

Columbia University in the City of New York

Measuring Impact of Increase in High-Skilled Workers on the Livelihoods of Medium- and Low-Skilled Workers

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Advisor: Prof. Lance Freeman
Reader: Prof. Moshe Adler
Student: Aleksey M. Martynyuk

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Abstract

This paper assesses the impact of high-skilled labor on the unemployment and wages of low- and medium-skilled workers in the Netherlands. Using annual panel data from the Netherlands' *Centraal Bureau voor de Statistiek* (National Bureau of Statistics, CBS), a statistically significant negative impact of an increase in high-skilled labor on the livelihoods of low- and medium-skilled workers can be shown. An increase in high-skilled labor is associated with a significant decrease in the income share of the bottom tenth percentile of the population as well as a decrease in jobs for the low- and medium-skilled workers.

1. Introduction

As technology and information play an increasingly important role in the economies of rich nations, moving them away from manufacturing and heavy industry toward creative industries, services and science, economists have started to pay more attention to the role of labor and skills. Higher education and specialized skills have come to be seen as necessary for countries to succeed in the twenty-first century. The Organization for Economic Development and Cooperation's (OECD) *Skills Outlook 2013* is typical in this regard. It describes in detail the kinds of skills and areas of study that will be in demand and which policy-makers should focus on. It argues,

*"With manufacturing and other low-skill tasks in the services sector becoming increasingly automated, the need for routine cognitive and craft skills is declining, while the demand for information-processing skills and other high level cognitive and interpersonal skills is growing."*¹

The report predicts a further shift toward high-skilled jobs in most countries and promotes policies that would increase the high-skilled share of the workforce.

Many governments have followed the advice to encourage their people to attain higher levels of education and incentivize companies to invest more in research and development. But now a growing body of research is seeing a simultaneous rise in income inequality across the developed world. Michael Piore cautioned against this in *The Second Industrial Divide* (1984). More recently, Thomas Piketty's *Capital in the Twenty-First Century* (2013) has drawn attention to the issue.

In 2003, Piketty and Emmanuel Saez² looked at the income distribution in the United States and how it changed throughout the twentieth century. They found that wealth was increasingly concentrated in the top 1 percent of population, a finding that has prompted more research into the relationship between high-skilled labor and income inequality.

To establish a link between the two – specifically, by seeing if an increase in high-skilled labor has an inadvertent effect on the livelihoods of low- and medium-skilled workers – this paper looks at developments in the Netherlands from 2003 to 2014.

The Netherlands is a good case study. It has a high per capita income: \$51,060, compared to an OECD average of \$44,479.³ The country is highly integrated in the world economy, especially in the high-skilled sectors of finance and ICT. Three-thirds of the Dutch economy relies on services, with the rest primarily in industry and some agriculture,⁴ so it is very skills dependent. 72 percent of the working population has the equivalent of a high-school

¹ OECD, *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills* (2013)

² Thomas Piketty and Emmanuel Saez, "Income Inequality In the United States, 1913-1998," *Quarterly Journal of Economics* 118:1 (February 2003) 1-39

³ World Bank Data: Netherlands, <http://data.worldbank.org/country/netherlands>

⁴ CIA World Factbook: Netherlands, <https://www.cia.gov/library/publications/the-world-factbook/geos/nl.html>

degree or higher⁵ and the population as a whole has an above-average proficiency in literacy for technology-rich countries in the OECD.⁶

The Netherlands has also taken the advice to concentrate on higher education and high skills to heart. It has tried for decades to push students into the sort of skills-intensive areas that define the modern economy with tuition and employment tax reductions. In 2010, the government unveiled a “top sectors” program that is designed to enhance Dutch competitiveness by tailoring policies to those industries that produce the most income for the country and contribute the most to research and development spending. They include the chemical industry, creative industries, energy, high-tech, life sciences and water management.

Is this focus on the top performers of the economy benefiting the whole of the country? Or are those at the bottom losing out?

