Pillars

PILLARS – Pathways to Inclusive Labour Markets:

Industrial dynamics and regional wage disparities

Deliverable 1.4

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Structure of the report

Abstract

In this project we examine the relationship between the rise and decline of industries and the wage distribution at the regional scale. We did a study on NUTS-2 regions in Europe, for which we combined information from different data sources. Our preliminary results show that entry of industries is only associated with higher wages in regions if they are related to the existing industrial structure of the region. Exiting industries are associated with lower wages in regions in general, but exiting industries related to existing industries are linked to higher wages in regions. We also showed that European regions with a more related industrial structure are less likely to experience high intra-regional wage inequality across sectors. As the European study was not detailed in terms of sectors, regions and period, we also did a study on the Netherlands using micro-data, examining the relationship between industry dynamics and wage inequality for NUTS-3 regions in the period 2010-2019. Preliminary results show that entry of industries related to existing specializations of a region tends to reduce inequality in the region. We find no significant impact of exits of industries on regional inequality. The findings suggest that related diversification bring benefits to regions both in terms of smart and inclusive growth.

1. Introduction

The EU aims to combine smart and inclusive growth in Europe (Lee 2016), since there has been a sustained increase of both inter- and intra-regional inequality (Terzidis et al. 2017; Rosés & Wolf, 2018; Iammarino et al. 2019; Feldman et al. 2021). Scholars have identified the cause of the rising income disparities to technological change and globalization (Moretti 2012; Storper 2013; Rosés and Wolf 2018; Iammarino et al. 2019). However, little attention has been given to the role of structural change as a potential driver of regional disparities. This channel is of utmost importance given the EU agenda, which has focused on facilitating smart growth of regions, leveraging on local capabilities to develop and upgrade existing activities (Foray 2015; Balland et al. 2019). Whether smart growth goes hand in hand with inclusive growth is a topic that has not yet been empirically examined.

On the one hand, not every region has the same capacity to diversify into new (complex) activities. While more advanced regions tend to show a stronger capacity to do so, less advanced and peripheral regions lack such capacity to a greater or lesser extent (McCann and Ortega-Argiles 2015; Pinheiro et al. 2022). The evolution of inter-regional wage inequality therefore depends on where (in which regions) new industries emerge and grow, and in which regions in Europe existing industries stagnate, decline and disappear.

On the other hand, there is also an increasing concentration of complex industries in more advanced regions (Balland et al. 2020; Pinheiro et al. 2022). If these industries in regions would recruit primarily high- skilled and high-wage people, and exiting industries would lay off low-skilled and low-paid workers to a larger degree, these industrial dynamics are expected to contribute to growing wage inequality within regions.

This report presents Deliverable D1.4 of the PILLARS-project on the impact of industrial dynamics on regional labour markets with a policy brief. The key objective is to assess the effects of industrial dynamics on wage inequality within and between regions. Case studies have shown empirically that socio-economic inequality is on the rise in regions that tend to be very dynamic from a technological and economic perspective such as Silicon Valley (Florida 2017; Lee 2019). Systematic evidence is lacking to a large degree.

We present two empirical studies in this report. The first study presents for NUTS-2 regions in Europe how entries and exits of industries relate to higher or lower wages at the regional level during the period 2007-2013. However, wage data are not very detailed across European countries at the regional scale: we could distinguish between 10 NACE-2 sectors only at the NUTS-2 level. Therefore, we carried out another study on Dutch regions at the NUTS-3 level to examine the relationship between industry dynamics and inequality in the period 2010-2019. We used micro data to analyse the entry and exits of 4-digit industries at 40 labour market regions in the Netherlands, and we determined to what extent entries and exits can be associated with intra-regional wage inequality.

The report is structured as follows. Section 2 gives a short literature review on the regional industry dynamics, and proposes potential mechanisms on how they contribute to inter- and intra-regional wage inequality. Section 3 critically discusses datasets that are available for European regions and presents an overview of the data we use in this report. Section 4 explains how we calculate relatedness between sectors, and how the rise and decline of (related) industries affect the wage distribution between and within NUTS-2 regions in Europe. Section 5 presents a detailed analysis focusing on the Netherlands. Section 6 concludes and provides a short policy brief.

2. Industrial dynamics and wage inequalities in regions

There is a large body of literature that refers to local capabilities to explain why regions specialize. Recently, there has been a shift of focus from capabilities sustaining existing specializations in regions, to capabilities that lay the foundation of new specializations in regions. Local capabilities can give birth to new activities by providing a pool of local resources, such as similar knowledge, skills and institutions. However, at the same time, they also set limits to what can be achieved in this diversification process. If a region does not possess the capabilities required for a new activity, it will be much harder and more risky to develop it. Therefore, one expects regions to diversify into new activities related to existing local activities, to build on their local capabilities. By contrast, unrelated diversification requires a complete transformation of local capabilities, which is accompanied by high transition costs and high risks of failure, and thus less likely to happen (Boschma, 2017; Hidalgo, 2021).

However, there is a need to collect systematic evidence whether industrial dynamics increase or decrease inequalities across regions, and how. The regional diversification literature has not yet investigated how industrial dynamics may affect regional inequality (Boschma 2017). Studies show that the most complex activities concentrate in the richest cities, and there is a positive association with their economic performance (Balland and Rigby 2017; Antonelli et al. 2020; Balland et al. 2020; Mewes and Broekel 2020; Davies and Maré 2021; Rigby et al. 2022). This could imply that inter-regional inequality is likely to increase, as high-income regions would have a greater capacity to diversify into more complex activities that bring higher economic benefits than low-income regions. Pinheiro et al. (2022) found that diversification opportunities in more complex technologies and industries tend to be higher in high-income regions than low-income regions. However, they did not test whether this could explain rising inter-regional inequality in Europe.

Some studies have looked at the relationship between economic complexity and intra-regional inequality. These have been conducted at the country level, such as Hartmann et al. (2017, 2020), showing that the complexity of economies is negatively associated with income inequality. To our knowledge, there exists only one study at the sub-national scale by Morais et al. (2021). They found an inverted-U-shaped relationship between the income distribution and economic complexity for Brazilian states, implying that with higher levels of complexity inequality first increases and then decreases in Brazilian regions. However, it remains unknown what are the mechanisms behind this, and in particular how industrial dynamics may affect intra-regional inequality. One could hypothesize that both entry and exit of industries are likely to contribute to increasing levels of wage inequality in regions. Entries will mainly occur in more complex industries that are primarily related to existing industries in a region (Balland et al. 2019). These entries are expected to generate high-wage jobs and increase levels of wages in related industries in the region, and so might increase intra-regional wage inequality. Exits are expected to occur mainly in less complex industries that are more unrelated to local industries (Neffke et al. 2011), meaning that redundant people end up either unemployed or find alternative jobs in local skill-unrelated industries which would lower their wage level. This would contribute to a further increase in intra-regional wage inequality.

Table 1 provides a concise overview of current studies on regional wage inequalities. What can be noticed is that these studies focus either on regions within one single country, or they focus on countries and make a comparison. What studies tend to observe is that concentration of economic and innovative activity in certain locations often goes hand in hand with intra-regional inequalities (Rodríguez-Pose and Tselios 2009; Lindley and Machin 2014; Lee et al. 2016). For European regions, Lee (2011) and Lee and Rodríguez-Pose (2013) confirm a positive link between innovation and wage inequality. Educated workers tend to sort themselves according to their individual skills into cities with high employment densities (Combes et al. 2007). In turn, they raise the demand for local services and goods and thus create an employment multiplier for low-wage jobs (Moretti, 2010). Large cities draw in high- and low-skilled workers and are often characterized by thicker tails in the skill distribution, which Eeckhout et al. (2014) refer to as extreme-skill complementarity. For the UK, Lee and Clarke (2019) found substantial local employment multiplier effects for high-tech jobs. While low-skilled workers profited from new employment opportunities, they were also often in poorly paid service jobs and coping with high and rising local housing costs (see also Florida 2017).

