Employment polarization in regional labor markets: Evidence from the Netherlands

Nikolaos Terzidis1 | Raquel Ortega-Argilés2

1Department of Global Economics and Management, Faculty of Economics and Business, University of Groningen, Groningen, The Netherlands
2Department of Regional Economic Development, City-REDI Institute, Birmingham Business School, Birmingham, UK

Abstract

This study investigates the existence and extent of employment polarization in the Netherlands between 1999 and 2012. We first determine an asymmetrically polarized employment growth nationally and in local labor markets, especially among young workers. Second, our dynamic panel system-generalized method of moments instrumental variable approach documents that employment polarization is the combined outcome from the interplay between technology and international trade. Our analysis also uncovers novel insights considering the regional determinants of employment polarization; specifically, we demonstrate that employment growth is more likely to polarize in less densely populated regions and those with higher initial specialization in medium- and high-skilled sectors.

KEYWORDS
dynamic panel analysis, regional employment polarization, system-GMM, technology, trade

1 INTRODUCTION

Traditional labor economics (Autor & Dorn, 2009) and trade literature (Grossman & Rossi-Hansberg, 2012) converge on automation and the global division of labor as the main explanations for employment polarization. Both causes are often mentioned in tandem; however, their relative contribution is yet unclear and so are their implications especially at the regional level. In light of earlier evidence of polarized employment growth in the
Netherlands (Goos et al., 2009), the current analysis comprehensively investigates the polarization hypothesis for the Dutch national and local labor markets between 1999 and 2012.

The Netherlands is a particularly interesting candidate for our analysis. First, it is a technologically advanced country with high capital stock and a large pool of high-skilled workers (OECD, 2013). Similarly, it is increasingly integrated in the global value chains (OECD, 2012) and the subsequent division of labor. As such, the Dutch labor force is exceedingly exposed to the two principal determinants of employment polarization. However, Dutch-specific labor market characteristics distinguish the Netherlands from other developed countries and might mediate the impact from globalization. In particular, the Dutch labor force is organized into a relatively small and flexible segment comprising young and high-skilled workers and a much larger rigid segment of senior workers with low labor mobility (OECD, 2012). Low average labor mobility complemented with the ageing population and the inflexible labor market regulations (strict employment protection legislation, barriers to market entry or exit and high tenure-based payments) (IMF, 2017) might impede or delay the substitution of human labor with machines or the offshoring of domestic jobs (Acemoglu & Autor, 2011). Therefore, although its innovative capacity is comparable to other developed countries (the UK or the United States), its less flexible labor market institutions distinguish the Netherlands from the typical industrialized economy as to the employment effects from technology and trade (Autor et al., 2006; Goos & Manning, 2007) and might endanger its potential to fully realize the benefits of globalization. Along those lines, this study offers the following key main outcomes.

First, we document that employment growth in the Netherlands is indeed asymmetrically1 polarized, characterized by larger growth in high-skilled jobs compared to the growth in low-skilled ones. As often argued in the literature (Jaimovich & Siu, 2012), we reveal that the pattern is much stronger in the period including the economic recession (2006–2012). Second, our comprehensive local labor market analysis illustrates that employment polarization is not uniformly distributed across Dutch regions. In that, we advance the relevant literature by uncovering the initial local industrial structure and socioeconomic conditions which shape the probability of polarized employment growth. As opposed to earlier findings (Dauth, 2014), we demonstrate that employment polarization in the Netherlands is not primarily an urban phenomenon. Rather, the probability of polarized employment growth is negatively affected by regional population density and labor utilization. Notably, employment polarization is primarily evident in local labor markets with higher initial per capita income where the industrial specialization favors medium- (industry) and high-skilled (ICT) employment.

The current study’s major contribution lies in constructing a novel data set comprising Dutch worker-level data and our innovative measures of regional exposure to automation and the global division of labor to unravel the relative contribution of the two catalysts of employment polarization. By virtue of dynamic system-GMM analysis we advance the employment polarization literature and provide novel insights which are often overlooked when technology and trade theories are considered in isolation. Along the lines of the routine-biased technical change (Autor et al., 2003), our results indicate a more expanded impact from technology; however, our own-constructed indicators on trade exposure based on recently available input–output tables with data on intermediates (Thissen et al., 2018) document that a significant segment of the Dutch workforce is differentially exposed to the global division of labor. Taken together, we provide robust evidence that employment polarization in the Netherlands is the combined outcome of the interplay between technology and trade.

Finally, motivated by the ageing Dutch labor force (Hartog & Salverda, 2018) we investigate employment patterns across different age groups and document that polarized employment growth in the Netherlands is stronger among young workers, both nationally and regionally. We also show that young workers are more

---

1Following the concern of the anonymous referee, it is important to clarify the difference between the terms asymmetric polarization and professionalization/upgrading. Their primal difference lies in the employment of low-skilled jobs which in asymmetric polarization is necessarily positive but less than the increase in high-skilled jobs, while in professionalization, it is negative. Since this analysis provides robust evidence of positive employment growth in low-skilled employment, we borrow the term asymmetric polarization from the wage polarization literature (Autor et al., 2006) and use it throughout this paper.
exposed to the impact from technology as opposed to their older counterparts where both technology and trade shape their employment structure. Notably, the detailed nature of our trade exposure index reveals differential effects from trade with developed or developing countries across the various occupational-skill groups of young and senior workers in the Netherlands.

From a policy perspective, by identifying the winners and losers from globalization, the current study highlights the necessity for streamlining legislation towards relaxing Dutch-specific labor market rigidities such as high severance payments and fostering labor mobility both between and within sectors and regions. Similarly, a key factor is to encourage life-long learning by strengthening the science-business linkages, support innovation contracts for firms and increase performance-based wage arrangements at the expense of tenure-based ones. Such evidence-based policy prescriptions will foster the effective allocation of the relatively scarce labor resources, increase the economic competitiveness and evenly spread the benefits of globalization across all workers.

The remainder of the paper is structured as follows: Section 2 outlines the theoretical context leading to employment polarization and also briefly introduces the related empirical evidence. Section 3 describes our data sources and the relevant variable construction while Section 4 discusses our empirical strategy. Section 5 reports our main results at the national and regional level and Section 6 includes our sensitivity, age-related analysis. In Section 7 we summarize the main findings and indicate relevant policy suggestions and paths for further research.

2 | THE DETERMINANTS OF EMPLOYMENT POLARIZATION

Since the 1990s, extensive empirical literature has documented the pervasiveness of employment polarization, both in the United States (Autor et al., 2006; Autor et al., 2008) and in Europe (Goos et al., 2009). As to its main causes, labor market and trade economists converge on the differential employment impact from automation and the global fragmentation of production. In both cases, the main premise is that occupation-specific characteristics determine a job’s exposure to the above disruptive forces.

Earlier explanations of employment polarization focused on the Routine-Biased Technical Change (RBTC or routinization) hypothesis, which relies on the influential task model (Autor et al., 2003) and encapsulates the theoretical principles highlighting the more nuanced, task-based relationship between technology and employment transformation. Specifically, the RBTC first advocates that technology substitutes workers performing routine tasks (such as clerks, or production workers) since such tasks are easily codified and implemented by computer capital (labor displacing effect). Second, the extensive processing capacity of computers increases the productivity of workers performing analytic and interactive tasks (such as managers or researchers) thus increasing their relative demand (labor augmenting effect). Finally, technology has limited potential to affect workers performing manual tasks (such as janitors or personal care assistants) since their jobs require substantial interpersonal or situational adaptability.

The above dual effect of technology favoring high-skilled employment (analytic and interactive) at the expense of medium-skilled (routine-based) employees is coupled with evidence of intersectoral mobility (Acemoglu & Autor, 2011; Cortes, 2016) documenting that low-skilled (manual) jobs absorb the residual supply of the workers displaced from routine-based jobs. Taken together, the suggested framework offers a coherent account for employment growth clustering at the tails of the occupational skill distribution resulting in a U-shaped pattern (Figure 1), the visual illustration of employment polarization.

More recently, trade-related explanations for employment polarization are based on the trade in tasks theorem (Grossman & Rossi-Hansberg, 2012), which proposes that the task content of a job (Autor et al., 2003) determines its vulnerability to global competition. Accordingly, the main consensus is that routine tasks are the less costly and

For brevity, this section focuses on the theoretical considerations of employment polarization, only briefly discussing the related empirical evidence. Table A1 (Appendix A) offers a comprehensive review of the empirical findings.
thus easier to be remotely performed since they follow explicit rules and require minimum interaction with headquarters (Blinder, 2007; Blinder & Kueger, 2013). Therefore, similar to technology, offshoring primarily decreases domestic labor demand for routine-based jobs. Furthermore, cost reduction due to international specialization often induces positive spillover effects, mainly by generating labor demand in the nonroutine occupational segment either in low- (manual) or high-skilled (analytic or interactive) jobs. Consequently, although the direction of the overall effect cannot be a priori determined, since the early 2000s, the global division of labor considered the second major catalyst of employment polarization.

This paper is related to the labor economics literature linking technology (Autor & Dorn, 2009) and trade (Keller & Utar, 2016) arguments with polarized employment growth (Table A1—Appendix A, for review). However, the empirical literature so far investigates the impact from technology or trade mostly in isolation, with only a few notable exceptions (Goos et al., 2014; Michaels et al., 2014). Therefore, the primary contribution of this study is the construction of a comprehensive empirical framework to uncover the relative importance and possible complementarities between technology and trade as the main determinants of employment polarization in the Netherlands.

Our analysis is also related to the expanding strand of the employment polarization literature focusing on the subnational level (Autor & Dorn, 2009; Consoli & Sánchez-Barrioluengo, 2018; Kaplanis, 2007) and more specifically on the local economic and demographic characteristics that contribute to polarizing the employment growth (Dauth, 2014). A common premise of these papers is that employment polarization is primarily an urban phenomenon; however, our systematic investigation tests the validity of this conclusion for the Dutch local labor markets.

