Industrial dynamics and regional income inequality

Evidence from 29 Danish regions from 2001 to 2013

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Abstract

In light of past years' rapid growth of income inequality, increasing attention is paid to the dynamics behind inequality. Nonetheless, as of yet, little is known about industrial dynamics' consequences for income inequality at a sub-national level. The theoretical framework presented in this study argues that industrial dynamics influence regional inequality due to its impact on job dynamics. Through descriptive statistics and fixed effect panel regressions using micro-data from 29 Danish regions, spanning from 2001 to 2013, this study examines the impact of industrial entries and exits on regional income inequality in Denmark. Factoring in for the typology in terms of manufacturing and service sectors, the sector's knowledge intensity and the industries' skill level, no substantial effect on inter-regional income inequality in Denmark is evident. However, despite small effect sizes on regional income inequality in Denmark, there are two main findings of the study. First, the entry of low-skilled jobs causes an increase in income inequality, due to their stratifying effect of the regional job pool. Second, the total share of exiting industries shows a negative correlation with income inequality. Particularly the exits of high knowledge-intensive manufacturing sectors show a robust correlation with income inequality. Explanations are found in the skill composition of the high knowledge-intensive manufacturing sectors, where the skill- and wage-levels are substantially higher compared to the other sectors investigated in this study.

Keywords: Industrial Entries, Industrial Exits, Gini Coefficient, Regional specializations, Job dynamics

1. Introduction

Since the preeminent work of Piketty (2014), inequality has become a major topic both in public discourse as well as within academia. This interest takes point of departure in the dramatic rise in within-country income inequality in the majority of OECD countries over the past 40 years (Milanovic, 2016). According to OECD (2019), medium-income households have experienced marginal income growth and, in some countries, even stagnating income development during the past 30 years, whereas the wages of high-income households have been skyrocketing. This development is in line with the cost of living in many OECD countries, which has developed at a faster pace than the average income of the middle- and low-income households (Autor et al., 2005). Other than the feeling of injustice often expressed in public debate, consequences of increasing income inequality are – among other things – higher rates of populism, crime rates, health issues and attenuating economic growth (Wilkinson et al., 2009).

However, while Economic Geography (EG) long has investigated the role of industrial dynamics in regions and the driving forces behind industrial dynamics, few studies attempted to connect these structures to study inequalities (Hidalgo et al., 2018). Furthermore, while EG has a long tradition of examining differentiating, regional growth patterns and increasing inter-regional inequality, little focus has been paid to intra-regional inequality (Iammarino et al., 2018). To address these gaps, this study aims to understand how and in what ways industrial dynamics may impact income inequality regionally. This study, thus, aims to answer the following overarching research question:

> To what extent are industrial dynamics in terms of entry and exit of industries affecting income inequality regionally?

The study posits that income inequality is linked to a complex interplay of factors, such as industrial dynamics through the entries and exits of industries. The job creation and job destruction that follows entry and exits of industries impact the job structure within the economy, which due to subsequent changes in income, education and skill composition affect income inequality regionally.

To answer the research question, this study uses Danish micro-data to perform descriptive statistics and fixed effect panel regressions to investigate the impact of the relative share of exits and entries of industries and the impact of the change in the regional job dynamics on income inequality in 29 Danish regions in the period of 2001 to 2013. The measures for industrial dynamics are in this study are first divided into two categories of entering and exiting industries and then subdivided into categories of industry type (manufacturing or service sectors), the knowledge-intensity and the skill level of the jobs in the entering or exiting industries.

The study finds little evidence to support an impact of industrial dynamics in terms of exits and entries on regional income inequality in Denmark. Few of the industrial dynamics measures show significant effects and those that do have effects on income inequality that are substantially lower than those of the control variables. Nevertheless, through the study it is found that *i)* the exits of industries in total are lowering the regional income inequality; particularly, it is the exits of high knowledge-intensive industries that have the most prominent effect in the regions' income inequality in Danish regions. Explanations for this are found in the general high wage-levels for the high knowledge-intensive industries compared to the low knowledge- intensive manufacturing sectors and the service sectors, both low- and high knowledge-intensive sectors. *ii)* It is found that the share of low-skilled jobs entering alongside the new industries is increasing the regional income inequality in Denmark, this is explained by the stratifying effect the low-skilled jobs has on the regional job-pool.

The remaining paper is structured as follows. The second section discusses regional entries and exits, as discussed in the economic-geographical literature in connection with the income inequality literature on a regional basis. Section 3 discusses the data and methodology, and section 4 presents the main findings on the link between industrial dynamics and income inequality in Danish regions. Section 5 concludes.

2. Industrial dynamics and income inequality in regions

2.1. Drivers of inequality

The drivers behind inequality have long been investigated in relation to economic activities. One of the most influential ideas on this relationship is the Kuznets Curve hypothesis brought forward in the 1950s. This hypothesis theorizes that, as economic performance rises to higher levels, the level of inequality rises accordingly but eventually falls again when the economy reaches high-income levels (Kuznets, 1955).

The development of inequality seemed to confirm this until the 1980s. From this point on, an increase in inequality began manifesting, even in high-income countries like Denmark (Milanovic, 2016). Sixty years after Simon Kuznets, Milanovic (2016) argues for an extension of the Kuznets Curve, namely the Kuznets Wave, to explain this new trend.

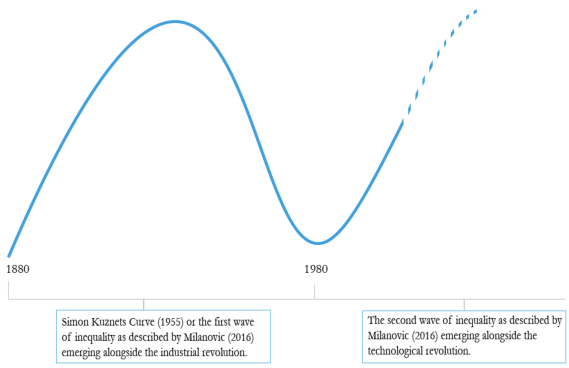


Figure 1: Kuznets curve (Kuznets, 1955) with extension by Milanovic (2016) (Amended from Milanovic (2016), pp. 191)

Kuznets waves occur throughout time, driven by different forces at different times. A central reoccurring force is structural, industrial changes. The second wave was a result of the second technological revolution in the 1980s that caused the industrial structure to alternate (Milanovic, 2016).

Changing industrial structures, therefore, play a pivotal role in the development of income inequality (Kuznets, 1955; Milanovic, 2016). Nonetheless, the impact of the dynamics behind these industrial changes on income inequality remains unclear. Industrial dynamics both create and destroy jobs through processes of industrial entries and industrial exits (Farinha et al., 2019). Industrial dynamics are therefore likely to impact the increasingly polarized job pool, that takes on the semblance of an hourglass with a growing bottom, a growing top and a shrinking middle class (Milanovic, 2016). Within academia there are two frequently used processes when explaining the impact industrial changes has on the job pool and thus income inequality; i) Skill Biased Technological Change "SBTC" and ii) Routine Biased Technological Change "RBTC".

First, SBTC is the process where the demand for high-skilled workers increases relative to that of workers with fewer skills, which enhance their earning power and thereby increase income inequality (Autor et al., 2003; Autor and Dorn, 2013).

Second, technological change is also biased towards labor in routine tasks in the process of RBTC, which is further lowering the demand for middling relative to high-skilled and low-skilled occupations (Goos et al., 2014).

This job polarization further reinforces income inequality due to a "Return to Skill"-tendency (E.g. Breau, 2007) where higher skill levels not only result in higher wages, but the development of these wages is also developing disproportionally, benefiting high-income households unequally compared to low- and the medium-income households (Acemoglu and Autor, 2011).

However, despite that it is evident that industrial, structural changes impact the job pool and hence income inequality, the nuanced picture of the dynamics lying behind the changing industrial landscape remains largely uninvestigated.

2.2. Entry of industries

The changes in the industrial landscape are by large due to an interplay of industrial dynamics, which is roughly divided into two categories; *i)* entries of industries and *ii)* exits of industries. As previously indicated, the skill level of the job-pool and the subsequent stratification of the job-force is a primary reason for the development of income inequality (E.g. Autor and Dorn, 2013). The knowledge-intensity of the entering industries utilizing employees with higher skill-levels are, therefore, likely to impact the growth of income inequality, due to the labor required in these industries.

Industrial entries can largely be explained through the industrial diversification framework, which tends to focus on the tradable industries.[1] Developed countries' economies generally diversify into more complex economic structures (Crespo et al., 2017). Nonetheless, if and how these high knowledge-intensive industries impact the development of income inequality is inconclusive. Hartmann et al. (2017), for instance, investigates the effect of economic complexity

[1] Tradable industries are the industries whose output in terms of goods and services are traded internationally. See Standard International Trade Classification (SITC; version 3).

and uses the composition of national export flows in terms of economic diversity and economic ubiquity to study the link between economic complexity and income inequality in 150 countries from 1963 to 2008 on the national level. They show that countries exporting more complex products have lower income inequality than countries exporting simpler products (Hartmann et al., 2017). Explanations for this are, for instance, the ability of firms to specialize and be more productive in diverse environments.

Whilst Hartmann et al. (2017) are interested in economic complexity, Lee (2011), one of the most prominent scholars within the inequality literature, on the other hand, focuses on the relationship between regional innovation and inequality in European regions by using patents and five different inequality measures to decompose regional inequality. The study infers that innovation may increase regional income inequality due to, among other factors, an influx of highly-skilled and thus highly-paid workers. In the same vein, Lee and Rodríguez-Pose (2016) show no evidence that high-technology industries in the US reduce poverty, although the study shows an impact of high-tech on the wages of non-degree educated workers. However, this wage-development for the non-degree educated workers is not high enough to reduce poverty. Instead, it causes inequality to rise due to differentiated development of wages of high-, medium- and low-skilled workers, as the wages of the high-skilled are surpassing the development of the wages of the medium- and low-skilled. The exact effect of the entry of high knowledge-intensive sectors is thus pointing in different directions.

In addition, these diversification processes also cause the entry of low knowledge intensive manufacturing industries to decline in many OECD countries (Crespo et al., 2017). A reason for this is, amongst others, the difficulty to internationally compete with the wages and that the general lack of ubiquity in the low-knowledge-intensive industries makes them more sensitive in the international competition. In terms of labor hired in the manufacturing sectors, it is evident that the low knowledge-intensive sectors generally employ low- and medium-skilled labor, who therefore receives substantive lower wages compared to the employees in the high knowledge-intensive manufacturing sectors (Buitelaar et al., 2017).

Whereas the diversification literature is commonly focusing on the tradable industries (E.g. Xiao et al., 2018), it is only part of the industrial entries. Studies have found an increase in industries within both high- and low knowledge-intensive service sectors entering the economy in developed countries in the last 20 years (Autor and Dorn, 2013).

For the low knowledge-intensive service sectors, there are two main reasons for this increase. First, the last forty years have seen rises in income, especially for high-income households, creating demands for luxury services like restaurants and hotels (Johnston and Huggins, 2018). Second, demographic changes such as an aging population and changing family structures, with intergenerational households, where elder generations remain in the same households as their children, are becoming rarer, creates a higher demand for service sectors focusing on, e.g. caretaking (Hermelin and Rusten, 2015). This development will typically bring along jobs that are either part-time or based on temporary contracts, referred to as *"precarious jobs"*. This leads to more unstable incomes for low-income households (Buitelaar et al., 2017).

For the high knowledge-intensive service sectors, also referred to as the *"innovation services"* (Witell et al., 2016), the increasing entries are to a higher extent connected to technological change and an increasing share of individuals with high incomes, which causes services within the fields of e.g. marketing, management, and operations research, to rise in demand. In general, workers within both the high- and low knowledge-intensive service sectors are less inclined to organize in trade unions and are subsequently generally more likely to accept lower wages and temporary contracts (Buitelaar et al., 2017).

In summary, due to the (high knowledge-intensive) manufacturing industries and service sectors (both high- and low knowledge-intensive sectors) are increasingly part of the industrial landscape in many OECD countries, it is expected that the entering industries are correlated with an increase in income inequality regionally. This is due to the instability of jobs for the low-knowledge service sectors and that the "Return to Skills" rewarding the high knowledge-intensive manufacturing and service sectors, which thus could be expected to strengthen the hourglass-shaped job pool. The first out of three hypotheses for this study is therefore that;

i) The industrial entries would create an increase in income inequality regionally in Denmark.

On the other hand, it can be disputed as indicated by Hartmann et al. (2017) and instead cause a reduction in income inequality regionally, due to the increasing complexity of economic activities.

This study looks beyond the new industries and their effect on income inequality and are thus also accounting for the impact of exiting industries on income inequality.

2.2.1. Exit of industries

The knowledge-intensity of the industries are also a key determinant of which industries will exit the market. Since the 1990s, many developed countries have experienced a process of de-industrialization (Crespo et al., 2017). A result has been the closure of many low knowledge-intensive manufacturing industries with larger shares of low- and medium-skilled labor as, e.g. described by Sbardella et al. (2017). Meanwhile, high knowledge-intensive manufacturing industries are not to the same degree increasing in their exits (Autor, 2015). Explanations for the de-industrialization are found in technological change interlinked with globalization, where labor prices cannot compete with production costs outside of the OECD countries and are therefore being off-shored (Goos et al., 2014). Knowledge-intensive manufacturing sectors are generally less likely to exit as the economy develops and becomes more globalized. This is due to the greater ubiquity in their products, which makes them more difficult to be replicated and are thus more competitive in international competition (Hartmann et al., 2017). Hence, they are not as sensitive in terms of the risk of closure.

However, it is not only the manufacturing industries that face the risk of closure. Acemoglu and Autor (2011) found that exits of service sectors are also the result of a technological change, where labor is being replaced due to automation and artificial intelligence. Like the manufacturing sectors, it is generally the low knowledge-intensive service industries that are prone to shrink, due to their likelihood of being replaced by automation (Buitelaar et al., 2017).

Summing up, judging from the above, it is evident that it is industries with less specialized labor and low- and medium-income levels that are prone to exit. Furthermore, it is expected that the most substantial consequences are for low- and medium- income households (more so for the latter), which creates a more stratified job pool. The second hypothesis for this study is therefore that;

ii) The industrial exits would create an increase in income inequality regionally in Denmark.

Until this point, the development of income inequality has been discussed on a more general level, mostly without paying attention to geographical differences. The next section seeks to elaborate on how geography is affecting industrial dynamics and income inequality.

