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in the Netherlands**

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Regional diversification and intra-regional wage inequality in the Netherlands

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Abstract

The literature has shown that related diversification in more complex industries enhances economic growth in regions but also inter-regional inequality. However, it has drawn little attention to the relationship between industrial dynamics (i.e. the rise and fall of industries) and intra-regional wage inequality. This explorative study examines the relationship between industry dynamics and wage inequality in NUTS-3 regions in the Netherlands in the period 2010-2019. Our study shows that related diversification in less complex industries tends to reduce wage inequality within a region. This implies it remains a policy challenge to combine smart and inclusive growth in regions. Our study also showed that there is no significant relationship between exit of industries and regional inequality, with one exception: unrelated low-complex exits tend to increase intra-regional wage inequality. Overall, these findings suggest that related diversification in less complex industries tends to bring benefits in terms of inclusive growth, while unrelated exits in less complex industries tend to do the opposite.

Keywords: intra-regional inequality, regional inequality, relatedness, structural change, inclusive growth

JEL codes: O18, O31, O33, R11

Introduction

Many regions have the ambition to combine smart growth and inclusive growth (Lee 2016). The objective of smart growth means that regions aim to develop new activities that build on local capabilities, as promoted by Smart Specialization policy in the European Union (Foray 2014). However, not every region has the same capacity to diversify into new industries (Neffke et al. 2011; Balland et al. 2019; Uhlbach et al. 2022). McCann and Ortega-Argiles (2015) among others have raised concerns that advanced regions have a strong capacity to do so, while backward and peripheral regions lag behind in this respect. If so, smart growth could lead to increasing regional income disparities and go at the expense of inclusive growth.

This begs the question how the entry of new industries affects regional wage inequality. Studies show how innovation has a tendency to increase income disparities across regions (Lee 2011, 2016). Iammarino et al (2019) suggest that technological change and globalization contribute to regional divergence of income levels in Europe (Moretti 2012). This is because high-income regions are well-endowed with human capital, advanced knowledge institutes, regional innovation systems, diversity and connectivity to other regions that trigger and enhance innovation (Feldman and Audretsch 1999; Asheim et al. 2019).

However, while innovation often contributes to economic growth, it does not necessarily ensure the socio-economic well-being of all residents, particularly in terms of wage equality (Rodríguez-Pose and Tselios 2009; Lindley and Machin 2014; Lee et al. 2016). What is well-known is that the success of Silicon Valley as a global innovative hub has led to crowding out of low-income people due to lack of affordable housing (Gyourko et al. 2013; Lee and Clarke 2019). Florida (2006) claimed that the most innovative cities in the US are also those that are the most unequal. There is indeed increasing evidence of positive relationship between innovation and wage inequality within regions (Lee 2011; Lee and Rodríguez-Pose 2013; Breau et al. 2014). This has partly been attributed to the local presence of high-skilled jobs that raise the demand for local services and create an employment multiplier for low-wage jobs (Moretti 2010; Florida 2017; Lee and Clarke 2019).

Lots of studies have observed job polarization in many developed countries, meaning a major shift of employment away from middle-skill occupations towards high- and low-skill occupations, leading to a hollowing out of the middle class and increased wage inequality.

However, its extent and causes remain widely debated in the literature (Terzidis and Ortega-Argiles 2021). One of the primary debates concerns whether it is driven by technological change or globalization and trade. However, little attention has been given to the relationship between industrial dynamics and intra-regional wage inequality.

There is little understanding of the extent to which industrial dynamics in regions (in terms of entries but also exits of industries) induce such intra-regional inequality. To our knowledge, systematic evidence is lacking what impacts the rise and fall of industries have on intra-regional inequality, in particular the impact of entry and exit of complex industries that rely on a wide range of capabilities and are difficult to imitate by other regions, and therefore bring higher economic growth (Hidalgo and Hausmann 2009) Studies show that the most complex activities tend to 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 2022; Rigby et al. 2022). This implies 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. This is in line with Pinheiro et al. (2022) that showed that regions with a high GDP per capita in Europe have the best opportunity to diversify into high-complex activities, while lagging regions focus mainly on the development of low-complex activities. However, no study yet exists that has examined the relationship between industrial diversification on intra-regional wage inequality, let alone how such relationship looks like in case of complex entries.

To examine the relationship between industrial dynamics and intra-regional wage inequality requires detailed data on the entry and exit of industries in regions and link them to wages of individuals within regions. At the European level, these regional data are not available, which makes it near to impossible to investigate this relationship for all European countries (Boschma et al. 2022). Therefore, we restrict our analysis to one single country (the Netherlands) where we use linked employer-employee micro-data from the Central Bureau of Statistics in the Netherlands. These provide data on detailed industry categories which can be linked to wages of individuals and their work location in 40 NUTS-3 regions (labor market areas). This enables us to make a first small step to determine whether smart growth can, or cannot, be combined with inclusive growth at the regional scale.

This relationship between industrial dynamics and intra-regional inequality will be investigated from a relatedness/complexity framework (Boschma 2017; Hidalgo et al. 2018; Balland et al. 2019). The relatedness principle has proven successful in explaining why entering industries in regions are often related to existing local industries, especially when these industries are highly complex and thus difficult to develop, and why exiting industries are often less related to existing local industries (Neffke et al. 2011; Boschma 2017; Balland et al. 2019). Whittle and Kogler 2019). Our study shows that entries, especially low-complex related entries, tend to reduce wage inequality within a region. We observe no significant relationship between exits of industries and regional inequality, with one exception: unrelated low-complex exits tend to increase intra-regional wage inequality. These findings suggest that related diversification in low-complex industries bring benefits to regions in terms of inclusive growth, while unrelated exits in low-complex industries do not.

The paper is structured as follows. First, we discuss the relationship between industrial dynamics and regional inequality. Then, we present the data and the indicators used, such as the skill-relatedness measure, the measurement of regional entries and exits, and the regional inequality variables. After that, we present the main findings of the Dutch study. Finally, we conclude and discuss implications for future research as well as for policy.

Industrial dynamics and regional inequality

Regional inequality is on the rise (Terzidis et al. 2017; Iammarino et al. 2019; Feldman et al. 2021). In the EU, income inequality across NUTS-2 regions has substantially risen since the 2000s (Rosés and Wolf 2018). In the US, inequality in income per capita between metropolitan areas has increased from 1980 to 2016 (Ganong and Shoag 2017; Rodríguez-Pose and Storper 2019). Scholars attribute these rising disparities to technological change and globalization (Moretti 2012; Iammarino et al. 2019; Kemeny et al. 2022). Advanced economies have witnessed concentration of knowledge-intensive activities in large cities in combination with the spread of low-value activities to less developed regions (Puga 1999; Kemeny and Storper 2020). Technological change has decreased trade costs which makes knowledge-intensive activities become increasingly concentrated in large cities (Levy and Murnane, 2005) where high-paid, high-skilled and non-routine jobs are found (Moretti 2004; Diamond 2016). Other regions, often those with a substantial presence of the manufacturing sector, are stagnating economically, due to trade and automation of routine tasks (Autor 2019).

There is a large body of literature on job polarization. Terzidis and Ortega-Argiles (2021) conducted a meta-study to analyze the impact of trade and technological progress on labour markets in the Netherlands. The findings suggest that both factors are important, but the relative contribution of each is unclear. Autor et al. (2003) analysed the growth of low-skill service occupations between 1980 and 2005 in the US labor market. They argue that this growth is driven by the polarization of labor demand, which reflects the complementarity between workers' skills and tasks performed on the job. They show that routine tasks, which are easily automated or offshored, are concentrated in middle-skill occupations, while non-routine tasks, which require problem-solving or interpersonal skills, are concentrated in high- and low-skill occupations. Goos et al. (2009) and Michaels et al. (2014) found similar patterns of job polarization in Europe and other developed countries. Other studies have focused on the role of globalization and trade in driving job polarization. Feenstra and Hanson (1996) showed that trade with China led to a significant increase in the demand for high-skill workers in the US in the 2000s, while Becker et al. (2013) found that regions with a high share of tradable industries were more susceptible to job polarization in Germany. Firpo et al. (2011, 2018) investigated the impact of international trade on wage inequality in Brazil and found that exposure to foreign competition contributed to rising wage inequality in the 1990s and 2000s.

Concentration of innovative activity in cities often goes hand in hand with intra-regional inequalities (Rodríguez-Pose and Tselios 2009; Lindley and Machin 2014; Lee et al. 2016). Florida (2006) claimed that the most innovative cities in the US are also the most unequal. Lee (2011) and Lee and Rodríguez-Pose (2013) found a positive relationship between innovation and wage inequality in European regions. Breau et al. (2014) confirmed this result for Canadian cities. Large cities draw in relatively high amounts of both high- and low-skilled workers (Eeckhout et al. 2014) where the high-skilled workers increase the demand for local services, resulting in an employment multiplier for low-wage jobs (Moretti 2010; Autor and Dorn 2013). Lee and Clarke (2019) found significant local employment multiplier effects from high-tech jobs in a study on the UK, where low-skilled workers profited from new employment opportunities in relatively poorly paid service jobs (see also Florida 2017).

The regional diversification literature (Boschma 2017) has focused on the entry of industries in regions and how they build on local capabilities from related industries (Neffke et al. 2011; Essletzbichler 2015). This literature tends to suggest that regional diversification is likely to increase inter-regional inequality. This is not because high-income regions necessarily

diversify more than low-income regions (Xiao et al. 2018), but because high-income regions have a stronger capacity to diversify more into more complex activities (Pinheiro et al. 2022) that also bring higher economic benefits to the region (Rigby et al. 2022). There is increasing evidence that complex activities concentrate in the richest cities, enhancing their economic performance (Balland and Rigby 2017; Antonelli et al. 2020; Balland et al. 2020; Mewes and Broekel 2022; Pintar and Scherngell 2020; Rigby et al. 2022). Balland et al. (2019) found that many regions have the ambition to diversify into more complex activities but lack the capabilities to do so. Pinheiro et al. (2022) showed that advanced regions have the best opportunity to diversify into high-complex activities, while lagging regions focus mainly on the development of low-complex activities. Their study showed that high-income regions (GDP per capita) in Europe do not only enter complex technologies and industries, they also have the highest potential to continue to do so, given their local capabilities.

