Master Thesis U.S.E.

Taming the Digital Beast: The Influence of Institutions on Labor Market Outcomes in the Context of Digitalization

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Abstract

This thesis studies the effect of Institutions on Labor Market Outcomes as Digitalization advances. The question of how different Institutions affect outcomes when ICT investment is undertaken is answered via sample split regressions in 18 European countries from 1995 to 2019. The thesis finds differing effects of ICT on outcomes between institutional groups, informing on how to capture the positive effects of Digitalization. Whereas countries with high levels of labor market institutions tend to capture lower but unilaterally positive effects of ICT on labor market outcomes, there is a tradeoff between monetary gains and employment in countries with lower levels of labor market institutions.

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Contents

1 Introduction

This thesis studies the effects of Labor Market Institutions (LMI) in 18 European countries on three Labor Market Outcomes (LMO), *monetary compensation, employment and hours worked*, in the context of advancing digitalization. Policymakers, especially in recent years, have been increasingly confronted with the problems of digitalization and automation due to the rapid technological advancements in the computer industry. While Keynes' (1930) [43] prediction of the 15-hour workweek has not materialized, an increasing trend towards the automation of human labor is visible. With what Schumpeter (1942) [108] called creative destruction in full effect, as digitalization and automation are everpresent, policymakers and other stakeholders are concerned about adverse effects of these developments such as large scale unemployment or a drop in wages. There is a considerable body of literature detailing the effects of digitalization on LMO [14, 17, 74, 79], finding both negative and positive effects of ICT investment, which is the proxy for digitalisation in this thesis. Most of these effects are marginal, as opposed to media sentiment of enormous negative (employment) effects. The literature also encompasses cross-country and multi-sectoral analyses [42, 47]. Differences between countries are found, but past papers lack the necessary detail to explain these differences. The aim of this thesis is to answer the following question:

In what way do the effects of digitalization technologies which affect labor market outcomes depend on labor market institutions?

This then leads to the subquestion:

Do countries with specific institutional frameworks capture positive/negative effects of Digitalization more than others?

Digitalization and other automating technologies (e.g. robots) pose a novel challenge to labor markets as well as to their institutions. Institutions such as trade unions can be responsive themselves, others like EPL (Employment Protection Legislation) need government legislation to change. It is crucial for policymakers, workers and other stakeholders to be informed about their current institutional environment to correctly assess the threat of adverse outcomes and hence act accordingly.

This research project therefore aims at augmenting the decision-making process of policymakers and other societal stakeholders by introducing institutional context to digitalization and automation, thereby also filling a gap in the literature. The results of this thesis should inform societal stakeholders on the path that

digitalization and automation will take depending on the institutional context by answering the question how LMI affect LMO with ever-increasing investment in ICT.
The results of this thesis are quantitatively similar to the existing literature and indicate significant differences between institutional contexts. Higher levels of LMI indicate less positive effects for compensation but more positive effects for employment and hours worked. There is considerable heterogeneity between institutional groups. These results confirm the necessity of adapting institutions to the digital age. Specifically in countries with lower levels of LMI, the trade-offs between monetary gains from ICT and employment losses need to be considered.

The remainder of the thesis is structured as follows. Section 2 details the extensive literature surrounding these topics and gives a theoretical overview of the concepts used. Section 3 details the Data used and details the institutional groupings of countries on the basis of the Data. Section 4 details the construction of the main variables used in the regression models. Section 5 explains the methodology used and provides some descriptive statistics. It also provides the main regression results. In section 6, the results are discussed and two surprising dynamics are highlighted. Section 7 concludes and provides some policy recommendations.

2 Literature Review and Theory

2.0.1 Definitions and Overview

Before the literature is reviewed, it is necessary to define some terms and thereby limit the scope of this thesis. Digitalization in the context of the labor market is a relatively vague category. The literature uses a variety of criteria for digitalization, namely information technology, general computer hardware, computer-controlled equipment or software networks [34]. Digitalization is, however, not only defined by its technical traits, but also by its functions. These include the augmentation of human workers, organizational changes to work processes and automation of (routine) tasks [34]. Second, automation differs from digitalization and is usually a sub-category of technological progress in the labor market. The process of a machine, an algorithm or a robot doing a task of or even all tasks of a job that has been previously done by a human is called automation [105]. Nevertheless, automation is relevant, as without digitalization, automation is unlikely to happen in the current economy. The focus of this thesis lies on Information and Communication Technology (ICT) which is being used as a proxy for digitalization, as ICT is central to digitalization [90].

Labor market outcomes will be more narrowly defined in this thesis. Labor market outcomes encompass a wide variety of economic issues such as (un)employment, which sectors and where people work, wage inequality, gender differences et cetera (for different examples of LMO see e.g. the online appendix of Acemoglu and Restrepo 2020 [5]). For the purposes of this thesis, labor market outcomes will refer to the following 3 phenomena: Unemployment, hours worked and monetary compensation. As the literature is more widely dispersed, this literature overview will also include other countries, mainly the USA.
This literature review will be structured along the three overarching topics of this thesis: digitalization, its effect on labor market outcomes and labor market institutions. The literature will be discussed and synthesized to lay the theoretical groundwork for this thesis.

2.1 Technology and Labor Market Outcomes

2.1.1 Monetary Compensation - ICT

The literature on digitalization, automation and robotization (categories that usually go together and are sometimes used synonymously, digitalization being often viewed as as an enabling factor for automation/robotization [92]; DAR hereinafter) is very broad. In the context of digitalization, two aspects are usually highlighted: returns to skills and wage differences (see e.g. [17, 79, 74, 14]). For wages, effects are twofold. First, digitalization technologies increase wages (at the micro-level) in establishments that invest in such technologies [64]. On the macro-level, wage polarization/wage inequalities across countries are rising due to digitalization while jobs in the 'platform economy' (a result of digitalization) are usually badly paid [14, 74, 41, 62]. The effect of DAR technology on monetary compensation overall is well established and does not warrant a big discussion. Technology use increases productivity and hence increases compensation [89, 32, 38, 69]. A large body of literature also deals with the specific effect of technology on compensation of different skill groups [16, 100, 47], which is beyond the scope of this thesis, nevertheless is needed to understand some results of this thesis.
The literature highlights the returns to skills of technology. The concept of Skill-Biased Technical Change summarizes this phenomenon aptly:

> Skill-biased technical change (SBTC) is a shift in the production technology that favours (sic!) skilled (for example, more educated, more able, more experienced) labour (sic!) over unskilled labour (sic!) by increasing its relative productivity and, therefore, its relative demand. Ceteris paribus, SBTC induces a rise in the skill premium – the ratio of skilled to unskilled wages [118].

2.1.2 (Un-) Employment - ICT

The literature in this field presents a myriad of studies on the effects of DAR on (un)employment. These effects tie in with the aforementioned effects on wages. Technologies that are introduced into the labor market have three primary effects: substitution, complementarity and reinstation. The substitution effect can be observed when new technologies substitute for labor previously done by humans [7, 3], hence eliminating the need for human labor in the specific application. The complementarity effect can mostly be seen in high-skill jobs, where DAR does not displace labor, instead it complements it, making the factor input "labor" (see Solow (1957) [111]) more productive. The reinstatement effect is the most complex out of the three. New technologies that automate certain tasks and digitize the workplace substituting and complementing labor to varying degrees. However, these new technologies often create new tasks for human labor [4]. The reinstatement effect is one of the reasons why empirical work on the effects of digitalization, automation and robotization often finds small (both negative and positive) to no effects on overall employment [45, 14, 5, 49, 69]. These three effects usually appear simultaneously, hence the effects on employment depend on the relative strength of each effect. In the transition from partial to full automation, automation turns from being human-complementary to labor-replacing [70]. The findings of small effect sizes go contrary to Frey and Osborne's (2017) [63] prediction of 47% of US jobs being at high risk of automation. This finding is furthermore contrasted by reevaluations of the task model and basing the methodology on already demonstrated technologies, which results in much smaller percentages for jobs at risk [13, 16]. This is also substantiated by Ju (2014)[77], Goos et al (2009)[66], as well as Jerbashian (2017) [76] who find small effects and job polarization (*id est* a decline in the middle-skill share of occupations and an increase at the extremes). However, recent work by Acemoglu and Restrepo [2, 4] provides evidence on the sluggish productivity growth of recent decades in the context of automation. They identify "so-so" technologies, which generate low productivity improvement and hence reduce labor demand because they lack a meaningful reinstatement effect - resulting in less employment overall. Tying the concepts of skill- complementarity and

SBTC back to wages, Perez-Laborda and Perez-Sebastian (2020) [103] show, that capital-skill-complementarity and SBTC explain a large part of the wage skill premium. Future effects of digitalization on employment are hard to quantify due to the ever changing nature of technology and what constitutes a ”routine” task [46]. Technological change is not only skill-biased, but, especially in the context of automation, it is also routine-biased. This means that tasks or jobs that are routine are more easily replaced, due to the ease of codifying each step. For a more detailed overview of routine-biased technological change (RBTC) refer to [20, 66, 16, 18]. For the purposes of this thesis, it suffices to know that different sectors have different amounts of tasks that can be automated depending on the amount of routine, abstract and manual tasks. With continuing technological progress, an increasing number of tasks are likely to fall under the 'routine' category [8, 46], hence the future of employment, to borrow Frey and Osborne's phrase, remains uncertain.

2.1.3 Hours Worked - ICT

Concerning hours worked, the literature becomes more sparse. Graetz and Michaels [69] find no significant change in hours worked due to robots from 1993 to 2007. This is in line with a more general trend of a stagnation in the speed of which working hours have fallen since the mid 19th century [80]. Following the employment trends shown above, in the case that there is less demand for labor, hours worked per employee may drop [46]. This is, nevertheless, uncertain. This thesis will contribute to the understanding of the impact of digitalization on hours worked depending on the institutional context. A methodological issue arises due to digitalization: working hours become more irregular, more flexible and have also been shifted towards the home, making them harder to account for [94]. This, unfortunately, cannot be corrected for in this thesis. Nevertheless, country-sector aggregates of working hours are used throughout, hence the results are unlikely to be biased. Furthermore, results shown in Section 5 show a close association between hours worked and employment, hence the concern is likely unwarranted.

2.2 Labor Market Institutions

The literature on labor market institutions (LMI) and their direct effect on labor market outcomes (LMO) is well-developed. The LMI this thesis focuses on are Trade unions, Employment Protection Legislation (EPL) and Public Expenditure on Job-related Issues (e.g. unemployment benefits(UB), direct job creation, active labor market policies (ALMP)), though these institutions will later be aggregated to group countries. The effects of these LMI on outcome variables differ.

2.2.1 Monetary Compensation - Institutions

Trade unions are a labor market institution representing the interests of the workers part of the union [31]. Economic theory predicts that unions lead to inefficient allocation of labor and a "union wage premium" for covered workers [29, 31]. Empirical evidence on the effect of unions is ambiguous and depending on the institutional and local context of the area in question. For example, unions are found to reduce wage inequality in the US [37, 33] whereas they do not significantly affect wages in Germany [33]. The union wage premium in the US is found to be around 15% [84]. In Norway, unions are found to have a positive effect on both productivity and wages [23] while the overall productivity effects are near zero or even negative [72]. Pertaining to digitalization, Hope and Martelli [74] find mitigating effects on digitalization's wage polarizing effects.

EPL is used to describe the legal environment in which a labor market functions when it comes to dismissals of workers [29]. The effects of EPL on wages are varied and heterogeneous. In theory, the introduction of stricter EPL reduces labor demand as it becomes relatively more expensive [12]. One empirical study confirm this theoretical prediction in Italy [87], though the literature on EPL's effects on wages remains scant. A view of productivity is sometimes taken [112], though literature remains scarce.

Social expenditure on job-related matters need to be disaggregated. Unemployment benefits increase the reservation wage of job seekers [29] and hence the wages of employed people. Job creation programs, in theory, can increase wages across the economy [22] and have been shown to increase earnings on the household-level [93]. The effect of job training programs are unilaterally positive [28, 91, 15]. Overall, expenditure on jobs increases compensation of employees.

2.2.2 (Un-)Employment - Institutions

Trade union's effects on employment are well-documented. In theory, trade unions reduce employment, with more reductions depending on the degree of centralization of the unions (more centralization - less unemployment) [29]. Empirical studies underpin this theoretical prediction, though finding heterogeneity among different demographics [120, 26].

EPL's effect on employment is subject to a large debate in the literature. Lazear (1990)[86] finds that more stringent EPL and the legal enforcement of severance pay reduces employment. More modern studies find weaker effects of EPL on employment [109, 6, 60, 40] and emphasize the large heterogeneity in employment effects depending on the worker group affected and on firm size, as well as its effect on the amount of temporary contracts [12, 78]. In general, the effects of EPL on employment are ambiguous [96].

The effects of social expenditure related to employment is ambiguous, but self-explanatory when disaggregated. Increasing the duration (and hence public spending) on unemployment benefits reduces job-seeking speed and hence increase overall unemployment [29]. In Europe, training programs create modestly positive effects on employment while job creation programs have detrimental effects [82], the latter being the only somewhat surprising result.

2.2.3 Hours Worked - Institutions

Trade unions have aimed at reducing working hours for their members since their advent [102, 113]. An increase in union density is associated with higher bargaining power [29], if unions have a reduction of working hours on their agenda, higher bargaining power translates into more union-favored outcomes. Reductions in working hours have gained media attention again in recent years, though there is no modern literature detailing effects.

EPL's effect on hours worked has been somewhat studied with broad trends emerging that stricter EPL lowers hours worked somewhat, as well as incentivizing firms to hire part-time labor [39, 25, 24].

Expenditure on jobs is theoretically uncorrelated with hours worked. The employment effects described above are most likely the main driver of hours worked of employed people.