2.2.2. Inequality on a sub-national level

Ever since the highly influential works of Romer (1986, 1990) and Lucas (1988), the discussion of *"Divergence"* and *"Convergence"* has been one of the central topics within EG. This discussion has, in recent years, paved the way for a substantive amount of literature on inter-regional inequality (E.g. Iammarino et al., 2019). Still, how inequality is developing *within* a region has, so far, been a largely neglected topic within the EG literature, with only a few studies exploring the development of income inequality on a regional level (Lee, 2011). The regional characteristics play a role in both the type of industries present in the region and the frequency the industrial dynamics occurs (Boschma, 2018). Furthermore, due to knowledge spill-overs, it is more common to see high knowledge-intensive industries in the denser urban regions compared to the rural regions. In general, the sparser the network as in rural regions the less likelihood for industrial survival in times of crises and thereby industrial exits (Crespo et al., 2017). At the same time is the general activity in the urban regions higher meaning that the urban regions could be more likely to see more entries of industries compared to the rural regions.

In terms of the general development of inequality in different regions, there are at least four interlinked factors in which regional characteristics, in terms of urban and rural regions, may impact the development of income inequality; *i*) urban density, *ii*) economic development, *iii*) moving patterns and *iv*) the housing market.

First, studies on inequality often indicate that density is a primary cause for increasing income inequality (Baum-Snow and Pavan, 2013). Several studies found that larger economies house more inequality than smaller economies (Glaeser et al., 2009). This may seem counter-intuitive, as it is easier to organize workers in more densely populated regions (Combes et al., 2010; Neffke, 2017). Nevertheless, densely populated areas offer more opportunities for quality-sorting between employers (Wheeler, 2001), meaning that highly-skilled workers tend to work at more knowledge-intensive firms, whereas more low-skilled workers tend to work in less knowledge-intensive firms, resulting in a more stratified structure. Other scholars, such as Sassen (2001), have suggested that together with the increasing population number in the urban areas, the population will also become more heterogeneous and the divide/inequality within the population will increase subsequently.

Second, economic development has, as mentioned, long been connected to income inequality. Rodríguez-Pose and Tselios (2009) investigate this development on a regional level, by mapping regional personal income distribution in western Europe, where they found a robust negative correlation between income per capita and inequality – thus the higher the level of income in the region, the lower the income inequality. This is explained by arguing though the Kuznets Curve (1955) that when cities are becoming increasingly prosperous, inequality levels will fall.

Third, there is an influx of people moving from more peripheral areas towards metropolitan areas to attend university or to pursue the broader variety of job opportunities that exist in these areas (Iammarino et al., 2018). This moving pattern tends to leave rural areas depopulated and with a more homogeneous, low-skilled population (Iammarino et al., 2018). It has been found in Denmark that workers from rural regions were, to a considerable extent, seen moving away from their municipality to find new employment. The same tendency could not be observed in urban regions (Holm et al., 2017). The influx to the urban areas could be expected to create more significant differences within the population and thus larger degrees of inequality in the urban areas and lesser degrees of income inequality in the rural areas (Sassen, 2001).

The fourth factor is also linked to the moving patterns; namely the housing market. The popularity of urban areas results in rents increasing rapidly and many urban areas experiencing a shortage of affordable housing. This development is to be seen together with the steady deregulation of the housing market since the 1990s (Larsen and Lund Hansen, 2015). This deregulation further allows housing prices to inflate.[2] Today, in many cities, the development of housing prices by far surpasses the development of average incomes of low- and medium-income households (OECD, 2019).

Although few studies are dealing with income inequality on a regional level (Lee, 2011; Iammarino et al., 2018), there are still studies showing the geographical structures of income inequality. On this theoretical foundation, this study hypothesizes that urban regions will, due to their expected higher levels of industrial entries, higher population densities, (Baum-Snow and Pavan, 2013), higher amounts of skilled workers (Lee and Sissons, 2016), highest innovation

[2]See Larsen and Lund Hansen (2015), Brenner et al. (2010), Peck et al. (2013), Rolnik (2013) and Marcuse and Madden (2016) to mention a few for excellent descriptions of this development.

degrees (Lee, 2011) and denser housing markets (Larsen and Lund Hansen, 2015) see higher income inequality levels, compared to rural regions. This gives rise to the third and final hypothesis, which is that;

iii) Urban regions will contain higher levels of income inequality compared to rural regions.

Still, there are some insecurities since urban regions are more likely to have lower industrial exit rates, which according to the literature mentioned above is expected to increase the regional income inequality. Furthermore, urban regions also have the highest economic development per capita, which has also been connected to lower levels of income inequality (Rodríguez-Pose and Tselios, 2009). Nevertheless, this calls for a clear distinction of urban and rural regions since inequality and industrial dynamics will not only develop differently in these two categories, the characteristics of respectively urban and rural regions might interfere in the effect of industrial dynamics on income inequality.

2.2.3. Industrial dynamics and income inequality

Together, these studies provide valuable insights into how the industrial dynamics in terms of entry and exit of industries lead to inequality and how geography may interfere in this relationship. The impact of the entries and exits of industries is, however, at this point, not conclusive. Nonetheless, based on the literature as mentioned above, it is expected that both industrial entries and industrial exits will cause income inequality to rise.

Three main industrial characteristics of industrial dynamics are expected to influence the development of income inequality; *i)* knowledge intensity, due to their differentiating demand of skill-level and wage-level for the workers, are likely to impact the growth of income inequality. The knowledge intensity of industries also proved to be a key determinant of industrial entries and exits. *ii)* The typology of the industries, in terms of the service vs manufacturing sectors, is likely to play a role in the development of income inequality, due to their effect on, e.g. wage levels and the stability of the contracts being offered to employees. *iii)* The skill level of the labor in the entering and exiting industries, due to their impact on the job pool.

The vast majority of studies on income inequality is either focused on the national or urban level, and only a few studies have investigated the development of income inequality on the sub-national or regional level.

This study will, therefore, examine the industrial dynamics in terms of entry and exit of industries and its effect on the job pool from a regional perspective. In the following section, the methodological approach will be described .

3. Methodology

3.1. Data and study area

This study aims to understand if and in what ways industrial dynamics may impact income inequality regionally. To investigate these issues, this study takes advantage of comprehensive micro-data on the dynamics of the Danish economy. The data-sets used for these analyses come from "Integrated Database for Labor Market Research" (IDA). IDA connects information on every Danish individual and establishments from several different registers. IDA is suitable for this study due to a number to factors defining IDA. First, IDA consists of detailed information on individual characteristics, such as education, wages and income, age, work experience and unemployment. Second, individuals are linked to employers and firms, which can be defined in numerous ways, including industry affiliation. Third, the data are longitudinal. This means that people who change industry can be tracked (Timmermans, 2010).

This study considers only individuals of the working age, which in Denmark is from 16 to 64 years of age. This restriction results in a sample of approximately 3.500.000 individuals and 300.000 firms spread out over 724 6-digit NACE industries (version 2) in the thirteen-year time-frame from 2001 to 2013.

After a cleansing and geocoding process, the original dataset was aggregated into 29 Danish labor market regions. This study follows the same methodological approach for determining the regional scale as Eriksson et al. (2017). The regions are thereby calculated using cluster-robust standard errors, which are clustered at the local labor-market level for each municipality ($n = 29$ in Denmark in 2013). These regions are defined in terms of their inter-municipal commuting flows and represent the functional region for each of the local economies. The scale thus captures employment opportunities not only within the municipal boundaries but in neighboring municipalities, as well (Eriksson et al., 2017).

The literature review found that inequality develops differently in different geographical contexts and that there was an apparent variation between urban and rural regions. Therefore this study divides the regions follows the DORS (2015) distinction into either urban or rural regions as portrayed in Figure 2. A rural area is, in this study, defined as a region where the average citizen has more than a half hour drive to get to the center of a town with more than 45.000 inhabitants. An urban region is defined as a region where the majority of the population lives in towns with more than 45.000 inhabitants. This definition gives a total of 19 rural regions and ten urban regions. The 29 labor market regions differ in population size, in terms of employment rates and in terms of industrial variety and will be described in further detail under section 3.3 and in the Appendix.

3.2. Variables

3.2.1. The measure of regional income inequality

To date, various methods have been introduced and developed to measure income inequality, and according to which measure is chosen, the results may considerably vary (Lee, 2011). In recent studies, income inequality has typically been measured in five different ways;

First, the Theil L Index, which is a generally established entropy measure of inequality sensitive to changes at the extremes of the distribution (Shaw et al., 2007). The Theil Index has, e.g. been use in studies such as Sbardella

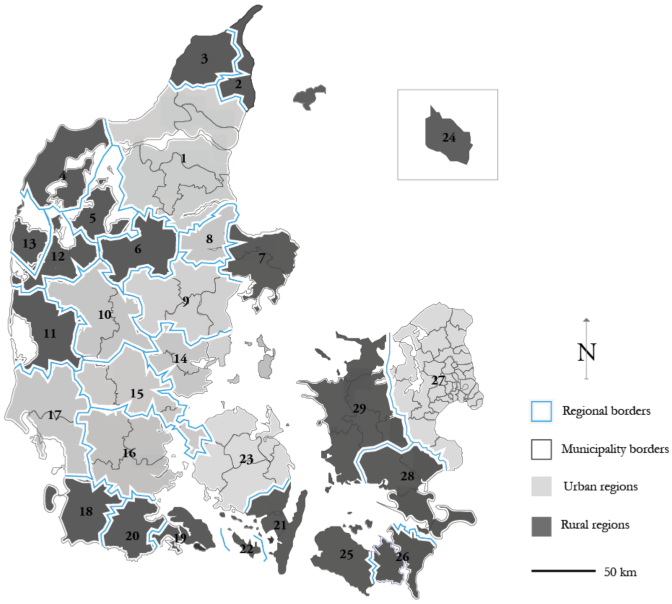


Figure 2: Map of the 29 regions used for the study divided into Urban or Rural (Source: Personal collection)

et al. (2017), where they aim to link the development and industrialization of a country to economic inequality.

The second inequality measurement is the Atkinson 0.5 parameter. This measurement has a weighting parameter (which measures aversion to inequality) (Buitelaar et al., 2017). Atkinson has been adapted among others in Lee (2011), where the connection between innovation degree and income inequality is investigated in European regions.

The third and fourth inequality measures are two different types of inequality ratios. E.g. the 90th percentile ratio, which is a crude inequality measure widely used within inequality literature. For instance, Lee et al. (2016), where the patterns of income inequality in 60 British cities are investigated have adapted this ratio. The measure displays the ratio of the wealthiest 10 percent and the bottom 10 percent in the income distribution. Another ratio measure is the 80th percentile ratio that shows the ratio of the richest 20 percent and the bottom 20 percent. The 80th percentile ratio is thus more robust towards extreme cases in the dataset than the 90th ratio. The 80th percentile ratio is, amongst others, used in Lee and Sissons (2016), who look into the relationship between economic growth and poverty in British cities. The ratio measures are an intuitive but fairly simple way of understanding inequality (Lee, 2011).

Fifth, the Gini Coefficient is the most commonly accepted method for measuring income inequality (Lee, 2011; Glaeser et al., 2009). An advantage of the Gini Coefficient is among other things, that compared to the types of inequality measurements involving the top and bottom, the Gini Coefficient is sensitive to flows around the mode of the distribution, meaning that it will be less exposed to unsteadiness owing to errors in data sample (Jenkins, 2009). Nevertheless, a frequent critique is that the Gini Coefficient can be challenging to interpret. Despite its drawbacks and the differences in the different inequality measures, the Gini Coefficient is still the most widely used inequality measure and is therefore used as the primary measure of inequality in this study.

3.2.2. The measure of regional entry and exits of industries

This study measures industrial dynamics in similar ways to previous studies (Neffke et al., 2011; Xiao et al., 2018) and looks at the entry and exits of industrial specializations in a region. This study employs the location quotient (LQ) as a measure of the level of specialization of industry i in region c relative to the overall specialization of that said industry in all 29 regions used in this study. The LQ is defined by the equation:

$$LQ^{ic} = \frac{E_{ic}/E_{*c}}{E_{i*}/E_{**}} \tag{1}$$

where i and c represent industry i and region c; E_{ic} denotes employment of industry i in region c; E_{*c} is total employment of all industries in region c; E_{i*} is total employment of industry i in all regions; E_{**} represents total employment of all industries in all regions. The higher the LQ, the higher the level of specialization of industry i in region c compared to the national specialization of the industry.

However, how high does the LQ need to be in order to determine a specialization? There is no widely acknowledged value of where to delimit the specialization of an industry in a region. Inspired by similar studies (Xiao et al., 2018), this study makes use of a method for determining a statistically significant cut-off value for each industry in a region developed by Tian (2013). First, the Standardized Location Quotient (SLQ) is calculated, as shown in Equation (2):

$$SLQ^{ic} = \frac{LQ_{ic} - \bar{LQ_i}}{std(LQ_i)} \tag{2}$$

where $\bar{LQ_i}$ is the mean value of the LQ for industry i, and $std(LQ_i)$ is the standard deviation of the LQ for industry i. Second, the SLQ is split for each industry. Third, a bootstrapping procedure is carried out, creating 1.000 samples for all the SLQs for every industry in every region. Fourth, the 95th percentile of each bootstrap sample is calculated. By calculating the mean value of the 95th percentile of 1.000 bootstrap samples, the critical cut-off value of SLQ for each industry is obtained.[3]

[3] For a more detailed description of the method, see Tian (2013) or Cortinovis et al. (2017).

Since the LQ is a ratio dependent on the relationship between the employment at the national level and employment at the regional level, it is unclear whether the increase or decrease in LQ is due to a rise in employment in the respective industry regionally or if it is due to a drop or increase in the national employment. For this study, it is of interest to look at the changes regionally. This was achieved by measuring the partial increase in employment for each new specialization for both the national and the regional level. If the employment change only took place at the national level, then the industry was not counted as a new specialization. The majority of the entering and exiting specializations - in over 95% of the cases - was, however, related to a change in regional employment.

