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Master Thesis

Technological Change, Occupational Structures and Income Inequality in European Labor Markets

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Pieter Bruegel, The Land of Cockaigne (1567)

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Abstract

The inquiry how labor markets tend to react to technological changes has been a core concern of economists ever since the early foundations of economics. Until recently, the notion existed that skill-biased technological change (SBTC) could explain all observed phenomena in labor markets. During the last decade however, economists raised concerns that SBTC fails to account for disparate patterns, which induced several economists to develop more ‘nuanced’ models. This paper capitalizes the task-approach framework to labor markets by Acemoglu and Autor (2011), and attempts to show a decomposition of how distinct measures of technological change exert a differential impact on the occupational and income structure of European labor markets. The employed dataset is a panel of 27 European countries abiding the time-period 1995-2014. The analysis indicates that the extent of ‘job polarization’ in European labor markets has been dependent upon the domestic automation patent and R&D expenditure intensity, while especially the domestic high-tech patent intensity mitigates this pattern. Further results show that the effects of technological change on occupational structures resonate fairly well with changes in relative gross income distributions, but have not been translated to similar changes in the disposable income distribution.

Keywords: Technological change, occupational structures, income inequality, job polarization, task-based approach to labor markets. (**JEL** J21, J23, J24, J31, O33**)**

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I. Introduction[1]

Life in the middle ages was often harsh for peasants, which led them to wonder about an utopian world of idleness and gluttony. The so-called land of plenty described the medieval myth of Cockaigne. Today, wondering about such a world might have ceased, frankly so, because this world might become attainable for newer generations. The recent publication of '*The Second Machine Age'* by Brynjolfsson and McAfee sketches such a world. These authors argue that humanity is on the verge of an explosion of technological developments. This essentially reduces the need for human labor, although the occupational displacement of labor by technology is not evenly distributed. Where machines were able to amplify our physical power during the first machine age, the second machine age will augment the role of our brains, referring to skill-biased technological change that many economists have seized to explain developments in income inequality during the last couple of decades (e.g. Acemoglu (2002); Albrecht & Vroman (2002)). However, genuine concerns were raised whether skill-biased technological could legitimately account for all changes within the wage structure in economically advanced countries. The first 'puzzles' were addressed by DiNardo and Card in 2002, which induced several labor economists to develop more 'nuanced' models to account for adjustments in the wage structure since the early nineties. Seminal work by Autor, Levy and Murnane (2003) revolutionized the standard skill-biased technological change narrative by redirecting its attention to the occupational 'task' structure of labor markets. In this regard, the authors found evidence that the 'computerization' of economies tends to substitute laborers performing cognitive and manual routine tasks, while complementing laborers performing nonroutine tasks. Since this study, the implicit distinction between routine and nonroutine tasks has become one of the foundations on which novel models were build, and similarly, the approach to elucidate adjustments in the occupational and income structure of labor markets.

The effect of technology on labor markets has been a core concern ever since the early foundations of the principles of economics. This actuality is not startling; the widespread historical narratives providing evidence that labor-economizing technologies were replacing laborers were already numerous during the Industrial Revolution. The most eminent example were the Luddites, the 19th century textile workers hailing from England, who revived widespread rebellions against the introduction of spinning frames and stocking frames, technologies that severely threatened artisan occupations to be dissipated. Following this

[1] The author gratefully acknowledges Dana Sisak for her supervision and helpful suggestions. Also thanks to Lorenzo Pozzi for his valuable suggestions.

notion, John Maynard Keynes expected unprecedented technical progress eventually to result in 'technological unemployment', however empirical evidence simply documented grounded support that this notion was invalid, later coined as the '*Luddite fallacy'*. Economists widely agreed that technological developments would surge the productivity levels of laborers, pushing up their incomes, thereby generating augmented demand for new products and services. For this reason, technical progress was mainly perceived as a Schumpeterian creative destruction process of replacing old jobs by novel ones. In many advanced countries this tendency was clearly discernible until the 1980's. However, the last couple of decades this propensity has displayed deteriorations; productivity levels have soared, while wages and employment levels have been stagnant in most Western countries, increasingly putting pressure on the Luddite Fallacy. A few factors have been inferred to justify this phenomenon; the de-unionization of labor markets, rising globalization, migration, and above all technological developments. The latter have become more and more persuasively capable of rendering some human labor tasks superfluous, indirectly induced by the impelling prediction of Gordon Moore in a 1965 article. Moore postulated the prognosis that the computational power of machines per unit cost roughly doubles each two years, and would held up at least for another decade. Perhaps marvelous, this prediction has held up remarkably well until the present time being.

The ongoing 'train' of Moore's law has however, also been conjoined with severe societal and political consequences. Thomas Piketty, among others, conducted extensive research on the evaluation of gross top incomes throughout decades. His findings suggest that the earners at the top of the income distribution, the 'superstars', have gained a growing share of the income distributions in several countries. The premise that the shifting division between labor and capital incomes is behind this phenomenon, was the notion of his recent book '*Capital in the twenty-first century'*. A thought-provoking work that led to a revival of the public interest in (gross) distribution of incomes and wealth. The contemporary view that technological change is a major determinant behind these developments cannot be refuted anymore. Empirical evidence provides us several cases in which innovative technologies have created enormous levels of wealth for its inventors, while the bounty is increasingly less spread among workers. Simply put, technology in the form of capital allows companies to use less labor, the productivity gains being captured by capital owners.

This paper will exploit the growing implications of computer technology, digitalization and automation on domestic occupational and income structures of European countries. It will initiate by capitalizing the ‘task approach’ framework to labor markets by Acemoglu and Autor (2011), which builds upon the ‘canonical’ skill-biased technological change (SBTC) model, in order to elucidate several patterns that received widespread academic attention in the US. These patterns include phenomena like ´job polarization´ and non-monotone changes in income distributions, phenomena that cannot be explained by the standard SBTC model (e.g. Goldin and Katz (2009) for an overview). The comparative statics of the task-based framework are seized to submit the hypotheses. The principal purpose of this paper is to unravel the effect of different measures of technological change on the occupational –and income- structure of labor markets. Thus, formulated in the subsequent research question:

In what way has technological change attributed to adjustments within domestic occupational structures of European countries? Accordingly, have technological developments also altered the income structures of European countries in a similar manner?

The availability of detailed occupational tasks data has induced American researchers to assign a scale of ‘routineness’ of tasks in different occupations. This paper employs a different strategy where different measures of technological change have been measured on a scale dependent upon their relative intensity. The main contribution of this paper -using panel data to estimate elasticity models with time fixed effects- is to show that the distinct measures of technological change exert a differential impact on occupational- and income- structures of 27 European labor markets throughout the period 1995-2014. In particular, it will demonstrate that the pervasiveness of the ‘job polarization’ phenomenon can be elucidated by means of the domestic intensity of automation patents and R&D expenditures, while the domestic high-tech and ICT import intensity tend to mitigate this pattern. These occupational results resonate remarkably well with the gross income distribution results. However above all, the technical progress measures suggests that technological developments have especially been biased towards those at the very top of the gross income distribution, the ‘superstars’. Further scrutiny shows that this pattern hasn’t been translated towards the disposable income distribution, giving rise to what some call the ‘Krugman hypothesis’, which entails that European labor market institutions are effectively capable of compressing wages to limit income inequality developments.

The remainder of this paper is organized as follows. The next section will provide a synopsis of the related literature regarding the effects of technological change on the occupational structure of labor markets. What follows is an overview of ‘puzzles’ of the canonical model, giving rise to the task-approach to labor markets of Acemoglu and Autor (2011). This section also contains related literature about the effects of technological change on the income distribution. The third section will develop and describe the arguments for the employed data, while section IV contemplates the econometric framework. Section V presents the results and addresses some limitations and suggestions for further research. The last section will wrap up the main findings and highlight some of their implications.

II. **Related literature**

Developments in the effects of technological change on labor market structures and corresponding income inequality have received considerable attention in recent decades. The conjecture that technology would surge the demand for skilled labor was broadly accepted since early 1970´s (e.g. Welch (1970); Tinbergen (1975)). Even though the supply of high skilled laborers has been increasing during the past 40 years, returns to schooling have been pushed up too. Some economists (e.g. Acemoglu (2002); Bresnahan et al. (2002)) have seized this pattern to state there has been an accelerating skilled labor bias since the early 1980´s. Put differently, technology has created a discontinuity in the growth rate of demand for skilled labor. Katz and Autor (1999) and Berman et al. (1998) document that this pattern has been evident in the USA as well as other advanced OECD countries. During the 1970´s wage differentials diminished modestly, despite an accretion in the supply of skilled labor. This suggests that in the short run an increase in the supply of skilled labor reduces the skill premium. Then during a transition period technological developments converge the economy towards a long run demand for the different types of labor, where technology is biased towards skilled labor, leading to a rise in the skill premium[2]. The latter pattern is essentially documented from the 1980´s onwards (Acemoglu, 1998).

Nonetheless, the term technological development[3] remains an abstract and comprehensive concept, therefore often posing difficulties how to measure it. Still it is of crucial importance for a government to get a grasp of the measurement of technological advancement, as Weitzman (1998: 331) has stated; "*The long-term growth of an advanced economy is dominated by the behavior of technological progress.*" In the past, economists have primarily focused on how technological process soared the productivity of workers, thereby propagating through the economy by GDP growth. In a neoclassical growth production function, technological change was, and still is, generally modelled as $Y_t = A_t f(K_t, L_t)$, where an increase in A augments the total factor productivity (TFP) within the

[2] Appendix figure 1 provides a graphical overview of the short and long run equilibria

[3] In Greek etymology the term technology literally contemplates; 'the science of mechanical or industrial arts'.

economy. Using this production function, Solow (1957) developed an ingenious method to quantify the role of technological change in GDP growth, by simply subtracting the latter by labor- and capital growth. The remaining 'unexplained' part- now recognized as the 'Solow residual'- accounts for technological change. It is though, that workers composing the labor force are not homogenous. As shown by the skill bias in technological change above, technical progress affects the input of labor in the production function differentially. More specifically, the demand for distinct types of skilled laborers changes as technological change makes some tasks obsolete, while novel tasks are created (e.g. Autor et al. 2008).

Since the dawn of the new millennium, technological change is perceived to have made astonishing progress. Certainly recent years, robots and computers have carried out tasks beyond ever imagined. Technological progress is generally regarded as gradual and then very sudden[4]. This may seem like some sort of paradox, since Moore's law essentially implies that the integrated circuit computational power consumers can buy for one unit cost roughly doubles each eighteen months. However, despite the doubling is *constant*, the number of integrated circuits grows *exponentially*. The constant doubling can therefore elegantly be portrayed on a logarithmic scale[5]. Over time these numbers have grown immensely big. Certainly the latest years, the constant doubling implies that the computational power has grown to staggeringly large numbers, numbers beyond our imagination. Basically, the gradual doubling of the computational power has just recently led to very sudden changes in several capital devices having the competence to take over labor tasks (Kurzweil, 2004).

During recent decades, technological development is often seen as the rapid diffusion of information technology spurred by the internet. This last virtue has received voluminous attention. Scholars have mainly focused on how it is has affected the interaction between people (or communities), why and in what manner people make use of it and what factors determine its diffusion. These studies have been summarized in the book '*The Internet in everyday life*' compiled by Wellman and Haythornthwaite. Notwithstanding, the peculiarity of the effect of internet diffusion on the occupational structure is less known.

Autor et al. (1998) find that their technology parameters (e.g. computer usage) may account up till one half of the entire amount of skill upgrading within industries in the USA.

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[4] To illustrate this IBM's artificial intelligent computer system Watson has been put forward often. The American tv-quiz *Jeopardy!* provided the incentive to develop a competition between Watson and human beings. Initially, Watson was only able to answer 30% of the questions and was constantly defeated by human beings. However, the astonishing progress of Watson eventually caused Watson to defeat the most intelligent human beings. Jennings one of the best players of *Jeopardy!* replied: "*Quiz show contestant' may be the first job made redundant by Watson, but I'm sure it won't be the last*."

[5] See appendix figure 2 for several technologies subject to Moore´s law on a logarithmic scale.

In this regard, Bresnahan et al. (2002) provide evidence that information technology and other types of technological innovations have spurred the demand for skilled labor. This pattern has been observed in several OECD countries (Machin and Van Reenen (1998)). Levy and Murnane (e.g 1996; 2012) diverted their main focus on technological progress as the 'computerization of work' and how it has affected the occupational structure in the US labor market. Their results show that computers have mainly complemented high skilled workers to increase their productivity, while computers have primarily destroyed routine-based middle-class occupations. Aside from the capacity of technology to change the skills demand, also the location of work is changing. Felstead et al. (2003) illustrate this pattern in the UK, by presenting evidence that technology has contributed to an enlargement of the group of workers doing work regularly at their homes. This group primarily consisted of non-manual workers like professionals and managers. Elaborating on their work, Felstead et al. (2007) report that about half of the total employees in the UK state that computerized equipment is an 'essential' component in their job. These observations though, are not evenly distributed among distinct occupational types, as the degree of technology 'complexity' is related to the skills required for occupational groups, thereby referring to the augmenting role of technology to our brains. The argument is that the adoption of technology often involves a period of learning and processing novel information, and skills provide humans the tools to be better able to adopt technology.

This development is unlikely to cusp since technological development remains attractive as a response to profit incentives (Acemoglu, 2002). More specifically, whether technology is developed and used is largely determined by its profitability. During the 19th century, England experienced several de-skilling developments induced by a rapid increase of unskilled rural workers that migrated towards cities. Since the 1970's such an equivalent phenomenon is occurring; the incremental supply of skilled workers induced companies to invent technologies which have been largely skill biased. This is related to the market size argument that economists have put forward why invention -being pursued for gain- is largely skill biased (Schmookler, 1966). As an opposite argument, the price effect argues that innovation is directed towards the relatively scarce factor (unskilled labor). Considering that the scarce factor generally demands a higher price for its good, innovations pursued for gain are directed towards unskilled labor. The net effect of the preceding arguments determines whether innovations are directed to either skilled or unskilled laborers[6].

[6] Acemoglu et al. (2012) provide dynamics in directed technological change in an offshoring framework.

The canonical model

Until the beginning of the 21st century the ‘canonical’ skill-biased technological change model served as a tool to elucidate the effects of technological change on respectively low and high skilled labor. This framework was set up with a constant elasticity of substitution production function: $Y = \left[(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_H H)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, where σ resemblances the elasticity of substitution between low and high skilled labor. The implications of technology shocks - assumed to be factor-augmenting (i.e. increasing the productivity of either one type or both type of skilled workers)- can be observed by differentiating the production function to respectively low and high skilled labor. It is straightforward to show that if the elasticity of substitution is larger than one, i.e. $\sigma > 1$, the skill premium expands when technology shocks are relatively high skilled labor augmenting. Tinbergen commented on developments in the skill premium as the ‘race’ between technological change and the access to education. According to Goldin (2009) sovereign investments in education caused workers to have mostly ´won´ this race. In this regard, Katz and Murphy (1992) provided a model to account for developments in the skill premium for US workers. Using US data from 1963 until 1987, evidence was found that their canonical prediction model closely fitted the observed wage gap, however this fit has started to deteriorate since the 90’s. The canonical model is also unable to explain other observed patterns in the occupational and wage structure in labor markets since the 1980’s:

(i) The occupational polarization of income distributions, that is, employment levels in the lowest and the highest paid occupations have increased, while employment levels of middle class occupations has contracted, also referred to as the ‘*hollowing out of the middle class*[7]’ (e.g. Acemoglu (2002); Goos et al. (2009))[8].

(ii) In the canonical model technological change is modeled to be labor augmenting, therefore it fails to account for certain groups experiencing real wage declines. This observation is related to (i) since occupational employment polarization is reciprocal with a declining wage inequality among the 50/10 percentile wage gap and a growing wage inequality among the 90/50 percentile wage gap

(iii) Technology shocks in the canonical model are exogenous and labor augmenting, hence it does not provide the dynamics of technology developments that might substitute labor occupations or tasks by capital, while simultaneously complementing laborers in novel tasks.

[7] This describes a non-monotonic relationship between changes in jobs and corresponding skill levels

[8] Jaimovich and Siu (2010) find evidence that job polarization most primarily occurs in the wake of economic downturns, suggesting that negative economic shocks assert a negative impact on middle class occupations.

These patterns have induced several authors to come up with a more 'nuanced' view of skill-biased technological change (e.g. Autor et al. (2006)). While the canonical model was developed with the conjecture that skill-biased technological change led to a contraction in the relative demand for low-skilled workers (e.g. Berman et al. (1994)), new models were developed to account for patterns that emerged since the 1980's in advanced OECD countries.

The task-based approach

Therefore, Acemoglu and Autor (2011) propose an extension on the canonical model in a task-based Ricardian approach (e.g. Feenstra and Hanson (1999); Grossman and Rossi-Hansberg (2008)). These authors make use of three distinct labor factors of production: low, medium and high skilled workers. Each type of worker is assumed to have a comparative advantage using their skill at a respective task suited to their skill. Consequently, the mapping of skills to task is simply determined by comparative advantage of each type of worker. The key discrepancy between canonical model and the task-based model is that the former implicitly equates workers skills and their job tasks, whereas the latter draws a distinction between skills and tasks. Basically, each worker possesses a stock of skills to perform a set of tasks, in which tasks are combined to produce output. This model allows for technological developments to automate a certain task initially performed by a certain type of worker, which relates to points (i) and (ii) in the paragraph above, in the sense that middle-income jobs have been most predominantly prone to automation. Therefore, since technological change and other patterns like offshoring and trade are disrupting and reallocating the mapping of skills to tasks, it is valuable to consider a richer framework than posed in the canonical model.

The task-based production function consists of a continuum of job tasks to produce a unique final good $Y = \left[\int_0^1 y(i)^{\frac{\eta-1}{\eta}} di\right]^{\frac{\eta}{\eta-1}}$ in which tasks are drawn from a unit distribution [0,1] and $y(i)$ represents the production level of task i. In addition, η resemblances the elasticity of substitution between tasks. The production function of each task is given by:

$$y(i) = A_L\alpha_L(i)l(i) + A_M\alpha_M(i)m(i) + A_H\alpha_H(i)h(i) + A_K\alpha_K(i)k(i)$$

where $\alpha_L(i)$, $\alpha_M(i)$ and $\alpha_H(i)$ are the task productivity schedules of respectively low, medium and high skilled workers in tasks complementary to their skill[9]. In similar fashion $\alpha_K(i)$ is the productivity schedule of capital in task i. $l(i), m(i)$ and $h(i)$ and refer to the allocation of respectively low, medium and high skilled laborers to task i, whereas $k(i)$ refers

[9] For example, $\alpha_M(i)$ is the productivity of a middle skilled worker in task (i)

to the capital allocation to task *i*. In the task-based model technological developments A_i do not augment the productivity and wages in equal manners, which will be shown below.

The assumption that skill groups have a comparative advantage in performing their respective tasks resonates with the notion that high skilled laborers are more productive performing 'complex' tasks than middle skilled laborers, and middle skilled laborers are more productive at performing such tasks than low skilled laborers[10]. Acemoglu and Autor (2011) solve the model after factor market clearing, under the initial assumption that the capital allocation to labor task *i* is zero, i.e. $\int_0^1 l(i)di \leq L$, $\int_0^1 m(i)di \leq M$, $\int_0^1 h(i)di \leq H$

Under the comparative advantage assumption and the law of one wage (and price), the model eventually yields an equilibrium where three different sets of tasks are separated within the continuum of mass one. More specifically, given the distribution of complexity of labor tasks: $[0 - I_L - I_H - 1]$, the least complex set of labor tasks is supplied by the low skill workers L $(0 \leq i \leq I_L)$, the intermediate set of tasks is supplied by middle skilled workers M $(I_L \leq i \leq I_H)$, and the remaining most complex set of tasks is supplied by high skilled workers H $(I_H \leq i \leq 1)$. The law of one wage together with the no arbitrage condition[11] implies that each set of workers earns the same wage. That is, there is no within-skills wage dispersion, the between-skills wage dispersion is endogenously determined and relate to the relative positions of I_L and I_H.

Comparative statics of occupational thresholds

In order to retrieve comparative statics, logs are taken from the no-arbitrage conditions outlined in footnote 11. Now the effects of distinct types of factor augmenting technological development on the allocation of tasks to different types of workers can be assessed. Similarly, the effect of developments in skill supplies on the allocation of tasks can be estimated. These comparative statics are summarized below:

Low skilled workers $\frac{dI_L}{d\,lnA_L} = \frac{dI_L}{d\,lnL} > 0,\ \frac{dI_L}{d\,lnA_M} = \frac{dI_L}{d\,lnM} < 0\ and\ \frac{dI_L}{d\,lnA_H} = \frac{dI_L}{d\,lnH} < 0$

Middle skilled workers $\frac{d(I_H - I_L)}{d\,lnA_L} = \frac{d(I_H - I_L)}{d\,lnL} < 0, \frac{d(I_H - I_L)}{d\,lnA_M} = \frac{d(I_H - I_L)}{d\,lnM} > 0\ and\ \frac{d(I_H - I_L)}{d\,lnA_H} = \frac{d(I_H - I_L)}{d\,lnH} < 0$

High skilled workers $\frac{dI_H}{d\,lnA_L} = \frac{dI_H}{d\,lnL} > 0,\ \frac{dI_H}{d\,lnA_M} = \frac{dI_H}{d\,lnM} > 0\ \ and\ \frac{dI_H}{d\,lnA_H} = \frac{dI_H}{d\,lnH} < 0$

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[10] More formally, $\alpha_L(i)/\alpha_M(i)$ and $\alpha_M(i)/\alpha_H(i)$ are strictly decreasing

[11] The no-arbitrage condition determines tasks are separated into different thresholds and that different types of workers cannot obtain arbitrage in the performance of the same task. In conventional form: for high and medium skills: $\frac{A_M \alpha_M(I_H) M}{I_H - I_L} = \frac{A_H \alpha_H(I_H) H}{1 - I_H}$ and for medium and low skills: $\frac{A_L \alpha_L(I_L) L}{I_L} = \frac{A_M \alpha_M(I_L) M}{I_H - I_L}$

The behavior of the task thresholds performs similar to intuitive logic; an increase of technological developments that augments the productivity of a certain group of workers leads to an enlargement of the set of tasks performed by these type of workers, simultaneously the set of tasks by other groups is narrowed. This reasoning can be applied in similar manner to an increase of the supply of a certain type of workers.
Empirical evidence suggests that over the past decades several developments (e.g. offshoring and automation) have especially been malicious to tasks performed by middle skilled workers (e.g Goos et al. (2009)). Therefore, the domestic occupational thresholds I_L and I_H are endogenously determined by the relative technological development of an European country.