Table 1. Concise overview of studies on regional wage inequality

Study	Data source	Regional Level	Link
Lee, Sission and Jones (2016): The geography of wage inequality in British cities	Annual Survey of Hours and Earnings, ONS	Regional: British cities	https://www.tandfonline.com/doi/full/10.1080/00343404.2015.1053859?casa_token=e-iX9PWBOeMAAAAA%3AER8UF2_Z93wGrpiW8WEee9PitW3X_VRIsWNw-3daa1MqoAxnLB4ArPJJ7cHrC0tT1RLu9uZFN2Rm
Pereira & Galego (2014): Intra-regional Wage Inequality in Portugal	Portuguese Ministry of Employment – Quadros de Pessoal, matched employer–employee dataset	Regional: Portugal regions	https://www.tandfonline.com/doi/full/10.1080/17421772.2014.992360?casa_token=PpQfqmpJZsMAAAAA%3AARshIBF7fE46htIFfuJItR_PC-MqZiDFTAT6Ckki4DDjlZPqnIL6yG-qOGT4UDjD8EOwTpT1F_we
Vacas-Soriano, Fernandez-Macias and Munoz de Bustillo (2019) Occupations and the recent trends in wage inequality in Europe	EU-SILC, LIS	National: European countries	https://journals.sagepub.com/doi/10.1177/0959680119866041
Acemoglu (1999) Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence	Current Population Survey	National: US	https://www.aeaweb.org/articles?id=10.1257/aer.89.5.1259
Hölscher, Perugini & Pompei (2011)	EU-SILC	National: European countries	https://www.tandfonline.com/doi/abs/10.1080/14631377.2011.595119?casa_token=cx164od7gzUAAAAA:6O_9Lao2_h_5DS2w8IEKHQxzVR5ptGadlxS7Kk0YiY9v6yu7jBmuHjP-Ywx8MBVMRWKf50qmL8G5
Lindley and Machin (2014) Spatial changes in labour market inequality	US Census in 1980, 1990 and 2000 & ACS pooled across 2009 to 2011	National: US	https://www.sciencedirect.com/science/article/pii/S0094119013000545?casa_token=cNOpPPW-XOUAAAAA:PkJ7wiAjwZ9nl6qD2bl2EUaidJOkMSwn3nwkkrjQPw6QI2Xnz6dsQcBg85_-1PyF5BhbhdFSyw
Moretti (2013) Real wage inequality	US Census in 1980, 1990 and 2000	National: US	https://pubs.aeaweb.org/doi/pdfplus/10.1257/app.5.1.65

Mueller, Ouimet and Simintzi (2015) Wage Inequality and Firm Growth	LIS *LIS data have been previously used in cross-country studies of wage inequality by Gottschalk and Smeeding (1997) and Acemoglu (2003), a.o.	National: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Spain, Sweden, United Kingdom, and United States	https://www.nber.org/system/files/working_papers/w20876/w20876.pdf
Mahler (2002) Exploring the subnational dimension of income inequality: An analysis of the relationship between inequality and electoral turnout in the developed countries.	LIS "intra- and inter-household inequality for 191 regions in 12 developed countries for the late 1980s and early 1990s, and for 149 regions in 8 countries for the mid-1990s"	Regional "country's geographical breakdown is determined by national statistical authorities."	http://www.lisdatacenter.org/wps/liswps/292.pdf
Taylor (2006) UK Wage Inequality: An Industry and Regional Perspective	General Household Survey, ONS	Regional: 10 regions	https://onlinelibrary.wiley.com/doi/epdf/10.1111/j.1467-9914.2006.00335.x
Fallah, Partridge and Olfert (2010) New economic geography and US metropolitan wage inequality	US Department of Labor's Occupational Employment Statistics (OES) program survey 2001	Regional: US MSA	https://academic.oup.com/joeg/article-abstract/11/5/865/939937
Savoia (2020) Income Inequality Convergence Across EU Regions	LIS	Regional: European regions NUTS-2 constructed as often not directly available: aggregated households' incomes at NUTS-3 or LAUs (lower levels) to NUTS-2	http://www.lisdatacenter.org/wps/liswps/760.pdf

This project assesses the relationship between the rise and decline of industries and the wage distribution within and between NUTS-2 regions in Europe, a topic that has not yet been touched upon in the literature. We combine information from the European Labour

Force Survey database, EUROSTAT, and ORBIS. After collecting information of wages and employment in NACE sectors by NUTS-2regions, we will obtain a measure of relatedness between industries, following other studies (Hidalgo et al. 2018) that calculate the similarity of capability requirements between all industries from normalized employment co-location patterns. Second, we use this information to identify in all regions the extent to which regions diversified in new industries, to what extent these were related to existing local industries, the extent to which regions exited existing industries, and to what extent these were unrelated to existing local industries. Third, we measure the evolution of wage inequality within and between regions, and correlate that with the previous data on industrial dynamics.

3. Data sources

Evaluating the impact of industrial diversification on inter- and intra-regional wage inequalities requires high-quality wage data at the region-industry level.

Studies on industrial dynamics have often been carried out for regions in a single country, using national data. A limited number of studies has made comparisons between regions in Europe. Balland and Boschma (2019) used the European Labour Value Survey data to derive industry data for NUTS-2 regions in Europe. Cortinovis et al. (2017) and Xiao et al. (2018) used ORBIS data to identify industry entries in 118 and 173 NUTS-2 regions respectively. Both studies are rather outdated, as both covered the period 2004-2012.

With respect to wage inequality data at the regional scale, it is possible to use employer-employee data for individual countries in many European countries, such as the Netherlands. We report about such study in Section 5. But they do not allow to make a comparison between regions in different European countries. However, there are several sources of wage data covering European regions but they also have their limitations.

A key data source is the Luxembourg Income Study (LIS) Database which collects monetary payments from regular and irregular dependent employment[1] from surveying individuals in about 50 countries. Although income microdata is not directly available at NUTS 2 level in the LIS database, several studies have carefully aggregated households' incomes at NUTS-3 or LAUs (lower levels) to reconstruct the NUTS-2 regions and generate regional inequality measures when the availability of territorial disaggregation of data (NUTS-1, NUTS-2, NUTS-3, or LAUs) is not regular over time (Mahler 2002; Savoia 2020).

In addition, there is the European Union Statistics on Income and Living Conditions (EU-SILC) which is aimed to collect timely and comparable cross-sectional and longitudinal data on income, poverty, social exclusion and living conditions. Two types of data are provided in the EU-SILC: 1) Cross-sectional data over a given time or a certain time period with variables on income, poverty, social exclusion and other living conditions; 2) Longitudinal data on individual-level changes over time, observed periodically over a 4-year period. Most research employed this database are conducted at the national level (Holscher et al. 2011; Vacas-Soriano et al. 2020).

In this project, we use Eurostat data on wages per NACE sector in NUTS2 regions and complement it with data employment per sector and region from the European Labour Force Survey (ELF) and the ORBIS database.

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[1] This includes cash wage and salary income (gross of social security contributions and income taxes) and monetary supplements to the basic wage, such as overtime pay, employer bonuses, 13th month bonus, profit-share, tips.