3.2.3. Entry and Exit of different types of industries

As indicated in the literature review, it is likely that different types of industrial sectors will affect the development of income inequality differently according to the knowledge intensity and the type of industry in terms of manufacturing and service sectors. This is due to the wage differences and likelihood of employees to join unions for service and manufacturing sectors with subsequent effect on the conditions of the jobs. So, in order to understand the nuances of the industrial dynamics of each region, the paper follows the OECD classification (Xiao et al., 2018; Eurostat, 2015); and divides industries into four general categories: *1)* High manufacturing - "HM" consisting of the categories high-tech manufacturing and medium high-tech manufacturing; *2)* Knowledge-intensive service: "KIS" consisting of the knowledge- intensive service sectors; *3)* Low manufacturing "LM" consisting of medium low-tech manufacturing and low-tech manufacturing and *4)* Less knowledge-intensive service "LKIS" consisting of the less knowledge-intensive service sectors. This distinction, on average, takes up 91,2% of the industries in Denmark in the time period 2001 to 2013 with 8,8% falling out of the classification.

3.2.4. Entry and Exit of different types of jobs

A central objective of this study is to understand the job dynamics that are being influenced by industrial dynamics in the regions. As the literature review indicated, the polarization of different skill levels in the job pool is a primary factor for increasing income inequality. The study, therefore, follows Goos et al. (2014) and Holm et al. (2018) and hence uses the International Standard Occupational Classification (ISCO) first-digit occupational categories (See Table 1) as an indicator for skill-level for the different types of jobs within each regional economy. All workers are divided into three skill-set categories: high, medium and low, which is a distinction often adopted in the literature on RBTC (Goos et al., 2014) and SBTC (Autor and Dorn, 2013).

3.2.5. Control variables

A range of control variables is used to account for other factors associated with regional income inequality. The study is inspired by variables used by Lee (2011), who investigates the relationship between income inequality and

Table 1: Occupational skill levels divided into categories of high, medium and low

First digit of ISCO-08	ISCO-08 label	Group
1	Managers	High
2	Professionals	High
3	Technicians and Associate Professionals	High
4	Clerical Support Workers	Middling
5	Services and Sales Workers	Low
7	Craft and Related Trades Workers	Middling
8	Plant and Machine Operators and Assemblers	Middling
9	Elementary Occupations	Low

the innovation degree measured by the patent level regionally in Europe. Four control variables are, therefore, being used as follows.

First, a variable is included measuring regional GDP. Although GDP on the national is the measure most commonly used in inequality research, studies have also shown that similar tendencies operate at a sub-national level (Tselios, 2008). GDP per capita at a regional level has previously been identified as having a negative relationship with income inequality (Rodríguez-Pose and Tselios, 2009). Data about GDP on a regional level is available from Eurostat.

The second control variable measures population density, which is a common explanation for inequality in both cities and regions. Numerous studies have attempted to link inequality to population density. Nevertheless, the estimated effect is not conclusive. Glaeser et al. (2009) found that the higher the population density is, the higher the inequality level. However, unlike Glaeser et al. (2009), Rodríguez-Pose and Tselios (2009) found a negative relationship between population density and income inequality explained, among other things, through the chance of knowledge spillovers in the more densely populated areas. Population density is, in this study, defined as population per square kilometer and data from Denmark's statistical database (DST) is used for this variable.

Third, unemployment is calculated following the International Labour Organization, who classified unemployment as a percentage of the population within the working age and is also using data from IDA. Unemployment rates are one of the most commonly-used explanations of inequality. Previous studies conclude that unemployment is linked positively to income inequality (Autor and Dorn, 2013), drawing on the logic that the larger the share of individuals standing outside the workforce is, the higher the overall difference between individuals in the population is.

Finally, the fourth control variable used in this study is the educational composition of the population. The educational composition is also a leading factor in the development of inequality (Wheeler, 2005). Several studies investigating the educational composition concerning income inequality have been carried out (Tselios, 2008; Glaeser et al., 2009). The main conclusion is that educational composition is linked positively to income inequality, due to the reasoning that rises in both low- and high levels of educational backgrounds would cause the hourglass figure to differentiate and thus cause higher levels of income inequality. To capture the educational composition in the regions, the International Standard Classification of Education (ISCED) has been used to calculate the

Table 2: Description of variables

Domain	Name	Description	Source
Inequality Measure	*GINI*	Gini Coefficient of income for population within the working age 16-64 years.	IDA
Industrial Dynamics	*ENTRY*	Share of entries of new specializations in a region.	IDA
Industrial Dynamics	*EXIT*	Share of exits of new specializations in a region.	IDA
Industrial Dynamics - Jobs	*Entry_ISCO1*	Share of high-skilled labor in entries of new specializations in a region.	IDA
Industrial Dynamics - Jobs	*Entry_ISCO2*	Share of medium-skilled labor in entries of new specializations in a region.	IDA
Industrial Dynamics - Jobs	*Entry_ISCO3*	Share of low-skilled labor in entries of new specializations in a region.	IDA
Industrial Dynamics - Jobs	*Exit_ISCO1*	Share of high-skilled labor in exits of new specializations in a region.	IDA
Industrial Dynamics - Jobs	*Exit_ISCO2*	Share of medium-skilled labor in exits of new industrial specializations in a region.	IDA
Industrial Dynamics - Jobs	*Exit_ISCO3*	Share of low-skilled labor in exits of new industrial specializations in a region.	IDA
Industrial Dynamics - Industries	*Entry_HM*	Share of high knowledge-intensive manufacturing industries among entries of new industrial specializations in a region.	IDA
Industrial Dynamics - Industries	*Entry_LM*	Share of low knowledge-intensive manufacturing industries among entries of new industrial specializations in a region.	IDA
Industrial Dynamics - Industries	*Entry_LKIS*	Share of low knowledge-intensive service industries among entries of new industrial specializations in a region.	IDA
Industrial Dynamics - Industries	*Entry_KIS*	Share of high knowledge-intensive service industries among entries of new industrial specializations in a region.	IDA
Industrial Dynamics - Industries	*Exit_HM*	Share of high knowledge-intensive manufacturing industries among exits of industrial specializations in a region.	IDA
Industrial Dynamics - Industries	*Exit_LM*	Share of low knowledge-intensive manufacturing industries among exits of industrial specializations in a region.	IDA
Industrial Dynamics - Industries	*Exit_LKIS*	Share of low knowledge-intensive service industries among exits of industrial specializations in a region.	IDA
Industrial Dynamics - Industries	*Exit_KIS*	Share of high knowledge-intensive service industries among exits of industrial specializations in a region.	IDA
Control	*EDcompo*	Educational composition as a mean of categories inspired by ISCED.	IDA
Control	*UNEMP*	Unemployment as a percentage of population of the working age.	IDA
Control	*POPDEN*	Population density in population per square kilometer.	DST
Control	*GDP*	Gross domestic product per capita.	EUROSTAT

mean of educational backgrounds for each region. Data from IDA is also used for this variable.

3.3. Descriptive statistics

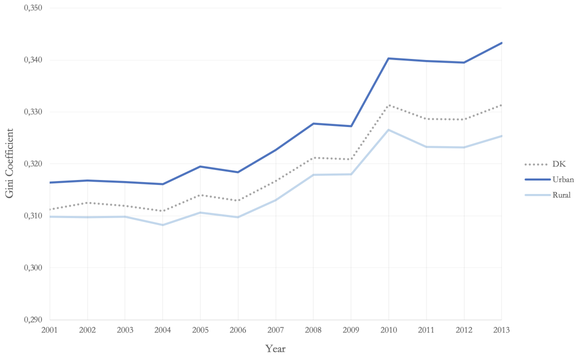
Descriptive statistics of the main variables are reported in the Appendix in Table 7. The correlation coefficients among the main variables are displayed in the Appendix in Table 8. This paper purports to link the industrial dynamics of Danish regions in the shape of the entry and exit of industrial specializations within a region to income inequality within regions. The following will provide an overview of the main changes within income inequality, exiting and emerging industries and the jobs connected to these industries on a regional level in Denmark from 2001 to 2013. Throughout the following section two periods, 2001 to 2007 and 2007 to 2013, will be used to differentiate in nuances in the development. By dividing the time period in two it is possible to see more robust tendencies not affected by extreme years such as the year 2007, where the financial crisis struck many countries, including Denmark, and it is still possible to observe the development over throughout the time-period.

3.3.1. Development of inequality in differing geographical contexts

The national income development in Denmark is changing differently for the different deciles of the population nationally. From 2001 to 2013, the wealthiest ten percent have experienced a growth in income of 57.37%, whereas the bottom ten percent have experienced a growth in income of 13,26%. Income inequality measured by the Gini Coefficient rose in Denmark in all 29 regions from 2001 to 2013. The highest levels of inequality are generally in regions with the highest population densities and within urban regions in Denmark (See Table 9 and 10 in the Appendix for region-specific numbers). Still, both the urban and rural regions are experiencing growth in income inequality. The level of inequality is higher in urban regions than in rural regions, and this development is also occurring at a slightly higher rate of 0,3% in the time period from 2001 to 2013 than in the rural regions. However, the development of the Gini Coefficient roughly follows the same pattern for national, urban and rural regions (See Figure 3), which could be expected since all regions are within Denmark and they are, therefore, having the same national legislation and thus similar social policies.

As portrayed in Figure 3, there is a steady incline in the Gini Coefficient throughout the entire time period. The most dramatic rise was in the years from 2007 to 2010, just around and in the aftermath of the financial crisis. In the year from 2008 to 2009, there is a small reduction of the Gini Coefficient followed by a sharp increase until 2010. The sharp increase can be explained by individuals starting employment again after being laid off in crisis in 2008 but beginning at low starting wages (Lee et al., 2016). In addition, it was mostly firms requiring medium skilled labor as the low knowledge-intensive service and manufacturing sectors that were struck by the financial crisis compared to high knowledge-intensive service and manufacturing industries that employed high-skilled labor

Figure 3: Gini Coefficient in DK, urban and rural regions from 2001 to 2013



(Westergaard-Nielsen and Neamtu, 2012). Another reason for medium income households being hit the most was that when house prices collapsed in 2008, the value of middle-class households' portfolios dropped drastically, whilst a quick rebound in stock markets enhanced income at the top of the income distribution. This meant that the top 10% wealthiest households were the primary beneficiary from the stock market boom while being at the same time relatively less affected by the drop in residential real estate prices (Kuhn et al., 2017). The initial reduction of the Gini Coefficient from 2008 to 2009 can be seen as an initial effect on the stock market but, as already mentioned, the actions taking to recover the stock-market came quickly, resulting in higher income for the top ten percent in the income distribution (Kuhn et al., 2017).

3.3.2. Entry and exit of industries in differing geographical contexts

The 29 regions used for this study experience entries and exits of industrial specializations at different rates.[4] Interestingly, in general, the lower the population size and the lower the total number of industries in the industrial portfolio, the higher the percentage of entries and exits of industrial specializations in the region. In the time period from 2001 to 2013, the urban regions are, on average, experiencing declines in rates of LM-exits, HM-exits and KIS-

[4]The average rural region has an industrial portfolio of, on average, 366 industries and 48 industrial specializations. The average urban regions have 521 industries and 64 industrial specializations. The average size of an industry in terms of employees is higher for the urban regions than for the rural regions. The size of the specialized industries is not always is higher than the average industry. In 38% of the 377 cases of observation is the size of specialized industries in terms of the number of employees lower than the average industry in the region in years from 2001 to 2013. This is due to the LQ being a ratio comparing the local economy to the national level, which means that it is possible to be specialized in an industry despite a lower employee number compared to the regional average. Urban regions have generally higher levels of manufacturing industries, both HM and LM, whereas rural regions, in general, have higher levels of service sectors, both LKIS and KIS-industries. See Table 11 and Table 12 in the Appendix for more details on the regional differences.

exits, with the KIS-exits having the highest decline of almost 14%. At the same time, the exits of LKIS-industries are increasing with almost 13,2%. For the entries, there are, interestingly, differences in the high knowledge-intensive sectors and low knowledge-intensive sectors. Both manufacturing and service high knowledge-intensive sectors experienced an increase from 2001 to 2013. The low knowledge-intensive industries are, on the other hand, experiencing declines for both the service and the manufacturing industries. The highest decline can be found in the low knowledge-intensive manufacturing sectors, which are going from 19,1% to 13,1% in the time period from 2001 to 2013. Thus, the urban regions in the time period from 2001 to 2013 are experiencing stronger specializations within knowledge-intensive sectors, particularly within the service sectors.

For the rural regions, there are some slight variations. The entries of both high- and low knowledge-intensive manufacturing sectors are growing. Specifically, the high knowledge-intensive manufacturing industries are growing. At the same time, the entries of high- and low knowledge-intensive service declining, especially the low knowledge-intensive service industries are experiencing a steep decline from 2001 to 2013. Whilst the exits of LKIS-industries are increasing rapidly from 2001 to 2013, the exits of HM-, LM- and KIS-industries are declining, leaving the rural region more influenced by manufacturing sectors.

A surprising aspect of the data is that the income is higher for the manufacturing sectors than the service sectors, but the educational background is higher for the service sectors compared to the manufacturing sectors (see Table 13 in the Appendix). For the development of HM, LM, KIS and LKIS-industries for each of the 29 regions, see Table 14 and Table 15 in the Appendix.

Table 3: Share of types of industries for average, entering and exiting industries on a national, urban and rural level in percent, 2001 to 2007 and 2007 to 2013

	HM	**LM**	**LKIS**	**KIS**	**HM EN.**	**LM EN.**	**LKIS EN.**	**KIS EN.**	**HM EX.**	**LM EX.**	**LKIS EX.**	**KIS EX.**
DK 2001 to 2007	8,1	18,7	35,3	26,0	7,1	16,8	40,1	24,6	8,4	19,2	36,1	23,3
Urban 2001 to 2007	9,4	20,8	33,5	24,9	10,4	16,7	35,8	28,3	10,0	21,3	35,7	22,8
Rural 2001 to 2007	7,4	17,6	36,3	26,6	5,3	16,9	42,3	22,7	7,5	18,1	36,3	23,6
DK 2007 to 2013	7,9	18,0	35,2	26,3	6,6	15,8	37,8	26,1	7,9	16,5	37,6	24,5
Urban 2007 to 2013	9,3	20,1	33,5	25,0	6,2	17,9	34,7	29,2	9,8	21,5	30,1	26,5
Rural 2007 to 2013	7,3	16,6	36,0	27,2	7,0	12,7	39,9	27,0	7,6	11,6	43,2	25,1

3.3.3. Entry and exit of different jobs in differing geographical contexts

The educational level of the jobs in the emerging and exiting specializations is, despite a difference in speed of development, similar in urban regions and rural regions. In general, the share of the population with high educational degrees (following the ISCED classification) is increasing (15,2% in 2001 to 2007 increased to 17,1% in 2007 to 2013 on a national level) and the population with low educational backgrounds decreasing (40,3% in 2001 to 2007 declined to 37,5% in 2007 to 2013 on a national level). This is despite a drop in the share of people with high educational levels in the entering industries of almost 2% between the time periods 2001 to 2007 and 2007 to 2013. Furthermore, there is an increase in entries with low educational backgrounds of 2% between the time periods 2001 to 2007 and 2007 to 2013. This tendency is also occurring in the exits of industries, resulting in a general job pool in the industrial specializations that are higher educated (See Table 4). For the development of the educational level of the average industries, the entering and departing industries for each of the 29 regions, see Table 16 and Table 17 in the Appendix.