The replacement and reallocation of tasks by capital relative to labor is not uncommon within economic history. During the Industrial Revolution, James Watt developed a steam engine that conceded continuous process (batch) methods in factories by massively enhancing the available power for workers. This made several jobs obsolete, while it enhanced the demand for skilled laborers (Goldin and Katz, 1998). In addition, several labor (artisanal) tasks were mapped to capital, while at the same time new labor tasks were demanded. The latter consisted primarily of high skilled white-collar occupations and low skilled laborers like operatives (e.g. James and Skinner (1985); Katz and Margo (2013)). Since the introduction of computer technology such task reallocation -that is, capital replacing labor- has been observed at tasks that were carried out in a routine-based approach or were codifiable. Put differently, occupations consisting of tasks of a well-defined set of cognitive and manual activities have been most susceptible to automation, referred to as the demise of production-line tasks. At the same time, computer technology has complemented workers to carry out (novel) complex nonroutine tasks (Autor et al. (2003)). For this reason, Acemoglu and Restrepo (forthcoming), build upon the task-based model, and embed technological innovations as labor replacing tasks, while at the same time, creating novel complex labor-intensive tasks. This process has been referred to as a bifurcation into a limited group of workers that comply to the skills of machine technologies (Cowen, 2013). Or as Hubbard has put it "*One machine can do the work of fifty ordinary men. No machine can do the work of one extraordinary man.*" Within the organization literature, the view that technical change fundamentally changes the organization of firms has been formalized often. For example, Kremer and Maskin (1996) consider a model where skills are imperfect substitutes. In their model accretions in technical progress or inflows of skilled workers increase the matching between skilled workers (similar for unskilled workers). These developments were suffice for several economist (e.g. Caselli

(1999)) to argue human mankind is in the midst of experiencing a 'Third Industrial Revolution'; the information age.

Still, the question remains why low skilled labor 'easy' tasks are so hard to replace by capital. This has become known as the Moravec's paradox; the computational power for robots and computers to carry out high-level reasoning is comparatively low to the enormous computational resources needed for robots to master human actions like perception and mobility, which are needed to carry out low-skilled jobs. As Autor (2014) puts it; these skills are frankly those we almost tacitly apply, but do not explicitly understand. Advances within this field have been sluggish, as documented by high-prize tournaments, where research teams are asked to develop robots with the capability to master several tasks. In this regard, the DARPA Robotic Challenge (DRC) provides an exquisite overview of the scope to which the finest developed robots from all over the world are capable to do 'simple' human tasks. The narrative of falling robots, not capable of getting back up, remains problematic among these 'humanoid' robots. With this comprehension in mind, it is not remarkable that low-skilled manual nonroutine occupations have been less susceptible to automation than middle skilled routine occupations. Contenders widely believe that within a decade this gap may be closed, increasingly making low-skilled jobs susceptible to automation too (The Economist, 2015).

To incorporate automation of tasks in the model noted above, capital with fixed cost r is introduced within the middle skill thresholds: $[I', I"] \subset [I_L - I_H]$. Technological developments that augment the productivity of capital ensures that capital replaces tasks earlier performed by middle skilled workers[12]. In a new equilibrium where thresholds I_L and I_H have been shifted, some middle class workers are now supplied to tasks initially performed by low skilled workers, giving rise to the subsequent hypothesis:

Hypothesis 1: Routine intensive-tasks have been adversely subject to technological developments in European labor markets during the time period 1995-2014, whereas technological developments have surged employment in nonroutine tasks.

It is important to note that while technology may allow certain tasks to be automated, it doesn't imply it necessarily will be. This argument is pointed out by Autor (2013) in a relative cost manner; more advanced countries may comply high labor costs and therefore

[12] Capital only replaces tasks within the middle skilled threshold, i.e. for $i \notin [I', I"]$ capital is zero $\alpha_k(i) = 0$

base its production on robots, while less advanced countries may rely on cheap labor as a production strategy.

Hypothesis 2: The relative domestic technological development has a contracting effect on the middle skilled thresholds, whereas it has an enhancing effect on low- and high skilled thresholds.

The kind of technological development posed in the task-based model above has next to its capability to paraphrase developments in employment levels (e.g. job polarization), also the capability to explain why wages of middle skilled workers did not raise despite vast increases in productivity levels (figure 1). The process of capital replacing labor tasks, has caused an 'excess supply' of middle class workers now performing tasks in which they have a lower comparative advantage. Simply put, if machines produce the same output per hour as (close substitutable) workers for 1 euro, profit-maximizing employers won´t offer hourly wages higher than 1 euro. Research so far tends to confirm the conjecture that the rapid diffusion of computer technology has led to changes in the wage structure (e.g. Krueger (1993); Greenwood and Yorukoglu (1997)).

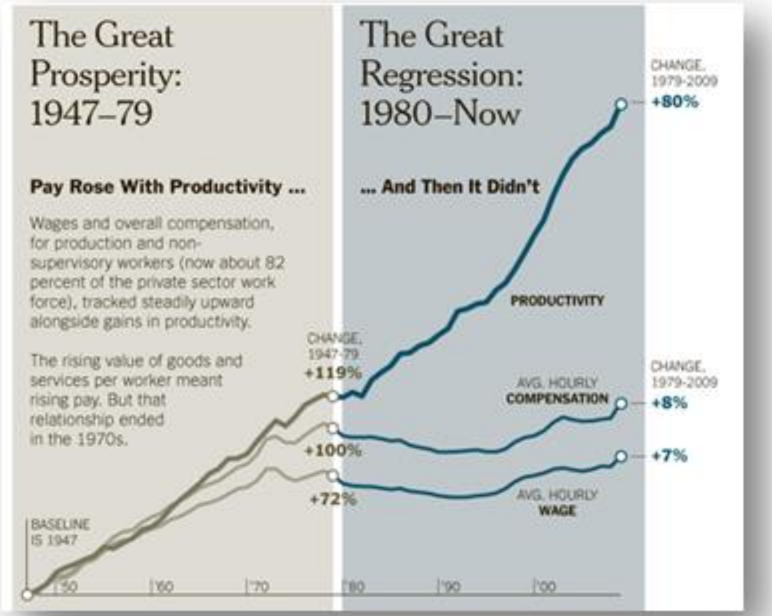

Figure 1; *Source:* Reich, R. B. (2011). The limping middle class. *New York Times*,

Thus, technological development complementing nonroutine tasks coupled with a squeeze of middle skilled workers into lower and higher skilled jobs has attributed towards a widening gap between productivity and average wages. This often has been referred to as *´The Great Decoupling´*. This phenomenon directly subverts the validity of some economic principles put forward as stylized facts by Kaldor (1961) namely; (i) hourly wages keep increasing, and (ii) the relative income shares of capital and labor do not exhibit any trend. Recent evidence by Karabarbounis and Neiman (2014) has shown that the global income share of labor has declined since the early 1980's. These authors document that price declines in information technology were the most dominant factors behind this phenomenon. Many scholars investigating the role between technological change and economic growth subsumed these stylized facts into their theories, in fact, it has been one of the foundations on which macroeconomic models were build.

Analogous to the decoupling of wages, also employment levels have become decoupled from advances in productivity. In the past, technology was mainly perceived to displace ‘dull’ jobs by better ones, and thus the ‘technological employment’ coined by Keynes was only temporary, effectively describing the Luddite Fallacy. Recent advances in technology induced many influential economists to argue otherwise. For example, Leontief (1983) stated that the replacement of workers by capital will be increasingly outrunning the new uses found for labor. If advancements in technology continuously require new type of skills and laborers just simply cannot keep up with the skill sets required, unemployment may not be temporary, but structural.

It has also become increasingly easy to introduce technologies that create enormous amounts of wealth with very few resources in terms of labor and capital. A famous example within the photography industry is the case of Instagram versus Kodak. Only just 15 people were needed to create Instagram, which created a lot of wealth for these owners. Whereas Kodak employing 145000 primarily middle class occupations, filed for bankruptcy at 2012. This is just one example of a larger trend where large firms have a propensity to reduce their need of labor, while their market capitalization is augmented.

In terms of developments in income distributions technology seems to characterize a crucial role. A role in which only the very best within a market gravitate towards gathering all profits. The vital difference between digital- and physical goods markets is that capacity constraints have become relatively unimportant for the former, whereas for the latter it is and remains one of the principles within many fields of economics. When a software engineer creates an application that is comparatively better than the existing ones, it might constitute towards the engineer completely dominating the market, and is likely to make some tasks performed by laborers redundant (e.g. TurboTax). Therefore, relative performance in digital markets has become key for income distributions, whereas physical markets are still subject to absolute performance. The key feature of information technology fosters this process; it gives power to the consumer by giving them the ability to rank products, which reveals transparency about which digital products are perceived to be the best. In addition, the digital market has become a global market, with a steadily increasing audience, due to information technology also spreading through less developed countries. As marginal costs in digital markets tend to converge towards zero, market leaders experiencing economies of scale can keep undercutting possible aggressive entrants. For this reason, Frank and Cook (1996) coined the term '*the winner-take-all society'*. Being second best in a digital market is simply not good enough (e.g. Rosen, 1982). Technological change may thus next to being skill-biased, even be more biased towards superstars.

Comparative statics of relative wages

The relative wages of each skill group of laborers in the task-based model can be found under the assumption that the law of one price prevails within each skill group[13]. These conditions provide the insight that the relative wages are simply a function of the tasks assignments to skills (in equilibrium) and relative supplies of skills. In order to retrieve comparative statics logs are taken from the relative wage conditions outlined in footnote 13. Now the effects of distinct types of factor augmenting technological development on relative wages of workers will be assessed. Similarly, the effect of developments in skill supplies on the relative wages can be estimated. These comparative statics are summarized below:

Directed low skilled $\frac{d\ ln(w_H/w_L)}{d\ lnA_L} < 0$, $\frac{d\ ln(w_M/w_L)}{d\ lnA_L} < 0$ $\frac{d\ ln(w_H/w_M)}{d\ lnA_L} > 0$ *Supply low skilled* $\frac{d\ ln(w_H/w_L)}{d\ lnL} > 0$, $\frac{d\ ln(w_M/w_L)}{d\ lnL} > 0$ *Directed middle skilled* $\frac{d\ ln(w_H/w_M)}{d\ lnA_M} < 0$, $\frac{d\ ln(w_M/w_L)}{d\ lnA_M} > 0$, $\frac{d\ ln(w_H/w_L)}{d\ lnA_M} \lesseqgtr 0$ *Supply middle skilled* $\frac{d\ ln(w_H/w_M)}{d\ lnM} > 0$ $\frac{d\ ln(w_H/w_L)}{d\ lnM} \lesseqgtr 0$ *Directed high skilled* $\frac{d\ ln(w_H/w_L)}{d\ lnA_H} > 0$, $\frac{d\ ln(w_M/w_L)}{d\ lnA_H} < 0\ and\ \frac{d\ ln(w_H/w_M)}{d\ lnA_H} > 0$ *Supply high skilled* $\frac{d\ ln(w_H/w_L)}{d\ lnH} < 0$ $\frac{d\ ln(w_H/w_M)}{d\ lnH} < 0$

The response of the relative wages to technological developments directed towards a skill group is intuitive; an increase of technological developments that augments the productivity of a certain group of workers leads to an improvement of relative wages of this group relative to the other groups. Perhaps less intuitive is the response of for example w_M/w_L to technical progress directed towards high skilled workers. This effect consists of both a direct effect, which reduces the tasks performed by middle skilled workers, and an indirect effect, which reduces the wages of middle skilled workers, expanding the set of tasks these workers perform, thereby having a negative impact on low skilled workers. In this model the direct effect always dominates the indirect effect and therefore w_M/w_L declines.

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[13] The no-arbitrage condition outlined in footnote 11 together with the assumption of the law of one price determines that the costs of different tasks thresholds are equalized. In conventional form: for high and medium skills: $\frac{P_M A_M M}{I_H - I_L} = \frac{P_H A_H H}{1 - I_H}$, which after rewriting gives; $\frac{P_H}{P_M} = \left(\frac{A_H H}{1-I_H}\right)^{-1}\left(\frac{A_M M}{I_H - I_L}\right)$, similar for medium and low skills: $\frac{P_M}{P_L} = \left(\frac{A_M M}{I_H - I_L}\right)^{-1}\left(\frac{A_L L}{I_L}\right)$. Given that each skill group obtains its marginal product, (i.e. for low skilled workers $w_L = P_L A_L$), relative wages are given by: $\frac{w_H}{w_M} = \left(\frac{1-I_H}{I_H - I_L}\right)\left(\frac{H}{M}\right)^{-1}$ and $\frac{w_M}{w_L} = \left(\frac{I_H - I_L}{I_L}\right)\left(\frac{M}{L}\right)^{-1}$

The behavior of relative wages to an accretion in the supply of a certain group of workers is straightforward; it puts pressure on the wages of this group of skilled workers due to a higher within-skill competition. Lastly, the effect of an increase in the supply of middle skilled workers and technical progress directed towards middle skilled workers is unambiguous, and merely depends on the comparative advantage of low and high skilled workers relative to middle skilled workers. In the situation where high (low) skilled workers have a strong (weak) comparative advantage relative to middle skilled workers, medium workers will primarily replace tasks performed by low skilled workers and thus w_H/w_L expands. In light of the superstar phenomenon, technological change seems to be primarily biased towards high skilled workers. Beside this, capital has displaced many middle skilled workers that carried out routine-based tasks. To incorporate automation of tasks in the model noted above, capital with fixed cost r is introduced within the middle skill thresholds: $[I', I"] \subset [I_L - I_H]$. Technological developments that augment the productivity of capital ensures that capital replaces tasks earlier performed by middle skilled workers[14]. In a new equilibrium where thresholds I_L and I_H have been shifted, some middle class workers are now supplied to tasks initially performed by low skilled workers. Assuming that high (low) skilled workers have a strong (weak) comparative advantage relative to middle skilled workers, generates the subsequent hypothesis:

Hypothesis 3: Technological developments in Europe during the past two decades have caused a widening wage inequality in terms of w_H/w_L and w_H/w_M and a contracting wage inequality in terms of w_M/w_L.

Related literature about wage inequality

There are numerous other factors provided within the economic literature that have attributed to some observed patterns of wage inequality. Firstly, after World War II, political movements in favor of social reform caused governments to devote more weight to workers' rights and to widely stimulate access to education. This resulted in the ´Great Prosperity´ abiding until the 1980´s. At the dawn of the 80´s though, labor unions in most advanced countries have lost their powerful influence partly determined by labor market institutions (e.g. Freeman & Needels, 1991). It is skill biased technological change that has enlarged the outside option of skilled workers. In this way the cooperation between workers with different

[14] Capital only replaces tasks within the middle skilled threshold, i.e. for $i \notin [I', I"]$ capital is zero $\alpha_k(i) = 0$

skill sets has contracted, leading to de-unionization and loss in power of labor unions (Acemoglu et al. (2001). Evidence found by several authors (e.g. DiNardo et al. 1996) suggests that de-unionization may account up till ten percent of the wage gap between graduates in high schools relative to college graduates in the USA.

Second, another major consideration of the recent upsurge in information technology has directly been coupled with flourishing gains from trade. The latter element stimulated businesses to offshore part of their production in goods and services to other (low-wage) countries. Dating back to the comparative advantage principles of David Ricardo, Mankiw commented on offshoring as the ´*latest manifestation of the gains from trade*', which initially expressed a favorable arrogation of offshoring under economists. At the dawn of the 2000's however, economists expressed their distress about the implications of offshoring to the amount of domestic jobs and its rewards (e.g. Blinder (2006)). More specifically, factor price equalization is especially malicious to workers in relative high wage countries, as the incremental global supply of substitutable workers will put downward pressure on these wages (Spence, 2011). Earlier research suggest that the incremental labor force of low- and high skilled workers in the global economy has most primarily reduced wages of low-skilled workers in Western countries (e.g. Wood (1994). It must be noted that recent advances in automation technologies may now reverse the location strategy of multinationals, as the costs of automation technologies are decreasing, being bound to Moore's law, thereby decreasing the comparative advantage of developing countries that rely on low wages.

Recent literature has put forward another explanation for the divergence in real wages; the increasing size of firms. Mueller et al. (2015) argue that the benefits of economies of scale are not equally distributed among workers within firms. Using data of Britain, they found that the expansion of firm sizes generally perpetuates the wages of the most high skilled workers relative to low and moderately skilled workers. That is, unique skills at the top of firms tend to reap all the benefits of economies of scale. Bollard et al (2014) state that the pattern of increasing firm sizes will only accelerate the upcoming years. According to these authors, larger firms have higher productivity levels that keep increasing over time. Their relative competitive advantage will therefore increase, raising the barriers of entry costs for possible startups. The role of labor market institutions is exemplified herein, and should promote competition to hinder the divergence in firm sizes eventually to lead to divergences in wages.

III. Data description

This section describes the dataset used in order to estimate the effect of technological developments on the occupational structure of labor markets. The evaluation period endures from 1995 until 2014, for both practical and empirical reasons. Practically, this is the most extensive period for which annual data for an European sample of occupational employment levels and technological development measures are available. Empirically, this period was coupled with a rapid diffusion of computer- and information technologies, which have led several economist to argue human mankind is in the midst of a 'Third Industrial Revolution'.

A. Employment statistics

This paper employs one main data source for annual domestic occupational structures; the harmonized European Union Labor Force Survey (LFS), collected by national labor institutions and correspondingly modified and reported by Eurostat for a 20-year period ranging from 1995 -2014. The LFS includes a wide variety of annual country data about employees with information about educational attainment, age group, economic activity, occupational status and gender. In total, the domestic occupational structure data consists of employment levels of nine distinct occupational types, which are divided according to the International Standard Classification of Occupations (ISCO)[15]. These employment levels per occupation are correspondingly rescaled [0,1] and ranked on a range of skills that are required within the occupational category (figure 2). This ranking is similar to other studies that have studied developments within the structure of employment (e.g. Goos et al. (2009).

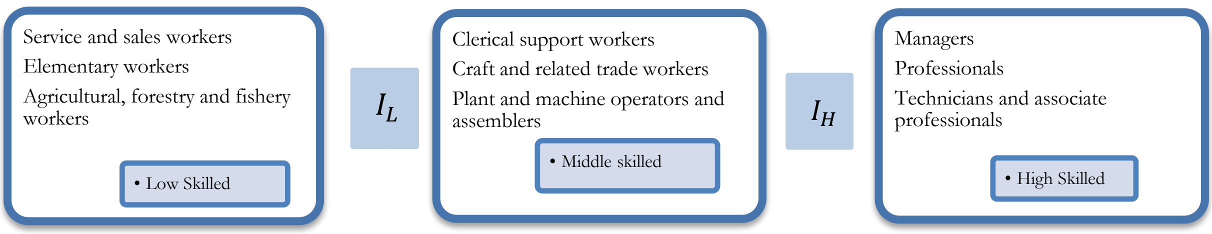

Figure 2: *Mapping of occupational types to skill requirements*

In an European dataset of 33 countries the following countries are excluded due to limited available data; Turkey, former Yugoslavian republic of Macedonia, Malta, Cyprus, Croatia and Bulgaria[16].

[15] See appendix table 10 for further detailed information about the division of workers among occupations.
[16] Therefore, for the empirical analysis, data is used for all subsequent countries; Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia,

B. Income distribution data

In this paper, both gross- and disposable income inequality will be examined. The most extensive set of data concerning the latter is available in the World Income Inequality Database (WIID V3.0B) reported by UNU-WIDER. To ensure high reliability of the presented data, the dataset consists of a combination of national survey statistics, estimates from the OECD and Eurostat. In each country, annual statistics are represented in both quantiles and deciles. Income inequality between occupational groups is computed as the ratio of for example the highest income decile relative to the third decile.

The recent publication '*Capital in the twenty-first century'* by Thomas Piketty marked a revival in the public interest of the (gross) distribution of incomes. For economist however, this trend already started at the dawn of the 2000's, with studies by Piketty (2001, 2003) of the long-run distribution of top incomes using tax data. This has induced several economist to study the evolution of top incomes throughout the twentieth century at a country level (e.g. Dell (2007); Nolan (2007); Alverado et al (2010), which has been summarized by Atkinson and Piketty (2010) at a global perspective. Although, the use of tax data is still subject to underestimations of the top-income shares, e.g due to tax avoidance and tax evasion, the presented dataset; The World Top Incomes Database, presents the most reliable dataset of gross top income shares to date. This dataset has been made available by the Paris School of Economics. Making use of the gross interdecile ratios by the OECD, the top 10% gross income shares have been used to compile interdecile ratios for the top 5, 1, 0,5 and 0,1%. Developments in these ratios are simply compiled from changes from annual ratios through time.