⁵ OECD Better Life Index: Netherlands, <http://www.oecdbetterlifeindex.org/countries/netherlands/>

⁶ OECD, “Country Note: Netherlands,” *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills* (2013), <http://www.oecd.org/site/piaac/Country%20note%20-%20Netherlands.pdf>

2. Literature Review

The basis for this paper are previous studies on the spillover effect of education. Enrico Moretti in 2004 found⁷ a significant and large positive spillover effect of increased education in the city on wages, especially those of the lower classes. This finding is consistent with the demand/supply theory of labor: if the demand side prevails, an increase in one factor of production should raise the productivity of complimentary inputs. Low- and high-skilled labor should complement each other. However, from the supply point of view, substitute inputs compete with each other and an increase in one input would decrease the price of the other.

Moretti uses individual data as well as firm level productivity and finds that the wages of uneducated workers benefit for two reasons.

First, an increase in the number of educated workers raises uneducated workers' productivity because of imperfect substitution. Second, the spillover further raises their productivity. The impact of an increase in the supply of educated workers on their own wage is determined by two competing forces, as I mentioned above: the first is the conventional supply effect which makes the economy move along a downward sloping demand curve. The second is the spillover that raises productivity.

A similar study, conducted in China by Zhiqiang Liu,⁸ found a similar positive externality effect. Although in that study, most of the productivity gains come from an increase in education in primarily low-educated rural areas.

The Netherlands' University of Groningen conducted another study, using city-level data, to look at the relationship between the share of the high-skilled workforce and the general unemployment rate.⁹ It found that on average, cities with more highly-educated workers have a higher unemployment rate (See Figure 1). The authors tried to find if the so-called "trickle down" effect would hold for their data; if, as high-skilled employment rises, the increased incomes would generate demand for services and induce employment in low- and medium-skilled positions. They found only a small effect and only in some industries (such as retail and hospitality).

⁷ Enrico Moretti, "Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data," *Journal of Econometrics* 121 (2004) 175–212

⁸ Zhiqiang Liu, "The external returns to education: Evidence from Chinese cities," *Journal of Urban Economics* 61:3, (May 2007) 542-564

⁹ Roderik Ponds, Gerard Marlet and Clemens van Woerkens, "Trickle down in the stad: De invloed van hoogopgeleiden op de arbeidsmarkt voor laagopgeleiden," Rijksuniversiteit Groningen, Atlas voor Gemeenten, Platform31 (April 2015), <http://www.platform31.nl/publicaties/trickle-down-in-de-stad>