The complexity literature (Hidalgo and Hausmann 2009; Hausmann et al. 2014) has investigated the relationship between economic complexity and intra-regional inequality. At the country level, studies have shown that the higher the complexity of an economy, the lower the wage inequality (Hartmann et al. 2017; 2020). This finding at the national scale stands in contrast with studies done at the regional scale that show there is instead a positive relationship between economic complexity and inequality at the sub-national scale (e.g. Sbardella et al. 2017; Heinrich Mora et al. 2021; Marco et al. 2022; Hartmann and Pinheiro 2022). New York and San Francisco are prime examples of complex cities that show the highest inequalities. According to Hartmann and Pinheiro (2022), the positive relationship may be attributed to the co-existence of simple and complex activities in large cities where relatively little job opportunities exist for middle-income people in semi-complex activities. However, Gao and Zhou (2018) and Zhu et al. (2020) found a negative relationship for Chinese regions.

So, while the relationship between innovation, complexity and intra-regional inequality is being explored, there is yet little understanding of the extent to which industrial dynamics (in terms of entries as well as exits of industries) induce intra-regional inequality. Some scholars (Aghion 2002; Mendez 2002) have paid attention to the relationship between creative destruction and inequality. However, the literature has not yet investigated how entry and exit of industries may affect intra-regional inequality (Boschma 2017).

It is not straightforward what relationship to expect between entry and wage inequality at the regional level. As high-complex industries pay higher wages than low-complex industries, entries in more complex industries are likely to pay higher average wages than entries in less complex industries. Following Pinheiro et al. (2022), we expect that entries in high-income regions occur mainly in complex industries, while in low-income regions, entries occur mainly in less complex industries. While it is clear that this is likely to increase wage inequality between regions, it is uncertain what to expect in terms of their effect on intra-regional wage inequality. This is likely to depend on whether entries in high-income regions are mainly in high-complex industries and whether these industries pay higher wages than the average wage in these regions, but we cannot assume *a priori* whether this is the case. The same uncertainty is true for entries in low-income regions. In those regions, it depends on whether entries are mainly in low-complex industries and whether these industries pay lower wages than the average wage in such regions. On these bases, it is uncertain what kind of effect the complexity of entries will have on intra-regional wage inequality.

The same uncertainty applies to the effect of relatedness of entries on regional wage inequality. Entries in related industries share similar skill requirements with other related industries in the region (Neffke and Henning 2013). Therefore, related entries need to compete for labor with other related local industries, so they might have to offer higher wages to their employees. This may also lead to an increase of wage levels in the other related industries in the region (Glaeser 1992; Rosenthal and Strange 2004; Fitjar and Timmermans 2019; Rørheim and Boschma 2022). However, it remains unclear whether related entries will increase wage inequality within regions. This depends on whether entries in related industries would pay higher wages than the average industry in the region, but there is no strong reason to assume that related entries would pay higher wages than the regional average. The same uncertainty concerns the effect of related entries in complex industries. As complex entries are expected to pay higher wages on average, especially when they compete with other related industries in the region, this might imply that related complex entries have a higher probability to enhance intra-regional wage inequality. However, we already explained before that it is uncertain what kind of effect the complexity of entries will have on intra-regional wage inequality.

In other words, we have no *ex ante* expectations what the relationship between industry entry and intra-regional wage inequality will look like. This means our study is explorative. We examine whether a high intensity of complex entries in a region is associated with a higher or

lower wage inequality within the region, whether more related entries in a region goes hand in hand with a higher or lower intra-regional wage inequality, and whether more complex related entries that occur in a region is correlated with a higher or lower wage inequality in the region.

How about exits of industries? To our knowledge, no study has yet examined the relationship between exiting industries and intra-regional inequality. It is not entirely clear how exits in general might affect intra-regional inequality from a theoretical perspective. This depends on whether exits will happen mainly in less complex industries and whether these pay lower average wages. But the effect on intra-regional wage inequality will also depend on where the unemployed will go after. What is well-known is that industries are more likely to exit a region when unrelated to local industries (Neffke et al. 2011). This might imply that redundant people will end up either unemployed (their skills will not be in high demand), or they find alternative jobs in skill-unrelated industries in the region. Because their skills are of no immediate relevance in unrelated industries where they find new employment, this may contribute to a lowering of their wages. This has been observed in studies that have examined the effects of closures of major companies or losses of industries in regions on skill destruction, reallocation of skills and the employment careers of the displaced workers (Holm and Østergaard 2015; Eriksson et al. 2016; Holm et al. 2017; Hane-Weijman et al. 2018; Hane-Weijman 2021; Kekezi and Boschma 2021 Rørheim and Boschma 2022). This move to skill-unrelated industries in regions may possibly cause an increase in intra-regional wage inequalities, but this depends on what wages are paid in these industries, which is hard to assume beforehand.. For (related) exits in general, it is also unclear *ex ante* what relationship to expect. Therefore, this study will explore whether different types of exits in terms of relatedness and complexity, such as those in low-complex and unrelated industries in a region, go hand in hand with a higher or lower wage inequality in the region.

Methods, data and descriptives

Data and methodology

This paper explores the interplay between industry dynamics and wage inequality at the regional level. This makes the paper distinct from studies that focused on the correlation between innovation and regional inequality that primarily use patent data, such as those by Lee (2011) and Lee and Rodríguez-Pose (2013). It is a well-established fact that patenting is a practice limited to a relatively small subset of firms, with innovation itself typically concentrated in specific regions. Audretsch and Feldman (1996) notably spotlighted the greater

spatial concentration of innovation compared to production activities. More recent research supports this, demonstrating that the relationship between patenting and population, as well as scientific activities and population, is significantly stronger than the connection between employment and population (Balland et al 2020).

Our methodology, which leverages employment data, captures the diverse and intricate landscape of human capital and skills within a region. These are crucial for the creation and assimilation of innovation and knowledge (Hidalgo et al., 2018). Conversely, patent data measures the technological innovation output of certain sectors and regions, and is often highly concentrated across sectors and space. Furthermore, patents might not capture all innovation types, such as process, organizational, or social innovation, which could be pivotal for regional development and diversification. In light of these observations, we posit that the use of employment data across industries can provide a more accurate portrayal of sectoral dynamics¹.

This requires detailed data on the entry and exit of industries in regions that can be linked to wages of individuals. The downside of using such detailed industry data is that these are not available across regions in Europe (Boschma et al. 2022). Therefore, we restrict our analysis to one single country (the Netherlands). We use a newly constructed dataset on linked employer-employee data that contains detailed labor market information on individuals and their work locations in 40 labor market regions (NUTS-3) for the period 2010-2019. The use of labor market regions is important since it reduces concerns for commuters and mobility across regions². These micro-data have been obtained from the National Bureau of Statistics in the Netherlands.

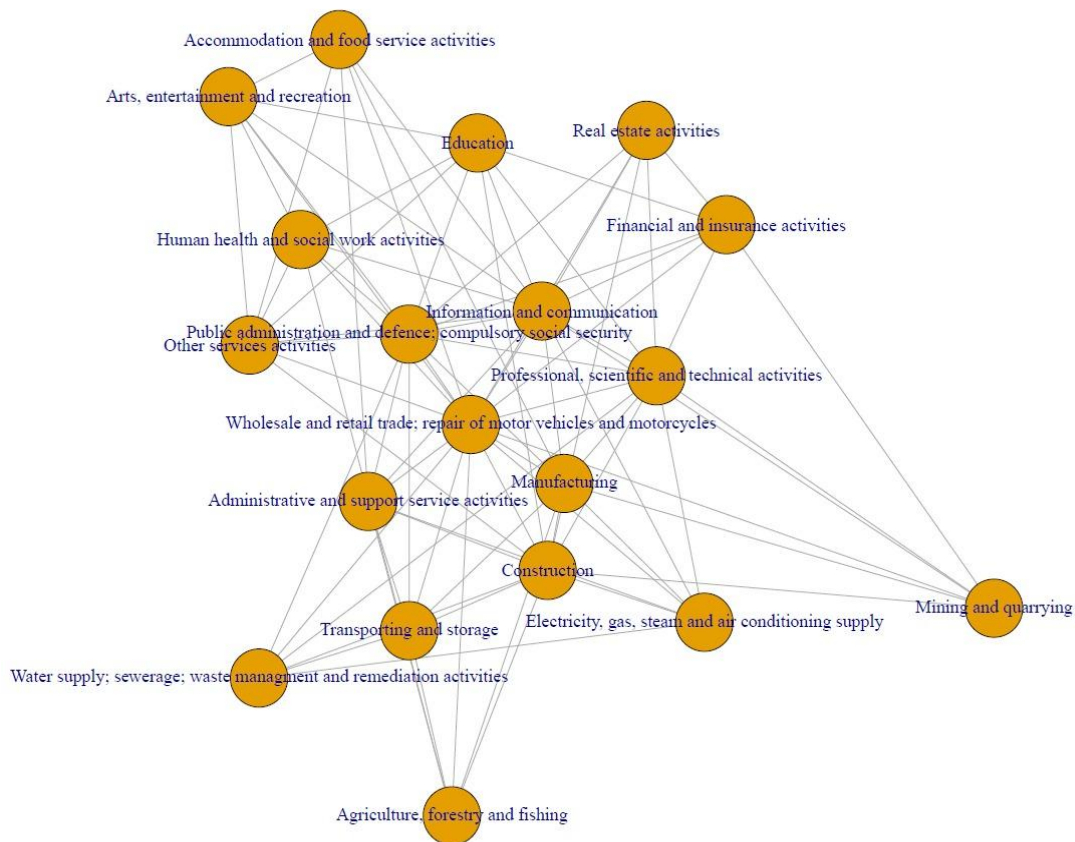
First, we have to compute the relatedness between industries in the Netherlands. To this end, we calculate the degree of skill-relatedness between industries following Neffke and Henning (2013), making use of the richness of the linked employer-employee data. Industries are considered skill-related when they share similar skill requirements. This can be identified by looking at the intensity of labor flows between industries. When many workers change jobs

¹ We checked and can confirm that the distribution of patent specializations in the Netherlands is indeed more concentrated than that of industry specializations.

