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Different degrees, the same causes?

Analysing the mechanisms underlying the degree of job polarization across NUTS-2 regions

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Foreword

This thesis was written for my study ‘Economic geography; Regional competitiveness and trade’ at the University of Groningen. This thesis touches upon a lot of subjects I learned in my study. In this thesis, I explained the fascinating trend of job polarization with the active labour market policies in a country. Deepening my knowledge about this phenomenon with statistical analysis has proven difficult but rewarding. In the period writing this thesis, I have learned a lot about statistical analysis, job polarization, and myself. I would like to thank my supervisor dr. S. Koster for his qualitative feedback and for guiding me through the process. When, however, writing this foreword I cannot forget all my friends, family, and girlfriend who I would all like to thank for their support in the process.

Abstract

This study analyses the effect of active labour market policies on regional (NUTS-2) job polarization. This is done to provide policymakers with a useful framework to examine the possible causes for job polarization on a regional level. This is done by using the European Labour Force Survey, openness to trade data and data on active labour market policies. A comprehensive model is established containing the three main explanatory factors for job polarization: technological change, globalization, and institutions. In addition, multiple interaction effects and control variables are added to make the model more robust. After adding interaction effects and control variables, it is found that active labour market policies decrease inequality in hours worked in a region. This conclusion can help adapt to the changing labour market demands, if policymakers react to the threat of job polarization adequately; they might prevent people from falling behind on the labour market.

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1. Introduction

Over the last few decades, a shift in the employability of the workforce has taken place. When looking at the wage distribution, employment has grown in high- and low paying occupations whereas it has declined in the middle of the wage distribution (Dauth, 2014). This is known as a phenomenon called 'job polarization'. The mechanism causing the polarization of employability is called routine biased technological change (Autor et al., 2003). This means that technological change is complementary to the complicated tasks at the higher end of the wage distribution, shrinks the demand for routine tasks in the middle and does not directly influence the non-routine jobs (Autor & National Bureau of Economic Research, 2019). Job polarization thus decreases the employability of the middle-schooled workers (see figure 1). When not dealt with properly, this could cause long-term unemployment and exclusion of the labour market of the middle-schooled (Lund et al., 2019). It is therefore important to anticipate on the expected job polarization to prevent a group from being excluded from the labour market.

When plotting observed and counterfactual changes in employment and hourly wages in a graph, a clear u-shaped pattern can be observed (see figure 1). This pattern and its relation to routine biased technological change can be found in many recent studies (Goos et al., 2010; Autor et al., 2006; Goos & Manning, 2007).

Figure 1: Observed and Counterfactual Changes in Employment and Hourly Wages, 1980-2005 (Autor & Dorn, 2013)

Job polarisation has three causes namely: the increasing globalization, institutions, and the rise of technology (Goos et al., 2010). However, Goos et al (2010) state that technology is the most important driving factor when trying to explain job polarization. This technological change causes job polarization but is however unable to explain the regional differences in job polarization. In some regions, job polarization takes a u-curved shape whereas in other regions job polarization is weak or non-existent. This can be explained by the fact that there must be forces that are strong enough to neutralize the effect of technology on employment (Fernandez-Macias, 2012). According to Fernandez-Macias (2012), institutions have a major role in weakening the polarization effects of technological change.

When analysing job polarization, it is therefore important to consider at which scale level the study must be conducted. Local or national institutions can significantly affect the degree of job polarization (Lund et al., 2019). Take for example unions, a minimum wage, health and safety state regulations or employment construction schemes. These labour market institutions all have a dampening effect on the employment growth in the low paying occupations (Dustmann et al., 2009). The effect of institutions also has a great influence on the market capability to adapt to changing circumstances: the more flexible institutions are, the more they will help to keep the system durable (Amin & Thrift, 1994). One might argue that a more flexible and adaptive system of institutions is better prepared for changing circumstances in the local labour market. The degree of job polarization might therefore also be dampened by institutions in this way.

Many studies have been conducted about job polarization on the national level (Goos et al., 2009; Goos et al., 2010; Jerbashian 2019). In these studies, it is shown that every country to some degree has experienced job polarization in the last 20 to 30 years. However, as mentioned above: countries or regions might differ significantly in the degree of job polarization. This leads to the conclusion that there are forces in play that dampen or increase the degree of job polarization as mentioned by Fernandez-Macias (2012). These differences are interesting to explore because of the factors that cause these differences. Understanding the underlying factors could provide policymakers with a framework to adapt to the changing labour market.

In Europe, job polarization on a national level is widely investigated: (Goos & Manning, 2007; Goos et al., 2009; Goos et al., 2010; Jerbashian 2019; Wang et al., 2015, Dustmann et al., 2009). When analysing a local scale, less research about job polarization has been conducted. The studies available athe t local level compare counties/provinces in one country (Dauth, 2014.; Terzidis & Ortega-Argilés, 2021, Terzidis et al., 2017). Furthermore, the individual influence of technological change, globalisation, and institutions on the degree of job polarization have not widely been investigated. Especially the active labour market policies have been neglected in economic research for a long time (Rodríguez-Pose, 2013). This study aims to find the effects that national active labour market policies have on the degree of job polarization on a regional scale level. This is done by, not only analysing the direct effect that institutions have on job polarization but also by studying the interaction effect between institutions and globalization (trade openness) and the interaction effect between institutions and automation risk. According to the literature, it is very plausible that the quality and reliability of institutions correlate with the degree of globalization in a region (Dustman et al., 2009; Rodríguez-Pose, 2013). The other interaction effect between institutions and automation risk is also derived from the literature. It is to be expected that the higher the institutional spending, the lower the automation risk will be (Lund et al., 2019; Greatz, 2019).

These effects of institutions on job polarization are the focus of this study. To find this effect, technological change and the degree of globalization are also included in the study. A model that can analyse the multiple causes of job polarization (technology, institutions, and globalization) and their effect on the degree of polarization can help employers and policymakers with their decisions. Creating a preventive and all-encompassing policy to adapt to new circumstances can help create an inclusive and upgraded workforce (Lund et al., 2019).

1.1 Research aim & questions

This paper aims to fill the literature gap about the degree of polarization in NUTS-2 regions in Europe and analyse the effect that active labour market policies have on job polarization. Such a study could help understand job polarization on a local scale and analyses the underlying mechanisms. Having a clear insight into the ongoing labour market trends and mechanisms in place can help policymakers to adapt their policy to these factors (Graetz, 2019).

The research design is aimed at comparing and analysing the degree of job polarization in different regions and constructing a viable explanation for the degree of polarization in the analysed regions. The causes are defined as the factors that Goos et al. (2010) mentioned as the causes for job polarization namely: technology, institutions, and globalization. As stated before, these causes do not have the same effect everywhere. Institutions are possibly the most important factor when trying to explain these differences (Fernandez-Macias, 2012). These differentiated effects of the active labour market policies are the focus of this study.

The institutions of a country thus might play a role in explaining the different degrees of job polarization in the analysed regions. Creating a model that links the degree of polarization to the existing institutions in a country helps understand the mechanisms behind job polarization and the potential role that institutions play better. In addition, from multiple earlier papers, it can be concluded that institutions influence globalization processes (Rodrik et al., 2004; Rodríguez-Pose, 2013). Therefore, the effect that institutions have on the relationship between globalization and the degree of polarization is interesting to consider in this study. Especially when considering that policymakers (through institutions) also might influence this relationship.

To analyse the goals stated above, the main research question of this thesis will be:

'To what extent do institutions play a role in the differentiated degree of job polarization on European NUTS-2 level?'

To answer the main question of this thesis, a few sub-questions have been formulated:

- *How does the degree of job polarization in the analyzed NUTS-2 regions differ from each other?*

- *What is the direct effect of national institutions on job polarization in the analyzed NUTS-2 regions?*

- *What role do institutions have on the relationship between globalization and the degree of job polarization?*

- *What role do institutions have on the relationship between automation risk and the degree of job polarization?*

The first question will be answered by analysing the European Labour Force Survey (hereafter: ELFS), the second question is answered by incorporating national data on active labour market policies (OECD,2019) in the dataset and analysing their effect on job polarization. As institutions most likely also influence the relationship between globalization and the degree of polarization, this relationship is also further investigated. The last question is aimed at the effect that institutions have on the relationship between automation risk and job polarization. The answer to these questions combined will provide the framework for the answer to the main question.

1.2 Structure of the paper

This paper will try to offer a framework for the effect of institutions on job polarization at the NUTS-2 level. In chapter 2 the theoretical framework is outlined. Hereafter, the method of research is explained in chapter three. Chapter 4 presents the found results after which chapter five concludes and tries to answer the research question based on the found results.

2. Theoretical framework

The central theme of this study is to analyse the effect of active labour market institutions on job polarization at a different scale (NUTS-2) than already has been done. To achieve this goal, the theoretical framework will start with the reasoning of why job polarization is the most suitable explanation for the trends that can be observed from the current labour market in chapter 2.1. Thereafter, the study will elaborate on the influence that respectively skill-biased technological change, globalization and offshoring, and institutions have on the degree of job polarization. In chapter 2.5, the interaction effect between institutions and the degree of globalization (openness to trade) is analysed. The effects of job polarization and the current situation of job polarization are analysed in chapter 2.6 & 2.7. In 2.8, the relevance of this study is analysed by explaining the effects of active labour market policies on a local level based on the earlier chapters of the theoretical framework. The theoretical framework will conclude with the importance of analysing the degree of job polarization on a local level in European countries and a conceptual model to answer the research question is introduced.

2.1 Job polarization

Over the last few decades, a shift towards more skilled, non-routine, professions has taken place. This causes the employability of high-skilled workers to rise. When analysing the relative advantage of skills, a possible comparison between the wages of college graduates relative to their high school graduates can be made. Until recently this was done by the canonical model, this model assumed that increases in technology possibilities automatically raises the demand for skilled workers (Acemoglu & Autor, 2011). This is due to the so-called 'skill-premium'. This links the wages in an economy to the supply of skills and demand generated by the technological advances in the economy (Acemoglu, 2002). Important to realise is the fact that high-skilled and low-skilled labour are imperfect substitutes. According to Acemoglu (2002), this is because only then the skill premia can be understood using the changes in the relative supply of labour to analyse the polarization.

However, when defining so-called 'skill-quartiles' the canonical model cannot explain the sharp rise in the lowest skill-quartile (Autor & Dorn, 2013). The development of employability was more u-shaped than expected according to the canonical model. Therefore, a more comprehensible model was needed to explain the current labour market trends. It is argued that technology can replace human labour in routine tasks (relatively easy tasks, and can be explained by a step-by-step procedure or rules). However, non-routine tasks are (not yet) replaceable by technological solutions (Autor et al., 2003). Technology, therefore, does not directly affect unskilled jobs that are non-routine; it does however affect these jobs indirectly. Technological advance in other sectors of the economy causes the availability of jobs in non-routine low skilled jobs to increase (Goos & Manning, 2007). Technological advance therefore not only increases the high skilled jobs through the 'skill premium' but also the lower-skilled non-routine jobs. For the current labour market trends, it is, therefore, better to use the job polarization explanation. As discussed in chapter 1, job polarization is not only caused by skill bias but also by institutions and globalization. All these three causes for job polarization will be elaborated on in the coming chapters.

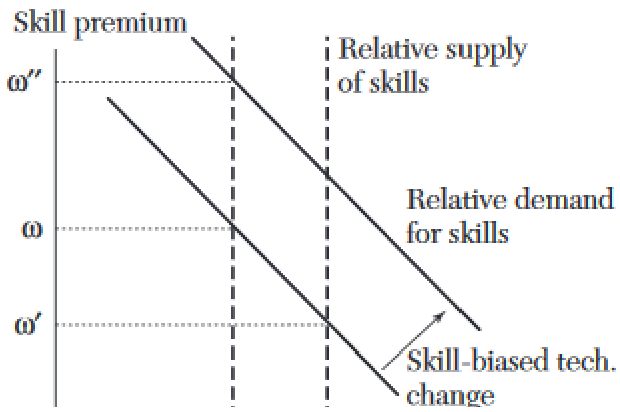

Figure 2: The Relative Demand for Skills with W being the wage (Acemoglu, 2002)

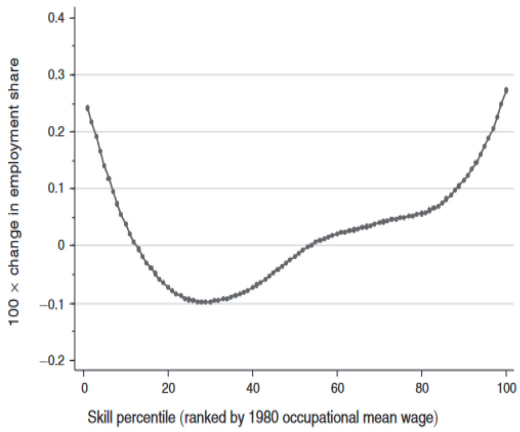

Figure 3: Job polarization (Autor & Dorn, 2013)

2.2 Job polarization due to skill bias

The skill-biased technological change (hereafter: SBTC) is one of the main driving forces behind job polarization. This is the theory stated by Autor et al. (2003). To understand the implications of such a polarization trend, a distinction between the different kinds of jobs must be made. There is a difference between the routine (step-by-step processes) and non-routine jobs (see table 1). SBTC is complementary or only limited substitutable for the non-routine jobs whereas it is directly substitutable for routine jobs.

Task	Task description	Example occupations	Computer impact
Routine	Cognitive	Bookkeepers	Direct substitution
Routine	Manual	Assembly line workers	Direct substitution
Non-routine	Cognitive	Lawyers, scientists	Complementary
Non-routine	Manual	Janitors, truck drivers	Limited substitution or complementary

Table 1: Differences in substitutability (Goos et al., 2010)

According to Fernandez-Macias (2012), the different kinds of jobs seen in table 1 can be defined as follows:

- Routine cognitive tasks: This is the repetitive kind of jobs, which involve the processing of information. Until the IT revolution, it was very hard to substitute manpower with machines in these kinds of jobs. The need for more processing in the upcoming capitalist society meant that these kinds of jobs experienced a major growth until the IT revolution where after they were easily outperformed by computers. This caused the demand for these kinds of jobs to drop dramatically.
- Routine manual tasks: Repetitive labour of physical nature. These were the industrial low--skilled and semi schooled jobs. These were replaced by machines on big scales during the industrial revolution. The introduction of computers made it possible to substitute these jobs even further.
- Nonroutine cognitive tasks: these kinds of jobs involve non-codifiable and tacit knowledge. This is mostly involving the production, processing, and manipulation of information. At this moment in time, machines are not capable to substitute these kinds of jobs. Autor et al. (2003) argue that the demand for these jobs increases due to the fact of the decreasing costs for routine manual and cognitive tasks.

- Nonroutine manual tasks: these are the nonrepetitive tasks of a physical nature and require so-called ‘hand-eye coordination’. This is normally associated with low-skilled service jobs. Autor et al. (2003) state that their model does not have a hypothesis for this group of workers. However, their model states that if this sector is unaffected by computerization, the demand should remain unaffected as well resulting in a relative expansion of the sector.

Many middle-schooled jobs can be defined as routine jobs whereas low schooled also have many non-routine jobs such as housekeeping, catering and personal care. This causes the distribution of jobs to polarize. High schooled workers are complemented by technology and low-schooled non-routine workers profit from this higher employability of the high schooled. Middle-schooled routine workers however are substituted by new techniques (Goos & Manning, 2007).

This is where a current debate steps in; would it not be more logical to state that there is a routine biased technological change? Recent empirical studies have shown that this happens in many places around the world (Acemoglu 1999; Autor and Dorn 2010; Acemoglu and Autor 2011), the UK (Goos and Manning 2007), and across European countries (Goos et al., 2009; Michaels et al., 2010).
In addition, when looking at Goos et al. (2010), it can be concluded that over the last decades the decline in routine-intensive employment is by far the largest. How does, however, the differentiation in high-schooled jobs arise (see figure 4)? As stated before, these jobs are non-routine and are complemented by technology. This can be differentiated into a:

1) Capital-skill argument: This states that the elasticity of substitution between capital and unskilled labour is higher than that between capital and skilled labour. This can also explain the wage inequality between high- and low skilled labour.
2) Skill augmenting argument: This states that technologies by complementing high or low-schooled workers, a demand shift can appear (McAdam & Willman 2015).