The income level is generally higher in the urban regions, compared to rural regions. In the urban regions, the average income in the entering industries is well above the national level of almost 14.000 DKK (approximately 2.000 Euros). At the same time, the income of the entering industries in the rural regions is just a bit lower than the average level of just over 5.000 DKK (approximately 700 Euros). The income for the departing industries in the urban regions is virtually the same as on the national level. For the rural regions, the income level for the departing industries is a bit lower than the national level of approximately 10.000 DKK (approximately 1.400 Euros) (See Table 4).

Interestingly, the income is higher for the manufacturing industries than for the service sectors. Likewise, the income is higher for the entering manufacturing industries compared to the exiting ones, but this is reversed when looking at the service sectors with lower income for the entering service industries compared to the exiting. In general, despite the knowledge-intensity for the service sectors creates differentiated wage developments, the general wage level for the service-sectors is in no small extent lower than for the manufacturing sectors. For the development of the income level of the average industry, the entering and the departing industry for each of the 29 regions, see Table 18 and Table 19 in the Appendix.

Concerning differences in the skill level of jobs in the exiting and emerging industries, the development of the rural and urban regions between the exiting and the emerging industries are minimal. There is a substantial increase in the entry and the exit of high skilled labor and a more limited increase in medium skilled labor for both the urban and the rural regions. There is a steady decline of low-skilled jobs for both the urban and rural regions (See Table 4). See Table 20 and Table 21 in the Appendix for regions specific statistics.

Table 4: Descriptive demographics for Denmark, Urban and Rural regions divided by entering and exiting industries

	DK AV.	**DK EN.**	**DK EX.**	**Urb. AV.**	**Urb. EN.**	**Urb. EX.**	**Rur. AV.**	**Rur. EN.**	**Rur. EX.**
Income, 2001 to 2007	211.187	213.737	205.300	223.614	234.131	223.786	204.647	203.003	195.570
High Ed, 2001 to 2007	15,2	14,7	15,6	17,0	19,3	18,2	14,2	12,2	14,3
Low Ed, 2001 to 2007	40,3	30,7	29	39,2	31,9	32,0	40,8	35,3	34,6
ISCO1, 2001 to 2007	20,0	22,8	22,4	22,8	29,2	27,2	18,6	19,3	19,8
ISCO2, 2001 to 2007	21,7	32,6	32,1	21,4	30,6	30,9	21,9	33,7	32,7
ISCO3, 2001 to 2007	46,1	40,8	39,2	44,5	37,9	37,0	47,0	42,4	40,4
Income, 2007 to 2013	244.394	242.263	234.327	261.252	272.446	261.180	236.643	229.919	221.083
High Ed, 2007 to 2013	17,1	12,6	11,8	19,7	17,7	14,2	15,8	9,9	10,6
Low Ed, 2007 to 2013	37,5	36,1	37,5	36,7	33,6	35,9	38,0	37,5	38,3
ISCO1, 2007 to 2013	22,5	30,2	31,3	26,0	37,6	37,2	21,0	28,4	30,8
ISCO2, 2007 to 2013	17,6	35,4	35,3	17,2	32,2	32,9	17,3	34,6	33,0
ISCO3, 2007 to 2013	36,4	33,3	33,2	35,1	29,8	29,6	37,1	35,3	36,0

So, from the descriptive statistics, it is evident the income inequality is rising in all 29 regions used for this study, with the highest levels found in the urban regions and in the aftermath of the financial crisis of 2008. Moreover, the development of industries is differing among urban and rural regions. In general, the industrial specializations of the urban regions are increasingly being influenced by high-knowledge service sectors, whereas the manufacturing sectors are influencing the rural region to a higher extent. Lastly, jobs are changing by being in general higher paid and higher educated, nevertheless, the differences are between different groups are increasing with a higher number of low- and high-skilled workers among the industrial specializations in the regions and fewer medium-skilled workers.

4. Analysis

4.1. Regression

This study seeks to test whether industrial dynamics and what types of industrial dynamics lead to greater inequality in Danish regions. To test this, a series of regressions is presented which investigate the relationship between a variety of industrial dynamics and the level of inequality in Danish regions. It is specified as a fixed effects panel data regression model and is given by:

$$\begin{aligned} Gini_{it} = \alpha + \beta_1 Entry_{it} + \beta_2 Exit_{it} + \beta_3 EDcompo_{it} + \\ \beta_4 GDP_{it} + \beta_5 Unemp_{it} + \beta_6 PopDen_{it} + v_i + \varepsilon_{it}, \end{aligned} \tag{3}$$

where i refers to each of the 29 regions and t is the time-period from 2001 to 2013. The models are panel regression models and so require a choice to be made between fixed or random effects. After conducting Hausman tests the statistics indicated that the fixed effect model was a more suitable method of estimation.[5]

4.2. Estimation issues

As there is evidence of heteroscedasticity, independent variables are logged as is common practice when working with panel data. Durbin Watson testing, furthermore, showed signs of autocorrelation but was assessed to be within a justifiable level of 1.56 (Bhargava et al., 1982). However, this gave a further justification of lagging with three years since the lowest level of autocorrelation was found here.

[5]In addition to the Hausman tests, the use of random effects, in this case, appears to have little theoretical justification. Fixed effects models control for unobserved time-invariant regional heterogeneity by assuming that the constant varies by region. This makes them appropriate for a model such as this where there are likely to be regional social factors which will alter the data, but which are unlikely to change meaningfully in the time period in question, such as are likely to operate in Danish regions. In this case, they are more appropriate than cross-sectional models where this would bias the estimation (Frondel and Vance, 2010).

The 29 local labor-market regions are as previously mentioned calculated by taking the point of departure in the year 2013 and is thereafter held to the same level for the entire time period from 2001 to 2013. This is justified despite changes in the regional scale in the time period since these changes are marginal.

4.3. Results

Table 5 and Table 6 report the effects of industrial dynamics on the Gini Coefficient in the 29 regions in the years 2001 to 2013. The basic model includes variables for GDP per capita (GDP), the unemployment rate (UNEMP), educational composition (EDcompo), population density (POPDEN) and the industrial dynamic variables. The adjusted R^2 indicates a strong model fit and varies between 0.715 and 0.723 for the different measures of industrial entry and exit. Moreover, the control variables perform well. All control variables show a positive, significant relationship at the 1% level, except regional GDP which was positive and significant on a 5% level.

4.3.1. Entering industries, increasing inequality?

The first hypothesis for this study was that industrial entries would cause income inequality to rise regionally in Denmark. However, looking at the effect of entries of industrial specializations, it shows that the direct effect of new specializations is insignificant and the same goes when factoring in for the four different types of sectors (HM, LM, KIS and LKIS) used in this study.

Nonetheless, when looking at the type of labor that the entering industries bring along, it is evident that the effect of low-skilled labor in the new industrial specializations has a significant (5% level on the Gini Coefficient) positive correlation. This result indicates that the low-skilled labor that enters alongside the new industries are pushing an increase in job polarization and hence income inequality. This is despite the descriptive analysis showed a decreasing number of low- skilled workers in the entering industries with (40,8%), compared to the medium- (32,6%) and high-skilled (22,8%) workers in 2001 to 2007 to 33,3% low-skilled, 35,4% medium- and 30,2% high-skilled workers in 2007 to 2013.

This might support the two central ideas within inequality studies; *i)* SBTC, where high-skilled labor is being increasingly prioritized compared to those with low- and medium skill level. *ii)* This process is being enforced by the "Return to Skill"-trend, where while the wage-level is increasing for all layers of society, the wages of the high-skilled are developing at a five times faster rate than the wages of the lowest 10th in the wage distribution in the years from 2001 to 2013. As mentioned earlier, the income for low-income households has increased with 13,3% from 2001 to 2013, whereas for high-income households it has increased with 57,4% in the same time period. Secondly, the external factors such as developments in the housing market are increasingly pressuring low-income households. This is especially the case in urban regions (OECD, 2019).

Still, it is noteworthy that despite the significant effect of low-skilled labor, the estimated effect is notably lower with a coefficient of 0.003 compared to those of the control variables that have ranged from 0.020 for UNEMP up to 0.715

for the EDcompo. These levels are, however, comparable to previous similar studies such as Lee (2011).

So, with only one out eight industrial dynamics measures being significant and coefficients strikingly lower than those of the control variables, it can be concluded that the entry of industries has little to no impact on regional income inequality in Denmark from 2001 to 2013.

4.3.2. Exiting industries, reducing inequality?

The second hypothesis for this study was that industrial entries would cause income inequality to rise regionally in Denmark. Similarly to the industrial entries, the majority of the measures of industrial dynamics focusing on the exiting industries are insignificant. Nonetheless, two measures were found to have significant effects. The total of exiting industrial specializations was significant by itself in a negative relationship on a 5% level, and when looking into if there were specific industries that affected more than other industries it showed that the share of HM sectors in the exiting industries had a significant on a 1% level, negative correlation. This indicates that it is mainly due to the HM sectors that the exiting industries are lowering the regional level of income inequality. High manufacturing sectors are experiencing the highest level of workers with medium level educational backgrounds with 66,5% on average compared to 59,7% for the LM-sectors and 54,8% in the LKIS-sectors. This might indicate that if a HM-sector is no longer an industrial specialization of the region, it is less likely to be due to a loss of the medium-skilled workers. Thus, the share of workers representing the middle of the educational composition is still much higher than the other sectors. Furthermore, the HM-sectors are surpassing the income level of the remaining three sectors investigated in this study with respectively 8,4 % (LM), 4,1% (KIS) and 17,7 % (LKIS). This also means that when HM-sectors exits then more of the highest earning will also disappear and the population thus becomes more homogeneous.

The jobs dynamics of the exiting firms have an insignificant relationship. This can be due to the higher number of entering industries of on average 1,77% compared to the exiting industries with an average 1,56%. It seems that the exiting industries are, in terms of jobs, being replaced by the jobs in the entering industries wherefore the exiting jobs are having an insignificant correlation with the development in income inequality and the entering industries have a significant relationship.

Also here, it is necessary to state that the coefficients are notably lower than for those of the control variables, with effect sizes just around 0.002 for the Exits in total and a slightly higher effect of 0.006 for the Exits of the HM sectors. Nevertheless, as already mentioned, these results are comparable to similar studies (Lee, 2011).

So, also for the exiting industrial dynamics, the effect on regional income inequality in Denmark from 2001 to 2013 is scant. This is due to both the high numbers of insignificant variables, but mainly due to the limited effect of the coefficients. The variables that did show significant effects showed negative correlations with the Gini Coefficient.

4.3.3. Geographical patterns of inequality

The third hypothesis for this study was that urban regions would contain the highest level of income inequality in Denmark. It is clear that urban regions are in fact developing income inequality in a similar pattern as the rural ones, but the level is increasing faster than for the rural regions, and, in general, the level is approximately 3% higher compared to rural regions. This is despite a higher influx and outflux of industries as a share of the total industrial portfolio in rural regions (influx = 1,86%, outflux = 1,79% from 2001 to 2013) compared to urban regions (influx = 1,49%, outflux = 1,30% from 2001 to 2013). Interestingly, it is evident that the rural regions are experiencing higher rates of both industrial exits, but also of exits of HM-sectors compared to the urban regions (See Table 14 and Table 15 in the Appendix). At the same time, the urban regions are experiencing higher rates of entering low skilled labor (See Table 20 and Table 21 in the Appendix). Although the effect size of the coefficients is small, this could be contributing to the slower inequality development that can be observed in the rural regions and the more dramatic development in the urban regions.

Still, the small effect size also indicates that other reasons may play a more prominent role for the development of income inequality than industrial dynamics and regional characteristics, but that the geographical characteristic will work in a tandem to enforce or reduce the consequences of industrial dynamics on income inequality regionally. For instance, urban regions possess higher GDP per capita, higher educational compositions and higher population densities compared to the rural regions investigated in this study. The results showed highly significant levels for all three variables, all of which are in a positive relationship with income inequality.

Moreover, the housing market in urban regions is likely to worsen the situation for entering low-skilled labor. Consequently, the lack of industrial variety in rural regions forces workers in the exiting HM-sectors to move to a new region to find new employment, leaving the rural regions population-wise gradually more homogeneous. The impact of industrial dynamics on income inequality in a region should, therefore, be seen in an interplay with other regional characteristics, such as moving patterns, the housing market and proximity to other similar industries.

Overall, this study finds little to no effect of industrial dynamics on income inequality regionally in Denmark from 2001 to 2013. Only a few variables show significant values. First, entering industries result in higher levels of income inequality, due to the higher share of low-skilled labor in the new industrial specializations. Secondly, exiting industries seem to reduce income inequality. Specifically, the share of industries within the HM-sector that loses their specialization is lowering the level of income inequality.

However, common for all three of these variables are the notably smaller effect sizes compared to the control variables. An explanation for the reasonably statistically, insignificant results found in this study may be the broadness of the industrial dynamic measures used, but it may also simply be that other factors are of greater importance.

