms. 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 and Ter Weel (2015) show that a significant amount of the polarization in the Netherlands can be explained by changes in labor supply. However, constructing a regional labor supply is extremely difficult in the Netherlands, given the high degree of commuting between regions (for instance 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:

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

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

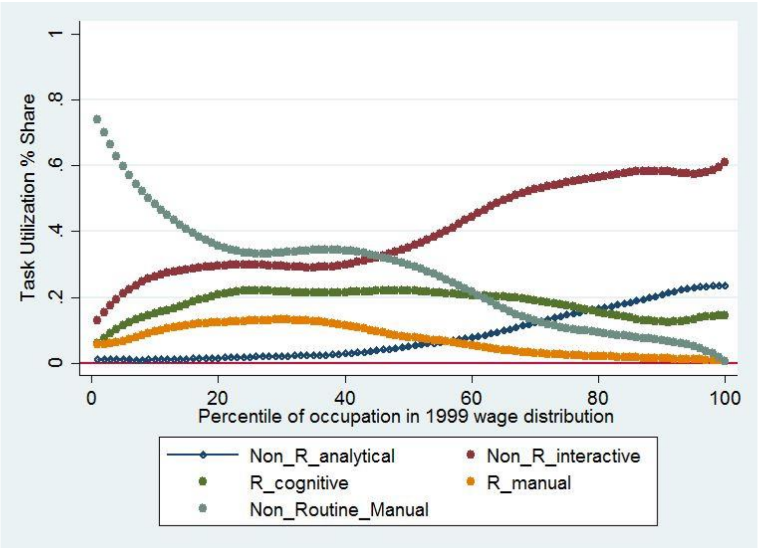

**Figure A2.1. Task Utilization per Occupational Percentile (5 – Category Taxonomy)**

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

## Appendix A3 – Degree of urbanization by region

### Arbeidsmarktregio's

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).

Table A.3.1: 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 |

**Provinces**

For the sake of consistency we employ the same procedure for the provinces, again using the 1999 population densities. The results are listed below

Table A.3.2: Urbanization Index of Provinices

| **Region** | **Pop. Density** | **Urbanization Index** |
|---|---|---|
| Zuid-Holland | 1179 | Urbanized |
| Noord-Holland | 941 | Urbanized |
| Utrecht | 806 | Urbanized |
| Limburg | 525 | Relatively urbanized |
| Noord-Brabant | 474 | Relatively urbanized |
| Gelderland | 382 | Relatively urbanized |
| Overijssel | 321 | Relatively rural |
| Groningen | 239 | Relatively rural |
| Flevoland | 215 | Relatively rural |
| Zeeland | 207 | Rural |
| Friesland | 185 | Rural |
| Drenthe | 176 | Rural |

**Appendix A4 - Regional employment shares in Science and Technology**

The *Human Resources in Science and Technology* index measures the workers with at least tertiary education and/or employment in Science and Technology. Below we present the 1999 index values for the 12 Dutch provinces.

Table A4 - Provincial Classification

| **Province** | **Science and Technology Index** |
|---|---|
| **Drenthe** | 26.3 |
| Flevoland | 27.3 |
| **Friesland** | 24.2 |
| Gelderland | 29.8 |
| **Groningen** | 27.8 |
| **Limburg** | 25.7 |
| **Noord-Brabant** | 28.1 |
| **Noord-Holland** | 33.6 |
| **Overijssel** | 25.7 |
| **Utrecht** | 36.4 |
| Zeeland | 21.8 |
| **Zuid-Holland** | 31.9 |