² The Dutch Statistical Office defined COROP regions on commuting flows (CBS 2023). In one of our robustness checks, we further test for possible spatial effects through spatial econometric modelling. Our results are consistent.

between two industries, we assume the skills of these workers are in high demand in both industries. We used the CBS micro-data 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 1 presents the skill space of 1-digit industries in the Netherlands. As is typical for a skill space, some industries such as Information and Communication are skill-related with many industries, while some industries like Agriculture, Fishery and Forestry are positioned more in the periphery of this network. In the remaining part, our data and analyses are based on 265 3-digit industry data, allowing us to measure the skill-space at a more fine-grained industry scale.

Figure 1. Skill space of the Netherlands for 1-digit industries, 2019-2020



Second, we linked employees to their job location (NUTS-3 level). We used this information to 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 observe changes in the specialization patterns over time to identify industries that have entered and exited a region.

Using binary variables to capture entry (and exit) is a common approach in the evolutionary literature on relatedness (Boschma 2017) as it allows to capture when an industry becomes significantly present (or no longer present) in a region. We do so by comparing the vector of sectoral specializations for the same region over a period of time. If a specialization in industry i was not present in region r at time $t-3$, but it became present at time t , we consider it as an entry. An exit would occur if a specialization in industry i and region r is “lost” between time $t-3$ and time t . Our measures of entry and exit are binary, so they take value 1 when entry or exit occurs, 0 when it could occur but did not³.

To understand the role of relatedness linking industrial dynamics and inequality, we combine the information on entry and exit with the skill relatedness matrix derived from information on job switchers. As the skill-relatedness matrix is not symmetric (labor flows from industry A to industry B is not necessarily the same as that from industry B to industry A), we take the average score between two industries as a measurement of their relatedness. This allows us to create a symmetric matrix. We further split the skill relatedness matrix in two mutually exclusive 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). We compute the top and bottom deciles in the relatedness scores of each industry and apply those as thresholds to define relatedness (top 10 percentile) and unrelatedness (bottom 10 percentile)⁴. For every industry i in region r at time t , we first measure how related (or unrelated) each industry is to existing specializations in the region as follows:

$$reld_{i,r,t} = \sum_j \mu_{i,j} * spec_{j,r,t} \text{ for } i \neq j \text{ (1a)}$$

$$unrd_{i,r,t} = \sum_j \nu_{i,j} * spec_{j,r,t} \text{ for } i \neq j \text{ (1b)}$$

³ As a robustness check, we also consider a 5-year time difference (e.g. 2015 and 2010) rather than a 3-year one. The choice of using 3- and 5-year periods is based on providing enough time for observing dynamics of specializations while ensuring a suitable number of observations in our model.

⁴ The choice of using deciles rather than other cutoffs is due to the fact the skill-relatedness matrix is rather sparse (about 50% of the cells are 0), making the sectoral distribution of skill relatedness skewed. As a result, the difference between using 0 as a cutoff or quartiles as thresholds is minimal.

where $\mu_{i,j}$ ($\nu_{i,j}$) measures the pairwise skill relatedness (unrelatedness) between sector i and sector j . We then filter the observations in the vector $reld_{i,r,t}$ ($unrd_{i,r,t}$) keeping only industries that have entered (or exited) region r at time t . We do so as shown below:

$$ren_{i,r,t} = en_{i,r,t} * reld_{i,r,t} \quad (2a)$$

$$uen_{i,r,t} = en_{i,r,t} * unrd_{i,r,t} \quad (2b)$$

with the $en_{i,r,t}$ being the entry vector binarily identifying which industries have entered region r at time t . The variable $ren_{i,r,t}$ captures the how related each entry is to existing specializations of the regions, while $uen_{i,r,t}$ measures the unrelatedness of each entry to existing specializations. However, the same entering industry i in region r at time t can have non-zeros score for both related ($ren_{i,r,t}$) and unrelated entry ($uen_{i,r,t}$) since matrices \mathbf{M} and \mathbf{N} are mutually exclusive⁵. To unambiguously define whether an entry is related or unrelated, we compare the two values of the two variables:

$$rel_entry_{i,r,t} = \begin{cases} 1, & \text{if } ren_{i,r,t} > uen_{i,r,t} \\ 0, & \text{otherwise} \end{cases} \quad (3a)$$

$$unr_entry_{i,r,t} = \begin{cases} 1, & \text{if } uen_{i,r,t} > ren_{i,r,t} \\ 0, & \text{otherwise} \end{cases} \quad (3b)$$

Further, we explore the role of complexity in the relation between industrial dynamics and inequality. To this end, we use information on sectoral specializations in the Netherlands using our LEED database to compute a measure of economic complexity for each industry. To limit the chances of spurious fluctuations in the complexity score across the years, we define the average level of employment for each sector in each municipality⁶ across the years and apply the eigenvector method to estimate complexity (Balland 2018). As shown in Table 10 Appendix A.7, more knowledge-intensive industries report a higher score of economic

⁵ For instance, the chemical industry may be related to the food industry if many people switch from one industry to the other, and, at the same time, being unrelated to the construction industry (if there are few switches between those two).

⁶ The choice of using municipalities rather than NUTS3 regions comes from the importance of having a high number of cross-sectional units for the method to work effectively. Using only the 40 NUTS3 regions in the Netherlands would not have been sufficient.

complexity⁷. We also define binary variables for high and low complexity industries based, respectively, on the top and bottom decile of the complexity index. As a robustness check, we also took as thresholds the top 20 and bottom 20 percentiles. Using the entry and exit vectors, we build

$$ECI_entry_{i,r,t} = en_{i,r,t} * ECI_i \quad (4a)$$

$$HECI_entry_{i,r,t} = en_{i,r,t} * high_ECI_i \quad (4b)$$

$$LECI_entry_{i,r,t} = en_{i,r,t} * low_ECI_i \quad (4c)$$

which respectively measure the complexity level of each entry (or exit) (4a), and whether each entry (or exit) refers to a high or low complexity industry (4b and 4c)⁸.

Since our focus is on studying regional-level inequality, we aggregate the variables (e.g. entry, related and unrelated entries, high and low complexity entries, etc.), obtaining different measures of industrial dynamics varying by NUTS3 and year. We replicate the same approach when computing the variables concerning industrial exits.

Finally, the micro data from CBS provides information on individual wages and work location, which we use to construct our dependent variable. As we are mostly interested in studying inequality across regions, our baseline analysis will use the Gini coefficient as dependent variable. The Gini coefficient is the most widely used measure of inequality and captures the deviation of the observed income distribution from a theoretically perfectly equal benchmark, allowing to effectively compare inequality across regions (Buitelaar et al. 2018). However, as Gini coefficient may have a nonnegligible downward bias when comparing inequality among subsamples (Deltas 2003), for robustness checks, we also use the widely used Theil index which is based on the regional wage distribution⁹.

⁷ The table reports the scores for the bottom two and top two deciles. The table with the complexity score for each industry is available upon request.

⁸ The approach of categorizing variable in low- and high-complexity industries allows us to simply allocate entries (and exits) into specific sub-groups, which sum up to the actual number of entries (and exits).

⁹ We use the Gini coefficient as our dependent variable because of its properties, especially with respect to its comparability across regions with different populations and its upper bound (Buitelaar et al. 2018). The properties of alternative variables are different. For instance, the Theil index is sensitive to population size and has no upper

Econometric model

The objective of our analysis is to explore the relation between intra-regional inequality and industrial dynamics. To this end, we regress region-wide measure of inequality on the number of entries (and exits) in each region, characterizing sectoral dynamics on the basis of their relatedness and complexity. In its most simple form, we estimate the following model:

$$ineq_{rt} = \beta_0 + \alpha * entry_count_{rt} + \delta * C_{rt} + \rho_r + \tau_t + \epsilon_{it}(12)$$

where the dependent variable $ineq_{rt}$ represents the score of the Gini coefficient in region r at time t , while $entry_count_{rt}$ (and $exit_count_{rt}$) are respectively the total count of entries (and exits) in region r and time t . We further specify the role of industrial dynamics by modelling the count of related and unrelated entries (and exits), total complexity of entries (and exits) and the count of high- and low-complexity entries (and exits), also for both related and unrelated entries (and exits). We also include various control variables (C), capturing different socio-demographic and economic characteristics of Dutch regions. In terms of socio-demographic features, we control for total population, unemployment level and foreign-born population. The inclusion of these variables allows us to account for differences across COROP regions in terms of size and lower income groups (unemployed, foreign population), which are often associated with higher levels of inequality (Moretti 2010; Eeckhout et al. 2014; Lee and Clarke 2019; Kemeny and Storper 2020). We also control for various characteristics of the regional economy, such as the local levels of human capital (proxied by the number of university graduates) and average income (captured by GDP per capita) (Lee and Rodriguez-Pose 2013; Balland and Rigby 2017). We further control for other potentially relevant factors, such as exposure to company failures (number of companies gone bankrupt) and level of self-employment (share of self-employed full-time equivalent (FTE) over total FTE). Finally, we exploit the panel setup of our data and add region (ρ_r) and time (τ_t) fixed effects.