Table 5: The impact of industrial dynamics on income inequality

	Dependent variable:									
	log(GINI)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lag(log(GINI), 3)	−0.026	−0.040	−0.022	−0.025	−0.026	−0.034	−0.026	−0.041	−0.025	−0.024
	(0.060)	(0.060)	(0.061)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
log(1 + ENTRY)	−0.001									
	(0.003)									
log(1 + EXIT)		-0.006^{*}								
		(0.003)								
log(1 + Entry_LM)			0.0003							
			(0.001)							
log(1 + Exit_LM)				0.0001						
				(0.001)						
log(1 + Entry_LKIS)					0.0001					
					(0.001)					
log(1 + Exit_LKIS)						−0.001				
						(0.001)				
log(1 + Entry_HM)							−0.0003			
							(0.001)			
log(1 + Exit_HM)								-0.002^{***}		
								(0.001)		
log(1 + Entry_KIS)									0.001	
									(0.001)	
log(1 + Exit_KIS)										0.0003
										(0.001)
log(UNEMP)	0.020^{***}	0.021^{***}	0.020^{***}	0.020^{***}	0.020^{***}	0.020^{***}	0.020^{***}	0.021^{***}	0.020^{***}	0.020^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(EDcompo)	0.751^{***}	0.806^{***}	0.768^{***}	0.754^{***}	0.756^{***}	0.769^{***}	0.750^{***}	0.765^{***}	0.762^{***}	0.754^{***}
	(0.193)	(0.192)	(0.193)	(0.193)	(0.191)	(0.191)	(0.192)	(0.189)	(0.191)	(0.191)
log(POPDEN)	0.216^{***}	0.215^{***}	0.211^{***}	0.214^{***}	0.214^{***}	0.217^{***}	0.216^{***}	0.228^{***}	0.209^{***}	0.218^{***}
	(0.045)	(0.044)	(0.045)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)
log(GDP)	0.089^{**}	0.101^{***}	0.083^{**}	0.086^{**}	0.086^{**}	0.087^{**}	0.087^{**}	0.090^{**}	0.086^{**}	0.083^{**}
	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Observations	290	290	290	290	290	290	290	290	290	290
R^2	0.750	0.753	0.750	0.750	0.750	0.751	0.750	0.757	0.751	0.750
Adjusted R^2	0.715	0.719	0.716	0.715	0.715	0.717	0.715	0.723	0.717	0.716
F Statistic (df = 7; 254)	108.738^{***}	110.529^{***}	108.871^{***}	108.707^{***}	108.701^{***}	109.554^{***}	108.798^{***}	112.744^{***}	109.466^{***}	108.869^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6: Industrial diversification as skill levels in jobs

	Dependent variable:							
	log(GINI)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(log(GINI), 3)	−0.026	−0.040	−0.033	−0.033	−0.019	−0.023	−0.027	−0.038
	(0.060)	(0.060)	(0.061)	(0.060)	(0.060)	(0.060)	(0.060)	(0.061)
log(1 + Entry_ISCO1)			−0.001					
			(0.001)					
log(1 + Entry_ISCO2)				−0.002				
				(0.001)				
log(1 + Entry_ISCO3)					0.003^{**}			
					(0.001)			
log(1 + Exit_ISCO1)						−0.001		
						(0.001)		
log(1 + Exit_ISCO2)							−0.001	
							(0.001)	
log(1 + Exit_ISCO3)								−0.002
								(0.002)
log(UNEMP)	0.020^{***}	0.021^{***}	0.020^{***}	0.021^{***}	0.020^{***}	0.020^{***}	0.020^{***}	0.020^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(EDcompo)	0.751^{***}	0.806^{***}	0.751^{***}	0.756^{***}	0.715^{***}	0.749^{***}	0.791^{***}	0.769^{***}
	(0.193)	(0.192)	(0.191)	(0.191)	(0.190)	(0.191)	(0.195)	(0.191)
log(POPDEN)	0.216^{***}	0.215^{***}	0.221^{***}	0.223^{***}	0.207^{***}	0.215^{***}	0.214^{***}	0.218^{***}
	(0.045)	(0.044)	(0.045)	(0.045)	(0.044)	(0.044)	(0.044)	(0.044)
log(GDP)	0.089^{**}	0.101^{***}	0.086^{**}	0.092^{**}	0.075^{**}	0.086^{**}	0.086^{**}	0.088^{**}
	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Observations	290	290	290	290	290	290	290	290
R^2	0.750	0.753	0.751	0.752	0.755	0.750	0.750	0.751
Adjusted R^2	0.715	0.719	0.716	0.717	0.721	0.716	0.716	0.717
F Statistic (df = 7; 254)	108.738^{***}	110.529^{***}	109.298^{***}	109.782^{***}	111.754^{***}	109.032^{***}	109.142^{***}	109.627^{***}
Note:								$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.4. Robustness tests

The present study attempted to present robust results, e.g. by avoiding the common critique of the LQs by employing the cut-off value of the SLQs obtained by the bootstrapping method proposed by Tian (2013) and by using employment rates as an additional indicator for the entries and exits of regional specializations. However, this study conducted a number of additional robustness tests to test the validity of the findings.

First, this study has only used the Gini Coefficient as a measure for income inequality. The main reason was that the Gini Coefficient is the most widely-accepted measure for income inequality. Still, the Gini Coefficient is only one way of understanding income inequality, and the Gini Coefficient has been criticized for missing nuance. Several studies have reported analyses of trends in income inequality that demonstrated that results differ greatly according to the type of inequality measure adapted (E.g. Lee, 2011). To test different types of inequality measures, the study has used four additional models; Theil Index, Atkinson 0.5 Parameter, 90:10 Ratio and 80:20 Ratio. The additional robustness tests found similar results across the different inequality measures with the entering industries correlated positively to the inequality measures and the exit of industries correlated negatively to the inequality measures. See Table 22, Table 23, Table 24 and Table 25 in the Appendix for full regression results (Theil Index, Atkinson 0.5 Parameter, 90:10 Ratio and 80:20 Ratio). This indicates that the results correspond to many different types of income inequality measures. The only noticeable difference was that for the 90:10 Ratio and 80:20 Ratio high-skilled labor for the entering industries showed a negative relationship. This indicates that the high-skilled would not necessarily be among the top ten and top 20% highest earning and would, therefore, reduce the income differences between the top ten and bottom ten on one side and between the top twenty and bottom twenty on another side.

Second, in 2007, which lies right in the middle of the study's time frame, two main events in Denmark occurred, which could play an impact on the results. First of all, in 2007, the financial crisis struck Denmark, which changed the industrial landscape (Westergaard-Nielsen and Neamtu, 2012). Secondly, in 2007, Denmark underwent a large-scale structural reform, which changed the administrative planning landscape of Denmark (Eriksson et al., 2017). In order to further test the validity of the results, two additional analyses were therefore conducted by splitting the time-frame into two time-frames (2001 to 2006 and 2008 to 2013) and by removing the year 2007. The results show strong negative values for the exiting industries, as the primary study also showed, but insignificant values for the entering industries. An explanation for this could be that the sample becomes too small for the entering industries to have significant values.

Third, this study has used an unrestricted industrial sample of all 724 industries available in NACE rev. 2. In order to test the validity of the sample, the same analyses have been conducted using only tradable and non-tradable industries, respectively. For identification of tradable and non-tradable industries, the

Standard International Trade Classification (SITC; version 3) was used. The results showed significant, negative results for the exiting industries and positive results for the entering industries and were consistent for all five measures of inequality. For the entering industries, the effect was insignificant for the Gini Coefficient. However, for the remaining four inequality measures, the entering industries were significant and positive, just as the primary analysis.

5. Conclusion

In summary, this study investigated how industrial dynamics impact the development of regional income inequality in 29 Danish regions from 2001 to 2013. The study has used the Gini Coefficient as a main inequality measure and 16 different measures of industrial dynamics (the direct effect of entering and exiting industrial specializations, four different types of knowledge intensity in the entering and the exiting industrial specializations and three different occupational skill levels of the jobs in the entering and exiting industrial specializations). The study found little evidence for an effect of industrial dynamics on income inequality with only three of the 16 measures showing significant values in their effect on income inequality; namely the low-skilled jobs entering (significant at a 5% level) explained by the stratifying effect the low-skilled jobs has on the regional job-pool, the share of exiting industrial specializations (significant at a 10% level), particularly due to the share of high knowledge-intensive manufacturing sectors (significant at a 1% level) with explanations found in the substantively higher wage-levels for the high knowledge-intensive industries compared to the low knowledge-intensive manufacturing sectors and the service sectors (both low- and high knowledge-intensive sectors). The effect of the coefficients was, although comparable to similar studies (E.g. Lee, 2011), substantially lower than those for the control variables. The control variables performed very well with explanatory powers far surpassing those of the industrial dynamics.

So, to answer the research question set out for this study; industrial dynamics in terms of entering and exiting industries are affecting income inequality to a minimal extent at a regional level in the Danish context in the years 2001 to 2013.

This study is a first step in linking the literature on income inequality with the literature on industrial dynamics within economic geography on a sub-national scale. Although these findings show an effect of industrial dynamics on income inequality, they also call for further investigation. First, this study has been conducted in a Danish setting, where although there are regional differences and the differences are increasing, the institutional landscape is very similar. It could, therefore, be beneficial to unravel the specific capabilities that the institutional role plays by investigating these patterns in more extreme geographical settings. In addition, one explanation for the largely statistically insignificant results in the present study could be the broadness in both the skill-level and the industrial categories. Nevertheless, with the activity level of the industrial dynamics in Denmark, a further distinction could not be justified. The study could, therefore, have had different results on different geographical scales, such as in the US or on the European level. This warrants further research.

Second, there is a further need to investigate the role of relatedness of industrial dynamics in the development of income inequality. Previous studies have shown that regions with industries of similar skill capabilities perform stronger when hit by an external crisis owing to the possibility for workers to transform into new, yet similar, work (Neffke and Henning, 2013), as long as the firms are not connected in terms of input-output relations (Boschma, 2015). Besides, it is known that relatedness between firms in the same region enables knowledge spillover, can result in reductions of resource consumption and relatedness of skills is associated with regional productivity growth (Neffke, 2017; Wixe and Andersson, 2017). These could be reasons for relatedness playing a role for regional development of income inequality. However, this still needs further investigation.

In addition, the role of increasing robot technologies and automation been left untouched in this study, which calls for further investigation of how these dynamics might enforce or reduce income inequality. Some fear that it will further the job polarization processes (Frey and Osborne, 2017), others that it will create new jobs, although temporarily adjustment costs may be high for some (Autor, 2015).

Last but not least does this study call for a deeper understanding of first of all how the tendencies function at a micro level, e.g. firm level, and, secondly, which tools agents at the micro level can make use of in order create quality jobs for all workers and to not further increase income inequality.

This study, furthermore, through additional robustness tests, found that the choice of the inequality measure impacts the result of the study to a rather large extent. The theoretical implications of this study are therefore clear, and the study emphasizes the necessity of proper reflection of inequality measures in future research.

The results of the present study call for awareness among policymakers to develop targeted interventions aimed at economic policies interlinked with social policies.

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Appendix

Table 7: Mean, Max, Min and Std of main variables, 2001 to 2013

	MEAN	MAX	MIN	STD
GINI	0,32	0,40	0,29	0,02
ENTRY	1,70	7,38	0,00	0,91
EXIT	1,59	7,38	0,00	0,96
ISCO1_Entry	25,80	83,52	0,00	16,92
ISCO2_Entry	33,69	90,91	0,00	19,54
ISCO3_Entry	36,43	94,44	0,00	20,27
ISCO1_Exit	26,12	90,48	0,00	18,26
ISCO2_Exit	33,62	85,90	0,00	18,51
ISCO3_Exit	35,54	100,00	0,00	18,99
HM	7,97	10,27	2,33	1,65
LM	18,35	22,67	8,37	2,63
LKIS	35,30	43,29	31,56	1,98
KIS	26,17	35,74	24,17	1,76
HM_Entry	6,87	66,67	0,00	11,39
LM_Entry	16,04	100,00	0,00	17,13
LKIS_Entry	39,19	100,00	0,00	21,62
KIS_Entry	25,09	100,00	0,00	19,10
HM_Exit	8,05	100,00	0,00	13,15
LM_Exit	17,96	100,00	0,00	18,07
LKIS_Exit	37,43	100,00	0,00	23,18
KIS_Exit	23,49	100,00	0,00	20,47
UNEMP	4,13	8,39	1,13	1,26
LOWED	38,92	47,31	33,20	2,74
HIGHED	16,17	29,96	9,85	3,54
POPDEN	103,11	643,60	30,89	103,30
GDP	276103,93	441592,00	185652,00	44334,41

Table 8: Correlation Matrix

	GINI	ENTRY	EXIT	ISCO1	ISCO2	ISCO3	XISCO1	XISCO2	XISCO3	HM	LM	LKIS	KIS	UNEMP	LOWED	HIGHED	POPDEN	GDP
GINI	1	0.078	-0.029	0.106	-0.179	0.094	0.066	-0.195	0.044	0.298	0.317	-0.359	-0.244	-0.144	-0.643	0.819	0.671	0.547
ENTRY	0.078	1	0.436	-0.033	-0.035	0.159	-0.085	-0.090	0.174	-0.462	-0.481	0.346	0.489	0.011	-0.064	-0.001	-0.034	-0.009
EXIT	-0.029	0.436	1	-0.043	0.012	0.085	-0.122	0.0004	0.211	-0.494	-0.534	0.385	0.519	0.038	-0.003	-0.083	-0.082	-0.093
ISCO1	0.106	-0.033	-0.043	1	-0.288	-0.398	0.233	-0.041	-0.070	0.252	0.247	-0.355	-0.166	-0.023	-0.083	0.306	0.295	0.009
ISCO2	-0.179	-0.035	0.012	-0.288	1	-0.566	-0.074	0.157	-0.085	-0.020	-0.081	0.129	-0.004	-0.045	0.088	-0.189	-0.168	0.007
ISCO3	0.094	0.159	0.085	-0.398	-0.566	1	-0.106	-0.054	0.150	-0.162	-0.105	0.125	0.128	0.017	0.011	-0.045	-0.035	-0.019
XISCO1	0.066	-0.085	-0.122	0.233	-0.074	-0.106	1	-0.323	-0.470	0.173	0.132	-0.251	-0.089	0.028	-0.043	0.225	0.263	-0.056
XISCO2	-0.195	-0.090	0.0004	-0.041	0.157	-0.054	-0.323	1	-0.493	0.021	0.026	0.052	-0.101	-0.058	0.144	-0.204	-0.177	0.011
XISCO3	0.044	0.174	0.211	-0.070	-0.085	0.150	-0.470	-0.493	1	-0.155	-0.135	0.139	0.146	0.028	-0.003	-0.055	-0.060	-0.040
HM	0.298	-0.462	-0.494	0.252	-0.020	-0.162	0.173	0.021	-0.155	1	0.801	-0.809	-0.841	-0.241	-0.261	0.394	0.352	0.290
LM	0.317	-0.481	-0.534	0.247	-0.081	-0.105	0.132	0.026	-0.135	0.801	1	-0.835	-0.895	-0.161	-0.276	0.462	0.357	0.363
LKIS	-0.359	0.346	0.385	-0.355	0.129	0.125	-0.251	0.052	0.139	-0.809	-0.835	1	0.661	0.126	0.278	-0.548	-0.470	-0.164
KIS	-0.244	0.489	0.519	-0.166	-0.004	0.128	-0.089	-0.101	0.146	-0.841	-0.895	0.661	1	0.241	0.181	-0.302	-0.254	-0.386
UNEMP	-0.144	0.011	0.038	-0.023	-0.045	0.017	0.028	-0.058	0.028	-0.241	-0.161	0.126	0.241	1	0.283	-0.157	-0.030	-0.439
LOWED	-0.643	-0.064	-0.003	-0.083	0.088	0.011	-0.043	0.144	-0.003	-0.261	-0.276	0.278	0.181	0.283	1	-0.766	-0.345	-0.549
HIGHED	0.819	-0.001	-0.083	0.306	-0.189	-0.045	0.225	-0.204	-0.055	0.394	0.462	-0.548	-0.302	-0.157	-0.766	1	0.709	0.464
POPD	0.671	-0.034	-0.082	0.295	-0.168	-0.035	0.263	-0.177	-0.060	0.352	0.357	-0.470	-0.254	-0.030	-0.345	0.709	1	0.411
GDP	0.547	-0.009	-0.093	0.009	0.007	-0.019	-0.056	0.011	-0.040	0.290	0.363	-0.164	-0.386	-0.439	-0.549	0.464	0.411	1

Note: For layout-purposes entry and exit of different skill levels are marked with ISCO for entry and XISCO for exit.