Eurostat data on wages provide the average hourly compensation of employees which is calculated by dividing the compensation of employees by the number of hours worked. The data is available at different regional levels, including NUTS 2, and for different industries. We obtain average hourly compensation measures for the whole region but also for 14 industries, by dividing the overall compensation of employees (nama_10r_2coe) by the overall number of hours worked (nama_10r_2emhrw) and do the same for every industry. Industry refers to NACE Rev. 2, which are the “statistical classification of economic activities in the European Community” (Eurostat, 2008) that allow to distinguish between aggregated industries such as Manufacturing, Construction or Information and Communication. The data enables us to satisfy a broad coverage of NUTS 2 regions and analyze how wage patterns differ across industries.

However, several challenges surfaced when trying to connect these different databases, on the one hand, the ELF survey suffers from having many missing values over the years. This forced us to pool all observations for the period available (2014-2017), which made a dynamic analysis impossible. On the other hand, the more complete data in ORBIS allowed us to create yearly measures and thus have a dynamic data structure but at the cost of having to work with older data (2007-2013). We use employment data at the region-industry level aggregated from the firm-level employment weighted data from the ORBIS database by Bureau Van Dijk and EUROSTAT for wages.

In what follows we first investigate how industrial dynamics relate to inter- and intra-regional wage inequality. First by providing a meta-analysis for all EU regions (Section 4) and later by digging deeper into the issue using the Netherlands as a case study (Section 5), leveraging matched employer-employee data from the National Bureau of Statistics.

4. Industry dynamics and change of wage distribution within and between EU NUTS-2 regions

In the present section, we analyse whether industrial dynamics, i.e. the rise and decline of industries, can give rise to wage inequalities between and within EU NUTS-2 regions.

First, we determine in which industries regions are specialized. We define regional specialization based on the Revealed Comparative Advantage (RCA) index, given by the ratio of the employment share of a given activity i in a given region r compared to the reference region (EU as a whole):

$$RCA_{r,i} = \frac{employment_{r,i}/\sum_i employment_{r,i}}{\sum_r employment_{r,i}/\sum_r \sum_i employment_{r,i}} \quad (1)$$

Figure 1 shows two examples of sectors and how revealed comparative advantages are distributed across NUTS-2 regions for these sectors in Europe: agriculture, forestry and fishing (Sector A) and real estate activities (Sector L). Figure 2 shows how wages in these two sectors are distributed across NUTS-2 regions.

Figure 1. Revealed comparative advantage of NUTS 2 regions in Agriculture, forestry and fishing (left panel), and Real estate activities (right panel) in 2013.

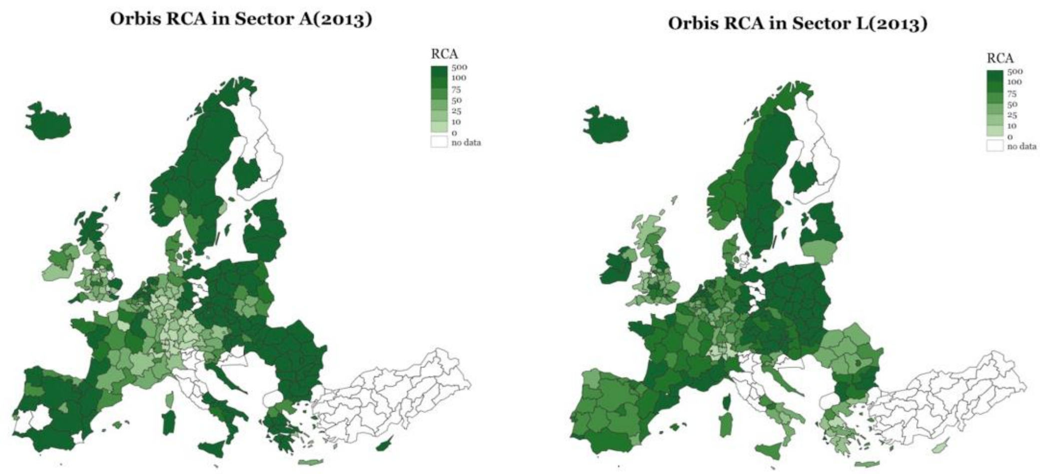
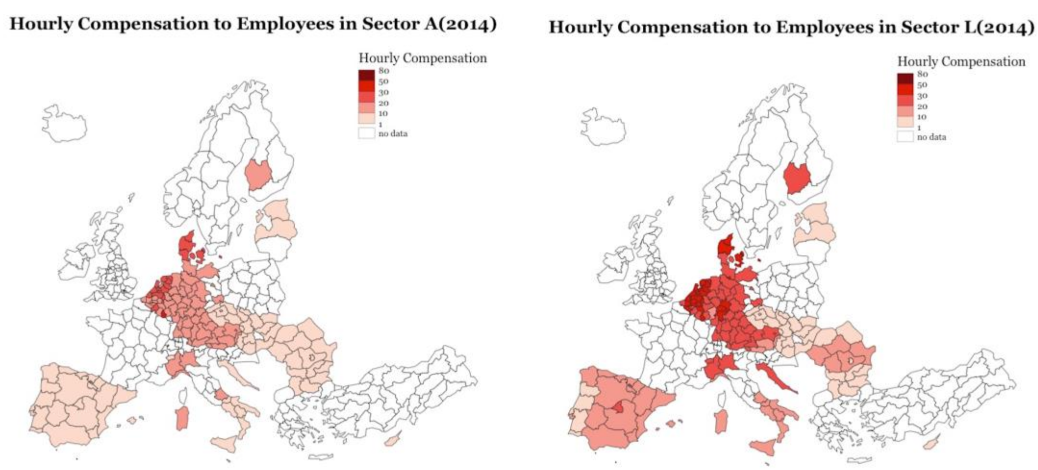


Figure 2. Wages of employees in Agriculture, forestry and fishing (left panel), and Real estate activities (right panel) across NUTS-2 regions in 2014



We define entries and exits in sectors by evaluating the change of their RCA in sectors over time. We consider a region to enter in a particular sector in which it was not specialized before when $RCA_{r,t-1} < 0.5$ and $RCA_{r,t} > 1$. This means that an entering sector not only acquired a substantial presence in the region (RCA>1) but also involved a significant increase in its RCA from *t-1* to *t* (at least an increase of 0.5). Analogously we consider an exit event when $RCA_{r,t-1} > 1$ and $RCA_{r,t} < 0.5$.

We further measure the degree of relatedness between a sector and other sectors for individual regions, expressed as relatedness density (Hidalgo et al., 2018; Balland et al., 2019). First, this requires a measure of relatedness between NACE industries. Following other studies (Hidalgo et al. 2018), we calculate the similarity of capability requirements between all industries from normalized employment co-location patterns. This enables us to identify complementarities between 1-digit industries (NACE). Second, we calculated for each region *r* the density of employment in the vicinity of individual sectors *i*. Following Hidalgo et al. (2007) and Balland et al. (2019), the density of employment around a given sector *i* in region *r* is derived from the relatedness $\emptyset_{ij}$ of sector *i* to all other sectors *j* in which the region has relative comparative advantage (RTA), divided by the sum of relatedness of sector *i* to all the other sectors *j* in the reference region (Europe):

$$RELATEDNESS\_DENSITY_{i,r} = \frac{\sum_{j \in r, j \neq i} \emptyset_{ij}}{\sum_{j \neq i} \emptyset_{ij}} * 100 \quad (2)$$

We estimate whether the wage levels in sectors are related to the rise and decline of industries based on the following two equations:

$$\log(Wage_{irt}) = \beta_0 + \beta_1 Entry_{irt} + \beta_2 Relatedness_{irt} + \beta_3 Relatedness_{irt} * Entry_{irt} + \varepsilon \quad (3)$$

$$\log(Wage_{irt}) = \beta_0 + \beta_1 Exit_{irt} + \beta_2 Relatedness_{irt} + \beta_3 Relatedness_{irt} * Exit_{irt} + \varepsilon \ (4)$$

where $Wage_{irt}$ is the hourly compensation to employees working in sector i from region r at time t. $Entry_{irt}$ and $Exit_{irt}$ are dummy variables indicating whether region r entered (exited) in sector i at the time t. We included the interactions of $Entry_{irt}$ and $Exit_{irt}$ with $Relatedness_{irt}$ to explore whether the relatedness of entering and exiting industries to the existing industrial structure of regions are relevant for explaining the wage differences. We included both regional and year fixed effects in these two models. The analyses are run on NUTS-2 regions for the period 2007-2013 for 10 NACE-2 sectors.