3 | DATA AND VARIABLE CONSTRUCTION

3.1 | Data sources

Our analysis combines highly reliable micro-data from Statistics Netherlands and in particular the quarterly Labor Force Survey (Enquete Beroepsbevolking) which closely mirrors the Dutch economically active workforce aged from 16 to 64. Individual-level data are of paramount importance since they allow us to control for unobserved
worker-level heterogeneity in human capital (Groot et al., 2014) which could otherwise bias our regression estimates. The data expands from 1999 to 2012\(^3\) while standard data cleaning practices (removing incomplete entries together with agricultural and government officials as state-sponsored sectors) resulted in a detailed data set of 719,820 observations, including inter alia multiple occupational codings, hours worked, living- and workplace and age. Based on the median age (39 years), we separate between young (age < 39) and senior (age ≥ 39) workers to investigate more subtle employment patterns (Section 6). Employment information is combined with high-quality administrative data on hourly wages from the Dutch tax authorities. Table 1 lists summary statistics for our main worker characteristics in the entire sample and by age group.

### Table 1

| Variable                  | Observations | Mean  | SD    | Min. | Max. |
|---------------------------|--------------|-------|-------|------|------|
| **Panel A—Entire sample** (N = 719,820) |              |       |       |      |      |
| Hours worked              | 719,820      | 30.71 | 13.41 | 1    | 95   |
| Age                       | 719,820      | 38.86 | 12.30 | 15   | 64   |
| Hourly wage (year 2000 euro's) | 719,820 | 21.43 | 15.96 | 4.60 | 373.19 |
| Low skilled occupations   | 235,272      | 17.05 | 14.10 | 4.60 | 368.82 |
| Middle skilled occupations| 230,706      | 19.60 | 13.78 | 4.61 | 373.19 |
| High skilled occupations  | 253,842      | 26.75 | 17.64 | 4.63 | 361.18 |
| **Panel B—Young (age < 39) employees** (N = 343,834—47.8%) |              |       |       |      |      |
| Hours worked              | 343,834      | 29.32 | 13.76 | 1    | 95   |
| Age                       | 343,834      | 28.01 | 6.75  | 15   | 38   |
| Hourly wage (year 2000 euro's) | 343,834 | 18.93 | 14.51 | 4.61 | 373.19 |
| Low skilled occupations   | 137,043      | 16.67 | 14.79 | 4.61 | 368.82 |
| Middle skilled occupations| 104,051      | 18.15 | 13.70 | 4.61 | 373.19 |
| High skilled occupations  | 102,740      | 22.38 | 14.29 | 4.63 | 343.67 |
| **Panel C—Senior (age ≥ 39) employees** (N = 375,986—52.2%) |              |       |       |      |      |
| Hours worked              | 375,986      | 31.98 | 12.95 | 1    | 95   |
| Age                       | 375,986      | 48.80 | 6.45  | 39   | 64   |
| Hourly wage (year 2000 euro's) | 375,986 | 23.77 | 16.87 | 4.61 | 363.01 |
| Low skilled occupations   | 98,229       | 17.59 | 13.04 | 4.61 | 363.01 |
| Middle skilled occupations| 126,650      | 20.82 | 13.73 | 4.65 | 359.74 |
| High skilled occupations  | 151,107      | 29.86 | 19.08 | 4.75 | 361.18 |

\(^3\)An inconsistency in the data collection process prevents us from using data from 2012 (Q4) onwards.
spillovers from adjacent areas (Groot et al., 2014). Therefore, for our time-consistent definition of local labor markets, we rely on the NUTS-3 classification, which separates the Netherlands into 40 local labor markets based on population thresholds and reflecting the national administrative units. NUTS-3 regions are the most extensively used in the regional analysis for European countries since they are considered among labor economists as the most reasonable approximations of local labor markets for economic geographical research (Groot et al., 2014) and particularly fit our analysis for the following reasons: First, despite being a relatively small territorial unit, they are large enough to cover at least the relatively short-distance commuting to work, which is particularly extensive in the Netherlands.4 Second, the NUTS classification is used by international organizations (such as the OECD) for the harmonized collection of European statistics. Such data allow us to thoroughly capture the local environment and address the impact of confounding factors when estimating the regional employment effects of technology and trade.5

3.2 Regional exposure to automation

We approximate the region-specific labor market exposure to automation by applying a modified version of the composite Routine Task Intensity (RTI) index (Autor & Dorn, 2013) which considers the relative importance of different task dimensions (routine manual [RM] and routine cognitive [RC], nonroutine analytic [NRA], nonroutine interactive [NRI], and nonroutine manual [NRM]). Relevant task weights are acquired from the German Qualifications and Career Survey (Spitz-Oener, 2006) and are based on the employees’ description of their work activities. Each weight is the ratio of the actual tasks performed over the total number of tasks per category. To capture the routine task intensity of the local employment structure, we exploit the task content of jobs and the local occupational composition of employment (Autor & Dorn, 2013) and perform two additional steps: First, we associate the occupational task weights for all the abovementioned task dimensions with their corresponding jobs. Based on this, we derive the time-invariant, occupation-specific measure of routine-task-intensity ($RTI_i$) according to Equation (1):

$$RTI_i = \ln RM_i + \ln RC_i - \ln NRM_i - \ln NRA_i - \ln NRI_i$$

Second, to capture the local employment structure, we calculate the mean values of the $RTI_i$ index by region ($r$) and year ($t$). Therefore, the region- and yearly-specific $RTI_{rt}$ index (Table B1—Appendix B, for detailed results) reflects the relative importance of all types of tasks within the regional occupational distribution. This aspect makes it particularly appropriate for our subsequent system-GMM analysis focusing on different occupational segments.

By construction, our regional index of exposure to automation increases monotonically in local labor markets with a high share of routine-intensive jobs, while it decreases with the dominance of nonroutine-intensive occupations. As such, similar to the index by Autor and Dorn (2013), it scores low in urban regions exhibiting a large share of high-skilled nonroutine task intensive occupations (such as Greater Amsterdam or The Hague Agglomeration) while high regional $RTI_{rt}$ values indicate increased relative importance of routine jobs in the local occupational distribution (like Delfzijl and surroundings or South-East Drenthe).

4Following the concern of the anonymous reviewer about the extensive commuting flows in the Netherlands, we compared the living and working NUTS-3 regions in our sample. The high correlation coefficient (0.8936) shows that the undeniable commuting flows occur mostly within the boundaries of the applied local labor markets. As such, we are confident that commuting flows in the Netherlands do not contaminate our analysis.

5Our present analysis is also robust to Dutch-specific administrative units (arbeidsmarktregios).
3.3 | Regional exposure to international trade

Following Feenstra and Hanson (1999), we develop a region- and yearly-specific index of exposure to international trade building upon a recent extension of the World Input-Output Database (WIOD) with regional trade data on intermediates (Thissen et al., 2018). Values of intermediate input flows are particularly appropriate for our analysis since they illustrate the local exposure to global markets in a vertical specialization setting.

We calculate the regional dependency on the global division of labor in two steps. First, we extract bilateral trade volumes between Dutch NUTS-2 provinces and their major trade partners (Europe, the United States, and China) for all market-oriented sectors. For each province, we derive the value of net imported intermediates by subtracting the value of the ones domestically produced from the overall value of intermediates consumed. Since trade volumes are available at the provincial (NUTS-2) level, in the second step, we convert the trade data to the regional (NUTS-3) level. For this, we model the impact of trade exposure on different spatial units using a factor loading (Gagliardi et al., 2015). Specifically, we weight the yearly value of the net imported intermediates at the NUTS-2 level by the yearly share of employment in each NUTS-3 region making up a NUTS-2 province, as illustrated in Equations (2) and (3):

\[ \text{TrExp}_{r,t} = \text{IntM}_{r,t} \times \text{EmplSh}_{t} \]  

where:

\[ \text{EmplSh}_{t} = \frac{\text{Empl}_{t}}{\sum_{r=1}^{R}\text{Empl}_{r}} \]  

In Equation (2), \( \text{TrExp}_{r,t} \) is our trade exposure index by NUTS-3 region \( r \) and year \( t \) calculated as the product of the net value of imported intermediates at the NUTS-2 level \( \text{IntM}_{r,t} \) and the employment share of each NUTS-3 region making up the NUTS-2 province. The employment shares \( \text{EmplSh}_{t} \) are calculated in Equation (3) as the ratio of regional employment \( \text{Empl}_{r,t} \) divided by the total employment into all NUTS-3 regions making up each NUTS-2 province.

By construction, our regional trade exposure index exhibits the exogeneity conditions of the shift-share approach (Moretti, 2010) since it measures the impact of a trend captured at a broader spatial unit (NUTS-2) to local labor markets (NUTS-3), weighted by their respective employment shares. Finally, to address the different nature of trade between developed and developing countries (Debaere et al., 2006), we construct different indexes for trade with developed (EU and the United States) and developing (China) trade partners.

**FIGURE 2**  Trade in intermediates [Color figure can be viewed at wileyonlinelibrary.com]
The country-level trade volumes by year (Figure 2—detailed data on Table B2—Appendix B) clearly illustrate the increasing integration of the Netherlands in the global value chains between 2000 and 2010. The total value of imported intermediates in constant 2010 US$ (solid line—left axis) increases by almost 40% (from almost 3.3 billion euros in the year 2000 to 4.6 billion in 2010). For the same period, the value of imported intermediates from China (dashed line—right axis) increased by six times, from 20 million euros in the year 2000 to 120 million in 2010. The overall increasing trends were temporarily reversed at the onset of the global economic downturn (2008); however, the value of trade reached its precrisis levels very soon.