2.3 Interaction and Theory

The literature on the interactions of DAR and labor market institutions is not fully developed yet. There have been instances of trying to see how trade unions affect labor market outcomes with the introduction of AI and robots[88, 42], or how labor protection interacts with routine-task replacing technologies [11], but there has been no systematic approach to this question. The main approach taken posits the advent of labor-replacing technologies as given and designs changes to institutions to deal with arising problems such as, among others, unemployment, labor market polarization, out-of-date welfare state models or to assess the policy preferences towards e.g. redistribution in the context of technological change [35, 51, 85, 104, 107, 116, 117]. Hope and Martelli (2019) [74] are the only paper, to the best of my knowledge, employing a somewhat similar approach to the one used in this thesis.

The empirical explanatory interactions between the two fields are, as mentioned, limited. While institutional context is of paramount importance in scholarship around labor market outcomes, labor market institutions are hardly mentioned in the context of the economics of DAR. This thesis, therefore, employs theory synthesized out of the two strands of literature. Based on the DAR literature, I expect to find small effects of ICT on my outcome variables (*monetary compensation, employment, hours worked*) that differ by the institutional context. I expect low levels of LMI to predict higher overall compensation, as productivity rises faster when ICT can be more quickly adopted. I expect small effects on employment, negative overall, with more negative employment effects in countries with lower levels of LMI as workers can be laid off more easily. This is consistent with Krugmans's 1994 [83] observation that the USA deals with shocks (in his case to trade) via unemployment whereas Europe deals with them through wages. Within Europe, where more USA-like institutions are present, similar reactions to the USA are expected. Where LMI that protect workers from being fired are stronger, I expect more marginal negative effects on employment [73]. Hours worked are ambiguous, but I expect them to have the same sign and similar size to employment effects, due to their clear link. The general relationship studied in this thesis can be formalized as follows:

$$Y = f(D|I) \tag{1}$$

where Y is the outcome, D represents the digitalization proxy and I stands for institutions.

3 Data

This Thesis relies on 2 main data sources and one supplementary one: the *EU-KLEMS* database, the *OECD* and *Eurostat*. The data cover 18 European countries (*Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Portugal, Slovakia, Slovenia, Sweden and the United Kingdom*) and full sectors (*id est* no sub-sectors) at the Nace rev. 2 level (European classification of sectors in the economy) from A to T (for a more thorough explanation please consult [54]). The decison to omit sub-sectors has been taken due to the limited data on ICT in these sub-sectors. The sector U (Activities of extraterritorial organisations and bodies)is excluded due to limited data availablity. The choice on the 18 countries was primarily made on the availability of ICT data in the *EU-KLEMS* capital accounts - countries that had no data on *I_CT* and *I_IT* have been excluded, as these are needed to construct the ICT measure (see Section 4). Moreover, the countries chosen are located across Europe, hence ensuring differences in LMI between them. Also excluded from the analysis are the United States and Japan, as instrumental variables are built out of these data and this thesis focuses on Europe. The data cover years from 1995 to 2019. While this includes the shock of the global financial crisis, it does not include the global shock from COVID-19 which had a larger impact on digitalization and ICT expenditure.

3.1 Institutions and the Sample Split

Across Europe, Labor Market Institutions vary widely. This leads to issues when conducting regressions, because institutional factors have an influence on LMO (see Section 2). As will be explained below, this thesis will make use of the Instrumental Variable (IV) statistical technique to avoid issues of endogeneity in the variable of digitalization. To address issues of endogeneity that arise in the institutional variables, a sample split will be conducted.

Countries will be grouped into different datasets based on the extent of their LMI, using different theoretical frameworks in an iterative process. As can be seen in Figure 1, there is considerable heterogeneity within the sample. This is in line with the literature on variations in Labor Market Institutions (see e.g. [27, 52, 61]. A similar sample split approach, though on a different topic, has been taken by Eicher and Leukert (2009) [50]. The simplest way to divide the countries is two groups, one with a high level of Labor Market Institutions, one with a low level of LMI. Whereas this preserves the most observations per split, the theoretical foundations are weakest for this. Hence, this split is done using an aggregated LMI index (see 1d). As is visible, the sample countries can be split into two relatively equal sized groups. High LMI countries are: *Austria, Belgium, Germany, Denmark, Finland, France, Luxembourg, the Netherlands, Portugal and Sweden*, Portugal being there by virtue of its incredibly high level of EPL (see Figure 1a. Low LMI countries are: *the Czech Republic, the United Kingdom, Italy, Lithuania, Latvia, the Slovak Republic, Spain and Slovenia.*

Grouping countries into three groups reduces the observations per group, nevertheless, this grouping has a strong theoretical underpinning in Gøsta Esping-Andersen's seminal work "The Three Worlds of Welfare Capitalism" [52]. These groups are Scandinavian (*Denmark, Finland, Sweden and Luxembourg*), with the latter grouped based on OECD data, as they are not grouped by Esping-Andersen, Liberal (*United Kingdom, the Czech Republic, Lithuania, Latvia, Slovenia and the Slovak Republic*), again with the aid of OECD data, and Corporatist (*Austria, Germany, France, Italy, Spain, the Netherlands, Portugal and Belgium*). For an extensive discussion, please refer to Esping-Andersen [52], in short, the Scandinavian countries have the highest levels of trade union density and expenditure on jobs, with weak EPL. Liberal countries have the lowest levels of LMI for all three institutions discussed. Corporatist countries have decently high levels of LMI, with more emphasis on EPL than Scandinavian countries though less union density.

Using the categorizations of Bertola [27] and the discussion in Fialová and Schneider [61], five subgroups of countries can be established: The Scandinavian model (*Denmark, Sweden, Finland*), the Anglo-Saxon model (*Lithuania, Latvia, the United Kingdom*), the Bismarckian model (*Austria, Germany, France, Luxembourg, Belgium, the Netherlands*), the Southern European model (*Italy, Spain, Portugal*) and the Eastern European model (*the Czech Republic, Slovenia, the Slovak Republic*). While there is still some considerable heterogeneity among Eastern European/post-Soviet States, a broad category can be applied once the Baltic States have been added to the Anglo-Saxon category, which is in line with literature [71, 21]. Scandinavian countries have a high level of LMI, making use of the flexicurity [44] model characterized by weak EPL, high trade union density and high levels of expenditure on jobs such as UB, job creation and others. The Anglo-Saxon model has low levels of LMI with a focus on the market. Union density is low, hiring and firing of workers is easy. The Eastern European model also has low levels of LMI, owing to the restructuring after the collapse of the Soviet Union. The Bismarckian model has a blend of all 3 relevant institutions, with medium to high levels of trade union density,

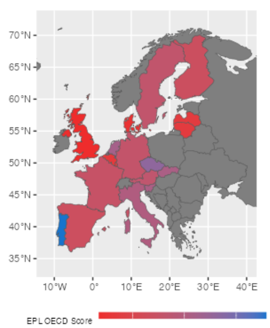
medium levels of EPL and relatively high levels of expenditure on jobs. Lastly, the Southern European model has particularly strong EPL but low levels of institutions otherwise. This method of grouping has the added benefit of ensuring roughly equal amounts of states in each group.
To avoid issues of changing institutions which would introduce complexity far outside the scope of this paper, initial (1995) institutions have been chosen to group the countries where theory is insufficient. Nevertheless, institutions are highly path-dependent [1], so large-scale changes are unlikely.

3.2 EU-KLEMS

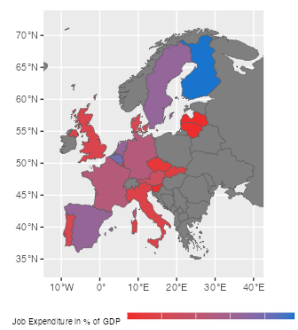
The *EU-KLEMS* database is the most relevant source [30]. The *National Accounts* and the *Capital Accounts* provide crucial variables for this analysis. For all chosen countries, *EU-KLEMS* data provides yearly observations of I_CT and I_IT investment, which constitute the main variables used to construct a digitalization measure. Furthermore, three labor market outcome variables for the country-year pairs are supplied: Employment (in thousands), hours worked by employed people (in thousands) as well as compensation (current prices, millions of the national currency). As the *EU-KLEMS* data are based off *Eurostat*, the observations are not only available at the country-level, but also disaggregated into Nace2.rev sectors (for a detailed overview of the Nace2.rev classifications please refer to [54]). The added depth of the sectoral disaggregation allows for a more detailed analysis as variaton between industries can be exploited. The chosen European countries for which data availability is good enough are: *Austria, Belgium, the Czech Republic, Germany, Denmark, Spain, Finland, France, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Portugal, the Slovak Republic, Slovenia, Sweden and the United Kingdom.*

3.3 OECD

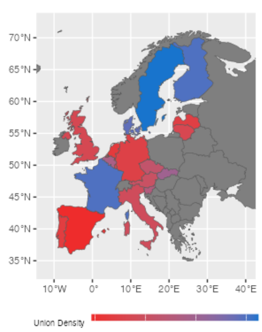
The *OECD*'s datasets are pivotal to this thesis, as they make data on labor market institutions available. The variables considered are union density ([98]), EPL ([97]) and government expenditure related to jobs([99]). Union density is given in percent, for every country-year pair. EPL (employment protection legislation) is an index from 1 to 6, with a higher number indicating more strict employment protection legislation. Expenditure related to jobs is categorized into *Unemployment*, *Training*, *Direct Job Creation* and *Supported Employment and Rehabilitation*. These variables are expressed in percent of GDP. An aggregate measure summing these variables has also been created. These three variables encompass the largest part of labor market institutions, in line with previously discussed literature. These variables are used to supplement the theoretical groupings of the sample split. The theory on grouping labor market institutions relies on welfare state models. Not all countries in the sample are considered by the cited authors, e.g. Esping-Andersen misses Southern European and Eastern European countries. Hence, the LMI of the described countries are taken and matched with non-described countries based on similar institutional values. This ensures robust groupings. For a brief overview of the LMI see Figure 1.



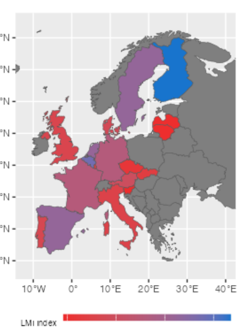
(a) OECD Emplyoment Protection Legislation Index (1-6) for chosen European countries. Initial 1995 values.



(b) Map for Total Social Expenditures related to Jobs in percent of Gross Domestic Product taken from the OECD SOCX Database. Initial 1995 values.



(c) Union Density in chosen European countries, taken from the OECD TUD Database. Initial 1995 values.



(d) Normalized Index for Labor Market Institutions for European countries. Values have been created using factor analysis based on the Institutions just discussed.

Figure 1: Initial (1995) Labor Market Institutions and their distribution in chosen European countries

3.4 Eurostat

As stated above, RBTC presents a challenge to labor markets. Data from the Eurostat LFS (Labour Force Survey) in 2022 has been used to construct a Routine Sector Index. This index shows how 'routine' the overall tasks in a given full (no sub-industries) Nace rev.2 industry (for the datasets used please refer to [58, 57, 56]. The index has been constructed following Autor and Dorn (2013) [19] and Goos et al. (2014) [67]. The Eurostat datasets give information on the repetitiveness (routine), the amount of cognitive (abstract) work and the amount of manual work. As automation (also via ICT) is easiest to implement in routine, non-manual, non-abstract tasks, in this case sectors, it follows naturally that these data are to be used. For a brief overview of the so-called RBTC (Routine-Biased Technological Change), refer to Autor (2015) [18] and the discussion in the review of the literature. For the construction process see Section 4. The RSI will be used as an IV where it has a higher relevance than other IVs, which will be explained below.

4 Construction of Main Variables

4.1 Construction of the Outcome Variables

This thesis focuses on three main outcome variables: compensation, employment and hours worked in country-sector pairs. The *EU-KLEMS* dataset provides nominal values for these three variables in the countries of interest. Compensation is given in millions of national currency, employment is given in thousands and hours worked is given in thousands. NAs in these variables are rare, only in the Nace rev.2 sector U (Activities of extraterritorial organisations and bodies) NAs are very frequent. The high NA frequency in this sector is also an issue in other variables, namely the ICT measure, which is why it has been dropped. The compensation measure has been divided by hours, as to give hourly compensation. The outcome variables and the ICT measure, to make them comparable and to improve their functional form, have been turned into an approximately natural logarithmic form using the Inverse Hyperbolic Sine (IHS) transformation, as there are meaningful zeros and negative values present in all three variables. Following the procedure laid out in Aihounton and Henningsen (2019) [9], there is very little danger of biased results, as the zeros in the outcome variables are the only "small" numbers and ICT measures are almost uniformly positive and large. Hence, the IHS transformation closely approximates the natural logarithmic form for the overwhelming majority of values. The IHS transformation for outcome variables has also been used for the *EU-*

KLEMS data before [10, 106]. Furthermore, the outcome variables have been weighted by the initial (1995) shares of employment in a country-sector pair to improve the reliability of the outcomes [110]. This transformation can be seen below in equations 2 to 6

$$Y = \ln(Y_{\text{nominal}} + \sqrt{Y^2_{\text{nominal}} + 1}) \tag{2}$$

$$EMP_{\text{total1995ci}} = \sum EMP_{x\epsilon EMP1995}(y) \tag{3}$$

$$EMP_{\text{total1995c}} = EMP_{x\epsilon EMP1995}(y) \tag{4}$$

$$EMP_{\text{share1995}} = \frac{EMP_{\text{1995ci}}}{EMP_{\text{total1995c}}} \tag{5}$$

$$Y_{\text{W}} = Y \times EMP_{\text{share1995}} \tag{6}$$

where 2 calculates the IHS transformation for the nominal values of the outcome variable, 3 calculates the sectoral employment in each country, 4 calculates the total country employment, 5 calculates the sector shares with which to weight the outcome variables and 6 shows the calculation for the weighting process. In the equations, the subscript W indicates weighted, i indicates sector, c indicates country and y represents the values of Y. The filtering procedures of the datasets are not shown in these equations.
To ensure comparability, the compensation outcome variable has been converted into dollars using the *Penn World Table 10.01* before the IHS transformation and weighting [59].