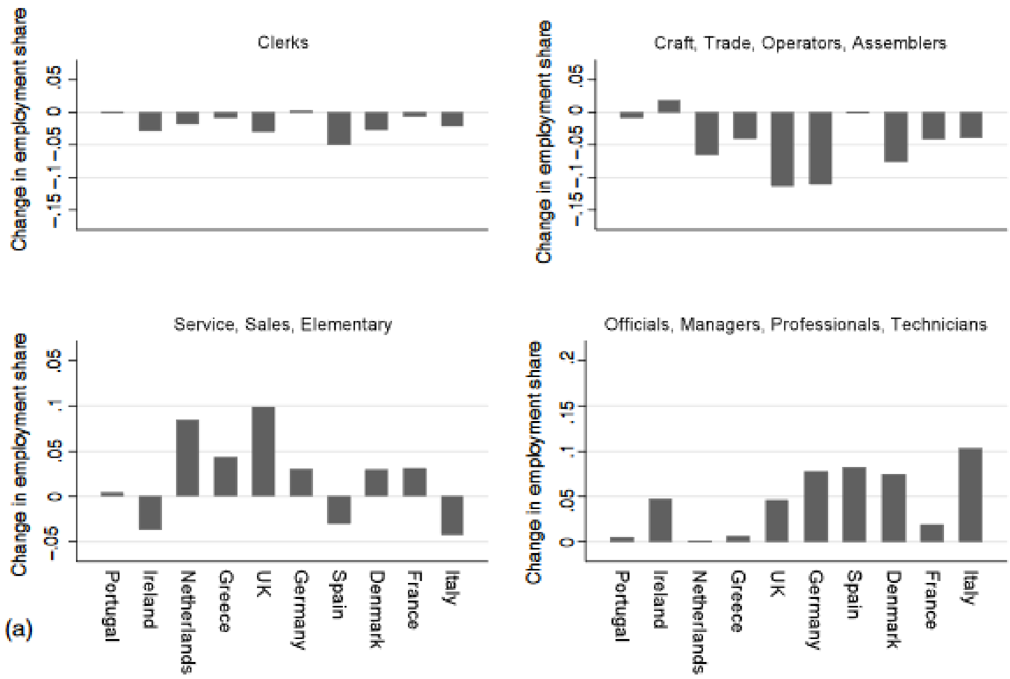

Figure 4: Change in employment shares of young male workers (age<40) by country 1992-2008 (Acemoglu & Autor, 2011)

These two facts, therefore, explain a trend in high-schooled labour. This is because technology is complementary to these jobs. The pressure on labour markets is increasingly high and wage inequality is rising (McAdam & Willman 2015). The troubles that regions experience might differ from place to place, it is therefore important to look at the characteristics defining a local labour market. It can be concluded that the structure and development of the regional labour market matters, this might be a possible explanation for the differentiated degree of polarization and therefore relevant for this study.

2.2.1 Difference in innovation adoption

As already discussed, polarising factors do not have the same effect everywhere (Fernandez-Macias, 2012). This is also relevant for technological change. The same technological innovations do not lead to the same effect in every place. This can be explained by a few indicators:

- Receptiveness: The likeliness of a firm to adopt new technology is correlated with the size of the firm. The bigger the firm, the more likely it is that it will adopt the new technology.
- Information: The other reason that might explain the extent to which firms adopt new technology is the information effect. This can also be described as 'the neighbourhood effect'. When a firm adopts new technology, firms around it are more likely to adopt this technology as well. This is because interpersonal discussions can trigger firms to adopt the technique more easily (Hägerstrand & Pred, 1967).

Technological change thus has a differentiated impact on different countries/regions. When analysing job polarisation on the NUTS-2 level, the impact of technology on the different regions cannot be expected to be homogenous. For this study, it means certain factors might influence the degree of innovation adaptation. Therefore, the interaction effect between institutions and technological change is added.

2.3 Job polarization due to globalization and offshoring

Globalization/offshoring is the second explanatory variable for the degree of job polarization. They have a two-sided effect on job polarization and correlate strongly with each other. On the one side, companies must deal with competition from all over the world due to the decreasing relative distances whereas offshoring is becoming easier as well because of this effect.

- Offshoring: The trend of offshoring has been around for many years (Goos et al., 2010). Many jobs in European countries are being moved to developing countries. Whereas in the 1980 and 1990's the main concern about globalization was the relocation of companies this now has shifted towards the outsourcing of part of the production cycle. Globalization causes companies can much easier offshore specific parts of their production process. When a specific part of the production process is transferred towards developing countries, it could lead to more polarization in the labour market of the country it came from. This is because routine-based (middle-schooled) occupations are much more likely to be off-shored (Goos et al., 2010). When these parts of a company are offshored, the employability of these workers becomes even lower and thus increases job polarisation.
- Globalization: Companies are facing competition from all over the world. Companies can deliver their products all over the world. Because of this increased competition effect, companies must compete at the international level. This can cause profitability to decrease

and companies to close/partially close their routine-based activities (Cirillo, 2018; Goos et al., 2010).

Globalization and offshoring have, just like technology, a differentiated effect on specific regions. This is due to the trade openness of that region. The more open a region is to trade, the more likely it is that the effects of job polarization and offshoring will be tangible in a region (Keller & Utar, 2016). To analyse the effect on NUTS-2 level, NUTS-2 level interregional trade data is used to measure the openness to trade of each specific NUTS-2 region.

2.4 The effects of institutions on job polarisation

The role that institutions have in economic development must not be underestimated. Economic institutions can weaken or reinforce the effects of polarization (Fernandez-Macias, 2012). Policymakers, therefore, have a say in the development of local economies. For long, it has been the consensus in the literature that, with national policies, economic convergence of regions could be established (Rodríguez-Pose, 2013). Institutions were not considered in mainstream economic theory. It is only since a few years that mainstream economic theory adopted the idea that institutions matter in the economic development of a region just as human resource endowments, trade or technology transfers do (Rodríguez-Pose, 2013).

One could state institutional thickness has a great impact on the development of a region. Institutional thickness can be defined as 'a combination of features including the presence of various institutions, inter-institutional interactions and a culture of represented identification with a common industrial purpose and shared norms and values which serve to constitute 'the social atmosphere' of a particular locality" (Amin & Thrift, 1994, page 104). According to Amin & Thrift (1995), the institutional thickness can be used to determine the capacity of a region to adapt to changing conditions and help foster innovation.

This theory is also true when considering the influence that institutions have on job polarization in a specific region. Labour market institutions such as 'employment protection schemes, minimum wages or health and safety regulation might dampen the employability growth at the lower half of the wage distribution' (Dustman et al., 2009). The opposite is also true; the absence of these labour market institutions causes employability at the lower half of the wage curve to grow. By analysing the institutional system of a country/region, one could come up with 'institutional families' in Europe, the countries approximately have the same institutional measures (see figure 4).

When analysing job polarization on the NUTS-2 level, institutions can therefore have a highly differentiated effect on the chosen regions. It is very dependent on the national labour market institutions in place. Trying to explain the difference in the degree of job polarization in NUTS-2 regions must, therefore, according to the literature, incorporate institutions in the equation. In this study, this is done by adding the active labour market policies (on the national level) as an explanatory variable. This will be further elaborated on in chapter 3.2.3.

2.5 The institutional effect on the effects of globalization of polarization

Institutions can be defined as 'manly devised constraints that structure political, economic, and social interactions' (North, 1991 pg. 97). Essentially, every manmade and regulative construct is, therefore, an institution. Therefore, there might be a possible relationship between the institutional labour market framework and the degree of globalization a region undergoes. For the interest of this study, this is also an interesting relationship to analyse. Institutions are only since recently seen as a factor in economic theory. However, they could also correlate and therefore influence the relationship between globalization and the speed of polarisation.

Minimum wage, the degree of unionization or health/safety regulations can have a great impact on the job polarisation in a region (Dustmann et al., 2009). The quality and reliability of institutions in a certain country might however also determine the degree of globalization in a region (Rodríguez-Pose, 2013). This again influences the degree of job polarization. Therefore, the relationship between the institutions in a region and the degree of globalization is also considered in this study.

2.6 The effects of job polarization on employability

A lot of research has been done about job polarization. However, what would the consequences be if we were to do nothing about it? It is very important to analyse labour trends and anticipate on those trends. The middle-schooled working class is most likely to be affected by ongoing job polarization. Their employability decreases and wages will drop (van den Berge & Weel, 2015; Graetz, 2019). If nothing is done in the coming ten years, displacement of workers will cause uncredentialed workers to compete for the same jobs. This will have the effect that the market is flooded with workers in the lower part of the wage distribution.

The mean hours worked may therefore be a useful indicator for job polarization. As stated above, the middle-schooled workers will be affected most by job polarization. Not only will their salaries drop behind relative to their low- and high-schooled peers (see figure 1), but their employability will also decrease (Da Silva & Laws, 2019; Lund et al., 2019). According to Da Silva & Laws (2019), the hours worked may therefore also qualify as an indicator for job polarization.

2.6.1 Relevance of the degree of job polarisation

The degree of job polarization on a local scale has not widely been investigated until now. This however might be a relevant piece of information to policymakers. As explained above, job polarization might have an enormous impact on local labour markets. The degree specifically is interesting to look at because of the measures that policymakers might have to take (Graetz, 2019; Lund et al., 2019).

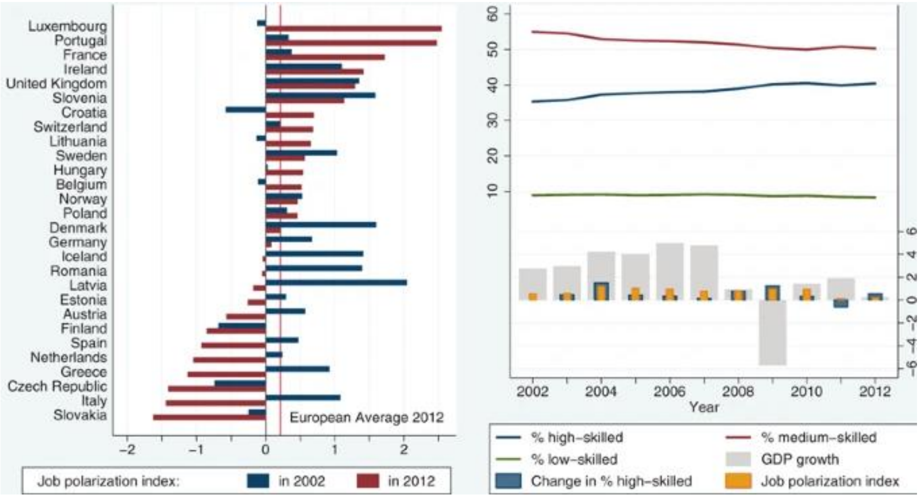

Figure 5: Differentiated degrees of job polarization (Sparreboom & Tarvid, 2016)

In figure 3, the different developments in the degree of job polarization on a national level can be seen. Sparreboom & Tarvid (2016) make the comparison between 2002 and 2012. From this figure, one might argue that the degree of job polarization differs greatly in the analysed countries. To policymakers, this degree of job polarization is relevant because every region probably needs a differentiated approach to the job polarization in their region. Amin & Thrift (1994) for example argue that policymakers and institutions indeed influence the flexibility and resilience of local labour markets. This study offers an insight into this local degree of job polarization. This is done by conducting an inequality in hours worked analysis, whereafter the effect of multiple variables on this inequality is measured.

2.7 Job polarization trends in Europe

Before analysing job polarization at the local level, it is useful to examine the conducted studies on job polarization in Europe. Job polarization in Europe has been widely investigated (Goos & Manning, 2007; Goos et al., 2009; Goos et al., 2010; Jerbashian 2019; Wang et al., 2015). Goos et al. (2010) have studied job polarization in 16 different European countries. They find that over the period 1993-2006 there was a notable increase in the employability of high-skilled and low skilled workers in all the 16 countries. On the contrary, they find that there is a significant decrease in the employability of manufacturing and routine office workers. By developing a framework for the demand for different workers, Goos et al. (2009) use this developed framework to estimate the effects of technological change, globalization (offshoring), institutions and product demand effects on the demand for different occupations. They find that some factors, like institutional differences between countries or homothetic preferences, are relatively unimportant when trying to explain job polarization. In all the 16 analysed countries, the routinization argument found by Autor et al. (2003) is the reason with the most explanatory power when analysing job polarization.

2.7.2 Upgrading or polarization?

Further studies about job polarization in these countries have been done (Fernandez-Macias, 2012). Fernandez-Macias (2012) states that not only job polarization matters but many economies also see the process of upgrading or mid-upgrading (see figure 3). Upgrading was the prime expectation of the SBTC-theory; the high skilled jobs would see a rise in employability whereas lower-skilled jobs would face a decrease in employability: the lower the skill-level needed, the lower the employability of this quartile would be. Fernandez-Macias (2012) argues that this pattern of upgrading or polarization differs per country and is dependent on factors other than technology.

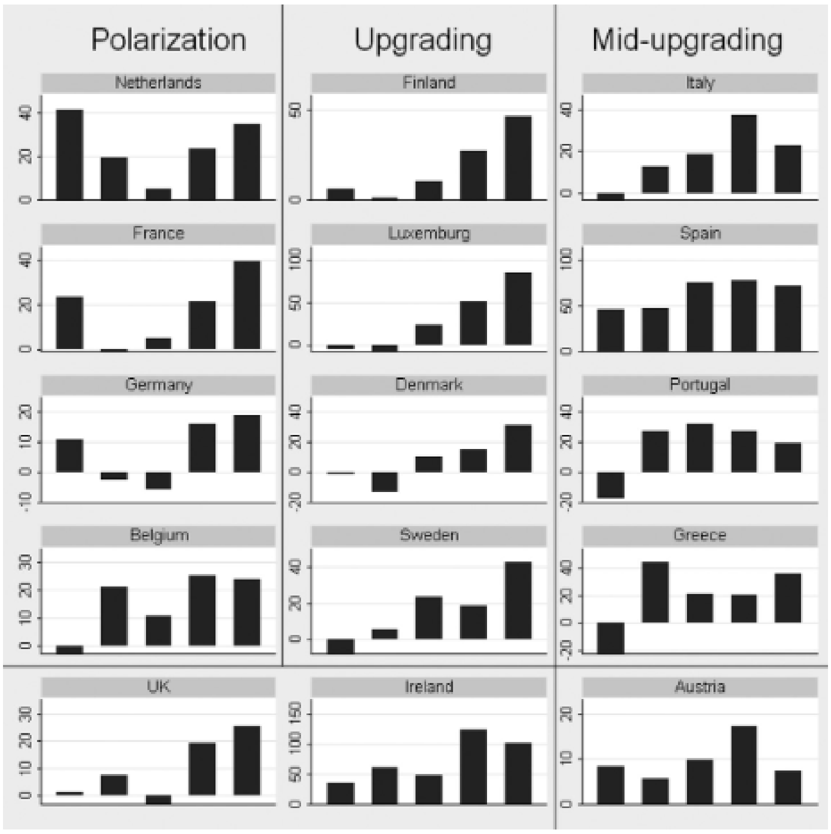

Figure 6: Relative change in employment by wage quintiles (Fernandez-Macias, 2012)

It can well be that there is a technology effect that drives the U-shaped effect on employment. However, in some countries, some forces are strong enough to neutralize these effects on employment (Fernandez-Macias, 2012). This means that changing circumstances do not have the same effect everywhere. Contradictory to Goos et al. (2010), Fernandez-Macias (2012) states that this can be explained by several factors of which institutions is the most important. This can be interpreted from figure 6; the countries that experience polarization, mid-upgrading or upgrading can be placed in the same European institutional family.

The fact that the differences between countries can mainly be found in the bottom and the middle of the employment structure points out that there is a more detailed explanation needed to describe the trend in multiple countries. Like Fernandez-Macias (2012) states, national institutions significantly impact the degree of polarization. For this study this is a relevant finding, it gives reason to further study the impact of institutions on a local level.