Conceptually, our measure of local exposure to trade shocks reflects the differential exposure of local labor markets from the substitution of production of intermediates by imports from abroad (Partridge et al., 2017) which primarily depends on the local pre-existing industrial specialization (Autor et al., 2013). Figure 3 illustrates the Dutch regional exposure to global markets for the year 2000 (detailed data on Table B3—Appendix B). Considering either total trade volumes (Panel A) or trade with China (Panel B), we reveal greater trade exposure for the labor markets in the "Randstad" metropolitan conurbation (Amsterdam, Rotterdam, Utrecht), in contrast to more peripheral labor markets (Delfzijl and surroundings, Drenthe or Limburg) which participate less to the global value chains.

Finally, similar to Autor et al. (2013), the negative correlation coefficient (−0.488 significant for α = 1%; Table B4—Appendix B) between our regional exposure to automation and trade indexes reflects that local labor markets with increased global integration are the ones with the lowest RTIr values. This implies that while the greater trade openness of the heavily urbanized areas may favor the emergence of polarized employment growth, the lower exposure to automation of these regions may counteract these pressures. As such, we cannot a priori predict whether the more urbanized areas will be more or less polarized compared to less densely populated localities, although recent international evidence suggests that employment polarization tends to be higher in urbanized areas (Dauth, 2014).

FIGURE 3 Trade exposure by region [Color figure can be viewed at wileyonlinelibrary.com]
4 | EMPIRICAL STRATEGY

This study adopts a dual approach to thoroughly investigate the spatial profile of employment polarization in the Netherlands. First, we provide systematic evidence of polarized employment growth for the national and local labor markets. Importantly, we follow Dauth (2014), who introduces a single quantitative measure of employment polarization (Polarization Index [PI]) and calculate regional PI values which allow us to quantitatively compare then “strength” of employment polarization across different local labor markets. Notably, we contribute to the literature by estimating probit models to uncover the local industrial and socioeconomic factors shaping the probability of polarized employment growth which reveal new insights that depart from common premises in the regional employment polarization literature.

The primary contribution of our study lies in disentangling the relative importance of technology and the global division of labor as catalysts of employment polarization. For this, we advance the relevant literature by applying system-GMM instrumental variable (IV) approach to novel data sets comprising Dutch micro-data and our own-constructed measures of regional exposure to technology and international trade. Exploiting the merits of an IV design and an extensive set of control variables and fixed effects, we establish causal relationships between the regional impact from technology and trade to employment growth along the various occupational-skill segments.

4.1 | Determining a U-shaped employment pattern

The standard practice of identifying U-shaped curves (Grossman & Krueger, 1995) requires establishing significant negative linear and positive nonlinear terms in a model similar to Equation (4):

$$\Delta s_{i,1999-2012} = \alpha_0 + \alpha_1 \text{rank}_i + \alpha_2 \text{rank}_i^2 + \varepsilon_i$$

where $\Delta s_{i,1999-2012}$ is the percentage change in the employment share of each occupational percentile ($i$) between 1999 and 2012 while $\text{rank}_i$ (and $\text{rank}_i^2$) represent the occupational sorting into percentiles. We sort occupations into percentiles based on their initial (1999) median wages and weight them by their initial employment shares. Therefore, large occupations (i.e., retail sales employees) extend over multiple percentiles, while small ones (i.e., librarians) fit into single ones. This ensures that each percentile represents a substantial number of workers and therefore our regression outcomes are not driven by compositional effects.

Despite being theoretically sound, the above criteria are potentially misleading since they often conclude on a U-curve even when the true relationship is convex but monotone within the relevant data range. Therefore, we extend the employment polarization literature and apply an appropriate breakpoint detection method (Lind & Mehlum, 2010) which imposes additional restrictions to verify that the estimated curve exhibits a significantly negative slope at low values of the occupational spectrum and a significantly positive one at higher occupational percentiles. Furthermore, we test that the two trends are separated by a significant change in slope occurring at a single inflexion point, observed within the relevant data range.7

7Based on Equation (4), the additional restrictions are combined into the following null hypothesis:

$H_0: \alpha_1 + 2\alpha_2 \text{rank}_{1999} \geq 0$ and/or $H_0: \alpha_1 + 2\alpha_2 \text{rank}_{1999} \leq 0$, tested against the alternative $H_a: \alpha_1 + 2\alpha_2 \text{rank}_{1999} > 0$ and/or $H_a: \alpha_1 + 2\alpha_2 \text{rank}_{1999} < 0$ where $H_0: \alpha_1 + 2\alpha_2 \text{rank}_{1999} \geq 0$ and $H_0: \alpha_1 + 2\alpha_2 \text{rank}_{1999} \leq 0$ are the lowest $H_0: \alpha_1 + 2\alpha_2 \text{rank}_{1999} \geq 0$ and highest $H_0: \alpha_1 + 2\alpha_2 \text{rank}_{1999} \geq 0$ percentile.
4.2 Regional analysis—PI

To uncover regional patterns of polarized employment growth in the Netherlands, we re-estimate Equation (4) for each local labor market. Furthermore, based on Dauth (2014), we utilize the $t$-value of the squared term (Equation 5—Appendix C, for the technical details) as a quantitative PI.

$$t_{ran}^2 = \frac{\hat{e}_2^2}{\hat{\sigma}^2} = \text{PI}$$

Several advantages of the PI justify its qualities as a quantitative measure of employment polarization. In general, significant PI values indicate good regression fit and larger absolute values of the index reveal higher curvature (depth of the U-shaped curve) which in turn demonstrates the strength of the polarization effect. Therefore, based on the regional PI values and the applied robust breakpoint detection method, we classify Dutch local labor markets as significantly polarized (significant PI but smaller than the national value), strongly polarized (regional PI significant and larger than national PI), or not polarized (insignificant PI).

4.3 Regional determinants of employment polarization

This section addresses a central theme in the regional employment polarization literature; namely how the region-specific conditions shape the probability of polarized employment growth. For this, we estimate probit models as in Equation (6) based on comprehensive data sets appropriately reflecting the local industrial and socioeconomic structure.

$$\Pr(\text{Pol}_t = 1) = \alpha_0 + \beta \mathbf{X}_t;2000 + \varepsilon$$

Our region-specific dependent variable ($\text{Pol}_t$) is a dummy indicator reflecting our regional analysis as follows:

$$\text{Pol}_t = \begin{cases} 1 & \text{for strong or significant polarization} \\ 0 & \text{for no polarization} \end{cases}$$

$\mathbf{X}_t$ is the set of our independent predictors (Table C1 for data sources and summary statistics and Table C2 for the correlation matrix—Appendix C) appropriately describing the local industrial specialization and socioeconomic conditions for the year 2000. Specifically, we include regional employment shares by economic sector (industry, distributive trade, construction, information and communication technology, finance, other services, professional and scientific activities, and real estate) merged with regional economic (GDP per capita, unemployment rate, labor utilization) and demographic (male-to-female ratio, population density) indicators.

4.4 Automation and international trade as catalysts of employment polarization

A key objective of the current paper is to combine technology- and trade-related measures in a unified empirical framework and identify their relative contribution as the main determinants of employment polarization. Our identification strategy draws on earlier evidence documenting that the local socioeconomic structure (industrial specialization and demographic conditions) determines the vulnerability of the workforce to automation (Acemoglu & Restrepo, 2019) and the global division of labor (Autor et al., 2013).
Empirically, we follow earlier literature in labor economics (Rodriguez-Pose & Tselios, 2009) and adopt a dynamic framework to address the high persistence of regional employment, where current values depend on their past realizations. Specifically, our small-T, large-N panel data set calls for a dynamic estimation framework (Roodman, 2009). Therefore, to investigate the regional employment effects from technology and trade while controlling for confounding factors, we estimate Equation (7) for a strictly balanced panel data set of Dutch NUTS-3 regions between 2000 and 2010.

$$\Delta \text{Ln}E_{rt} = \beta_0 + \beta_1 \Delta \text{Ln}E_{r,t-1} + \beta_2 RTI_{t} + \delta \text{Ln}Tr\text{Exp}'_{rt} + \beta \ln X'_t + \gamma d'_t + \mu_r + u_t$$  

(7)

where the dependent variable ($\Delta \text{Ln}E_{rt}$) is the annual change in the employment share of low-, medium- and high-skilled jobs per region ($r$) and year ($t$) (Table C3—Appendix C, for summary statistics). $RTI_t$ is our region- and year-specific measure of regional exposure to automation and $Tr\text{Exp}_t$ is our regional trade exposure index reflecting the global division of labor. Finally, $X_t$ is our set of control variables including the industrial and socio-economic factors that impact employment growth. $d_t$ are year dummies, while $\mu_r$ is the region-specific unobserved part of the error term and $u_t$ is the observation-specific error (Table C4, for the detailed summary statistics and Table C5 for the correlation matrix—Appendix C).

4.5 Identification and estimation method

The presence of a lagged dependent variable in Equation (7) makes both the ordinary least squares (OLS) and least-squares dummy variables (LSDV) estimators for fixed-effects models biased and inconsistent because of the correlation between the lagged dependent variable and the time-invariant part of the error term (Nickel, 1981). As a result, to obtain unbiased and consistent estimates that will allow causal interpretation of our results, we estimate system-GMM dynamic panel data models (Arellano & Bover, 1995; Blundell & Bond, 1998) which first-difference Equation (7) to eliminate the time-invariant fixed effect ($\mu_r$). Despite this transformation, the lagged dependent variable is potentially endogenous, requiring appropriate instrumentation. Roodman (2009) illustrates that longer lags of the regressors ($t-2$ and earlier) remain uncorrelated with the error term, therefore qualify as internal instruments (Appendix D, for methodological details).

Econometric work on GMM estimators reveals that when the explanatory variables are persistent over time, their lagged levels (difference-GMM) are weak instruments for the first-differenced equation. In that respect, Arellano and Bover (1995) develop the system-GMM estimator, which exploits the additional assumption that first differences of the instrumental variables are uncorrelated with the fixed effects (in the levels equation). Based on this, Blundell and Bond (1998) propose the use of lagged differences as potential instruments for the equations in levels. Therefore, system-GMM methodology simultaneously estimates a system of two equations (one in level and one in first differences) and generates additional instruments for equations in levels, thus dramatically increasing the efficiency and reducing the bias of difference-GMM estimators. As a result, they are particularly appropriate in small-N, large-T and highly autoregressive panel data series, such as our own.