Table 9: Inequality measures for all regions, 2001 to 2007

	GINI	THEIL	ATKINSON	RAT90	RAT80
DK	*0,313*	*0,168*	*0,104*	*16,857*	*6,321*
1	0,316	0,168	0,104	16,277	6,398
2	0,302	0,155	0,097	15,051	5,836
3	0,308	0,159	0,102	16,438	6,200
4	0,309	0,158	0,103	17,088	6,358
5	0,301	0,156	0,096	14,494	5,847
6	0,307	0,160	0,100	15,479	6,078
7	0,310	0,160	0,103	17,146	6,290
8	0,300	0,153	0,092	12,697	5,541
9	0,342	0,269	0,122	18,454	7,220
10	0,309	0,169	0,100	14,910	5,987
11	0,307	0,163	0,102	16,363	6,232
12	0,306	0,159	0,099	15,144	6,009
13	0,316	0,162	0,108	19,664	6,811
14	0,307	0,162	0,099	14,709	5,916
15	0,310	0,169	0,099	14,420	5,888
16	0,312	0,167	0,101	15,237	6,115
17	0,310	0,163	0,099	14,605	6,003
18	0,315	0,164	0,109	20,484	6,825
19	0,311	0,168	0,103	15,921	6,059
20	0,319	0,174	0,109	19,111	6,692
21	0,320	0,170	0,109	19,236	6,822
22	0,324	0,170	0,118	26,082	7,309
23	0,317	0,171	0,102	15,290	6,278
24	0,297	0,151	0,097	15,665	5,863
25	0,309	0,158	0,102	16,608	6,205
26	0,303	0,152	0,098	14,987	5,866
27	0,358	0,222	0,130	23,869	8,003
28	0,317	0,169	0,106	17,059	6,394
29	0,313	0,163	0,103	16,361	6,257

Table 10: Inequality measures for all regions, 2007 to 2013

	GINI	THEIL	ATKINSON	RAT90	RAT80
DK	*0,325*	*0,172*	*0,108*	*19,378*	*6,702*
1	0,329	0,175	0,114	22,325	7,324
2	0,311	0,162	0,107	19,768	6,548
3	0,321	0,167	0,114	25,168	7,387
4	0,315	0,163	0,111	22,940	7,061
5	0,312	0,163	0,107	20,639	6,835
6	0,321	0,175	0,112	22,121	7,132
7	0,326	0,171	0,115	25,579	7,552
8	0,312	0,176	0,106	17,669	6,513
9	0,354	0,237	0,126	23,540	8,122
10	0,320	0,173	0,111	21,072	6,943
11	0,321	0,176	0,116	25,047	7,389
12	0,316	0,171	0,109	20,297	6,937
13	0,327	0,172	0,118	28,394	7,851
14	0,319	0,172	0,109	20,092	6,770
15	0,330	0,190	0,115	21,608	7,137
16	0,328	0,183	0,115	22,457	7,275
17	0,326	0,182	0,113	21,313	7,137
18	0,324	0,169	0,120	31,096	7,879
19	0,327	0,201	0,117	21,984	7,111
20	0,330	0,181	0,120	27,014	7,669
21	0,334	0,186	0,119	25,083	7,809
22	0,333	0,179	0,118	25,044	7,916
23	0,329	0,180	0,112	20,376	7,145
24	0,303	0,153	0,104	19,594	6,420
25	0,319	0,163	0,112	23,757	7,121
26	0,310	0,165	0,111	21,103	6,846
27	0,382	0,249	0,145	37,013	9,833
28	0,331	0,177	0,118	25,831	7,613
29	0,329	0,177	0,120	27,819	7,802

Table 11: Regional industrial statistics, 2001 to 2007

Region	**Pop. Size**	**#Industries**	**#Special.**	**Entry%**	**Exit%**	**#Employees in mean industries**	**#Employees in Spec. industries**	**Rural or Urban**
DK	*5.407.090*	*419*	*54*	*1,77*	*1,56*	*189*	*324*	*DK*
1	376758	561	46	0,87	0,82	304	181	Urban
2	66340	374	54	2,15	1,76	67	32	Rural
3	67861	392	51	2,00	1,60	69	50	Rural
4	68916	392	46	1,36	1,17	78	96	Rural
5	48603	353	55	2,19	1,49	61	64	Rural
6	88750	420	43	1,05	1,19	124	510	Rural
7	82263	415	48	1,37	1,47	70	67	Rural
8	95798	426	52	1,72	1,57	118	693	Urban
9	495249	577	62	1,78	1,36	495	1674	Urban
10	121948	462	73	1,73	1,51	132	174	Urban
11	57886	370	36	1,27	0,72	99	33	Rural
12	79099	391	52	2,05	1,54	92	248	Rural
13	23015	251	52	2,62	2,50	39	224	Rural
14	121536	452	55	1,64	1,23	125	231	Urban
15	212979	521	56	1,62	1,21	226	438	Urban
16	180572	506	62	1,27	1,53	163	191	Urban
17	167913	489	48	1,46	1,02	166	145	Urban
18	47198	309	50	1,66	2,08	52	124	Rural
19	73823	370	54	1,47	1,35	89	618	Rural
20	60050	369	50	1,85	1,41	90	100	Rural
21	72533	394	54	2,43	1,95	66	112	Rural
22	7026	152	50	3,73	4,22	16	40	Rural
23	360081	553	57	1,49	0,95	298	153	Urban
24	43655	320	40	2,01	1,78	52	59	Rural
25	63652	359	32	1,46	1,20	82	9	Rural
26	49842	317	53	2,52	2,07	47	66	Rural
27	1833943	662	134	1,71	1,53	1929	2790	Urban
28	281766	519	45	1,21	1,24	208	167	Rural
29	158033	479	52	1,58	1,79	112	118	Rural

Table 12: Regional industrial statistics, 2007 to 2013

Region	Pop. Size	#Industries	#Special.	Entry%	Exit%	#Employees in mean industries	#Employees in Spec. industries	Rural or Urban
DK	*5.530.047*	*430*	*56*	*1,69*	*1,68*	*176*	*281*	*DK*
1	381866	576	53	1,12	0,89	288,2	123,7	Urban
2	63911	396	55	2,32	2,15	58,1	36,0	Rural
3	66652	396	54	1,59	1,80	61,9	46,7	Rural
4	66819	406	44	1,23	1,20	71,1	99,7	Rural
5	48005	349	55	1,55	1,80	56,9	53,2	Rural
6	92965	430	29	0,65	0,97	164,4	491,3	Rural
7	79689	431	50	1,59	1,83	63,2	42,9	Rural
8	94669	439	52	1,27	1,36	106,8	499,2	Urban
9	524258	590	64	1,48	1,29	461,4	1737,2	Urban
10	125589	476	81	1,98	1,80	130,5	89,9	Urban
11	58173	378	53	1,51	1,55	66,2	70,5	Rural
12	79431	403	52	1,56	1,81	79,8	127,5	Rural
13	21743	264	53	3,07	2,70	35,1	114,7	Rural
14	127745	476	61	1,65	1,50	115,7	155,0	Urban
15	219987	537	58	1,25	1,23	254,4	508,8	Urban
16	187529	525	60	1,17	1,14	156,5	266,4	Urban
17	168182	501	52	1,43	1,31	142,5	173,4	Urban
18	39694	329	45	1,47	1,75	45,9	88,5	Rural
19	76427	382	49	1,34	1,57	77,7	487,4	Rural
20	59887	375	54	1,79	1,72	67,7	44,4	Rural
21	72218	405	55	2,08	2,40	60,3	97,0	Rural
22	6673	159	51	4,36	4,61	13,6	14,5	Rural
23	367666	567	68	1,34	1,23	258,0	136,4	Urban
24	42056	330	45	2,25	1,73	44,3	51,9	Rural
25	62711	357	49	2,02	1,49	54,5	8,2	Rural
26	46769	318	47	2,02	2,41	45,5	65,9	Rural
27	1895910	673	139	1,74	1,49	1817,1	2276,9	Urban
28	290502	528	45	1,16	1,06	212,5	157,3	Rural
29	162322	486	47	1,09	1,06	107,8	83,1	Rural

Table 13: Share of high and low educational backgrounds and income level for average, entering and exiting HM-, LM-, KIS-, LKIS-sectors

	High Ed. 2001 to 2007	**High Ed. 2007 to 2013**	**Low Ed. 2001 to 2007**	**Low Ed. 2007 to 2013**	**Income (DKK) 2001 to 2007**	**Income (DKK) 2007 to 2013**
HM	5,15	3,49	27,59	30,70	235.550	234.330
HM EN.	7,23	8,27	31,12	33,26	223.864	275.257
HM EX.	7,42	4,28	33,79	35,93	252.783	251873
LM	2,68	1,71	36,24	40,14	215.796	207.066
LM EN.	3,98	5,02	38,51	40,57	200.177	247.657
LM EX.	3,73	3,60	36,54	41,94	241.603	226.065
KIS	8,37	7,48	42,6	42,4	225.701	235.498
KIS EN.	15,16	11,75	39,5	39,8	218.825	257.159
KIS EX.	12,30	13,83	40,2	40,1	270.317	249.064
LKIS	3,02	2,27	3	2,3	193.880	202.879
LKIS EN.	4,19	3,40	4,2	3,4	194.639	221.843
LKIS EX.	3,79	3,25	3,8	3,3	226.454	218.036

Table 14: Share of types of industries for average, entering and exiting industries divided by regions in %, 2001 to 2007

Region	HM	LM	LKIS	KIS	HM En.	LM En.	LKIS En.	KIS En.	HM Ex.	LM Ex.	LKIS Ex.	KIS Ex.
DK	*8,1*	*18,7*	*35,3*	*26,0*	*7,1*	*16,8*	*40,1*	*24,6*	*8,4*	*19,2*	*36,1*	*23,3*
1	9,2	21,4	32,9	24,7	10,0	2,4	33,6	38,1	4,1	14,1	30,1	35,3
2	7,4	18,3	36,4	26,2	4,2	20,8	52,1	11,3	2,9	17,6	51,4	21,9
3	7,2	19,2	35,9	26,0	1,1	15,3	41,0	23,2	6,0	16,7	30,4	25,9
4	6,9	17,5	37,3	26,4	3,3	24,9	35,4	18,9	10,0	12,1	38,3	28,6
5	6,8	18,1	36,6	26,0	3,2	24,6	46,9	22,1	2,0	37,8	32,7	18,0
6	9,1	20,2	33,8	25,2	2,9	8,5	38,4	31,1	8,3	21,2	22,8	29,4
7	8,7	19,0	35,4	25,6	5,2	13,7	41,4	30,6	2,4	35,1	18,7	34,5
8	9,4	20,1	34,1	25,0	20,8	19,3	35,1	22,0	12,1	17,5	44,4	24,2
9	9,7	21,7	32,5	24,6	7,5	10,7	27,5	44,1	15,4	13,7	34,7	31,3
10	8,8	20,2	34,3	24,9	15,1	27,7	31,1	19,6	10,1	31,5	30,8	19,6
11	7,7	19,3	36,3	25,2	11,9	50,3	10,9	17,7	34,7	41,7	0,0	9,7
12	7,7	20,1	35,2	25,6	3,5	15,5	40,5	30,1	9,5	15,6	36,6	28,0
13	6,7	16,0	37,2	27,3	8,8	9,9	42,4	25,4	3,8	10,2	39,8	19,8
14	9,9	19,7	34,1	25,2	9,8	21,4	38,4	28,1	23,6	24,0	42,9	9,4
15	9,5	21,1	33,4	24,4	5,0	21,0	42,3	19,1	1,8	31,4	43,3	15,6
16	9,1	21,1	33,8	25,1	12,8	17,0	50,0	16,6	8,6	18,7	37,2	18,5
17	9,0	19,6	35,1	25,0	4,8	14,6	37,1	33,9	2,0	34,8	30,9	25,3
18	7,2	17,1	37,5	26,3	0,0	15,4	53,0	22,8	0,0	12,5	51,2	17,3
19	8,5	16,0	37,8	26,7	12,5	24,9	33,4	19,7	16,9	22,5	31,4	18,1
20	7,2	17,7	37,3	26,6	1,6	4,8	63,9	22,2	8,1	16,5	42,2	23,2
21	7,9	18,6	35,5	26,3	3,6	15,6	38,9	33,2	2,9	11,7	38,3	41,4
22	3,0	10,3	40,2	30,8	2,4	6,0	59,8	12,4	5,2	4,6	56,5	17,2
23	9,5	20,7	32,9	25,0	12,9	15,0	35,2	20,9	17,2	15,3	37,3	18,8
24	4,1	15,8	38,1	29,8	7,1	8,9	65,0	12,4	5,2	9,3	45,3	25,1
25	7,9	17,0	36,2	27,0	0,0	24,4	28,3	29,8	3,6	14,3	37,1	32,4
26	7,6	14,9	37,2	28,1	12,0	8,8	32,7	21,9	7,6	7,9	39,3	18,9
27	9,9	21,9	31,8	24,5	5,4	17,6	27,8	40,9	5,3	12,1	25,2	29,5
28	9,5	20,3	33,1	25,3	10,1	11,3	45,4	16,6	4,0	26,5	41,5	15,3
29	9,3	20,1	33,4	25,4	7,7	18,1	34,7	29,2	9,8	10,1	36,8	23,6