Data and descriptives

Table 1 below reports the descriptive statistics for the variables used in our analysis. Interestingly, the numbers of entries and exits have very similar distributions, with the average Dutch region recording about 7 entries and exits per 3-year period. Related entries and exits,

bound, while the Coefficient of Variation is sensitive to extreme values and has no upper bound either (for a short and comprehensive discussion of the different measures, see Trapeznikova 2019).

as expected, occur more frequently than unrelated ones, regardless of whether they belong to the high or low complexity category. In Appendix A1, we present the spatial distribution of the average number of entries and exits during the period 2010-2019 across the 40 COROP regions of the Netherlands. To complete the description of our data, we report the pairwise correlation for the same variables in Table 9 in Appendix A6.

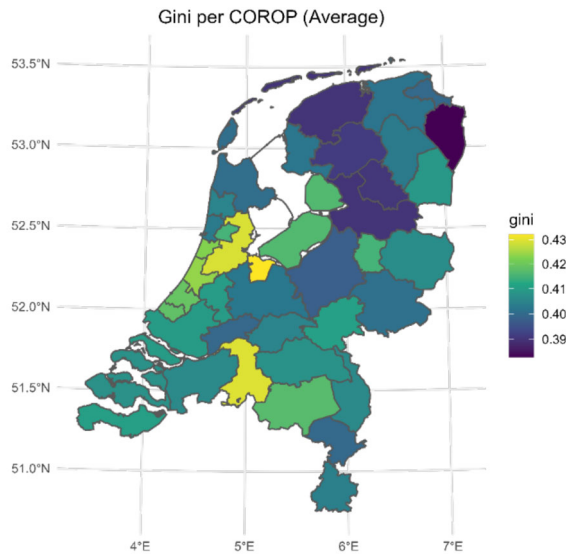
Table 1. Descriptive statistics

	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
Gini	0.407	0.014	0.369	0.439
Entry	6.921	2.696	1	16
Rel. Entry	4.336	2.263	0	11
Unr. Entry	2.586	1.743	0	8
Total ECI Entry	0.026	0.044	-0.062	0.187
Count HECI Entry	0.554	0.736	0	3
Count LECI Entry	0.568	0.805	0	3
Count R-HECI Entry	0.400	0.626	0	3
Count U-HECI Entry	0.154	0.399	0	2
Count R-LECI Entry	0.389	0.694	0	3
Count U-LECI Entry	0.179	0.402	0	2
Exit	7.029	2.745	1	16
Rel. Exit	4.557	2.362	0	15
Unr. Exit	2.471	1.615	0	8
Total ECI Exit	0.026	0.049	-0.114	0.179
Count HECI Exit	0.593	0.850	0	4
Count LECI Exit	0.600	0.890	0	6
Count R-HECI Exit	0.446	0.731	0	4
Count U-HECI Exit	0.146	0.393	0	2
Count R-LECI Exit	0.411	0.733	0	5
Count U-LECI Exit	0.189	0.436	0	3
Univ. grad.	1,694.589	2,520.103	19	12,9
Unemployed (000)	13.704	12.409	1	68
Failures	157.707	138.654	4	703
Migrant pop.	4,495.868	5,632.860	303	38,07

Total pop.	314.854	244.225	35	1,058
Self-employed share	0.179	0.029	0.125	0.280
GDP pc	34,769.220	9,110.919	18,008	79,831

Figure 2 shows a map of the average Gini coefficient in all 40 regions. There are clear differences in wage inequalities across Dutch regions although these are not that marked (see also PBL 2016). Wage inequality levels are most pronounced in the Northern part of the Randstad area: Groot-Amsterdam and its neighboring regions such as Gooi en Vechtstreek show the highest scores, as well as Midden Noord-Brabant region in the South. Relatively low levels of wage-inequality can be found in the Northern part of the Netherlands, such as Oost-Groningen, Noord-Friesland, Zuidoost-Friesland, Zuidwest-Drenthe and Noord-Overijssel. We also calculated the Theil index for all regions which is an alternative inequality measure widely used. As shown in Appendix A2, the map of the Thiel index looks very similar to the one of the Gini coefficient.

Figure 2. Map of wage-inequality 2010-2019 (average Gini coefficient)



Regression analysis

We regress level of wage inequality (Gini coefficient) on entries/exits that occurred in that region in the same three-year period during 2010-2019 for 7 overlapping periods (2010-2013,

2011-2014, 2012-2015, 2013-2016, 2014-2017, 2015-2018 and 2016-2019). This means we have a total of 280 observations (40 regions x 7 periods). It is common to study entry-exit dynamics in industries taking a specific time interval, as entries and exits are rare events per year. In most studies on regional diversification, 5-years intervals are taken (Boschma 2017). The choice of the 3-year period in our study is to secure a substantial number of observations, as we study only a relatively short time period. To ensure the robustness of our findings, we also conducted analysis using 5-year intervals.

Table 2 presents the findings for entries. We find a negative relationship between entry and levels of inequality: the higher the number of entries in a region, the lower wage inequality. This is true for related but not unrelated entries (Model 2), even though the coefficient for related entries is only weakly significant (at 10% level). There is no relationship between the complexity level of entries and the Gini coefficient: the coefficient in Model 3 is positive but not significant. This is despite the fact that there is a positive correlation of 0.34 between the Economic Complexity Index and the Gini coefficient in a region (as shown in Appendix A3), and a positive correlation of 0.37 between the mean wage level of an industry and its complexity (as shown in Appendix A4). This latter outcome confirms results of other studies: complex regions have higher wage inequality levels (e.g. Hartmann and Pinheiro 2022).

However, we found in Model 4 that less complex entries tend to reduce the level of inequality, especially when it concerns related but also unrelated entries (Model 5). This is an intuitive result, as lower salaries are paid in less complex industries, as compared to more complex industries, and entry in more complex industries does not reduce inequality, while low-complex entries do. We did not find a positive relationship between related complex entries and intra-regional inequality, which might suggest that complex entries do not pay higher wages on average when they have to compete with other related industries in the region.

Table 2. Relationship between Entry and Gini coefficient

	(1)	(2)	(3)	(4)	(5)
Entry	-0.0003* (0.0001)				
Related entry		-0.0003* (0.0002)			
Unrelated entry		-0.00005 (0.0002)			
ECI entry			0.011		

			(0.009)		
HECI entry				-0.0004 (0.0004)	
LECI entry				-0.001** (0.001)	
R-HECI entry					-0.0003 (0.0004)
U-HECI entry					-0.001 (0.001)
R-LECI entry					-0.001* (0.001)
U-LECI entry					-0.001** (0.0005)
Univ. graduates (log)	-0.011** (0.004)	-0.012** (0.004)	-0.011** (0.004)	-0.010** (0.004)	-0.010** (0.004)
Unemployed (log)	-0.009* (0.005)	-0.010* (0.005)	-0.009* (0.005)	-0.009* (0.005)	-0.009* (0.005)
Failures (log)	-0.002 (0.002)	-0.002 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Migration pop. (log)	-0.003* (0.002)	-0.003* (0.002)	-0.003* (0.002)	-0.003** (0.002)	-0.003* (0.002)
Total pop. (log)	0.197*** (0.047)	0.200*** (0.047)	0.207*** (0.044)	0.198*** (0.043)	0.197*** (0.042)
Self-employed share	-0.095 (0.075)	-0.104 (0.073)	-0.105 (0.080)	-0.102 (0.074)	-0.105 (0.074)
GDP pc	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Proj. R2	0.247	0.254	0.24	0.269	0.271
NUTS3 FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	280	280	280	280	280
R2	0.930	0.931	0.930	0.932	0.932
Adjusted R2	0.914	0.914	0.913	0.916	0.915

Clustered standard errors at NUTS3 level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3 summarizes the results in the case of exits. The main outcome is that we did not find a significant relationship between exit and wage inequality at the regional level. There is one exception to this interesting outcome though. Model 4 shows that exits of low-complex industries tend to increase inequality, especially when it concerns low-complex unrelated exits, as shown in Model 5. This is a plausible result, as the displaced workers may have to accept lower wages, because they are likely to find jobs in other local low-complex industries where their skills are of little value, as these are unrelated to the industry they worked for before (Eriksson et al. 2016; Holm et al. 2017).

Table 3. Relationship between Exit and Gini coefficient

	(1)	(2)	(3)	(4)	(5)
Exit	0.00000				

	(0.0001)				
Related exit		-0.00004 (0.0001)			
Unrelated exit		0.0001 (0.0002)			
ECI exit			-0.008 (0.007)		
HECI exit				-0.0001 (0.0004)	
LECI exit				0.001* (0.0004)	
R-HECI exit					-0.0004 (0.0004)
U-HECI exit					0.001 (0.001)
R-LECI exit					0.001 (0.0005)
U-LECI exit					0.001* (0.001)
Univ. graduates (log)	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.012*** (0.004)
Unemployed (log)	-0.010* (0.005)	-0.010* (0.005)	-0.010* (0.005)	-0.010* (0.005)	-0.011** (0.005)
Failures (log)	-0.002 (0.002)	-0.002 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.001 (0.002)
Migration pop. (log)	-0.003* (0.002)	-0.003* (0.002)	-0.003* (0.002)	-0.003 (0.002)	-0.003 (0.002)
Total pop. (log)	0.204*** (0.045)	0.201*** (0.045)	0.201*** (0.046)	0.198*** (0.045)	0.195*** (0.046)
Self-employed share	-0.110 (0.078)	-0.106 (0.079)	-0.114 (0.078)	-0.114 (0.075)	-0.107 (0.074)
GDP pc	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
Proj. R2	0.234	0.234	0.238	0.247	0.255
NUTS3 FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	280	280	280	280	280
R2	0.929	0.929	0.929	0.930	0.931
Adjusted R2	0.912	0.912	0.913	0.917	0.914

Clustered standard errors at NUTS3 level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The coefficients for our models seem relatively small in size. For example, in Table 2, model (1), for each unit increase in “Entry”, the Gini coefficient decreases by 0.0003 on average, holding all other variables constant. While the coefficient may appear small, it is crucial to recall that the Gini coefficient ranges between 0 (perfect equality) and 1 (perfect inequality). Therefore, even small changes can have meaningful effects on the wage distribution.