Inflating the number of instruments in system-GMM estimations often decreases the estimation efficiency, especially in finite samples (Roodman, 2009). Therefore, it is important to limit their proliferation. For this, we first follow the related literature (Bogliacino & Vivarelli, 2012) and confine the instrumental lag range between $t-2$ and $t-4$ and secondly we use a restricted (collapsed) instrument matrix which generates

---

9Roodman (2009) shows that the OLS estimator tends to bias the estimated term of the lagged dependent variable upwards, while the (LSDV estimator produces a downward-biased estimate of the autoregressive term. Therefore, OLS and LSDV estimations provide indicative boundaries for the true parameter of the lagged dependent variable.
only one instrument per variable and lag distance, instead of one for each period, variable and lag distance. Also, we report two-step system-GMM estimates with heteroscedasticity robust st. errors clustered by region. This triggers the finite-sample correction to the SEs (Windmeijer, 2005), without which the SEs would be severely downward biased.

Two specification tests assess the unbiasedness, consistency, and efficiency of our estimates. First, we check for second-order correlation in differences. Absence of second-order correlation in differences ensures that lags longer than \( t - 2 \) can be used as valid instruments. Second, we perform the Hansen test of over-identifying restrictions under the null hypothesis that all moment conditions are jointly valid.

### RESULTS

#### 5.1 National-level analysis

Table 2 reports the results from estimating Equation (4) for the Dutch national labor market. Considering the entire period of analysis (Column 1), our estimation fulfills all the significance criteria of our breakpoint detection method for a U-shaped employment pattern (Lind & Mehlum, 2010). Specifically, we verify a significantly negative employment trend at the lower occupational skill segment followed by a positive one at high-skilled jobs separated by a unique and significant change in slope occurring at the 40th occupational percentile, thus illustrating that printing and arts/crafts employees (BRC 4-digit: 0755) experience the greatest employment decline in the Netherlands between 1999 and 2012.

The regression fit line (Figure 4) illustrates a U-shaped employment change pattern. Notably, the most profound employment growth in high-skilled jobs is accompanied by a modest one in low-skilled occupations and a hollowing out of employment on average-skilled jobs, thus resulting in an asymmetric pattern of employment polarization (Autor et al., 2006, 2008; Goos & Manning, 2007).
Two explanations mainly account for such a modest employment increase in low-skill occupations, especially compared to similar trends in the United States (Acemoglu & Autor, 2011). First, the relative inflexibility of the Dutch labor market, typical of Continental Europe, featuring increased unionization and national statutory minimum wage-setting regulations which inhibit the expansion of low-wage jobs (Oesch & Rodriguez Menes, 2011). In addition, we reveal that employment gains among low-skilled jobs in the Netherlands are associated with service occupations (such as personal care assistants and related service workers or transport and logistics personnel). These jobs involve a wide range of routine and nonroutine tasks. Consequently, our results support the view that employment polarization at the lower tail is associated with low-wage service occupations with diverse task content (Autor & Dorn, 2009; Goos et al., 2009).

To investigate whether employment polarization is a business cycle phenomenon precipitated during recessions (Autor, 2010), in Columns 2 and 3 we re-estimate Equation (4) for two nonoverlapping periods (1999–2005 and 2006–2012). The former represents a period of economic expansion while the latter incorporates the economic recession of 2008–2010. Our current analysis indicates two distinct trends, with polarized employment growth occurring only between 2006 and 2012. Notably, the employment polarization trend between 2006 and 2012 is particularly strong, with the respective PI exceeding the one for the entire period of analysis (2.95
compared to 2.28). The above conclusion is also illustrated by the regression fit lines (Figure 5), where we indicate a U-shaped employment change pattern only for the period 2006–2012. The current analysis offers suggestive evidence that the 2008 economic crisis transformed Dutch employment according to the polarization dynamics; however, this evidence is only implicit and not causal; therefore, it should be interpreted with caution.

5.2 | Regional-level analysis

This section investigates the regional variation in the employment patterns by repeating the above analysis for the 40 Dutch NUTS-3 regions. Regional employment change was fitted to constant occupational rankings based on the national analysis to allow for regional comparisons. Table 3 (detailed results in Table E1—Appendix E) reports the regional employment polarization patterns by classifying local labor markets with PI larger than the national analysis (Table 2—Column 1–PI = 2.28) as strongly polarized, regions with significant PI but less than the national value as significantly polarized and regions with insignificant PI as not polarized.

The results ascertain that employment polarization is prevalent across some, but not all Dutch regions. In total, 10 local labor markets are significantly polarized, while eight of them are polarized stronger than the aggregate country. Compared to similar analyses in other countries (Dauth, 2014; Senftleben-Konig & Wielandt, 2014, for Germany; Jones & Green, 2009; Kaplanis, 2007 for the UK), the share of Dutch local labor markets with polarized employment growth is smaller; however, this partially reflects our stricter criteria for determining a U-shaped employment pattern. Even so, the 10 polarized regions account for one-third of our employed individuals in 1999, while most of them exhibit a stronger level of employment polarization compared to the national labor market.

Simply eyeballing the geography of employment polarization in the Netherlands (Figure 6) illustrates that polarization is the main employment trend in regions with contrasting economic and demographic characteristics. In that sense, employment growth is polarizing in both highly urbanized, metropolitan labor markets with a substantial share of high-skilled employment (Greater Amsterdam, Rijnmond) as well as in peripheral intermediate (East Groningen, South Limburg) and rural ones (Zeeland Flanders) with a considerable share of low-skilled (nonroutine manual) jobs. Therefore, the next section adopts a more systematic approach to uncover how the regional initial economic, industrial and demographic characteristics shape the probability of employment polarization.

5.3 | Regional determinants of employment polarization

In this section, we advance the employment polarization literature by estimating probit models (Equation 6) to evaluate how the local industrial organization and various socioeconomic conditions shape the probability of polarized employment growth.

---

**TABLE 3** Regional employment polarization in the Netherlands

| Regional status          | PI          | Frequency |
|-------------------------|-------------|-----------|
| Strongly polarized      | PI > 2.28   | 8         |
| Significantly polarized | 1.68 < t < 2.28 | 2         |
| Not polarized           | PI < 1.68   | 30        |

Abbreviation: PI, polarization Index.

10Following the standard criterion of a significant quadratic term (thus abandoning the additional restrictions of our breakpoint detection method) increases the number of polarized regions to 14.
Table 4 reports the resulting marginal effects, calculated as elasticities (Table E2—Appendix E for the detailed estimation results and specification details). Considering the industrial structure, we first identify a positive association between the initial share of industrial employment and regional employment polarization. Specifically, a 1% increase in the regional share of employment in industry is associated with a 1.6% higher probability of polarized employment growth. This outcome is mostly in line with earlier evidence showing that higher initial share of routine-based (industrial) employment is positively linked with employment polarization (Consoli & Sánchez-Barrioluengo, 2018). Compared to the country average of 34.4% of industrial employment share, Dutch regions with polarized employment show only marginally higher industrial employment share (34.9%). However, certain Dutch peripheral local labor markets with polarized employment growth exhibit some of the highest shares of initial industrial employment in the country, ranging from 39% in East Groningen and Zeeland Flanders to 38.2% in South Limburg. A notable exception is Amsterdam, where employment polarization is combined with one of the lowest regional shares of initial industrial employment (23.3%), illustrating the importance of other factors.

In that, we highlight the importance of specialization in the ICT sector. The reported elasticity indicates that a 1% increase in the initial ICT employment share is associated with a 0.26% increase in the likelihood of regional employment polarization. Nevertheless, not all regions with polarizing employment growth exhibit similar ICT employment shares. Some local labor markets are relatively more specialized in ICT (such as Amsterdam with 16.4% or Overig Groningen with 12%) compared to the country average of 6.7%. In comparison, some regions combine employment polarization with the lowest ICT employment share (for instance Zeeland Flanders with 0.1% or East Groningen with 0.2%).

**FIGURE 6** The geography of employment polarization in the Netherlands [Color figure can be viewed at wileyonlinelibrary.com]
Employment in the tradable sector is also positively linked with polarized employment growth. The estimated elasticity indicates that 1% increase in the initial share of tradable sector employment increases the probability of regionally polarizing employment by 1.1%. Given that the polarizing regions exhibit only marginally higher average share of tradable employment (25.5% compared to the country mean value of 24.9%) the above finding seems to be predominantly driven by a small number of regions where polarized employment growth is combined with the highest values of initial employment share in the tradable sectors, such as Zeeland Flanders (32%), Amsterdam and Southwest Gelderland (29%). Finally, higher employment share in the real estate sector favors regional employment polarization; however, this result should be interpreted with caution because the effect is only weakly specified (for $\alpha = 10\%$) and the meager share of real estate employment (the country average equals only 0.07%).

Taken together, the findings regarding the effects from the regional industrial organization largely support the transitional employment patterns of employment polarization, contending that displaced medium-skilled (industrial

| Variable                                      | Marginal effect |
|-----------------------------------------------|-----------------|
| Regional GDP per capita$_{r,2000}$             | 1.843**         |
| Employment share in industry$_{r,2000}$        | 1.620**         |
| Employment share in ICT$_{r,2000}$             | 0.259*          |
| Employment share in finance$_{r,2000}$         | 0.200           |
| Employment share in other services$_{r,2000}$  | 0.104           |
| Employment share in professional, scientific activities$_{r,2000}$ | 0.250 |
| Employment share in real estate activities$_{r,2000}$ | 0.749* |
| Employment share in trade, repairs, transport, accommodation$_{r,2000}$ | 1.117* |
| Employment share in construction$_{r,2000}$    | −0.359          |
| Unemployment rate$_{r,2000}$                   | −0.049          |
| Labor utilization$_{r,2000}$                   | −2.285**        |
| Male-to-female ratio$_{r,2000}$                | −3.247          |
| Population density$_{r,2000}$                  | −0.554**        |

Note: Probit regression analysis. Dependent variable: $PrPol = 1$. Robust SEs, clustered by region are reported in brackets. Industries are classified by the ISIC rev. 4 taxonomy. Marginal effects derived as elasticities. *$p < 0.1$ and **$p < 0.05$. 
or real estate) employees potentially sort either to high-skilled (ICT) or low-skilled (trade, repairs, transport, and accommodation) occupations.