4.2 Regressors

The main regressors of the models are an ICT measure and interactions of it with labor market institutional dummies. The ICT measure is the sum of the *I_IT* measure and *I_CT* measure, denoting investment in computing technology and communications technology, respectively.

$$ICT = I_I T + I_C T \tag{7}$$

The ICT measure has been converted into dollars [59] and has also been subjected to the IHS transformation. The dollar-adjusted ICT variable is weighted analogously to the outcome variables. As previously mentioned, the ICT measure created and subsequently used in the models deals with country-industry pairs, leading to potential endogeneity issues that are not captured by country dummies, such as industry-specific endogeneity or with simultaneity bias and reverse causality issues.
To avoid this problem, an instrumental variable (IV) is constructed. The *EU-KLEMS* dataset does not only provide data on European countries, but also on the USA and Japan. Both of these countries' data have been chosen to construct an IV, depending on the model. The IHS transformed ICT investment values of the USA/Japan are mapped onto the chosen European countries in the same manner as the country-specific ICT measure. The long difference dataset has been tested on both IVs, neither one was able to cross the threshold of an F-statistic of 10 or higher. The majority of the models in stacked long differences dataset, with more observations, passed the threshold. The IV which provided the higher F-statistic has been chosen for each model. There are still some models remaining where the F-statistic is not close enough to 10 to justify the usage of the USA/Japan IV. These will be explicitly discussed and the estimates resulting out of these regressions should be viewed and interpreted with caution. As the IV need not only be relevant but also exogenous, *id est* uncorrelated with the error term of the first-stage equation, a theoretical argument has to be employed. The USA's/Japans ICT measure provides a break between the European countries' spending on ICT and the relevant outcome variables. Hence, the outcome variables are only affected through the direct channel of ICT expenditure. A slightly weaker, but nevertheless still relvant argument concerns sector-specific shocks. Treating the European countries as an economy and the USA/Japan as another economy, shocks to European sectors and potential endogenity arising therein are avoided in using the IV.

Where the relevance of the IVs just discussed is smaller (*id est* the F-statistic), the RSI discussed in Section 3 will be used, when it is more relevant. This is the case in the Esping-Andersen group of Scandinavia and for two models in the Southern European group. Overall, the RSI correlates strongly with the ICT measure. The theoretical justification is simple and found in the literature (see [69, 67]). Sectors that have a higher level of routine tasks are subject to more automation, as these tasks are easily codified. This, in turn, means that these sectors will likely have more ICT technology introduced to automate tasks. The RSI is not dependent on LMO, hence can be treated as purely exogenous, making it a suitable IV (routine indeces are also often used in the literature, see below). The routine sector index (RSI) is constructed in equation 8:

$$RSI_{nace} = ln(S^{R}_{nace}) - ln(S^{C}_{nace}) - ln(S^{M}_{nace}) \tag{8}$$

where R denotes routine (indexed), C denotes cognitive (abstract), M denotes manual and S denotes the share of LFS respondents in country-sector pairs that stated, their work was routine/cognitive/manual at least more than half of the working time. The RSI has been normalized around zero with unit standard deviation, again following Goos et al. [67]. Using the RSI as an instrumental variable is not novel and is accepted in the literature (see e.g. [67, 19, 69]).
As country dummies are introduced into the regression (see below), relevant country fixed effects such as corporate tax rates [81] or spending on education [48] are already accounted for. The combination of the instrumental variable strategy coupled with a full set of country dummies provides extra robustness to the estimates.

As stated, some of the endogeneity and potential reverse causality of the ICT measure is dealt with through IV while possible endogeneity issues in the institutional measures is dealt with via splitting the sample into institutional groups.
The control variables for this thesis a full set of country dummies, depending on the sample split. Only countries that are in the sample have their dummies included in the model. The full set of country dummies are self explanatory in construction. As long differences are employed in the datasets, the country dummies control for any country-specific policy changes and country-specific trends. The stacked long differences models have been augmented with period dummies. As differences are taken in smaller intervals to increase observations, time specific effects could influence the outcomes, hence controlling for this becomes necessary.

5 Empirical Method

5.1 Descriptive Statistics

To begin the empirical analysis, I want to give a brief overview of digitalization in the countries subject to my analysis. The DESI (Digital Economy and Society Index) of the European Commission provides summary statistics on digitalization adoption in four domains: Human Capital, Digital Public Services, Connectivity and Integration of Digital Technology [53]. This index goes beyond the scope of this thesis, which primarily deals with the adoption of or the expenditures for digitalization technologies. Nevertheless, the index shows general trends of ICT adoption in European countries. Unsurprisingly, the Scandinavian countries and the Netherlands are found towards the top in 2022 [53]. The increase in adoption is also found by OWID [101] At the bottom of the index, Eastern and Southern European countries such as Slovakia and Italy are to be found. Nevertheless, adoption of ICT has increased in all countries in the sample over the past decades [68]. This increase follows a marked decline in the price of ICT [36, 75, 119, 95].

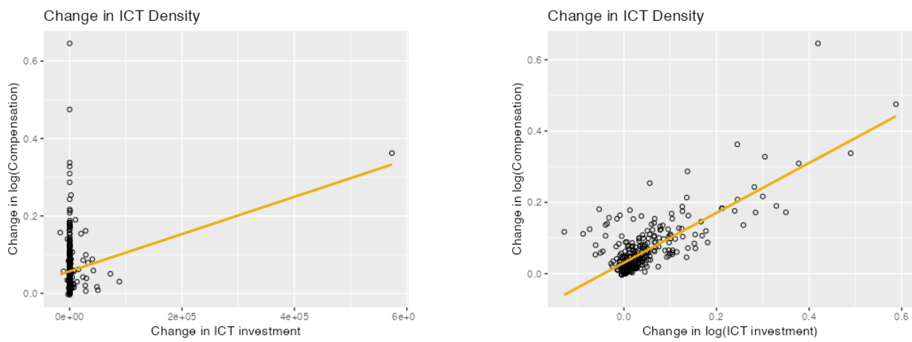
Before continuing with the regressions, the appropriate functional form is examined. Figure 2 plots the log of the change of compensation against measures of ICT density in the Long Difference dataset. Figure 2a plots the change in ICT expenditure while Figure 2b plots the weighted log score of that change. As is evident from the regression lines and the scatterplots of observations, the log values are preferred for a linear model. The regression line for the percentile score is upward sloping, statistically significant and has a value of 0.69927. The slope for the non-logarithmic change is not statistically significant but also upward sloping. The functional forms for the Stacked Long Differences dataset are similar. Hence, the linear functional form is only appropriate to the logarithmic values. In the following analysis, the log form will be used. This is very similar to what Graetz and Michaels [69] did in their study on robots.

5.2 Modeling

The regression equation used throughout this thesis follows the following form

$$\Delta Y_{ci} = \beta_1 + \beta_2 \Delta(ICT_{ci}) + \beta_3 \Delta(controls_{ci}) + \epsilon_{ci} \tag{9}$$

where $\Delta\ Y_{ci}$ indicates the outcome variable of interest in industry i in country c expressed in long differences.ΔICT_{ci} expresses the change in the measure of Information and Communication Technologies in country c and industry i.



(a) (b)

Figure 2: Observations are country-industry cells. One long difference from 1995 to 2019.

$\Delta controls_{ci}$ represents a set of controls for the specifications such as country fixed effects and the period dummies in the SLD specifications. This methodology is similar to Graetz and Michaels' 2018 paper [69] which serves as the blueprint for this thesis. The analysis is conducted with two different datasets observing the change over time. The first dataset employs a long difference estimation from 1995 to 2019. The second dataset makes use of stacked long differences in 5 year intervals, yielding more observations and providing extra robustness to the estimates. Both WLS and IV-2SLS methods will be applied. For the long difference, only WLS will be applied, as the IV is weak. For the stacked long difference, WLS and 2SLS will be employed. Weak IV models will be explicitly mentioned.

5.3 Main Regression Results

5.3.1 Structure and a note on IV Estimate Sizes

The regression results will be discussed for each outcome variable individually. All results are fully reported in the Appendix. Only relevant results will be reported in text and discussed in detail. For each outcome variable, the institutional groupings and different models will be discussed.

The instrumental variable estimates sometimes look out of place. Normally, they are slightly different to the estimates of the weighted OLS (WLS) results, which are potentially biased by endogeneity. In some cases, however, the values are extremely far removed from the WLS estimates. This is likely due to some data issues and how the IVs are constructed. In the stacked long differences, where the IVs are used, the majority of models have an F-statistic of 10 or higher, some models only barely miss the threshold and the remaining models can not be considered to have a strong IV. The estimates of the weak IVs should therefore be viewed critically. The IV assumptions of relevance are therefore sometimes violated. The exogenity assumption discussed above still holds, correcting for potential endogeneity and reverse causality bias. IV estimates not considered are colored in red, RSI estimates are colored in teal.

5.3.2 Compensation

Starting with overall compensation of employees, ICT has a universally positive effect on earnings. These results do not provide evidence for equally distributed wage gains, different to Hope and Martelli (2019) [74] nothing can be causally stated about inequality. There is variation in the increase of compensation between different institutional groups.

As can be seen in the first two rows of Table 1, there is a large difference between the effects for high LMI countries and low LMI countries. The higher levels of Labor Market Institutions dampen the effects of ICT. Whereas a 1% increase in ICT investment for the LD-WLS (Long Difference - Weighted Least Squares) models increases the overall compensation by 0.808% in low LMI countries, the estimate of 0.319% in high LMI countries is much lower. The SLD-WLS (Stacked Long Differences - Weighted Least Squares) reflects this image, albeit with smaller estimates of 0.26% and 0.186% respectively. The instrumental variable results for low LMI countries are quantitatively different to the LD-WLS, indicating an underestimate in both WLS models. The R-squared on all WLS models are high, showing a good model fit. The R-Squared of the IV estimates is slightly negative and close to zero, meaning a function that predicts the mean of the values would provide a better fit. This indicates a bad model fit. Nevertheless, the estimates that are somewhat comparable to the WLS-LD model, hence while the IV estimates should be viewed critically, they are not to be wholly dismissed.

Table 1: ICT's effect on the change in log(Compensation) by Institutional Groups

	Dependent Variable: log(Compensation)		
	LD-WLS	SLD-WLS	SLD-IV
Broad Groups – High LMI	0.319***	0.186***	0.697***
	(-0.0001)	(-0.0001)	(-0.0005)
Broad Groups – Low LMI	0.808***	0.264***	0.861***
	(-0.001)	(-0.001)	(-0.001)
EA Groups – Scandinavian	0.154***	0.121***	0.861***
	(-0.0002)	(-0.0002)	(-0.001)
EA Groups – Liberal	0.831***	0.275***	0.952***
	(-0.002)	(-0.0001)	(-0.002)
EA Groups – Corporatist	0.526***	0.228***	0.392***
	(0.00000)	(-0.00003)	(-0.00003)
Small Groups – Scandinavian	0.159***	0.320***	0.729***
	(-0.001)	(-0.0001)	(-0.001)
Small Groups – Anglo-Saxon	0.637***	0.160***	11.132
	(-0.0004)	(-0.00004)	(-9.385)
Small Groups – Bismarckian	0.380***	0.156***	0.570***
	(-0.001)	(-0.0002)	(-0.001)
Small Groups – Southern Europe	0.565***	0.226***	0.660***
	(0.0000)	(-0.00002)	(0.0002)
Small Groups – Eastern Europe	1.573***	0.371***	0.754***
	(-0.000)	(0.0003)	(0.0004)

Note: Stars indicate conventional significance levels. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Estimate sizes which are to be disregarded are colored in red. R^2 and F-Statistics have been omitted in this table due to legibility reasons. For each model, they can be found in the corresponding appendix table. All estimates reported are with full controls: country dummies (all columns), period dummies (SLD columns). Standard errors are reported in parentheses.

The institutional grouping on the basis of Esping-Andersen [52] also yields differing estimates for the groups, with dampened effects of ICT on compensation for higher levels of LMI. The group of Scandinavian countries has the

lowest estimates for WLS models. Liberal countries, with weaker LMI and a greater focus on market mechanisms yields the highest estimates.
Corporatist countries' estimates are middling. The SLD-WLS estimates for a 1% increase in ICT investment are 0.121% for Scandinavian, 0.275% for Liberal and 0.228% for Corporatist countries. The IV results for the latter two are close in size to the LD-WLS estimates, with a bigger difference for Scandinavian estimates. The R-squared for the SLD-WLS models are, again, ranging from around 0.3 to around 0.5 (see Appendix), indicating that the estimates are solid. The R-squared for Scandinavian and Liberal countries is negative, though for Corporatist countries it is positive at 0.34. This lends validity to the claim that for Corporatist countries, the LD estimate is likely close to its true value. The same inference cannot be made for the remaining two groups. Hence, the focus should lie on the overall trend, *id est* lower levels of LMI indicating higher compensation per hour due to ICT.