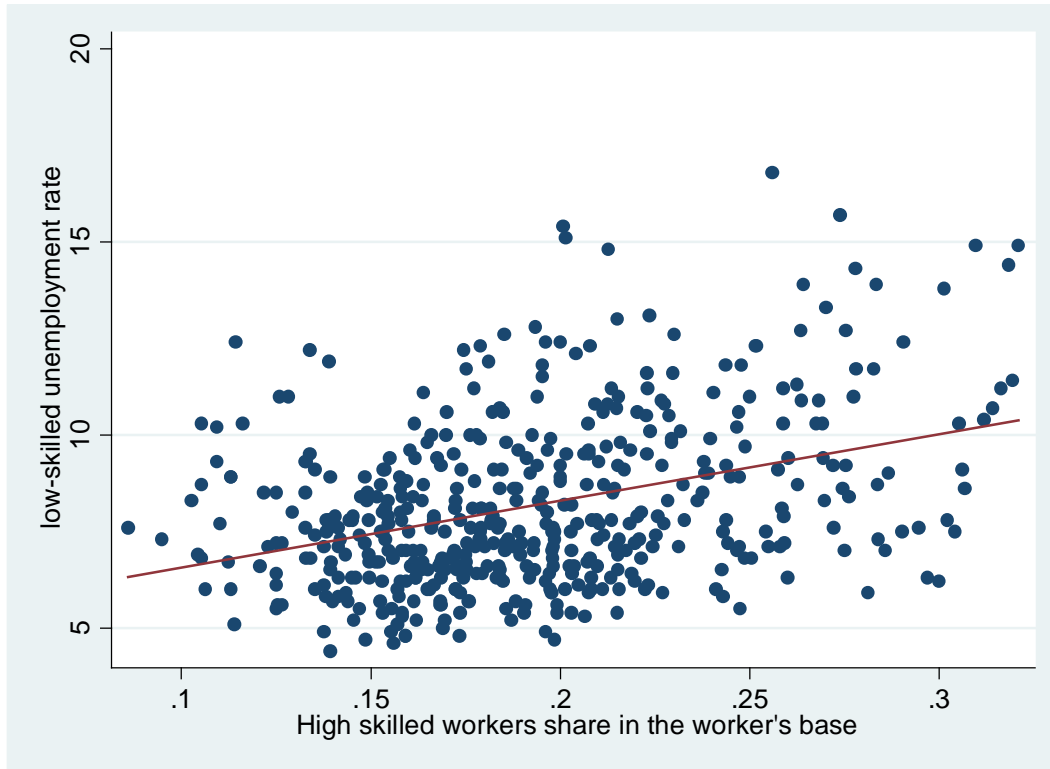


Figure 1: Dutch cities with a higher share of high-skilled workers tend to have higher unemployment (Source: Ponds, Marlet and Van Woerkens)

However, the Groningen study is limited by the data sample it used and the relationships it looked at. The authors chose cities (municipalities) as their unit of measurement. But because workers are mobile – especially in the Netherlands, where many live outside the municipal borders of the place they work – the analysis was unable to factor in the effect of commuters. Moreover, the research looked at specific industries and their employment, not at the effect of high-skilled labor on employment in the whole urban agglomeration.

This paper takes the analysis one step further. By using a different unit of measurement – Dutch COROP regions – it will better account for employment in areas that include economic hubs and residential areas outside the city. This provided an enhanced understanding of the effect of high-skilled labor on income distribution as well as the basis for a hypothesis for a possible transmission mechanism for those changes.

3. Methodology & Data

The goal of this research is to measure the impact of an increase in the high-skilled population of an urban area on the livelihoods of low- and medium-skilled workers. Livelihood is measured by income distribution and employment opportunities.

Using cross-sectional longitudinal record of the evolution of incomes and employment, this paper will test the impact of the change in the number of high-skilled workers on the relative income distribution and the number of low- and mediums-skilled workers in the jobs that require different levels of skills.

3.1 Data Used

The data available is not as extensive as it would be in the United States. The Dutch National Bureau of Statistics (CBS) collects individual data for internal research purposes, but does not publish this information in order to protect the privacy of Dutch citizens. However, pooled regional data is available for the twelve provinces, the country's four largest cities, the 393 municipalities and forty special agglomerations that were created for statistical purposes – the COROP regions, named after the *COördinatiecommissie Regionaal OnderzoeksProgramma* (Coordinating Committee for Regional Research).

The unit of observation is the NUTS 3 region. The NUTS (Nomenclature of territorial units for statistics) classification is used to divide up the economic territory of the European Union for the purpose of collection, development and harmonization of regional statistics and socio-economic analyses of the regions.¹⁰ The NUTS 3 regions fall between the size of Dutch provinces and municipalities, which are best compared to states and cities, respectively, in the United States. The borders of the agglomerations are specifically drawn to represent an area that includes a nodal city, which has most economic activity and jobs, and surrounding residential areas – without being too large not to be able to isolate a specific policy impact.

Final panel data was created from several datasets on income and labor participation by skill level.

For incomes, yearly data is available from the CBS from 2005 to 2012. For labor participation, yearly data is available from 2003 to 2014.

3.2 Skills Classification

The CBS divides skills into three categories: low, medium and high. This roughly corresponds with the Dutch educational system. After completing elementary school, Dutch students advance to one of three levels of high school, determined by test scores and teachers' evaluation. The lowest, VMBO, prepares students for a vocational training program (MBO). The medium level, HAVO, prepares students for a professional tertiary education comparable to American colleges (HBO). The highest level, VWO, prepares

¹⁰ Eurostat, <http://ec.europa.eu/eurostat/web/nuts/overview>

students for a university education (WO). (See Figure 2; A more detailed overview of the Dutch education system is available in Appendix 1.)