When looking at figure 6&7, the difference between the European areas can be seen. Continental Europe has seen a significant increase in non-standard jobs in the lowest wage quantile. The Scandinavian countries show another trend, as can be seen in figure 6, these countries show more signs of an upgrading labour market. The lowest quantiles show no or little growth whereas the upper quantiles show significant growth levels. These markets however cannot be compared one on one as can be seen in figure 7, the Scandinavian labour markets show little to no change in the relative shares of non-standard and standard employment (Fernandez-Macias, 2012). According to Fernandez-Macias (2012), this can be explained by the fact that these countries have the strongest unions and the most compressed wage structures in Europe. This causes low paying jobs to be relatively expensive and shifts production to higher value-added activities.

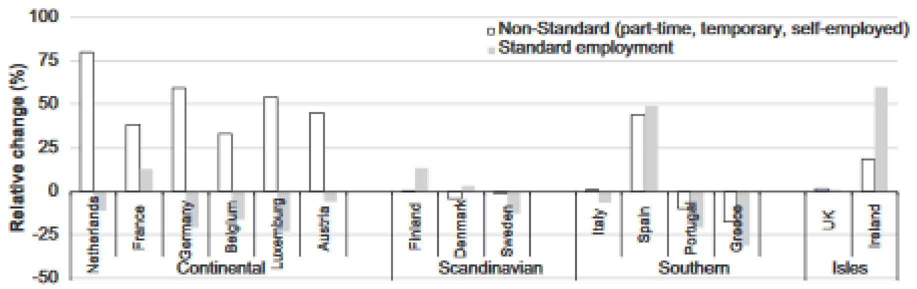

Figure 7: Relative change in nonstandard and standard employment in the lowest wage quintile, 1995-2007 (Fernandez-Macias, 2012).

The south of Europe is associated with the significant upgrading of the middle-schooled layers of employment. This process of the expansion of the middle-schooled jobs can be explained by the creation of the European Monetary Union and access to unprecedentedly lax financial conditions. This led to a booming construction sector in which many of the middle-schooled workers were needed (Fernández-Macías & Hurley, 2008).

The islands (the United Kingdom & Ireland) which show a mild polarization with a very strong upgrading also can be explained by the flexibility of their labour markets and the increase of the financial sectors in these countries in the ’90s and 2000s. The difference between the continental and Anglo-Saxon countries is that the continental countries experience a stronger force of polarization when compared to the Anglo-Saxon countries. This can be explained by the attempt of continental Europe to deregulate the lower-paying jobs to create more jobs (Fernandez-Macias, 2012).

Fernandez-Macias (2012) argues that the fact that main differences can be found in the lower quantiles of the employment distribution, provides support for the argument that institutions do have a great effect on employment structures. Continental countries could show this growth in low skilled jobs because of the earlier mentioned deregulation process whereas Scandinavian countries do not experience this growth because of unions and their policy of wage compression.

Trying to explain job polarization, upgrading or mid-upgrading, therefore, is quite a complicated process. There could be multiple reasons that are underlying processes in job structures in countries/regions. The main explanatory factors are:

- the first is that computers complement both high- and low skilled labour whereas it substitutes the middle-skilled jobs.
- the second is that there is a decrease in skill supply growth; this can be caused by a slower educational expansion and immigration of low skilled workers (Goldin & Katz, 2007).
- the third reason as already elaborated upon above, is the role of institutions. These institutions affect the employment structures by for example wage-setting institutions (Oesch & Menes, 2011).

For this study, this means that these individual causes can have different impacts in different places (NUTS-2 regions). The effects of technology, institutions, and educational levels of the workforce on a local level can have differentiated effects on the rate of substitution. The role of institutions on regional development has been underestimated in economic theory for a long time (Rodríguez-Pose, 2013). For this study, a measure for the active labour market policies is used (OECD, 2019). By including this variable in the model, the expectation is that the degree of job polarization can be better predicted and analysed.

2.8 The institutional effect on a local level

The main goal of this study is to analyse the effect that institutions have on local labour market policies. In the previous chapters, it has been discussed that institutions have a substantial effect on local labour markets. For long, the institutional effect has been neglected in economic theory (Rodríguez-Pose, 2013). However, in the last few years institutions are seen as a key variable in explaining certain economic trends. Fernandez-Macias (2012) found that the institutional family of a country matters greatly in explaining job polarization on a national level. These institutional families have a highly differentiated effect on the degree of polarization in a country. It is therefore likely that these institutions also have a differentiated effect on a local scale.

Policymakers, therefore, have a tool to intervene in local job polarization. This can be a critical tool for dampening the effects of job polarization on a local scale. Policymakers and employers can respond to job polarization by making large-scale workforce transformations possible and in that way adapting the workforce to the new demand of employees. When done right, this could cause those jobs to be upgraded and become more rewarding. Choices that policymakers and employers make influence the communities in which they operate (Lund et al., 2019; van den Berge & Weel., 2015; OECD, 2017). By finding a way to predict this future labour demand, policymakers can adapt to changing occupational demands (Graetz, 2019). Policymakers can adapt to the expected job polarization by:

- Stimulating employees without vocational training to finish higher education.
- Enhancing the employability of people without vocational training by retraining/re-education.
- More emphasis on analytic and interactive skills in education (van den Berge & Weel, 2015; OECD, 2017).

Despite the growing interest in the role of institutions in economic development, little research has been done about these effects. The role of institutions is however highly relevant when trying to find the causes for job polarization. This study will aim to fill the literature gap and therefore provide a useful framework for local policymakers to respond- and adapt to local labour market shifts.

2.9 conceptual model

This study is aimed at finding the effect of institutions on job polarization at the NUTS-2 level. This is done by examining the three main reasons for job polarization in a region. By offering these insights, valuable lessons about job polarization can be learned. Policymakers can adapt their policies to these developments on their (NUTS-2) labour markets and thereby create a coherent and future proof labour market policy.

The hypothesis of this study states that the three main explanatory variables for the degree of polarization are: technological change, globalization, and institutions. With a regression, the correlation value for each variable is calculated (see figure 5). The effect of institutions on the relationship between globalization and the degree of polarization is also analysed. This is to get a better understanding of the driving factors behind the degree of globalization and the effects that institutions have on job polarization. In addition, as can be seen in figure 8, the effect of institutions on the relationship between technological change and the degree of polarization is researched. According to the literature, institutions might also affect this relation (Lund et al., 2019; van den Berge & Weel., 2015; OECD, 2017). In these interaction effects, the active labour market policies are lagged by two years because these policies take time to have their effect on these relations.

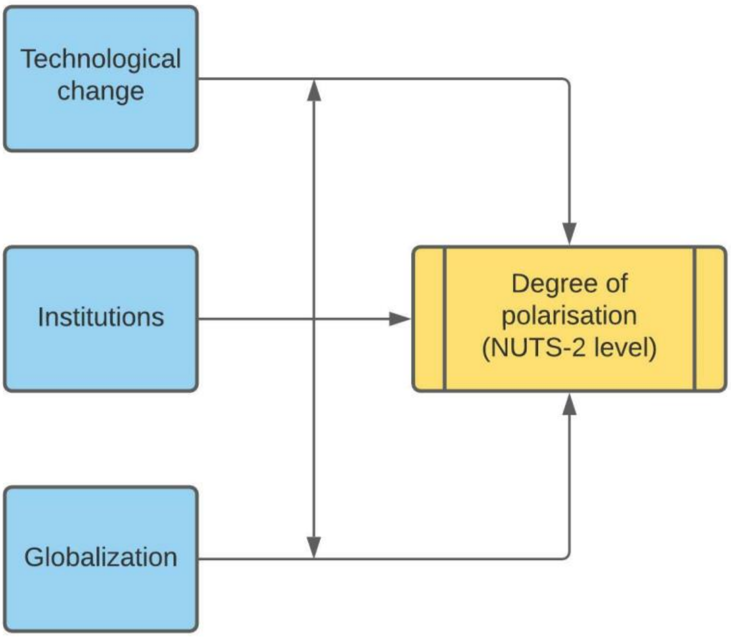

Figure 8: Conceptual model job polarization at NUTS-2 level

From existing literature, one might conclude that the independent variables take time to have their effect on the GINI coefficient (Autor & Dorn, 2013). Therefore, for this study lag values are used as instruments and their validity is extensively discussed. The values for active labour market policies are lagged two years to examine their effect on the mean GINI coefficient in a region. Furthermore, in the appendixes, multiple lags have been explored to examine their impact on the GINI coefficient in a region.

3. Research method

This study aims to find the effects of the active labour market policy spending have on the degree of job polarization in NUTS-2 regions. This is done by analysing the GINI coefficient of inequality in hours worked, the effect of globalization, and the mean automation risk. The GINI coefficient of inequality is chosen as an operator because of the usability to compare different years and regions with each other (Ferreira, 2020). For this study, the GINI is, therefore, a good fit for a measure of inequality among regions.

The inequality of work is calculated by using the Gini coefficient for inequality in hours worked along the workforce of a country. A correlation between this Gini coefficient and the polarizing effects (globalization, technological change, and institutions) is sought after by linear regression. In this chapter, the method of research is presented by going through the different steps that have been made to study the effects of active labour market policies on job polarization. In 3.1 the dependent variable is discussed, after which in 3.2 until 3.4 the main independent variables are elucidated. Section 3.5 will thereafter describe the composition of the dataset.

3.1 Dependent variable

The dependent variable of this study is the inequality in hours worked. This is measured by the GINI coefficient per region and year. This calculated Gini coefficient will be calculated for all years in the data sample (2000-2019) to extract the degree of polarization of the workforce. The data utilised for this purpose will be derived from the European Labour Force Survey (hereafter: ELFS). This data provides hours worked at the NUTS-2 level from which the GINI coefficient and therefore regional inequality can be derived (Eurostat, 2021). The inequality index is usually used for income, for this study, however, more data is available for the hours worked (see 3.4). As described in 2.6, the inequality in hours worked form a good operator for measuring job polarization. Therefore, the inequality in hours worked is used. Having this data for multiple years, a trend can be extracted. The Gini coefficient for each year per region can be calculated by the following formula:

$$G = 1 + (1 / N) - [2/(m . N^2)]$$

In this formula, N is the number of cases and m is the arithmetic mean of hours worked for the population. This formula is applied to all the NUTS-2 regions included in the research.

3.2 Main independent variables

The main independent variables of this study are technological change, globalization, and institutions. These variables are the main drivers of job polarization as defined by Goos et al. (2010). In the following chapter, the main three variables and how they are deployed are explained. This gives a clear understanding of the role of the variables in answering the main question.

3.2.1 Technological change

Technological change is one of the variables described in the theoretical framework as a variable that can explain the degree of job polarization in a region. This effect is caused by the substitution of jobs by growing technological possibilities. To analyse the possible implications of technological change, a measure of 'automation risk' is needed (Frey & Osborne, 2017). Frey & Osborne (2017) developed a measure with which the automation risk of jobs can be predicted. By analysing the jobs listed in the Standard Occupational Classification (hereafter: SOC) dataset. By hand labelling occupations with a 1 (automatable) or a 0 (non-automatable). In this way, Frey & Osborne (2017) came up with 70 occupations of which they were sure that they are highly respectively highly automatable or non-automatable. The model was considered a good predictor for the mean risk of automation of jobs. Frey & Osborne (2017) therefore extrapolated the data to cover all the 702 SOC-occupations. Having done this, an index of 'risk of automatability' between zero and one is created. The values of this index indicate the likelihood of automation for all the 702 SOC-occupations.

When using the ELFS, a technique to evaluate the impact of technological change is to match the ISCO-8 occupational codes to those identified by Frey & Osborne (2017). For redefining the Frey & Osborne (2017) occupational variables at the SOC-occupational level, the overlapping occupations with different terminology in the ISCO-8 ELFS dataset must be identified. The 702 SOC-occupations can be redefined to 126 3-digit ISCO-8 occupations. The automation risk score on the ISCO-8 level will be an average of the corresponding SOC occupations (Koster & Brunori, 2021).

By doing this for all the professions that Frey & Osborne identified, a variable with the corresponding automation risk for ISCO-8 occupations is created. The higher the average of this number in a NUTS-2 region, the more likely it is that technological change substitutes jobs in this region in time.

According to Koster & Brunori (2011), the index composed by Frey and Osborne (2017) tends to construct a relatively high risk of automation value. However, for the aim of this study that should not result in major complications. When comparing multiple regions and their exposure to automation of jobs, the difference between regions is more important than the absolute value of regions themselves. Therefore, for this study, it is assumed that this upward bias has the same effect on all the NUTS-2 regions.

When utilising the data on automation risk, the data must first be made suitable for this study. This is done by reclassifying the SOC scores on occupational automation risk to ISCO-08 occupational automation risk scores. This is based on the crosswalks of the US Bureau of Labor Statistics (US Bureau of Labor Statistics, 2015). When multiple SOC occupational codes correlate with a SOC-08 code, the average of the corresponding SOC occupations is used.

3.2.2 Globalization

Globalization also is an explanatory variable for job polarization. The degree of job polarization depends on the demand for offshoring and competition from the world market. Therefore, this variable also needs to be incorporated in the model when trying to explain the degree of job polarization on the NUTS-2 level.

To incorporate globalization in the model, an indicator for the degree of globalization of a NUTS-2 region is needed. The variable that is used to quantify the globalization variable is 'openess to trade'. This variable can be defined as 'imports + exports as a percentage of GDP'.

This variable is chosen for this study because it has proven to be a relevant measure for the degree of globalization in a region (OECD, 2011). According to the OECD (2011), the more a region imports/exports compared to their GDP; the more open they are to trade and therefore globalization. Openness to trade can have an impact on job polarization in multiple ways. For example, increased imports of products that need middle-schooled workers to make and therefore fewer employment opportunities for those middle-schooled workers on the domestic market. Trade openness can also directly affect skill-biased technological change in a country, this happens through:

- firms may import more machinery which is complementary to skilled labour and a direct substitution of routine jobs (Acemoglu, 2002).
- productive firms innovate to compete with foreign companies. These innovations are skilled-biased (Aghion et al., 2008, cited by Signoret et al., 2020, pg. 14).
- the increase in exports is caused by the firms that employ skilled workers (Goldberg & Pavcnik, 2004, cited by Signoret et al., 2020, pg. 14).

By having this as an indicator for the degree of globalization, a possible correlation between the degree of globalization and the rate of polarization can be investigated. The input-output data for NUTS-2 regions is available (Thissen et al., 2019). From this data, the imports and exports are extracted for all available NUTS-2 regions. These are then divided by the local GDP to get the indicator for openness to trade.

3.2.3 Institutions

The main goal of this study is to find the effect that institutions have in explaining the differentiated degree of polarization of NUTS-2 regions. Institutions determine how flexible the labour market is and therefore how resilient in case of an economic shock. Active labour market policies include for example (re-)-training of the workforce to adapt to the changing demands (van den Berge & Weel, 2015; OECD, 2017). By implementing these institutional measures, policymakers could adapt to changing demands in the labour market. In this way, a whole labour market can be upgraded instead of being polarized (Buyst et al., 2018).

Data about regional active labour market policies is hardly available; a possible explanation for this given fact is that these policies are mostly implemented at the national level. However, this does not leave out the fact that these policies have a significant impact on NUTS-2 regions (Amin & Thrift, 1995; Rodríguez-Pose, 2013). For the data on national active labour policies, the data of the OECD on 'Public expenditure and participant stocks on labour market policies' will be utilised (OECD, 2021). This dataset provides data about the active labour market policies and the passive labour market policies of a country. The policies included in the study are training, institutional training, workplace training, integrated training, special support for apprenticeship, sheltered and supported employment and rehabilitation, employment initiatives, recruitment initiatives, sheltered and supported employment, rehabilitation, start-up initiatives, direct job creation, job rotation and job sharing, employment maintenance incentives (OECD,2021).

The data relevant for analysing the effect of institutions on the degree of job polarization is the active policy measures. This total is given in percentage of the total GDP in a country. The data is available for most of the analysed countries from 2004 until 2019.