C. Technological development indicators

In the midst of the 1970´s productivity growth levels stagnated among the advanced economic powers of that time, which induced economist (e.g. Cowen) to state that: *"We have been living off low-hanging fruit for several hundred years. The trees have become more bare than we think."* During the early 1990's, Robert Solow made a statement reciprocal to this tenor of thinking: "*We see the computer age everywhere, except in the productivity statistics.",* which is known as the productivity paradox (Brynjolfsson and Hitt, 1998). In response, several economists argued that the economic benefits (or fruits) of computer technologies already had been captured. For example, Gordon (2000) stated that the internet was only a minor

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Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom.

innovation compared to earlier great innovations. However, a rampant consensus has spread that technological developments in form of innovations can actually regrow the fruits of these trees, or equivalently, new trees with new fruits have been planted. This predominantly occurs due to *general purpose technologies* (GPTs), which have a deep new pervasive impact on productivity growth in several sectors within the economy (Jovanovic and Rousseau, 2005). Furthermore, they should be improving over time and able to foster (complementary) innovations. The latter is especially relevant and has led to so called 'new growth' theory, which is perhaps best portrayed in the mathematical model of Weitzman's '*Recombinant Growth'* paper. In this model capital forms (e.g. machine tools, laboratories) are processing new forms of knowledge (seed ideas) over time. The combination and recombinations of these forms of knowledge fosters productivity growth. Recently several cloud-based innovation platforms (e.g. Innocentive and Kaggle) have been set up where companies can demand ideas and solutions to specific problems. To tackle these problems, anyone can enter a competition to provide ideas and solutions. Correspondingly, the best solutions and ideas are rewarded by companies. This phenomenon is currently recognized as *´crowdsourcing´*. These platforms essentially draw inspiration from the Recombinant Growth paper by Weitzman. For this reason, information and communication technology (ICT) has been called an GPT, being able to spur new innovations by combining and recombining ideas.

This paper draws from two main databases of measures of technological advancement; (i) one collected by UNESCO, and correspondingly reported by the World Bank, and (ii) one by Eurostat. The measures of technological development can be disaggregated in three separate indicator groups. First, annual domestic internet diffusion per 100 people is used a proxy for computer use among the working force, thereby it may also measure the enhancement of ICT, which could have induced firms to offshore part of their production to foreign countries. In addition, as these cloud-based platforms have shown, it may also proxy for import of ideas which can be turned into innovations. Second, gross domestic R&D expenditures (as a % of GDP) and researchers in R&D (per million people) are used as a broad measure of the production of 'knowledge'. The latter may include new patents, which enable new production methods. Generally speaking, the intensity of R&D expenditures will affect the comparative advantage of a certain sector or in this case, primarily high skilled labor occupations. Third, different measures of patent applications are employed[17]. One

[17] Patent applications are either worldwide (filed at the Patent Cooperation Treaty), or at domestic patent offices. When patents are granted, inventors have the exclusive right to exert the invention for a limited time of 20 years.

holistic measure of the number of patent applications per 1000 residents of the workforce, the number of high-tech patents per million domestic residents, and the number of patents for computer and automated business equipment per million inhabitants. The latter is expected to exert a contracting effect on the demand for jobs carried out in a routine-based approach, the former two are mainly expected to enhance the demand for high skilled labor.

By all means, the production of 'knowledge' does not have to be confined within domestic boundaries. Acharya and Keller (2009) found that foreign technology spillovers are a major determinant of income differences between countries. These spillovers naturally occur due to technology imports. For this reason, a measure of ICT imports as a share of total domestic imports, reported by the World Bank, will be included in the estimations to control for spillovers. It must be assured that all technological advancement indicators employed in this paper only aim to capture the effect of technology related patents. Thus when a company develops certain technologies without patenting its innovations, it could possibly diffuse through the economy and affect domestic occupational and wage structures. This public good view of technology is generally seen as potentially closing the 'technology gap' between countries (Barro and Martin, 1995). Research so far has mainly focused on how foreign direct investments affect the diffusion of knowledge (Barrel and Pain, 1997). This mechanism is beyond the scope of this paper.

The domestic technological advancement of each measure is computed on a scale of $[0,1]$, where the value of 1 is designated to the country with the largest sum of the measure of technological advancement throughout the period 1995-2014. Correspondingly the technical advancement of particular country is measured using the domestic sum of the measure up till that year. For example, Finland has had the largest number of high-tech patent applications per million residents throughout 1995-2014, namely 1682. This is correspondingly rescaled to 1 for Finland in 2014, whereas each years´ aggregated value of the high-tech patents applications is used as the relative measure of technological advancement up till that year for a domestic entity. In this paper, it is assumed that the patented inventions affect domestic occupational- and income structures in recombinant growth fashion. That is, similar innovations that recombine ideas act as complement to earlier patented technologies during specific time intervals. Weitzman (1998) has provided an exquisite overview of inventions that occurred in recombinant growth fashion. A fashion that already arose during the invention of the electric candle by Thomas Edison. The implicit use of technical invention patents as proxy for technological advancement entails the recombinant growth notion that inventions –most primarily GPTs- need time to propagate through the economy and surge productivity levels of workers.

Technological advancement is often perceived to occur in S-waves around an exponential growth sequence. Thus, slow growth is ensued by rapid growth, which matures as time goes by, superseded by (in)finite consequential waves. This could be seen as a process of incremental innovations that foster slow growth, while suddenly the recombinations of incremental inventions provides a radical innovation, coupled with rapid technical growth. Such a process can also be referred to as a Schumpeterian creative destruction wave, where each wave represents a certain technology paradigm[18]. In particular, Bresnahan et al. (2002) have shown that innovations in terms of new technologies are complementary to reorganizations within the workplace. These reorganizations were coupled with more sophisticated systems like incentive systems and information flows, which tend to require more educated workers. Earlier research by Brynjolfsson and Hitt (2003) has shown these time intervals tend to endure roughly five to seven years[19].

Thus, for each of these measures, technological change is computed in time intervals, for example the value of year *t+5* minus year *t*. It must be noted that this measurement approach tacitly assumes that a certain patent type exerts an identical effect on domestic occupational structures and relative income distributions. Although it is conceivable that individual patents have a differential impact, on an aggregate country level it is presumable that the relative amount of patent types roughly exert a similar effect.

Lastly, as an alternative for the precedent technological advancement measures, the holistic technological development quantification by prominent economist Robert Solow (1957) will be employed. The OECD has reported annual multifactor productivity growth levels (MFP) for fifteen European countries, which builds upon work of Maddison whom has made several data statistics concerning economic growth available at the Groningen Growth and Development Centre. The MFP statistics are reciprocal to the Solow residual, i.e., the remaining part in GDP growth which cannot be accounted to labor and capital input growth. It is urgent to note that MFP only reflects disembodied technological change and therefore does not embody technological developments captured in labor and capital inputs (e.g. factory redesign or enhancement in quality of capital).

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[18] These waves have been observed within many technical industries- e.g. recently the mobile phone industry- and are occurring at an exceeding frequency over time (see Kurzweil (2005: 51-55) for a detailed analysis).

[19] Thus, complementary investments in (information) technologies and reorganizational structures within firms affect labor demand with a lag in time (e.g. Aguirregabiria and Alonso-Borrego, 2001). This finding can be inferred by Cappelli and Wilk (1997), who document that technical changes have surged the extent of screening for new applicants in most primarily high-wage occupations.

D. Educational attainment statistics

The response of task thresholds emanated from the task-based model implied that an increase of the supply of a certain type of workers perpetuates to an enlargement of the set of tasks performed by these type of workers, simultaneously the set of tasks by other groups is narrowed. For this reason, educational attainment levels collected by the European Union LFS are once again adopted (World Bank). The educational attainment of the labor force is measured in nine distinct levels ranging from [0,8]. The domestic labor forces are mapped to three educational attainment groups referring to the International Standard Classification of Education (ISCED); below primary, primary and lower secondary [0,2], upper and post-secondary [3,4], and tertiary or higher [5,8]. The relative shares of each group are simply measured on scale of [0,1].

E. Control variables

The emergence of the steady jobs notion after the second World War implied that trade unions characterized a compelling and efficacious factor to fight for- and defend rights- of laborers. This notion has started to crumble the last couple of decades, most predominantly due to deregulation in labor markets and the dispersion of occupation types (Fairbrother and Yates, 2013). In addition, the rising importance of globalization and technological change induced several governments to implement neo-liberal policies to augment their labor competitiveness, thereby reducing the vigorous influence of trade unions to compress wages. Therefore, the trade-union membership rate is used as a proxy for whether labor market institutions either favored international labor competitiveness policies, or gave (more) priority to rights of laborers. Alesina and Zeira (2006) have shown how the diffusion of technology was related to labor institutions. In particular, strong rights of low skilled workers in Europe encouraged employers to substitute labor by machines. Hence, the trade-union membership density indicator is introduced as a control variable, reported by the OECD.

The inflow of different types of skilled workers to advanced European countries may have induced companies to develop technology complementing the skills of these immigrants. To control for these developments, net migration as percentage of the domestic labor force, supplied by the Worldbank, is taken in consideration. Table 1 provides an overview of descriptive statistics of the key variables of interest.

Grossmann and Rossi-Hansberg (2006) have raised voice of redefining offshoring in a task-trade based paradigm instead of a goods trade paradigm. Several authors have tried to introduce an offshorability measure correspondingly mapped to tasks[20]. Despite a disagreement about this measure, this paper draws from the offshorability measure of Goos et al. (2014), which builds on a survey approach by Blinder and Krueger (2013), where both employees and experts designate an offshorable scale to tasks.

Table 1: Mean Levels of Key Variables	**Descriptive Statistics**				
	Entire Sample	Percentage Point Change 1995-2014		Entire Sample	Percentage Point Change 1995-2014
Dependent Variables			*Independent Variables*		
Services and Sales Workers	0.1498 (0.0354)	0.0407 (0.0256)	Internet Diffusion	0.3733 (0.3224)	0.7741 (0.1270)
Elementary Workers	0.0991 (0.0375)	-0.00996 (0.0226)	Total Patents	0.1603 (0.1689)	0.2467 (0.228)
Agriculture, forestry and fishery	0.0122 (0.0056)	-0.0039 (0.0049)	High-tech Patents	0.1002 (0.1548)	0.2055 (0.2563)
Clerical Support Workers	0.1176 (0.0404)	-0.0384 (0.0279)	Automation Patents	0.1030 (0.1667)	0.2271 (0.272)
Craft and Related Trade Workers	0.1520 (0.0493)	-0.0584 (0.0435)	R&D Expenditures	0.2225 (0.1920)	0.3890 (0.232)
Plant and Machine Operators and Assemblers	0.1033 (0.0363)	-0.0229 (0.0273)	Trade Union Density	0.3633 (0.2179)	-0.1370 (0.150)
Managers	0.0554 (0.0299)	0.0015 (0.0220)	Net Migration	0.0058 (0.0137)	0.1225 (0.257)
Professionals	0.1522 (0.0469)	0.0833 (0.0585)	Primary Education	0.3345 (0.1419)	-0.1826 (0.0919)
Technicians and Associate Professionals	0.1584 (0.0451)	0.0010 (0.0379)	Secondary Education	0.4653 (0.1339)	0.03730 (0.0751)
			Tertiary Education	0.2003 (0.0796)	0.1453 (0.0542)
Observations	540	27		540	27

Notes: Standard errors in parentheses. The dependent variables are occupational shares scaled on a range of [0,1] and make up to a total of 1. The measures of domestic technological advancement are also scaled on a range of [0,1] where the value 1 is given to the country with the highest respective technological attainment in 2014 of the relevant measure, each domestic annual value within this category is scaled relative to this value. Furthermore, also the control variables refer to a scale of [0,1], where the educational measures add up to 1. Details about the relative gross and disposable income distributions reported in the dataset references.

Even though tasks that are exercised in a task-based paradigm are both susceptible to offshoring and automation, the latter concepts are distinct features. The offshorability of tasks

[20] It must be noted that offshoring and offshorability aren´t two sides of the same coin; the former relates to an observable action, whereas the latter is merely a characteristic of a certain task.

has also been relevant for complex tasks, requiring high levels of skill. For example, several professional and technical service jobs appear to be more offshorable than jobs where lower skills are required. The offshorability measures are reported in Appendix table 1, and are employed as comparison to the estimates of the internet diffusion variable.

IV. Econometric framework

In an attempt to estimate the effects of technological change on the occupational structure of European labor markets data of a balanced panel of 27 countries is used for a duration of 20 years. The precedent recombinant growth assumption entails that the sample is broken down to five year intervals. In the technological advancement manner, the response variable is the proportional employment level at year t of an occupational group j relative to the sum of all distinct occupational groups, designating to the task-based approach scale; $[0 - I_L - I_H - 1]$. The main explanatory variables comprise the measures of technological development[21] outlined in the precedent section. In addition, a number of control variables will be included to mitigate the omitted variable bias, these consists of the measures of trade union density membership, the relative magnitude of net migration flows towards the relevant country, and the educational attainment level of the workforce. The following multivariate equation form will be estimated:

$$Occup\_emp_{ijt} = TD_{it}'\alpha + X_{it}'\gamma + \varphi_i + \delta_t + \epsilon_{it} \qquad (1)$$

Where TD_{it} is a vector of five year aggregated technological development measures and X_{it} is a vector of five year aggregated control covariates $[i = 1,2 \ldots .27; j = 1,2 \ldots 9]$. Still, unobserved country-specific effects may be related to technological developments as the determinant of the occupational structure of European countries. If this is the case, unobserved heterogeneity between countries is correlated with the error term ($cov(\alpha_j, \epsilon_{it}) \neq 0$), which may cause biased OLS estimations of α_j. Generally, the diffusion of technology is largely embedded in the time-invariant cultural roots of a country. Therefore, country-specific fixed effects (φ_i) are included dependent upon the outcome of a likelihood-ratio test of the redundancy of fixed effects. Additionally, the same method is used for fixed time effects denoted by δ_t.

[21] (i) internet diffusion (per 100 people), R&D expenditures (as % of GDP), (iii) patent applications (per 1000 residents) , (iv) high-tech applications (per million inhabitants), (v) automation patents (per million residents).

To address the effects of technological change on the occupational structure of domestic labor markets the following first differenced equation form will be estimated;

$$(\Delta Occup\_emp_{ijt}) = \mu + \Delta TD_{it}{}'\alpha + \Delta X_{it}{}'\gamma \; + \delta_t + \epsilon_{it}^{*} \qquad (2)$$

Where the regressand is the relative five year change in occupational employment of occupation type *j* for country *i* (*t* reflects five year intervals). The slope coefficients ought to be estimated are epitomized by the vector ΔTD_{it} which resemble the five year technological change parameters in percentages. The vector of coefficients can therefore be interpreted as the five year elasticity of technological change measures with respect to the relative change in the share of domestic occupational group *j*. Furthermore, five year changes in control variables are included that may be related to technological change as determinant of occupational structures. By the virtue of first differenced data, only time fixed effects δ_t will be included to absorb unobserved year-specific influences[22]. Lastly, the error term ϵ_{it}^{*} $(= u_{it} - u_{i,t-5})$ is assumed to be contemporaneous. For this assumption to hold, the responsiveness of the right-hand covariates are assumed to be the same across all countries, to correct for a possible disparate responsiveness white period standard errors will be employed in all estimations.

To address the effects of technological change on domestic relative income distributions estimation strategy (2) is stipulated using first differences, where only the dependent variable is conversed to the domestic relative income share between two income groups:

$$(\Delta Income\_sh_{irt}) = \mu + \Delta TD_{it}{}'\alpha + \Delta X_{it}{}'\gamma \; + \delta_t + \epsilon_{it}^{*} \qquad (3)$$

The slope coefficients ought to be estimated are again presented by the vector ΔTD_{it} which resemble the five year technological change parameters in percentages. In this matter, the vector of coefficients can be interpreted as the five year elasticity of technological change measures with respect to the relative domestic income share of two income groups (*r*). Furthermore, five year changes in control variables are included that may be related to technological change as determinant of income inequality. By the virtue of first differenced data, only time fixed effects δ_t will be included to capture unobserved year-specific influences. Alternatively, period weights (estimated generalized least squares) will be used to correct for a disparate covariate responsiveness, in order to satisfy the assumption that the error term ϵ_{it}^{*} is contemporaneous.

[22] First-differenced data takes account of unobserved country variables, therefore merely a method to capture unobserved country- specific fixed effects.

V. **Results**

First this paper will shed scrutiny on the effects of technological development on the occupational structures of European labor markets. Estimation equation (2) is reported in table 2 for each distinct occupation[23]. All measures can be interpreted as the five year elasticity of the relevant variable with respect to the relative share of the domestic occupational group *j*. For example, a ten percent increase in the domestic internet adoption rate is associated with a 0,25% increase (decrease) in the occupational thresholds of respectively technicians and clerical laborers (cp).

The outputs essentially display no uniform pattern among the technological advancement measures. The diffusion of internet has complemented three occupations; (i) services and sales workers, (ii) technicians and associate professionals and (iii) managerial laborers, whereas increases in the internet diffusion have led to contracting thresholds of clerical and craft workers. Comparing these effects with the offshorability scale for occupations of Goos et al. (2014, Table 1 Appendix) yields the insight that both measures are considerably related; internet diffusion as a proxy for ICT has business provided the ability to be better able to offshore part of their production to foreign (low) wage countries. Similarly, those occupations that are hard to offshore have taken advantage using the internet, which is imaginative using the combinatorial growth fashion. It should not be surprising that occupations that require effective decision making rely on good quality information, the internet has offered this by making a stunning amount of information available for everyone. Also, the internet as a communication tool has increasingly closed the gap between developing countries and advanced Western countries. Brynjolfsson and McAfee (2014) portray this as more ‘eyeballs’ that have been added to our stock of useful knowledge. Occupations that require quality information and solutions to problems have been able to use the world´s enhancing stock of knowledge creators and innovators to their own benefit.

The estimation outputs for the variable R&D expenditures confirm the conjecture that (changes to higher) expenditures in the production of ‘knowledge’ indeed complements high-skilled occupations, while the low and middle skilled class occupational thresholds are declining in the domestic R&D expenditure intensity. Simply put, R&D expenditures seem to

[23] More specifically, the measures are computed for the intervals 2000-2004, 2005-2009 and 2010-2014. For continuity of the results, the interval 1995-1999 is not reported in table 2. Further details enclosed at the robustness tests part A using longer time intervals. Appendix table 2 provides an overview of the same estimation strategy using annual changes. This table reports the ‘productivity’ paradox; even though mankind is experiencing unprecedented advances in technology, on an annual basis there seems to be no clear pattern. The same estimation strategy has also been employed for three year intervals, the results for this regression indicated that the measures of patents and R&D expenditures do indeed more time to have a significant impact on the occupational thresholds. The other variables were of similar sign and significance as the regression in table 2.

produce technologies where higher skilled laborers are required, thereby enhancing the comparative advantage of high-skilled labor occupations. On the other hand, it consequences in contracting thresholds of the low- and middle skilled occupations.

Table 2: Technological change effects on changes in occupational thresholds	**Dependent Variables**[a,b,c]								
	Δ Service and Sales	Δ Elementary	ΔAgriculture, forestry and fishery	ΔClerical support	Δ Craft and related trade	Δ Plant and machine operators	Δ Managers	ΔProfessionals	Δ Technicians
Independent Variables									
ΔInternet diffusion	0.0178 (0.010)*	-0.0011 (0.0030)	-0.0044 (0.0009)***	-0.0249 (0.0092)***	-0.0174 (0.009)*	0.0268 (0.094)	0.0221 (0.0046)***	-0.00345 (0.0146)	0.0251 (0.010)**
ΔTotal patents	0.0138 (0.029)	0.00590 (0.044)	0.0173 (0.0061)***	-0.0171 (0.025)	-0.0132 (0.046)	-0.0426 (0.045)	0.0289 (0.029)	-0.0211 (0.049)	0.0513 (0.048)
ΔHigh-tech patents	0.110 (0.030)***	0.0960 (0.023)***	0.0137 (0.0085)	0.0748 (0.042)*	-0.101 (0.076)	0.0823 (0.015)***	0.127 (0.042)***	-0.375 (0.091)***	-0.0661 (0.052)
ΔAutomation patents	-0.0218 (0.014)*	-0.0595 (0.018)***	-0.0073 (0.0092)	-0.0901 (0.023)***	-0.0896 (0.037)**	-0.0517 (0.0090)***	-0.112 (0.073)	0.236 (0.071)***	0.0290 (0.051)
ΔR&D expenditures	-0.138 (0.059)**	-0.0571 (0.011)***	-0.0157 (0.0068)**	-0.0535 (0.011)***	0.144 (0.087)*	-0.0632 (0.023)***	0.0174 (0.074)	0.0195 (0.067)***	0.0567 (0.026)**
ΔICT Imports	-0.00402 (0.019)	0.0276 (0.015)*	-0.0085 (0.0048)*	0.0507 (0.016)***	0.0041 (0.025)	0.0219 (0.0041)***	-0.010 (0.027)	0.0400 (0.025)	-0.0365 (0.0036)***
ΔUnionization	-0.0411 (0.046)	0.166 (0.012)***	-0.0159 (0.013)	0.0279 (0.0090)***	0.0285 (0.034)	-0.0161 (0.0095)*	-0.00007 (0.021)	-0.0513 (0.053)	-0.0700 (0.018)***
ΔNet migration	0.0203 (0.030)	0.0089 (0.0097)	0.0084 (0.0014)***	-0.0253 (0.0085)***	-0.0479 (0.017)***	-0.0247 (0.012)**	0.0061 (0.030)	-0.0049 (0.030)	0.0372 (0.042)
ΔPrimary education	-0.0357 (0.0061)***	-0.0215 (0.002)***	0.0072 (0.0035)***						
ΔSecondary education				0.0103 (0.0050)**	-0.0242 (0.0044)***	0.0183 (0.0027)***			
ΔTertiary education							0.0195 (0.0051)***	0.069 (0.019)***	0.0214 (0.0052)***
Constant	0.0188 (0.0037)***	0.0076 (0.0027)***	-0.00022 (0.00010)**	0.0493 (0.026)**	-0.0213 (0.0020)***	-0.00312 (0.0024)	-0.0023 (0.0057)	0.00179 (0.0081)	-0.0089 (0.0021)***
Model Information									
Time FE	Yes	Yes	No	Yes	No	No	Yes	No	Yes
Observations	81	81	81	81	81	81	81	81	81
R^2	0.254	0.367	0.216	0.372	0.201	0.237	0.268	0.533	0.310

[a]Dependent variables in percentage point five year change in respective occupational share of total domestic employment levels, independent variables refer to five year changes in the relevant variable, evaluation period intervals include 2000-2004, 2005-2009 and 2010-2014. [b]White period standard errrors in parentheses; [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively, task-intensity and offshorability scale reported in Appendix

The behavior of the thresholds to developments in total patents applications per 1000 residents do not reveal a clear pattern, except that it leads to an accretion in the thresholds for the skilled agriculture, forestry and fishery laborers. A closer look at the type of patents indicate that, perhaps strikingly, changes to higher high-tech patent applications intensities do not widen the high-skilled labor occupations (only managerial), yet it does widen the thresholds of most of the low- and middle skilled occupations. Possibly therefore, high-tech innovations reduce the need for high-skilled laborers; new highly technical processes thus make high-skilled occupations obsolete.