The current analysis also uncovers significant relationships between socioeconomic factors and the likelihood for regional employment polarization. In line with earlier findings that polarizing employment is more likely in prosperous regions (Autor & Dorn, 2013; Dauth, 2014), we indicate that 1% higher initial per capita income is positively associated with 1.8% increase in the likelihood of regional employment polarization. This finding is reflected by the higher average per capita income of local labor markets with polarizing employment (40,000 US$ compared to a country average of 36,600 USD) which is predominantly driven by certain Dutch regions with polarizing employment growth and substantially high per capita income (such as Amsterdam with 67,000 US$ and Overig Groningen with 52,000 US$). East Groningen is the exception to the above trend since it combines regional employment polarization with the lowest per capita income in the country (22,000 US$).

Contrary to the often-cited conclusion that employment polarization is an urban phenomenon (Dauth, 2014), Table 4 points to a negative relationship between population density and regional employment polarization. The estimated elasticity shows that a 1% increase in the population density is associated with a 0.55% lower likelihood of polarizing employment growth. This finding reflects the lower average population density in regions with polarizing employment growth (491 inhabitants per km² compared to a country average of 643). Despite that some central regions exhibit polarizing employment and relatively high population density (such as Amsterdam with 1627 and Rijnmond with 1979 inhabitants per km²), the general trend in the Netherlands associates regional employment polarization with low urbanization rates. Typical examples include Zeeland Flanders, North Drenthe and East Groningen (with 146, 171, and 184 inhabitants per km², respectively).

Finally, our analysis indicates that a 1% increase in regional labor utilization is associated with a 2.2% lower probability of polarizing employment growth. However, this should be interpreted with caution, since labor utilization in the regions with polarized employment growth is almost identical with the country average (50.3% working ratio compared to the mean country value of 49.3%). As such, the above finding is mostly driven by East Groningen, which combines employment polarization with the lowest value of labor utilization in the country (39%).

Overall, the current analysis crucially contributes to a key segment of the regional employment polarization literature; namely identifying its’ regional determinants. In that, we first provide evidence that various employment categories (industry, ICT, trade and real estate) are differentially linked with the likelihood of regional employment polarization. Specifically, we reveal that industrial employment is more critical in peripheral regions such as Zeeland Flanders or East Groningen. In contrast, employment in the ICT or the tradable sector is positively linked with employment polarization in the metropolitan Dutch regions (in the “Randstad” area). Therefore, our analysis indicates a benign and differential effect from the local industrial structure in the likelihood of regional employment polarization.

Considering the most important socioeconomic factors, first, we verify earlier evidence (Autor & Dorn, 2013; Dauth, 2014) that employment polarization is more likely in prosperous regions. Nevertheless, we also uncover different trends which depart from the often-cited conclusion that polarization is an urban phenomenon. Specifically, we show that employment polarization is negatively linked with urbanization rates, indicating no overall world-wide pattern in the relationship between polarizing employment growth and the regional employment structure. Overall, the current analysis is rather promising since it highlights both the unique case of the Netherlands in the international labor economics and the necessity for a more nuanced approach to uncover the regional determinants of employment polarization.

5.4 Automation and international fragmentation as catalysts of employment polarization

This section investigates the relative contribution of automation and international trade as the two most prominent catalysts of polarizing the employment growth. Our analysis is based on a strictly balanced panel data set
comprising our region-specific measures of exposure to automation and the global division of labor together with an extensive set of industrial and socioeconomic indicators for the 40 NUTS-3 regions in the Netherlands between 2000 and 2010. We capitalize on the panel structure of our data set by applying instrumental variable, dynamic system-GMM techniques in estimating Equation (7) separately for low-, medium- and high-skilled employment. To address the different nature of trade based on the development status of the trade partner (Debaere et al., 2006), we further decompose our trade indicator between trade with developed (EU and the United States) and developing regions (China).

Overall, the specification tests satisfy the necessary conditions for a consistent and unbiased estimation. Specifically, the Hansen test verifies the validity of the lagged values used as instruments, since the null hypothesis that all moment conditions are jointly valid is never rejected while the AR(2) test verifies the absence of second-order autocorrelation in the first-differenced models. Finally, the lagged dependent variable is largely significant (detailed results in Table E3—Appendix E), thus supporting the past dependency of current employment values, which justifies the appropriateness of our dynamic panel approach.11

| TABLE 5 System GMM regressions |
|--------------------------------|
| **Low-skilled jobs** | **Medium-skilled jobs** | **High-skilled jobs** |
| (1) | (2) | (3) | (4) | (5) | (6) |
| Routine task intensity$_{rt-1}$ | $-0.324^{**}$ | $-0.247^{**}$ | $-0.037$ | $-0.001$ | $0.264^{**}$ | $0.242^{***}$ |
| | (0.106) | (0.081) | (0.035) | (0.134) | (0.097) | (0.098) |
| ln trade exposure (Total)$_{rt-1}$ | $0.528^{**}$ | $-0.373^{*}$ | $-0.427$ | | | |
| | (0.251) | (0.205) | (0.719) | | | |
| ln trade exposure (Developed)$_{rt-1}$ | 0.514 | 0.514 | 0.514 | 0.514 | 0.514 | 0.514 |
| | (0.677) | (0.540) | (0.967) | (0.767) | (0.950) | (0.421) |
| ln trade exposure (Developing)$_{rt-1}$ | $-0.190$ | 0.121 | 0.143 | 0.143 | 0.143 | 0.143 |
| | (0.677) | (0.719) | (0.694) | (0.590) | (0.590) | (0.590) |
| Constant | 2.258 | 2.913 | 0.627 | 0.015 | 1.353 | 3.684 |
| | (4.558) | (4.251) | (2.317) | (7.409) | (8.362) | (5.656) |
| Observations | 440 | 440 | 440 | 440 | 440 | 440 |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Instruments | 40 | 40 | 39 | 41 | 39 | 40 |
| Wald χ²-stat | 478.58^{***} | 494.72^{***} | 242.72^{***} | 128.4^{***} | 384.05^{***} | 984.43^{***} |
| AR(2) (p-val) | 0.555 | 0.960 | 0.305 | 0.327 | 0.644 | 0.844 |
| Hansen (p-val) | 0.604 | 0.525 | 0.126 | 0.210 | 0.370 | 0.451 |

Note: Dependent variables: d. lnEmplShLSt, d. lnEmplShMSt, d. lnEmplShHSt. Independent variables: RTI$_{rt-1}$, ln OffshEur$_{rt-1}$, ln OffshChi$_{rt-1}$. Estimation method is two-step with robust SEs clustered by region and implementing the Windmeijer finite sample correction of the SEs. The detailed specifications include the lagged dependent variable, a constant and a full set of control variables (all continuous right-hand side variables are in logarithms, lagged one period): GDP per capita, fixed capital formation (total), GVA in manufacturing, GVA in ICT, GVA in finance, GVA in professional and scientific, and so on activities, GVA in public administration, labor utilization, population density, frontier and keeping-pace productivity dummies. *p < 0.1, **p < 0.05, and ***p < 0.01.

11For completeness, Tables E4 and E5—Appendix E report identical estimations following an OLS and a static panel (LSDV) approach. Qualitatively the results are very similar. Quantitatively, system-GMM estimates appear larger, indicating that the employment effects of technology and trade are not driven by endogeneity issues.
Table 5 reports the system-GMM estimation results on the regional employment effects from exposure to automation and international trade. Considering low-skilled employment, the estimated elasticities (Columns 1 and 2) indicate a negative impact from technology. Depending on the exact specification, the decrease in the growth rate of low-skilled employment varies from 0.32% (Column 1) to 0.25% (Column 2) for each 1% increase in the regional routine task intensity index. This negative effect reflects the increased share of routine tasks across low-skilled jobs in the Netherlands (Figure E1—Appendix E). The negative effect of automation on low-skilled jobs is counteracted by the positive impact of participating in the global value chains. Based on total trade volumes (Column 1), we estimate that a 1% increase in the regional trade exposure index increases the growth rate of low-skilled jobs by 0.55%. As such, our analysis for low-skilled employment indicates labor-displacing effects from technology in contrast to labor augmenting ones from trade. However, disaggregating by trade destination (Column 2) fails to provide any significant differential effects from trade on Dutch regional low-skilled employment.

Our findings for medium-skilled employment (Columns 3 and 4) indicate the greater relative importance from the global division of labor. Column 3 shows that for each 1% increase in the regional trade exposure index, the growth rate of medium-skilled employment decreases by 0.37%. Nevertheless, Column 4 does not provide any significant evidence of differentiated effects by type of trade destination. Considering the impact of automation, both specifications (Columns 3 and 4) fail to uncover any significant effects on medium-skilled employment. Although this may challenge the theoretical predictions of the RBTC hypothesis, it seems appropriate for the Dutch case since medium-skilled jobs in the Netherlands are less routine-intensive than low-skilled ones (Figure E1—Appendix E). Therefore, the negative impact of automation is expected to be mainly concentrated on low-skilled employment. Interestingly, our results highlight that the criteria determining the technological exposure of medium-skilled jobs (routine-task-content) potentially differ to the ones determining their exposure to international competition (personal delivery) as suggested by Blinder (2007) for the US case.

The results on high-skilled employment (Columns 5 and 6) indicate a positive effect from automation, consistent with the complementary effects of innovative technologies on the productivity of high-skilled, abstract-based workers. The estimated elasticity points to an average 0.25% increase in the growth rate of high-skilled employees caused by a 1% increase in the regional routinization index. The impact of international trade on high-skilled employment is statistically insignificant.