3.3 Controls

This study also contains controls to enhance the explanatory value of the model. The control used are age, income, degree of urbanization, level of education, and economic growth. These controls are derived from the existing literature about job polarization. Age can directly affect the degree of job polarization in certain occupations (Autor & Dorn, 2009). Therefore, it has added value to incorporate it in the model. According to Lund et al (2019); income, degree of urbanization, and economic growth might also influence the degree of polarization in a region. These are all factors that might determine the job availability and personal preferences of the local workforce (Lund et al., 2019). Income is also an important control variable because it has a direct effect on the degree to which employees face a budget constraint when trying to receive training (Koster & Brunori, 2021). To capture the effects of these variables they must also be added to the model.

The mean level of education in a region might seem the most obvious control variable. As already established in the theoretical framework; middle-schooled workers are most likely to face the consequences of job polarization in a region (see 2.1 &2.2). One might therefore expect a possible correlation between the mean level of education in a region and the mean GINI coefficient.

3.4 Data sample

The main sources of data for this study will be the ELFS, the European NUTS-2 trade flows dataset and the OECD public expenditure and participant stocks on labour market policies. These datasets offer insight into the possible explanations for the degree of job polarization. The ELFS is however not complete for all countries and years. To get a good overview of the changing Gini coefficient, one must carefully consider possible shortcomings in the dataset. When analysing the ELFS the following countries do not have data for all included years or have other shortcomings (see table 2).

Country	Shortcoming
Germany (DE)	No regional data before 2002, thereafter aggregated at NUTS-1 level
Austria (AT)	Data aggregated at NUTS-1 level
United-Kingdom (UK)	Data aggregated at NUTS-1 level, data on ALM until 2011
Denmark (DK)	No regional data until 2007
Croatia (HR)	Data starts in 2002 & no data on ALM
Romania (RO)	No data on ALM
Cyprus	No data on ALM
Iceland	No data on ALM
Malta (MT)	No data available before 2009 & ISCO3D and ISCOPR3D aggregated at 2-digit level
Bulgaria (BG)	ISCO3D and ISCOPR3D aggregated at 2-digit level
Poland (PL)	ISCO3D and ISCOPR3D aggregated at 2-digit level
Slovenia (SI)	ISCO3D and ISCOPR3D aggregated at 2-digit level
The Netherlands	All regional data suppressed

Table 2: shortcomings ELFS

Furthermore, the income control variable is optional for the years 2000-2008. This means that this variable is only provided for certain countries only until 2008. From 2009 onwards, this data becomes compulsory for the ELFS (European Commission, 2021). This makes that only for the countries that provide the data before 2008, income can be a control variable for these years. This can be corrected for by utilising data on the Gross Domestic Product (GDP) per NUTS-2 region, which is more widely available.

As it is in the interest of this study to evaluate the 'risk of automation' of jobs (see 3.2), the ISCO 3-digit codes of the occupations are crucial to complete this analysis. Malta, Bulgaria, Poland, and Slovenia are therefore dropped from the dataset, these countries do not offer insight into the detailed information on ISCO 3-digit codes (see table 2). The data on the active labour market policies is missing in Croatia, Cyprus, Romania, and Iceland. Without this data, it is not possible to answer the main question of this study. These countries are therefore also dropped from the dataset.

The countries that aggregated the regional data to the NUTS-1 level will be included in the dataset, all the other data for these regions will also be aggregated from NUTS-2 to NUTS-1. The Netherlands is aggregated at the national level because all regional data is suppressed. The Netherlands therefore will be aggregated at the national level in this study.

3.4.1 Code- and boundary changes

The NUTS-2 regions as established in 2003 have been susceptible to changes in their names or changes in their composition of regions. For France, Italy, and Greece this means that there is a code change for nearly all NUTS-2 regions. This can be rearranged to serve the study relatively easy by recoding the old NUTS-2 regions to their new names. The recoding is done according to the NUTS-recoding tables as provided by Eurostat (Eurostat, 2021).

When a NUTS-2 region is split into multiple others or a NUTS-2 region is divided into multiple existing ones, it is not possible to analyse the regions before the name change. In the dataset used for this research, five countries split their NUTS-2 regions respectively in 2006 or 2013 (Hungary, Denmark, Finland, Portugal & Ireland). For Portugal, this means that for the two newly created NUTS-2 regions (PT20& PT30), there is no data on trade openness. In Hungary, the NUTS-2 region 'HU10' has been divided into two new NUTS-2 areas (HU11 & HU12). To minimize data loss, these two regions are aggregated and together form HU10 in this study again

For the countries Ireland, Denmark, and Finland, it is harder to prevent regional data loss. This has different causes: Denmark did not record regional information on the NUTS-2 level. The regions in the input-output analysis (openness to trade analysis) do not match the regions as stated in the ELFS. As for Finland and Ireland, the codes and borders of NUTS-2 regions have changed substantially in the analysed years. This means regional information cannot be utilised or (dis)aggregated in scientific research. National data is therefore used up until 2010 for Denmark and Finland and up until 2011 for Ireland. Also in Latvia, the data is aggregated on the NUTS-2 level. This is done because of lacking data on NUTS-2 level data on variables and therefore preventing data loss.

3.4.2 Data dropped

In the dataset from the ELFS, a few observations did not include their region. These observations were found in France and Slovakia. Because these observations came from different years, there was no way to tell what their corresponding region was. For this study, it is important to know the corresponding regions of these observations. Therefore, the 162 observations in Slovakia and 354 cases in France are dropped from the dataset.

3.4.3 Missing data

In the multiple sources of data used in this study. Some data is missing for certain countries. For the United Kingdom and Switzerland, there is no data on economic growth on the level this study requires the data (NUTS-2 Switzerland or NUTS-1 level the United Kingdom). Within the trade openness data, provided by Thissen et al. (2019), Switzerland and Norway are not considered. This effectively means that these countries cannot be included in the analyses about the effect of economic growth or trade openness.

3.4.4 Testing data

The data must also be tested for autocorrelation in the panel data. This is done by a Woolridge test for autocorrelation in panel data. The test gives a significant result, which means the 0-hypothesis of no autocorrelation must be rejected (see appendix 11). This means that there is autocorrelation in the panel data used for this study, which is to be expected for panel data. For this study, it means that when doing a time-specific analysis, a model which allows autocorrelation must be used or correlation corrections should be added.

When considering which model to run. It is relevant to analyse if random effects or random effects are suitable for the aim of the study. This is checked by running a Hausman test, when running this test, the fixed effects and random effect model are compared. The outcome of this test is that the effects are not randomly divided (see appendix 13). So, for this study, the fixed effects model is used. At last, it is important to check if the residuals follow a normal distribution. As can be seen in appendix 12, this is indeed the case.

3.4.5 Final analysis

After these computations to the dataset, the countries that used in the analysis are:

Austria, the United Kingdom, Belgium, Denmark, Estonia, France, Greece, Ireland, Italy, Latvia, Lithuania, Hungary, Slovakia, Finland, Luxembourg, Switzerland, Portugal, Sweden, Norway, Czech Republic, Spain, and Germany.

It is of course important to realise that not all regions of these specific countries contain regional-specific data (see table 2); these missing variables cannot be considered when running a linear regression. The summary statistics of the data used can be found in appendix 1.

Dependent variable	Description variable
Gini coefficient	A statistical dispersion to demonstrate the inequality in hours worked across NUTS-2 regions.
Independent variables	
Openness to trade	A variable that shows the receptivity of a NUTS-2 region to global trade.
Automation risk	This variable shows the 'automatability' of each ISCO-8 classification job. Based on the index of Frey & Osborne (2017)
Active labour market policies	The amount of spending on active labour market policies on a national level as a percentage of GDP (OECD, 2019).
Highest level of education attained	A variable that provides coded information about the highest level of education someone attained. In which 1=low, 2=medium, and 3=high.
Country	Country dummies

Table 3: Description variables

3.4.5 Data availability

The data used for this study comes from multiple sources. This means the availability of the data does not perfectly align with each other (see table 4). The data available however is at least suitable to look at a period from 2004-2010 for all variables and analyse the correlations between these variables (see table 2). The data available for each variable is shown in the table below.

Year → Variable ↓	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Openness to trade	V	V	V	V	V	V	V	V	V	V	V
ALM	X	X	X	X	V	V	V	V	V	V	V
Automatization risk	V	V	V	V	V	V	V	V	V	V	V
Gini	V	V	V	V	V	V	V	V	V	V	V
	2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**		
Openness to trade	X	X	X	X	X	X	X	X	X		
ALM	V	V	V	V	V	V	V	V	V		
Automatization risk	V	V	V	V	V	V	V	V	V		
Gini	V	V	V	V	V	V	V	V	V		

Table 4: Data availability

3.7 Approach

The goal of this study is to measure the impact that and institutions have on the degree of job polarization at the NUTS-2 level. To examine this effect, the other explanatory variables as defined by Goos et al. (2010) must also be included in the model. Therefore, globalization, technological change, and institutions are included in the basic model. To assess the influence that those variables have; a regression model is run to examine the influence of these variables. Also, when running a linear regression, some key assumptions must be made about the regression. For example, the addition of fixed- or random effects. This will be further elucidated in chapter 4.3. The basic model will look as follows:

$$GINI = c + x_1\beta_1 + x_2\beta_2 + x_3\beta_3 + fe/re + u_i$$

In which Gini is the Gini coefficient over multiple years, c is constant, x_1 is the automation risk, x_2 is the openness to trade, x_3 is the active labour market spending, fe/re are the respectively fixed- and random effects and u is the error term. All the main independent variables are lagged 2 years as explained in the conceptual model.

However, as stated in 2.5, institutions might also influence the impact of globalisation on the GINI coefficient. In addition, institutions might also affect the impact of technological change on the GINI coefficient. In the more complex model, these interactions are also considered which might increase the explanatory value of the model. The model including the interaction effects will be:

$$GINI = c + x_1\beta_1 + x_2\beta_2 + x_3\beta_3 + x_4\beta_2\beta_3 + x_5\beta_1\beta_3 + fe/re + u_i$$

In which x_4 is the added interaction effect between institutions and globalization and x_5 is the interaction effect between institutions and technological change. At last, control variables are added to the model. These variables enhance the internal validity of this model by decreasing the influence of confounding or any other extraneous variables. In this study, controls for age, education, degree of urbanisation, economic growth and income are added. By having these control variables, the expectation is that the effect of active labour market policies on job polarization can be filtered out more precisely. The model including the control variables will be:

$$GINI = c + x_1\beta_1 + x_2\beta_2 + x_3\beta_3 + x_4\beta_2\beta_3 + x_5\beta_1\beta_3 + x_6\beta_6 + x_7\beta_7 + x_8\beta_8 + x_9\beta_9 + x_{10}\beta_{10} + fe/re + u_i$$

In this formula: x_6 controls for age, x_7 controls for education, x_8 controls for income, x_9 controls for the degree of urbanisation, and x_{10} controls for economic growth. However, (as Koster & Brunori (2021) state and as described in 3.5) the income in the ELFS is not available for each country and year in the dataset. This makes that there cannot be controlled for income for the whole dataset. The income control variable is however added to countries that do have data on income to evaluate the effect of income. In addition, the income variable might be replaced with the GDP per capita variable, which is a substitution of the income variable. There is also corrected for the density of a NUTS-2 region (inhabitants per km^2). This is done because from previous studies it can be concluded that the density of a region directly influences the degree of polarization in that region (Terzides et al., 2017; Lund et al., 2019). The economic growth control variable is added because a crisis or booming economic growth can also have an impact on the rate of job polarization (Fernandez-Macias, 2012; van den Berge et al., 2015)

4. Results

The goal of this study is to find the effect that active labour market policies have on the degree of job polarization on the NUTS-2 level. By analysing the results of the ELFS, a clear indication can be given about the different effects on job polarization. Before using the data to test for possible effects, the data is first summarized and examined by using scatterplots. This summary and the 'tests for normal distribution' plots can be found in appendix 1-3. The main findings of the summary and plots are that the GDP and openness to trade are not normally divided. This means no tests that require a normal distribution can be used. Furthermore, the standard deviation of the GINI coefficient is calculated. This is done to study if there are differences in the mean GINI coefficients of regions. As depicted in appendix 15, this is indeed the case.

The different outcomes of the labour market analysis are analysed to establish an overall trend development before running the final regression. This is done for the variables that, according to the literature, should- or might correlate with each other.

4.1 Trend GINI coëfficiënt

First, the overall development of the GINI is projected in figure 9. In this boxplot, the mean GINI coefficient per year is plotted by NUTS-2 region (or NUTS-1/national level if aggregated). A remarkable development can be observed after 2008. The mean GINI coefficient decreases after this year. This can have multiple causes: one of these causes was the economic recession of 2008; this can have a significantly big impact on the inequality of hours worked in an economy (University of Strathclyde, 2020; Lund et al.,2019). In addition, the labour market trend until the year 2010 was that men started working less and women started working more. This might also affect the inequality of the hours worked (University of Strathclyde, 2020). It could also be that there was a definition change in the GINI coefficient. The sharp cut in 2008 might therefore be interesting to further examine using time dummies.

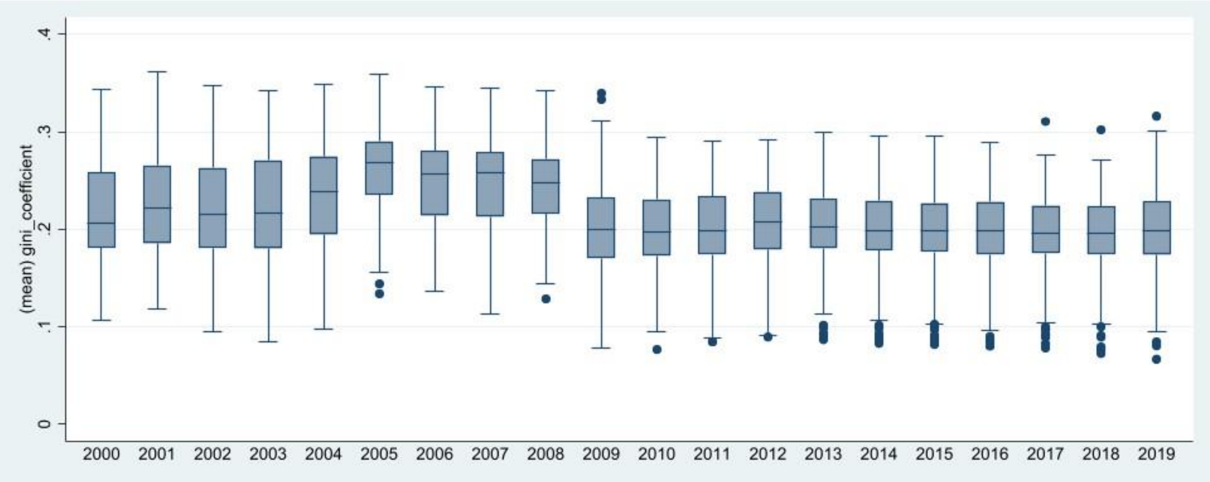

Figure 9: GINI development over the years

The inequality in hours worked is defined as the GINI coefficient in this research. This boxplot shows us that there is indeed variation in the GINI coefficient over the years. When doing the analysis, the explanation for this difference in this GINI coefficient is sought after. This is done by analysing the multiple variables that might affect this change in the inequality of hours worked.

4.2 Independent variables

The focus of this study is, however, is the effect that labour market institutions have on the GINI coefficient. From economic theory, it can be deduced that it might take some time to see the effect of active labour market policies (see 2.9). When plotting the averages of the GINI coefficient and the (2-year lagged) active labour market policies (overall aggregated average), a correlation can be seen between the two lines. From these statistics, it can be concluded that the institutional spending on active labour market policies correlates with the degree of job polarization (for other versions of this correlation see appendixes 4&5).