The results for changes in automation patents resonates with the notion that predominantly middle-class (and elementary) occupations have been susceptible to automation of tasks these workers initially performed, which is not startling since these occupations possess most routine-based task characteristics (See Appendix table 1). So innovative technologies making use of logarithms that handle pattern recognition systems have made routine task laborers increasingly replaceable. More interestingly, automation innovations also enhance the high skilled occupational thresholds, which can be justified by the actuality where automation innovations usually enable or even urge organizational co-inventions. This phenomenon is not unconventional within economic history; while factories were mainly driven by steam engines during the Industrial Revolution, the invention that electricity brought to factories was initially not conjoined with a reorganization of factory design. Even new factories were built on old designs. However, when time passed by, factories designs were modified, demanding new types of laborers, which eventually led to a vast enhancement in the productivity levels of factories (David, 1990).

Furthermore, the results seem to indicate that less advanced European countries in terms of technology import ICT goods and services at a higher intensity. This can be seen as domestic technological companies not having the competence to automate routine-based tasks, which induce companies to import ICT goods and services that enhance the capability of laborers performing middle skilled tasks, to process novel information. Obviously, changes towards a higher ICT intensity also reduce the demand for domestic technicians, and thus has a contracting effect on the thresholds of technicians and associate professionals.

The decline in trade union membership rates has been emphasized in the economic literature primarily to elucidate patterns in wage inequality. The estimates suggest this phenomenon has been most malicious to clerical support and elementary laborers in terms of employment levels. It must be acknowledged that the presence of endogeneity in this indicator cannot be ruled out. For example, the existence of strong trade unions could have induced employers to develop technologies that have substituted labor for capital, which reduced trade union membership (e.g. the Alesina and Zeira, 2006 channel). In addition, these occupations have been susceptible to automation and offshoring, which is likely to have led to a decrease in these types of jobs and thus trade-union membership.

Lastly, the behavior of the tasks thresholds to changes in net migration and the educational attainment of workers invoke the market size theory of Schmookler; the relative decline of primary educated workers and increase tertiary educated workers has induced companies to invent skill-biased technologies. In magnitude, an increase in the relative supply group of skilled workers of one percent over a time interval of five years is associated with enhancing occupational thresholds respective to the skill ranging from 0,01% to 0,07%. The negative signs for elementary and service/sales occupations seem to indicate that despite the decline of primary educated workers, the thresholds of low skilled occupations still have widened due to an increase of displaced secondary middle class workers.

Robustness checks

A. Sensitivity to longer time intervals

The first sensitivity control conducted to test the robustness of the presented results in table 2 is the extension of the time intervals from five to six years. More specifically, the measures are recomputed for the intervals 1997-2002, 2003-2008 and 2009-2014 (see table 3). As discussed in the previous section, technology needs time to propagate through the economy and affect domestic occupational structures. Therefore, the extension in time intervals is presumed to generate larger magnitudes in the estimation outputs. This pattern is documented in the technology measure estimations of service and sale workers, and agricultural related laborers, though the technology estimates for most other occupations are relatively kindred to the five year interval estimates. Within some occupations, that are elementary, clerical laborers and technicians, the magnitude of the technology development measures actually declined. Further scrutiny reveals that the exemption of the time interval 1997-2002 in the regression for these occupations yields enlargements in the estimates of technology effects on domestic occupational structures (except the internet diffusion), which is analogous to the finding that the addition of the time interval 1995-1999 yields contracting estimates in table 2 (not shown). So before the 2000's most of the technology indicators in the sample were less competent to exert a significant impact on the occupational thresholds of clerks and craft laborers in European labor markets. During the 2000's however, technology being bound to Moore's law has become increasingly powerful. This resonates with the notion that technological development is gradual and then very sudden. It is likely that business investments in R&D have recently become more effective in terms of new forms of capital displacing routine-tasks laborers, while creating new tasks for most predominantly high-skilled laborers.

Table 3: six year estimates of technological change indicators	**Dependent Variables[a,b,c]**								
	Δ Service and Sales	Δ Elementary	ΔAgriculture, forestry and fishery	ΔClerical support	Δ Craft and related trade	Δ Plant and machine operators	Δ Managers	ΔProfessionals	Δ Technicians
Independent Variables									
ΔInternet diffusion	0.0143 (0.0056)**	-0.00884 (0.0061)	-0.0060 (0.00025)**	-0.0212 (0.0072)***	-0.0356 (0.016)**	0.00853 (0.0042)**	0.00124 (0.011)	-0.0299 (0.0047)**	0.0132 (0.008)*
ΔTotal patents	0.0190 (0.0015)	0.0266 (0.037)	0.0129 (0.0048)***	-0.0165 (0.012)	-0.0285 (0.019)	-0.0347 (0.0022)***	-0.00578 (0.029)	0.0332 (0.042)	0.0257 (0.021)
ΔHigh-tech patents	0.297 (0.067)***	0.0245 (0.0028)***	0.0229 (0.013)*	-0.0067 (0.043)	-0.0023 (0.058)	0.0793 (0.026)***	0.0652 (0.0098)***	-0.272 (0.077)***	-0.0751 (0.043)*
ΔAutomation patents	-0.186 (0.047)***	-0.0399 (0.0037)***	-0.0181 (0.0070)**	-0.0483 (0.0092)***	-0.0110 (0.037)	-0.0427 (0.0010)***	-0.0570 (0.0099)***	0.199 (0.058)***	0.0272 (0.042)
ΔR&D expenditures	-0.193 (0.0025)***	-0.0288 (0.0023)***	-0.0182 (0.0012)***	-0.0199 (0.051)	0.067 (0.055)	-0.0474 (0.017)***	-0.0259 (0.019)	0.0957 (0.012)***	0.0857 (0.036)**
ΔICT Imports	-0.00537 (0.037)	0.0288 (0.025)*	-0.0020 (0.0015)	0.0713 (0.020)***	0.0466 (0.013)***	0.0108 (0.0093)	-0.0259 (0.013)**	-0.0743 (0.022)***	-0.0288 (0.0036)***
ΔUnionization	-0.0923 (0.052)	0.0861 (0.016)***	0.0092 (0.0042)**	0.0174 (0.0023)***	0.0923 (0.011)***	-0.0690 (0.0013)***	-0.0077 (0.024)	-0.0426 (0.055)	-0.0426 (0.024)*
ΔNet migration	0.041 (0.014)***	0.0156 (0.012)	0.0012 (0.0013)***	-0.0623 (0.0015)***	-0.0178 (0.020)	-0.0093 (0.010)	0.0064 (0.017)	-0.00298 (0.033)	0.0372 (0.042)
ΔPrimary education	-0.0161 (0.0010)***	-0.0311 (0.0069)***	0.0087 (0.0002)***						
ΔSecondary education				0.0253 (0.0039)**	-0.0170 (0.0042)***	0.0267 (0.0034)***			
ΔTertiary education							0.080 (0.024)***	0.0171 (0.0010)*	0.155 (0.067)**
Constant	0.0250 (0.0041)***	0.0076 (0.0027)***	-0.00022 (0.00010)**	0.0495 (0.0003)***	-0.0174 (0.0027)***	-0.00279 (0.0025)	0.00054 (0.0056)	0.0139 (.0026)***	-0.0035 (0.0021)*
Model Information									
Time FE	Yes	No	No	No	Yes	No	Yes	Yes	Yes
Observations	81	81	81	81	81	81	81	81	81
R^2	0.428	0.380	0.338	0.429	0.263	0.263	0.168	0.632	0.213

[a]Dependent variables in percentage point six year change in respective occupational share of total domestic employment levels, , independent variables refer to five year changes in the relevant variable, , evaluation period intervals include 1997-2002, 2003-2008 and 2009-2014. [b]White period standard errrors in parentheses; [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

The magnitude of the estimation outputs of the remaining indicators are fairly congruent to different time intervals and to the removal the first time interval. In other words, the results do not indicate that the relative supply of different kinds of skilled laborers and net migration have a differential impact on occupational structures over time. Furthermore, the effects of de-unionization on European labor markets are quite similar over time too. In most European countries, the deregulation of domestic labor markets started in the early 1980's, which reduced the influence of trade unions. The estimates indicate that this has been malicious to predominantly low skilled workers and clerical, craft related laborers.

B. Sensitivity to a different measure of technological change

Now the emphasis is diverted the holistic method of measuring disembodied technological change. The latter being recognized as the Solow residual is included in the main regression as an alternative for the technological development indicators. It must be noted that the current regression includes solely Western-European and Scandinavian countries[24], due to the unavailable Solow residuals for the remaining countries. The conjecture that (disembodied) technological change has mainly surged the demand for high skilled laborers is confirmed by the estimation outputs presented in table 4. Generally speaking, countries experiencing more technological progress are able to increase their production frontier, which enhances its comparative advantage. To effectuate this shift in demand for certain occupational types, more skilled laborers that are able to adopt technology are needed. For this reason, disembodied technological progress is associated with enhancements in the high skilled laborers thresholds. Even though the Solow residual is not as informative the technological change indicators above, it still confirms the notion that primarily routine-based tasks occupations are declining in the rate of disembodied technological progress. The occupational thresholds for clerks, craftsman and elementary laborers have presumably declined due to reorganizational co-inventions which are required after the introduction of new technologies. The exemption of the interval period 1998-2002 again yields larger magnitudes in the estimates for these occupations (not shown). Simply put, to race *with* technology, one needs to be able to adopt technology to its own benefit. Routine based task occupations have been running *against* technology over the past decades, and to race against exponential growth embodied in Moore's law, is a race laborers cannot win.

Overall, the control variables are in line with the baseline estimates in terms of significance and sign. However most of the estimates increase in magnitude. In particular, the coefficients of the variable ICT imports- aiming to capture embodied technological change in terms of international knowledge spillovers- become more pronounced in this estimation

[24] In particular: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

output. It is likely that the degree of ICT imports is negatively correlated with both the R&D expenditure intensity and the amount of (automation) patents within a country. Since the latter measures of technological change exert a negative impact on the thresholds of mainly the middle class occupations, the coefficients of ICT imports are plausibly overestimated.

Table 4: Solow residual estimates	**Dependent Variables[a,b,c]**								
	Δ Service and Sales	Δ Elementary	ΔAgriculture, forestry and fishery	ΔClerical support	Δ Craft and related trade	Δ Plant and machine operators	Δ Managers	ΔProfessionals	Δ Technicians
Independent Variables									
ΔSolow Residual	0.0174 (0.029)	-0.0544 (0.024)**	0.0150 (0.0087)*	-0.0920 (0.061)	-0.0553 (0.031)*	-0.0200 (0.0168)	0.0758 (0.036)**	0.0306 (0.024)*	0.0551 (0.041)
ΔICT Imports	0.00309 (0.020)	0.0576 (0.020)***	-0.00652 (0.0043)	0.483 (0.027)*	0.102 (0.025)***	0.00938 (0.014)	-0.0579 (0.027)**	-0.0912 (0.041)**	-0.0514 (0.046)
ΔUnionization	-0.0354 (0.054)	0.125 (0.072)*	0.00481 (0.010)	0.259 (0.14)*	0.0636 (0.077)	-0.0239 (0.034)	-0.00887 (0.071)	-0.248 (0.014)*	-0.0283 (0.15)
Δ Net migration	0.0714 (0.12)	-0.164 (0.12)	0.0995 (0.032)***	-0.316 (0.29)	0.279 (0.18)	0.159 (0.10)	-0.0907 (0.073)	0.459 (0.29)	-0.271 (0.39)
ΔPrimary education	-0.00481 (0.036)	-0.0616 (0.0020)***	0.0116 (0.0132)						
ΔSecondary education				0.306 (0.16)*	-0.0251 (0.0050)***	0.0736 (0.027)***			
ΔTertiary education							0.00484 (0.0043)	0.382 (0.17)**	0.0170 (0.010)
Constant	0.00951 (0.0022)***	0.00191 (0.0022)	-0.00068 (0.00035)*	0.00124 (0.0050)	-0.0163 (0.0021)***	-0.00546 (0.0016)***	0.00408 (0.0028)	0.00752 (0.0046)*	0.00023 (0.0041)
Model Information									
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Observations	45	45	45	45	45	45	45	45	45
R^2	0.430	0.305	0.174	0.418	0.387	0.307	0.239	0.501	0.078

[a]Dependent variables in percentage point five year change in respective occupational share of total domestic employment levels, Solow residual refers to aggregated five year interval values, evaluation period intervals include 1998-2002, 2003-2007 and 2008-2012. [b]White period standard errrors in parentheses; [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

C. *Sensitivity to dynamic panel approach*

In general sense, current (economic) behavior often depends on past behavior. In this context, changes in the distinct occupational thresholds may be dependent upon the size of these thresholds in periods prior to the adjustments. For this reason, several econometrists have come up with dynamic approaches to model panel data. As a robustness check, this paper employs the first-difference generalized method of moments (GMM) approach developed by Arellano and Bond (1991). For each estimation per occupation, a lagged occupation variable (*t-1)* is included, being instrumented with the lagged values of the occupation variable prior to that period *(t-2, t-3).* The validity of this instrumental variable approach depends on the presence on autocorrelation, which is excluded by assumption.

The dynamic panel model results are reported in Appendix table 3. Intuitively, when countries possess larger thresholds of each occupation, these are more subject to change in terms of absolute size. This intuition is partly reflected in the results; a larger size of the occupational threshold prior to the change period is associated with a (positive) change in each respective occupational threshold- while the technological change estimators remain fairly robust to this inclusion. Thus, large middle-class occupational thresholds for countries are not a precondition to experience negative changes. Rather a 'unexplained' part^{f} in the model causes these occupational thresholds to expand – whereas technological developments^{l} generally reduce the middle-skilled occupational thresholds (where $^{l > f}$). However, one major concern should be addressed; the conduction of a Sargan test of over-identifying restrictions indicates that the imposed restrictions do not hold in the agricultural estimation. Therefore, the employed instruments are not entirely convincing (i.e. the endogeneity problem). So in this regression the GMM estimates should be interpreted with caution.

Evaluation of hypothesis 1: Overall, a compelling but miscellaneous pattern emerges from the effects of technological developments on the occupational structure of labor markets, a pattern that has become more pronounced since the dawn of the new millennium. The aggregate technical progress- encapsulated by the Solow residual- estimates suggest that indeed predominantly routine intensive middle skilled tasks have been adversely subject to technological developments, while especially the demand for high-skilled laborers has surged. However, close scrutiny at the type of technological developments reveals that this pattern is not uniform. Those countries that are converging towards higher automation patent and R&D expenditures intensities have been associated with contracting low and predominantly middle skilled laborer thresholds, while those countries that are converging towards larger high-tech patent and ICT import intensities mitigate this pattern. It must be noted that the effects of the former always dominate the effect of the latter, thereby giving rise to job polarization. Furthermore, the effects of internet diffusion exhibit considerable resemblance to the offshorability scale of occupations.

V.II. The factors determining the domestic occupational thresholds

The results thus far show that technological developments have primarily substituted routine-based tasks occupations, while analogously having created demand for non-routine white collar occupations. However, it is not yet known to what extent the technological advancement of a country determines the occupational thresholds. For this reason, estimation strategy (1) is reported in table 5 applying five year intervals of the technological development indicators. The aim of these regression is to ascertain whether more (less) technological advanced countries tend to have larger high (middle) skilled occupational thresholds, or more technology advanced countries are merely converging towards larger high skilled occupational thresholds, while the occupational structures of economies are more determined by other factors like its (economic) history. Interestingly, the estimates generally suggest the latter pattern has occurred in European countries. The indicator internet diffusion provides weak evidence for the notion that the domestic internet adoption rate is associated with larger high skilled occupational thresholds, which is largely in accordance with earlier findings. More precisely, following the conjecture that the domestic rate of internet diffusion is a convenient proxy for the offshorability scale of occupations, less internet diffused countries tend to have a deficient ability to offshore primarily low skilled occupations to foreign low wage countries. On the other hand, those countries with a lower internet diffusion may be countries that rely on low-wages themselves, and therefore may have more widened low skilled occupational thresholds.

In terms of technological advancement measured by patents there seems to be a complementarity between professionals and service and sales laborers. That is, the pair occupational thresholds are increasing in the domestic total patent and automation patent intensity, whereas the domestic high tech patent intensity conduces to lower occupational thresholds of the two. In prospective decades, unprecedented advances in technology insinuate further complementarities in terms of polarized labor markets subsisting of mostly low and high skilled laborers. A phenomenon coined by Goos and Manning (2007) as the polarization into ´lousy and lovely´ jobs. Technology advanced countries such as Switzerland, Norway and Sweden already indicate evidence for this pattern of high complementarity between certain high- and low skilled occupations. Certainly service occupations resemble this pattern for low skilled occupations. Autor and Dorn (2013) attribute this to the fact that these rely on dexterity, flexibility and physical proximity, making them hard to automate.

Furthermore, as hypothesized in the previous section, less technology advanced countries are more inclined to import information and communication technologies, presumably due to an inferior capability to invent these technologies themselves. The results indeed point out those countries that import ICT goods at a higher intensity are associated with lower professional and technician thresholds. This conveys the impression that ICT goods are not necessarily imported to automate routine tasks, but rather to complement the operation of these tasks. In addition, ICT goods are discernably technologies not necessarily requiring high skilled laborers.

Table 5: Factors determining occupational thresholds	**Dependent Variables[a,b]**								
	Service and Sales	Elementary	Agriculture, forestry and fishery	Clerical support	Craft and related trade	Plant and machine operators	Managers	Professionals	Technicians
Independent Variables									
Internet diffusion	0.0646 (0.040)	-0.0312 (0.023)	-0.00555 (0.036)	0.0212 (0.016)	-0.0275 (0.012)**	0.0176 (0.030)	0.0122 (0.012)	0.0120 (0.0085)	0.0386 (0.021)*
Total patents	0.180 (0.047)***	-0.291 (0.16)*	0.0422 (0.030)	-0.250 (0.26)	-0.178 (0.074)**	-0.143 (0.085)*	0.0532 (0.18)	0.270 (0.12)**	0.0231 (0.20)
High-tech patents	-0.250 (0.065)***	0.0924 (0.042)**	0.0351 (0.017)**	-0.0828 (0.12)	0.0586 (0.048)	-0.0655 (0.071)	-0.234 (0.080)***	-0.107 (0.51)*	-0.105 (0.083)
Automation patents	0.206 (0.034)***	-0.0303 (0.028)	-0.0135 (0.019)	-0.0393 (0.089)	-0.0858 (0.026)***	-0.0944 (0.042)**	0.163 (0.082)**	0.126 (0.057)**	0.0760 (0.067)
R&D expenditures	0.0243 (0.021)	-0.0189 (0.093)	-0.0497 (0.021)**	0.586 (0.20)***	0.248 (0.21)	-0.228 (0.094)**	-0.275 (0.17)	-0.241 (0.19)	-0.0399 (0.23)
ICT Imports	0.0357 (0.049)	0.0476 (0.014)***	0.0231 (0.0089)**	0.215 (0.068)***	0.0695 (0.032)**	0.0891 (0.058)	-0.0589 (0.055)	-0.189 (0.034)**	-0.210 (0.071)**
Unionization	-0.0904 (0.054)*	0.0821 (0.025)***	-0.00649 (0.0094)	-0.0556 (0.060)	0.0519 (0.032)*	-0.0507 (0.032)	0.104 (0.041)**	0.0454 (0.064)	-0.0539 (0.080)
Net migration	-0.178 (0.070)**	-0.0618 (0.042)	-0.00902 (0.0081)	0.203 (0.069)***	0.135 (0.053)**	0.0367 (0.043)	0.0196 (0.055)	0.165 (0.073)**	0.00478 (0.068)
Primary education	0.0021 (0.026)	0.0193 (0.0088)**	0.00895 (0.0043)**						
Secondary education				0.00769 (0.067)	-0.159 (0.067)**	0.0612 (0.041)			
Tertiary education							0.161 (0.031)***	0.295 (0.051)***	0.130 (0.062)**
Constant	0.177 (0.018)***	0.0688 (0.0097)***	0.0110 (0.0032)***	0.0652 (0.037)*	0.242 (0.061)***	0.0920 (0.011)***	0.0203 (0.019)	0.141 (0.008)***	0.179 (0.043)***
Model specifications									
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	No	Yes	No	Yes	No
Observations	81	81	81	81	81	81	81	81	81
R^2	0.946	0.930	0.922	0.928	0.946	0.976	0.957	0.941	0.935

[a]Dependent variables reflect the respective occupational share of total domestic employment levels at 2004, 2009 and 2014, evaluation period intervals include 2000-2004, 2005-2009 and 2010-2014 [b]White period standard errrors in parentheses; [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

The educational attainment measures largely confirm the conjecture that countries with more educated workforces tend to have larger thresholds of high skilled laborers. This pattern is not surprising since technological advances generally require higher educated workers that are able to adopt new technologies, referring to a process of skill-biased technological change (e.g. Bresnahan et al. 2002).