Robustness checks

Three robustness checks have been performed to assess the solidity of our findings. We focused on the dependent variable (using the Theil index, rather than the Gini coefficient; using the lag

1 year variable of inequality measures), the length of the time window we used (5-year period in the robustness checks, 3-year window in the baseline), on different specifications of the variables for relatedness and complexity and on possible spatial effects. Findings are reported in Table 4-8 in Appendix A5. We included the control variables in all regressions in the robustness checks, but for sake of brevity, we did not report the coefficients. Broadly speaking, our key findings are confirmed in the robustness analyses, but there are some exceptions that are discussed in Appendix A5¹⁰.

Concluding remarks

This explorative study on Dutch regions has shown that entry in low-complex industries that are skill-related to existing local industries tends to reduce wage inequality in a region. We observe no significant relationship between exit of industries and intra-regional inequality, with one exception: unrelated low-complex exits tend to increase wage inequality in regions. Overall, these findings might suggest that diversification (entry), and possibly related diversification (related entries) in less complex industries might bring benefits to regions in terms of inclusive growth (lower wage inequality), while unrelated exits in less complex industries might tend to do the opposite (higher wage inequality). Even though with some differences, the general finding about low-complexity entries and exits is confirmed in our robustness checks.

Having said this, it is good to remind that any study opens up many new questions, and this paper is no exception to that rule. First of all, we have to be cautious not to jump into too strong conclusions based on this single study, as the relationship between industrial dynamics and inequality at the regional level is a highly complex one. While our findings may be promising, it is just based on one single case study on the Netherlands. This enabled us to use micro-data in which we could link more closely the relationship between industrial dynamics and wage inequality at the regional level under the same set of national institutions. A logical next step is to replicate these findings in other countries, such as the US where the institutional set-up is very different and inequalities are more pronounced.

¹⁰ The main differences between robustness checks and baseline regressions pertain the level of significance rather than the sign of the coefficients. Specifically, when using 5-year time interval, the variable Related entry turns non-significant while Unrelated entries become significant. Defining relatedness and complexity in a stricter way negatively affects the significance of the coefficients for related entry (Related entry) and low-complexity entry (LECI entry).

This paper has also been explorative and descriptive rather than explanatory. Therefore, future research should focus on theory development and derive clear hypotheses and study possible mechanisms behind our findings. This need for further research also concerns some of our findings, such as to why related entry of industries reduces intra-regional wage inequality. That this also applied to related diversification in less complex industries was more intuitive, as lower salaries are paid in less complex industries. We do indeed find that entry in more complex industries does not reduce inequality, while low-complex entries do, but this requires further investigation. Another key finding was that unrelated low-complex exits tend to increase wage inequality in regions. This is in line with literature on displaced workers and the reallocation of their skills (Holm et al. 2017). In that context, future research should explore more in detail (using micro-data) for all unrelated low-complex exits how the displaced workers were actually re-allocated (to which industries), and how that affected their wage levels after the shock, in order to understand more fully how this affected wage inequality in the respective regions. What is still left to do for further research as well is to investigate whether industrial dynamics have different effects on intra-regional wage inequality in high- versus low-income regions. Using a more fine-grained perspective would also allow to model with greater attention the spatial dimension of inequality and industrial dynamics.

We also did not investigate what could be the effect of inter-regional linkages on intra-regional wage inequalities, such as inflows of labor (immigration), goods (imports) and foreign multinationals. Each of those have been investigated extensively in the literature (e.g. Rigby et al. 2017; Cortinovis et al. 2020; Crescenzi et al. 2022) but not so much their effects on intra-regional wage inequality. An exception is Breau and Rigby (2010) who found a negative effect of import competition from low-income countries on wages of less-skilled workers in Canadian regions, increasing wage inequality. We also did not investigate whether multiplier effects might affect inequality levels within regions (Moretti 2010; Florida 2017; Lee and Clarke 2019). For instance, entries of complex high-wage sectors might create demands for jobs in low-complex low-paid industries. Institutional factors are also likely to determine inequality levels, not only at the national scale (Hartmann and Pinheiro 2022) but also at the regional scale. This requires comparative research across regions in different countries which is not easy given the severe limitations of data comparability across those units at the micro-scale. For instance, at the European level, such detailed regional data in which industry data can be linked to wages of individuals and their locations are not available (Boschma et al. 2022).

This necessarily implies this study makes only a first small step to determine whether smart growth can, or cannot, be combined with inclusive growth (proxied as intra-regional inequality) at the regional scale. The latter is also true for yet another reason. Our study tends to indicate that related diversification in low-complex industries might be good for inclusive growth in regions, while Rigby et al. (2022) showed that related diversification in high-complex industries is best for smart growth in regions. This implies it remains challenging how to combine the two policy objectives in practice.

Based on the above discussion, we are reluctant to draw strong policy implications from our findings at this stage, given the many questions that remain to be answered. Having said that, our findings are still relevant for regional policy. Our point of departure was to throw more empirical light on the relationship between smart and inclusive growth. While there is a traditional policy focus on regional convergence/divergence (i.e. inter-regional inequality), for instance in Cohesion policy, little attention so far has been directed to intra-regional inequality. For instance, in Smart Specialization policy in the EU, there is hardly any mentioning of possible effects on intra-regional inequality when promoting smart growth (i.e. new entries). This implies an additional challenge has to be taken up by Smart Specialization policy, on top of aligning its policy objective of smart growth to the objective of Cohesion policy of inclusive growth in terms of narrowing inter-regional inequality (McCann and Ortega-Argilés 2015; Balland et al. 2019). While studies have shown that related diversification in complex industries enhances economic growth in regions (Rigby et al. 2022) but also inequality between regions (Pinheiro et al. 2022), our study suggests (related) diversification in less complex industries tends to reduce wage inequality within a region. This opens the question how policy should be designed to combine smart growth and these two dimensions of inclusive growth in regions.

This implies that policy actions in Smart Specialization policy should account for implications for intra-regional inequality. When setting priorities, one could apply a third criterion (do they reduce wage inequality) besides relatedness (do they build on relevant capabilities in the region) and complexity (do they increase the complexity of the regional economy) to identify diversification opportunities in regions. This implies policy should make an effort to assess the types of jobs (skills, wages) that those priorities are likely to generate in the region. Second, this is especially important for European regions that are being trapped (Diemer et al. 2022) or

left behind (Rodríguez-Pose 2018; Dijkstra et al. 2020) which are confronted with huge economic and social problems. This implies it is crucial that this priority-setting targets the specific needs of the low-skilled and unemployed in these regional settings, so to ensure that regional restructuring also provide solutions to those who are most in need.

Another policy implication of this study is that promoting smart growth cannot be seen in isolation from exits of industries in regions and their socio-economic consequences. While the literature shows that unrelated exits in low complex activities favors economic growth in regions (Rigby et al. 2022), our study found these types of exits have a tendency to increase wage inequality in regions. This means these exits are not necessarily bad but policy intervention is needed to counterbalance this particular negative outcome. This is a serious policy issue that many old industrial regions have been confronted with in the past (Boschma and Lambooy 1999), but it is still on the policy agenda, especially in coal mining regions that go through major transitions (Alves Dias et al. 2018; Breul and Atienza 2022). It is still not entirely clear under what specific circumstances that can be accomplished, and what policy can do and how. Time has come to acquire more understanding on these matters, so as to contribute to more effective policy that accounts for multiple goals and challenges at the same time.

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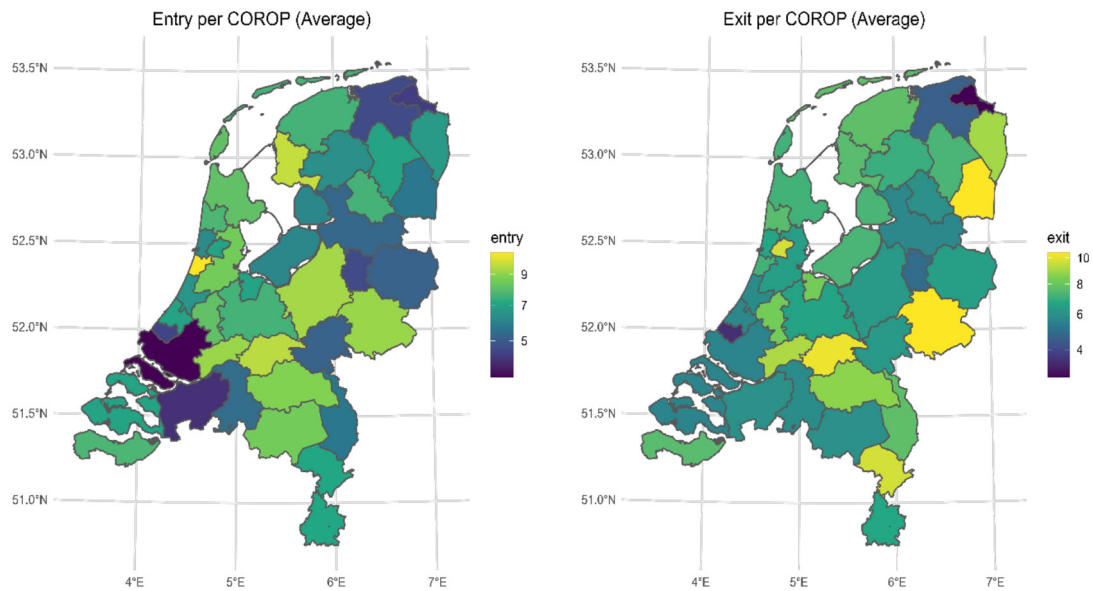
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Appendices