In total, our instrumental variable, dynamic system-GMM approach offers comprehensive evidence as to the relative importance of automation and global division of labor in polarizing the employment growth in the Netherlands. First, we show that both technology and trade impose significant differential effects on various occupational skill segments. Specifically, technology harms low-skilled domestic employment while it complements high-skilled employees. In contrast, integration in the global value chains decreases the growth rate of medium-skilled employment while it benefits low-skilled workers. Our analysis indicates that the combination of automation and international trade generates the full pattern of employment polarization, mostly due to their combined effect in low-skilled jobs where the positive impact from trade potentially negates the negative impact from automation and leads to the modest employment increase indicated by our earlier analysis (Figure 4). Finally, distinguishing between developed and developing trade partners does not provide any significant evidence so far; however, in the sensitivity analysis, we investigate whether this holds across different age groups.

6 | SENSITIVITY ANALYSIS—AGE GROUPS

6.1 | National-level analysis

The ageing labor force and the large differences in the employment profiles between young and senior Dutch workers where the latter often enjoy full-time positions with permanent contracts which inhibits their labor mobility (OECD, 2012) motivate the current, in-depth investigation of employment restructuring in the
The results from estimating Equation (4) for young (age < 39) and senior (age ≥ 39) Dutch workers by time period (Table 6) reveal substantially divergent employment patterns. In particular, we indicate polarized (U-shaped) employment growth for young workers between 1999 and 2012 (Column 1) with the significant change in slope between low- and high-wage occupations occurring in the 49th percentile. In contrast, employment growth across senior workers during the same period is not consistent with a quadratic relationship on skills. The respective model (Column 4) fails to capture any significant trend since both the linear and quadratic terms are insignificant.

The above conclusions are also illustrated in Figure 7, which reveals a U-shaped regression fit line for young workers, contrary to a relatively stable employment change curve for senior ones. Our age-related analysis

### Table 6

|        | Young employees |         | Senior employees |         |
|--------|-----------------|---------|------------------|---------|
|        | 1999–2012       | 1999–2005 | 2006–2012        | 1999–2012 | 1999–2005 | 2006–2012 |
| rank₁ᵢ | -0.01508***     | -0.00291 | -0.01197***      | 0.00189  | 0.00249  | 0.00059  |
|        | (0.00395)       | (0.00234) | (0.00231)        | (0.00265) | (0.00209) | (0.00164) |
| rank²ᵢ | 0.00015***      | -0.000002| 0.00013***       | -0.00001 | -0.00004* | 0.00001  |
|        | (0.00004)       | (0.00002) | (0.00002)        | (0.00002) | (0.00002) | (0.00002) |
| Constant | 0.24211**      | 0.08009*  | 0.14051          | -0.05227 | -0.00004 | -0.06804** |
|        | (0.08632)       | (0.04536) | (0.05380)        | (0.05440) | (0.04194) | (0.0276)  |
| F(2,97) | 8.33***         | 1.92     | 23.08***         | 0.48     | 3.55**   | 6.34**   |
| R²     | 0.13            | 0.03     | 0.29             | 0.01     | 0.07     | 0.12     |
| U-shape test (p-value) | 0.000***   | 0.350    | 0.000***         | 0.405    | 0.121    | -        |
| Inflexion point (percentile) | 49.13 | 73.68    | 45.62            | 73.98    | 33.50    | -        |

**Note:** Dependent variable: ΔEmplᵢ₊₁. Independent variables: rankᵢ, rank²ᵢ. N = 100 observations (1-period × 100 percentiles). U-shape test hypotheses: H₀: Monotone or Inverse-U shape, against the alternative H₁: U-shape. Missing values for the U-shape test denote that the inflexion point is outside the relevant interval (1–100 percentiles).

*p < 0.1, **p < 0.05, and ***p < 0.01.

### Figure 7

Quadratic regression fit line by age group [Color figure can be viewed at wileyonlinelibrary.com]
advances the employment polarization debate for particular demographic groups (Anghel et al., 2014; Salvatori, 2015) by showing that employment polarization in the Netherlands is primarily a young workers’ phenomenon.

The divergent employment trends are mainly accounted for by the worker-specific labor market adjustments to macroeconomic conditions between young and senior employees, closely associated with labor mobility. In particular, senior workers in routine-based jobs have typically acquired occupation-specific skills via extensive on-the-job training throughout their careers, making job-switching more costly (Autor & Dorn, 2009). In addition, they often enjoy permanent contracts (OECD, 2012) that involve high social protection or tenure-based payments, further inhibiting their labor mobility. Similarly, social restrictions to mobility such as the increasing social cost with age may further explain why senior Dutch employees opt to stay in routine-based occupations, thus explaining the relative stability of medium-skilled senior employment. In contrast, the above constraints are less binding for young workers who often engage in job-shopping at the beginning of their working lives because of their low job tenure (Neal, 1999). Combined with their easier adjustment to technological innovations implemented in the labor market, young workers are more likely to engage in occupational mobility. Along the lines of Autor et al. (2014), our results show that workers with a weaker foothold in the labor market experience more considerable employment redistribution than their older counterparts. In the case of young workers in the Netherlands, this redistribution results in polarizing employment growth.

The regression results distinguishing between periods of economic expansion and recession (Table 6—Columns 2 and 3 for young workers and Columns 5 and 6 for senior ones) reveal dissimilar employment evolution across age groups. Considering young workers, polarized employment growth occurs only in the period including the global recession. In line with the main analysis (Table 2—Columns 2 and 3), the PI between 2006 and 2012 is larger compared to the 1999–2012 period (6.15 compared to 4.07), thus indicating that polarized employment growth is indeed precipitated by the economic downturns (Autor, 2010). Regarding senior ones, our regression models fail to capture any quadratic employment growth pattern since we only find significant evidence for decreasing high-skilled employment between 1999 and 2005.

The regression fit lines by subperiod validate our earlier results. In the case of young employees (Figure 8) and similar to the main analysis, the employment pattern of relative stability between 1999 and 2005 is followed by a clear asymmetrically polarized employment growth pattern between 2006 and 2012. In contrast, employment growth across senior employees (Figure 9) shows no sign of polarized growth. Instead, we come across two
remarkably different trends: while employment growth between 1999 and 2005 disfavors high-skilled jobs, it is high-skilled biased (upskilling or professionalization) from 2006 till 2012.

### 6.2 | Regional-level analysis

This section uncovers age-specific regional employment patterns by estimating Equation (4) by age group and region. Both the regional classification of employment patterns (Table 7) and the geographical illustration (Figure 10, detailed results in Table F1–Appendix F) reveal strikingly different employment dynamics across age groups. Panel A shows that employment growth among young workers is polarizing in 17 regions with 14 of them exhibiting stronger PI values compared to the entire labor market; in contrast, employment polarization across senior workers (panel B) it is only evident in two local labor markets.

Similar to the main analysis, simple inspection of the distribution of local labor markets with polarized employment growth (Figure 10) indicates regions with very different characteristics (for instance the industrial organization in rural Drenthe is very different compared to the one in urban Amsterdam). Therefore, in what
follows, we provide more robust evidence by estimating probit models (Equation 6) to evaluate how the local initial employment structure and socioeconomic environment shape the probability of polarized employment growth.

6.3 | Regional determinants of employment polarization: Age-related analysis

Regarding the impact from the regional industrial structure on the likelihood of polarized employment growth among young employees, the estimated marginal effects (Table 8—estimation results in Table F2—Appendix F) reveal a positive association between higher initial industrial (medium-skilled) and other services (low-skilled) employment and polarizing employment growth in young workers. Like the main analysis (Table 4) the largest effect refers to the industrial sector, where a 1% increase in the initial share of industrial employment is associated with a 2.3% increase in the likelihood of regional employment polarization. The average initial share of industrial employment in the 17 regions with employment polarization (34.3%) is almost identical to the country average (34.4%); however, this masks two different trends.

First, industrial employment seems to be more relevant for employment polarization in peripheral regions such as South Limburg (39.1%) or Twente (39%) as opposed to more central and prosperous ones such as the Hague (17%) or Amsterdam (23%) where other types of employment seem to be associated with polarizing employment growth. In that sense, our analysis indicates a positive link between regional polarization among young workers and employment in other services. Specifically, a 1% increase in the initial share of employment in other services is associated with a 0.9% increase in the likelihood of regional employment polarization. On average, the Dutch regions with polarized employment growth exhibit similar initial share of employment in other services (10%) compared to the country average (9%). Nevertheless, some central and prosperous

---

12 Lack of sufficient number of local labor markets with polarized employment growth among senior workers prevented the convergence of the estimated probit model.
regions combine polarized employment growth with very high initial employment shares in other services (the Hague Agglomeration with 25% or Amsterdam with 15%). In turn, this potentially reflects the consumption spillovers theoretical argument (Mazzolari & Ragusa, 2007) that a large pool of high-skilled workers typically found in metropolitan regions (“Randstad” area) also increases the demand for low-skilled labor in personal care or maintenance services while it also coincides with similar evidence for the US commuting zones (Autor & Dorn, 2013).