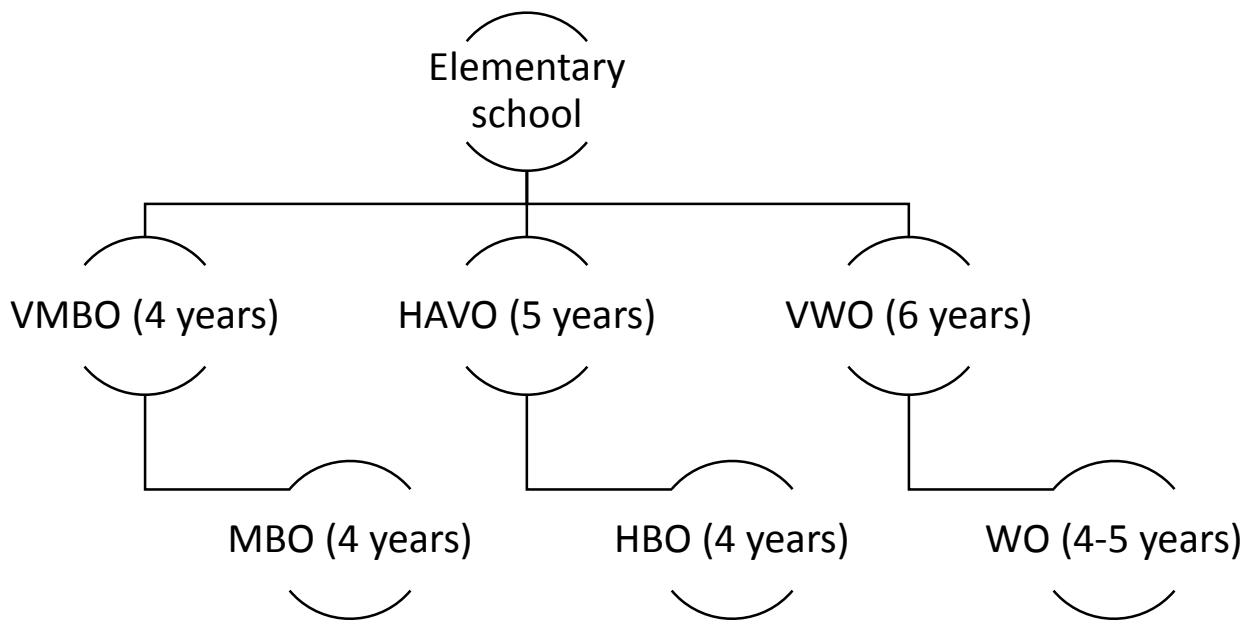


Figure 2: Chart of Dutch education levels.

The CBS' low skill category includes those who have completed the VMBO, the first three years of either HAVO or VWO or an assistant vocational training program at the MBO level.

The medium skill category refers to those with a full HAVO or VWO diploma or those who have completed a professional, middle management or specialist training program at the MBO level.

The high skill category means a person has at least a college degree at the HBO or university level.

For each skill level, data is available from the CBS on labor force participation, type of employment and unemployment.

3.3 Jobs Level Classification

For each skill level, the CBS divides employment into four levels: 1 through 4. The levels are determined by the complexity of a job and the scope of the tasks it involves, with 1 requiring the least amount of skill and minimal training and 4 requiring complex skills and specialized training or a degree.

In the data analysis, the breakdown by job level allows the impact of the growing high-skilled workforce on employment in each job category to be measured by skill level.

3.5 Unemployment Among Low-Skilled Workers

One of the most important variables in this analysis is the unemployment level of low-skilled workers in each region. Figure 3 illustrates the low-skilled unemployment rate in each COROP region from 2003 to 2014. There is a significant volatility, even though it seems that in many regions unemployment has been moving in different directions. There is also a lot of variation between the regions. For example, in 2010, the difference between the lowest and the highest unemployment rate for low-skilled workers in the Netherlands was around 7 percent. These regional and time variations in joblessness will be absorbed by the panel data analysis. Inherent characteristics of the regions, such as industry composition, share of the immigrants, etc., will be absorbed by the regional fixed effect.