Table 2 shows the results for the correlation between wage levels of industries and entry of industries at the regional scale. Entry coefficient is negative but only significant at the 10 level. Only the interaction term with relatedness is positive and significant. Entering industries are only associated with high wages in regions if they are related to the existing industrial structure of the region: the higher the relatedness around industry i that enters the region, the higher the wage of that industry i in a region.

Table 2. Regression results for entry model

	$\log(Wages_{rst})$
$Entry_{irt}$	-1.882*
	(0.986)
$Relatedness_{irt}$	0.007
	(0.015)
$Relatedness_{irt} * Entry_{irt}$	0.105***
	(0.040)
Region fixed effect	Yes
Time fixed effect	Yes

R2	0.773
Observations	2641

Table 3 shows the results for the correlation between wages levels of sectors and exit of industries in regions. The results show that exiting industries are associated with lower wages: the exit of an industry *i* in a region is negatively correlated with wage levels of that industry *i* in a region. However, relatedness can compensate the negative impacts of industry decline on wages in regions. Exiting industries that are more related to the existing industrial structure of regions are still associated with higher wages.

Table 3. Regression results for exit model

	$\log\left(Wages_{rst}\right)$
$Exit_{irt}$	-3.943***
	(0.833)
$Relatedness_{irt}$	0.098***
	(0.013)
$Relatedness_{irt} * Entry_{irt}$	0.301***
	(0.043)
Region fixed effect	Yes
Time fixed effect	Yes
R^2	0.893
Observations	4263

We perform a similar analysis using more recent data from the European Labour Force Survey between 2014 and 2017. However, given the issue of missing value we discussed earlier in the European Labour Force Survey in Section 3, we cannot repeat the dynamic analysis of entry and exit. Instead, we evaluated the relationship between wage levels of sectors in different regions and their relatedness to the existing industrial structure of regions. We estimated the following equation:

$$\log(Wage_{irt}) = \beta_0 + \beta_1 * Relatedness\ Density_{irt} + \ \varepsilon \ (5)$$

Table 4 reports the results. What they show is that industries that are more related to the existing industrial structure of regions are more likely to be associated with higher wages.

Table 4: Relationship between wages and relatedness to industrial structure of regions

	$\log\ (Wage_{irt})$
Relatedness	0.173***
	(0.013)
Constant	2.314***
	(0.043)
Year fixed effects	Yes
R^2	0.025
Observations	7915

In order to identify whether there exists a relationship between intra-regional inequality and the average relatedness of the industrial structure of regions, we first computed the inter-sectoral wage inequality for each region. We then aggregated the relatedness index to the regional level to measure the average relatedness of their existing industrial structure. After that we estimated the following formulation:

$$\log(Gini_{rt}) = \beta_0 + \beta_1 * Relatedness\ Density_{rt} + \ \varepsilon \ \ (6)$$

Table 5 shows the relationship between intra-regional wage inequality across industrial sectors and the average relatedness of the industrial structure of regions. The relatedness is negatively correlated with the wage inequality across different industrial sectors in regions. This indicates that regions with a more coherent industrial structure are less likely to have high wage inequality across different sectors.

Table 5: Relationship between intra-regional wage inequality and the average relatedness of industrial structure of regions

	$\log(Gini_{rt})$
Relatedness	-1.462***
	(0.052)
Constant	-0.101***
	(0.016)
Year fixed effects	Yes
R^2	0.064
Observations	792

To summarise, our preliminary results of the study of European NUTS2 regions indicate that entry of industries is only associated with high wages in regions if they are related to the existing industrial structure of the region. By contrast, exiting industries are associated with lower wages in regions, unless exiting industries are related to the existing industries in regions. In the latter case, they are associated with higher wages. We also showed that regions with a more coherent industrial structure (i.e. a higher average relatedness between their industries) are less likely to experience high intra-regional wage inequality across sectors.

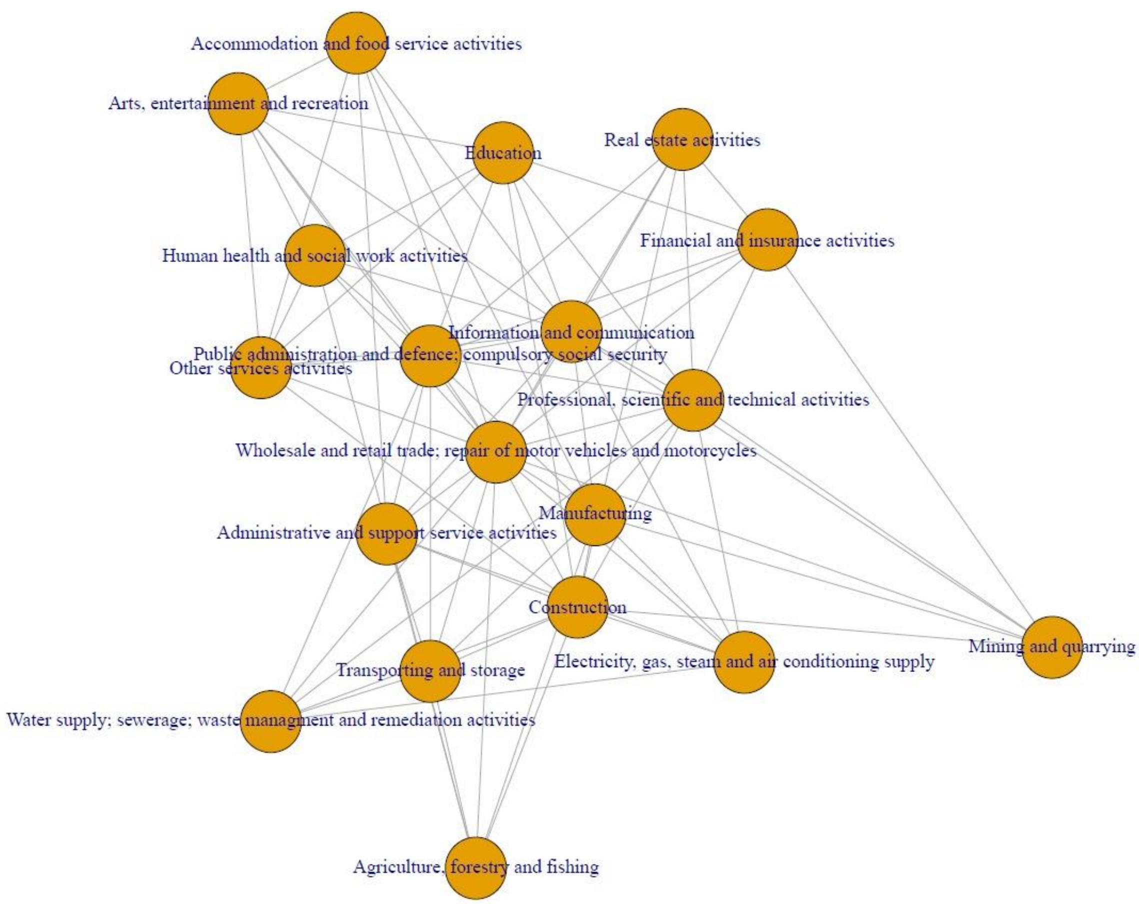
Due to data limitations, we could not provide evidence of the impacts of industrial diversification on inter- and intra-regional wage inequality at a more fine-grained level of industries. Therefore, we present in the next section a case study of the Netherlands which allows us to provide more detailed answers to these questions.