The final split of the sample is the biggest. Five groups are made, with 3 countries per group, except for the Bismarckian group, which has more countries. The red estimate in the table for Anglo-Saxon countries is one of the outliers previously mentioned. Due to its large difference from any other value and obvious falseness, it will not be interpreted. It is reported in Table 1 for reasons of completeness and transparency.
For Scandinavian countries in the small groupings, WLS estimates are very close to each other. The R-squared values for all 3 models are positive and range from 0.12 (IV) to 0.54 (LD and SLD). The IV estimate of 0.862% for every 1% increase in ICT investment is comparatively quite high, which is subject to discussion in Section 6.
For Anglo-Saxon countries, the SLD-WLS model with the increased amount of observations and an R-squared of 0.319 is the most relevant. In line with expectations, the LD estimate of 0.637% is bigger than the Scandinavian one. This is also similar to the Esping-Anderson grouping, where Liberal countries had the highest estimates. However, the LD model suffers from a lower number of observations.
The Bismarckian estimates are unsurprising. The LD estimate of 0.380% is consistent with earlier observations and theory, as LMI in these countries are decently strong. The SLD estimate of 0.156% is smaller than both the Anglo-Saxon and the Scandinavian Estimate, which is slightly unexpected. The IV estimate is quantitatively similar to the LD estimate, suggesting a downward bias. Again, the R-squared on it is slightly negative, which hinders interpretation.
The Southern European countries are characterised by a lower level of LMI than

Bismarckian and Scandinavian countries, though the level of EPL is quite high. The LD estimate is in line with expectations, as is the IV. Compared to the Anglo-Saxon LD estimate, the Southern European is slightly lower at 0.565%. However, the SLD-WLS estimate is around half at 0.226%. The R-squared values of these two estimates are 0.61 and 0.45 respectively. The IV estimate is slightly bigger than the LD estimate, but the R-squared is close to zero, hence the LD estimate is likely to have the most explanatory power.
Eastern European states, when compared to others, have weaker labor market institutions. Investment in ICT in the regression table has a large positive effect on compensation of employees with values of 1.573% in the LD model and 0.371% in the SLD model for an additional 1% increase. The IV estimate has a positive R-squared, giving it legitimacy. The higher value of the IV estimate compared to the SLD is consistent with expectations, as a low level of LMI and a lower initial level of development (for a theoretical background see [115]) could potentially yield higher benefits when ICT is introduced. The IV estimate is likely close to the true value of the coefficient.

In total, compensation is positively affected by ICT with clearly identifiable differences between different institutional landscapes. The sizes and economic meanings of the coefficients in Table 1 will be briefly discussed again in Section 6.

5.3.3 Employment

The effects of technology on employment have been researched extensively (see Section 2). ICT investment, as can bee seen in Table 2, has mixed effects on employment, depending on the institutional framework.

The broad groupings into high and low LMI countries yields interesting results. Whereas ICT investment in high LMI countries have a positive effect on employment, the opposite is true in low LMI countries. In the long difference, every 1% increase in ICT investment boosts employment by 0.122% in high LMI countries while reducing it by 0.028% in low LMI countries. Respective R-squared values are adequate. While interesting, the grouping is quite broad, hence not much can be said at this stage. Important to note is the similar value of the IV to the LD estimate in low LMI countries, providing evidence for small, slightly downward biased WLS effects. In high LMI countries, the IV estimate is not interpretable by virtue of its somewhat large negative R-squared.

Table 2: ICT's effect on the Change in log(Employment) by Institutional Groups

	Dependent Variable: log(Employment)		
	LD-WLS	SLD-WLS	SLD-IV
Broad Groups – High LMI	0.122***	0.035***	0.319***
	(-0.00004)	(-0.00004)	(-0.0002)
Broad Groups – Low LMI	-0.028***	-0.009***	-0.041***
	(-0.0001)	(-0.0001)	(-0.0002)
EA Groups – Scandinavian	0.148***	0.034***	0.005***
	(-0.0001)	(0.00000)	(-0.0002)
EA Groups – Liberal	-0.037***	-0.015***	-0.087***
	(-0.0001)	(-0.00001)	(-0.0001)
EA Groups – Corporatist	0.085***	0.034***	0.192***
	(-0.0000)	(-0.00000)	(-0.00001)
Small Groups – Scandinavian	0.070***	0.009***	2.043
	(-0.00003)	(0.00001)	(-1.331)
Small Groups – Anglo-Saxon	-0.015***	0.006***	2.193
	(-0.0001)	(0.00001)	(-0.494)
Small Groups – Bismarckian	0.142***	0.031***	0.341***
	(-0.0002)	(0.00000)	(-0.0003)
Small Groups – Southern Europe	0.068***	0.060***	0.031***
	(0.000)	(-0.00003)	(0.0002)
Small Groups – Eastern Europe	-0.121***	-0.034***	-0.055***
	(-0.000)	(-0.00005)	(-0.0001)

Note: Stars indicate conventional significance levels. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Estimate sizes which are to be disregarded are colored in red. R^2 and F-Statistics have been omitted in this table due to legibility reasons. For each model, they can be found in the corresponding appendix table. All estimates reported are with full controls: country dummies (all columns), period dummies (SLD columns).

The Esping-Anderson groupings illuminate the differences between institutions in response to ICT investment more thoroughly. For the Scandinavian group, all models are positive, though small. The IV estimate is closest to 0,

suggesting upward bias in WLS models. This is an interesting result when one recalls the previously explained flexicurity model. This outcome will be more extensively discussed in Section 6.
The Liberal group's coefficients are as expected. Due to the low level of LMI in these countries, when labor-replacing technology is introduced, employment levels are lowered, as the displacement effect dominates without institutional pushback. The coefficients in liberal countries for WLS models are quite small, -0.037% and -0.015% respectively for each additional percent of investment. The IV coefficient has the same sign, but due to the negative (though close to 0) R-squared, the WLS models possess more explanatory power. The IV estimate, nevertheless, would suggest upward bias.
Corporatist countries suffer from the same IV issue as Liberal ones, but the WLS models are very informative. In line with expectations, the specific combination of Labor Market Institutions present in these countries ensure that ICT does not lead to more unemployment. WLS estimates of 0.085% and 0.034% for every additional percent of ICT investment suggest only marginal benefits in employment from ICT, as these numbers are quite close to zero.

The smallest groupings provide some more evidence which is generally in line with earlier observations and provides more detailed evidence. Scandinavian countries have slightly positive coefficients, again due to the flexicurity model. The IV model has a negative R-squared, which makes it unreliable. The increased amount of observations in the SLD-WLS adds reliability and is in line both with theory and earlier observations.
The Anglo-Saxon estimates confirm earlier observations of low levels of LMI being associated with less employment when more ICT investment is taken. However, coefficients of -0.015% and 0.006% are smaller when compared with broader groupings, with the SLD estimate being marginally above 0. The IV, due to its very large, negative R-squared cannot be interpreted. Nevertheless, the interpretable coefficients point towards the Anglo-Saxon institutional environment allowing for reductions in employment when ICT investment is undertaken.
The Bismarckian countries suffer from the same IV problem (though the absolute value of the R-squared is much smaller than for Anglo-Saxon countries). The WLS coefficients provide further evidence for the positive effects of ICT on employment when ICT investment is undertaken in the Bismarckian institutional landscape. The estimate of interest is the SLD-WLS increasing employment by 0.031% for every 1% increase in ICT investment. This is in line with earlier observations, as the small coefficient points towards the institutions mitigating negative employment effects and reaping some small rewards from

ICT investment.
The coefficient of interest for Southern European countries is the IV estimate of 0.031% employment gain for every additional percent of ICT investment. The IV model has an R-squared of 0.198, which is large enough to use it. The coefficient suggests a slight upward bias in the WLS models. The primary LMI in Southern European countries is a high level of EPL, making it hard to terminate workers' contracts. This yields the close-to-zero coefficient of the IV, as ICT investments are made, the high level of EPL leads to ICT having a positive employment effect.
Eastern European countries have low levels of LMI, hence it is expected that an increase in ICT investment leads to a decline in employment. This prediction is confirmed in Table 2. The IV estimates a -0.055% employment change for every 1% increase in ICT investment. Whereas compensation was largely positively affected, Eastern European countries have the largest negative employment change out of the small groups. This will be subject to discussion in Section 6.

The effects of ICT on employment have been thoroughly explored (see Section 2. This contribution fits nicely into the existing body of literature, documenting both positive and negative employment effects, depending on the institutional landscape. Overall, Labor Market Institutions such as EPL or the right combination of smaller institutions (such as in Bismarckian countries) protect the workforce from negative employment effects of ICT on a country basis. Low levels of LMI lead to ICT displacing workers, resulting in negative employment effects. Overall, the effect sizes are quite small for all groups.

5.3.4 Hours Worked

The hours worked by employed people in the sample are closely connected to overall employment. Labor markets have become more flexible over the past decades in terms of working hours [55], but the decline in overall hours worked, which was largely trending downward for about one and a half centuries, has somewhat slowed [65]. ICT and other automating technologies have been documented to have a positive impact on productivity [114, 69], which is a measure of output per hours. Labor market institutions have the potential to reallocate these productivity gains into a lower ouput increase, instead reducing overall hours worked. Table 3 documents the relevant regression coefficients. Higher levels of LMI are associated with an increase in hours worked, somewhat mirroring the results from Table 2.

Table 3: ICT's effect on the Change in log(Hours Worked) by Institutional Groups

	Dependent Variable: log(Hours Worked)		
	LD-WLS	SLD-WLS	SLD-IV
Broad Groups – High LMI	0.121***	0.034***	0.352***
	(-0.00001)	(-0.0001)	(-0.0002)
Broad Groups – Low LMI	-0.049***	0.002***	-0.026***
	(-0.0001)	(-0.0001)	(-0.0002)
EA Groups – Scandinavian	0.164***	0.037***	-0.029***
	(-0.0004)	(0.00000)	(-0.0001)
EA Groups – Liberal	-0.057***	-0.004***	-0.029***
	(0.0001)	(-0.00001)	(-0.0001)
EA Groups – Corporatist	0.061***	0.034***	0.196***
	(-0.000)	(-0.00000)	(-0.00002)
Small Groups – Scandinavian	0.102***	0.012***	3.335***
	(-0.0001)	(0.00000)	(-3.210)
Small Groups – Anglo-Saxon	-0.035***	0.012***	1.516***
	(-0.0002)	(0.00001)	(-0.181)
Small Groups – Bismarckian	0.128***	0.029***	0.373***
	(-0.0002)	(0.00000)	(-0.0003)
Small Groups – Southern Europe	0.034***	0.074***	0.027***
	(0.000)	(-0.00003)	(0.0002)
Small Groups – Eastern Europe	-0.137***	-0.019***	0.112***
	(-0.000)	(-0.00005)	(-0.0002)

Note: Stars indicate conventional significance levels. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Estimate sizes which are to be disregarded are colored in red. R^2 and F-Statistics have been omitted in this table due to legibility reasons. For each model, they can be found in the corresponding appendix table. All estimates reported are with full controls: country dummies (all columns), period dummies (SLD columns), Routine Task Index (all columns).

The broad groupings into low LMI and high LMI countries document the overall effects of ICT on Hours Worked. In high LMI countries, more investment in

ICT leads to more hours worked, in tandem with the employment increase. The opposite is true in low LMI countries. The coefficients of the Long Difference models show larger changes in hours worked with 0.121% and -0.049% for every 1% increase in ICT investment. The SLD models show smaller effects, with an increased number of observations. However, the R-squared for the Long Difference models are higher at 0.232 for high and 0.162 for low LMI countries, while the respective values for the SLD models are 0.189 and 0.088. Unfortunately, the regressions for Hours Worked have almost unilaterally bad IV model fits, hence the focus of this regression table analysis will lie on the WLS models.

The grouping on the basis of Esping-Andersen's categories is similar to the broad grouping. For countries grouped under Scandinavian institutions, the WLS models have a positive sign. The IV estimate, on the other hand, has a negative sign. When comparing this to the changes in employment in Table 2, a dilemma emerges. The evidence for negative effects of ICT on employment in Scandinavian countries provided by the IV goes contrary to the positive signage of the WLS models on hours worked and all estimates for employment in Table 2, which are potentially affected by endogeneity. The IV estimate for Scandinavian countries has the expected sign and a coefficient of -0.029% for every 1% increase in ICT spending. This is a larger negative change in hours worked than in employment. This ambiguous evidence will briefly be discussed in Section 6. The WLS coefficients for Liberal countries are as expected. Low LMI in these countries have negative effects on both employment and hours worked. The IV model fit is negative and far from 0, hence should be disregarded. The LD coefficient for Liberal countries of -0.057% and an adequate R-squared value provides evidence for the theoretical prediction of low LMI reducing employment and therefore hours worked.
Corporatist countries' institutions protect workers from negative employment effects of ICT, this is reflected in the positive coefficients of the regression models. The SLD coefficient showing an increase in hours worked of 0.034% for every additional percent investment in ICT has an R-squared of 0.165 and provides somewhat robust and coherent evidence for Corporatist institutions' curbing of negative effects on employment and hours worked.

The smallest groupings generally confirm previous observations and are in line with expectations. In the smaller group of Scandinavian countries, the LD and SLD models yield a small coefficient with a positive sign. The IV model has a negative R-squared, providing a bad model fit. Slight increases in hours worked are similar to results obtained in Table 2
For Anglo-Saxon countries, the best model fit is found for the Long Difference

model. The negative coefficient of -0.035% change in hours worked for a one percent increase in ICT investment is consistent with observations of employment and with expectations.
WLS estimates for Bismarckian countries are positive, though sizes differ. Both models have acceptable R-squared values, hence the SLD model with more observations yielding a coefficient of 0.029 is likely to be close to the true value. Bismarckian institutions, as seen above in the description of results for employment, respond to ICT investment with an increase in employment and hence hours worked. The coefficient for the WLS-SLD model is almost identical in both Table 2 and Table 3. These results are evidence contrary to the prediction that high levels of institutions, when employment is increasing due to ICT, dampen the increase in hours worked. Instead, the evidence points towards a close to 1:1 relationship between employment increases and hours worked due to ICT.
For Southern European countries, the IV estimate of 0.007 documenting a slight increase in hours worked for increases in ICT investment is relevant. With an R-squared of about 0.2, the estimate is believable and is free of a large part of endogeneity issues as opposed to the WLS estimates, which are upward biased. The coefficient is close to 0 and slightly smaller than the corresponding IV estimate for employment.
WLS estimates for Eastern European countries with low levels of LMI have negative coefficients, in line with expectations. The size of the coefficients differs largely between LD and SLD WLS models. The IV coefficient for Eastern Europe in Table 2 was -0.55. The IV estimate for hours worked has a negative R-squared, which explains the positive signage. Both WLS estimates in Table 3 have decent R-squared values, the better fit being present in the LD model. However, due to endogeneity issues and when compared to the IV employment coefficient, the true value is likely to lie between the two estimates.