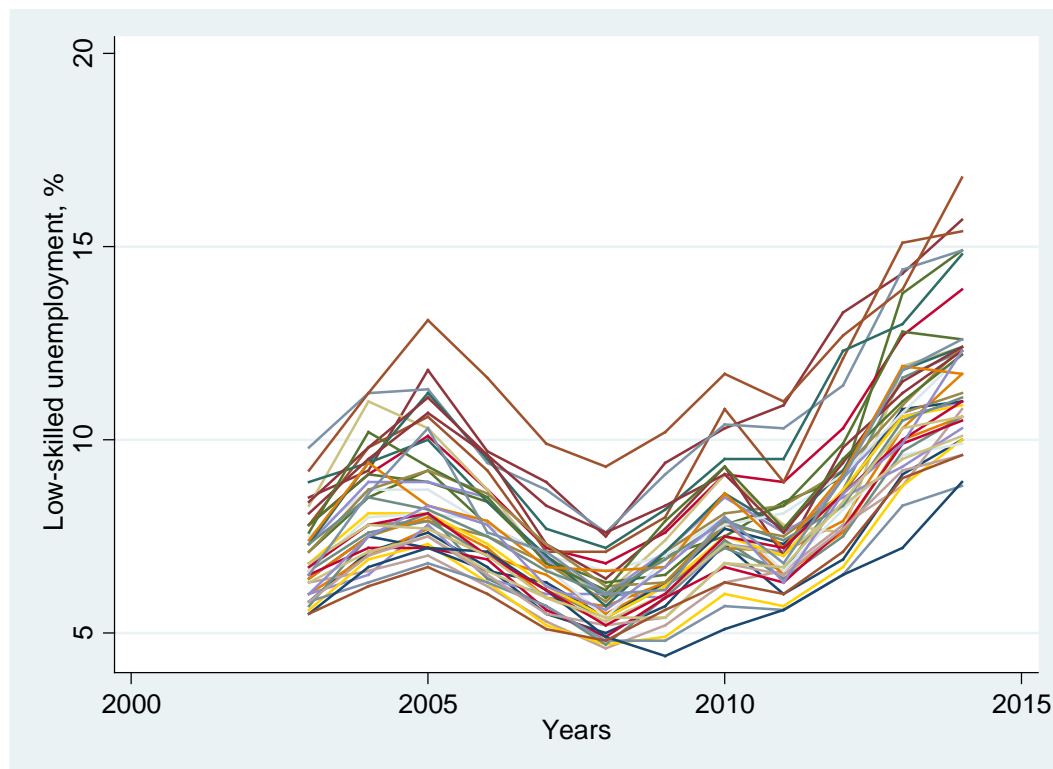


Figure 3: Unemployment of low-skilled workers per COROP region, 2003-2014 (Source: CBS)

3.5 Employment Among High-Skilled Workers

High-skilled employment is the second important variable of interest in this analysis. Dutch policies are aimed at either increasing the number of workers with HBO and university degrees, especially in technical disciplines, or increasing the number of high-skilled workers employed in industries that invest the most in research and development. The externality – unintended consequence – on other workers in the economy is not taken into account. Dutch policy assumes that if the high value added part of the economy does well, everyone will benefit.

The data shows that Dutch policy had the intended effect of increasing the number of high-skilled workers. Figure 4 shows that the numbers of high-skilled workers as a share of the overall employment is volatile across regions, but in most it has been steadily increasing.

This difference across regions allows cross-sectional analysis to differentiate between trends in the country, regional characteristics and specific increases in employment, which can be due to the policy effect.