## Appendix A5 – Non – Parametric Sub – National Analysis

Table A5 - Arbeidsmarktregio Results – Full Sample

| | | Employment Share % Change (1999-2012) | | |
|---|---|---|---|---|
| Regions | Urbanization status | Lowest 20% | Middling 20% | Highest 20% |
| **Haaglanden** | Urbanized | 5.21% | -15.25% | 1.87% |
| **Groot Amsterdam** | Urbanized | 12.33% | -17.31% | 6.09% |
| **Drechtsteden** | Urbanized | 2.43% | -6.44% | 8.84% |
| **Zuid Kennemerland en Ijmond** | Urbanized | 4.72% | -4.36% | 10.31% |
| Zuid Holland Centraal | Urbanized | 5.35% | -5.87% | -0.60% |
| **Rijnmond** | Urbanized | 4.29% | -10.26% | 9.04% |
| Gooi en Vechtstreek | Urbanized | -3.37% | -20.24% | 18.42% |
| **Holland Rijnland** | Urbanized | 0.22% | -9.82% | 13.36% |
| **Zuid Limburg** | Urbanized | 4.29% | -12.25% | 23.85% |
| **Midden Utrecht en Gooi** | Urbanized | 5.19% | -17.82% | 11.53% |
| **Zaanstreek Waterland** | Relatively urbanized | 1.88% | -11.92% | 20.87% |
| **Amersfoort** | Relatively urbanized | 2.26% | -5.51% | 3.19% |
| **Rijk van Nijmegen** | Relatively urbanized | 15.08% | -6.44% | 14.11% |
| **Midden Holland** | Relatively urbanized | 20.42% | -18.92% | 3.05% |
| Midden Gelderland | Relatively urbanized | -2.53% | 8.10% | 2.62% |
| **Midden Brabant** | Relatively urbanized | 2.90% | -3.89% | 24.00% |
| **Zuidoost Brabant** | Relatively urbanized | 6.35% | -14.97% | 24.93% |
| Food Valley | Relatively urbanized | -1.69% | -8.14% | 14.79% |
| **West Brabant** | Relatively rural | 2.27% | -4.46% | 8.60% |
| Noordoost Brabant | Relatively rural | -4.06% | -10.16% | 17.60% |
| Helmond - De Peel | Relatively rural | 1.11% | -4.33% | -0.44% |
| Noord Holland | Relatively rural | -2.55% | 0.79% | 8.45% |
| **Twente** | Relatively rural | 2.96% | -10.22% | 15.95% |
| Gorinchem | Relatively rural | 9.48% | 10.65% | 29.18% |
| **Midden Limburg** | Relatively rural | 16.43% | -12.00% | 4.46% |
| **Rivierenland** | Relatively rural | 4.26% | -14.34% | 22.92% |
| **Noord Limburg** | Relatively rural | 0.68% | -1.92% | 7.53% |
| Stedendriehoek B.V. | Rural | -0.30% | 1.95% | 8.64% |
| Flevoland | Rural | -4.74% | -12.10% | 8.72% |
| Achterhoek | Rural | 0.93% | 5.69% | 9.77% |
| **Groningen** | Rural | 8.94% | -20.45% | 24.36% |
| Ijsselvechtstreek | Rural | -5.56% | -6.55% | 32.33% |
| Zeeland | Rural | -5.08% | -2.59% | 2.27% |
| **Friesland** | Rural | 5.05% | -13.00% | 12.67% |
| Drenthe | Rural | 8.01% | 5.59% | 1.08% |

Occupations are classified using the BRC 4-digit occupational sorting. Polarized regions are bold