Table 3's estimates somewhat mirror those of Table 2. Differences in the effects of ICT on hours worked can be distilled, nevertheless due to weak IV model fits, coefficients might be biased. Effects are generally in line with expectations, showing similar signs for institutional groups as in Table 2. Countries with lower levels of institutions have their working hours reduced by more investment in ICT, in tandem with a loss in employment.

5.3.5 Robustness Checks

To further substantiate the reliability of these results, robustness checks for all 90 individual specifications (*10 groups * 3 outcome variables * 3 specifications (LD-WLS, SLD-WLS, SLD-IV)*) have been conducted. These checks consist of removing each Nace.Rev2 sector once for each specification to see if there are certain sectors driving the effect.

Coefficient sizes are largely robust to these tests, so are significance levels, even though in some instances they drop from passing the 1% threshold of significance to the 5% or even 10% level.

There are three specification where coefficients deviate both in size and significance. In the specification on employment (Table 2) the Esping-Anderson grouping of Liberal countries and the small groupings of Anglo-Saxon countries and Eastern European countries, the coefficients of the ICT variable change considerably and lose significance at conventional levels when sector C (Manufacturing) is removed. This result is unsurprising. Manufacturing is a sector that is vulnerable to digitalization as well as automation. Some of the literature discussed in Section 2 specifically highlights the manufacturing sector being affected by new labor-replacing technologies. Sector C driving the effects in these groupings is therefore somewhat expected. Interestingly, the same loss in significance and change of coefficients does not occur in the outcome variable for compensation. The coefficients for hours worked change similarly to employment, but do not lose significance at conventional levels in the Liberal and Anglo-Saxon groupings. In the grouping of Eastern European countries, the coefficient for compensation remains unaffected but changes drastically when sector C is removed, hence providing evidence that effects on employment and hours worked in Eastern European countries are driven by this sector.

The overall low level of LMI in these groupings coupled with the vulnerability of the manufacturing sector to new, labor-replacing technologies results in the 'driving' effects of this sector. Employment losses due to technology concentrated in manufacturing can, on the basis of this insight, be ascribed to low levels of LMI, making them subject to possible change via policy.

6 Discussion

The results just presented warrant further discussion. This section will briefly restate the general trends of the results as well as compare and synthesize the 3 presented tables to identify broader economic implications of these results.

Finally, this section will pay specific attention to ambiguous and particularly interesting results.

6.1 General Trends

The overall picture the results draw is similar to the already existing body of literature on the effects of ICT on the three chosen labor market outcomes. Compensation is affected positively by ICT, in line with the literature on productivity and growth (see Section 2). Sizes of the effect differ between different institutional groups, but are unilaterally positive. This provides evidence for a macro-level increase in wages, as opposed to the micro-level described in Section 2 [64]. The gain in overall compensation of employees is larger in countries with lower levels of labor market institutions as is evident in Table 1. However, the literature on compensation usually focuses on wage inequality and the returns to skills in the context of ICT (see e.g. [100, 16, 74]). These factors lie outside the scope of this thesis in terms of data. Nevertheless, when inspected together with the results on employment and supplemented with the literature discussed earlier, the results for compensation lend some evidence towards the SBTC/RBTC hypotheses, as well as to a positive contribution of ICT to wage inequality, as an outcome. In institutional landscapes where ICT has had a more positive effect on compensation, it has had more negative effects on employment/hours worked. This dynamic can be explained by ICT replacing jobs in middle/lower skill (and hence wage) sectors and complementing higher skill work, thereby making it more productive. Recalling the work on SBTC and RBTC [118, 16, 18, 20, 66], the evidence offered in this thesis can be explained by these concepts. Furthermore, the theory put forward by Acemoglu and Restrepo [4] about displacement, reinstatement and complementarity can be applied. Overall, the displacement effect of ICT seems to dominate, apparent from compensation growth and the negative effects on employment in three out of five of the small groups. Higher levels of LMI, particularly a combination of EPL and trade union density seems to mitigate the displacement effect so that employment does not decline. Contrary to economic theory discussed in Section 2, trade unions do not seem to inhibit employment, rather they protect it from being displaced. Country groups such as Bismarckian and Southern European exemplify this, This is a valuable addition to the theory on unions [29, 31] and contributes to the debate around EPL [86, 109, 6, 60, 40], specifically also with a view to EPL inhibiting hiring, which this thesis does not find evidence for. The result of the dynamic of higher compensation growth with a larger decline in employment, as discussed, points towards growth in wage inequality in country groups with lower/more market based institutions as a result of investment in ICT, similar to the findings of Hope and Martelli [74]. However, causal statements about wage inequality can not be definitively made. Eastern European countries, which have low levels of LMI, serve as an example for these dynamics. The absence of protection via institutions such as EPL or trade unions allow for easier dismissal of workers. Labor-replacing technologies are therefore more unequivocal in their effects when weak institutions are present, leading to less employment but higher compensation, indicating SBTC and a possible trend towards wage inequality.

Hours worked, as stated in Section 2, are mostly not discussed in the literature on ICT. In this thesis, the results for hours worked are closely associated with those on employment. Again, differences between institutions are found, following the same patterns as with employment.

There are also some results where hours worked and employment do not perfectly mirror each other. While some of this may be due to measurement error, the relationship does not seem to be fully analogous. Further research in the allocation of hours worked when employment changes is warranted (also see below for a first exploration). While there are no big surprises in this thesis, two interesting results will be discussed below.

6.2 Allocation of Benefits and Flexicurity

As just mentioned, this section deals with two particularly interesting results.

First, economics generally deals with trade-offs. This thesis also puts forward a certain type of trade-off, namely one between overall compensation gains from ICT and employment changes. As can be seen in Tables (1 and 2), country groups that have lower/more market based institutions tend to have higher gains in compensation following ICT investment, while experiencing negative employment effects. Bismarckian and Southern European countries do not experience this effect as strongly, instead benefiting from ICT in both outcome variables. Though their compensation gains are comparatively smaller than Anglo-Saxon or Eastern European countries (particularly in the Long Difference), the positive sign for both outcome variables indicates that the LMI present in these two groups allow for unilateral positive effects. The most likely explanation for this is the relatively high level of EPL present in both groups. This prevents ICT from displacing a larger number of employees, hence the avoidance of loss in employment.

Second, Scandinavian countries' results in Table 2 and 3 warrant some discussion. In Table 2, it can be seen from the all estimates that employment in the flexicurity model of Scandinavian countries rise when more ICT investment is undertaken. The same unambiguous relationship does not hold up when looking at hours worked in the Esping-Andersen grouping (IV estimate). The WLS estimates are positive, the IV estimate is negative. The WLS estimates for hours worked are likely to be biased. The flexicurity model can explain these coefficients. Recalling that flexicurity is a model focused on ease of hiring and firing, coupled with high levels of trade union density and job expenditure (e.g. ALMP, UB), the coefficients make sense. The evidence for Scandinavia contributes to the literature on institutions in an interesting way. First, in line with expectations, the low level of EPL allows for labor displacement due to ICT. Second, high levels of trade union density lead to a positive, though smaller, increase in compensation, as (almost) everyone is covered under union contracts which increase wage [29]. Third, expenditure on jobs such as ALMP or UB seem to alleviate the displacement effect, resulting in the employment coefficient being positive but close to zero for employment. The negative coefficient for hours worked (IV, Esping-Andersen)points toward a disconnect between the two outcome variables. Benefits from ICT investment such as greater productivity (see Section 2) seem to be more evenly distributed in the Scandinavian model. Rising productivity, wages and employment with a reduction in hours attributable to ICT points towards institutions allowing for lower working hours on the basis of other benefits that ICT investment contributes to the economy.

6.3 Limitations

The approach taken and results extrapolated are subject to some caveats.
The first caveat has already been stated above. Since the data on monetary compensation are not separated by wage percentiles, overall compensation benefits of ICT is the only observation which can be made. While other results such as wage inequality can be somewhat speculated about, this was not the aim of this thesis as it has been researched before [74].
The second caveat is the limited data availability for some countries. Countries such as Ireland, Poland, Greece or the Balkan countries. Having more data would not only enrich the groupings but also allow for deeper insights into institutional differences in the effects of Digitalization on the European continent.
Lastly the biggest caveat are the thoroughly discussed endogeneity issues and the insufficiency of the Instrumental Variable in some cases. Whereas it is obvious that there is a link between the institutional landscape and the effect sizes

and signs of Digitalization on LMO, the coefficients might be slightly biased in some cases. To circumvent this bias, other IVs would need to be found or different statistical methods employed.

7 Conclusion and Policy Recommendations

This thesis has detailed the effects of ICT on three relevant labor market outcomes between different institutions. Compensation increases due to ICT are less pronounced in countries with higher institutional levels, trading off with the avoidance of employment losses which are present in countries with lower levels of LMI. Middle to high levels of LMI, such as are present in Bismarckian countries, allow for moderate gains in all three outcome variables. Reconfirming findings from the literature, effects of ICT are visible in all sectors but negative effects often manifest in the manufacturing sector, as it is vulnerable to automation [63]. Due to the institutional context in Anglo-Saxon and Eastern European countries, manufacturing seems to drive negative effects of ICT, as workers can be laid off more easily. Overall, the results confirm the existing body of literature with the added benefit of illuminating differences due to Labor Market Institutions. These results have important implications for policymakers. With increasing investment in ICT and DAR technology generally, which is likely to be undertaken in the future, it is crucial that economies adapt to avoid undesirable outcomes. It is recommended that policymakers at the national and international level gear the relevant Labor Market Institutions towards capturing the full benefits of ICT, depending on the timeframe of technological process and the desired trade-offs. This is especially important for vulnerable sectors in countries with low levels of LMI. Changing institutions to capture more positive effects will increase satisfaction within an economy as well as allow for an easier transition towards a more automated economy.

Moreover, the results discussed have important implications for other societal stakeholders. Managers that want to automate their workers through ICT investment need to be aware of the institutional context (macro-level) which has influence on their firing practices (micro-level) through institutions such as EPL. Workers face similar issues. Being aware of the institutional context they are in can influence decisions of which party to vote for, whether or not to join trade unions and even job choice, specifically with regards to vulnerable sectors. The observed heterogeneity between institutional contexts could induce different behavior, making local markets more efficient.

Further research into the exact levels of institutions which are optimal for different economies and their stakeholders is necessary. As this thesis is only an exploration into the institutional factors determining ICT's influence on LMO, no exact policy prescriptions or recommendations for stakeholders can be made beyond the broad ones given. More specific recommendations need to be determined on a case-by case basis. Furthermore, institutional interactions need to be considered going forward. Changing path-dependent institutions changes the interactions with other institutions, potentially yielding undesirable outcomes. Caution needs to be applied at each step to ensure the best trade-offs possible in the digital transition.

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A Appendix

A.1 Long Difference Models - WLS; 1995-2019

Table A.1.1: WLS Regression Results with Clustered Standard Errors - Broad Groups in High LMI countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.319***	0.122***	0.121***
	(−0.0001)	(−0.00004)	(−0.0001)
geo_codeAT	−0.029***	−0.004***	−0.007***
	(0.00001)	(0.00000)	(0.00000)
geo_codeBE	−0.026***	−0.004***	−0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeDE	−0.016***	−0.002***	−0.006***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeDK	−0.017***	−0.005***	−0.005***
	(0.00000)	(0.00000)	(0.00000)
geo_codeFI	−0.009***	0.004***	0.001***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeFR	−0.025***	−0.004***	−0.005***
	(0.00000)	(0.00000)	(0.00000)
geo_codeLU	−0.020***	0.021***	0.019***
	(0.00000)	(0.00000)	(0.00000)
geo_codeNL	−0.023***	−0.0004***	−0.001***
	(0.00000)	(0.00000)	(0.00000)
geo_codePT	−0.052***	−0.008***	−0.008***

Table A.1.1: WLS Regression Results with Clustered Standard Errors - Broad Groups in High LMI countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeSE			
	(−0.0001)	(−0.00004)	(−0.0001)
Constant	0.052***	0.008***	0.008***
	(0.00000)	(0.00000)	(0.00000)
Observations	188	188	188
R^2	0.216	0.246	0.232
Adjusted R^2	0.171	0.204	0.189
Residual Std. Error (df = 177)	0.041	0.020	0.020
F Statistic (df = 10; 177)	4.864***	5.783***	5.359***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.1.2: WLS Regression Results with Clustered Standard Errors - Broad Groups in Low LMI countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.808***	−0.028***	−0.049***
	(−0.001)	(−0.0001)	(−0.0001)
geo_codeCZ	0.023***	−0.010***	−0.011***
	(−0.00003)	(−0.00000)	(−0.00000)
geo_codeIT	−0.011***	−0.002***	−0.006***
	(−0.00003)	(−0.00000)	(−0.00000)