Considering our socioeconomic variables, two main conclusions stand out: First, we document negative relationship between regional unemployment and the likelihood of polarized employment growth among young workers. In particular, a 1% increase in the initial regional unemployment rate is associated with a 0.15% decrease in employment polarization probability. Although unemployment is relatively low in the Netherlands (2.7% in 2000), closer inspection of the regional evidence reveals that unemployment is marginally lower in regions with polarized employment growth. This is mostly driven by a number of local labor markets where polarized employment growth coincides with some of the lowest

| Variable                                      | Marginal Effect |
|-----------------------------------------------|-----------------|
| Regional GDP per capita<sub>r,2000</sub>      | 0.620           |
| Employment share in industry<sub>r,2000</sub> | 2.256***        |
| Employment share in ICT sector<sub>r,2000</sub>| 0.095           |
| Employment share in the finance<sub>r,2000</sub>| 0.191           |
| Employment share in other services<sub>r,2000</sub>| 0.897**        |
| Employment share in professional activities<sub>r,2000</sub>| 0.571          |
| Employment share in real estate activities<sub>r,2000</sub>| −0.242         |
| Employment share in trade, repairs, transport, accommodation<sub>r,2000</sub>| −0.400         |
| Employment share in construction<sub>r,2000</sub>| −0.221         |
| Unemployment rate<sub>r,2000</sub>           | −0.148*         |
| Labor utilization<sub>r,2000</sub>           | 0.364           |
| Male-to-female ratio<sub>r,2000</sub>        | 9.451**         |
| Population density<sub>r,2000</sub>         | 0.087           |

Note: Probit regression analysis. Dependent variable: PrPol<sub>r</sub> = 1. Robust SEs, clustered by region are reported in brackets. Industries are classified by the ISIC rev. 4 taxonomy. Marginal effects are derived as elasticities, *p < 0.1, **p < 0.05, and ***p < 0.001.
unemployment rates in the entire country (for instance Southwest Gelderland with 0.9% or Alkmaar with 1.7%).

Second, we show that a higher percentage of male residents is associated with a higher probability of regional employment polarization across young employees. The relevant marginal effect indicates that a 1% increase in the male-to-female ratio is linked with a 9.4% increase in the likelihood of polarized employment growth. Nevertheless, the gender ratio in polarized regions (98.2%) is almost identical to the country average (97.8%). Therefore, we uncover potentially different, gender-specific employment trends; however, the direction of the relationship with the likelihood for employment polarization is still relatively unclear. Despite the current analysis focusing on young workers, the estimated elasticities between unemployment and gender ratio on one side and the probability of employment polarization on the other largely reflect earlier evidence for the US commuting zones (Autor & Dorn, 2013).

The above results shed light on certain industrial organisation forms (industry, other services) and socio-demographic conditions (unemployment, gender composition) conducive to polarized employment growth across young workers in the Netherlands. Besides elucidating important regional aspects, they mostly indicate that investigating the drivers of regional employment polarization among different age cohorts in the Netherlands requires a more nuanced approach, as suggested by much of the literature.

6.4 Automation and international fragmentation as catalysts of employment polarization: Age-specific analysis

In this section, we re-estimate Equation (7) utilizing an instrumental variable, system-GMM approach to investigate more subtle patterns as to the employment effects from automation and international trade on regional employment growth of young and senior workers in the Netherlands. Along the lines of the main analysis, standard dynamic panel data diagnostic tests (Wald $\chi^2$, AR(2), and Hansen test) establish the unbiasedness, consistency and validity of our estimates.

The estimated elasticities (Table 9—detailed results on Table F3 [young workers] and Table F4 [senior workers]—Appendix F) reveal differential employment effects from automation and international trade across different age groups. Considering young employees (Panel A), our analysis indicates more extensive employment effects from technology, extending across the entire occupational distribution. In contrast, young workers are relatively unaffected by the global division of labor, except for two contrasting effects on low-skilled jobs.

Specifically, we first document a negative impact from technology on medium-skilled young workers in the Netherlands (Columns 3 and 4). The estimated elasticities show that for each 1% increase in the routine task intensity index, the growth rate of medium-skilled employment across young employees decreases by 0.1% on average. In contrast, technology complements high-skilled young domestic workers. The respective terms (Columns 5 and 6) indicate that a 1% increase in regional exposure to automation increases the growth rate of high-skilled young employment by 0.2% on average. Finally, automation also benefits low-skilled young workers (Column 1); however, this effect is only weakly specified (at the 10% level) and only significant in one empirical model.

Nevertheless, low-skilled young workers in the Netherlands are significantly impacted by participation in the global value chains. Although the regional trade index based on total trade volumes fails to provide significant evidence (Column 1), distinguishing between developed and developing trade partners (Column 2) reveals two contrasting effects. First, we show that trade with developed countries increases the growth rate of low-skilled young workers in the Netherlands by 0.74% per 1% increase in the respective index, as opposed to trading with developing countries which decreases the growth rate of low-skilled domestic employment by 0.61%. Our analysis

13 For completeness Tables F5 and F6 for young workers and Tables F7 and F8 (Appendix F) for senior ones report similar OLS and fixed effects (LSDV) estimation results.
|                        | Low-skilled jobs | Medium-skilled jobs | High-skilled jobs |
|------------------------|------------------|---------------------|-------------------|
| **Panel A—Young (age < 39) employees** |                  |                     |                   |
| Routine task intensity_{rt-1} | 0.131* (0.079)   | 0.063 (0.040)       | -0.123*** (0.034) |
| In trade exposure (Total)_{rt-1} | 0.066 (0.531)    | -0.102 (0.346)     | 0.257 (0.366)    |
| In trade exposure (Developed)_{rt-1} | 0.742** (0.351) | 0.136 (0.511)      | -0.308 (0.494)  |
| In trade exposure (Developing)_{rt-1} | -0.615* (0.322) | -0.086 (0.376)     | 0.641 (0.419)   |
| Constant                | -1.205 (4.434)   | 2.946 (5.289)       | -7.791* (4.106)  |
| Observations            | 440              | 440                 | 440              |
| Year dummies            | yes              | yes                 | yes              |
| Instruments             | 38               | 40                  | 37               |
| Wald χ²-stat            | 268.71***        | 135.12***           | 1037.87***       |
| AR(2) test              | 0.157 (4.351)    | 0.006 (0.057)       | -0.221 (0.212)  |
| Hansen test χ²-stat     | 0.575 (5.091)    | 0.271 (3.884)       | -0.508 (3.871)  |

| **Panel B—Senior (age ≥ 39) employees** |                  |                     |                   |
| Routine task intensity_{rt-1} | -0.195*** (0.052) | 0.006 (0.057)       | -0.221 (0.212)   |
| In trade exposure (Total)_{rt-1} | 0.138* (0.351)    | -0.158 (0.379)     | -0.508 (0.734)   |
| In trade exposure (Developed)_{rt-1} | -0.892** (0.285) | 1.028* (0.565)     | -1.760** (0.648) |
| In trade exposure (Developing)_{rt-1} | 0.938** (0.287)  | -0.768 (0.674)     | 0.979* (0.530)   |
| Constant                | 4.505 (5.091)    | 4.952 (3.884)       | 5.939 (8.271)    |
| Observations            | 440              | 440                 | 440              |
| Year dummies            | Yes              | Yes                 | Yes              |
| Instruments             | 38               | 40                  | 40               |
| Wald χ²-stat            | 426.81***        | 113.88***           | 226.95***        |
| AR(2) test              | 0.393 (5.091)    | 0.177 (3.884)       | 0.425 (8.271)    |
| Hansen test χ²-stat     | 0.116 (5.091)    | 0.440 (3.884)       | 0.731 (8.271)    |

Note: Dependent variables (Panel A): d.InEmpShLSYoung_{rt}, d.InEmpShMSYoung_{rt}, d.InEmpShHSYoung_{rt}. (Panel B): d.InEmpShLSSen_{rt}, d.InEmpShMSSen_{rt}, d.InEmpShHSSen_{rt}. Independent variables: RTI_{rt-1}, InTrExpTotal_{rt-1}, InTrExpDeveloped_{rt-1}, InTrExpDeveloping_{rt-1}. Estimation method is two-step with robust st. errors clustered by region and implementing the Windmeijer finite sample correction. The detailed specifications include the lagged dependent variable, a constant and a full set of control variables (all continuous right-hand-side variables are in logarithms, lagged one period): GDP per capita, fixed capital formation (total), GVA manufacturing, GVA ICT, GVA finance, GVA professional and scientific etc. activities, GVA public administration, labor utilization, population density, dependency ratio, frontier and keeping-pace productivity dummies *p < 0.1, **p < 0.05, and ***p < 0.01.
fails to trace significant effects from integration to the global value chains in medium- and high-skilled young employment, further illustrating the greater relative importance of technology among young workers in the Netherlands. However, taken together, automation and trade contribute to polarizing employment growth among young Dutch workers, as evident in our earlier analysis (Figure 7).

Contrary to young workers, their senior counterparts (Panel B) are differentially affected by both technology and trade. Concerning technology, the dual effect is conditional on the skill level of the workforce. First, technology hurts low-skilled senior workers. Columns 1 and 2 indicate that a 1% increase in regional exposure to automation decreases the growth rate of low-skilled senior workers by 0.2%. Conversely, technology favors high-skilled senior workers in the Netherlands. The estimated elasticities (Columns 5 and 6) document that a 1% increase in the regional routinization index increases the growth rate of high-skilled senior employment by 0.45%. Similar to the main analysis (Table 5), technology does not affect medium-skilled senior workers.

On the other hand, senior workers in the Netherlands are substantially affected by the integration of the global value chains. Notably, the overall effect is conditional on both the skill level of employment and the development status of the trade partner. First, international trade benefits low-skilled senior employees when trade volumes are aggregated across all types of trade partners. Our analysis indicates that a 1% increase in the total trade index increases the growth rate of senior employees by almost 0.14% (Column 1). However, Column 2 shows that this effect is qualitatively different across different trade partners. Specifically, trade with developing countries benefits low-skilled senior employees as opposed to trading with developed regions which hurts low-skilled senior workers. The two effects are quantitatively similar and equal to almost 0.9% change in the growth rate of low-skilled senior employment caused by a 1% change in the respective trade index.

In contrast, trade with developed countries benefits medium-skilled senior Dutch workers. The estimated elasticity (Column 4) shows that a 1% increase in the regional trade exposure index with developed countries increases the growth rate of medium-skilled senior employees by 1.03%. Finally, despite the absence of a significant effect on high-skilled senior workers from total trade volumes- disaggregating trade by the development status of the trade partner (Column 6) reveals differential effects. In particular, trade with developed countries hurts high-skilled senior workers while trade with developing regions increases the growth rate of high-skilled senior domestic employment. Such differences are predominantly explained by the different nature of trade with developed (intra-industry) or developing (inter-industry) trade partners where the former is associated with economies of scale as opposed to the latter which mostly reflects the global fragmentation of production. In both cases, the direction of the effect across various skill groups cannot be a priori determined, as evident in the above analysis.