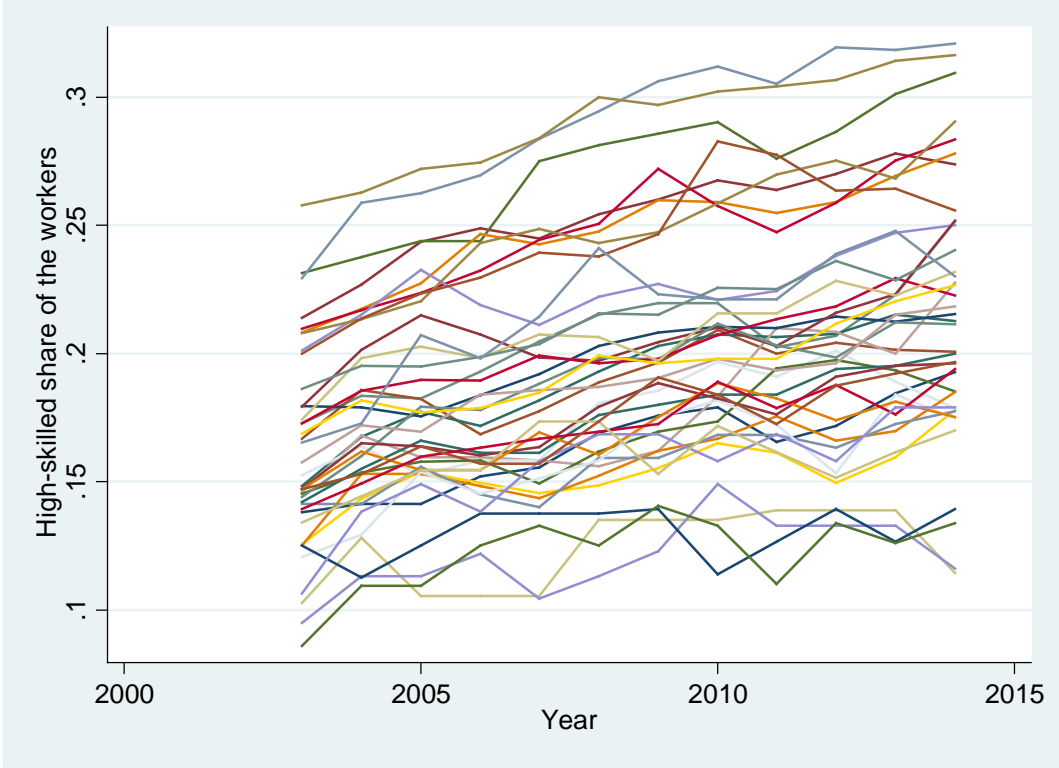


Figure 4: High-skilled workers as a share of the workforce in each COROP region (Source: CBS)

3.6 Incomes

Incomes are broken down by ten percentiles, with median incomes for each group. Average income for all workers in the region is provided separately.

Income distribution in the Netherlands is relatively equitable. In comparison to other developed countries such as the United Kingdom and the United States, the difference between the lowest and highest earners is small.

The data shows that over the last decade, the top and bottom income groups have nevertheless fared very differently. While the median income of the top tenth percentile has grown steadily from 2005 to 2013, with a brief stagnation between 2008 and 2010, the median income of the bottom tenth percentile has not grown compared to 2005 – and in some cases even decreased (See Figures 5 and 6).