5. A regional analysis of the Netherlands on industry dynamics and regional inequality

This section examines the relationship between industry dynamics and wage inequality at the regional level in one single country in the period 2010-2019. We use a newly constructed dataset on linked employer-employee data (LEED) that contains detailed labor market information on individuals and their work locations in 40 labor market regions (NUTS-3) in the Netherlands. These micro-data have been obtained from the National Bureau of Statistics in the Netherlands.

First, we have to assess the relatedness between industries in the Netherlands. Unlike the European study in Section 4, we calculate the degree of skill-relatedness between industries following Neffke and Henning (2013), making use of the richness of the linked employer-employee data. Industries are considered skill-related when they share similar skill requirements. This can be identified by looking at the intensity of labor flows between industries. When many workers change jobs between two industries, we assume the skills of these workers are in high demand in both industries. We used the CBS microdata to determine the intensity of labor mobility between industries: the more labor flows between two industries compared to what would be expected given the industries' respective sizes, the more skill-related the two industries are. Figure 3 presents the skill space of 2-digit industries in the Netherlands. We will run the analyses with 4-digit industry data, making use of the skill-space at this more fine-grained industry scale.

Figure 3. Skill space of the Netherlands for 2-digit industries, 2019-2020



Second, having linked employees to their job location (NUTS-3 level), we calculate what industries each region in each year is specialized in, based on location quotients and applying a bootstrapping technique (see Tian 2013; Cortinovis et al. 2017). Using information on sectoral specializations, defined as binary variables, we are able to identify industries that have become part of the regional portfolio of industry over the last five years (each of which we qualify as an entry) and industries that, over the five-year period, are no longer part of the regional set of specializations (exit). We do so by essentially comparing the vector of sectoral specializations for the same region over a period of five years. For instance, the two vectors below show the specialization patterns of region R in 2010 and 2015, with cells reporting values of 1 indicating the existence of a specialization in that industry (row):

$$Spec_{r,2010} = \begin{matrix} 1 \\ 0 \\ 0 \end{matrix}, \qquad Spec_{r,2015} = \begin{matrix} 1 \\ 1 \\ 0 \end{matrix} \quad (7)$$

In the case of region R, we would then define a entry vector for the year 2015 as follows:

$$en_{r,2015} = \begin{matrix} NA \\ 1 \\ 0 \end{matrix} \quad (8)$$

The first row reports the value NA since the industry in the first row was present in 2010 as well as in 2015 (so entry could not take place). The second row shows instead an entry, since the region was not specialized in that industry in 2010 but gained a specialization in 2015 (the value of the second row was 0 in 2010 and 1 in 2015). Finally, the third row of entry vector report 0, since region R was not specialized in that industry neither in 2010 nor in 2015 (so an entry could have been possible, but it did not occur). We applied a mirroring logic in the case of exits.

To understand the role of relatedness linking industrial dynamics and inequality, we further combine the information of the entry and exit vectors with the skill relatedness matrix derived from information on job switchers. To this end, we start by dividing the skill relatedness matrix in two matrices M containing information on related sectors (with skill relatedness greater than 0, and setting the remaining cells to 0) and N containing information on unrelated sectors (with the absolute values of cells for which skill relatedness below 0 and setting the remaining cells to 0). For every industry i in region r at time t, we first measure how related (or unrelated) each industry is to the existing specializations in the region as follows:

$$reld_{i,r,t} = \mu_{i,j} * spec_{j,r,t} \quad i \neq j \ \ (9)$$

where $\mu_{i,j}$ measures the intensity of the skill relatedness between sector i and sector j. We then interact the vector $reld_{i,r,t}$, capturing the total relatedness of sector i to the rest of the regional specializations, with the entry vector $en_{i,r,t}$ (identifying which industries have entered region r at time t), as shown below:

$$relentry_{i,r,t} = en_{i,r,t} * reld_{i,r,t} \ \ (10)$$

The variable $relentry_{i,r,t}$ therefore captures the total relatedness of entries to existing specializations of the regions. We replicate the approach we just outlined for computing related exits as well as unrelated entries and exits (using information from matrix N).

Finally, the micro data from CBS (SPOLISBUS) gives us information on individual wages, which we use to construct our dependent variables. Specifically, we calculate several conventional inequality measures, namely the Theil index, the coefficient of variation and the ratio between the 90th percentile and the 10th percentile of the income distribution.

Figure 4 shows the spatial distribution of entries and exits in 2019, the most recent year in our sample. The number of entries is rather homogeneously spread across the country, with high number of entries being recorded even in peripheral areas while regions part of the Randstad conurbation (Delft, Rotterdam) performing relatively less well. In terms of exits, the advantages of more densely populated areas appear more evident, with the region of Amsterdam having the lowest number of exits, together with other urban regions (Groningen, Den Haag). At the same time, less central (e.g. Twente, in the East) and rural regions (Zeeland in the South West) also shows low number of exits.

Figure 4: The spatial distribution of entries (left panel) and exits (right panel) in 2019

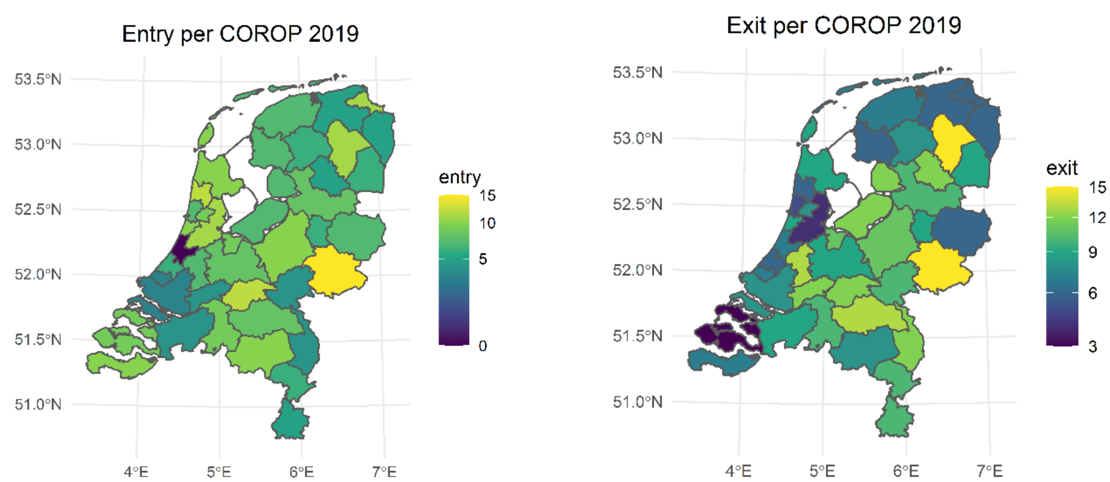
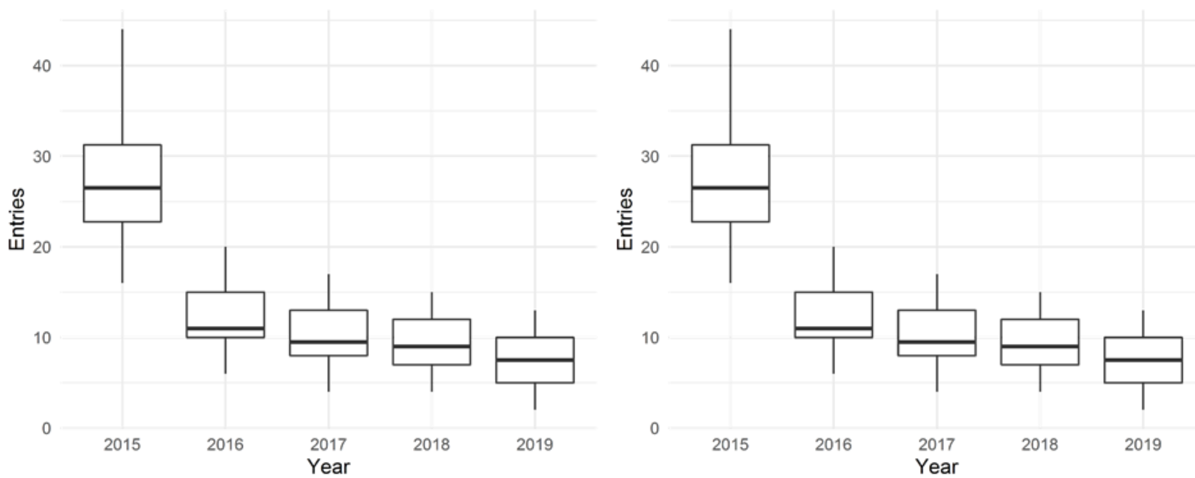