Appendix A1

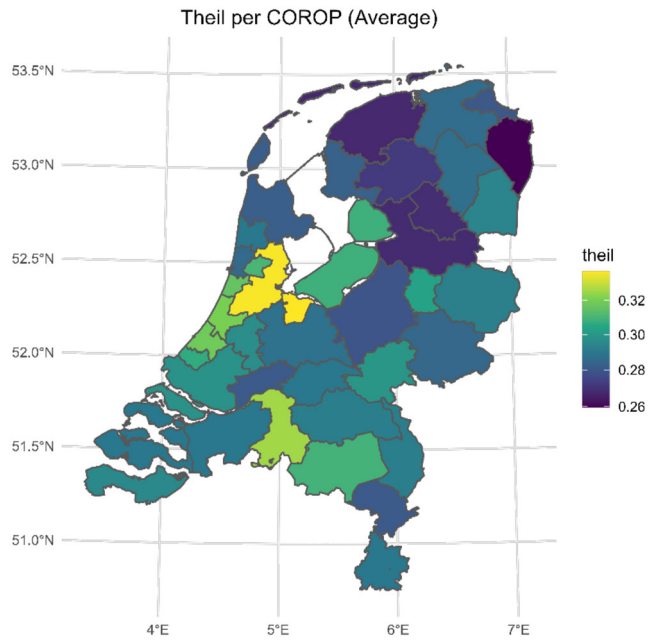
Map of entries (left) and exits (right) 2010-2019 (average 3 year overlapping periods)



The maps present the spatial distribution of the average number of entries and exits during the period 2010-2019 across the 40 COROP regions of the Netherlands. The highest numbers of entries occur outside the most urbanized regions, like in Agglomeratie Haarlem, Zuid-West Friesland, Zuid-West Gelderland, Veluwe and Achterhoek. The lowest numbers of entries are recorded in Groot-Rijnmond, West Noord- Brabant, Delft and Westland, Delfzijl en Omgeving, Overig Groningen, and Zuid-West Overijssel. The highest numbers of exits concentrate outside the most urbanized regions, such as Achterhoek (also scoring high on entries), Zuid-Oost Drenthe, Zuid-West Gelderland (also scoring high on entries) and Zaanstreek. The lowest numbers of exits happen in Delfzijl en Omgeving, Overig Groningen (both scoring low on entries) and Delft and Westland.

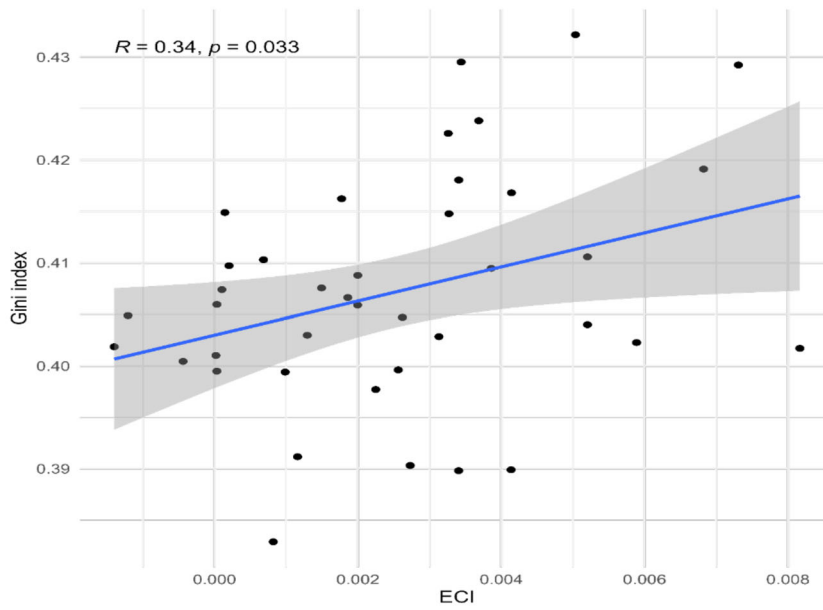
Appendix A2

Map of wage-inequality 2010-2019 (average Theil index)



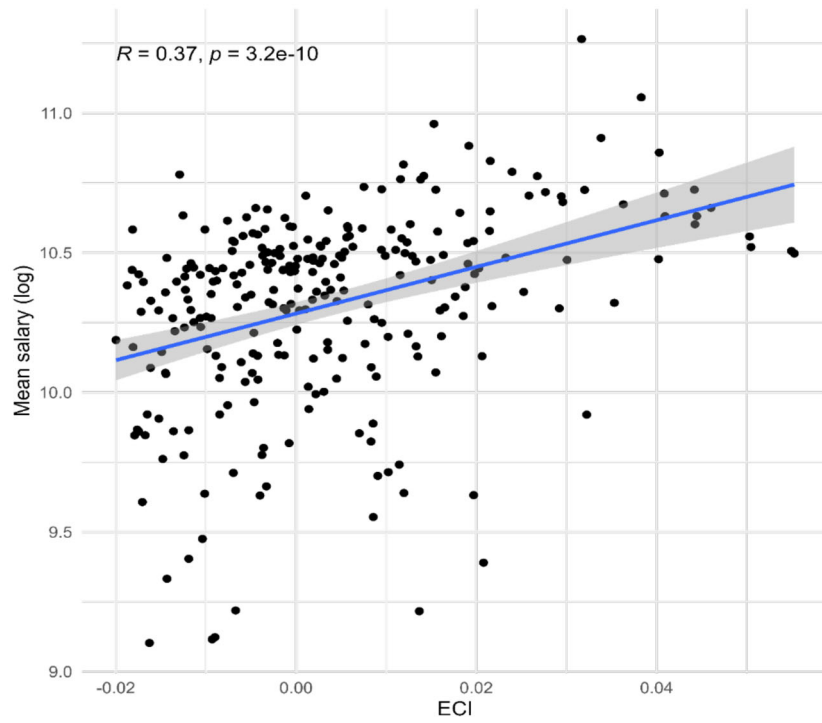
Appendix A3

Correlation between Gini coefficient and Economic Complexity index for 40 COROP regions



Appendix A4

Log Mean Wage and Economic Complexity index by industry



Appendix A5 Robustness checks

Table 4: Relationship between Entry and Exit and Theil-index

	Entry and Theil Index				Exit and Theil Index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Entry/Exit	-0.0004* (0.0002)				0.00000 (0.0002)			
Rel. Entry/Exit		-0.0005* (0.0003)				-0.00000 (0.0002)		
Unr. Entry/Exit		-0.0001 (0.0002)				0.00002 (0.0003)		
Count HECI Entry/Exit			-0.001 (0.001)				-0.0001 (0.001)	
Count LECI Entry/Exit			-0.002* (0.001)				0.001 (0.001)	
Count R-HECI Entry/Exit				-0.0005 (0.001)				-0.001 (0.001)
Count U-HECI Entry/Exit				-0.001 (0.002)				0.001 (0.001)
Count R-LECI Entry/Exit				-0.002* (0.001)				0.001 (0.001)
Count U-LECI Entry/Exit				-0.001* (0.001)				0.002* (0.001)
Proj. R2	0.23	0.237	0.247	0.248	0.217	0.217	0.226	0.233
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS3 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	280	280	280	280	280	280	280	280
R ²	0.937	0.938	0.939	0.939	0.936	0.936	0.937	0.938
Adjusted R ²	0.923	0.923	0.924	0.924	0.921	0.921	0.922	0.922

Clustered standard errors at NUTS3 level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The first check considers the use of the Theil-index as dependent variable, another measure of inequality widely used in the literature (Trapeznikova 2019). Table 4 reports the results for the most relevant models for both entry and exit. Specifically, columns 1 to 4 in Table 4 focus on entries and are the analog to columns 1, 2, 4 and 5 in Table 2. Columns 5 to 8 in Table 4 focus

on exits and should be compared to columns 1, 2, 4 and 5 in Table 3. The results of Table 4 are well aligned with our previous findings: entry is associated with a lower Theil index (column 1), due to related entries (column 2). When splitting entries across levels of complexity and relatedness, we find that a higher number of low-complex entries – both related and unrelated – relates to lower levels of regional inequality (columns 3 and 4). As in the case of Table 3, the relations between exit dynamics and inequality are generally insignificant, with the exception of the number of unrelated and low-complex exits which is positively associated to regional wage inequality.