Somewhat remarkable are the estimates of the R&D expenditure indicator, which overall suggest that those countries investing heavily in the production of knowledge are not associated with larger high skilled occupational thresholds. Apparently, R&D expenditures seem to be only a precondition to converge towards larger high skilled thresholds, though the latter are more likely to be determined a country's historical and cultural roots[25]. In this regard, Acemoglu et al (2005) provide a riveting background apologue to illustrate the differential rise of Europe. Differences between Western and Eastern European countries economic fortunes have been largely established in favor of the former due to its benevolent geographic position. More precisely, the access to the Atlantic Ocean operated as a catalyst for substantial trade flows with parts all over the world, conducing to rising power of merchant groups while limiting the power of the monarchy. Subsequently, merchant groups favored institutional reforms protecting property rights, which have a persistent positive effect on current institutions, generally regarded as the most decisive determinant of the economic fortune of countries. Therefore, institutions reflecting the historic roots of countries are likely to remain a major determinant of the occupational structure of countries, despite technological advances restructuring the occupational structure just like during the Industrial revolution (e.g. Katz and Margo, 2013). In this manner, Comin et al. (2009) have examined whether the use of technology in 1500 AD and before, determines the domestic economic outcomes of today. These authors find strong robust relationship between the two, and therefore state that the adoption of technology is merely embedded within the cultural historical roots of a country. Unfortunately, the question how old technology persists throughout decades and how this relates to institutions remains ambiguous within the development economics literature. An inquiry the proponents of endogenous growth theory have aimed to clarify by focusing on the supply side. Endogenous growth theory merely submits a view where laws, institutions, customs and regulations determine the playing field for innovators (economic rents), and thus

[25] In order to test the robustness of the presented results the same strategy is applied with an extension of the time interval from five to six year intervals for the technology indicators. The estimates –reported in Appendix table 4- are fairly similar to the results provided in table 5, suggesting that technological advances merely conduce countries to expand their high skilled thresholds, while the occupational structures of countries are more substantially determined by its historical and cultural roots.

incentive to pursue new inventions (Aghion et al. 1998). In other words, institutions should aim to provide an economic playing field for all, incentivizing people to pursue technological developments, which will eventually propagate through the economy benefiting the entire society. This process may be impeded by economic inequality, leading to enlargements in political inequality (Acemoglu and Robinson, 2012), a point which will be investigated in the consecutive section. Within the development literature, it has become a custom to use an index for the domestic rule of law as a proxy for institutions, a strategy analogously pursued to test whether current institutions still have a differential impact in Western-European countries on occupational thresholds. Or alternatively, the persistence of (non)absolutist institutions merely being embedded in the time-invariant historical roots of a country, captured by the country fixed effects. The results are reported in Appendix table 5 and provide some weak evidence that Western countries bearing strong property rights and high contract enforcement are associated with larger (smaller) high (middle) skilled occupational thresholds. To some extent it gives rise to the conjecture that in especially Western European countries inventors and investors value a strong prevailing rule of law to protect their investments in technology. As shown before, many technologies (primarily automation) tend to diminish the demand for middle skilled workers, while surging demand for higher skilled workers. However, it is urgent to note that these effects are minor, which is not surprising since Acemoglu et al. (2005) show that the emphasis on strong property rights has already been established several hundred years ago, embedding them in time-invariant country fixed effects.

Evaluation of hypothesis 2: The estimates of the measures of technical progress provide weak evidence for the notion that more technical advanced countries tend to have larger occupational thresholds. However, this pattern is analogous to the precedent hypothesis not uniform. In sum, the results indicate that technological advances merely conduce countries to expand their high skilled thresholds, while the occupational structures of countries are more substantially determined by its time-invariant historical and cultural roots.

V.III. The effects of technological developments on changes in the wage distribution

In the precedent sections evidence was found that technical progress has attributed towards considerable changes in the occupational structure of European labor markets. These changes are often perceived as threads by laborers and policymakers alike, although this leaves out an even more important fact; technology has been extraordinarily enhancing laborers the capability to increase their productivity, which in turn have led to vast increases in our standards of living. So how has a growing economic pie (the bounty) been divided among the workforce (the spread)? This question has become paramount in the public debate since the widespread attention for the publication '*Capital in the twenty-first century'* by Thomas Piketty. There have been several emerging patterns -such as a widening divergence between median and average income levels of workers- which have induced prominent economist to raise their voice for equitable growth. Their argument can best be portrayed by a statement of the Greek philosopher Plutarch: *"An imbalance between rich and poor is the oldest and most fatal ailment of all republics."* Proponents of equitable growth primarily argue that a diminishing spread may eventually impede economic growth. An argument that already had been raised sixty years ago by Simon Kuznets (1955). The documentary '*Inequality for all"* by American economist Robert Reich provides several cases in which enormous companies and their employers (the 1 %) alike do not create demand for new jobs, rather they would lower the demand for jobs generating an exacerbating income distribution. The argument goes that if the middle class also benefits from an increasing bounty, a larger demand for products and services is created, which generates a positive feedback loop through the economy, creating demand for new jobs. This feedback loop will be hindered or even transform into a negative feedback loop if the increasing bounty is solely captured by the top earners, only consuming a fixed portion to satisfy their needs. In a recent report, the International Labour Organization (ILO) estimated that the effects of lagging incomes and persistent high unemployment levels may have shortened global demand by an amount of $3,7 trillion (ILO, 2015). To study the effects of technological progress on the relative income distribution this paper first will take a look at relative gross income levels. Secondly, in light of concerns of equitable growth, this paper will additionally study the effects of technical progress on the distribution of disposable incomes, thereby exemplifying the role of domestic labor institutions.

The results for the relative gross income shares are reported in table 6. The first column presents estimates of the technical progress indicators on developments in the share of median income laborers relative to those in the first decile (low-end inequality). The estimates reveal that most of the technical progress indicators have reduced the wage gap between the two groups. The variable of the automation patents confirms the notion that automation has adversely affected laborers with median incomes. This observation is not startling and resonates with the results found in the previous section, where the estimates suggested that predominantly middle skilled occupations possessing high routine-based tasks were adversely susceptible to automation. However it does not imply that all technical developments contribute to a shrinking wage gap between low and median income laborers. The estimates indicate that the domestic total patent intensity is associated with a widening wage gap, presumably due to a larger competence of middle skilled laborers to adopt technology.

Table 6: Gross income estimates	**Dependent Variables**[a,b,c]					
	$\Delta\frac{D5}{D1}$	$\Delta\frac{D10}{D1}$	$\Delta\frac{P95}{D1}$	$\Delta\frac{P99}{D1}$	$\Delta\frac{P995}{Q1}$	$\Delta\frac{P999}{Q1}$
Independent Variables						
ΔInternet diffusion	-0.0135 (0.033)	0.239 (0.10)**	0.0642 (0.18)	0.0625 (4.2)	0.0770 (0.11)	0.0283 (0.082)
ΔTotal patents	0.474 (0.14)***	0.635 (0.37)*	1.001 (0.17)***	0.765 (0.16)***	0.580 (0.20)**	0.288 (0.13)**
ΔHigh-tech patents	-0.178 (0.23)	-0.332 (0.46)	0.172 (0.51)	0.271 (0.18)*	0.0346 (0.16)	-0.327 (0.52)
ΔAutomation patents	-0.270 (0.11)**	0.392 (0.19)**	0.112 (0.31)	0.155 (0.54)**	0.0478 (0.084)	0.145 (0.18)
ΔR&D expenditures	-0.216 (0.29)	-0.355 (0.67)	-0.854 (0.34)**	-0.814 (0.31)**	-0.438 (0.16)**	-0.0662 (0.19)
ΔICT Imports	-0.0567 (0.11)	0.142 (0.18)	0.341 (0.51)	0.235 (0.12)*	0.154 (0.18)	0.0823 (0.14)
ΔUnionization	-0.387 (0.17)**	-1.379 (0.56)**	-0.946 (0.31)***	-0.757 (0.36)**	-0.642 (0.14)***	-0.428 (0.24)*
ΔNet migration	-0.105 (0.15)	0.303 (0.26)	0.513 (0.23)**	0.378 (0.26)	0.395 (0.30)	0.070 (0.14)
ΔPrimary education	0.447 (0.18)**	0.525 (0.74)	0.615 (0.42)	0.212 (0.25)	0.0140 (0.60)	0.185 (0.091)*
ΔSecondary education	0.303 (0.19)*					
ΔTertiary education		0.185 (0.55)	0.341 (0.87)	0.872 (0.38)**	0.654 (0.27)**	0.0776 (0.24)
Constant	-0.0213 (0.033)	-0.0671 (0.053)	-0.0184 (0.051)	-0.0282 (0.044)	-0.0337 (0.042)	-0.00646 (0.026)
Model Information						
Observations	72	72	36	39	36	36
R^2	0.287	0.315	0.573	0.653	0.545	0.485

[a]Dependent variables in percentage point five year change in respective gross domestic relative income shares , evaluation period intervals include 1996-2000, 2001-2005 and 2006-2010 [b]Standard errrors in parentheses; period EGLS employed in all estimations [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively, regressions exclude Iceland, Romania and Slovenia due to limited available data, remaining columns refer to relative top gross incomes, only available for limited set of countries, see data section for further details, regressions including Solow residuals available upon request.

Furthermore, the de-unionization of labor markets has especially shown to be malicious to low skilled workers, both documented in terms of the amount of occupations in the previous section, and in terms of wage inequality relative to middle skilled workers. Consistent with the idea that compelling trade-unions in the past were able to provide a ‘safety net’ for less skilled workers, the deregulation of labor markets has greatly enhanced the power of employers, providing them the capability to hire more less skilled workers against lower wages (Borjas, 2013).

In terms of shifts in the relative supply of educated workers, the effect of the relative decrease of laborers with a primary educational attainment dominates the effect of the relative increase of laborers with a secondary educational attainment, which is associated with a declining 50-10 wage gap in most countries.

The remainder of columns in table 6 show estimates for the ‘superstars’ (i.e. respectively the highest decile, the top five, top one, top half and top 0,1 percent of the gross income distribution) relative to the lowest decile. A clear pattern emerges from this table. Aside from the second column including all countries, the estimates of the effects of technological development on changes in the wage structure decrease monotonically, which basically entails that when the group of top earners become more petite, a smaller share of the bounty is captured. So far just resonates with common sense, nonetheless, the monotonic decreases are quite minor. For example, a domestic increase in the total patent intensity with ten percent points over five years effectuates into a widening 95-10p wage gap of ten percent, whereas it widens the 99-10p wage gap with almost eight percent (cp). Put differently, the spread of the bounty has been increasingly biased towards a very small group of superstars, a phenomenon notorious as rising top-end (and low) inequality.

Also other indicators of technical progress tend to confirm the conjecture of superstar biased technological change, in particular, the estimates regarding automation patents and high-tech patents provide weak evidence that displaced middle class workers may have depressed wages for low skilled workers, although these estimates are just fragile. More vigorous are the estimates concerning the extent of (de-)unionization and relative supply of educated workers. More precisely, the intensity of de-unionization and relative increase of tertiary educated workers are associated with large increases in the wage gaps of superstars relative to those of the bottom of the wage decile. Usually, an increase of a certain group (tertiary) of educated workers is associated with a downward pressure on wages. The current estimates show however that those at the very top may benefit, either due to superstars (e.g CEOs) capturing significant pieces of the bounty which their counterpart high skilled laborers create, or because superstars simply benefit from rising disposable incomes -and thereby demand- of more high skilled laborers for the products and/or services that superstars provide. It must be noted that not all technical progress measures are skill biased, the domestic R&D

expenditure intensity of a country tends to contract the wage disparity, possibly therefore businesses in more technologically advanced (R&D) countries experience more competition which condenses the effects of skill-biased technological change on the 90-10 wage gap.

The columns in table 7 show estimates for the 'superstars' (i.e. respectively the highest decile, the top five, top one, top half and top 0,1 percent of the gross income distribution) relative to the median decile. The same pattern emerges again; the estimates of the effects of technological development on changes in the wage structure decrease monotonically when the size of the superstar group is narrowed down. In comparison to the estimates in the previous table, several compelling patterns arise. Firstly, the effect of the domestic total patent intensity become less pronounced for median income laborers relative to those of the first decile, which conforms to the idea that technological developments in general tend to increase the comparative advantage of more skilled workers. Moreover, the variable domestic automation patent intensity is associated with a widening superstar-median income gap. This result simply follows from earlier findings, where was shown that middle skilled jobs in possession of routine-based tasks characteristics were most susceptible to automation. Secondly, high-tech inventions seem -adjacent to the reduction of demand for high skilled employment- also put downward pressure on the wages of high-skilled laborers, resulting into a loss in the comparative advantage of high-skilled workers. Thirdly, the remaining variables –i.e. internet diffusion, ICT imports and R&D expenditures- only exert a minor and insignificant impact on the top-end income gap. The former two indicators partly convey the impression that offshoring has been less malicious to middle skilled workers relative to their low skilled counterparts, in conjunction to earlier research (e.g Blinder, 2006). Also the de-unionization of labor markets engages in this pattern, that is, it has widened low-end (50-10) inequality as well as top-end (90-50) inequality. Therefore, since trade-union in the past were efficaciously able to compress wages both within- and between skill groups, the de-unionization of labor markets has effectively abated this mechanism, resulting into widening gross income disparity between skill groups (Card, 1996). Lastly, the covariates regarding changes in the educational attainment of the workforce do partly invoke the conjecture of Lemieux (2006a), which contemplates that large increases in the return of secondary schooling have caused a convexification of the gross wage distribution. The estimates rather suggest that high skilled laborers- and predominantly superstars- have experienced vast increases in their gross incomes relative to everyone else (see Saez and Piketty, 2006 for a detailed analysis). This phenomenon has been positively associated with inflows of tertiary educated workers.

Table 7: Gross income estimates (top-end)	**Dependent Variables**[a,b,c]				
	$\Delta\frac{D10}{D5}$	$\Delta\frac{P95}{D5}$	$\Delta\frac{P99}{D5}$	$\Delta\frac{P995}{D5}$	$\Delta\frac{P999}{D5}$
Independent Variables					
ΔInternet diffusion	0.0715 (0.054)	0.0536 (0.18)	0.0296 (0.19)*	0.0406 (0.073)	0.0142 (0.051)
ΔTotal patents	0.278 (0.16)*	0.489 (0.23)**	0.439 (0.098)***	0.267 (0.091)***	0.131 (0.062)**
ΔHigh-tech patents	-0.498 (0.11)***	-0.210 (0.18)	-0.350 (0.24)	-0.286 (0.343)	-0.276 (0.24)
ΔAutomation patents	0.451 (0.13)***	0.324 (0.20)*	0.268 (0.13)**	0.167 (0.061)***	0.122 (0.083)*
ΔR&D expenditures	0.345 (0.19)*	0.0828 (0.24)	0.0723 (0.21)	0.0325 (0.25)	0.0478 (0.16)
ΔICT Imports	0.0634 (0.086)	0.264 (0.14)*	0.0938 (0.095)	0.0818 (0.073)	0.0459 (0.13)
ΔUnionization	-0.405 (0.13)***	-0.332 (0.16)**	-0.377 (0.09)***	-0.346 (0.23)*	-0.391 (0.21)**
ΔNet migration	-0.0656 (0.13)	-0.105 (0.33)	0.154 (0.23)	0.140 (0.21)	-0.00327 (0.22)
ΔSecondary education	-0.050 (0.17)	-0.196 (0.25)	0.129 (0.15)	0.0736 (0.094)	0.132 (0.12)
ΔTertiary education	0.139 (0.21)	0.765 (0.36)**	0.730 (0.24)***	0.385 (0.23)*	0.366 (0.17)**
Constant	-0.0526 (0.020)**	-0.0693 (0.021)***	-0.0120 (0.021)	-0.0317 (0.020)	-0.0155 (0.021)
Model Information					
Observations	72	36	39	36	36
R^2	0.364	0.514	0.638	0.429	0.358

[a]Dependent variables in percentage point five year change in respective gross domestic relative income shares , evaluation period intervals include 1996-2000, 2001-2005 and 2006-2010 [b]Standard errrors in parentheses; period EGLS employed in all estimations [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively, main regressions exclude Iceland, Romania and Slovenia due to limited available data, remaining columns refer to relative top gross incomes, only available for limited set of countries, see data section for further details.

So far the results indicate that technological developments have significantly changed the income distribution, primarily in favor of those at the very top. In light of concerns of equitable growth, this paper will additionally study the effects of technical progress on the distribution of disposable incomes. Therefore, again estimation strategy (3) is employed using disposable income statistics among different deciles of the income distribution. The results are reported in table 8. Overall, the estimates have limited explanatory power, which is evidently determined by the measurement error in the disposable income data. This error however, is unlikely to be related to the independent variables, which bears the impression there is no (severe) attenuation bias. Column 1-3, 4-6, 7-9 respectively present estimates of the technical progress indicators on low-end inequality, top-low and top-end inequality.

Table 8: Disposable income estimates	**Dependent Variables**[a,b,c]								
	$\Delta\frac{D5}{D1}$	$\Delta\frac{Q3}{Q1}$	$\Delta\frac{[D4,\ D6]}{[D1,\ D3]}$	$\Delta\frac{D10}{D1}$	$\Delta\frac{Q5}{Q1}$	$\Delta\frac{[D8,\ D10]}{[D1,\ D3]}$	$\Delta\frac{D10}{D5}$	$\Delta\frac{Q5}{Q3}$	$\Delta\frac{[D8,\ D10]}{[D4,\ D6]}$
Independent Variables									
ΔInternet diffusion	-0.0760 (0.52)	-0.0769 (0.14)	0.000454 (0.0087)	0.642 (0.51)	0.558 (0.41)	0.428 (0.25)*	0.458 (0.18)**	0.264 (0.12)**	0.240 (0.11)**
ΔTotal patents	0.0640 (0.097)	0.0249 (0.037)	0.0341 (0.023)	-0.0445 (0.36)	0.0878 (0.14)	0.0331 (0.077)	-0.0332 (0.052)	-0.0193 (0.028)	-0.0118 (0.023)
ΔHigh-tech patents	0.210 (0.16)	0.102 (0.048)**	0.0646 (0.035)*	-0.745 (0.34)**	-0.365 (0.11)***	-0.235 (0.063)***	-0.194 (0.057)***	-0.0967 (0.030)***	-0.0810 (0.019)***
ΔAutomation patents	-0.264 (0.13)*	-0.0670 (0.041)*	-0.0393 (0.023)*	0.951 (0.28)**	0.518 (0.13)***	0.310 (0.10)***	0.333 (0.075)***	0.179 (0.041)***	0.142 (0.034)***
ΔR&D expenditures	-0.0246 (1.98)	-0.0437 (0.073)	-0.0389 (0.040)	0.201 (0.72)	0.253 (0.26)	0.157 (0.15)	0.0967 (0.098)	0.0471 (0.057)	0.0308 (0.049)
ΔICT Imports	0.0451 (0.053)	0.0230 (0.22)	-0.0628 (0.011)	-0.102 (0.22)	-0.135 (0.098)	-0.0997 (0.055)*	-0.0872 (0.040)**	-0.0597 (0.026)**	-0.0537 (0.020)***
ΔUnionization	0.0906 (0.084)	0.0621 (0.033)*	0.0223 (0.020)	0.246 (0.20)	0.0439 (0.12)	-0.0147 (0.066)	-0.0523 (0.045)	-0.0434 (0.025)*	-0.0471 (0.016)***
ΔNet migration	0.0370 (0.10)	0.0406 (0.045)	0.0331 (0.027)	0.0992 (0.46)	0.0729 (0.19)	0.0559 (0.12)	-0.0160 (0.074)	-0.0123 (0.046)	-0.0134 (0.037)
ΔPrimary education	0.253 (0.22)	0.0209 (0.081)	-0.0146 (0.052)	-0.375 (0.48)	-0.229 (0.17)	-0.927 (0.458)**			
ΔSecondary education	0.325 (0.22)	0.0648 (0.076)	0.0191 (0.046)				-0.170 (0.071)**	-0.0900 (0.042)**	-0.0811 (0.033)**
ΔTertiary education				-0.977 (0.54)*	-0.296 (0.16)*	-0.0807 (0.154)	-0.0328 (0.094)	-0.0303 (0.056)	-0.0613 (0.049)
Constant	-0.0990 (0.19)	0.0264 (0.071)	-0.0278 (0.037)	-0.0150 (0.75)	0.0807 (0.28)	-0.00279 (0.0025)	0.0685 (0.12)	0.0368 (0.071)	0.00980 (0.058)
Model Information									
Observations	78	78	78	78	78	78	78	78	78
R^2	0.112	0.070	0.065	0.048	0.093	0.106	0.184	0.202	0.218

[a]Dependent variables in percentage point five year change in respective domestic disposable relative wage shares evaluation period intervals include 1996-2000, 2001-2005 and 2006-2010 [b]Standard errrors in parentheses; period EGLS employed in all estimations [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

Even though adjustments in the distribution of domestic disposable incomes through time are overwhelmingly determined by other factors (the constant captures the 'residual growth' e.g. labor market institutional changes, public acceptance, business cycles), a few features merit attention from this table.