**Appendix A6 – Occupational Ranking Regression Analysis**

Table A6.1 - Provincial Results

| Province | Urbanization status | PI-value | Eq.(2) holds? | F-statistic | Polarization status |
|---|---|---|---|---|---|
| Noord Holland | Urbanized | 2.43 | Yes | 3.63 | Strong |
| Utrecht | Urbanized | 1.95 | Yes | 3.56 | Significant |
| Zuid Holland | Urbanized | 2.30 | Yes | 3.37 | Strong |
| Gelderland | Relatively urbanized | 1.56 | Yes | 2.15 | None |
| Noord Brabant | Relatively urbanized | 2.80 | Yes | 8.39 | Strong |
| Limburg | Relatively urbanized | 3.09 | Yes | 5.41 | Strong |
| Flevoland | Relatively rural | 0.09 | No | 1.69 | None |
| Overijssel | Relatively rural | 2.70 | Yes | 6.41 | Strong |
| Groningen | Relatively rural | 4.55 | Yes | 9.64 | Strong |
| Drenthe | Rural | 2.89 | Yes | 2.77 | Strong |
| Friesland | Rural | 2.27 | Yes | 3.97 | Strong |
| Zeeland | Rural | -0.16 | No | 0.64 | None |

Table A6.2 - Arbeidsmarktregio Results

| | Urbanization status | PI-value | Eq.(2) holds? | F-statistic | Polarization status |
|---|---|---|---|---|---|
| Drechtsteden | Urbanized | 1.68 | Yes | 2.55 | Significant |
| Gooi en Vechtstreek | Urbanized | 1.74 | Yes | 1.24 | None |
| Groot Amsterdam | Urbanized | 2.24 | Yes | 2.54 | Strong |
| Haaglanden | Urbanized | 1.15 | Yes | 0.91 | None |
| Holland Rijnland | Urbanized | 1.29 | Yes | 1.83 | None |
| Midden Utrecht en Gooi | Urbanized | 2.60 | Yes | 5.80 | Strong |
| Rijnmond | Urbanized | 3.01 | Yes | 5.29 | Strong |
| Zuid Holland Centraal | Urbanized | 2.85 | Yes | 4.40 | Strong |
| Zuid Kennemerland en Ijmond | Urbanized | 1.40 | Yes | 0.87 | None |
| Zuid Limburg | Urbanized | 4.21 | Yes | 10.99 | Strong |
| Amersfoort | Relatively urbanized | .33 | Yes | 0.06 | None |
| Food Valley | Relatively urbanized | .17 | No | 2.59 | None |
| Midden Brabant | Relatively urbanized | 1.91 | Yes | 4.42 | Significant |
| Midden Gelderland | Relatively urbanized | -.31 | No | 0.18 | None |
| Midden Holland | Relatively urbanized | 1.44 | Yes | 3.69 | None |
| Rijk van Nijmegen | Relatively urbanized | 2.82 | Yes | 4.41 | Strong |
| Zaanstreek Waterland | Relatively urbanized | .87 | Yes | 1.01 | None |
| Zuidoost Brabant | Relatively urbanized | 5.16 | Yes | 15.51 | Strong |
| Gorinchem | Relatively rural | .10 | No | 2.46 | None |
| Helmond - De Peel | Relatively rural | .97 | Yes | 0.74 | None |
| Midden Limburg | Relatively rural | 2.26 | Yes | 2.06 | None |
| Noord Holland | Relatively rural | .17 | Yes | 0.24 | None |
| Noord Limburg | Relatively rural | .50 | Yes | 1.19 | None |
| Noordoost Brabant | Relatively rural | 1.84 | No | 7.61 | None |
| Rivierenland | Relatively rural | 3.72 | Yes | 7.92 | Strong |
| Twente | Relatively rural | 1.79 | Yes | 3.24 | Significant |
| West Brabant | Relatively rural | .56 | Yes | 1.41 | None |
| Achterhoek | Rural | -.02 | Yes | 0.31 | None |
| Drenthe | Rural | .90 | Yes | 0.46 | None |
| Flevoland | Rural | .35 | No | 1.54 | None |
| Friesland | Rural | 2.34 | Yes | 4.70 | Strong |
| Groningen | Rural | 4.52 | Yes | 10.74 | Strong |
| Ijsselvechtstreek | Rural | 2.35 | Yes | 5.59 | Strong |
| Stedendriehoek B.V. | Rural | 0.89 | No | 3.22 | None |
| Zeeland | Rural | -.08 | No | 0.46 | None |

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