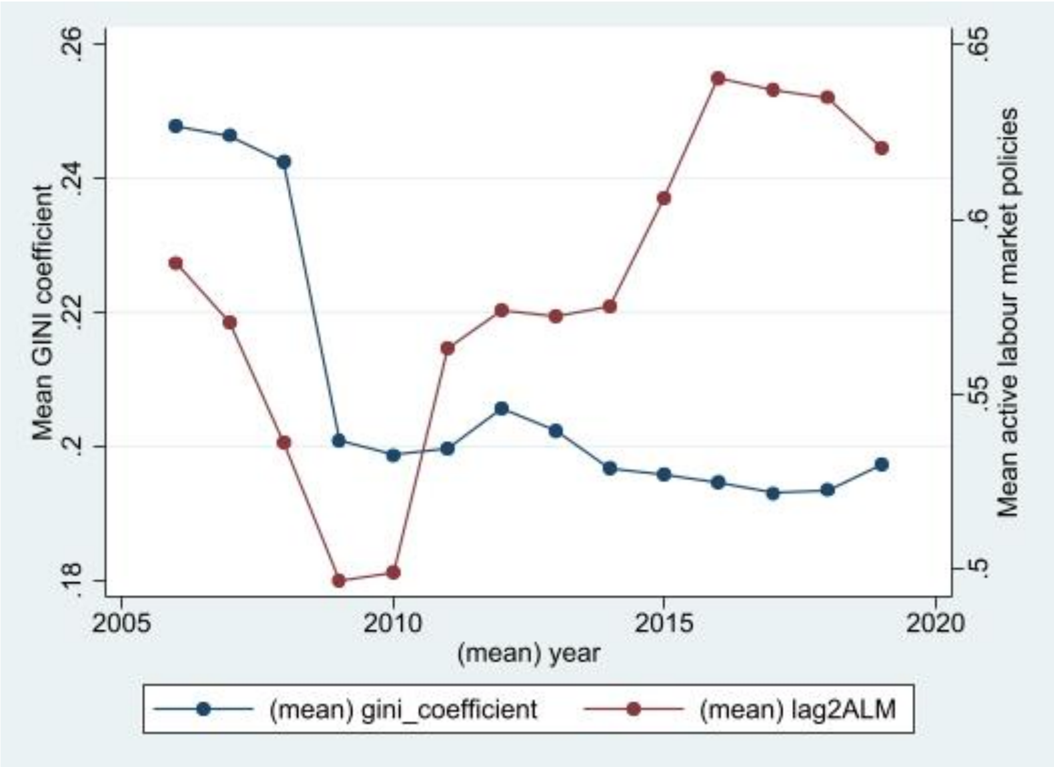

Figure 10: Average development of ALM& GINI coefficient (including two-year temporal lag)

This finding is crucial for this study. If there were to be no correlation between the active labour market policies in a region and the degree of polarization, the active labour market policies would lose their explanatory value. As can be derived from the theoretical framework, active labour market policies do not only affect the GINI coefficient in a region (see 2.5). These interaction effects are further elaborated on in chapter 4.3.

It is now established that the active labour market policies do indeed correlate with the inequality of hours worked in a labour market. However, according to the literature, the active labour market policy spending is not the only variable that affects the mean GINI coefficient in a region. The other two main independent variables considered in this study are technological change and trade openness.

The first main independent variable included in the model is technological change. Earlier studies found that there might be a positive relationship between the technological change and the GINI coefficient in a region (Goos & Manning, 2007; Autor et al, 2003; Frey & Osborne, 2017). A higher mean risk of automation by technology leads towards more inequality in a region. This is because, in this region, more jobs will be automated in the coming future.

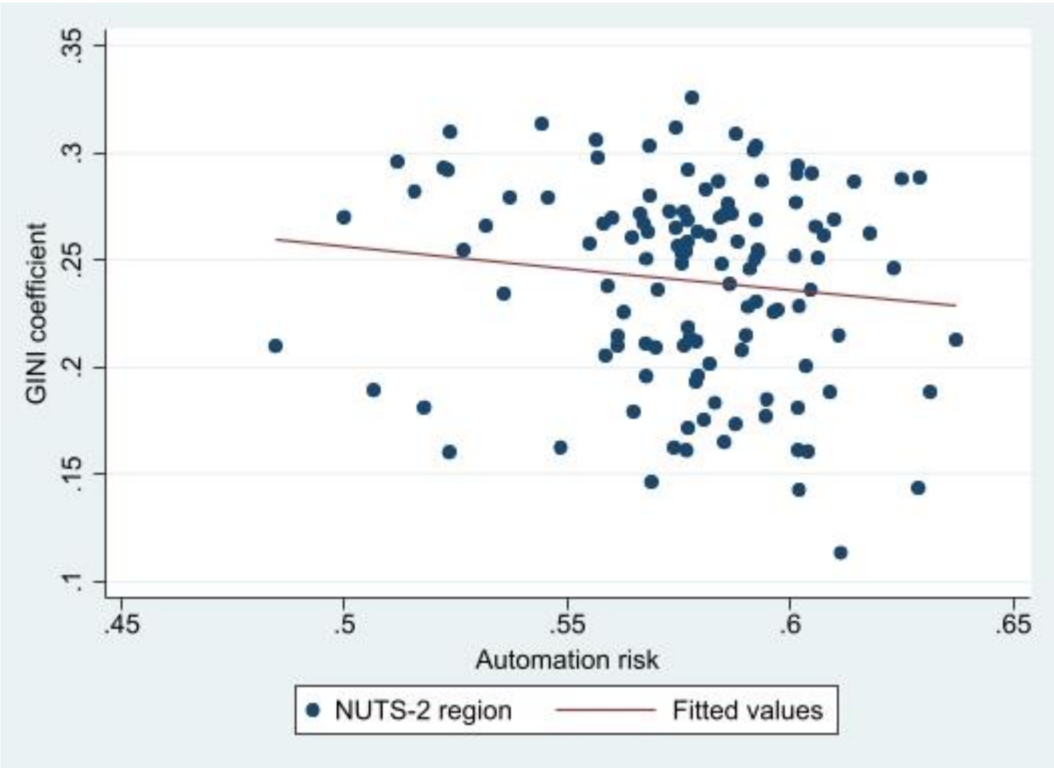

Figure 11: Correlation GINI coefficient & automation risk

When plotting the automation risk (with a 2-year lag) and the GINI coefficient, a negative correlation can be seen (see figure 11). This is quite a remarkable finding considering the literature about the correlation between the GINI coefficient and automation risk. This is however merely a correlation plot; in the regression, this interaction effect will be analysed.

The other explanatory variable in the model is the openness to trade of a region. According to the literature it is to be expected that the higher the openness to trade, the higher the GINI coefficient will be (Acemoglu, 2002; Aghion et al., 2008, cited by Signoret et al., 2020, pg. 14; Goldberg and Pavcnik, 2004, cited by Signoret et al., 2020, pg. 14). Trade openness might also cause a higher GDP because it enhances the abilities of a region to produce and trade efficiently. As the trade openness of a region is also one of the explanatory variables of this study, it is interesting to see if this variable correlates with the GINI coefficient in a region. In figure 12, the correlation between the trade openness and the GINI coefficient of a region is plotted.

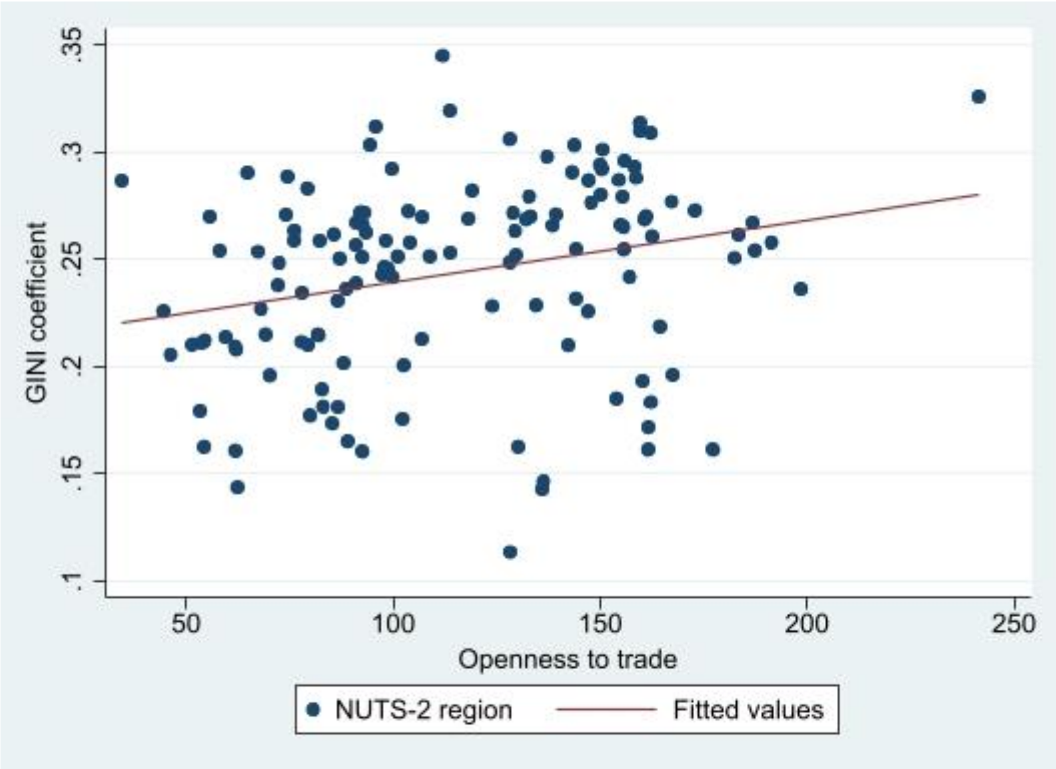

Figure 12: Correlation openness to trade & GINI coefficient

In this graph, a clear relationship between the openness to trade of a region and the degree of inequality in hours worked can be spotted. When running a Pearson correlation test this relation is positive and highly significant. This means that the higher the openness to trade a region is, the higher the inequality in hours worked will be. This is in line with what was to be expected from the literature at hand. Through globalization and offshoring, the regions with a high openness to trade are much more vulnerable to the effects of job polarization.

4.3 Interaction effects

Having active labour market policies on a national level could enhance regional development and drive economic growth on a regional scale. By keep adapting the workforce to the current demands of the regional labour market through active labour market policies, the regional labour market is most likely more resilient to changes in the constantly developing labour market (Lund et al., 2019; van den Berge & Weel, 2015). Therefore, as explained in the conceptual model, a possible interaction effect between active labour market policy spending and automation risk can be expected. When correlating the lagged(n-2) active labour market policy spending in a region to the mean automation risk a low, but highly significant negative correlation is found (see figure 11). This indeed corresponds with the literature about the automation risk of a workforce. When more is spent to prevent a workforce to become unemployable, the automation risk of that same workforce is likely to decrease.

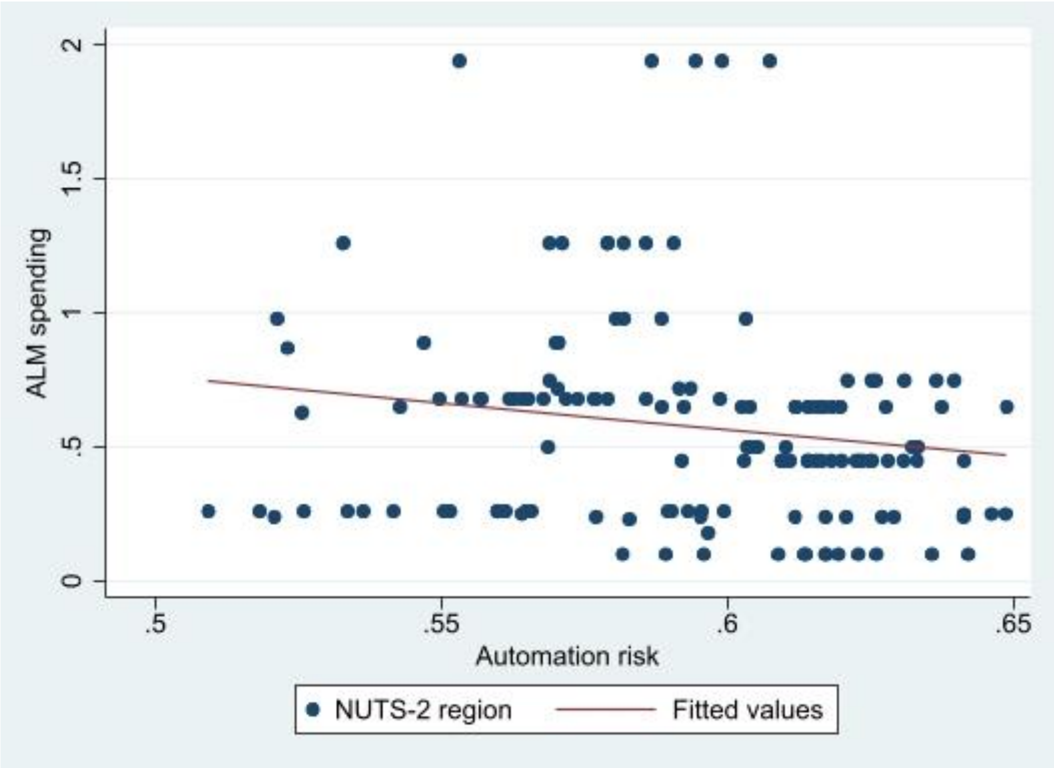

Figure 11: ALM spending correlation with automation risk

The other interaction effect included in the conceptual model is the interaction between the active labour market policies and globalization. It is likely that the active labour market policies in a region might influence the degree of openness to trade.

When plotting this interaction effect, a negative correlation can be observed (see figure 12). This is quite a remarkable find because one might expect from the literature that regions with a high openness to trade also spend more on their active labour market policies (Lund et al., 2019).

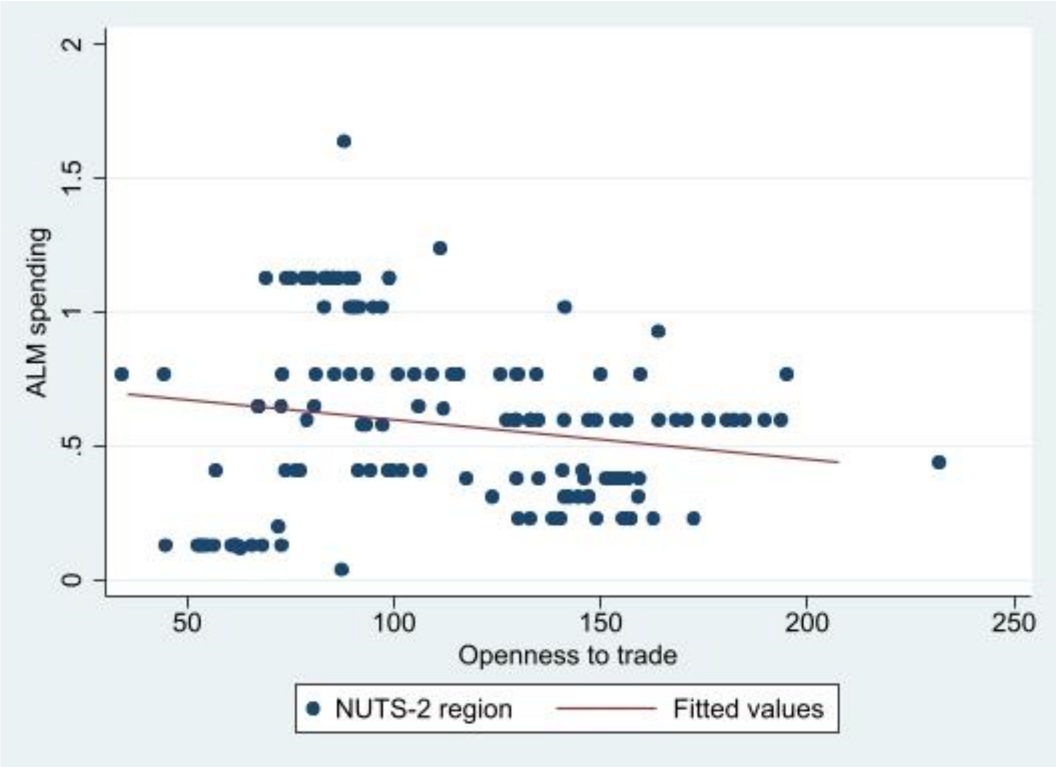

Figure 12: Interaction effect ALM-Openness to trade

When trying to answer the main question of this study, these plots give an insight into the expected direction of the coefficients and provide a good overview of the data. In the coming chapter, the model will be further elucidated on.