In general, the evidence on senior regional employment indicates substantial differential effects from both technology and trade. As evident by the above analysis, these effects often cancel out, thus resulting in the relatively stable employment change pattern for senior employees indicated by our earlier analysis (Figure 7).

As can be seen, the age-related evidence is consistent with the theoretical predictions of both technology and trade theories (Autor et al., 2003; Blinder, 2007). One notable difference in the gender-specific employment transformation patterns is that the negative impact of technology is concentrated on medium-skilled young workers as opposed to their low-skilled senior counterparts. Such differences call for a more nuanced age-specific approach on the labor market effects of automation and trade. National employment polarization analyses hide many detailed and different effects concerning different regions and age groups. As such, the headline results emerging from US and German data do not necessarily reflect the employment patterns in other countries.

### CONCLUSIONS AND IMPLICATIONS

This study systematically investigates the geography of employment polarization in the Netherlands between 1999 and 2012. Our analysis draws on uniquely detailed datasets comprising individual micro-data with innovative, own-constructed indexes of regional exposure to automation and international trade merged with an extensive set of
regional socioeconomic and demographic indicators. Based on those, we combine in a unified empirical framework the most prominent technology and trade-related hypotheses put forward to explain employment restructuring and extend the analysis which often treats them in isolation. As such, our analysis contributes to the employment polarization literature in four main ways:

Firstly, similar to European labor markets (Goos et al., 2009) and unlike the US (Autor et al., 2006) we provide evidence that employment growth in the Netherlands is asymmetrically polarized, with a substantial increase in the share of high-skilled employment compared to a modest increase in the share of low-skilled jobs. Also, we show that employment polarization is stronger during economic recessions due to the greater decline in routine-based employment (Jaimovich & Siu, 2012). Second, our location-specific analysis documents that employment polarization is substantially represented across Dutch local labor markets. Within this context, we estimated probit models providing new insights which depart from much of the existing evidence on the regional determinants of employment polarization. In contrast to the often-cited conclusion that employment growth tends to polarize in urban regions (Dauth, 2014), our results for the Netherlands illustrate that regional employment polarization is predominantly associated with medium and lower densely populated areas, exhibiting higher initial per capita income and specializing in medium- (industry) and high-skilled (ICT) sectors.

The main contribution of the current study is the combination of technology and trade-related arguments in a unified empirical framework to investigate their relative contribution as catalysts of employment polarization. The panel structure of our data is exploited by a system-GMM analysis which indicates that both automation and the global division of labor impose differential employment effects. Taken together, we conclude that it is the interplay between technology and trade that generates the entire pattern of employment polarization. Interestingly, our age-related analysis highlights more subtle employment patterns by establishing that polarized employment growth in the Netherlands occurs mostly among young employees, a pattern evident both at the national and the regional level.

The above results stress the unique position of the Netherlands in international labor economics. Despite the contribution of technology and trade to polarizing employment growth, the characteristics of the Dutch labor market (low average labor mobility, relative inflexibility, etc.) mediate the impact of globalization. From a social and economic perspective, our results highlight the importance of an evidence-based policy agenda to increase labor mobility and relax labor market rigidities. Easing the employment protection legislation or reducing tenure benefits to increase job flow will counterbalance the exacerbated income inequalities due to the polarizing employment (Salverda, 2014) and the subsequent destruction of routine-based jobs. Therefore, socially-desirable labor market interventions at the local level such as safety net programs are necessary to protect the most vulnerable, low- and medium-skilled workers, promote equality, and evenly spread the benefits of globalization voiced in other countries (DCLG, 2007).

Our results notwithstanding, three caveats are in order. First, in line with the main strand of the employment polarization literature, we investigate demand-side explanations of employment restructuring; however, employment polarization is by no means a pure demand-side phenomenon. In that respect, van den Berge and ter Weel (2015) indicate that the increased supply of skilled labor can partially explain employment polarization. The importance of such an explanation is further emphasized by the recent record levels in net migration flows in the Netherlands, partly explained by the increased number of international students (CBS—Statline14). Unfortunately, the lack of consistent data on migration flows at the regional level prevented us from using regional migration as an additional control variable in our investigation of the impact of technology and trade in employment restructuring.

Secondly, labor market institutions (i.e., minimum wage regulations, union coverage) are well-established mediators of the employment effects from technology and trade (Blanchard & Wolfers, 2000) due to their effect mainly on low-skilled employment. However, the regional approach of our study together with the lack of diversity

---

14Data from: CBS—StatLine—Population, households and population dynamics; from 1899 indicator, see the relevant discussion on the political and economic factors accounting for the surge in migration.
in the labor market institutional environment across Dutch regions accounts for our choice to exclude the interplay between macroeconomic shocks and the domestic institutional environment from our analysis. Future research at the multi-national level would exploit institutional diversity and adequately account for their effects in polarizing employment growth.

Finally, a typical caveat of dynamic panel data estimations considers the uniqueness of the system-GMM specification, since the estimation outcome might be dependent on the instrumentation choices. Since a dynamic panel data approach is the most appropriate empirical framework for our context, we address the above caveat by following consistent rules both in the number of instruments and the applied lag structure, based on the relevant literature (Bogliacino & Vivarelli, 2012), while we also complemented our system-GMM results with—qualitatively—similar evidence-based OLS and LSDV models. In addition, the consistency between our results and the underlying theories further indicate the validity of our analysis. However, it is essential for subsequent evidence based on a longer time series to reinforce the current analysis.

Although the caveats outlined above merit further attention, our methodologically robust analysis which is based on uniquely detailed data sets uncovers many of the subtleties governing the emergence and exact forms of regional employment polarization masked by national-level employment patterns.

ACKNOWLEDGEMENTS
We wish to thank Steven Brakman, Philip McCann, Jouke van Dijk and the two anonymous referees for their insightful comments. This paper also benefited from the constructive comments from seminar participants at the 57th ERSA congress, the 2017 North American Regional Science Council, the Festival of Economics (Trento – 2018) and the 2018 Regional Science Association Annual Conference.

ORCID
Nikolaos Terzidis http://orcid.org/0000-0001-7252-3810
Raquel Ortega-Argilés http://orcid.org/0000-0002-7783-2230

REFERENCES
Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. Handbook of Labor Economics, 4b, 1043–1171.
Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30.
Anghel, B., de la Rica, S., & Lacuesta, A. (2014). The impact of the great recession on employment polarization in Spain. SERIES-Journal of the Spanish Economic Association, 5(2–3), 143–171.
Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68(1), 29–51.
Autor, D. H. (2010). The polarization of job opportunities in the US labor markets—Implications for employment and earnings. Center for American Progress and The Hamilton Project.
Autor, D. H., & Dorn, D. (2009). This job is “getting old:” Measuring changes in job opportunities using occupational age structure. American Economic Review, 99(2), 45–51.
Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. American Economic Review, 103(5), 1553–1597.
Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China syndrome. Local labor market effects of import competition in the United States. American Economic Review, 103(6), 2121–2168.
Autor, D. H., Dorn, D., Hanson, G. H., & Song, J. (2014). Trade adjustment: Worker-level evidence. The Quarterly Journal of Economics, 129(4), 1799–1860.
Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The polarization of the U.S. labor market. American Economic Review, 96(2), 189–194.
Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). Trends in the US wage inequality. Revising the revisionists. The Review of Economics and Statistics, 90(2), 300–323.
Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change. An empirical exploration. The Quarterly Journal of Economics, 118(4), 1279–1333.
Oesch, D., & Rodriguez Menes, J. (2011). Upgrading or polarization? Occupational change in Britain, Germany, Spain and Switzerland, 1990–2008. *Socio-Economic Review, 9*(3), 503–531.

Partridge, M. D., Rickman, D. S., Rose Olfert, M., & Tan, Y. (2017). International trade and local labor markets: Do foreign and domestic shocks affect regions differently? *Journal of Economic Geography, 17*, 375–409.

Rodriguez-Pose, A., & Tselios, V. (2009). Education and income inequality in the regions of the European Union. *Journal of Regional Science, 48*(3), 411–437.

Roodman, D. (2009). How to do xtabond2. An introduction to difference and system GMM in Stata. *The Stata Journal, 9*(1), 86–136.

Salvatori, A. (2015). *The anatomy of job polarization in the UK* (IZA Discussion Paper Series No. 9193).

Salverda, W. (2014). De tektoniek van de inkomensongelijkheid in Nederland. Published in: *Hoe ongelijk is Nederland? Een verkenning van de ontwikkeling en gevolgen van economische ongelijkheid*.

Senftleben-Konig, C., & Wielandt, H. (2014). Spatial wage inequality and technological change. *SFB 649 Discussion, 4*, 2014–2038.

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands. Looking outside the wage structure. *Journal of Labor Economics, 24*(2), 235–270.

Terzidis, N., van Maarseveen, R., & Ortega-Argilés, R. (2017). *Employment polarization in local labor markets. The Dutch case* (Central Bureau of Economic Policy Analysis Discussion Paper No 358).

Thissen, M., Lankhuizen, M., van Oort, F. G., Los, B., & Diodato, D. (2018). *Euregio. The construction of a global IO database with regional detail for Europe for 2000–2010* (Tinbergen Institute Discussion Paper, TI 2018-084-VI).

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics, 126*(1), 25–51.

**SUPPORTING INFORMATION**

Additional Supporting Information may be found online in the supporting information tab for this article.

---

**How to cite this article:** Terzidis, N., & Ortega-Argilés, R. (2021). Employment polarization in regional labor markets: Evidence from the Netherlands. *Journal of Regional Science*, 1–31. https://doi.org/10.1111/jors.12521