Figure 5 depicts the distribution of entries and exits across time. The number of entries and exits show a remarkably similar trend over time and relatively similar magnitudes. The first year for which we can measure entries and exits (2015, based on a comparison of specializations between 2015 and 2010) suggests 2015 was a rather turbulent year in terms of industrial dynamics, with about 15 entries and 10 exits as a minimum and more than 35 entries and exits as a maximum. The following years are marked by a slowing down of industrial dynamics, with overall declining and more consistent numbers of entries and exits from one year to the other.

Figure 5: The distribution of entries (left panel) and exits (right panel) across time



Then, we compared the average of the median wage between related and unrelated industries in the 40 COROP regions from year 2015-2019. Table 6 presents the results. For entries, 0 refers to potential entry that did not occur, 1 refers to entry that has occurred, and NA refers to industries that the region was already specialized in. The average and the standard deviation stand for the mean and the standard deviation (SD) of the median wage by the different groups. For instance, 26169.5 is the average of the median salary (in currency euros) for industries that could have entered a region but did not. Similarly, 28851.14 euros is the average of the median salary of industries that have entered a region and are related to its industrial portfolio. Finally, N is the number of observations for each category. Note that the number of entries do not add up because there are many "random" entries (i.e. entries from industries whose relation to the current industrial structure of the region is 0). For exits, 0 refers to sectors that are still present in the region, 1 refers to those sectors that exited. Present refers to those which were actually not present in the specialization portfolio in the first year (so either entries or minor industries that are not part of the specialization portfolio of the region).

The results in Table 6 suggests that on average, related industries tend to pay higher wages than unrelated industries in a region. In addition, the average wage tend to be higher in entering industries than in those industries that have not yet entered, and lower in exiting industries than in those industries that did not exit.

Table 6: The distribution of wages between related and unrelated industries (2015- 2019)

Status	Average	SD	N	Variables
0	26169.5	13900.86	100419	Entry
1	27751.33	12792.43	2618	Entry
Present	30229.54	12449.53	17563	Entry
0	26198.19	13888.81	102312	Related Entry
1	28851.14	11193.49	725	Related Entry
Present	30229.54	12449.53	17563	Related Entry
0	26223.58	13868.91	102896	Unrelated Entry
1	27471.18	12195.65	141	Unrelated Entry
Present	30229.54	12449.53	17563	Unrelated Entry
0	30698.68	11930.79	12763	Exit
1	27588.91	13938.93	2680	Exit
Present	26240.24	13890.3	105157	Exit
0	30328.85	12371.2	14670	Related Exit

1	28663.37	10695.07	773	Related Exit
Present	26240.24	13890.3	105157	Related Exit
0	30257.82	12294.54	15285	Unrelated Exit
1	28851.14	12291.15	158	Unrelated Exit
Present	26240.24	13890.3	105157	Unrelated Exit

Figure 6 provides an overview of the levels of inequality in 2019 across the Netherlands. As clearly shown by the Theil index and the coefficient of variation (CV), inequality levels are generally low, with the exception of the more densely populated areas. Amsterdam and its neighbouring regions, in particular, have the highest score. Based on the Theil index, some relatively high levels of inequality are found also in Tilburg (in the South) and in South-West Overijssel (in the East). The inequality trend depicted using the 90/10 wage ratio is slightly different from the CV and Theil index, with the highest levels of inequality found in Mid-North Brabant.

Figure 6: The distribution of inequality across COROP regions in the Netherlands in 2019

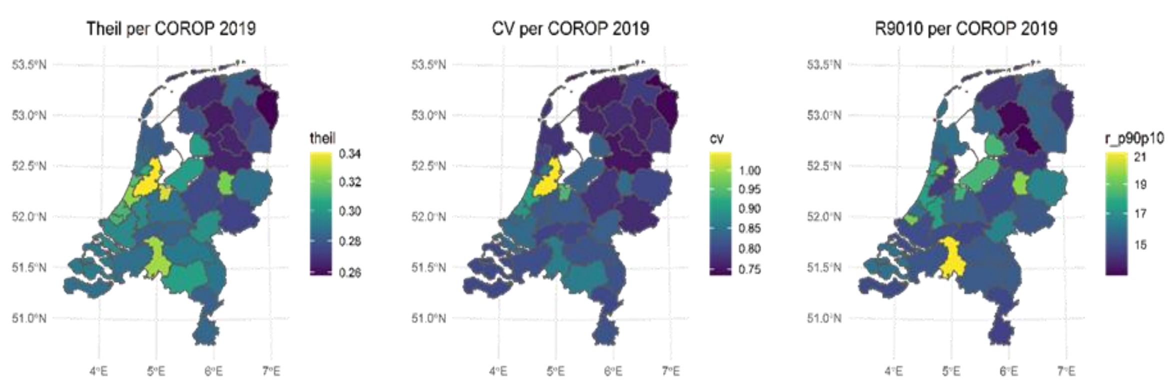
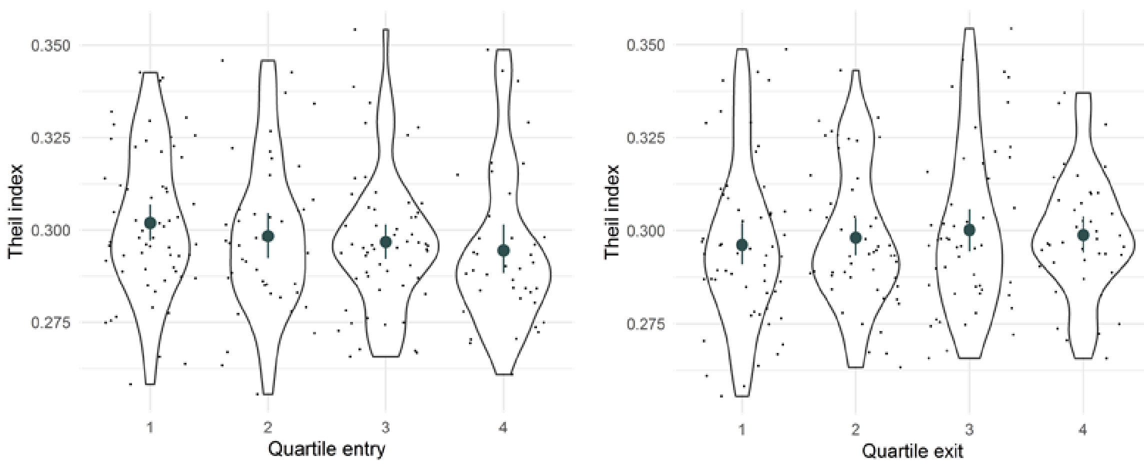