Table A.1.2: WLS Regression Results with Clustered Standard Errors - Broad Groups in Low LMI countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
geo_codeLT	-0.004^{***}	-0.009^{***}	-0.005^{***}
	(0.0001)	(0.00000)	(0.00000)
geo_codeES	-0.019^{***}	0.010^{***}	0.008^{***}
	(0.00000)	(0.00000)	(0.00000)
geo_codeLV	-0.009^{***}	-0.008^{***}	-0.014^{***}
	(0.0001)	(0.00001)	(0.00001)
geo_codeSI	0.036^{***}	-0.005^{***}	-0.007^{***}
	(0.00001)	(0.00000)	(0.00000)
geo_codeSK	-0.014^{***}	-0.010^{***}	-0.012^{***}
	(−0.0001)	(−0.00000)	(−0.00001)
geo_codeUK			
	(−0.001)	(−0.0001)	(−0.0001)
Constant	0.014^{***}	0.010^{***}	0.012^{***}
	(0.0001)	(0.00000)	(0.00001)
Observations	146	146	146
R^2	0.732	0.126	0.162
Adjusted R^2	0.717	0.075	0.113
Residual Std. Error (df = 137)	0.050	0.020	0.020
F Statistic (df = 8; 137)	46.881^{***}	2.466^{**}	3.317^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.1.3: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Scandinavian countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.154***	0.148***	0.164***
	(−0.0002)	(−0.0001)	(−0.0001)
geo_codeDK	−0.016***	−0.005***	−0.005***
	(0.00000)	(0.00000)	(0.00000)
geo_codeFI	−0.013***	0.004***	0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeLU	−0.017***	0.021***	0.018***
	(0.00001)	(0.00000)	(0.00000)
geo_codeSE			
	(−0.0002)	(−0.0001)	(−0.0001)
Constant	0.055***	0.008***	0.008***
	(0.00000)	(0.00000)	(0.00000)
Observations	79	79	79
R^2	0.055	0.331	0.332
Adjusted R^2	0.004	0.295	0.296
Residual Std. Error (df = 74)	0.049	0.021	0.021
F Statistic (df = 4; 74)	1.070	9.161***	9.212***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.1.4: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Liberal countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.831***	−0.037***	−0.057***
	(−0.002)	(−0.0001)	(−0.0001)
geo_codeCZ	0.024***	−0.010***	−0.011***
	(−0.00003)	(−0.00000)	(−0.00000)
geo_codeLT	−0.005***	−0.009***	−0.005***
	(0.0001)	(0.00000)	(0.00000)
geo_codeLV	−0.011***	−0.007***	−0.013***
	(0.0001)	(0.00001)	(0.00001)
geo_codeSI	0.036***	−0.005***	−0.007***
	(0.00001)	(0.00000)	(0.00000)
geo_codeSK	−0.013***	−0.011***	−0.012***
	(−0.0001)	(−0.00000)	(−0.00001)
geo_codeUK			
	(−0.002)	(−0.0001)	(−0.0001)
Constant	0.013***	0.011***	0.012***
	(0.0001)	(0.00000)	(0.00001)
Observations	107	107	107
R^2	0.736	0.078	0.152
Adjusted R^2	0.720	0.022	0.101
Residual Std. Error (df = 100)	0.055	0.019	0.019
F Statistic (df = 6; 100)	46.494***	1.404	2.982**
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.1.5: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Corporatist countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.526***	0.085***	0.061***
	(−0.000)	(−0.000)	(−0.000)
geo_codeAT	0.012***	0.006***	0.004***
	(0.000)	(0.000)	(0.000)
geo_codeBE	0.018***	0.006***	0.008***
	(0.000)	(0.000)	(0.000)
geo_codeDE	0.035***	0.006***	0.002***
	(0.000)	(0.000)	(0.000)
geo_codeES	0.010***	0.015***	0.014***
	(0.000)	(0.000)	(0.000)
geo_codeFR	0.022***	0.006***	0.004***
	(0.000)	(0.000)	(0.000)
geo_codeIT	0.013***	0.004***	0.002***
	(0.000)	(0.000)	(0.000)
geo_codeNL	0.020***	0.010***	0.010***
	(0.000)	(0.000)	(0.000)
geo_codePT			
	(−0.000)	(−0.000)	(−0.000)
Constant	−0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Observations	148	148	148
R^2	0.485	0.107	0.089

Table A.1.5: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Corporatist countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
Adjusted R^2	0.455	0.056	0.037
Residual Std. Error (df = 139)	0.030	0.019	0.019
F Statistic (df = 8; 139)	16.351***	2.092**	1.701
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.1.6: WLS Regression Results with Clustered Standard Errors - Small Groups in Scandinavian countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.159***	0.070***	0.102***
	(−0.001)	(−0.00003)	(−0.0001)
geo_codeDK	−0.016***	−0.005***	−0.005***
	(0.00001)	(0.00000)	(0.00000)
geo_codeFI	−0.013***	0.003***	0.0005***
	(−0.00002)	(−0.00000)	(−0.00000)
geo_codeSE			
	(−0.001)	(−0.00003)	(−0.0001)
Constant	0.055***	0.009***	0.009***
	(0.00002)	(0.00000)	(0.00000)
Observations	59	59	59
R^2	0.045	0.052	0.075
Adjusted R^2	-0.007	0.0005	0.024
Residual Std. Error (df = 55)	0.052	0.019	0.020

Table A.1.6: WLS Regression Results with Clustered Standard Errors - Small Groups in Scandinavian countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
F Statistic (df = 3; 55)	0.870	1.009	1.479
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.1.7: WLS Regression Results with Clustered Standard Errors - Small Groups in Anglo-Saxon countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.637***	−0.015***	−0.035***
	(−0.0004)	(−0.0001)	(−0.0002)
geo_codeLT	0.003***	−0.010***	−0.006***
	(0.00002)	(0.00000)	(0.00001)
geo_codeLV	0.004***	−0.009***	−0.015***
	(0.00003)	(0.00001)	(0.00002)
geo_codeUK			
	(−0.0004)	(−0.0001)	(−0.0002)
Constant	0.023***	0.009***	0.011***
	(0.00002)	(0.00001)	(0.00001)
Observations	58	58	58
R^2	0.775	0.067	0.149
Adjusted R^2	0.763	0.015	0.102
Residual Std. Error (df = 54)	0.045	0.020	0.021
F Statistic (df = 3; 54)	62.149***	1.297	3.157**

Table A.1.7: WLS Regression Results with Clustered Standard Errors - Small Groups in Anglo-Saxon countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.1.8: WLS Regression Results with Clustered Standard Errors - Small Groups in Bismarckian countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.380***	0.142***	0.128***
	(−0.001)	(−0.0002)	(−0.0002)
geo_codeAT	−0.007***	−0.004***	−0.006***
	(0.00001)	(0.00000)	(0.00000)
geo_codeBE	−0.003***	−0.003***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeDE	0.009***	−0.001***	−0.005***
	(−0.00002)	(−0.00001)	(−0.00001)
geo_codeFR	−0.001***	−0.003***	−0.004***
	(−0.00001)	(−0.00000)	(−0.00000)
geo_codeLU	0.002***	0.022***	0.020***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeNL			
	(−0.001)	(−0.0002)	(−0.0002)
Constant	0.027***	0.007***	0.007***

Table A.1.8: WLS Regression Results with Clustered Standard Errors - Small Groups in Bismarckian countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(0.00002)	(0.00001)	(0.00001)
Observations	119	119	119
R^2	0.302	0.294	0.276
Adjusted R^2	0.265	0.256	0.237
Residual Std. Error (df = 112)	0.035	0.020	0.020
F Statistic (df = 6; 112)	8.075***	7.759***	7.108***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.1.9: WLS Regression Results with Clustered Standard Errors - Small Groups in Southern European countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.565***	0.068***	0.034***
	(0.000)	(0.000)	(0.000)
geo_codeES	0.008***	0.015***	0.015***
	(−0.000)	(−0.000)	(−0.000)
geo_codeIT	0.011***	0.005***	0.003***
	(−0.000)	(−0.000)	(−0.000)
geo_codePT			
	(0.000)	(0.000)	(0.000)
Constant	0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)

Table A.1.9: WLS Regression Results with Clustered Standard Errors - Small Groups in Southern European countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
Observations	49	49	49
R^2	0.613	0.169	0.143
Adjusted R^2	0.588	0.113	0.086
Residual Std. Error (df = 45)	0.024	0.019	0.018
F Statistic (df = 3; 45)	23.793***	3.048**	2.502*
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.1.10: WLS Regression Results with Clustered Standard Errors - Small Groups in Eastern European countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	1.573***	-0.121^{***}	-0.137^{***}
	(0.000)	(0.000)	(0.000)
geo_codeCZ	0.012***	0.003***	0.004***
	(-0.000)	(-0.000)	(-0.000)
geo_codeSI	0.007***	0.010***	0.010***
	(-0.000)	(-0.000)	(-0.000)
geo_codeSK			
	(0.000)	(0.000)	(0.000)
Constant	0.000***	0.000	-0.000^{***}
	(0.000)	(0.000)	(0.000)

Table A.1.10: WLS Regression Results with Clustered Standard Errors - Small Groups in Eastern European countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
Observations	49	49	49
R^2	0.941	0.220	0.272
Adjusted R^2	0.937	0.168	0.224
Residual Std. Error (df = 45)	0.029	0.016	0.016
F Statistic (df = 3; 45)	238.615***	4.222**	5.612***
Note:			*p<0.1; **p<0.05; ***p<0.01

A.2 Stacked Long Differences Models - WLS and IV; 5 Year Intervals, 1995-2019

Table A.2.1: WLS Regression Results with Clustered Standard Errors - Broad Groups in High LMI countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.186***	0.035***	0.034***
	(−0.0001)	(−0.00004)	(−0.0001)
geo_codeAT	0.00002***	−0.0001***	−0.0005***
	(0.00001)	(0.00000)	(0.00000)
geo_codeBE	−0.001***	−0.0001***	−0.0002***
	(0.00000)	(0.00000)	(0.00000)
geo_codeDE	−0.0003***	−0.0004***	−0.001***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeDK	0.001***	−0.0001***	−0.00001***
	(0.00000)	(0.00000)	(0.00000)
geo_codeFI	0.002***	0.001***	0.0004***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeFR	−0.0001***	0.0002***	−0.0002***
	(0.00000)	(0.00000)	(0.00000)
geo_codeLU	0.001***	0.002***	0.002***
	(0.00000)	(0.00000)	(0.00000)
geo_codeNL	0.001***	0.001***	0.0002***
	(0.00000)	(0.00000)	(0.00000)
geo_codePT	−0.005***	−0.002***	−0.003***
	(−0.00000)	(−0.00000)	(−0.00000)

Table A.2.1: WLS Regression Results with Clustered Standard Errors - Broad Groups in High LMI countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
geo_codeSE			
	(−0.0001)	(−0.00004)	(−0.0001)
P1	−0.004	−0.001	−0.001
	(0.008)	(0.002)	(0.003)
P2	−0.011***	−0.002***	−0.002***
	(−0.0003)	(−0.0001)	(−0.0001)
P3	−0.010***	−0.002***	−0.002***
	(−0.0002)	(−0.0001)	(−0.0001)
P4	−0.003***	−0.002***	−0.002***
	(0.0001)	(0.00004)	(0.00004)
P5			
	(−0.0001)	(−0.00002)	(−0.00002)
Constant	0.011***	0.002***	0.002***
	(0.00000)	(0.00000)	(0.00000)
Observations	933	933	933
R^2	0.375	0.195	0.189
Adjusted R^2	0.365	0.183	0.177
Residual Std. Error (df = 918)	0.009	0.003	0.003
F Statistic (df = 14; 918)	39.286***	15.912***	15.325***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.2: WLS Regression Results with Clustered Standard Errors - Broad Groups in Low LMI countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.269***	−0.009***	0.002***
	(−0.001)	(−0.0001)	(−0.0001)
geo_codeCZ	0.006***	−0.002***	−0.001***
	(−0.00003)	(−0.00000)	(−0.00000)
geo_codeIT	0.001***	−0.0005***	−0.0004***
	(−0.00003)	(−0.00000)	(−0.00000)
geo_codeLT	0.002***	−0.002***	−0.001***
	(0.0001)	(0.00000)	(0.00000)
geo_codeES	0.002***	0.002***	0.002***
	(0.00000)	(0.00000)	(0.00000)
geo_codeLV	0.006***	−0.002***	−0.002***
	(0.0001)	(0.00001)	(0.00001)
geo_codeSI	0.008***	−0.001***	−0.001***
	(0.00001)	(0.00000)	(0.00000)
geo_codeSK	0.001***	−0.002***	−0.002***
	(−0.0001)	(−0.00000)	(−0.00001)
geo_codeUK			
	(−0.001)	(−0.0001)	(−0.0001)
P1	−0.006	−0.001	−0.0004
	(0.028)	(0.001)	(0.002)
P2	−0.009***	−0.0002***	0.0001***
	(0.001)	(0.00003)	(0.00004)

Table A.2.2: WLS Regression Results with Clustered Standard Errors - Broad Groups in Low LMI countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
P3	−0.012***	−0.002***	−0.002***
	(0.001)	(0.00003)	(0.00004)
P4	−0.004***	−0.0002***	−0.0002**
	(−0.001)	(−0.0001)	(−0.0001)
P5			
	(−0.00002)	(−0.00000)	(−0.00000)
Constant	0.008***	0.002***	0.001***
	(0.0001)	(0.00000)	(0.00001)
Observations	764	764	764
R^2	0.416	0.118	0.088
Adjusted R^2	0.407	0.104	0.073
Residual Std. Error (df = 751)	0.014	0.004	0.004
F Statistic (df = 12; 751)	44.644***	8.372***	6.010***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.3: IV Regression Results with Clustered Standard Errors - Broad Groups in High LMI countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.697***	0.319***	0.352***
	(−0.0005)	(−0.0002)	(−0.0002)
geo_codeAT	−0.003***	−0.002***	−0.003***

Table A.2.3: IV Regression Results with Clustered Standard Errors - Broad Groups in High LMI countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(0.00000)	(0.00000)	(0.00000)
geo_codeBE	−0.006***	−0.003***	−0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeDE	−0.004***	−0.002***	−0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeDK	0.0004***	−0.001***	−0.001***
	(0.00000)	(0.00000)	(0.00000)
geo_codeFI	0.004***	0.002***	0.001***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeFR	−0.003***	−0.002***	−0.002***
	(0.00000)	(0.00000)	(0.00000)
geo_codeLU	0.001***	0.002***	0.001***
	(0.00000)	(0.00000)	(0.00000)
geo_codeNL	−0.002***	−0.001***	−0.002***
	(0.00000)	(0.00000)	(0.00000)
geo_codePT	0.003***	0.002***	0.002***
	(−0.00001)	(−0.00000)	(−0.00000)
geo_codeSE			
	(−0.00001)	(−0.00000)	(−0.00001)
P1	0.007***	0.004***	0.005***
	(−0.00001)	(−0.00000)	(−0.00000)
P2	0.0003***	0.004***	0.004***