4.3 Further analysis

As described in chapters 4.1 and 4.2, all the independent variables show a correlation with the dependent variable. This is tested by using scatterplots and Pearson tests for correlation. Before further analysing the data, the data must be analysed to review if it meets the requirements for a test. The data must first be subjected to a Breusch–Pagan/Cook–Weisberg test for heteroskedasticity. When running this test for heteroskedasticity, it turns out that there is no heteroscedasticity and the residuals are homoscedastic (see appendix 10). For analysis purposes, this is relevant because data analysis models presume equal variance. With the data being homoscedastic, no other amendments to the data are therefore needed to obtain equal variance.

4.3.1 Linear regression

When further analysing the dataset, the aim is to find the effect of the active labour market policies in a region on the corresponding GINI coefficient of that specific region. In this chapter, the model will be tested for linear correlation including fixed effects. When regressing the main three independent variables as described by Goos et al. (2010), the time span of the regression is from 2004 up until 2010. This is caused by the limited availability of some data utilised in the analysis (see 3.5.1). In table 5, model 1 contains the main three variables. The lagged versions as described in the conceptual framework are deployed to examine the effect of each independent variable. Other versions of the model with differentiated lags are included in appendix 16-18. The model as shown in table 5 is however the best fit for explaining the different degrees of polarization.

VARIABLES	(1) gini_coefficient	(2) gini_coefficient	(3) gini_coefficient
lag2ALM	0.100***	-0.201	-0.439***
	(0.0168)	(0.136)	(0.105)
Automation_risk	-0.0100	-0.281	-0.414***
	(0.0819)	(0.173)	(0.133)
openness	0.00160***	0.00121***	-0.000653***
	(0.000151)	(0.000299)	(0.000236)
c.lag2ALM#c.Automation_risk		0.399*	0.491***
		(0.223)	(0.168)
c.lag2ALM#c.openness		0.000689	0.00187***
		(0.000458)	(0.000332)
age			0.0111***
			(0.00145)
degurba			0.0634***
			(0.00840)
hatlev1d			2.267
			(1.419)
Low education(%)			2.490*
			(1.446)
Medium education (%)			-0.386***
			(0.125)
High education (&)			-2.708*
			(1.453)
GDPpp			-1.31e-06*
			(7.55e-07)
GDPgrowth			0.0522***
			(0.0154)
Constant	-0.00285	0.194*	-4.441
	(0.0502)	(0.103)	(2.834)
Observations	672	672	603
R-squared	0.271	0.278	0.720
Number of group_id	135	135	122

Table 5: Regression

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 provides us with relevant information on the effect that active labour market policies have on the GINI coefficient in a region. Model one is the basic model only including the main independent variables, model two contains the interaction effects and in model three the control variables are added.

According to the findings as presented in table 5 and appendixes 16-18, it can be concluded that active labour market policies of national governments take some time to have their effect on the regional labour market. However, when reading these numbers, it is important to realise that the coefficient of the effect of ALM on the GINI coefficient is positive in model 1. This would presume that a higher ALM budget of countries leads to a higher inequality in hours worked two years later. According to the literature, this is a quite remarkable finding. Whereas the literature states that ALM can have a dampening effect on job polarization, these results might be contradictory (Fernandez-Macias 2012; Dustman et al., 2009). Therefore, interaction effects between variables can be a useful addition to the model. These interaction effects indicate the effect that independent variables might have on each other. Applying these interaction effects enables the model to adequately determine the direct effect of active labour market policies.
The interaction effects added are derived from the literature and the scatter plots as described in 4.1 (see 2.9). The interaction effects included in the model are: ALM (2-year lag)-Openness to trade and ALM (2-year lag)-Automation risk. When applying these interaction effects in model 2, it can be observed that the p-value is only significant at the 0.05 level for openness to trade. However, when the control variables are added in model 3, one can note that all the main effects and interaction effects show a significant impact on the mean GINI in a region (see table 5).

The main goal of this study was to find the impact that active labour market policies have on the inequality in hours worked in a region (GINI coefficient). As can be seen in table 5, a negative coefficient was found for this effect in the analyzed regions. This means that a higher percentage of GDP spending on active labour market policies lead to lower overall inequality in hours worked. This would suggest that, as expected, policymakers have powerful tools to adapt to the changing regional labour market. This study finds that by implementing reliable and efficient labour market institutions as described in chapter 3.2.3, the effects of job polarization can be dampened (see table 5).

An odd result from this study is the direct effect of globalization (openness to trade). The coefficient found in this study is negative. This means that the higher the openness to trade in a region, the lower the inequality in hours worked (GINI) will be. Based on the literature, one would expect this to be the other way around. Openness to trade leads to more easily offshorable jobs and more need for efficient business operations (Aghion et al., 2008, cited by Signoret et al., 2020, pg. 14 Goldberg & Pavcnik, 2004, cited by Signoret et al., 2020, pg. 14 Acemoglu, 2002; Frey & Osborne, 2017).

The other remarkable finding is the negative coefficient of automation risk. This coefficient implies that the higher the automation risk, the lower the GINI coefficient in a region is. This is an odd finding when considering the literature, which states that a higher automation risk leads to more inequality (Frey & Osborne, 2017). This can be explained by the fact that regions with a high mean risk of automation might still have a large percentage of the workforce working in professions that are to be automated in the coming years. Policymakers in these regions should be ahead of the job polarization in these regions by implementing policy measures that will enable the workforce to adapt to the changing demands in the labour market (Lund et al., 2019).

As stated above, the direct effect of active labour market policies is that they decrease inequality in a region, this is however not the only effect that these policies have. As expected in the conceptual model, the active labour market policies in a region also show a significant interaction effect with the openness to trade and mean automation risk in a region. As for the openness to trade, a positive coefficient is found. This effectively means that the higher the openness to trade in a region, the higher the active labour market policies will be. According to the literature, this can be explained by the consequences an open economy has (see chapter 3.3). Policymakers adapt to the globalizing labour market by higher spending on active labour market policies. This effect is also true for the interaction effect between active labour market spending and the mean automation risk in a region. For this interaction effect, a positive correlation coefficient is found which means that the higher the automation risk, the higher the active labour market policies will be. This can be explained because local policymakers already face the risk of jobs being automated. They can adapt to this by already having sufficient labour market policies in place to make the transition to less automatable jobs (Lund et al., 2019; van den Berge & Weel, 2015). One might argue that this interaction effect also partially explains the negative coefficient found for the direct effect of the automation risk. Policymakers in regions with a high mean automation risk spend more on active labour market policies to prevent job polarization from happening.

The other interesting development is the sharp decrease in inequality in 2008 as mentioned in chapter 4.1. To examine this effect, time dummies are inserted in the model (as deployed in model 3, table 5) to examine both 2 periods of time (2000 until 2007 & 2008 until 2010). Quite a few remarkable conclusions can be drawn from this regression (see table 6). As one might directly observe is that the time-dummy variable is highly significant and adding the time dummy increases the explanatory value of the model (see model 2, table 6). These different periods therefore differ in the development in inequality in hours worked. This can be related to a definition change or different economic circumstances.

VARIABLES	(1) gini_coefficient	(2) gini_coefficient
lag2ALM	-0.439***	-0.444***
	(0.105)	(0.0994)
Automation_risk	-0.414***	-0.379***
	(0.133)	(0.126)
openness	-0.000653***	-0.000481**
	(0.000236)	(0.000226)
c.lag2ALM#c.Automation_risk	0.491***	0.516***
	(0.168)	(0.160)
c.lag2ALM#c.openness	0.00187***	0.00148***
	(0.000332)	(0.000320)
age	0.0111***	0.0130***
	(0.00145)	(0.00141)
degurba	0.0634***	0.0685***
	(0.00840)	(0.00801)
hatlev1d	2.267	1.837
	(1.419)	(1.349)
perclow	2.490*	1.918
	(1.446)	(1.376)
percmed	-0.386***	-0.427***
	(0.125)	(0.118)
perchigh	-2.708*	-2.286*
	(1.453)	(1.381)
GDPpp	-1.31e-06*	1.24e-06
	(7.55e-07)	(8.00e-07)
GDPgrowth	0.0522***	-0.00555
	(0.0154)	(0.0167)
Timedummy		-0.0162***
		(0.00225)

Constant	-4.441	-3.681
	(2.834)	(2.694)
Observations	603	603
R-squared	0.720	0.748
Number of group_id	122	122

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Model including time dummies

As should be noted, the full linear regression is only run over 603 observations including 122 groups (NUTS-2 regions or (when aggregated) NUTS-1 regions /countries). This is done to get a clear overview of the full model and the corresponding coefficients. For more extensive regressions see appendixes 16-20.

5. Conclusion and discussion

The focus of this study was to find the effect of active labour market policies on the inequality in hours worked in NUTS-2 regions. This effect was empirically studied by analyzing the ELFS, the trade openness and the active labour market policies. From the analysis, a few main conclusions can be reached. When coming to these conclusions, a reservation about the linear regression must be made clear: the regression is run over only respectively 672 or 603 observations, this is done so that the complete regression could be run over the cases while all the variables were available for these years. To answer the main question of this study, the different sub-questions are answered to get an overall view of the causes of changing the GINI coefficient.

The degree of job polarization differs from region to region (see appendix 15). This makes it interesting to study the causes of these differences. In this study, these regional differences are studied by the three main factors that impact the rate of job polarization. These factors are technological change, globalization, and institutions (Goos et al., 2010).

The direct effect of national institutions on job polarization in NUTS-2 regions is the focus of this study. When correcting for interaction effects and adding control variables, it is found that the mean active labour market policies spending does indeed directly affect the inequality in hours worked in regions (see table 5). It is found that the coefficient of this relation is negative and highly significant, this means that higher average spending on active labour market policies leads to a more equal division of hours worked in the analyzed regions. This is in line with the current economic debate on labour market institutions. For long, those institutions were underexposed in economic theory (Amin & Thrift, 1995; Rodríguez-Pose, 2013). However, as shown in this study, national institutions affect the economic situation in regions considerably. Especially when lagging the active labour market policies by two years, a significant effect can be observed. Policymakers need to take this lag in effects into account when implementing these measures. Upgrading a workforce and leading them to jobs that are less likely to be automated in the coming years takes time but will ensure durable regional development (Buyst et al., 2018, van den Berge & Weel, 2015; OECD, 2017). Especially regions with a higher mean automation risk are highly susceptible to changing labour demands, these regions should have decent active labour market policies in place to prevent the labour market from polarizing (Goos & Manning, 2007; Frey & Osborne, 2017).

The direct effect of the other main variables found in this study is quite remarkable. According to the literature, one might expect a positive coefficient for both effects (Aghion et al., 2008, cited by Signoret et al., 2020, pg. 14 Goldberg & Pavcnik, 2004, cited by Signoret et al., 2020, pg. 14 Acemoglu, 2002; Frey & Osborne, 2017). In this study, however, a negative coefficient is found for both effects. This could be caused by the limited data available for this study, or by the fact that the effects of these effects have not yet have had their impact on the analysed local economies.

The active labour market policies in regions do not only affect the rate of job polarization. In this study, it is shown that the active labour market policies also significantly interact with other independent variables. The interactions of active labour market policies with trade openness and automation risk both show a positive and significant coefficient. This implies that the higher the trade openness or automation risk, the higher the mean active labour market spending is. This interaction is explainable with the theory at hand; regions with a higher mean automation risk and trade openness are more likely to face severe job polarization in the near future (Aghion et al., 2008, cited by Signoret et al., 2020, pg. 14 Goldberg & Pavcnik, 2004, cited by Signoret et al., 2020, pg. 14 Acemoglu, 2002; Frey & Osborne, 2017). One might argue that policymakers are therefore aware of the risk of job polarization in their region. Implementing active labour policies might, as explained above, decrease the risk of a polarizing labour market. Another angle of view for this correlation might also be relevant; having a high standard of institutional quality might attract foreign investment to a region (Amin & Thrift, 1994, page 104).

As depicted in graphs 15-20, the three main independent variables are not the only factors that might explain the GINI coefficient in a region. As can be concluded from table 5, a lot of control variables (age, GDP growth, and degree of urbanisation) show highly significant coefficients. This effectively means that by running this model, a comprehensive explanation of job polarization can be given. After adding time dummies for the different distinguishable periods of the GIN coefficient (as described in 4.1), the explanatory value of the model increases significantly. Meaning that these time periods also show significant impact on the GINI coefficient in a region. This can be caused by a definition change in the GINI or other factors that might influence this development.

As established in the previous chapters; job polarization on regional labour markets is a significant problem and might harm the durability of the regional labour market. It is therefore important to look at the causes of job polarization and the solutions of how to prevent job polarization from happening. Regional labour markets show highly differentiated degrees of polarization but as established in this study, active labour market policies help to adapt to the changing labour market demands. Policymakers, therefore, have a powerful tool to prevent that certain people in the labour market are left behind. When not acting on these changing demands; it will cause middle-schooled workers to compete for the same jobs and these workers are displaced in the lower part of the wage distribution (Lund et al., 2019). When however active labour market policies are implemented, jobs can be upgraded and made more rewarding. This has a positive influence on regional scale (Lund et al., 2019; van den Berge & Weel., 2015; OECD, 2017).

Policymakers, therefore, have a key role in adapting regional labour markets to the changing demand. It is however not to be expected that immediate changes or improvement can be expected. As established in this study, active labour market policies take time to affect the inequality of hours worked. It is, therefore, crucial to start implementing these active labour market institutions on time.

This study filled the literature gap of job polarization on a NUTS-2 level. Including multiple countries and analyzing multiple independent variables; a comprehensive model is established, explaining job polarization at the NUTS-2 level. This is an important contribution because job polarization might differ between regions significantly. Policymakers need to be provided with comprehensive models which explains the different causes of job polarization to intervene effectively. When, however, looking at the linear regression, quite some data is not considered. This is due to the data availability with multiple variables (see chapter 3.5). Further research could be done by adding more data and making the model more significant. By doing so, a regression in more regions could be run to make the model even more significant and comprehensive.

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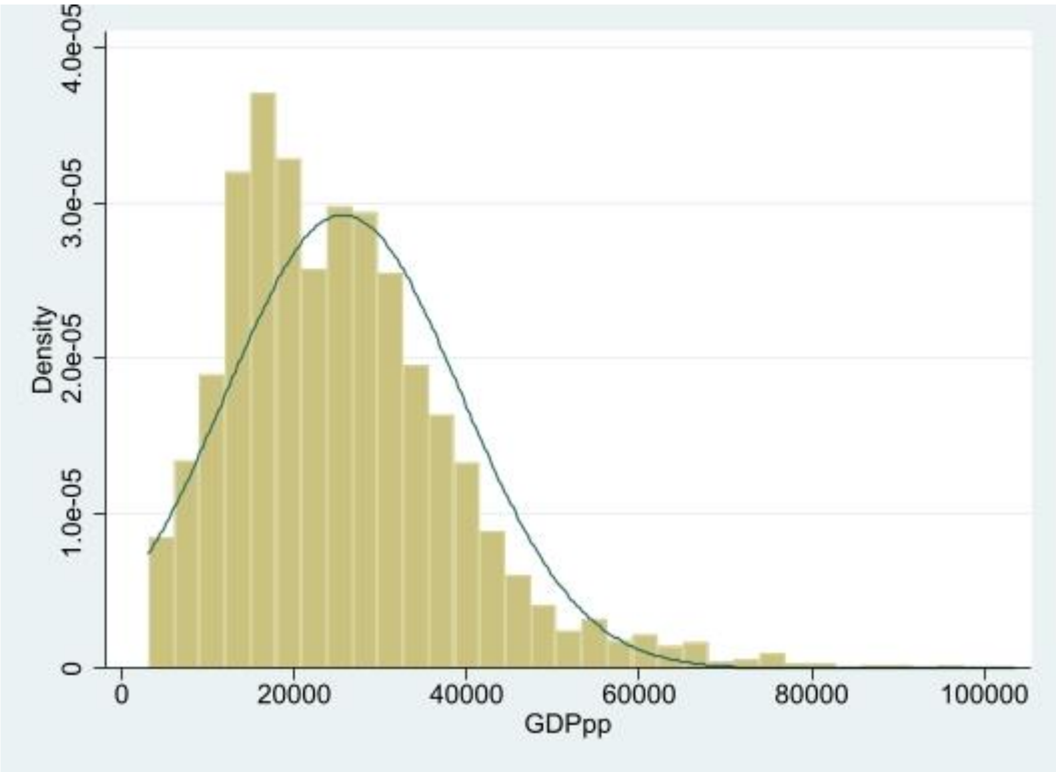
Appendixes