Table 5: Relationship between Entry and Exit with 5-year overlapping periods

	Entry with 5-year time intervals				Exit with 5-year time intervals			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Entry/Exit	-0.0004** (0.0002)				0.0001 (0.0001)			
Rel. Entry/Exit		-0.0004 (0.0002)				0.0002 (0.0001)		
Unr. Entry/Exit		-0.0003* (0.0002)				-0.00001 (0.0002)		
Count HECI Entry/Exit			-0.0001 (0.0004)				0.0003 (0.0003)	
Count LECI Entry/Exit			-0.002** (0.001)				0.001*** (0.0004)	
Count R-HECI Entry/Exit				0.0002 (0.0004)				0.0001 (0.0005)
Count U-HECI Entry/Exit				-0.001 (0.001)				0.001* (0.0004)
Count R-LECI Entry/Exit				-0.002** (0.001)				0.001** (0.0005)
Count U-LECI Entry/Exit				-0.001* (0.001)				0.002*** (0.0003)
Proj. R2	0.172	0.172	0.248	0.26	0.137	0.14	0.185	0.189
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS3 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	200	200	200	200	200	200	200	200
R ²	0.935	0.935	0.941	0.942	0.933	0.933	0.936	0.937

Adjusted R ²	0.913	0.912	0.920	0.921	0.909	0.909	0.914	0.913
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Clustered standard errors at NUTS3 level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

We also evaluated whether the length of the time period used to study entries and exits affect our results. Given our sample covers the period between 2010 and 2019¹¹, the choice of the time window has two implications. On the one hand, a longer time window reduces the number of observations we have in our regressions. On the other hand, longer time periods allow for more entries and exits. Using 5-year periods allows us to keep a reasonable number of periods in our sample for running the panel data models (5 periods for a total of 200 observations) while expanding the time dimension for entries and exits. Table 5 reports the results for both regressions on entry and exit using 5-year intervals and can be directly compared to Tables 2 and 3. Also in this case, the robustness checks largely confirm the findings of our baseline, with two differences. First, the baseline suggested a role for related entries in reducing inequality, while our robustness check indicates regions with higher number of unrelated entries tend to have lower levels of inequality. As for the finding in our baseline, this effect is only weakly significant, limiting the possibility to draw strong conclusions from it. Second, using a 5-year period provides some more results with respect to exit dynamics, with low-complex exits (column 7 in Table 5), either related or unrelated (column 8 in Table 5), associated with higher levels of wage inequality, as we would expect. Interestingly, exits of high-complexity and unrelated industries are also associated with higher levels of the Gini coefficient. These results are interesting because they suggest the impact of entries and exits may require different time span to become visible.

Table 6: Robustness checks on entries

	(1)	(2)	(3)	(4)	(5)
Rel. Entry (Q)	-0.0003 (0.0002)				
Unr. Entry (Q)	-0.0002 (0.0001)				
Log. Rel. Entry (S)		-0.002* (0.001)			
Count HECI Entry (20)			0.0001		

¹¹ The time dimension in our sample is influenced by data constraints, since Statistics Netherlands does not allow to match individuals to locations before 2010.

			(0.0003)		
Count LECI Entry (20)			-0.001 (0.0004)		
Count R(Q)-HECI Entry				-0.0002 (0.0004)	
Count U(Q)-HECI Entry				-0.001 (0.001)	
Count R(Q)-LECI Entry				-0.001* (0.001)	
Count U(Q)-LECI Entry				-0.002*** (0.001)	
Count R(Q)-HECI Entry (20)					0.0002 (0.0003)
Count U(Q)-HECI Entry (20)					0.0001 (0.001)
Count R(Q)-LECI Entry (20)					-0.0005 (0.0004)
Count U(Q)-LECI Entry (20)					-0.001*** (0.0004)
Proj. R2	0.248	0.255	0.253	0.275	0.262
Control var.s	Yes	Yes	Yes	Yes	Yes
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	280	280	280	280	280
R ²	0.930	0.931	0.931	0.933	0.932
Adjusted R ²	0.914	0.915	0.914	0.916	0.914

Clustered standard errors at NUTS3 level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We also tried to replicate our findings using different ways to define relatedness and unrelatedness as well as high- and low-complexity industries. Specifically, in our robustness checks we defined two industries as related if their pairwise skill-relatedness score is above the top 10th percentile of the skill-relatedness scores for that industry. Conversely, two industries are unrelated if the intensity of their pairwise relation is below the bottom 10th percentile of industry skill-relatedness distribution. As an alternative, we also rescaled the skill-relatedness score so that it takes values between 0 and 1, and for every region we simply sum the relatedness between entries (and exits) to the other industries in which the region is specialized. In this way, the variables *Log. Rel. Entry (S)* and *Log. Rel. Exit (S)* account for the total

relatedness of entries and exits in each region, in each time period. Finally, concerning the complexity of entries and exits, we define an industry as high-complexity if its economic complexity score is in the top 20th percentile, and as low-complexity if its score is lower than the bottom 20th percentile¹².

The robustness checks for entries and exits are reported in Tables 6 and 7. Column 1 in Table 6 reports the coefficients for related and unrelated entries defined based on the top and bottom 10th percentiles of skill-relatedness in each industry. While both coefficients are negative, none of the two is significant. Our previous findings on relatedness, however, are more aligned with the robustness check in column 2 of Table 6, which suggests regions with higher total relatedness of entries experience a reduction in the level of inequality. Another difference compared to our baseline is that, using a broader definition of high- and low-complexity industries, makes the coefficient for *Count LECI Entry* turn insignificant (column 3 of Table 6). This also represents an interesting finding as it shows that the inequality-reducing impact of low-complexity industries pertains to industries characterized by very low level of complexity. Finally, the coefficients reported in columns 4 and 5 of Table 6 provide an overall confirmation of our previous findings. Low-complex entries, either related but especially the unrelated ones, are important in driving down intra-regional inequality.

Table 7: Robustness checks on exits

	(1)	(2)	(3)	(4)	(5)
Rel. Exit (Q)	0.0001 (0.0001)				
Unr. Exit (Q)	-0.0002 (0.0002)				
Log. Rel. Exit (S)		-0.001 (0.001)			
Count HECI Exit (20)			-0.0001 (0.0002)		
Count LECI Exit (20)			0.0003 (0.0003)		
Count R(Q)-HECI Exit				-0.001	

¹² As a reminder, the baseline specification defined two industries as (un)related if their pairwise skill-relatedness core was above (below) zero. Besides, in the baseline models we used the top and bottom 10th percentiles for categorizing entries in high- and low-complexity, respectively.

				(0.0005)	
Count U(Q)-HECI Exit				0.001 (0.001)	
Count R(Q)-LECI Exit				0.001 (0.0005)	
Count U(Q)-LECI Exit				0.001* (0.001)	
Count R(Q)-HECI Exit (20)					-0.0002 (0.0003)
Count U(Q)-HECI Exit (20)					0.00003 (0.0004)
Count R(Q)-LECI Exit (20)					0.001 (0.0004)
Count U(Q)-LECI Exit (20)					-0.0004 (0.001)
Proj. R2	0.239	0.236	0.237	0.26	0.246
Control vars.	Yes	Yes	Yes	Yes	Yes
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	280	280	280	280	280
R ²	0.929	0.929	0.929	0.931	0.930
Adjusted R ²	0.913	0.913	0.912	0.914	0.913

Clustered standard errors at NUTS3 level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Our last robustness check (Table 8) concerns possible spatial effects and it is particularly focus in detecting possible bias induced by spatial autocorrelation or spatial dependency. Generally speaking, a spatial econometric model may make sense for the baseline models with the number of entry and exit as explanatory variables. However, the focus on relatedness makes the application of spatial models especially difficult. This is because what is related to the industrial structure of a region is not necessarily related to the industrial structure of a neighboring region. For instance, assuming Rotterdam is specialized in logistics, gaining a specialization in an industry related to logistics can have an impact on inequality in Rotterdam as a large part of the workforce in the area has relevant skills (e.g. people unemployed or under-paid in logistics may more easily find a new job). However, the logistics-related entry in Rotterdam cannot be considered as having an impact on inequality in The Hague – a city overwhelmingly specialized

in legal and administrative services – since the industry structure in the two regions is different. For this reason, we focus our robustness checks on the baseline models, only including entry and exit.

For our spatial econometric exercise, we use an inverse distance matrix and test three types of spatial models: the spatial autoregressive model (SAR/SAC), the spatial error model (SEM) and the spatial Durbin error model (SDE) (LeSage and Pace 2009). The results are largely consistent with our previous findings, with the main coefficients not deviating from our baselines and both the spatial autoregressive term (Lambda) and the spatial lag of entry and exit being largely insignificant. However, both in SEM and SDE capture some spatial dependency as the relevant coefficient (Rho) is negative and significant, suggesting that regression residuals follow some spatial pattern. Giving a convincing interpretation to this finding is rather complicated, since negative spatial dependency is less often encountered and overall understudied (Griffith and Arbia 2010, Griffith 2009). We speculate may be associated to specific spatial pattern of inequality, which tends to be a spatially concentrated and overwhelmingly urban phenomenon, unlike entry and exit dynamics.