Table 15: Share of types of industries for average, entering and exiting industries divided by regions in %, 2007 to 2013

Region	HM	LM	LKIS	KIS	HM En.	LM En.	LKIS En.	KIS En.	HM Ex.	LM Ex.	LKIS Ex.	KIS Ex.
DK	*7,9*	*18,0*	*35,2*	*26,3*	*6,6*	*15,8*	*37,8*	*26,1*	*7,9*	*16,5*	*37,6*	*24,5*
1	9,1	20,8	32,8	24,6	17,6	20,3	37,4	16,6	13,7	10,2	20,8	31,5
2	6,7	17,3	36,7	26,4	3,7	16,0	47,9	15,9	5,4	24,9	42,9	18,1
3	6,4	18,7	36,1	26,1	0,0	24,6	41,9	18,4	1,3	22,9	47,0	8,3
4	6,8	17,3	36,7	26,6	5,2	19,2	31,7	16,7	2,9	26,1	33,8	14,7
5	6,8	18,4	35,9	26,2	4,4	26,2	26,9	20,3	4,3	25,6	28,5	21,9
6	9,3	19,1	33,8	25,4	15,0	20,0	31,0	25,0	0,0	9,5	45,6	26,6
7	8,7	17,5	35,5	26,2	11,6	23,5	33,5	24,3	11,7	18,4	39,3	18,1
8	9,3	18,7	34,7	25,2	4,2	19,3	37,2	32,9	7,3	16,1	41,0	27,7
9	9,5	21,4	32,3	24,7	8,1	14,5	19,7	47,1	10,2	24,8	15,6	37,6
10	8,9	18,9	34,4	25,5	5,7	16,5	29,5	28,9	7,2	24,1	27,0	26,5
11	8,0	18,0	35,5	25,9	6,7	12,2	45,1	8,0	8,8	24,0	38,5	12,0
12	7,8	19,3	35,2	25,6	1,6	14,1	53,6	28,3	8,6	12,5	51,3	24,4
13	6,7	15,0	37,0	27,6	7,7	11,2	41,2	19,6	11,6	6,0	45,9	15,2
14	9,6	19,7	33,4	25,6	10,7	12,8	44,1	24,4	15,9	23,4	35,1	23,6
15	9,7	20,8	33,0	24,4	7,5	20,0	41,8	9,3	11,1	26,4	21,9	14,7
16	8,9	19,9	33,9	25,2	7,9	33,5	39,3	10,4	4,6	20,5	50,0	19,2
17	8,5	19,3	35,2	25,1	2,4	18,6	36,5	25,7	9,6	14,6	35,0	28,1
18	6,3	16,4	38,4	26,1	0,0	7,6	41,0	36,2	0,0	8,3	51,6	31,1
19	8,4	15,1	37,4	27,4	18,4	19,6	23,5	29,8	22,5	15,9	25,4	30,8
20	7,4	15,8	37,3	27,2	4,8	5,0	45,0	30,3	9,3	7,6	37,1	30,8
21	7,3	18,4	35,2	26,5	4,4	12,9	44,9	30,7	3,8	11,0	50,3	26,1
22	3,2	9,3	37,3	33,6	0,0	1,3	60,0	29,8	2,4	5,4	63,7	23,1
23	9,2	20,5	33,1	25,1	6,1	10,6	39,9	35,5	18,0	20,8	24,8	24,5
24	4,2	15,6	37,2	30,4	0,0	24,7	40,7	27,7	2,9	9,7	59,4	24,9
25	7,8	15,8	36,0	27,2	2,4	8,2	34,0	29,8	2,9	6,5	36,8	32,6
26	6,1	13,9	37,8	28,6	14,5	12,9	21,5	36,2	16,0	13,5	26,6	28,1
27	9,8	21,9	31,8	24,5	3,2	15,1	24,8	48,2	4,4	22,7	20,5	36,3
28	9,0	20,0	33,6	25,3	5,4	10,7	48,6	18,1	4,9	22,5	44,1	11,6
29	9,2	19,2	33,6	25,4	11,8	6,5	35,4	31,7	9,2	3,6	31,7	41,2

Table 16: Share high and low educational backgrounds for average, entering and exiting industries divided by regions in %, 2001 to 2007

Region	High Ed	Low Ed	High Ed Entry	Low Ed Entry	High Ed Exit	Low Ed Exit
DK	*15,2*	*40,3*	*14,7*	*34,1*	*15,6*	*33,7*
1	17,0	39,9	13,3	30,7	22,9	29
2	11,8	41,9	8,7	36,6	8,7	39,2
3	14,6	41,4	7,3	46,8	8,5	44,6
4	12,2	43,5	10,1	34,9	8,3	39,6
5	13,7	41,0	9	32,7	3,9	30,2
6	16,6	37,8	13,6	15,9	13,7	19,6
7	14,4	40,2	12	30,9	11,6	32,7
8	13,4	39,9	14,2	31	12,4	29,7
9	23,5	36,5	45,3	20,4	42	23,1
10	12,9	41,2	14,3	36,3	11,1	34,6
11	12,9	41,1	7,9	34,5	10,7	33,7
12	15,6	40,9	20,5	35	14,7	37,8
13	13,7	43,4	6,9	48,5	14,2	39,4
14	14,3	39,9	14,9	29,2	16,4	31,4
15	16,1	39,5	13,8	33,1	10,7	42,3
16	15,2	39,5	10,8	33,4	10,5	28,4
17	15,5	39,7	19,1	34,4	12,4	40,5
18	11,5	43,1	8,9	40,7	12,8	35,9
19	16,8	37,2	16	28,6	18,6	32
20	13,5	39,8	9,2	35,3	17	29,6
21	17,7	38,3	18,6	30,9	19	29,7
22	16,7	36,2	12,9	31,5	17,9	28,2
23	17,4	39,7	13,5	39,2	12,7	31,5
24	13,6	42,9	17,1	33,6	22,5	43,6
25	14,1	40,8	8,4	42,2	13	36,6
26	10,7	45,6	14,4	33,4	18,6	33,3
27	24,4	36,5	33,5	31,7	30,5	29,9
28	14,7	40,6	13,6	38,9	8,2	42,6
29	15,2	40,0	17,3	39,2	29,5	28,7

Table 17: Share high and low educational backgrounds for average, entering and exiting industries divided by regions in %, 2007 to 2013

Region	High Ed	Low Ed	High Ed Entry	Low Ed Entry	High Ed Exit	Low Ed Exit
DK	*17,1*	*37,5*	*12,6*	*36,1*	*11,8*	*37,5*
1	19,9	36,8	29,4	25,5	25,7	24,4
2	13,6	38,3	5,6	47,7	6,4	46,8
3	16,5	38,1	5,7	43,7	10,6	37,5
4	13,1	40,6	4,9	39,7	20,2	37,5
5	15,3	38,1	6,6	34,1	7,7	36,5
6	19,1	35,0	14,1	29	6,1	34,2
7	15,9	37,2	16,8	36,1	10,9	35,7
8	15,6	37,2	9,6	41,5	16,3	40,5
9	27,0	34,2	27,6	29,7	23,3	23,3
10	15,1	38,1	10,2	34,5	8,4	40,3
11	14,2	37,6	4,2	43,9	8,2	37,3
12	18,0	37,6	10,8	37,9	10,8	40,4
13	15,1	39,2	10,3	35,3	6,2	40,5
14	17,0	36,7	12,9	34,2	7,3	43,4
15	18,7	36,9	14,4	34,8	8,8	38,4
16	17,4	36,9	16,2	33,1	9,7	39,3
17	17,5	37,2	8,4	39,8	5,9	42,6
18	12,5	39,9	8,3	42,6	7,7	39,9
19	18,7	35,4	11,6	25,7	16,3	31,5
20	15,0	37,3	5,5	36,8	9,1	38,5
21	20,1	35,8	23,3	30,8	20,9	34,8
22	18,2	33,8	8,8	30,8	7,6	35,7
23	20,1	37,6	19,6	31,3	12,3	34,9
24	15,5	39,6	10,8	43,1	12,9	42,4
25	15,8	38,2	9,6	37,6	8,2	43,9
26	11,7	43,5	6,4	40,9	8,7	36,7
27	28,2	35,1	28,4	31,3	23,9	32
28	16,5	38,4	11,1	38,2	9,6	37,4
29	14,7	37,5	13,6	38,6	12,8	41

Table 18: Income level for average, entering and exiting industries divided by regions in %, 2001 to 2007

Region	Income Mean	Income Mean Entry	Income Mean Exit
DK	*211.187,2*	*213.736,9*	*205.299,7*
1	208.745,9	229.225,6	206.939,2
2	204.157,0	187.535,9	178.313,0
3	205.859,6	198.079,7	180.001,8
4	201.544,0	216.357,5	190.836,6
5	207.512,4	213.989,0	197.869,7
6	214.905,7	216.697,4	230.014,0
7	208.494,9	228.175,3	203.835,6
8	216.498,1	201.396,2	203.520,5
9	232.769,1	236.722,0	240.054,1
10	221.671,0	259.696,3	229.644,4
11	208.473,3	196.813,6	200.252,1
12	220.658,1	226.280,3	216.340,3
13	198.109,6	183.403,4	183.292,5
14	222.699,2	226.349,3	211.673,0
15	231.187,7	247.367,7	213.922,7
16	223.034,7	229.152,2	218.913,6
17	214.834,9	228.390,0	225.327,0
18	198.418,6	185.613,4	181.936,1
19	209.623,1	231.909,1	227.931,1
20	212.303,7	196.417,9	192.828,9
21	207.383,3	198.346,1	186.726,8
22	183.270,1	175.192,6	162.401,2
23	215.034,4	222.579,0	206.634,1
24	184.247,7	182.920,1	189.889,3
25	199.290,0	205.140,0	193.986,2
26	187.526,6	179.980,2	169.121,6
27	249.660,6	260.430,7	281.229,0
28	220.429,2	214.036,3	208.080,2
29	216.085,5	220.171,8	222.177,5

Note: In DKK (1 Euro corresponds to approximately 7,67 DKK per July 2019)

Table 19: Income level for average, entering and exiting industries divided by regions in %, 2007 to 2013

Region	Income Mean	Income Mean Entry	Income Mean Exit
DK	*244393,5*	*242262,9*	*234326,8*
1	243.476,7	229.300,2	246.881,9
2	237.333,0	212.489,7	212.623,3
3	231.945,2	205.481,8	198.830,7
4	232.000,7	256.844,8	234.898,9
5	241.751,6	220.720,3	235.379,8
6	251.523,2	261.620,7	261.089,9
7	242.409,7	247.682,3	205.342,0
8	251.899,2	251.609,7	252.897,9
9	269.214,6	272.102,4	236.878,2
10	253.722,5	261.791,3	254.292,1
11	245.005,5	222.794,1	220.595,8
12	246.593,5	210.088,6	224.266,7
13	235.392,4	211.868,6	184.042,9
14	255.819,0	275.282,3	253.628,1
15	267.921,4	278.737,0	253.043,5
16	259.072,4	271.297,0	250.574,2
17	254.762,1	265.560,0	254.531,7
18	224.984,3	198.675,6	195.616,8
19	245.769,3	247.362,1	248.685,5
20	243.386,4	285.033,2	263.210,9
21	244.333,5	251.919,1	226.610,7
22	220.438,8	224.737,3	203.749,1
23	249.668,8	243.436,0	270.479,7
24	213.942,2	200.663,9	191.903,6
25	222.733,2	220.333,7	217.514,4
26	208.904,0	224.133,1	216.120,9
27	289.184,2	332.195,3	324.295,2
28	254.150,5	226.772,5	215.465,4
29	250.073,2	215.092,5	242.027,5

Note: In DKK (1 Euro corresponds to approximately 7,67 DKK per July 2019)

Table 20: Share of skill levels for average, entering and exiting industries divided by regions in %, 2001 to 2007

Region	**ISCO1**	**ISCO2**	**ISCO3**	**ISCO1 En.**	**ISCO2 En.**	**ISCO3 En.**	**ISCO1 Ex.**	**ISCO2 Ex.**	**ISCO3 Ex.**
DK	*20,0*	*21,7*	*46,1*	*22,8*	*32,6*	*40,8*	*22,4*	*32,1*	*39,2*
1	22,1	21,0	44,8	42,7	17,8	38,1	40,2	18,6	34,6
2	15,7	24,0	46,8	13,6	27,5	53,7	10,7	23,7	57,2
3	19,0	21,6	47,4	11,9	25,1	54,7	21,6	26,2	47,7
4	15,5	25,8	46,8	12,9	50,5	32,3	21,6	36,0	38,4
5	18,8	26,7	42,9	19,1	45,9	30,2	19,9	41,6	31,7
6	22,5	23,0	42,9	31,5	33,6	27,8	19,8	44,3	26,8
7	18,3	21,5	47,7	15,7	20,3	58,3	19,1	33,1	39,5
8	20,2	22,9	45,4	22,1	34,6	41,7	23,7	24,6	46,3
9	28,5	17,6	43,0	36,4	21,2	38,2	39,3	19,3	34,5
10	20,0	24,2	45,0	19,3	46,2	30,9	20,6	41,2	36,5
11	17,9	25,6	45,9	13,1	49,3	35,7	30,2	49,2	18,7
12	21,3	25,5	42,2	28,2	37,9	31,2	25,4	43,0	27,1
13	17,8	23,8	47,2	19,1	38,3	39,7	9,8	30,3	43,6
14	20,5	24,8	44,0	25,1	38,5	34,5	18,6	43,8	33,8
15	22,6	22,4	44,2	33,5	33,8	29,5	23,6	36,1	35,9
16	21,2	21,9	45,6	27,4	34,1	36,1	27,2	32,5	34,6
17	20,8	22,7	45,0	17,7	27,1	53,1	13,7	35,3	45,9
18	15,0	22,2	50,1	13,3	22,1	60,7	9,9	34,6	49,4
19	22,7	23,9	42,1	24,3	44,8	28,9	34,3	28,8	31,9
20	19,0	22,4	46,4	15,3	32,2	49,9	22,5	33,4	39,5
21	20,6	18,8	47,5	29,4	27,0	39,5	24,4	23,1	47,1
22	16,7	16,0	51,9	11,4	31,0	49,8	7,4	24,5	58,4
23	22,2	19,9	46,0	29,9	34,6	34,0	25,7	36,3	33,4
24	16,6	18,0	50,5	26,6	21,4	48,4	28,8	23,4	35,2
25	18,8	19,2	48,7	19,3	38,7	42,6	18,3	38,6	37,3
26	14,7	18,1	52,7	20,9	31,4	37,9	19,3	30,1	44,3
27	30,1	16,3	42,3	38,3	17,7	42,8	38,9	21,5	34,8
28	20,8	20,6	46,7	23,9	28,9	43,0	17,6	31,7	40,5
29	21,1	20,0	46,5	18,1	33,8	40,9	16,5	25,1	52,5