Figure 7 provides some general insights on the relation between inequality and industrial dynamics in the Netherlands. It shows the distribution of inequality for different quartiles of entries (quartile 1 meaning the lowest number of entries, quartile 4 the highest number) in panel (a) and those of exits in panel (b). The green dot in each of the "violin" figures shows the mean for the group. With respect to entry, the distribution of the bottom quartiles appears more spread out, while it becomes more concentrated towards lower levels of inequality for the top two quartiles. This explains the slightly declining trend as shown by mean level of inequality across the four quartiles. In panel (b) instead, only the top quartile has a more concentrated distribution towards higher levels of inequality, as is also shown by the slightly upward trend in the average across groups. Overall, these graphs suggest a possible negative relation between entries and inequality (wregions with higher levels of entries showing lower levels of inequality) while a positive relation between exits and inequality.

Figure 7: The distribution of inequality per quantiles of entry (left panel) and quartiles of exit (right panel)



We regressed region-wide measures of inequality on the number of entries and exits in each region. Our main variables of interest are our measures of (related) entry and exit, which we study as potential drivers of wage inequality at different levels. From a regional perspective, we estimate the following equation:

$$ineq_{rt} \; = \; \beta_0 + \alpha * en_{rt} + \gamma * ex_{rt} + \delta * C_{rt} + \rho_r + \tau_t + \epsilon_{it} (11)$$

where the dependent variable $ineq_{rt}$ captures various measures of inequality (see below), while en_{rt} and ex_{rt} are respectively proxy for the total number of entries and exits in region *r* and time *t*. We also include various control variables (C) and, exploiting the panel setup of our data, we add region (ρ_r) and time (τ_t) fixed effects. To study wage inequality at a more fine-grained level, we take a similar approach while adding the sectoral dimension in the following equation:

$$\begin{aligned} ineq_{rit} \; = \; & \beta_0 + \alpha * en_{rit} + \mu * ren_{rit} + \gamma * ex_{rit} + \sigma * rex_{rit} + \delta * C_{rit} + i_i + \tau_{rt} \\ & + \epsilon_{rit} (12) \end{aligned}$$

Since equation (12) models inequality and industrial dynamics at a different level, our variables of interest en_{rit} and ex_{rit} are binary variables taking value 1 when industry *i* has entered or exited the regional specialization portfolio, and 0 otherwise. Interacting these measures with the relatedness matrix, we compute variables *ren* and *rex*, which capture the exposure of industry i to entry and exit dynamics in skill-related industries. As in equation (11), our industry-region-year model includes control variables (C) and fixed effects at industry (i_i) and region-year level (τ_{rt}).

The preliminary results obtained by our regression analysis are reported in Tables 7 and 8. Using the Theil index as inequality indicator, Table 7 indicates that regions experiencing a higher number of entries in their portfolio of specialization tend to show inequality reducing over time. When looking at exit dynamics, we do not observe a significant correlation with regional inequality. Splitting entries and exits based on their relatedness to the current industrial structure reveals further interesting results, as shown in Table 8. Entries that are more strongly related to the industrial structure of the region tend to drive the total effect of entries, while unrelated entries have no impact on the level of regional inequality as measured by the Theil index. Similar to Table 7, no significant effect is found for related and unrelated exits in Table 8.

Table 7: the impact of entry and exit on intra-regional inequality

	Dependent variable: Theil index			
	(1)	(2)	(3)	(4)
Entry	-0.0004*		-0.0004*	-0.0004*
	(0.0002)		(0.0002)	(0.0002)
Exit		-0.0001	-0.00006	-0.0000575
		(0.0002)	(0.0002)	(0.0002)
log(tot-uni)				-0.0133
				(0.0087)
log(unemployed)				-0.0094
				(0.0078)
log(migrant_pop)				0.0041
				(0.0036)
COROP fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.940	0.936	0.940	0.943
Observations	200	200	200	200

Table 8: the impact of related and unrelated entry and exit on intra-regional inequality

	Dependent variable: Theil index			
	(1)	(2)	(3)	(4)
Related entry	-0.0002**		-0.0003*	-0.0003*
	(0.0001)		(0.0001)	(0.0001)
Unrelated entry	0.0008		0.0004	0.0007
	(0.0008)		(0.0010)	(0.0008)
Related exit		$4.01*10^{-5}$	$1.66*10^{-5}$	$4.9*10^{-6}$
		(0.0001)	(0.0001)	(0.0001)
Unrelated exit		0.0014	0.0016	0.0019
		(0.0014)	(0.0013)	(0.0094)
log(tot-uni)				-0.0147
				(0.0094)
log(unemployed)				-0.0129
				(0.0092)
log(migrant_pop)				0.0038
				(0.0032)
COROP fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.938	0.938	0.940	0.944
Observations	200	200	200	200

In the Appendix, one can find the same analyses for the two other inequality measures: coefficient of variation (Tables A1 and A2) and 90/10 wage inequality ratio (Tables A3 and

A4). The results for the coefficient of variation are similar to those of the Theil index. While the overall effect of entries is not significant (Table A1), related entries are associated with lower regional inequality, while unrelated entries seem to have a regional inequality-increasing effect (Table A2). These opposing effects between related and unrelated entries are likely to explain the low or lack of significance for the estimated coefficient for entries as a whole. With respect to exits, modelling the coefficient of variation as dependent variable confirms the overall lack of impact of exits on regional inequality. The only exception pertains unrelated exits: Table A4 shows that a high number of unrelated exits is associated with higher levels of inequality.

In sum, the preliminary results of the Dutch study show that entry of industries that are related to the specializations of a region tends to reduce inequality within a region. However, we observe no significant impact of exit of industries on regional inequality, with one exception: unrelated exits tend to increase wage inequality when captured with the coefficient of variation. Overall, these findings suggest that related diversification tends to bring benefits to regions both in terms of smart and inclusive growth, while exiting industries tend not to have a significant effect on regional inequality.

6. Conclusion

While technological advances and globalization have a tendency to reinforce income inequalities, little is known about the role of industrial dynamics as potential driver of inequalities. We have conducted two studies to shed more light on this relationship between industrial dynamics and wage inequalities at the regional (i.e. sub-national) scale. First, we started with a study at the level of European regions. Second, to obtain a more detailed and updated view, we performed a study for the regions in the Netherlands.

The preliminary results of the study on NUTS-2 regions in Europe indicate that entry of industries is only associated with high wages in regions if related to the industrial structure of the region. Exiting industries are associated with lower wages in regions, while exiting industries related to existing industries in regions are associated with higher wages. We also showed that European regions with a more coherent industrial structure are less likely to experience high intra-regional wage inequality across sectors.