The widespread adoption of the internet has attributed to significant enlargements in the disposable income dispersion between those at the top thirty percent of the income distribution versus the rest. This finding is analogous to a study in the US by Firpo et al. (2011), which attribute this to the enhanced opportunity to offshore occupations to other countries. Furthermore, countries with more technological advanced methods to automate tasks are associated with both widening top-end inequality as top-low inequality. Seemingly, high-tech patents mitigate this process of widening wage inequality, and contribute to a lower competitive advantage of the highest income deciles. Since advanced technological countries often possess high values of high-tech and automation patent developments, the total effect of technological change on adjustments in wage dispersion among different deciles is quite limited. In comparison to the gross estimates, also the effects of de-unionization become much less pronounced and only significant as attribution to a widening top-end wage dispersion. This may be surprising in light of earlier findings, which suggested mainly low-wage occupations were most adversely affected by the de-unionization of labor markets. In reaction of the last virtue, it seems that governments have implemented redistribution policies in favor of low-income laborers. A similar narrative that happened after World War two in the US, where labor market institutions acted on 'The Great Compression' (Goldin and Margo,1992).

Actually, this gives rise to what some refer to as the '*Krugman hypothesis'*, which some economists have seized to elucidate why (disposable) income inequality in Europe did not rise in similar fashion as in the US. The Krugman hypothesis basically entails that labor market institutions in Europe are effectively able to compress wages, limiting the extent of inequality (Krugman, 1994). Empirical evidence suggests that European labor market institutions (centralized wage-setting, transfer programs) have been effectively able to compress wage dispersion at the low-end of the wage distribution, i.e. the 50-10 wage gap (Blau and Kahn, 1996). According to the results above, a pattern that still remains valid today, despite a diminishing power of trade-unions in most countries. In addition, close scrutiny at the data confirms the notion that in the majority of the countries disposable wage dispersion remained fairly stable, irrespective of the experienced technical progress of European countries. For some economists it is a persisting puzzle to account for the determinants of the changes in (disposable) wage distributions between different parts over the world. A possible justification that has been put forward views existing regulations as the incentive to adopt technologies. In this way, firms select technologies in accordance to imposed constraints by prevailing domestic institutional regulations. For example, firms in countries with high wage compression are encouraged to adopt technologies that augment the productivity of low skilled laborers (Acemoglu and Autor, 2011). This is another argument for the polarization of skills demanded among occupations.

Robustness checks

Earlier findings suggested that certain technologies (e.g. automation) became more pronounced over time as determinant of occupational thresholds. To control for potential differences through time of relative income distributions, the first time interval (1996-2000) is dismissed in the estimation strategy of table 8. The exemption does not yield more pronounced results on relative disposable income distributions, rather the estimates decline somewhat and even become more imprecise. On the contrary, the estimates of the technical progress variables on relative gross income distributions rise moderately, while the control variables are about similar through time (Appendix table 7). These findings are fairly congruent to the application of a dynamic panel model approach bound to the Arellano and Bond (1991) paradigm. This approach provides no evidence for the notion that the existence of a high (low) prevailing relative gross income disparity acts as a precondition for larger (lower) income disparity in later periods (see Appendix table 8). These results are in sharp contrast to the relative disposable income GMM estimates, which indicate that the a priori prevailing relative disposable income disparity, presumably acts as a precondition for the implementation of redistribution policies of governments, most primarily in favor of laborers with median income wages (Appendix table 6). Put differently, technological developments generally put downward (upward) pressure on median (high) gross income wages, and thus give rise to larger relative gross income disparity. The implementation of specific redistribution policies seem to mitigate this pattern, and therefore technological developments have a very minor impact on the disposable income distribution[26], effectively describing the Krugman hypothesis. In sum, European labor market institutions are effectively being able to compress wages, impediments that have been largely eliminated in the US. Furthermore, large income differences are probably less publically accepted in European labor markets, a feature more tolerated in Anglo-Saxon labor markets (e.g. Piketty and Saez, 2006).

[26] To some extent this portrays a governments' trade-off between the carrot and the stick. The prevalence of a favorable rule of law (or investment climate) stimulates innovators to develop technologies (the carrot), while redistribution policies (weakly) dissuade inventors to develop technologies (the stick).

Factor bias in trade

The inquiry why countries tend to trade with one another and its effect on factor prices has been one of the most debated principles of economics. Arguably the most influential economists of all time – Adam Smith and David Ricardo- contrived the principles of classical economics with the view that technological differences between countries were the determinant of international trade flows. Later on, neoclassical trade economists developed a quartet of trade theorems coined as the HO-S model, where the relative factor abundance of countries explained the tendency to trade. One of these theorems was developed by Stolper and Samuelson (1941) which vindicates that changes in goods princes have significant effects on factor prices. This theorem induced some economists (e.g. Leamer, 1996; Wood, 1995) to argue that the wages of low skilled workers declined due to the expanding (manufacturing) exports of primarily low-wage countries. This led to a repercussion of several studies (e.g. Krugman, 2000), accounting that technical change was the major force behind adjustments in the income distribution, and that the trade effects were only minor, particularly in large economies. To account for possible effects of trade prices on factor prices, firstly the indicator high-technology exports (computers, electrical machinery) as % of GDP has been incorporated in the regression, proxying for the price effects of technologies assumed to affect chiefly capital owners in the top of the income distribution. Secondly, also the indicator manufacturing exports as % of GDP has been incorporated in the regression. This indicator is employed as a proxy for the price effects of manufacturing goods (e.g chemical, machinery) and is assumed to primarily affect median and low income laborers[27]. It must be acknowledged that this is definitely an indirect approach of price effects on relative factor prices. More specifically, surges in productivity levels can be coupled with declines in goods prices but higher profit margins, that is, the total value of the exports can decline, while more profits are earned. Therefore, the relative gross income estimates reported in Appendix table 9 must be interpreted with some caution.

The estimates of the remaining indicators are fairly robust to the inclusion of the high-technology- and manufacturing export indicators. As hypothesized countries that tend to export more high-technology goods have experienced widening gross superstar gaps versus median and low income laborers, while this process is reversed when countries tend to export more manufacturing goods. The net effect thus depends on whether the comparative advantage of a country is embedded in manufacturing or high-technology goods, (or both).

[27] Both indicators are compiled in similar manner as the technology indicators, further details in data references.

The effects are most pronounced- and only significant- at the estimates of the top 5% and top 0,1% versus the median and low income laborers. So, this gives rise to the conjecture that superstars (e.g CEOs) at the very top of the income distribution accrue a significant portion of the bounty of technology goods, while the gains of manufacturing goods are more widespread and accrue most to median and low skilled laborers. Since technical advances are generally one of the main determinants of the comparative advantage of countries in the production of goods, technological advances are still a major determinant behind adjustments in relative gross incomes, and channel indirectly through the gains from trade with other countries.

The inclusion of both indicators to the relative disposable income estimates did not have any significant effect on the estimates, in fact, the estimates become more imprecise (not shown). This result is not startling since chiefly those at the very top were affected in terms of adjustments in the relative gross distributions. Unfortunately, disposable income distributions at the very top are not available (yet).

Evaluation of hypothesis 3: Overall, the effects of technological developments on gross wage inequality are fairly congruent to earlier findings that suggested mainly middle skilled occupations were most adversely susceptible to technological changes. This resonates with the comparative statics of the task-based model of Acemoglu and Autor (2011), which contemplates that technical progress has caused widening gross wage inequality in terms of w_H/w_L and w_H/w_M and contracting wage inequality in terms of w_M/w_L. Notwithstanding, the effects of technical progress are not uniform. More specifically, developments in automation patents have mainly been malicious to middle skilled workers, while in general patents are biased towards the most skilled workers. Above all, the estimates mainly suggest that technical progress has been especially biased towards superstars at the top of the gross income distribution. A pattern that has become more vigorous since the dawn of the new millennium. These developments however, have not been translated to considerable adjustments in the disposable income distribution, and therefore give rise to the Krugman hypothesis which entails that labor market institutions in Europe are effectively able to compress wages, limiting the extent of inequality.

Limitations

Although, effort is taken to ensure this study has presented some compelling results, some limitations have to be acknowledged before concluding. First, the current study has not effectively captured the amount of jobs among occupations that have been susceptible to offshoring. The use of internet adoption as a proxy for the offshorability of occupations is certainly a fragile one. There have been some attempts in the US (e.g. Blinder and Krueger, 2013) to assign an offshorability scale to occupations. Still, this often provides a static perspective and does not consider enhancing opportunities to offshore occupations through time. Future work is likely to be able to solve this ‘problem’, but overall an increasing consensus has emerged that the effects of offshoring are minor compared to the effects of technological development on occupational structures (e.g. Goos et al. 2009). Offshoring is often perceived as a precedent phase, before technologies being bound to Moore’s law will become so cheap that it is simply cost-effective to replace foreign laborers by domestic capital, entering a new production phase (Rifkin, 1996).

Secondly, the (standard) task-based model does not explicitly consider the unemployment rate within domestic labor markets. Hypothetically speaking, the thresholds of high-skilled workers could have expanded without expanding in terms of employment levels, that is, the occupational thresholds and levels of middle skilled occupations have declined without creating new forms of employment. In this manner, technological developments induce the domestic unemployment rates to expand, frankly reversing the Luddite Fallacy into the Luddite ‘accuracy’. However, in light of the Great Recession, it is too early to argue the Luddites were right, the upcoming decade will provide evidence how occupational structures evolve next to domestic unemployment rates. In addition, low- and high skilled employment levels have also risen during the last couple of decades, so the conjecture that employment levels are fixed is deceptive and incorrect.

It must be noted though, that governments impersonate a vital role in the developments of unemployment levels, as governments largely determine reservation wages of laborers, providing them unemployment benefits and other forms of subsidies. In this regard, high reservation wages could induce employers to replace labor by capital, making some tasks superfluous, thereby causing unemployment levels to rise. This could be seen as a trade-off for governments between the domestic international competiveness and to what extent (minimum) wages resemble subsistence levels to sustain the lives of workers. A phenomenon economists refer to as the ‘*iron law of wages’* (e.g. Ricardo, Marx, Lassalle). This trade-off is eventually determined by the prevailing norms and values within societies and especially relevant for workers at the bottom of the income distribution.

Another limitation of this paper is that it has implicitly equated occupations with job tasks, while in reality job tasks are subject to change, even within occupations. Since a worker possesses an array of skills to perform tasks, technological developments may adjusts the tasks laborers perform *within* occupations, however this does not necessarily affect the occupational tasks structure *between* occupations. Unfortunately, the data does not allow to study the former (the intensive margin) and therefore the previously employed approach solely captured the effects of technical progress on the occupational tasks structure *between* occupations (the extensive margin). In the US, the available databases (e.g. the Occupational Information Network) do concede researchers to study these tasks adjustments within occupations at much more detail, hopefully such European datasets are available within the near future too. It must be noted though, that the classification of tasks measures among occupations are always only a rough approximation, and can never fully reflect the full heterogeneity and adjustments in tasks within occupations. Simply put, the data should to some extent reflect a dynamic perspective of tasks among occupations. Spitz-Oener (2006) illustrated the benefits of this approach making use of a ‘unique’ dataset from West-Germany, she found that skills requirements within occupations generally had risen over time, attributable to more complex tasks laborers had to perform within occupations. This provides an example that it should be of high priority for European countries to improve and extent the availability of the occupational datasets, as studies could provide better insights and thus policy implications to enhance the capabilities of workers to be complementary to technological developments, instead of having laborers racing against it. Furthermore, the availability of datasets over longer periods of time would provide researchers to study the effects of technical progress in a historical perspective. The current analysis merely suggested that the effects of the measures of technical progress became more pronounced since the dawn of the new millennium, however this does not have to imply that technical progress did not have an impact on intensive margin of labor markets in the 90’s. For example, adjustments in the intensive margin of occupations could in general be preceding adjustments in the extensive margin. This could be an interesting avenue for new studies.

VI. **Conclusion**

This paper has studied the effects of technological change on the occupational and income structure of European labor markets. It has capitalized the task-based framework by Acemoglu and Autor (2011) in order to develop a better understanding in what manner technological change accounts for the pervasiveness of job polarization and adjustments in the distribution of incomes in European labor markets. Until recently, technological change is often perceived as a ‘black box’. For this reason, the opaqueness of technological change induced economists in the past to seize the Solow residual as the measure of disembodied technical progress. This paper has aimed to decompose the measures of technological change into separate measures. Therefore, panel data of 27 European countries abiding the time period 1995-2014 was employed for different measures of technical progress. These were correspondingly scaled dependent upon the domestic ‘intensity’ of the relevant measure. The technological development measures include the domestic intensities of the following; internet diffusion, patent, high-tech patent, automation patent, R&D expenditure and ICT imports. The first part of the empirical analysis suggested that a compelling but miscellaneous pattern has emerged from the effects of technological developments on the occupational structure of labor markets, a pattern that has become more pronounced since the dawn of the new millennium. Overall, countries that tend to converge towards higher technological intensities of automation patents and R&D expenditures are associated with contracting low- and predominantly middle skilled occupations, while this process is mitigated when countries increase their high-tech patent and ICT import intensities. The fact that the former effects always dominate the latter -also taking into account the effects of de-unionization and changes in the educational attainment levels- elucidates the pervasiveness of the job polarization phenomenon in European labor markets during the past decades.

More generally, weak evidence was found for the conjecture that more technologically advanced countries tend to have larger (smaller) high (middle) skilled occupational thresholds. The results merely indicated that technological advances induce countries to expand their high-skilled thresholds, while the occupational structures are more substantially determined by the time-invariant historical and cultural roots of a country. Further scrutiny has shown that the latter are also likely to contain a significant fraction of the emphasis on strong property rights in some Western European countries, which have been embedded in the historical roots of countries dependent upon the prevalence of (non)absolutist rule.

The remaining empirical section found that the effects of technological developments on gross wage inequality were fairly congruent to earlier findings that suggested mainly middle skilled occupations were most adversely susceptible to technological changes. This resonates with the comparative statics of the task-based model of Acemoglu and Autor (2011), which contemplates that technical progress has caused widening gross wage inequality in terms of w_H/w_L and w_H/w_M and contracting wage inequality in terms of w_M/w_L. It was shown that developments in automation patents have mainly been malicious to middle skilled workers, while in general patents are biased towards the most skilled workers. Above all, the estimates suggested that technical progress has been especially biased towards superstars at the top of the gross income distribution. A pattern that has become more vigorous since the dawn of the new millennium. Correspondingly, in light of concerns about equitable growth, it was examined whether technical progress has also induced adjustments in the disposable income distribution. The results gave –despite the widespread de-unionization of European labor markets- rise to the Krugman hypothesis, which entails that labor market institutions in Europe are effectively able to compress wages, thereby limiting the extent of inequality. This finding was robust to the inclusion of control measures regarding to a possible factor bias in trade.

Discussion

The conclusion merely contemplated that technical progress has attributed towards considerable changes in the occupational structures and gross income distributions of European labor markets. As stated before, these changes are often perceived as threads by laborers and policymakers alike, though this leaves out an even more important fact; technology has been extraordinarily enhancing our standards of living. In the future, human mankind is likely to experience technology carrying out tasks beyond ever imagined. However, sometimes it seems like people do not comprehend that the future has already begun. The German philosopher Immanuel Kant was concerned with one main inquiry; How can we comprehend the behavior of human mankind? Current bio-technical evolutions have made it feasible to 'design' babies, manipulate our DNA, and restructure our brain. The possibilities of humans to evolve themselves have become so numerous that scientists have argued humans have achieved a critical point within our evolution; humans have become their own creators (e.g. depicted in *Gattaca* (1997)). For this reason it has become vital to envision the future relationship between technology and humans. In his sci-fi masterpiece *2001*: A Space Odyssey, Stanley Kubrick envisioned a future of technologies making it feasible to make a journey through space. The portrayal of the technologies -we now are accustomed to use- is truly stunning, considering this movie was made in 1968. Some have argued this motion picture is basically a race between technology (HALL 9000) and humans, with the winner to achieve the next step in its evolution. Moravec (1988) portrayed this in a futuristic world where humans are surpassed by artificial counterparts, carrying on our 'cultural evolution'. In other words, a time in which we have lost our evolutionary race embedded in our DNA relative to artificial robots, giving rise to a new sort of robotic Darwinian evolution. So are we in a race between capital and labor? The data are increasingly suggesting that the rewards of capital are increasing relative to the rewards of labor. These developments are increasingly ceasing visions on norms and values of the past. For example, Abraham Lincoln argued about 150 years ago that: "*Capital is only the fruit of labor, and could never have existed if labor had not first existed. Labor is the superior of capital, and deserves much higher consideration."* These kind of statements obviously tell the narrative of how technology was perceived in the past. The former statement certainly remains true, however most people that profited of the increasing bounty of capital have certainly other views about the latter. Put differently, technology seems to have developed to a larger extent that our ethics. Therefore, it is urgent for policymakers to envision how to implement policies to race *with* technology, instead of *against*, in order to make the future economy a place for everyone.

Policy recommendations

First of all, it is crucial to emphasize the importance of work in societies and humans themselves. Work enhances the ability of people to engage in communities, to get self-worth and dignity. Several studies have shown the malicious effects of disappearing work in neighborhoods; deteriorating social capital, increasing crime rates, more incarceration (e.g. Murray, 2013; Wilson, 2011). Or how Voltaire had put it: "*Work saves us from the three great evils: boredom, vice and need.*" So foremost of all labor institutions should stimulate the incentive to work. This could be achieved by lowering taxes on labor income for especially lower and middle class workers (or providing subsidies). Furthermore, if the gross income distributions become exacerbating more unequal, institutions should consider to increase marginal tax rates at the very top of the income distributions. In addition, if incomes increasingly shift towards capital incomes relative to labor incomes, taxation institutions should consider to tax capital income more heavily (e.g. Diamond and Saez, 2011). Superstars have to comprehend that the their products and services can only be demanded if a rising tide is coupled with equally lifting boats.

So how can we lift our boats equally and –at least to some extent- the Luddite Fallacy operative? Domestic institutions should encourage entrepreneurs and inventors to create technologies that are complementary to human labor. It seems that during the past decades many technologies have mainly substituted human labor, while creating (limited) new uses of high skilled labor. If this pattern keeps emerging, societies may eventually experience the envisioned technological employment by Keynes. Therefore, governments could think of setting up prize competitions to invent technologies that enable humans to exploit their comparative advantage relative to capital; ideation, creativity and flexibility.

Furthermore, and more vital, domestic institutions should rethink our educational systems, best portrayed as an argument by Tinbergen's race between education and technology. Many economists have argued that primary schools should divert more emphasis to enable children to race with technology, instead of just emphasizing acquiring basic skills like reading, writing and arithmetic. The so-called self-organizing learning environments may provide children the tools to race with technology, stimulating them to employ technologies when doing assignments or problems. This learns them the tools to search for the relevant information and eventually come up with new ideas to solve assignments and problems. In the US, these schools have evidently been successful, considering the fact many founders of technology companies (e.g. Page and Brin from Google) were raised in this type of education system. Also high schools and universities may consider diverting more emphasis to students acquiring problem solving skills using technologies, certainly considering an increasing amount of educational resources are now available online. In the end, domestic institutions that remain lagging with the implementation of new educational systems may cause new workers to have to race against technology, and eventually be susceptible to be substituted by capital. Therefore, it is vital for institutions to arrange an educational system such that it provides humans the ability to be an indispensable complement to technology[28].

Finally, a few intriguing decades are ahead of humans, which might be a critical point within our evolution. It will provide us evidence how humans are going to evolve next to technologies. Whether the perceived automation 'wave' will indeed replace almost fifty percent of our jobs (Frey and Asborne, 2013). Whether we will experience artificial intelligence in 2045, having surpassed the highest level of intelligence of human beings (Kurzweil, 2004)[29]. And whether we have transformed the myth of Cockaigne into reality. Above all, it is likely to create a world with unprecedented bounty, but also a world with machines with enormous capabilities. Therefore, it is urgent for humans to envision and debate how to evolve next to technologies, our norms and values will become paramount in this. Whether we tolerate increasingly polarizing societies, how we cope with a possible reversal of the Luddity Fallacy into a Luddity 'accuracy'. In the end, we as humans shape our destiny, we will evolve ourselves, but it is vital to comprehend that the future has already begun.

[28] Further discussion purposes have been provided by e.g. The Economist (2015), where the suggestion is raised to rethink the world´s prevailing patent scheme (e.g. a novel scheme will be underpinned with a ´use it or lose it´ rule.) In addition, policy makers may think of reducing the exertion period of patents, as it may rectify the prevailing market structures. This could stimulate competition between firms, instead of patents being a tool for monopolists to raise their market power.
[29] For excellent thought-provoking overviews on future AI revolutions, see 'The AI Evolution: The Road to Superintelligence/Our Mortality or Extinction' by T. Urban and 'The Singularity is Near' by R. Kurzweil..