Table 21: Share of skill levels for average, entering and exiting industries divided by regions in %, 2007 to 2013

Region	ISCO1	ISCO2	ISCO3	ISCO1 En.	ISCO2 En.	ISCO3 En.	ISCO1 Ex.	ISCO2 Ex.	ISCO3 Ex.
DK	*22,5*	*17,6*	*36,4*	*30,2*	*35,4*	*33,3*	*31,3*	*35,3*	*33,2*
1	25,4	16,7	35,7	29,3	40,0	30,4	42,1	39,1	18,7
2	18,5	19,4	37,4	19,2	36,9	42,5	15,5	38,1	45,6
3	21,2	17,6	37,9	13,6	31,8	53,8	14,2	37,9	47,4
4	17,6	21,3	36,9	27,4	50,5	21,1	20,6	58,1	20,3
5	21,2	20,2	35,4	22,5	57,2	20,0	16,5	58,4	24,4
6	25,3	18,2	33,5	51,4	35,8	12,0	41,3	35,1	22,8
7	20,7	18,0	37,5	26,7	42,8	30,2	24,3	29,5	45,9
8	23,3	17,8	37,4	30,0	32,4	36,9	39,0	28,4	32,5
9	31,5	13,9	33,3	62,4	16,3	20,7	55,5	18,0	26,3
10	23,5	19,6	35,3	37,1	33,5	29,2	31,9	38,4	29,4
11	20,6	22,2	34,3	16,1	39,9	36,2	26,4	46,6	23,5
12	23,8	20,2	34,0	33,5	29,7	36,2	29,3	35,6	34,9
13	19,2	21,2	35,7	13,8	38,8	46,4	20,0	44,9	40,6
14	24,6	20,2	34,4	36,1	33,6	30,0	31,8	35,0	33,0
15	25,9	18,1	34,8	33,6	45,5	19,9	26,7	41,7	30,0
16	24,2	17,9	35,9	26,9	50,2	22,7	36,7	39,7	23,5
17	23,4	18,6	35,4	30,0	27,7	41,7	21,0	42,5	35,7
18	16,7	19,2	38,2	21,5	30,7	46,4	20,3	30,4	49,3
19	25,3	18,3	33,9	34,3	48,3	17,1	35,3	44,8	19,8
20	21,3	19,0	36,2	25,5	42,8	31,0	35,2	32,7	31,0
21	22,8	14,3	37,2	32,0	28,3	36,9	36,8	28,9	33,0
22	17,6	12,9	38,2	21,3	35,5	46,3	36,1	24,8	37,9
23	24,7	15,6	36,8	33,4	31,3	35,2	39,8	34,9	26,9
24	18,0	14,4	39,5	38,7	26,3	33,4	39,8	20,8	47,6
25	20,8	14,9	39,5	20,5	35,5	43,0	29,5	29,0	38,9
26	15,9	14,4	43,6	35,8	29,1	31,4	31,3	30,4	36,5
27	33,2	13,3	32,3	48,8	19,5	31,5	52,9	17,6	29,5
28	23,1	16,7	37,8	29,9	31,1	34,0	18,8	42,0	37,6
29	23,5	16,0	36,8	25,8	24,2	49,2	38,1	19,8	40,9

Table 22: Robustness test - Inequality measure: Theil Index

	Dependent variable:									
	log(THEIL)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lag(log(THEIL), 3)	0.118	0.113	0.122	0.120	0.117	0.097	0.117	0.117	0.131^{*}	0.117
	(0.075)	(0.075)	(0.076)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)
log(1 + ENTRY)	0.001									
	(0.013)									
log(1 + EXIT)		−0.008								
		(0.012)								
log(1 + LM_Entry)			0.001							
			(0.002)							
log(1 + LM_Exit)				0.001						
				(0.002)						
log(1 + LKIS_Entry)					0.002					
					(0.003)					
log(1 + LKIS_Exit)						-0.006^{**}				
						(0.003)				
log(1 + HM_Entry)							0.0002			
							(0.002)			
log(1 + HM_Exit)								−0.001		
								(0.002)		
log(1 + KIS_Entry)									0.005^{**}	
									(0.003)	
log(1 + KIS_Exit)										−0.0001
										(0.002)
log(UNEMP)	0.060^{***}	0.060^{***}	0.059^{***}	0.060^{***}	0.060^{***}	0.061^{***}	0.060^{***}	0.060^{***}	0.061^{***}	0.060^{***}
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
log(EDcompo)	−0.968	−0.918	−0.937	−1.016	−0.978	−0.924	−0.971	−0.975	−0.934	−0.977
	(0.716)	(0.717)	(0.718)	(0.715)	(0.711)	(0.706)	(0.714)	(0.711)	(0.706)	(0.712)
log(POPDEN)	0.150	0.155	0.142	0.147	0.150	0.173	0.151	0.162	0.118	0.152
	(0.168)	(0.166)	(0.167)	(0.166)	(0.166)	(0.165)	(0.167)	(0.167)	(0.165)	(0.168)
log(GDP)	0.579^{***}	0.602^{***}	0.573^{***}	0.579^{***}	0.571^{***}	0.588^{***}	0.582^{***}	0.585^{***}	0.582^{***}	0.583^{***}
	(0.138)	(0.138)	(0.136)	(0.134)	(0.135)	(0.133)	(0.135)	(0.134)	(0.133)	(0.136)
Observations	290	290	290	290	290	290	290	290	290	290
R^2	0.440	0.441	0.440	0.440	0.441	0.450	0.440	0.440	0.449	0.440
Adjusted R^2	0.362	0.364	0.363	0.363	0.364	0.374	0.362	0.363	0.373	0.362
F Statistic (df = 7; 254)	28.473^{***}	28.578^{***}	28.516^{***}	28.544^{***}	28.599^{***}	29.653^{***}	28.472^{***}	28.526^{***}	29.520^{***}	28.470^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 23: Robustness test - Inequality measure: Atkinson 0.5 Parameter

	Dependent variable:									
	log(ATKIN)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lag(log(ATKIN), 3)	−0.159**	−0.163**	−0.157**	−0.156**	−0.157**	−0.161**	−0.158**	−0.166**	−0.157**	−0.157**
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.066)	(0.067)	(0.067)
log(1 + ENTRY)	−0.002									
	(0.010)									
log(1 + EXIT)		−0.009								
		(0.009)								
log(1 + LM_Entry)			0.0001							
			(0.002)							
log(1 + LM_Exit)				0.001						
				(0.002)						
log(1 + LKIS_Entry)					0.0005					
					(0.002)					
log(1 + LKIS_Exit)						−0.002				
						(0.002)				
log(1 + HM_Entry)							0.0003			
							(0.002)			
log(1 + HM_Exit)								−0.003*		
								(0.002)		
log(1 + KIS_Entry)									0.001	
									(0.002)	
log(1 + KIS_Exit)										0.001
										(0.002)
log(UNEMP)	0.031***	0.032***	0.031***	0.031***	0.031***	0.031***	0.031***	0.032***	0.031***	0.031***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
log(EDcompo)	2.704***	2.796***	2.716***	2.667***	2.710***	2.737***	2.718***	2.737***	2.716***	2.705***
	(0.550)	(0.552)	(0.550)	(0.550)	(0.548)	(0.548)	(0.550)	(0.544)	(0.547)	(0.547)
log(POPDEN)	0.345***	0.343***	0.340***	0.337***	0.341***	0.346***	0.340***	0.367***	0.336***	0.355***
	(0.124)	(0.123)	(0.124)	(0.123)	(0.123)	(0.123)	(0.124)	(0.123)	(0.123)	(0.124)
log(GDP)	0.135	0.156	0.130	0.128	0.128	0.133	0.130	0.139	0.131	0.121
	(0.103)	(0.103)	(0.102)	(0.101)	(0.101)	(0.101)	(0.101)	(0.100)	(0.101)	(0.102)
Observations	290	290	290	290	290	290	290	290	290	290
R^2	0.662	0.663	0.662	0.662	0.662	0.663	0.662	0.666	0.662	0.662
Adjusted R^2	0.615	0.617	0.615	0.616	0.615	0.616	0.615	0.620	0.615	0.616
F Statistic (df = 7; 254)	70.957***	71.407***	70.949***	71.169***	70.965***	71.260***	70.955***	72.395***	71.068***	71.123***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 24: Robustness test - Inequality measure: 90:10 Ratio

	Dependent variable:									
	log(RAT90)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lag(log(RAT90), 3)	-0.236^{***}	-0.237^{***}	-0.237^{***}	-0.235^{***}	-0.235^{***}	-0.236^{***}	-0.235^{***}	-0.241^{***}	-0.235^{***}	-0.235^{***}
	(0.065)	(0.065)	(0.066)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
log(1 + ENTRY)	−0.010									
	(0.030)									
log(1 + EXIT)		−0.025								
		(0.028)								
log(1 + LM_Entry)			−0.002							
			(0.005)							
log(1 + LM_Exit)				0.003						
				(0.005)						
log(1 + LKIS_Entry)					0.0003					
					(0.007)					
log(1 + LKIS_Exit)						−0.002				
						(0.006)				
log(1 + HM_Entry)							0.001			
							(0.006)			
log(1 + HM_Exit)								−0.009		
								(0.005)		
log(1 + KIS_Entry)									−0.002	
									(0.006)	
log(1 + KIS_Exit)										0.004
										(0.005)
log(UNEMP)	0.108^{***}	0.109^{***}	0.109^{***}	0.107^{***}	0.107^{***}	0.107^{***}	0.107^{***}	0.109^{***}	0.107^{***}	0.108^{***}
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
log(EDcompo)	11.613^{***}	11.875^{***}	11.619^{***}	11.552^{***}	11.668^{***}	11.694^{***}	11.684^{***}	11.730^{***}	11.654^{***}	11.654^{***}
	(1.718)	(1.724)	(1.718)	(1.718)	(1.711)	(1.712)	(1.716)	(1.702)	(1.711)	(1.709)
log(POPDEN)	0.509	0.494	0.504	0.476	0.489	0.495	0.486	0.560	0.502	0.533
	(0.390)	(0.385)	(0.389)	(0.386)	(0.386)	(0.386)	(0.388)	(0.386)	(0.387)	(0.390)
log(GDP)	0.180	0.219	0.172	0.146	0.154	0.157	0.154	0.178	0.155	0.122
	(0.326)	(0.326)	(0.323)	(0.318)	(0.321)	(0.318)	(0.318)	(0.317)	(0.318)	(0.321)
Observations	290	290	290	290	290	290	290	290	290	290
R^2	0.663	0.664	0.663	0.664	0.663	0.663	0.663	0.667	0.663	0.664
Adjusted R^2	0.617	0.618	0.617	0.617	0.617	0.617	0.617	0.621	0.617	0.618
F Statistic (df = 7; 254)	71.505^{***}	71.786^{***}	71.496^{***}	71.639^{***}	71.457^{***}	71.496^{***}	71.460^{***}	72.593^{***}	71.507^{***}	71.661^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 25: Robustness test - Inequality measure: 80:20 Ratio

	Dependent variable:									
	log(RAT80)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lag(log(RAT80), 3)	-0.183^{***}	-0.189^{***}	-0.183^{***}	-0.181^{***}	-0.182^{***}	-0.184^{***}	-0.182^{***}	-0.192^{***}	-0.182^{***}	-0.182^{***}
	(0.060)	(0.059)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.059)	(0.060)	(0.060)
log(1 + ENTRY)	−0.004									
	(0.011)									
log(1 + EXIT)		-0.018^{*}								
		(0.011)								
log(1 + LM_Entry)			−0.0004							
			(0.002)							
log(1 + LM_Exit)				0.001						
				(0.002)						
log(1 + LKIS_Entry)					0.0002					
					(0.003)					
log(1 + LKIS_Exit)						−0.002				
						(0.002)				
log(1 + HM_Entry)							−0.001			
							(0.002)			
log(1 + HM_Exit)								-0.005^{**}		
								(0.002)		
log(1 + KIS_Entry)									0.001	
									(0.002)	
log(1 + KIS_Exit)										0.0004
										(0.002)
log(UNEMP)	0.066^{***}	0.067^{***}	0.066^{***}	0.066^{***}	0.066^{***}	0.066^{***}	0.066^{***}	0.067^{***}	0.066^{***}	0.066^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
log(EDcompo)	4.712^{***}	4.894^{***}	4.723^{***}	4.704^{***}	4.737^{***}	4.761^{***}	4.724^{***}	4.772^{***}	4.742^{***}	4.735^{***}
	(0.635)	(0.634)	(0.635)	(0.635)	(0.632)	(0.632)	(0.634)	(0.624)	(0.632)	(0.632)
log(POPDEN)	0.354^{**}	0.348^{**}	0.349^{**}	0.342^{**}	0.345^{**}	0.350^{**}	0.349^{**}	0.385^{***}	0.342^{**}	0.350^{**}
	(0.146)	(0.143)	(0.145)	(0.144)	(0.144)	(0.144)	(0.145)	(0.143)	(0.145)	(0.146)
log(GDP)	0.125	0.162	0.119	0.112	0.114	0.117	0.116	0.128	0.115	0.111
	(0.121)	(0.121)	(0.120)	(0.118)	(0.119)	(0.118)	(0.118)	(0.117)	(0.118)	(0.119)
Observations	290	290	290	290	290	290	290	290	290	290
R^2	0.779	0.782	0.779	0.780	0.779	0.780	0.779	0.785	0.779	0.779
Adjusted R^2	0.749	0.752	0.749	0.749	0.749	0.749	0.749	0.755	0.749	0.749
F Statistic (df = 7; 254)	128.237^{***}	130.103^{***}	128.172^{***}	128.289^{***}	128.143^{***}	128.500^{***}	128.181^{***}	132.201^{***}	128.177^{***}	128.167^{***}

Note: *p<0.1; **p<0.05; ***p<0.01