Due to data limitations at the European scale, we also conducted a case study on NUTS-3 regions in the Netherlands, making use of linked employer-employee data (LEED). The Dutch study showed that entry of industries that are related to the specializations of a region tends to reduce inequality within a region. However, we observe no significant impact of exit of industries on regional inequality. Overall, the findings from the Dutch study suggest that related diversification tends to bring benefits to regions both in terms of smart and inclusive growth, while exiting industries tend not to have a significant effect on regional inequality.

This report has been very explorative, as it was the first study to conduct an analysis on the relationship between industrial dynamics and regional inequalities. As discussed, there were quite a few challenges with regard to data availability that limited the possibility to make a comprehensive comparison of European regions. We also still have to investigate more deeply the extent to which, and how, industrial dynamics may have contributed to increasing wage inequalities in many countries. On top of that, we have not yet examined how industrial dynamics are impacted by processes of digitalization (some industries and jobs are more exposed and affected) and globalization which in turn impact regional inequalities. More systematic research is needed to unravel regional inequalities and its determinants. These and other questions will be further investigated in upcoming projects in the PILLARS framework.

7. Policy brief

To conclude this report, we prepared a short policy brief. This is not easy to do for several reasons. First, the report did not look at any policy actions and how these may have affected the relationship between industrial dynamics and regional disparities. In that sense, it is hard to derive any policy lessons from the studies conducted. Second, there are still a lot of unknowns concerning the relationship between industrial dynamics and regional inequality, as discussed in Section 6. Having said that, we bring together some insights from other studies and our report, and reflect on those in terms of possible policy implications.

The regional diversification literature (Boschma 2017) has convincingly shown in the last decade that relatedness is an important driver behind industrial dynamics at the regional level (Hidalgo et al. 2018). That is, new industries are more likely to emerge and develop in a region when these are related to existing industries in a region, while existing industries are more likely to exit a region when unrelated to other local industries (Neffke et al. 2011). On top of that, more advanced regions tend to show a stronger capacity to diversify into more complex industries that tend to bring more economic benefits (Balland et al. 2020), while less advanced and peripheral regions lack such capacity and face significant difficulties in establishing a long-term sustainable growth trajectory to a greater or lesser extent (Pinheiro et al. 2022).

These insights have been integrated in Smart Specialization policy in the EU that has the objective to stimulate the development of new economic activities in which regions have strong capabilities. Smart Specialization policy aims to promote smart growth in regions by accommodating and facilitating related diversification, that is, the development of new industries that can draw on local capabilities (McCann and Ortega-Argilés 2015). Balland et al. (2019) developed a framework to identify diversification opportunities of regions based on the local presence of relevant capabilities, in order to help out regional policymakers to set priorities. But the big question is: while doing that, would that also promote inclusive growth?

What studies tend to find is that wage inequality is widening in EU, whether by the level of workers' skills, by occupation, or across regions (Iammarino et al. 2019). There is also inequality in wages within countries according to the characteristics of the industries and the profile of workers. The question is whether smart growth is actually contributing to this growing wage inequality between and within regions. This depends on whether new industries in regions would recruit primarily high-skilled and high-wage people, while exiting industries would lay off low-skilled and low-paid workers to a large degree. The evolution of inter-regional wage inequality will depend on where new industries emerge and grow, and in which regions in Europe existing industries stagnate, decline, and disappear.

In this context, scholars and policymaker try to understand how local capabilities can support productive diversification towards a more sustainable and inclusive growth path (Boschma 2022). Preliminary results from our report on NUTS-2 regions in Europe show that European regions with a more coherent industrial structure are less likely to experience high intra-regional wage inequality across sectors. Moreover, a more detailed analysis based on the Netherlands brought to light that entries of industries that are related to the specializations of a region tend to reduce inequality within a region. These findings suggest that related diversification brings benefits to regions both in terms of smart and inclusive growth.

This might suggest that Smart Specialization policy with a focus on related diversification could have the potential to reduce regional inequalities. However, this is far too early to say, and we feel more research is needed before we can derive such strong policy recommendations. For sure, it makes us aware that policies aiming to reduce wage disparities across EU should consider the industrial and occupational structures in regions. Greater attention is recommended to differentiate policies for regions with an intense presence of complex industries and greater technological dynamism in relation to lagging regions or regions with most traditional sectors. For less technologically dynamic regions, policies may encourage, in a first step, the development of less complex industries (given the difficulty of installing complex industries). Having said this, it is still on the research agenda to advance the discussion to understand the effect on inequality considering the sectoral specificities of a region. This shows there are outstanding issues that need to be deepened, such as the influence of industrial sectors in the rise or fall of regional wage inequalities, and whether there are differences that are reinforced according to the profile of workers in each region. These issues will be investigated further in the PILLARS project.

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9. Appendix

Table A1: the impact of entry and exit on intra-regional inequality

	Dependent variable: Coefficient of variation			
	(1)	(2)	(3)	(4)
Entry	-0.0003		-0.0003	-0.0003
	(0.0003)		(0.0003)	(0.0003)
Exit		-0.0004	-0.0004	-0.0004
		(0.0004)	(0.0004)	(0.0003)
log(tot-uni)				-0.0229
				(0.0170)
log(unemployed)				-0.0168
				(0.0139)
log(migrant_pop)				0.0126
				(0.0090)
COROP fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.950	0.950	0.951	0.952
Observations	200	200	200	200

Table A2: the impact of related and unrelated entry and exit on intra-regional inequality

	Dependent variable: Coefficient of variation			
	(1)	(2)	(3)	(4)
Related entry	-0.0006**		-0.0006**	-0.0006**
	(0.0003)		(0.0003)	(0.0002)

Unrelated entry	0.0049**		0.0042*	0.0048**
	(0.0020)		(0.0021)	(0.0020)
Related exit		0.0001	$4.15*10^{-5}$	$1.81*10^{-5}$
		(0.0003)	(0.0003)	(0.0002)
Unrelated exit		0.0033	0.0031	0.0037*
		(0.0020)	(0.0019)	(0.0020)
log(tot-uni)				-0.0311*
				(0.0179)
log(unemployed)				-0.0250
				(0.0163)
log(migrant_pop)				0.0094
				(0.0072)
COROP fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.952	0.951	0.953	0.956
Observations	200	200	200	200

Table A3: the impact of entry and exit on intra-regional inequality

	Dependent variable: 90/10 wage inequality ratio			
	(1)	(2)	(3)	(4)
Entry	-0.0216		-0.0209	-0.0215
	(0.0171)		(0.0167)	(0.0163)
Exit		-0.0080	-0.0048	-0.0040
		(0.0178)	(0.0169)	(0.0148)
log(tot-uni)				-0.5816
				(0.9363)

log(unemployed)				-0.5247
				(0.8294)
log(migrant_pop)				0.0160
				(0.2912)
COROP fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.920	0.920	0.920	0.921
Observations	200	200	200	200

Table A4: the impact of related and unrelated entry and exit on intra-regional inequality

	Dependent variable: 90/10 wage inequality ratio			
	(1)	(2)	(3)	(4)
Related entry	-0.0103		-0.0119	-0.0128
	(0.0130)		(0.0138)	(0.0129)
Unrelated entry	-0.0411		-0.0666	-0.0504
	(0.0731)		(0.0803)	(0.0787)
Related exit		-0.0056	-0.0064	-0.0071
		(0.0131)	(0.0126)	(0.0122)
Unrelated exit		0.1148	0.1453	0.1583
		(0.1412)	(0.1331)	(0.1369)
log(tot-uni)				-0.6091
				(1.016)
log(unemployed)				-0.6985
				(0.8870)
log(migrant_pop)				0.0159
				(0.2691)

COROP fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.920	0.920	0.921	0.922
Observations	200	200	200	200