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Dataset references

Occupational data: European Union Labor Force Survey (LFS), collected by national labor institutions and correspondingly modified and reported by Eurostat for a 20-year period ranging from 1995 -2014.
Disposable income distribution data: The World Income Inequality Database (WIID V3.0B) reported by UNU-WIDER, which draws from several datasets among national surveys as OECD and Eurostat. This paper solely used statistics regarded in the dataset as high-quality.
Gross income distribution data: Decile ratios from gross income levels have been taken from the OECD statistics database, these include the interdecile ratios P90/P50, P90/P10 and P50/P10. Data concerning the gross income top 10%, 5% , 1% 0,5% and 0,1% have been collected from the World Top Income Database by Alverado, Atkinson, Saez and Piketty. This dataset refers to tax income statistics and have been reported by the Paris School of Economics. The 12 countries where gross income statistics are available for the top 5% and higher are; Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom
Technological development indicators: Three main databases have been employed, (i) a UNESCO dataset concerning internet adoption (per 100) people, patent applications (per million residents), R&D expenditures (as % of GDP), researchers in R&D (per million people), ICT imports (as % of total imports) and high technology exports (as % of GDP) these datasets have been reported by the World Bank, (ii) the second dataset is reported by Eurostat, with statistics concerning high-tech patent applications to the EPO (per million inhabitants), and automation and computerized business equipment patents (per million inhabitants) (iii) Thirdly, the Solow residual statistics are taken from the OECD database, which build upon work by Maddison, whom has established the Groningen Growth and Development Centre, which aim to collect harmonized data concerning several economic statistics.
Manufacturing exports: This dataset refers to exports of chemical, miscellaneous, machinery and basic goods, available at the World Bank as share of merchandise exports. Correspondingly, this dataset has been modified using World Bank datasets of absolute domestics GDP levels and absolute merchandise exports, compiling domestic manufacturing exports as % of GDP. These have been rescaled in similar matter as the technology indicators.
Educational attainment statistics: European Union Labour Force survey (LFS) reported by the World Bank, data refer to International Standard Classification of Education (ISCED).
Trade-union density statistics: The OECD Labour Force statistics database has been employed for 24 countries, the statistics for the remaining countries; Romania, Latvia and Lithuania, have been taken from the website workers-participation.eu at the subsection National Industrial Relations.
Net Migration data: The World Development Indicators dataset reported by the World Bank. This variable is rescaled using total domestic workforce data.
Rule of law statistics: The World Governance indicators, this dataset contains detailed information concerning several governance indicators including the rule of law, control of corruption and regulatory quality. This paper has employed the annual percentile ranks of the rule of law indicator as a proxy for institutional quality. This indicator captures the confidence of agents of others abiding to the rules of societies. In particular, this index emphasizes property rights, contract enforcement, existence of crime and violence (Kaufmann et al. 2011). *Other used sources:* R. Reich documentary: Inequality for All, VPRO documentaries: Tegenlicht, Het werken van morgen; Tegenlicht, De robot als mens

VIII. **Appendix**

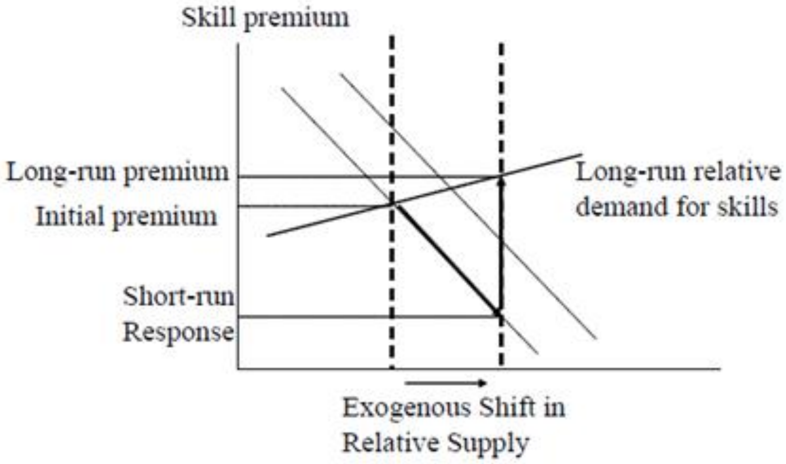

Figure: Dynamics of the skill premium in response to an exogenous increase in the relative supply of skills, with an upward-sloping endogenous-technology relative demand curve.

Figure 1: Developments in skill premium provided that the elasticity of substitution between low- and high skilled labor is sufficiently large (i.e. $\sigma > 2$, strong equilibrium bias).

Source: Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature*, p 40.

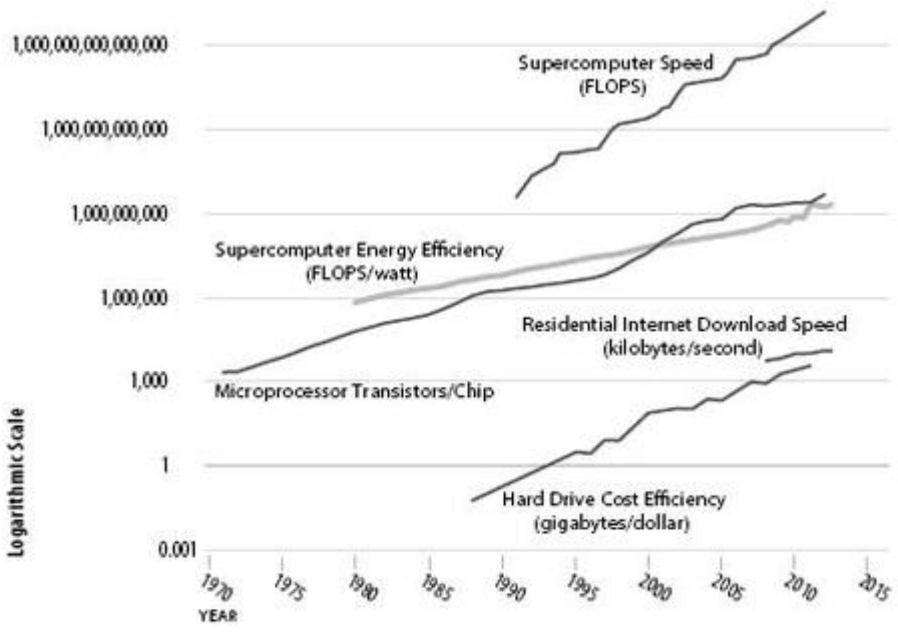

Figure 2: The Many Dimensions of Moore's law

Source: Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* WW Norton & Company, p 48.

Table 1: Offshorability and task-intensity scale of occupations	**Dependent Variables**[a]								
	Service and Sales	Elemen-tary	ΔAgricul-ture,forestry and fishery	Clerical support	Craft and related trade	Plant and machine operators	Profes-sionals	Mana-gers	Techni-cians
Offshorability	-0.91	-.0.81	-0.66	0.29	1.28	1.83	0.13	-0.53	-0.17
Routine-task int.	-0.60	0.41	0.45	2.10	1.34	0.34	-0.68	-1.08	-0.41

[a]Offshorability and routine task-intensity scale taken from Goos et al. (2009), values above refer to authors computations of disaggregated offshorability and routine-task intensity scales of occupations into the nine distinct occupations above. These values are stationary and are mapped on a scale of $[-2{,}5,\ 2{,}5]$, where 2,5 is an occupation with tasks with the highest offshorability (task-intensity) characteristics.

Table 2: Annual technological change effects on changes in occupational thresholds	**Dependent Variables**[a,b,c]								
	Δ Service and Sales	Δ Elemen-tary	ΔAgricul-ture, forestry and fishery	ΔClerical support	Δ Craft and related trade	Δ Plant and machine operators	ΔProfes-sionals	Δ Mana-gers	Δ Techni-cians
Independent Variables									
ΔInternet diffusion	0.00518 (0.059)	0.00466 (0.0077)	-0.0030 (0.0020)	-0.0097 (0.0099)	-0.00219 (0.0085)	-0.0096 (0.011)	-0.00231 (0.0011)	-0.00840 (0.0057)	0.0061 (0.0012)
ΔTotal patents	0.0234 (0.026)	0.00129 (0.047)	0.0120 (0.010)	0.0298 (0.034)	-0.0141 (0.030)	-0.0416 (0.028)	-0.0367 (0.036)	-0.00828 (0.035)	0.0330 (0.050)
ΔHigh-tech patents	0.0417 (0.086)	0.0392 (0.048)	0.00239 (0.018)	-0.0328 (0.042)*	0.0785 (0.056)	0.061 (0.039)	-0.155 (0.13)	0.0355 (0.055)	-0.0823 (0.059)
ΔAutomation patents	0.0233 (0.060)	-0.0219 (0.036)	-0.00906 (0.014)	-0.0257 (0.035)	-0.0541 (0.046)	-0.0462 (0.029)	0.0992 (0.089)	-0.0377 (0.051)	0.0240 (0.058)
ΔR&D expenditures	-0.110 (0.044)**	-0.0162 (0.056)	-0.0010 (0.013)	-0.0703 (0.054)	0.0462 (0.054)	-0.030 (0.034)	0.0960 (0.074)	0.0115 (0.036)	0.0742 (0.063)
ΔUnionization	-0.0091 (0.028)	0.023 (0.021)***	-0.0016 (0.0048)	-0.0021 (0.020)	-0.0051 (0.025)	-0.011 (0.020)	0.0265 (0.026)	-0.0015 (0.012)	-0.030 (0.029)
ΔNet migration	-0.092 (0.034)***	0.0876 (0.0037)**	-0.024 (0.017)	-0.00689 (0.027)	-0.0074 (0.0083)	0.0123 (0.086)	-0.0980 (0.037)***	0.0772 (0.028)***	0.0500 (0.055)
ΔPrimary education	0.00251 (0.012)	-0.0163 (0.0093)*	0.0529 (0.046)						
ΔSecondary education				-0.0589 (0.093)*	0.0972 (0.016)	-0.054 (0.061)			
ΔTertiary education							0.0055 (0.0021)**	0.0030 (0.024)	0.0039 (0.019)
Constant	0.0332 (0.0006)***	0.00035 (0.0006)	-0.00011 (0.00022)	-0.00043 (0.0012)	-0.0036 (0.0010)***	0.00057 (0.0007)	0.00151 (0.0013)	0.00179 (0.0081)	-0.00116 (0.0013)
Model Information									
Time FE	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	513	513	513	513	513	513	513	513	513
R^2	0.21	0.098	0.019	0.10	0.094	0.11	0.32	0.075	0.17

[a]Dependent variables in percentage point annual change in respective occupational share of total domestic employment levels, independent variables in annual change of the relevant variable, evaluation period includes 1995-2014
[b]Standard errrors in parentheses; [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

Table 3: Dynamic (GMM) model using first-differenced variables	**Dependent Variables[a,b,c]**								
	Δ Service and Sales	Δ Elementary	ΔAgriculture, forestry and fishery	ΔClerical support	Δ Craft and related trade	Δ Plant and machine operators	Δ Managers	ΔProfessionals	Δ Technicians
Independent Variables									
$j_{i,t-1}$	0.442 (0.31)	0.573 (0.26)**	0.426 (0.099)***	0.854 (0.36)**	0.617 (0.18)***	0.821 (0.39)**	0.0737 (0.43)	0.328 (0.20)	0.677 (0.35)*
ΔInternet diffusion	0.0124 (0.015)	-0.00485 (0.016)	-0.00119 (0.0039)	-0.0363 (0.016)**	-0.0478 (0.021)**	-0.00569 (0.0061)	0.0178 (0.0051)***	0.0132 (0.017)	0.0276 (0.013)**
ΔTotal patents	0.0170 (0.041)	-0.00095 (0.024)	0.00801 (0.0071)	-0.0389 (0.030)	-0.0241 (0.041)	-0.00485 (0.029)	0.0271 (0.021)	-0.0617 (0.041)	0.0314 (0.043)
ΔHigh-tech patents	0.151 (0.034)***	0.0399 (0.018)**	0.00274 (0.010)***	-0.0515 (0.043)	0.0440 (0.075)	0.0612 (0.021)***	0.0796 (0.038)**	-0.277 (0.071)***	-0.140 (0.091)
ΔAutomation patents	-0.0270 (0.036)	-0.0334 (0.033)	-0.00232 (0.0015)*	-0.0594 (0.0027)**	-0.0712 (0.032)**	-0.0713 (0.032)**	-0.0772 (0.065)	0.248 (0.057)***	0.110 (0.054)**
ΔR&D expenditures	-0.134 (0.053)**	-0.0414 (0.020)**	-0.00406 (0.0095)	-0.0653 (0.034)*	0.0388 (0.048)	-0.0125 (0.026)	0.0106 (0.081)	0.169 (0.045)***	0.0893 (0.061)
ΔICT Imports	-0.0211 (0.041)	0.0180 (0.050)	0.0332 (0.010)***	0.0531 (0.019)***	0.0593 (0.052)	0.0521 (0.0024)**	-0.0503 (0.027)*	-0.110 (0.070)	-0.0429 (0.014)***
ΔUnionization	-0.0175 (0.023)	0.114 (0.043)**	-0.0356 (0.010)***	0.0341 (0.039)	0.0203 (0.046)	0.0512 (0.051)	0.0185 (0.034)	-0.0689 (0.038)*	-0.0148 (0.043)
ΔNet migration	0.0234 (0.035)	0.0281 (0.023)	0.00107 (0.0039)	-0.0784 (0.023)***	0.0457 (0.041)	-0.0846 (0.091)	0.0519 (0.11)	-0.0674 (0.051)	0.0568 (0.048)
ΔPrimary education	-0.0447 (0.014)***	-0.0181 (0.0050)***	-0.0103 (0.094)						
ΔSecondary education				0.0253 (0.0039)**	-0.0202 (0.0051)***	0.0334 (0.024)*			
ΔTertiary education							0.137 (0.041)***	0.106 (0.031)***	0.0894 (0.026)***
Model Information									
Time FE	No	Yes	No	Yes	Yes	No	Yes	No	Yes
Observations	81	81	81	81	81	81	81	81	81
Instruments	$Serv_{i,t-2}$ $Serv_{i,t-3}$	$Elem_{i,t-2}$ $Elem_{i,t-3}$	$Agri_{i,t-2}$ $Agri_{i,t-3}$	$Clerk_{i,t-2}$ $Clerk_{i,t-3}$	$Craft_{i,t-2}$ $Craft_{i,t-3}$	$Plant_{i,t-2}$ $Plant_{i,t-3}$	$Man_{i,t-2}$ $Man_{i,t-3}$	$Prof_{i,t-2}$ $Prof_{i,t-3}$	$Tech_{i,t-2}$ $Tech_{i,t-3}$
Test of over-identifying restrictions (J-test)	2.203 (p = 0.33)	4.102 (p = 0.13)	6.464 (p = 0.039)	4.267 (p = 0.12)	3.499 (p = 0.17)	3.562 (p = 0.17)	3.251 (p = 0.20)	2.137 (p = 0.34)	2.873 (p = 0.24)

[a]Dependent variables in percentage point five year change in respective occupational share of total domestic employment levels, independent variables refer to five year changes in the relevant variable ($j_{i,t-1}$ refers to respective occupational share of the previous period, instrumented by the first and second period prior to $j_{i,t-1}$) , evaluation period intervals include 1999-2004, 2004-2009 and 2009-2014. [b]White period standard errors in parentheses; two-step iteration weighting matrix, Hadri-tests indicated presence of nonstationarity in column 3 [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

Table 4: Factors determining occupational thresholds (six year intervals)	**Dependent Variables[a,b,c]**								
	Service and Sales	Elemen-tary	ΔAgricul-ture, forestry and fishery	Clerical support	Craft and related trade	Plant and machine operators	Managers	Profes-sionals	Techni-cians
Independent Variables									
Internet diffusion	0.0285	0.0250	-0.00298	0.0273	-0.0129	0.0350	0.0962	0.00389	0.0190
	(0.041)	(0.038)	(0.024)	(0.029)	(0.020)	(0.061)	(0.023)***	(0.027)	(0.0273)
Total patents	0.127	-0.0943	0.0319	-0.0936	-0.254	-0.196	0.00107	0.140	0.0860
	(0.030)***	(0.052)*	(0.015)**	(0.099)	(0.11)**	(0.023)***	(0.0045)	(0.071)*	(0.054)*
High-tech patents	-0.187	0.120	0.0297	-0.0578	0.0943	-0.0459	0.147	-0.114	-0.0764
	(0.042)***	(0.030)***	(0.012)**	(0.076)	(0.10)	(0.064)	(0.051)***	(0.051)**	(0.056)
Automation patents	0.172	-0.202	0.00690	-0.0841	-0.218	-0.0953	0.127	0.0481	0.120
	(0.055)***	(0.019)***	(0.0051)	(0.059)	(0.032)**	(0.056)*	(0.046)***	(0.025)*	(0.051)**
R&D expenditures	-0.0931	-0.0630	-0.0473	0.340	0.124	-0.0594	-0.0177	-0.152	0.0958
	(0.12)	(0.15)	(0.014)***	(0.14)**	(0.17)	(0.077)	(0.090)	(0.11)	(0.17)
ICT Imports	0.0262	0.0335	0.00199	0.227	0.0466	0.0795	-0.0110	-0.106	-0.207
	(0.052)	(0.021)*	(0.0058)	(0.065)***	(0.035)	(0.029)**	(0.030)	(0.029)***	(0.034)***
Unionization	-0.0752	0.143	0.00235	-0.0527	0.124	-0.0117	0.0765	0.0422	-0.0762
	(0.035)**	(0.057)***	(0.0017)	(0.091)	(0.012)***	(0.0096)	(0.0042)*	(0.050)	(0.031)**
Net migration	-0.136	-0.0353	-0.0251	-0.138	0.102	-0.0492	0.0809	0.0296	-0.0179
	(0.063)**	(0.049)	(0.031)	(0.062)**	(0.038)***	(0.033)	(0.037)**	(0.039)	(0.097)
Primary education	0.0680	0.139	0.0159						
	(0.023)***	(0.029)***	(0.0044)***						
Secondary education				0.0497	-0.0635	0.0132			
				(0.012)***	(0.032)*	(0.0028)***			
Tertiary education							0.289	0.334	0.205
							(0.036)***	(0.047)***	(0.059)***
Constant	0.154	0.0782	0.00457	0.103	0.177	0.0897	0.0102	0.0982	0.167
	(0.037)***	(0.017)***	(0.0026)*	(0.011)***	(0.026)***	(0.025)***	(0.0031)***	(0.010)***	(0.051)***
Model specifications									
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	Yes	Yes	Yes	No	Yes	Yes
Observations	81	81	81	81	81	81	81	81	81
R^2	0.940	0.909	0.904	0.933	0.948	0.959	0.958	0.946	0.937

[a]Dependent variables reflect the respective occupational share of total domestic employment levels at 2002, 2008 and 2014, independent variables in six year change of the relevant variable, evaluation period intervals include 1997-2002, 2003-2008 and 2009-2014 [b]Standard errrors in parentheses [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

Table 5: Factors determining occupational thresholds, including rule of law	**Dependent Variables[a,b]**								
	Service and Sales	Elemen-tary	Agricultu-re,forestry and fishery	Clerical support	Craft and related trade	Plant and machine operators	Managers	Profes-sionals	Techni-cians
Independent Variables									
Internet diffusion	0.0263 (0.015)*	-0.0409 (0.12)	0.00694 (0.044)	0.0348 (0.018)*	-0.0441 (0.014)***	0.0172 (0.014)	0.0117 (0.015)	0.0125 (0.011)	0.0391 (0.021)*
Total patents	0.132 (0.67)*	-0.108 (0.16)	0.0297 (0.044)	-0.127 (0.21)	-0.378 (0.14)**	-0.122 (0.16)	-0.0726 (0.19)	0.0864 (0.097)	0.241 (0.20)
High-tech patents	-0.185 (0.064)***	0.138 (0.057)**	0.0379 (0.016)**	-0.0787 (0.13)	0.0615 (0.10)	0.0661 (0.062)	-0.253 (0.077)***	-0.165 (0.64)**	-0.128 (0.074)*
Automation patents	0.188 (0.053)***	-0.0294 (0.063)	-0.0245 (0.024)	-0.0152 (0.079)	-0.0866 (0.024)***	-0.0798 (0.041)**	0.182 (0.057)***	0.134 (0.057)**	0.0755 (0.068)
R&D expenditures	-0.0253 (0.16)	0.0326 (0.14)	-0.0385 (0.023)*	0.390 (0.17)**	0.275 (0.19)	-0.311 (0.14)**	-0.310 (0.17)*	-0.148 (0.11)	-0.0134 (0.26)
ICT Imports	0.0266 (0.049)	0.0548 (0.015)***	0.0259 (0.011)**	0.157 (0.062)**	0.109 (0.037)***	0.0527 (0.046)	-0.0404 (0.024)*	-0.0275 (0.041)	-0.204 (0.075)**
Unionization	-0.0832 (0.064)*	0.0774 (0.041)*	-0.0143 (0.012)	-0.0210 (0.077)	0.0873 (0.051)*	-0.0699 (0.054)	0.0935 (0.070)	0.0520 (0.037)	-0.0682 (0.084)
Net migration	-0.314 (0.12)**	-0.0941 (0.089)	-0.00606 (0.073)	0.281 (0.34)	-0.187 (0.22)	0.0674 (0.020)**	0.329 (0.26)	0.170 (0.018)	0.00601 (0.038)
Primary education	0.0792 (0.075)	0.0254 (0.037)	0.00975 (0.010)						
Secondary education				0.0241 (0.064)	-0.110 (0.060)*	0.00270 (0.046)			
Tertiary education							0.162 (0.046)***	0.257 (0.031)	0.128 (0.078)*
Rule of Law	-0.0326 (0.043)	-0.0821 (0.034)**	0.00695 (0.010)	0.118 (0.038)***	0.00445 (0.048)	0.0165 (0.049)	-0.0377 (0.055)	-0.0414 (0.055)	-0.0329 (0.053)
Rule of Law*West Europe	-0.0821 (0.099)	0.173 (0.095)*	-0.0292 (0.015)*	-0.129 (0.057)**	-0.310 (0.12)**	-0.177 (0.094)*	0.206 (0.074)**	0.181 (0.012)	0.0425 (0.12)
Constant	0.177 (0.018)***	0.0389 (0.064)	0.0110 (0.0032)***	0.0652 (0.037)*	-0.0207 (0.085)	0.0920 (0.011)***	0.219 (0.062)***	0.0874 (0.041)**	0.186 (0.081)**
Model specifications									
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	No	Yes	No	Yes	No
Observations	81	81	81	81	81	81	81	81	81
R^2	0.949	0.934	0.925	0.932	0.951	0.976	0.967	0.951	0.942

[a]Dependent variables reflect the respective occupational share of total domestic employment levels at 2004, 2009 and 2014, evaluation period intervals include 2000-2004, 2005-2009 and 2010-2014 [b]Standard errors in parentheses; [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