Table A.2.3: IV Regression Results with Clustered Standard Errors - Broad Groups in High LMI countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(−0.00001)	(−0.00000)	(−0.00001)
P3	0.001***	0.003***	0.005***
	(−0.00001)	(−0.00000)	(−0.00000)
P4	0.002***	0.0005***	0.001***
	(−0.0005)	(−0.0002)	(−0.0002)
P5			
	(0.022)	(0.007)	(0.010)
Constant	0.001***	−0.004***	−0.004***
	(0.00001)	(0.00000)	(0.00001)
Observations	752	752	752
R^2	-0.936	-3.536	-4.492
Adjusted R^2	-0.973	-3.623	-4.596
Residual Std. Error (df = 737)	0.017	0.009	0.009
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.4: IV Regression Results with Clustered Standard Errors - Broad Groups in Low LMI countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.861***	−0.041***	−0.026***
	(−0.001)	(−0.0002)	(−0.0002)
geo_codeCZ	0.004***	−0.001***	−0.001***

Table A.2.4: IV Regression Results with Clustered Standard Errors - Broad Groups in Low LMI countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(0.00000)	(0.00000)	(0.00000)
geo_codeIT	−0.001***	0.0003***	0.0003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeLT	−0.006***	−0.001***	0.0001***
	(0.00001)	(0.00000)	(0.00000)
geo_codeES	−0.002***	0.003***	0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeLV	0.008***	−0.001***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeSI	0.003***	−0.0001***	−0.0003***
	(0.00001)	(0.00000)	(0.00000)
geo_codeSK	0.005***		
	(−0.00001)	(−0.00000)	(−0.00000)
geo_codeUK			
	(−0.00004)	(−0.00000)	(−0.00000)
P1	0.009***	−0.002***	−0.001***
	(−0.00004)	(−0.00000)	(−0.00000)
P2	0.008***	−0.001***	−0.001***
	(−0.00002)	(−0.00000)	(−0.00000)
P3	0.0004***	−0.004***	−0.003***
	(−0.00005)	(−0.0002)	(−0.0002)
P4	0.009***	−0.001	−0.001

Table A.2.4: IV Regression Results with Clustered Standard Errors - Broad Groups in Low LMI countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(−0.001)	(0.009)	(0.011)
P5			
	(0.025)	(−0.00001)	(−0.00001)
Constant	−0.008***	0.002***	0.002***
	(0.00004)	(0.00000)	(0.00000)
Observations	686	537	537
R^2	-0.870	0.128	0.088
Adjusted R^2	-0.903	0.110	0.069
Residual Std. Error	0.026 (df = 673)	0.004 (df = 525)	0.005 (df = 525)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.5: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Scandinavian countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.121***	0.034***	0.037***
	(−0.0002)	(0.00000)	(0.00000)
geo_codeDK	0.001***	−0.0001***	−0.00003***
	(0.00000)	(−0.000)	(−0.000)
geo_codeFI	0.002***	0.001***	0.0004***
	(−0.00000)	(0.000)	(0.000)
geo_codeLU	0.001***	0.002***	0.002***

Table A.2.5: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Scandinavian countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(0.00000)	(−0.000)	(−0.000)
geo_codeSE			
	(−0.00000)	(−0.00000)	(−0.00000)
P1	−0.006***	−0.002***	−0.003***
	(−0.00000)	(−0.00000)	(−0.00000)
P2	−0.012***	−0.003***	−0.003***
	(−0.00000)	(−0.00000)	(−0.00000)
P3	−0.013***	−0.004***	−0.004***
	(−0.00000)	(−0.00000)	(−0.00000)
P4	−0.006***	−0.003***	−0.004***
	(−0.0002)	(0.00000)	(0.00000)
P5			
	(0.009)	(0.0001)	(0.0001)
Constant	0.014***	0.003***	0.003***
	(0.00000)	(0.00000)	(0.00000)
Observations	398	398	398
R^2	0.289	0.298	0.313
Adjusted R^2	0.274	0.284	0.299
Residual Std. Error (df = 389)	0.010	0.003	0.003
F Statistic (df = 8; 389)	19.735***	20.674***	22.199***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.6: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Liberal countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.275***	−0.015***	−0.004***
	(−0.0001)	(−0.00001)	(−0.00001)
geo_codeCZ	0.006***	−0.002***	−0.001***
	(0.000)	(0.000)	(0.000)
geo_codeLT	0.002***	−0.002***	−0.001***
	(0.00000)	(0.00000)	(0.00000)
geo_codeLV	0.006***	−0.002***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeSI	0.008***	−0.001***	−0.001***
	(0.00000)	(0.00000)	(0.00000)
geo_codeSK	0.001***	−0.002***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeUK			
	(−0.00002)	(−0.00000)	(−0.00000)
P1	−0.008***	−0.0004***	0.001***
	(−0.00001)	(−0.00000)	(−0.00000)
P2	−0.010***	0.001***	0.002***
	(−0.00001)	(−0.00000)	(−0.00000)
P3	−0.013***	−0.001***	−0.0005***
	(−0.00001)	(−0.00000)	(−0.00000)
P4	−0.005***	0.001***	0.001***
	(−0.0001)	(−0.00001)	(−0.00001)

Table A.2.6: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Liberal countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
P5			
	(0.012)	(0.001)	(0.0004)
Constant	0.009***	0.001***	0.0004***
	(0.00001)	(0.00000)	(0.00000)
Observations	569	569	569
R^2	0.416	0.093	0.058
Adjusted R^2	0.405	0.077	0.041
Residual Std. Error (df = 558)	0.016	0.004	0.004
F Statistic (df = 10; 558)	39.705***	5.709***	3.447***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.7: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Corporatist countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.228***	0.034***	0.034***
	(−0.00003)	(−0.00000)	(−0.00000)
geo_codeAT	0.004***	0.002***	0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeBE	0.003***	0.002***	0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeDE	0.004***	0.002***	0.002***

Table A.2.7: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Corporatist countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(0.00000)	(0.00000)	(0.00000)
geo_codeES	0.003***	0.004***	0.005***
	(0.00000)	(0.00000)	(0.00000)
geo_codeFR	0.004***	0.003***	0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeIT	0.003***	0.002***	0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeNL	0.005***	0.003***	0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codePT			
	(−0.00000)	(−0.00000)	(−0.00000)
P1	−0.002***	−0.001***	−0.001***
	(−0.00000)	(−0.00000)	(−0.00000)
P2	−0.009***	−0.002***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
P3	−0.007***	−0.003***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
P4	−0.002***	−0.002***	−0.002***
	(−0.00003)	(−0.00000)	(−0.00000)
P5			
	(0.004)	(0.0004)	(0.0004)
Constant	0.005***	−0.001***	−0.001***

Table A.2.7: WLS Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Corporatist countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(0.00000)	(0.00000)	(0.00000)
Observations	730	730	730
R^2	0.475	0.170	0.165
Adjusted R^2	0.467	0.156	0.151
Residual Std. Error (df = 717)	0.008	0.004	0.004
F Statistic (df = 12; 717)	54.148***	12.207***	11.781***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.8: IV Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Scandinavian countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	−0.253***	0.005***	−0.029***
	(−0.003)	(−0.0002)	(−0.0001)
geo_codeDK	−0.001***	−0.0001***	−0.00002***
	(0.00000)	(0.00000)	(0.00000)
geo_codeFI	−0.001***	0.001***	0.0002***
	(−0.00002)	(−0.00000)	(−0.00000)
geo_codeLU	−0.001***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)
geo_codeSE			
	(−0.0001)	(−0.00001)	(−0.00000)

Table A.2.8: IV Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Scandinavian countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
P1	-0.019^{***}	-0.004^{***}	-0.006^{***}
	(-0.0001)	(-0.00001)	(-0.00000)
P2	-0.030^{***}	-0.005^{***}	-0.007^{***}
	(-0.0001)	(-0.00001)	(-0.00000)
P3	-0.029^{***}	-0.007^{***}	-0.008^{***}
	(-0.00002)	(-0.00001)	(-0.00000)
P4	-0.013^{***}	-0.006^{***}	-0.007^{***}
	(-0.003)	(-0.0002)	(-0.0001)
P5			
	(0.094)	(0.006)	(0.007)
Constant	0.033^{***}	0.005^{***}	0.007^{***}
	(0.0001)	(0.00001)	(0.00000)
Observations	240	240	240
R^2	-0.152	0.399	0.280
Adjusted R^2	-0.192	0.378	0.255
Residual Std. Error (df = 231)	0.015	0.003	0.004
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.9: IV Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Liberal countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.952***	−0.087***	0.093***
	(−0.002)	(−0.0001)	(−0.0001)
geo_codeCZ	0.004***	−0.001***	−0.002***
	(0.00000)	(0.00000)	(0.00000)
geo_codeLT	−0.007***	−0.001***	−0.002***
	(0.00002)	(0.00000)	(0.00000)
geo_codeLV	0.008***	−0.002***	−0.001***
	(−0.00001)	(−0.00000)	(−0.00000)
geo_codeSI	0.003***	−0.001***	−0.002***
	(0.00001)	(0.00000)	(0.00000)
geo_codeSK	0.006***	−0.002***	−0.001***
	(−0.00002)	(−0.00000)	(−0.00000)
geo_codeUK			
	(−0.0001)	(−0.00001)	(−0.00000)
P1	0.014***	−0.003***	0.004***
	(−0.0001)	(−0.00001)	(−0.00000)
P2	0.010***	−0.001***	0.005***
	(−0.0001)	(−0.00001)	(−0.00000)
P3	0.003***	−0.003***	0.002***
	(−0.0001)	(−0.00001)	(−0.00000)
P4	0.011***	−0.001***	0.004***
	(−0.002)	(−0.0001)	(−0.0001)

Table A.2.9: IV Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Liberal countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
P5			
	(0.056)	(0.002)	(0.002)
Constant	-0.011^{***}	0.003^{***}	-0.003^{***}
	(0.0001)	(0.00001)	(0.00000)
Observations	511	511	464
R^2	-1.149	-0.365	-0.687
Adjusted R^2	-1.192	-0.392	-0.724
Residual Std. Error	0.031 (df = 500)	0.005 (df = 500)	0.006 (df = 453)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.10: IV Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Corporatist countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.392^{***}	0.192^{***}	0.196^{***}
	(−0.00003)	(−0.00001)	(−0.00002)
geo_codeAT	0.0005^{***}	-0.001^{***}	-0.001^{***}
	(0.00000)	(0.00000)	(0.00000)
geo_codeBE	-0.002^{***}	-0.001^{***}	-0.001^{***}
	(0.00000)	(0.00000)	(0.00000)
geo_codeDE	0.0001^{***}	-0.001^{***}	-0.001^{***}
	(0.00000)	(0.00000)	(0.00000)

Table A.2.10: IV Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Corporatist countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
geo_codeES	-0.0004^{***}	0.001^{***}	0.002^{***}
	(0.00000)	(0.00000)	(0.00000)
geo_codeFR	0.00001^{***}	-0.0004^{***}	-0.0003^{***}
	(0.00000)	(0.00000)	(0.00000)
geo_codeIT	-0.002^{***}	-0.001^{***}	-0.001^{***}
	(0.00000)	(0.00000)	(0.00000)
geo_codeNL	0.001^{***}	0.0003^{***}	0.0002^{***}
	(0.00000)	(0.00000)	(0.00000)
geo_codePT			
	(-0.00000)	(-0.00000)	(-0.00000)
P1	0.001^{***}	0.001^{***}	0.001^{***}
	(-0.00000)	(-0.00000)	(-0.00000)
P2	-0.005^{***}	0.002^{***}	0.001^{***}
	(-0.00000)	(-0.00000)	(-0.00000)
P3	-0.004^{***}	-0.0002^{***}	0.0001^{***}
	(-0.00000)	(-0.00000)	(-0.00000)
P4	0.001^{***}	-0.0001^{***}	-0.0001^{***}
	(-0.00003)	(-0.00001)	(-0.00002)
P5			
	(0.006)	(0.002)	(0.003)
Constant	0.005^{***}	-0.001^{***}	-0.002^{***}
	(0.00000)	(0.00000)	(0.00000)

Table A.2.10: IV Regression Results with Clustered Standard Errors - Esping-Andersen Groups in Corporatist countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
Observations	592	592	592
R^2	0.342	-0.759	-0.757
Adjusted R^2	0.328	-0.795	-0.793
Residual Std. Error (df = 579)	0.009	0.006	0.006
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.11: WLS Regression Results with Clustered Standard Errors - Small Groups in Scandinavian countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.320***	0.009***	0.012***
	(−0.0001)	(0.00001)	(0.00000)
geo_codeDK	0.001***	−0.0001***	0.00001***
	(0.00000)	(−0.00000)	(−0.000)
geo_codeFI	0.003***	0.001***	0.0003***
	(−0.00000)	(0.000)	(0.000)
geo_codeSE			
	(−0.00000)	(−0.00000)	(−0.00000)
P1	−0.004***	−0.002***	−0.003***
	(−0.00000)	(−0.00000)	(−0.00000)
P2	−0.009***	−0.002***	−0.003***
	(−0.00000)	(−0.00000)	(−0.00000)