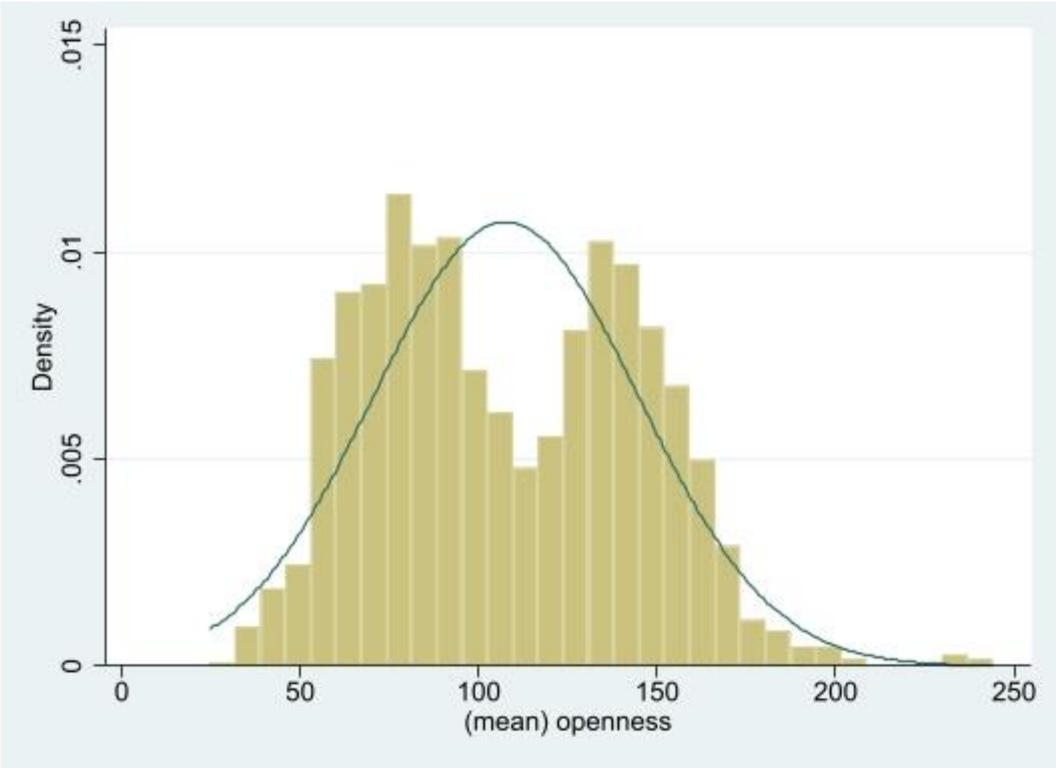
Appendix 1: Summary of data

Variable		Mean	Std. dev.	Min	Max	Observations
ALM	overall	.5829868	.3398316	.02	2.04	N = 2568
	between		.3493396	.14	1.964444	n = 190
	within		.1110319	.2554868	1.05013	T-bar = 13.5158
age	overall	45.29284	1.783304	39.00425	51.4901	N = 3295
	between		1.422449	41.53585	49.62307	n = 192
	within		1.105841	40.46257	51.06854	T-bar = 17.1615
degurba	overall	1.981068	.4192273	1	3	N = 3110
	between		.3807871	1	2.790345	n = 191
	within		.1527153	1.267147	2.762943	T-bar = 16.2827
hatlev1d	overall	1.948902	.1999268	1.217973	2.403234	N = 3295
	between		.1746119	1.395943	2.269632	n = 192
	within		.0896591	1.653099	2.193898	T-bar = 17.1615
incdecil	overall	5.256455	.4978712	2.851504	7.161616	N = 1706
	between		.3582938	4.54984	6.498461	n = 175
	within		.3409408	3.485187	6.420311	T-bar = 9.74857
mean_p~b	overall	.585755	.0347988	.4648069	.7041742	N = 3154
	between		.028188	.5136602	.6548634	n = 192
	within		.0210468	.500256	.6848449	T-bar = 16.4271
openness	overall	107.6091	37.17306	24.54056	244.0047	N = 1499
	between		36.93989	36.65102	213.9022	n = 158
	within		8.111639	24.80703	141.0185	T-bar = 9.48734
gini_c~t	overall	.2131601	.0494605	.0668476	.3620494	N = 3295
	between		.0373067	.107243	.3419585	n = 192
	within		.0329942	.0663958	.3928833	T-bar = 17.1615
GDPpp	overall	25706.44	13631.64	3106.582	103464.7	N = 2749
	between		13431.84	6316.333	78182.01	n = 171
	within		3961.079	-4207.261	50989.11	T-bar = 16.076
ALMlag~d	overall	.5824605	.3397068	.02	2.04	N = 2408
	between		.3536317	.1246667	1.9775	n = 190
	within		.1072281	.2531272	.9391272	T-bar = 12.6737
GDPgro~h	overall	.0302847	.0516203	-.2189657	.8557968	N = 2578
	between		.0218003	.001322	.1929049	n = 171
	within		.0474224	-.2755212	.6931766	T-bar = 15.076

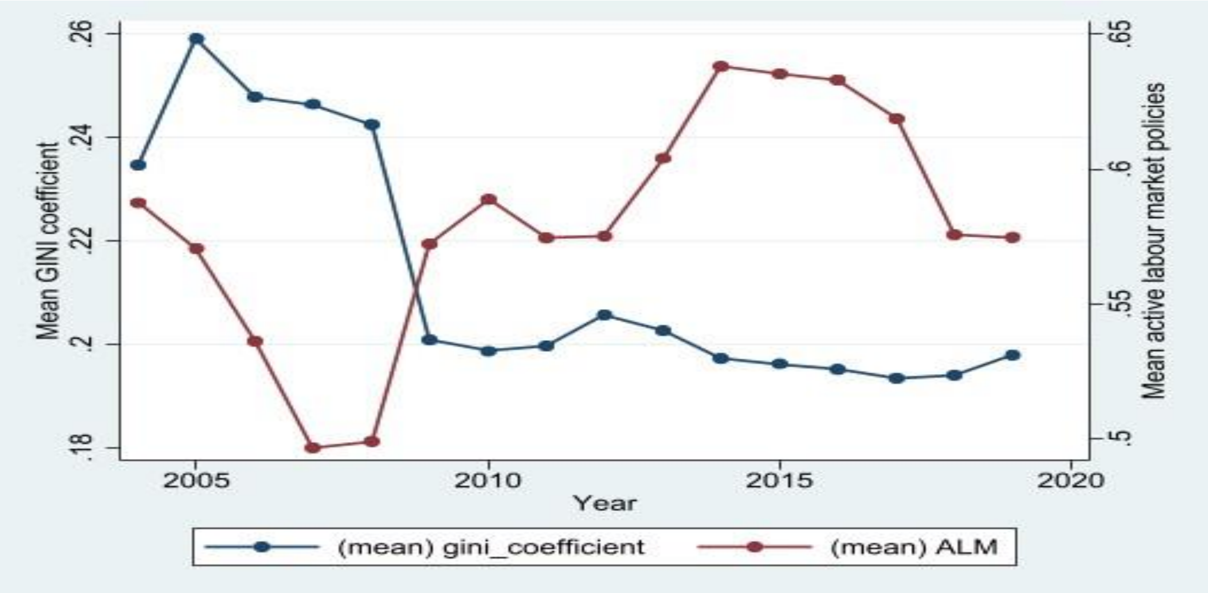
Appendix 2: Distribution of GDP



Appendix 3: Distribution openness to trade



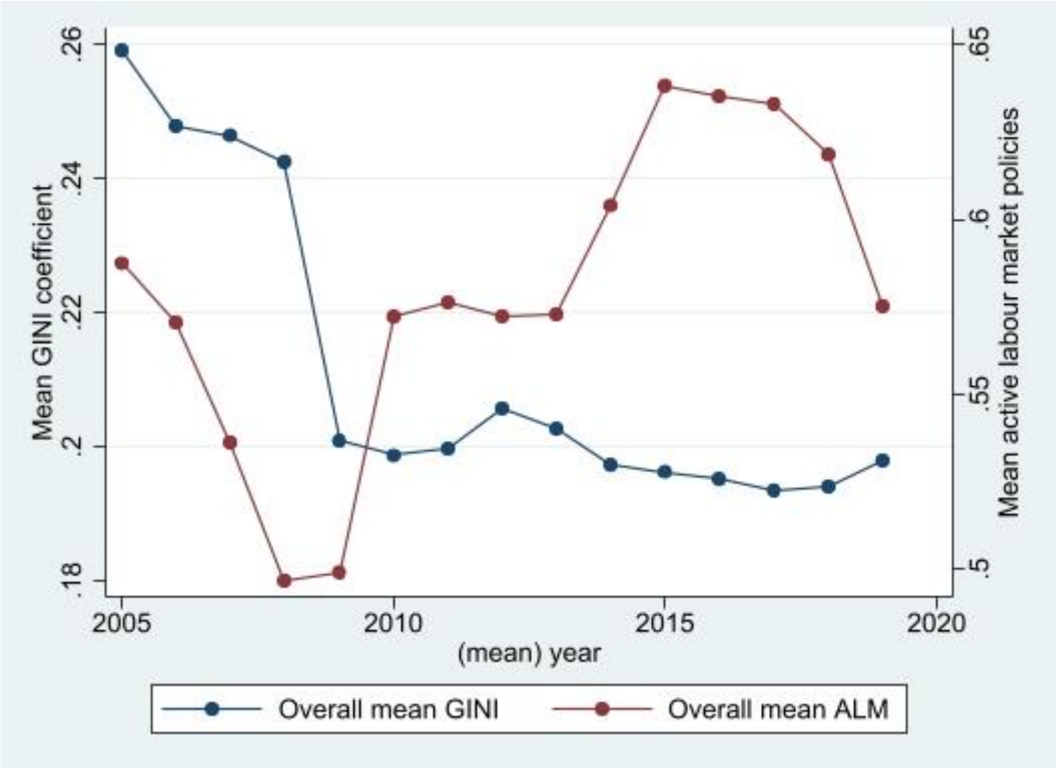
Appendix 4: ALM & GINI without temporal lag.



Appendix 5: Pearson correlation test ALM&GINI coefficient

	gini_c~t	ALM
gini_coeff~t	1.0000	
ALM	0.1119 0.0000	1.0000

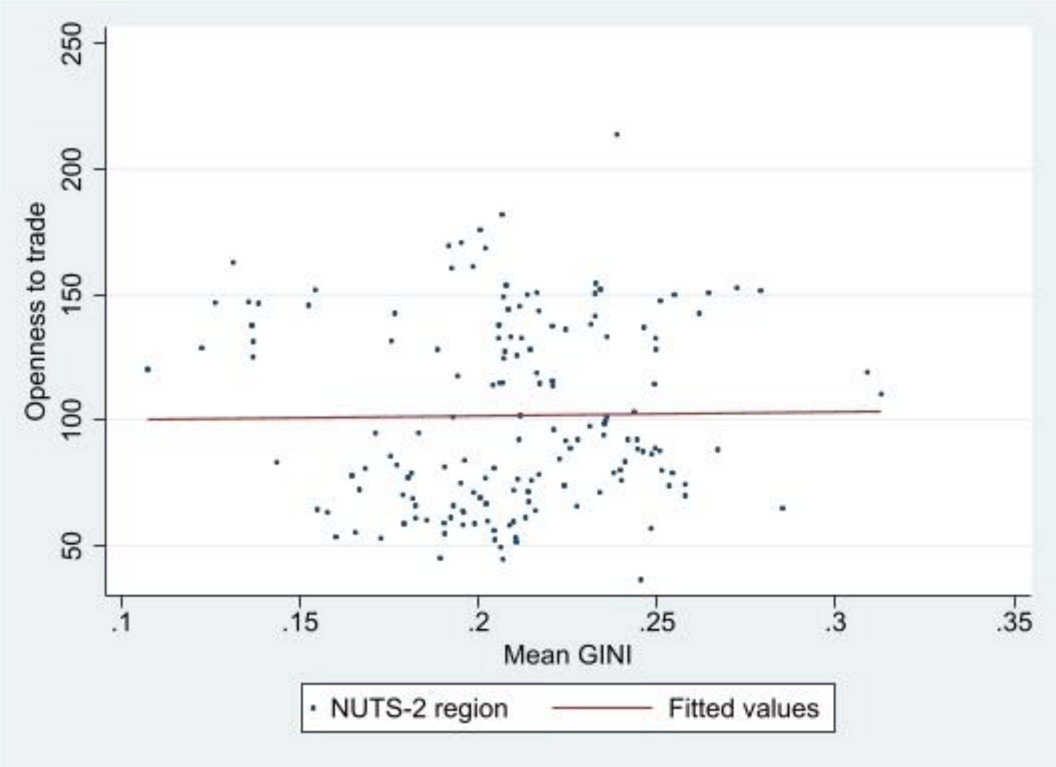
Appendix 6: Temporal lag GINI and ALM (1 year)



Appendix 6: Correlation GDP & GINI

	GDPpp	gini_c~t
GDPpp	1.0000	
gini_coeff~t	0.4776 0.0000	1.0000

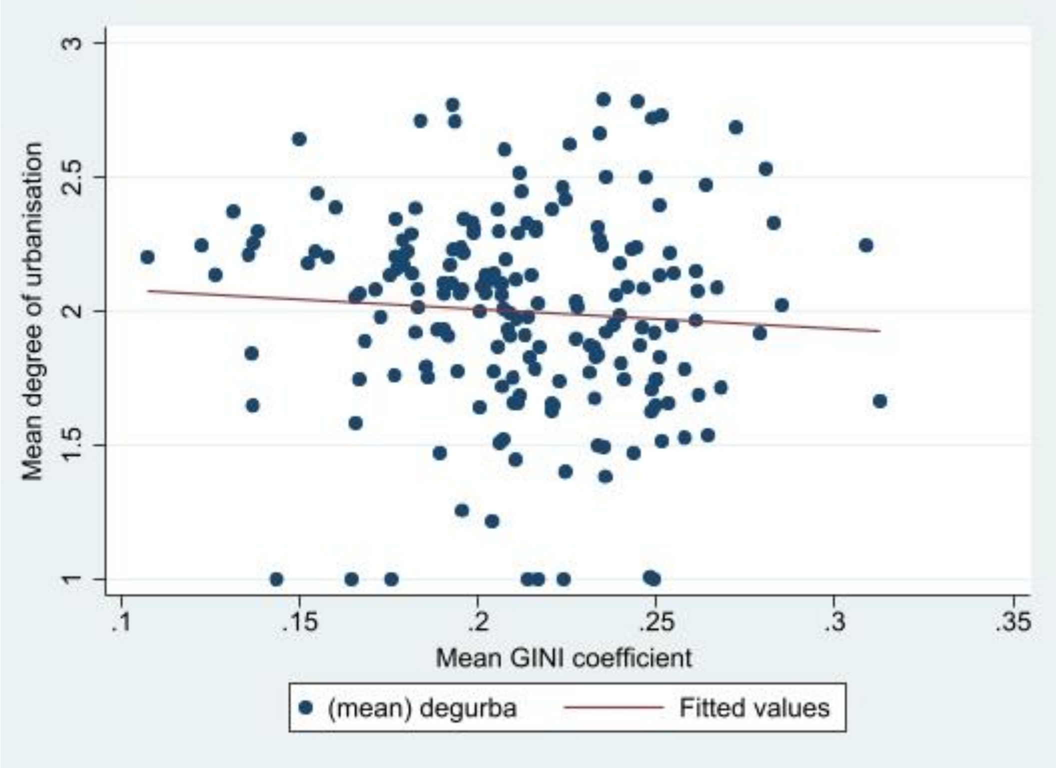
Appendix 7: Correlation openness to trade & GINI