Table 6: Dynamic GMM model of disposable income estimates	**Dependent Variables[a,b,c]**								
	$\Delta\frac{D5}{D1}$	$\Delta\frac{Q3}{Q1}$	$\Delta\frac{[D4,\ D6]}{[D1,\ D3]}$	$\Delta\frac{D10}{D1}$	$\Delta\frac{Q5}{Q1}$	$\Delta\frac{[D8,\ D10]}{[D1,\ D3]}$	$\Delta\frac{D10}{D5}$	$\Delta\frac{Q5}{Q3}$	$\Delta\frac{[D8,\ D10]}{[D4,\ D6]}$
Independent Variables									
$r_{i,t-1}$	0.801 (0.32)**	1.312 (0.43)***	1.238 (0.59)**	0.679 (0.38)*	0.815 (0.69)	0.607 (0.62)	-1.215 (0.42)***	-1.063 (0.47)**	-0.915 (0.38)**
ΔInternet diffusion	-0.0684 (0.11)	-0.124 (0.19)	0.0141 (0.018)	0.323 (0.57)	0.303 (0.74)	0.550 (0.34)*	0.152 (0.088)*	0.121 (0.076)*	0.252 (0.11)**
ΔTotal patents	0.167 (0.34)	0.0543 (0.51)	0.0957 (0.21)	-0.368 (0.41)	0.138 (0.23)	-0.323 (0.47)	-0.188 (0.22)	-0.112 (0.13)	-0.245 (0.18)
ΔHigh-tech patents	0.351 (0.37)	0.194 (0.64)	0.0756 (0.64)	-0.761 (0.67)	-0.540 (0.21)***	-0.429 (0.23)**	-0.181 (0.32)	-0.157 (0.31)	0.0605 (0.49)
ΔAutomation patents	-0.394 (0.29)	-0.541 (0.57)	-0.127 (0.22)	0.941 (0.57)*	0.684 (0.31)**	0.655 (0.24)***	0.245 (0.14)*	0.236 (0.21)	0.229 (0.11)**
ΔR&D expenditures	0.0780 (0.97)	0.246 (0.73)	0.317 (0.41)	0.342 (0.40)	0.491 (0.87)	0.204 (0.43)	0.0973 (0.081)	0.0934 (0.074)	0.0936 (0.066)
ΔICT Imports	0.146 (0.24)	0.0416 (0.38)	-0.0216 (0.13)	-0.218 (0.51)	-0.422 (0.64)	-0.140 (0.30)	-0.248 (0.22)	-0.116 (0.091)	-0.341 (0.12)***
ΔUnionization	0.368 (0.42)	0.282 (0.15)*	0.226 (0.17)	0.387 (0.51)	0.214 (0.38)	0.114 (0.44)	-0.327 (0.21)*	-0.244 (0.18)	-0.0894 (0.064)
ΔNet migration	0.0433 (0.12)	-0.0893 (0.12)	-0.147 (0.34)	-0.231 (0.35)	-0.281 (0.64)	-0.348 (0.61)	-0.143 (0.32)	-0.102 (0.14)	-0.237 (0.27)
ΔPrimary education	0.547 (0.58)	0.0354 (0.025)	0.147 (0.16)	-0.257 (0.19)	-0.148 (0.091)	-0.204 (0.33)			
ΔSecondary education	0.689 (0.61)	0.0446 (0.032)	0.192 (0.20)				-0.0799 (0.037)**	-0.0648 (0.026)**	-0.268 (0.012)**
ΔTertiary education				-0.842 (0.39)**	-0.428 (0.31)	-0.191 (0.23)	-0.101 (0.23)	-0.0661 (0.10)	-0.0347 (0.11)
Model Information									
Observations	52	52	52	52	52	52	52	52	52
Instruments	$D5/D1_{t-2}$ $D5/D1_{t-3}$	$Q3/Q1_{t-2}$ $Q3/Q1_{t-3}$	$D456/D123_{t-2}$ $D456/D123_{t-3}$	$D10/D1_{t-2}$ $D10/D1_{t-3}$	$Q5/Q1_{t-2}$ $Q5/Q1_{t-3}$	$[D8{,}10/D1{,}3]_{t-2}$ $[D8{,}10/D1{,}3]_{t-3}$	$D10/D5_{t-2}$ $D10/D5_{t-3}$	$Q5/Q3_{t-2}$ $Q5/Q3_{t-3}$	$[D8{,}10/D4{,}6]_{t-2}$ $[D8{,}10/D4{,}6]_{t-3}$
Overidentifying restrictions (J-test)	1.197 (p = 0.55)	0.783 (p = 0.68)	0.940 (p = 0.63)	4.115 (p = 0.13)	4.214 (p = 0.12)	4.597 (p = 0.10)	0.207 (p = 0.90)	0.161 (p = 0.92)	0.193 (p = 0.91)

[a]Dependent variables in percentage point five year change in respective domestic relative disposable income shares, independent variables refer to five year changes in the relevant variable ($r_{i,t-1}$ refers to respective domestic relative gross income share of the previous period, instrumented by the first and second period prior to $r_{i,t-1}$) , evaluation period intervals include 2000-2005 and 2005-2010. [b]White period standard errors in parentheses; two-step iteration weighting matrix, Hadri-tests indicated presence of stationarity in all estimations [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

Table 7: Gross income estimates containing two periods	**Dependent Variables**[a,b,c]										
	$\Delta\frac{D5}{D1}$	$\Delta\frac{D10}{D1}$	$\Delta\frac{P95}{D1}$	$\Delta\frac{P99}{D1}$	$\Delta\frac{P995}{Q1}$	$\Delta\frac{P999}{Q1}$	$\Delta\frac{D10}{D5}$	$\Delta\frac{P95}{D5}$	$\Delta\frac{P99}{D5}$	$\Delta\frac{P995}{D5}$	$\Delta\frac{P999}{D5}$
Independent Variables											
ΔInternet diffusion	0.0553	0.274	-0.341	-0.0250	-0.00194	-0.0146	0.0430	0.0571	0.0968	0.0258	0.0217
	(0.071)	(0.12)**	(0.26)	(0.11)	(0.095)	(0.064)	(0.10)	(0.14)	(0.13)	(0.080)	(0.049)
ΔTotal patents	0.622	1.394	1.212	0.856	0.689	0.360	0.517	0.616	0.428	0.332	0.163
	(0.21)***	(0.50)***	(0.24)***	(0.17)***	(0.21)***	(0.14)**	(0.25)**	(0.21)***	(0.097)***	(0.11)**	(0.075)**
ΔHigh-tech patents	-0.291	-0.351	0.629	0.295	0.0197	-0.270	-0.887	-0.452	-0.0226	-0.276	-0.130
	(0.41)	(1.31)	(1.21)	(0.72)	(0.97)	(0.52)	(0.30)***	(0.59)	(0.56)	(0.56)	(0.31)
ΔAutomation patents	-0.475	0.489	0.226	0.483	0.233	0.0418	0.708	0.234	0.142	0.0416	0.0761
	(0.29)*	(0.29)*	(0.99)	(0.52)	(0.58)	(0.29)	(0.26)**	(0.16)*	(0.062)**	(0.057)	(0.037)**
ΔR&D expenditures	-0.301	-1.117	-1.683	-0.456	-0.0941	-0.149	0.0489	0.172	0.0287	0.127	0.0459
	(0.53)	(1.21)	(0.75)**	(0.46)	(0.53)	(0.35)	(0.29)	(0.34)	(0.26)	(0.13)	(0.21)
ΔICT Imports	0.243	0.0510	0.336	0.463	0.521	0.338	0.0756	0.347	0.271	0.225	0.210
	(0.23)	(0.68)	(0.71)	(0.31)*	(0.19)**	(0.22)	(0.11)	(0.37)	(0.12)**	(0.26)	(0.15)
ΔUnionization	-0.520	-1.376	-1.158	-0.579	-0.137	-0.499	-0.117	-0.042	-0.189	-0.0803	-0.0597
	(0.16)***	(0.54)**	(0.49)**	(0.34)*	(0.91)	(0.45)	(0.28)	(0.82)	(0.62)	(0.65)	(0.37)
ΔNet migration	0.0543	0.827	0.470	0.675	0.616	0.234	0.195	0.224	0.319	0.281	0.127
	(0.27)	(0.34)**	(0.20)**	(0.20)***	(0.24)**	(0.24)	(0.19)	(0.20)	(0.16)*	(0.15)*	(0.16)
ΔPrimary education	0.556	0.968	0.783	0.0423	0.0704	0.0116					
	(0.32)*	(0.82)	(0.57)	(0.21)	(0.16)	(0.022)					
ΔSecondary education	-0.0646						-0.234	-0.261	0.0246	0.0703	0.0173
	(0.50)						(0.32)	(0.32)	(0.15)	(0.13)	(0.014)
ΔTertiary education		0.505	1.131	1.034	0.845	0.0737	0.608	0.781	0.773	0.668	0.578
		(1.68)	(1.38)	(0.60)*	(0.57)*	(0.089)	(0.39)*	(0.34)**	(0.42)*	(0.24)**	(0.23)**
Constant	-0.0134	-0.0304	0.0616	-0.108	-0.112	-0.0447	-0.0460	-0.127	-0.0738	-0.0757	-0.0418
	(0.051)	(0.14)	(0.10)	(0.042)**	(0.040)**	(0.046)	(0.038)	(0.084)	(0.030)**	(0.016)***	(0.030)
Model Information											
Observations	48	48	24	26	24	24	48	24	26	24	24
R^2	0.314	0.257	0.689	0.818	0.735	0.550	0.275	0.527	0.612	0.551	0.402

[a]Dependent variables in percentage point five year change in respective relative domestic income shares , evaluation period intervals include 2001-2005 and 2006-2010 [b]Standard errrors in parentheses; period EGLS employed in all estimations [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively, main regressions exclude Iceland, Romania and Slovenia due to limited available data, remaining columns refer to relative top gross incomes, only available for limited set of countries, see data section for further details.

Table 8: Dynamic (GMM) model using first differences:Gross income estimates	**Dependent Variables**[a,b,c]										
	$\Delta\frac{D5}{D1}$	$\Delta\frac{D10}{D1}$	$\Delta\frac{P95}{D1}$	$\Delta\frac{P99}{D1}$	$\Delta\frac{P995}{Q1}$	$\Delta\frac{P999}{Q1}$	$\Delta\frac{D10}{D5}$	$\Delta\frac{P95}{D5}$	$\Delta\frac{P99}{D5}$	$\Delta\frac{P995}{D5}$	$\Delta\frac{P999}{D5}$
Independent Variables											
$r_{i,t-1}$	0.271	0.256	-0.187	0.126	-0.00547	-0.183	0.326	0.239	0.274	0.140	-0.0940
	(0.22)	(0.77)	(0.56)	(0.55)	(0.45)	(0.62)	(0.37)	(0.60)	(0.78)	(0.69)	(0.45)
ΔInternet diffusion	0.0554	0.163	-0.219	-0.0932	-0.0701	-0.0613	0.124	0.152	0.143	0.0855	0.0356
	(0.083)	(0.14)	(0.16)	(0.16)	(0.12)	(0.081)	(0.19)	(0.17)	(0.21)	(0.12)	(0.048)
ΔTotal patents	0.436	1.293	1.516	0.894	0.875	0.552	0.669	0.658	0.488	0.438	0.318
	(0.14)***	(0.41)***	(0.34)***	(0.26)***	(0.16)***	(0.14)***	(0.20)***	(0.15)***	(0.11)***	(0.10)***	(0.14)**
ΔHigh-tech patents	-0.0893	-0.123	-0.398	-0.212	-0.207	-0.0622	-0.541	-0.258	-0.0957	-0.244	-0.209
	(0.51)	(0.95)	(1.07)	(0.84)	(0.44)	(0.67)	(0.21)**	(0.53)	(0.61)	(0.53)	(0.41)
ΔAutomation patents	-0.492	0.531	0.578	0.254	0.236	0.0807	0.377	0.291	0.129	0.0971	0.0574
	(0.22)**	(0.29)*	(0.48)	(0.61)	(0.37)	(0.39)	(0.17)**	(0.13)**	(0.44)	(0.21)	(0.081)
ΔR&D expenditures	-0.649	-1.426	-1.659	-1.013	-0.689	-0.532	0.341	0.172	0.334	0.271	0.229
	(0.48)	(0.81)*	(0.45)***	(0.52)*	(0.21)***	(0.27)*	(0.24)	(0.46)	(0.41)	(0.24)	(0.43)
ΔICT Imports	0.431	0.442	0.509	0.323	0.208	0.0163	0.0865	0.427	0.172	0.0537	0.0418
	(0.13)***	(0.59)	(0.36)	(0.27)	(0.23)	(0.21)	(0.13)	(0.34)	(0.081)**	(0.13)	(0.24)
ΔUnionization	-0.539	-0.871	-0.848	-0.784	-0.420	-0.374	0.341	-0.541	-0.517	-0.183	-0.481
	(0.17)***	(0.42)**	(0.41)**	(0.41)*	(0.94)	(0.60)	(0.21)*	(0.74)	(0.43)	(0.62)	(0.59)
ΔNet migration	0.0972	0.857	0.751	0.694	0.584	0.241	0.169	0.348	0.310	0.282	0.119
	(0.12)	(0.39)**	(0.18)**	(0.27)**	(0.25)**	(0.32)	(0.31)	(0.32)	(0.12)**	(0.11)**	(0.18)
ΔPrimary education	0.998	1.209	0.866	0.465	0.304	0.0209					
	(0.61)*	(0.95)	(0.35)**	(0.29)	(0.28)	(0.019)					
ΔSecondary education	-0.103						-0.108	-0.125	-0.224	-0.105	0.0763
	(0.54)						(0.34)	(0.10)	(0.31)	(0.24)	(0.022)
ΔTertiary education		1.781	1.481	1.054	0.768	0.486	0.514	0.846	0.428	0.417	0.381
Model Information		(1.84)	(1.44)	(0.89)	(0.57)	(0.41)	(0.21)**	(0.32)**	(0.46)	(0.28)*	(0.21)**
Observations	48	48	24	26	24	22	48	24	26	24	24
Instruments	$D5/D1_{t-2,t-3}$	$D10/D1_{t-2,t-3}$	$P95/D1_{t-2,t-3}$	$P99/D1_{t-2,t-3}$	$P995/D1_{t-2,t-3}$	$P999/D1_{t-2,t-3}$	$D10/D5_{t-2,t-3}$	$P95/D5_{t-2,t-3}$	$P99/D5_{t-2,t-3}$	$P995/D5_{t-2,t-3}$	$P999/D5_{t-2,t-3}$
Overidentifying restrictions (J-test)	3.031	1.211	1.472	1.674	0.869	0.320	2.093	1.848	3.873	3.513	0.490
	(p = 0.22)	(p = 0.55)	(p = 0.48)	(p = 0.43)	(p = 0.65)	(p = 0.85)	(p = 0.35)	(p = 0.40)	(p = 0.14)	(p = 0.17)	(p = 0.78)

[a]Dependent variables in percentage point five year change in respective domestic relative gross income shares, independent variables refer to five year changes in the relevant variable ($r_{i,t-1}$ refers to respective domestic relative gross income share of the previous period, instrumented by the first and second period prior to $r_{i,t-1}$) , evaluation period intervals include 2000-2005 and 2005-2010. [b]White period standard errors in parentheses; two-step iteration weighting matrix, Hadri-tests indicated presence of stationarity in all estimations [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively

Table 9: Gross income estimates incl. high-tech and manufacturing exports	**Dependent Variables**[a,b,c]										
	$\Delta\frac{D5}{D1}$	$\Delta\frac{D10}{D1}$	$\Delta\frac{P95}{D1}$	$\Delta\frac{P99}{D1}$	$\Delta\frac{P995}{Q1}$	$\Delta\frac{P999}{Q1}$	$\Delta\frac{D10}{D5}$	$\Delta\frac{P95}{D5}$	$\Delta\frac{P99}{D5}$	$\Delta\frac{P995}{D5}$	$\Delta\frac{P999}{D5}$
Independent Variable											
ΔInternet diffusion	0.00467	0.250	0.0637	0.0544	0.0755	0.00650	0.0717	0.0627	0.0408	0.0398	0.00225
	(0.055)	(0.10)**	(0.18)	(0.088)	(0.11)	(0.029)	(0.056)	(0.11)	(0.039)	(0.074)	(0.056)
ΔTotal patents	0.598	0.839	0.960	0.704	0.539	0.242	0.441	0.530	0.426	0.244	0.117
	(0.16)***	(0.37)**	(0.27)***	(0.11)***	(0.20)**	(0.010)**	(0.15)***	(0.23)**	(0.17)**	(0.11)**	(0.097)
ΔHigh-tech patents	-0.397	-0.407	-0.745	-0.883	-0.216	-0.205	-0.564	-0.457	-0.361	-0.243	-0.354
	(0.24)	(0.41)	(0.38)*	(0.19)***	(0.36)	(0.24)	(0.15)***	(0.17)**	(0.23)*	(0.31)	(0.16)**
ΔAutomation patents	-0.497	0.561	0.581	0.701	0.251	0.0681	0.477	0.256	0.427	0.0935	0.0510
	(0.21)**	(0.24)**	(0.24)**	(0.20)***	(0.30)	(0.14)	(0.13)***	(0.18)	(0.21)**	(0.14)	(0.031)*
ΔR&D expenditures	-0.242	-0.663	-0.822	-0.795	-0.492	-0.0233	0.136	-0.122	-0.226	0.00395	0.0723
	(0.30)	(0.71)	(0.45)*	(0.47)*	(0.46)	(0.19)	(0.21)	(0.18)	(0.16)	(0.24)	(0.14)
ΔICT Imports	0.281	0.459	0.324	0.271	0.0449	0.0493	0.121	0.176	0.108	0.0242	0.0417
	(0.15)*	(0.39)	(0.53)	(0.21)	(0.16)	(0.11)	(0.12)	(0.13)	(0.13)	(0.12)	(0.12)
ΔUnionization	-0.170	-1.309	-1.458	-0.608	-0.716	-0.693	-0.394	-0.350	-0.115	-0.214	-0.259
	(0.17)	(0.56)**	(0.67)**	(0.34)*	(0.64)	(0.23)***	(0.14)***	(0.28)	(0.21)	(0.39)	(0.11)**
ΔNet migration	-0.101	0.347	0.549	0.185	0.385	0.0637	-0.0593	0.159	0.108	0.0242	-0.0017
	(0.15)	(0.27)	(0.38)	(0.17	(0.31)	(0.12)	(0.14)	(0.24)	(0.21)	(0.12)	(0.22)
ΔPrimary education	0.421	0.136	0.326	0.0446	0.0252	0.0141					
	(0.22)*	(0.52)	(0.38)	(0.19)	(0.16)	(0.0095)					
ΔSecondary education	-0.0336						-0.0504	-0.169	-0.0233	-0.0610	-0.0505
	(0.21)						(0.16)	(0.18)	(0.11)	(0.093)	(0.11)
ΔTertiary education		0.561	0.414	0.778	0.571	0.0674	0.136	0.324	0.714	0.339	0.0272
		(0.79)	(0.36)	(0.35)**	(0.63)	(0.23)	(0.22)	(0.19)*	(0.32)**	(0.34)	(0.025)
ΔHigh-tech exports	-0.589	0.00125	1.512	0.577	0.251	0.478	0.202	0.549	0.140	0.194	0.269
	(0.22)**	(0.13)	(0.44)***	(0.70)	(0.71)	(0.021)**	(0.27)	(0.029)*	(0.33)	(0.12)	(0.10)**
ΔManufac exports	0.340	-0.244	-1.392	-0.474	-0.139	-0.423	-0.274	-0.498	-0.234	-0.471	-0.257
Model Information	(0.11)***	(0.21)	(0.66)**	(0.40)	(0.24)	(0.28)	(0.081)***	(0.36)	(0.20)	(0.26)*	(0.16)
Observations	72	72	36	39	36	36	72	36	39	36	36
R^2	0.346	0.331	0.646	0.751	0.563	0.592	0.378	0.687	0.751	0.623	0.566

[a]Dependent variables in percentage point five year change in respective gross domestic relative income shares , evaluation period intervals include 1996-2000, 2001-2005 and 2006-2010 [b]Standard errrors in parentheses; period EGLS employed in all estimations, constant not reported [c] */**/*** indicate marginal significance at 10, 5 and 1% level respectively, main regressions exclude Iceland, Romania and Slovenia due to limited available data, remaining columns refer to relative top gross incomes, only available for limited set of countries, see data section for further details.

	Table 10 - Occupational structure division according to ISCO codes[a]								
	1	2	3	4	5	6	7	8	9
	Managers	Professionals	Technicians and associate professionals	Clerical support workers	Service and sales workers	Skilled agricultural, forestry and fishery workers	Craft and related trades workers	Plant and machine operators, and assemblers	Elementary occupations
1	Chiefs executives, Senior Officials and legislators	Science and engineering professionals	Science and engineering associate professionals	General and keyboard clerks	Personal service workers	Market-oriented skilled agricultural workers	Building and related trades workers, excluding electricians	Stationary plant and machine operators	Cleaners and helpers
2	Administrati-ve and commercial managers	Health professionals	Health associate professionals	Customer services clerks	Sales workers	Market-oriented skilled forestry, fishery and hunting workers	Metal, machinery and related trades workers	Assemblers	Agricultura l, forestry and fishery labourers
3	Production and specialized services managers	Teaching professionals	Business and administra-tion associate professionals	Numerical and material recording clerks	Personal care workers	Subsistence farmers, fishers, hunters and gatherers	Handicraft and printing workers	Drivers and mobile plant operators	Labourers in mining, construc-tion, manufactu-ring and transport
4	Hospitality, retail and other services managers	Business and administra-tion professionals	Legal, social, cultural and related associate professionals	Other clerical support workers	Protecti-ve services workers		Electrical and electronic trades workers		Food preparation assistants
5		Information and communica-tions technology professionals	Information and communica-tions technicians				Food processing, wood working, garment and other craft and related trades workers		Street and related sales and service workers
6		Legal, social and cultural professionals							Refuse workers and other elementary workers

[a]The ISCO comprises of nine broad distinct occupational types which are represented on the horizontal axis. Further detailed levels within the occupational types are scaled on the vertical axis.