Table 8: Robustness checks on spatial dependency and autocorrelation

	Entry- SAR	Entry-SEM	Entry-SDE	Exit- SAR	Exit-SEM	Exit-SDE
Entry/Exit	-0.00025**	-0.00024**	-0.00024**	0.00001	0.00001	0.00000
	(0.00011)	(0.00011)	(0.00011)	(0.00011)	(0.00011)	(0.00011)
Entry/Exit spatial lag			0.00000			0.00003
			(0.00018)			(0.00018)
Lambda	-0.03142			-0.04249		
	(0.06706)			(0.06776)		
Rho		-0.20488***	-0.20515***		-0.21520***	-0.21452***

	Entry- SAR	Entry-SEM	Entry-SDE	Exit- SAR	Exit-SEM	Exit-SDE
		(0.07491)	(0.07490)		(0.07485)	(0.07485)
Control var.	Yes	Yes	Yes	Yes	Yes	Yes
COROP FE	Yes	Yes	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	280	280	280	280	280	280
RSQ	0.930	0. 930	0. 930	0.929	0. 929	0. 929

Clustered standard errors at NUTS3 level in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

Appendix A6

Table 9: Correlation table

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
Gini	1																											
Entry	2	-0.09	1																									
Rel. Entry	3	-0.07	0.77	1																								
Unr. Entry	4	-0.04	0.55	-0.11	1																							
Total ECI Entry	5	0.17	0.13	-0.07	0.29	1																						
Count HECI Entry	6	0.01	0.22	0.13	0.17	0.69	1																					
Count LECI Entry	7	-0.17	0.40	0.44	0.05	-0.46	-0.08	1																				
Count R-HECI Entry	8	0.08	0.24	0.24	0.06	0.61	0.84	-0.03	1																			
Count U-HECI Entry	9	-0.10	0.03	-0.13	0.23	0.32	0.53	-0.09	-0.02	1																		
Count R-LECI Entry	10	-0.11	0.30	0.47	-0.15	-0.43	-0.06	0.87	0.003	-0.11	1																	
Count U-LECI Entry	11	-0.15	0.28	0.06	0.35	-0.17	-0.06	0.51	-0.07	0.01	0.01	1																
Exit	12	-0.08	0.21	0.18	0.10	-0.11	-0.01	0.23	-0.11	0.15	0.17	0.17	1															
Rel. Exit	13	-0.02	0.14	0.18	-0.02	-0.15	-0.02	0.24	-0.11	0.12	0.18	0.18	0.81	1														
Unr. Exit	14	-0.12	0.16	0.04	0.20	0.04	0.02	0.04	-0.03	0.08	0.03	0.03	0.51	-0.09	1													
Total ECI Exit	15	0.13	0.02	-0.08	0.13	0.33	0.24	-0.13	0.22	0.11	-0.16	0.01	0.01	-0.12	0.20	1												
Count HECI Exit	16	0.04	0.06	-0.03	0.13	0.26	0.21	0.004	0.17	0.13	-0.07	0.13	0.18	0.07	0.20	0.79	1											
Count LECI Exit	17	-0.07	0.06	0.09	-0.02	-0.19	-0.08	0.17	-0.10	0.01	0.10	0.16	0.43	0.40	0.15	-0.46	-0.10	1										
Count R-HECI Exit	18	0.05	0.04	0.01	0.05	0.27	0.19	-0.01	0.17	0.08	-0.06	0.08	0.17	0.15	0.06	0.72	0.89	-0.12	1									
Count U-HECI Exit	19	-0.02	0.05	-0.08	0.19	0.07	0.10	0.03	0.04	0.13	-0.04	0.13	0.07	-0.13	0.31	0.37	0.51	0.004	0.06	1								
Count R-LECI Exit	20	-0.01	0.002	0.07	-0.09	-0.19	-0.04	0.13	-0.05	-0.01	0.09	0.10	0.32	0.37	0.002	-0.42	-0.12	0.87	-0.13	-0.02	1							
Count U-LECI Exit	21	-0.14	0.12	0.07	0.10	-0.08	-0.08	0.12	-0.12	0.04	0.05	0.15	0.35	0.19	0.31	-0.23	0.01	0.57	-0.02	0.05	0.10	1						
Univ. grad.	22	0.29	-0.09	-0.11	0.002	0.42	0.18	-0.33	0.29	-0.11	-0.27	-0.20	-0.22	-0.20	-0.08	0.37	0.22	-0.27	0.31	-0.09	-0.23	-0.16	1					
Unemployed (000)	23	0.28	-0.12	-0.12	-0.03	0.36	0.17	-0.24	0.27	-0.10	-0.22	-0.10	-0.16	-0.12	-0.10	0.41	0.31	-0.22	0.39	-0.05	-0.16	-0.17	0.80	1				

Failures	24	0.24	-0.05	-0.05	-0.02	0.34	0.13	-0.19	0.24	-0.13	-0.18	-0.08	-0.12	-0.05	-0.13	0.33	0.23	-0.17	0.32	-0.11	-0.13	-0.12	0.75	0.91	1				
Migrant pop.	25	0.33	-0.06	-0.10	0.04	0.41	0.20	-0.27	0.27	-0.06	-0.23	-0.14	-0.17	-0.14	-0.08	0.41	0.34	-0.23	0.42	-0.04	-0.20	-0.15	0.84	0.85	0.74	1			
Total pop.	26	0.21	-0.05	-0.05	-0.01	0.40	0.20	-0.22	0.31	-0.13	-0.20	-0.10	-0.13	-0.08	-0.09	0.41	0.31	-0.21	0.40	-0.08	-0.17	-0.16	0.83	0.96	0.93	0.84	1		
Self-employed share	27	-0.15	0.24	0.14	0.19	-0.32	-0.08	0.29	-0.15	0.09	0.23	0.18	0.26	0.14	0.23	-0.25	-0.14	0.17	-0.22	0.12	0.10	0.19	-0.58	-0.55	-0.61	-0.51	1		
GDP pc	28	0.33	-0.09	-0.08	-0.04	0.41	0.19	-0.26	0.26	-0.06	-0.25	-0.09	-0.23	-0.17	-0.15	0.35	0.21	-0.23	0.29	-0.08	-0.16	-0.20	0.84	0.66	0.62	0.79	0.68	-0.63	1

Appendix A7

Table 10: Economic complexity scores by NACE Rev. 2 Sector

Decile 1		Decile 2		Decile 3		Decile 4	
NACE	ECI Score	NACE	ECI Score	NACE	ECI Score	NACE	ECI Score
Aquaculture	-0.02	Holiday and other short-stay accommodation	-0.0136	Manufacture of pesticides and other agrochemical products	0.0155	Hospital activities	0.0253
Demolition and site preparation	-0.0187	Manufacture of footwear	-0.0135	Other education	0.0155	Water collection, treatment and supply	0.0258
Other specialised construction activities	-0.0182	Forging, pressing, stamping and roll-forming of metal	-0.0133	Sea and coastal passenger water transport	0.0157	Manufacture of railway locomotives and rolling stock	0.0268
Support activities to agriculture	-0.0181	Activities of holding companies	-0.0129	Renting and leasing of motor vehicles	0.016	Steam and air conditioning supply	0.0277
Construction of residential and non-residential buildings	-0.0181	Construction of roads and railways	-0.0125	Gambling and betting activities	0.0161	Radio broadcasting	0.0292
Growing of non-perennial crops	-0.0179	Retail sale of automotive fuel in specialised stores	-0.0125	Manufacture of pulp, paper and paperboard	0.0163	Manufacture of cement, lime and plaster	0.0294
Mixed farming	-0.0176	Manufacture of other textiles	-0.0124	Translation and interpretation activities	0.0165	Freight rail transport	0.0296
Animal production	-0.0175	Silviculture and other forestry activities	-0.0123	Educational support activities	0.0177	Activities of business, employers and professional membership organisations	0.0301
Manufacture of structural metal products	-0.0174	Manufacture of bodies (coachwork) for motor vehicles	-0.0123	Research and experimental development on natural sciences and engineering	0.0182	Extraction of natural gas	0.0317
Manufacture of products of wood, cork, straw and plating materials	-0.0172	Electrical, plumbing and other construction	-0.0122	Other human health activities	0.0186	Freight air transport and space transport	0.032
Growing of perennial crops	-0.0171	Retail sale of food, beverages and tobacco in specialised stores	-0.0119	Combined facilities support activities	0.0188	Activities of call centres	0.0322
Building completion and finishing	-0.017	Repair of personal and household goods	-0.0119	Manufacture of irradiation, electromedical and electrotherapeutic equipment	0.019	Pension funding	0.0338
Plant propagation	-0.0167	Cutting, shaping and finishing of stone	-0.0117	Legal activities	0.0191	Manufacture of motor vehicles	0.0353
Camping grounds, recreational vehicle parks and trailer parks	-0.0165	Manufacture of metal forming machinery and machine tools	-0.0117	Support activities for petroleum and natural gas extraction	0.0192	Passenger air transport	0.0363
Retail sale via stalls and markets	-0.0163	Manufacture of plastics products	-0.0114	Postal activities under universal service obligation	0.0197	Extraction of crude petroleum	0.0383
Tanning and dressing of leather, manufacture of luggage	-0.0162	Wholesale of food, beverages and tobacco	-0.0113	Provision of services to the community as a whole	0.0197	Wireless telecommunications activities	0.0402
Wholesale of agricultural raw materials and live animals	-0.0161	Processing and preserving of fruit and vegetables	-0.0106	Other telecommunications activities	0.0198	Transport via pipeline	0.0403
Manufacture of bakery and farinaceous products	-0.0152	Sawmilling and planing of wood	-0.0106	Publishing of books, periodicals and other publishing activities	0.0203	Wired telecommunications activities	0.0409
Manufacture of furniture	-0.0152	Primary education	-0.0106	Private security activities	0.0206	Activities of trade unions	0.0409
Landscape service activities	-0.0149	Manufacture of weapons and ammunition	-0.0104	Other human resources provision	0.0208	Reinsurance	0.0442
Amusement and recreation activities	-0.0148	Manufacture of prepared animal feeds	-0.0101	Manufacture of military fighting vehicles	0.0215	Passenger rail transport, interurban	0.0443
Processing and preserving of fish, crustaceans and molluscs	-0.0145	Hotels and similar accommodation	-0.0101	Satellite telecommunications activities	0.0215	Insurance	0.0445

Treatment and coating of metals	-0.0145	Processing and preserving of meat	-0.01	Computer programming, consultancy and related activities	0.0215	Activities of extraterritorial organisations and bodies	0.046
Veterinary activities	-0.0145	Maintenance and repair of motor vehicles	-0.0099	Market research and public opinion polling	0.0217	Compulsory social security activities	0.0503
Manufacture of agricultural and forestry machinery	-0.0143	Manufacture of articles of concrete, cement and plaster	-0.0096	Research and experimental development on social sciences and humanities	0.0233	Undifferentiated goods and services-producing activities	0.0505
Beverage serving activities	-0.0143			Electric power generation, transmission and distribution	0.024	Higher education	0.055
Freight transport by road and removal services	-0.0137					Television programming and broadcasting activities	0.0553