Table A.2.11: WLS Regression Results with Clustered Standard Errors - Small Groups in Scandinavian countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
P3	−0.010***	−0.003***	−0.003***
	(−0.00000)	(−0.00000)	(−0.00000)
P4	−0.005***	−0.003***	−0.003***
	(−0.0001)	(0.00001)	(0.00000)
P5			
	(0.006)	(0.0003)	(0.00003)
Constant	0.011***	0.003***	0.003***
	(0.00000)	(0.00000)	(0.00000)
Observations	298	298	298
R^2	0.413	0.159	0.192
Adjusted R^2	0.399	0.139	0.172
Residual Std. Error (df = 290)	0.010	0.003	0.003
F Statistic (df = 7; 290)	29.196***	7.822***	9.833***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.12: WLS Regression Results with Clustered Standard Errors - Small Groups in Anglo-Saxon countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.160***	0.006***	0.012***
	(−0.00004)	(0.00001)	(0.00001)
geo_codeLT	0.003***	−0.002***	−0.001***

Table A.2.12: WLS Regression Results with Clustered Standard Errors - Small Groups in Anglo-Saxon countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(0.00000)	(−0.00000)	(−0.00000)
geo_codeLV	0.006***	−0.002***	−0.002***
	(−0.00000)	(0.00000)	(0.00000)
geo_codeUK			
	(−0.00002)	(−0.00000)	(−0.00000)
P1	−0.010***	−0.002***	−0.001***
	(−0.00002)	(−0.00000)	(−0.00000)
P2	−0.007***	−0.0002***	0.001***
	(−0.00002)	(−0.00000)	(−0.00000)
P3	−0.014***	−0.003***	−0.003***
	(−0.00001)	(−0.00000)	(−0.00000)
P4	−0.003***	−0.0004***	−0.0004***
	(−0.00004)	(0.00001)	(0.00001)
P5			
	(0.012)	(0.0001)	(0.0002)
Constant	0.010***	0.002***	0.001***
	(0.00001)	(0.00000)	(0.00000)
Observations	294	294	294
R^2	0.319	0.195	0.148
Adjusted R^2	0.302	0.175	0.128
Residual Std. Error (df = 286)	0.013	0.003	0.003
F Statistic (df = 7; 286)	19.127***	9.880***	7.122***

Table A.2.12: WLS Regression Results with Clustered Standard Errors - Small Groups in Anglo-Saxon countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.13: WLS Regression Results with Clustered Standard Errors - Small Groups in Bismarckian countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.156***	0.031***	0.029***
	(−0.0002)	(0.00000)	(0.00000)
geo_codeAT	−0.001***	−0.001***	−0.001***
	(−0.00000)	(0.000)	(0.000)
geo_codeBE	−0.002***	−0.001***	−0.0004***
	(0.00000)	(−0.000)	(−0.000)
geo_codeDE	−0.001***	−0.001***	−0.001***
	(0.00000)	(−0.000)	(−0.000)
geo_codeFR	−0.001***	−0.001***	−0.0004***
	(−0.00000)	(0.000)	(0.000)
geo_codeLU	0.0002***	0.001***	0.002***
	(−0.00000)	(0.000)	(0.000)
geo_codeNL			
	(−0.00000)	(−0.00000)	(−0.00000)
P1	−0.004***	−0.002***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)

Table A.2.13: WLS Regression Results with Clustered Standard Errors - Small Groups in Bismarckian countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
P2	−0.012***	−0.003***	−0.003***
	(−0.00000)	(−0.00000)	(−0.00000)
P3	−0.010***	−0.003***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
P4	−0.005***	−0.003***	−0.003***
	(−0.0002)	(0.00000)	(0.00000)
P5			
	(0.005)	(0.0003)	(0.0003)
Constant	0.013***	0.003***	0.003***
	(0.00001)	(0.00000)	(0.00000)
Observations	595	595	595
R^2	0.390	0.264	0.245
Adjusted R^2	0.380	0.251	0.232
Residual Std. Error (df = 584)	0.009	0.003	0.003
F Statistic (df = 10; 584)	37.405***	20.939***	18.965***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.14: WLS Regression Results with Clustered Standard Errors - Small Groups in Southern European countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.226***	0.060***	0.074***
	(−0.00002)	(−0.00003)	(−0.00003)
geo_codeES	0.003***	0.004***	0.005***
	(0.00000)	(0.00000)	(0.00000)
geo_codeIT	0.003***	0.002***	0.003***
	(0.00000)	(0.00000)	(0.00000)
geo_codePT			
	(−0.00000)	(−0.00000)	(−0.00000)
P1	−0.001***	−0.001***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
P2	−0.005***	−0.001***	−0.002***
	(−0.00000)	(−0.00000)	(−0.00000)
P3	−0.006***	−0.004***	−0.005***
	(−0.00000)	(−0.00000)	(−0.00000)
P4	0.001***	−0.001***	−0.001***
	(−0.00002)	(−0.00003)	(−0.00003)
P5			
	(0.004)	(0.002)	(0.002)
Constant	0.004***	−0.001***	−0.001***
	(0.00000)	(0.00000)	(0.00000)
Observations	235	235	235
R^2	0.452	0.212	0.248

Table A.2.14: WLS Regression Results with Clustered Standard Errors - Small Groups in Southern European countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
Adjusted R^2	0.435	0.188	0.225
Residual Std. Error (df = 227)	0.008	0.005	0.005
F Statistic (df = 7; 227)	26.785***	8.726***	10.702***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.15: WLS Regression Results with Clustered Standard Errors - Small Groups in Eastern European countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.371***	−0.034***	−0.019***
	(0.0003)	(−0.00005)	(−0.00005)
geo_codeCZ	0.004***	−0.00003***	0.0003***
	(0.00000)	(0.00000)	(0.00000)
geo_codeSI	0.005***	0.001***	0.001***
	(−0.00000)	(0.00000)	(0.00000)
geo_codeSK			
	(−0.00004)	(−0.00000)	(−0.00000)
P1	−0.008***	0.002***	0.002***
	(−0.00003)	(−0.00000)	(−0.00000)
P2	−0.014***	0.002***	0.003***
	(−0.00003)	(−0.00000)	(−0.00000)
P3	−0.013***	0.0004***	0.002***

Table A.2.15: WLS Regression Results with Clustered Standard Errors - Small Groups in Eastern European countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
	(−0.00003)	(−0.00000)	(−0.00000)
P4	−0.011***	0.003***	0.003***
	(0.0003)	(−0.00005)	(−0.00005)
P5			
	(0.023)	(0.001)	(0.001)
Constant	0.012***	−0.002***	−0.003***
	(0.00002)	(0.00000)	(0.00000)
Observations	275	275	275
R^2	0.529	0.164	0.108
Adjusted R^2	0.517	0.142	0.084
Residual Std. Error (df = 267)	0.017	0.004	0.004
F Statistic (df = 7; 267)	42.879***	7.472***	4.597***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.16: IV Regression Results with Clustered Standard Errors - Small Groups in Scandinavian countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.729***	2.043	3.335
	(−0.001)	(−1.331)	(−3.210)
geo_codeDK	0.00000*	−0.004	−0.007
	(0.00000)	(0.003)	(0.007)

Table A.2.16: IV Regression Results with Clustered Standard Errors - Small Groups in Scandinavian countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
geo_codeFI	0.004***	0.008*	0.011
	(−0.00000)	(−0.004)	(−0.011)
geo_codeSE			
	(−0.00002)	(−0.015)	(−0.037)
P1	0.0004***	0.021	0.035
	(−0.00002)	(−0.024)	(−0.058)
P2	−0.003***	0.035	0.058
	(−0.00002)	(−0.028)	(−0.067)
P3	−0.002***	0.037***	0.063***
	(0.00000)	(−0.006)	(−0.014)
P4	−0.004***	0.006	0.010
	(−0.001)	(−1.331)	(−3.210)
P5			
	(0.055)	(74.777)	(180.070)
Constant	0.004***	−0.033	−0.055
	(0.00002)	(0.024)	(0.057)
Observations	268	240	240
R^2	0.102	-123.477	-322.086
Adjusted R^2	0.078	-127.232	-331.835
Residual Std. Error	0.012 (df = 260)	0.038 (df = 232)	0.062 (df = 232)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.17: IV Regression Results with Clustered Standard Errors - Small Groups in Anglo-Saxon countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	−11.137	2.193***	1.516***
	(−9.385)	(−0.494)	(−0.181)
geo_codeUK	0.029	−0.005***	−0.003***
	(0.029)	(0.002)	(0.001)
geo_codeLT	0.169	−0.034***	−0.022***
	(0.143)	(0.008)	(0.003)
geo_codeLV			
	(−0.439)	(−0.023)	(−0.009)
P1	−0.485	0.090***	0.063***
	(−0.329)	(−0.017)	(−0.007)
P2	−0.376	0.071***	0.050***
	(−0.261)	(−0.014)	(−0.005)
P3	−0.296	0.051***	0.035***
	(−0.352)	(−0.019)	(−0.007)
P4	−0.451	0.086	0.059
	(−9.385)	(−0.494)	(−0.181)
P5			
	(267.280)	(14.158)	(5.076)
Constant	0.396	−0.073***	−0.051***
	(0.330)	(0.017)	(0.006)
Observations	264	264	264
R^2	-616.734	-533.012	-218.488

Table A.2.17: IV Regression Results with Clustered Standard Errors - Small Groups in Anglo-Saxon countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
Adjusted R^2	-633.625	-547.614	-224.489
Residual Std. Error (df = 256)	0.403	0.078	0.054
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.18: IV Regression Results with Clustered Standard Errors - Small Groups in Bismarckian countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.570***	0.341***	0.373***
	(−0.001)	(−0.0003)	(−0.0003)
geo_codeAT	−0.001***	−0.001***	−0.001***
	(0.00000)	(0.00000)	(0.00000)
geo_codeDE	−0.001***	−0.001***	−0.001***
	(0.00000)	(0.00000)	(0.00000)
geo_codeBE	−0.004***	−0.002***	−0.002***
	(0.00000)	(0.00000)	(0.00000)
geo_codeFR	−0.001***	−0.001***	−0.0005***
	(−0.00000)	(−0.000)	(−0.000)
geo_codeLU	0.002***	0.003***	0.003***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeNL			
	(−0.00003)	(−0.00001)	(−0.00001)

Table A.2.18: IV Regression Results with Clustered Standard Errors - Small Groups in Bismarckian countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
P1	0.008***	0.007***	0.007***
	(−0.00003)	(−0.00001)	(−0.00001)
P2	−0.001***	0.006***	0.006***
	(−0.00002)	(−0.00001)	(−0.00001)
P3	0.0004***	0.005***	0.006***
	(−0.00002)	(−0.00001)	(−0.00001)
P4	0.003***	0.002***	0.003***
	(−0.001)	(−0.0003)	(−0.0003)
P5			
	(0.021)	(0.008)	(0.009)
Constant	0.0004***	−0.006***	−0.008***
	(0.00003)	(0.00001)	(0.00001)
Observations	480	480	480
R^2	-0.784	-6.433	-8.126
Adjusted R^2	-0.822	-6.592	-8.321
Residual Std. Error (df = 469)	0.016	0.010	0.011
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.19: IV Regression Results with Clustered Standard Errors - Small Groups in Southern European countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.660***	0.031***	0.027***
	(0.0002)	(0.0002)	(0.0002)
geo_codeIT	−0.005***	0.003***	0.004***
	(−0.00001)	(−0.00000)	(−0.00000)
geo_codeES	−0.005***	0.005***	0.006***
	(−0.00001)	(−0.00000)	(−0.00000)
geo_codePT			
	(−0.00000)	(−0.00000)	(−0.00000)
P1	0.001***	−0.002***	−0.002***
	(0.00000)	(−0.00000)	(−0.00000)
P2	0.003***	−0.002***	−0.003***
	(0.00000)	(−0.00000)	(−0.00000)
P3	−0.005***	−0.004***	−0.005***
	(−0.00001)	(−0.00001)	(−0.00001)
P4	0.003***	−0.001***	−0.001***
	(0.0002)	(0.0002)	(0.0002)
P5			
	(0.020)	(0.013)	(0.020)
Constant	0.004***	−0.001***	−0.001***
	(0.00000)	(0.00000)	(0.00000)
Observations	211	220	220
R^2	-0.659	0.198	0.212

Table A.2.19: IV Regression Results with Clustered Standard Errors - Small Groups in Southern European countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
Adjusted R^2	-0.716	0.171	0.186
Residual Std. Error	0.014 (df = 203)	0.005 (df = 212)	0.005 (df = 212)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2.20: IV Regression Results with Clustered Standard Errors - Small Groups in Eastern European countries

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
LNICT_W	0.754***	−0.055***	0.112***
	(0.0004)	(−0.0001)	(−0.0002)
geo_codeCZ	−0.00000**	−0.001***	0.001***
	(0.00000)	(−0.00000)	(−0.00000)
geo_codeSK	−0.0001***	−0.001***	0.001***
	(−0.00000)	(−0.00000)	(−0.00000)
geo_codeSI			
	(−0.0001)	(−0.00000)	(−0.00000)
P1	−0.001***	0.002***	0.006***
	(−0.00003)	(−0.00001)	(−0.00001)
P2	−0.002***	0.002***	0.007***
	(−0.00002)	(−0.00000)	(−0.00001)
P3	−0.003***	−0.0001***	0.005***
	(−0.00003)	(−0.00000)	(−0.00000)

Table A.2.20: IV Regression Results with Clustered Standard Errors - Small Groups in Eastern European countries (continued)

	Dependent variable:		
	Compensation	Employment	Hours Worked
	(1)	(2)	(3)
P4	-0.007^{***}	0.003^{***}	0.005^{***}
	(0.0004)	(-0.0001)	(-0.0002)
P5			
	(0.011)	(0.001)	(0.007)
Constant	0.005^{***}	-0.001^{***}	-0.007^{***}
	(0.00002)	(0.00000)	(0.00001)
Observations	247	247	224
R^2	0.133	0.135	-1.189
Adjusted R^2	0.108	0.109	-1.260
Residual Std. Error	0.024 (df = 239)	0.005 (df = 239)	0.007 (df = 216)
Note:			*p<0.1; **p<0.05; ***p<0.01