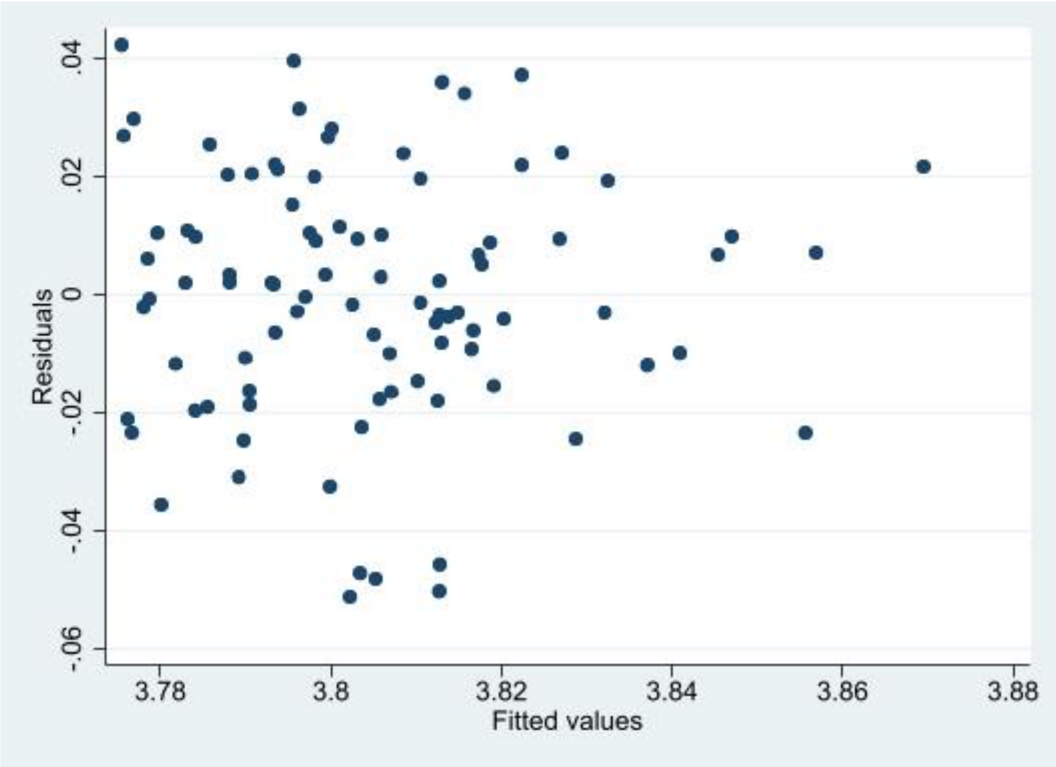
Appendix 8: Correlation GINI coefficient & openness

	gini_c~t	openness
gini_coeff~t	1.0000	
openness	0.0179 0.8234	1.0000

Appendix 9: Correlation degree of urbanisation and GINI coefficient



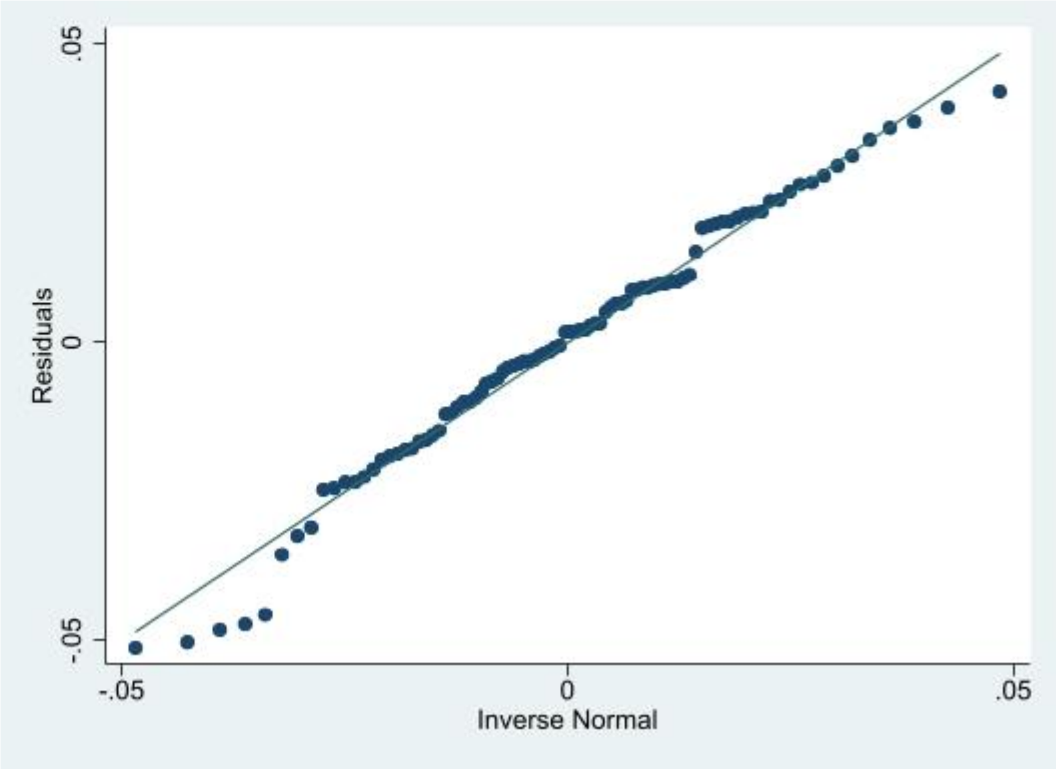
Appendix 10: Testing for heteroscedasticity



Appendix 11: Testing for autocorrelation in panel data

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       5) =     44.952
           Prob > F =      0.0011
```

Appendix 12: Testing for normal distribution of residuals



Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test Adj chi2(2)	Joint test Prob>chi2
res	92	0.1580	0.9630	2.05	0.3586

Appendix 13: Hausman test for random or fixed effects

```
Test of H0: Difference in coefficients not systematic

    chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            = 233.47
Prob > chi2 = 0.0000
```

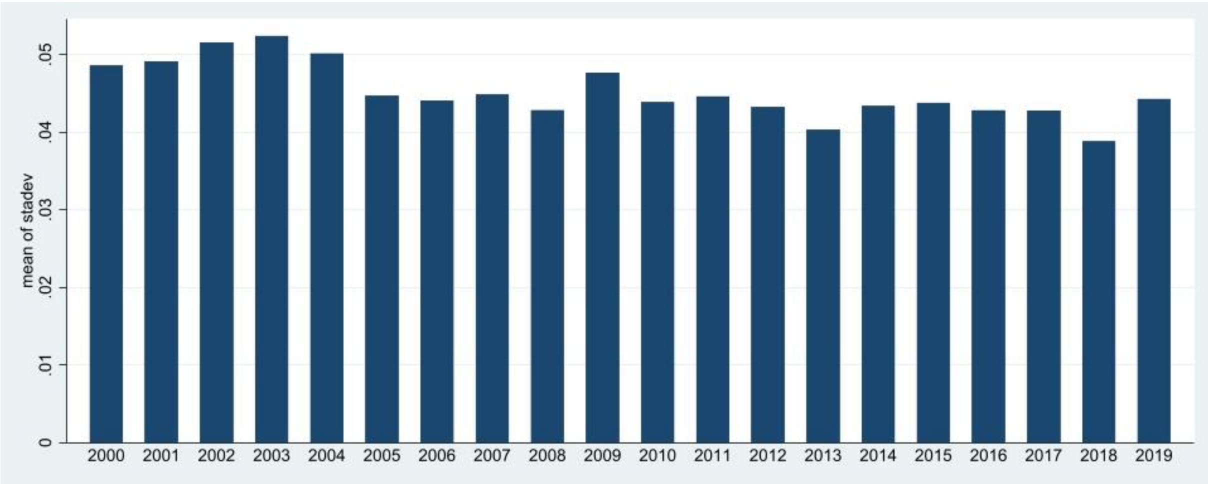
Appendix 14: ALM and openness lagged (1 year both)

```
Random-effects GLS regression                   Number of obs     =        941
Group variable: group_id                        Number of groups  =        137

R-squared:                                      Obs per group:
     Within  = 0.0418                                         min =          1
     Between = 0.1422                                         avg =        6.9
     Overall = 0.1080                                         max =          7

                                                Wald chi2(3)      =      56.96
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000
```

gini_coeffici~t	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lagopenness	.0001566	.0000765	2.05	0.041	6.73e-06	.0003066
lagALM	.0246195	.0087405	2.82	0.005	.0074884	.0417506
Automation_risk	-.3985509	.0575747	-6.92	0.000	-.5113953	-.2857065
_cons	.4245093	.0351597	12.07	0.000	.3555975	.493421
sigma_u	.03606171					
sigma_e	.03231275					
rho	.55466545	(fraction of variance due to u_i)				

gini_coeffici~t	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
ALM						
L1.	.0032124	.015521	0.21	0.836	-.0272542	.0336789
openness						
L1.	.000179	.0001532	1.17	0.243	-.0001218	.0004798
Automation_risk	-.3796922	.0639007	-5.94	0.000	-.5051247	-.2542596
_cons	.4232331	.042162	10.04	0.000	.340472	.5059942

Appendix 15: Standard deviation GINI coefficient



Appendix 16: Main independent variables lagged 1 year

VARIABLES	(1) gini_coefficient	(2) gini_coefficient	(3) gini_coefficient
lagALM	-0.00352	0.290**	-0.0124
	(0.0158)	(0.143)	(0.0957)
lagAutomation_risk	0.248***	0.510***	-0.0724
	(0.0788)	(0.172)	(0.117)
lagopenness	0.000229	0.000555**	0.000552***
	(0.000156)	(0.000244)	(0.000154)
c.lagALM#c.lagAutomation_risk		-0.405*	0.0996
		(0.234)	(0.155)
c.lagALM#c.lagopenness		-0.000583*	-0.000605***
		(0.000352)	(0.000223)
age			-0.00110
			(0.00109)
degurba			0.0494***
			(0.00755)
hatlev1d			4.513***
			(1.044)
perclow			5.594***
			(1.043)
percmed			0.127
			(0.107)
perchigh			-4.075***

			(1.085)
GDPpp			-3.26e-06***
			(5.17e-07)
GDPgrowth			0.107***
			(0.0146)
Constant	0.0575	-0.127	-9.310***
	(0.0511)	(0.105)	(2.074)
Observations	938	938	839
R-squared	0.014	0.021	0.670
Number of group_id	135	135	122

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 17: No lags imposed

VARIABLES	(1) gini_coefficient	(2) gini_coefficient	(3) gini_coefficient
ALM	-0.0232	0.0935	-0.00462
	(0.0141)	(0.131)	(0.115)
Automation_risk	0.158**	0.162	-0.0251
	(0.0726)	(0.157)	(0.140)
openness	0.000924***	0.00152***	0.000870***
	(0.000144)	(0.000224)	(0.000192)
c.ALM#c.Automation_risk		-0.0140	0.0273
		(0.213)	(0.185)
c.ALM#c.openness		-0.00112***	-0.000483*
		(0.000322)	(0.000269)
age			-0.00138
			(0.00129)
degurba			0.0337***
			(0.00914)
hatlev1d			3.821***
			(0.800)
perclow			4.558***
			(0.835)
percmed			-0.120
			(0.0770)
perchigh			-3.435***
			(0.803)
GDPpp			-1.22e-06**
			(5.88e-07)
GDPgrowth			0.0747***
			(0.0174)
Constant	0.0487	-0.0130	-7.751***
	(0.0469)	(0.0967)	(1.622)

Observations	940	940	837
R-squared	0.065	0.078	0.493
Number of group_id	135	135	122

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 18: Main independent variables all lagged 2 years

VARIABLES	(1) gini_coefficient	(2) gini_coefficient	(3) gini_coefficient
lag2ALM	0.0181	0.443***	0.150*
	(0.0144)	(0.129)	(0.0895)
lag2Automation_risk	0.189***	0.739***	0.216*
	(0.0713)	(0.155)	(0.111)
lag2openness	-0.000371***	-0.000713***	-0.000261*
	(0.000142)	(0.000219)	(0.000147)
c.lag2ALM#c.lag2Automation_risk		-0.843***	-0.260*
		(0.212)	(0.147)
c.lag2ALM#c.lag2openness		0.000710**	0.000176
		(0.000317)	(0.000215)
age			0.00439***
			(0.00120)
degurba			0.0272***
			(0.00540)
hatlev1d			3.142***
			(1.190)
perclow			3.953***
			(1.209)
percmed			-0.0241
			(0.121)
perchigh			-2.921**
			(1.214)
GDPpp			-5.90e-07
			(5.36e-07)
GDPgrowth			0.0541***
			(0.0145)
Constant	0.138***	-0.149	-6.729***
	(0.0464)	(0.0948)	(2.372)
Observations	935	935	841
R-squared	0.025	0.050	0.629
Number of group_id	135	135	122

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 19: Model with different controls

VARIABLES	(1) gini_coefficient	(2) gini_coefficient	(3) gini_coefficient	(4) gini_coefficient	(5) gini_coefficient
lag2ALM	-0.439***	-0.301**	-0.258**	-0.263**	-0.0545
	(0.105)	(0.118)	(0.109)	(0.103)	(0.116)
Automation_risk	-0.414***	-0.103	-0.203	-0.375***	0.0464
	(0.133)	(0.154)	(0.138)	(0.127)	(0.148)
openness	-0.000653***	-0.00117***	-0.000539**	0.000264	-0.000231
	(0.000236)	(0.000281)	(0.000244)	(0.000218)	(0.000273)
c.lag2ALM#c.Automation_risk	0.491***	0.226	0.234	0.358**	-0.0118
	(0.168)	(0.192)	(0.175)	(0.167)	(0.190)
c.lag2ALM#c.openness	0.00187***	0.00277***	0.00171***	0.000857***	0.00185***
	(0.000332)	(0.000391)	(0.000347)	(0.000328)	(0.000396)
age	0.0111***	0.0196***	0.00932***		0.0204***
	(0.00145)	(0.00142)	(0.00153)		(0.00136)
degurba	0.0634***	0.0277***			0.0190*
	(0.00840)	(0.00947)			(0.00982)
hatlev1d	2.267		4.276***	4.405***	
	(1.419)		(1.475)	(1.186)	
perclow	2.490*		4.653***	5.008***	
	(1.446)		(1.500)	(1.198)	
percmed	-0.386***		-0.200	-0.138	
	(0.125)		(0.130)	(0.108)	
perchigh	-2.708*		-4.556***	-4.686***	
	(1.453)		(1.513)	(1.228)	
GDPpp	-1.31e-06*	-4.04e-06***	-1.52e-06**		
	(7.55e-07)	(8.71e-07)	(7.54e-07)		
GDPgrowth	0.0522***	0.133***	0.0518***		
	(0.0154)	(0.0176)	(0.0164)		
Constant	-4.441	-0.507***	-8.555***	-8.497***	-0.810***
	(2.834)	(0.124)	(2.942)	(2.363)	(0.112)
Observations	603	603	607	672	668
R-squared	0.720	0.580	0.685	0.636	0.494
Number of group_id	122	122	122	135	135

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 20: Only observations with all variables included

*Note: the outcomes are the same. In the original model, only observations with all variables are included.

VARIABLES	(1) gini_coefficient	(2) gini_coefficient
lag2ALM	-0.439***	-0.439***
	(0.105)	(0.105)
Automation_risk	-0.414***	-0.414***
	(0.133)	(0.133)
openness	-0.000653***	-0.000653***
	(0.000236)	(0.000236)
c.lag2ALM#c.Automation_risk	0.491***	0.491***
	(0.168)	(0.168)
c.lag2ALM#c.openness	0.00187***	0.00187***
	(0.000332)	(0.000332)
age	0.0111***	0.0111***

	(0.00145)	(0.00145)
degurba	0.0634***	0.0634***
	(0.00840)	(0.00840)
hatlev1d	2.267	2.267
	(1.419)	(1.419)
perclow	2.490*	2.490*
	(1.446)	(1.446)
percmed	-0.386***	-0.386***
	(0.125)	(0.125)
perchigh	-2.708*	-2.708*
	(1.453)	(1.453)
GDPpp	-1.31e-06*	-1.31e-06*
	(7.55e-07)	(7.55e-07)
GDPgrowth	0.0522***	0.0522***
	(0.0154)	(0.0154)
Constant	-4.441	-4.441
	(2.834)	(2.834)
Observations	603	603
R-squared	0.720	0.720
Number of group_id	122	122

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1