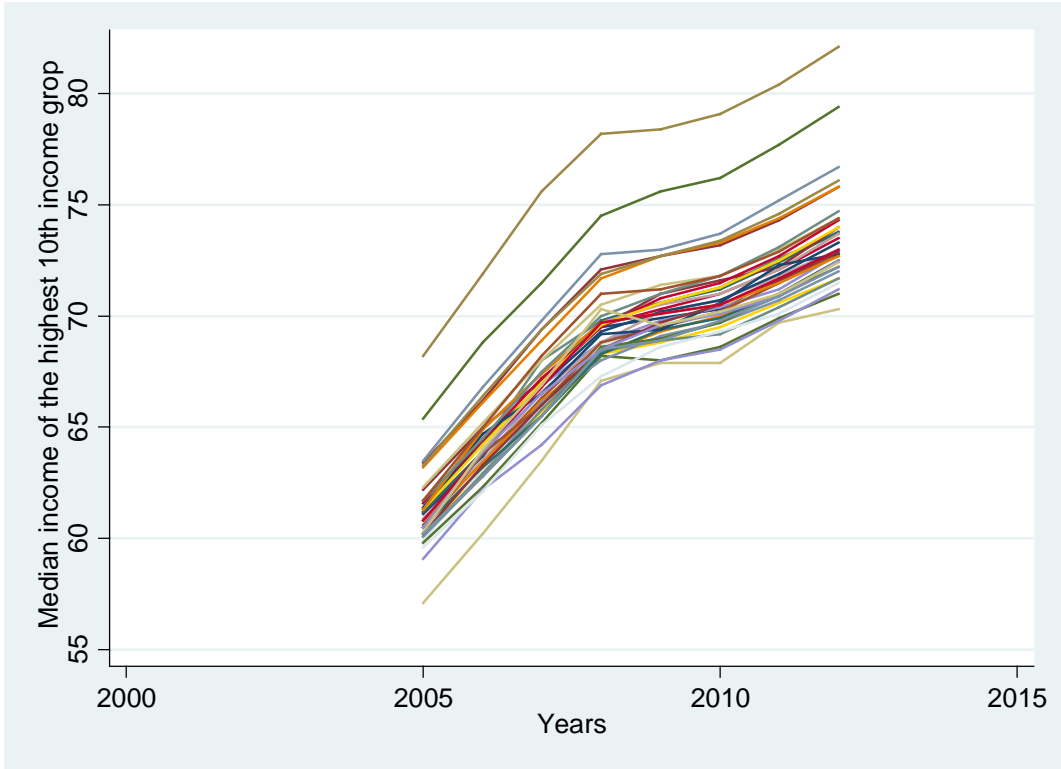


Figure 5: Evolution of the median income of the top 10th percentile income group per COROP region, 2005-2013 (Source: CBS)

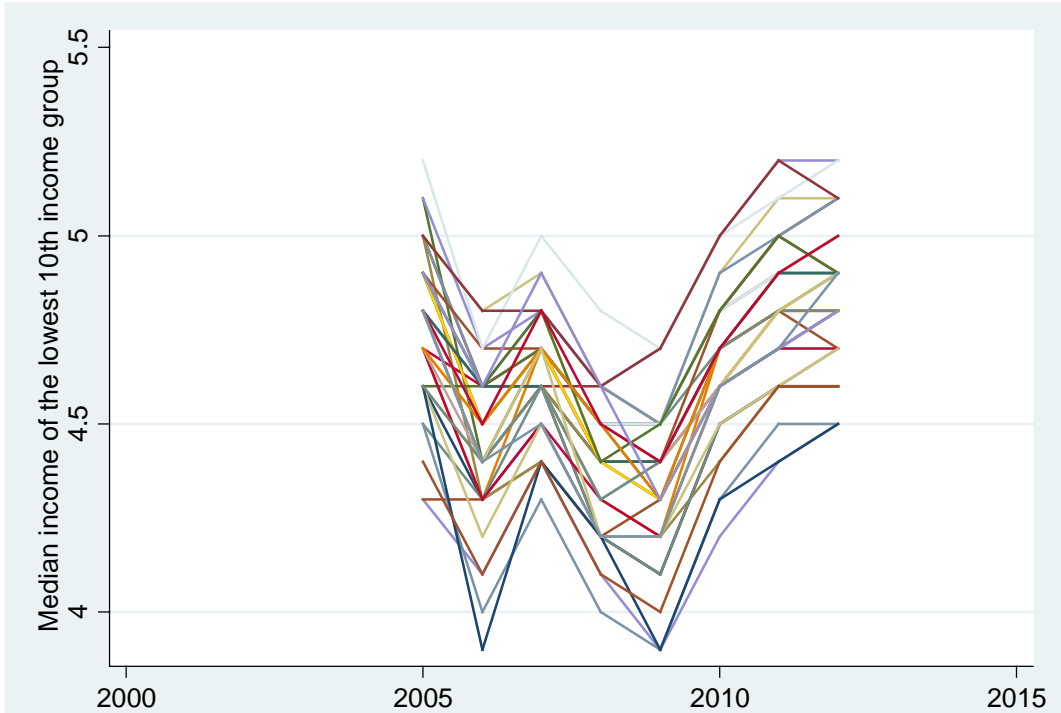


Figure 6: Evolution of the median income of the bottom 10th percentile income group per COROP region, 2005-2013 (Source: CBS)

The difference in income changes is even more striking when a group’s median income is expressed as a share of the income average across regions. In this sense, the earnings of the top income group have been stagnant, or only lightly increased. But for the bottom group, the share has been falling since 2005, only slightly leveling off in recent years but still significantly below their pre-2005 share (See Figures 7 and 8).

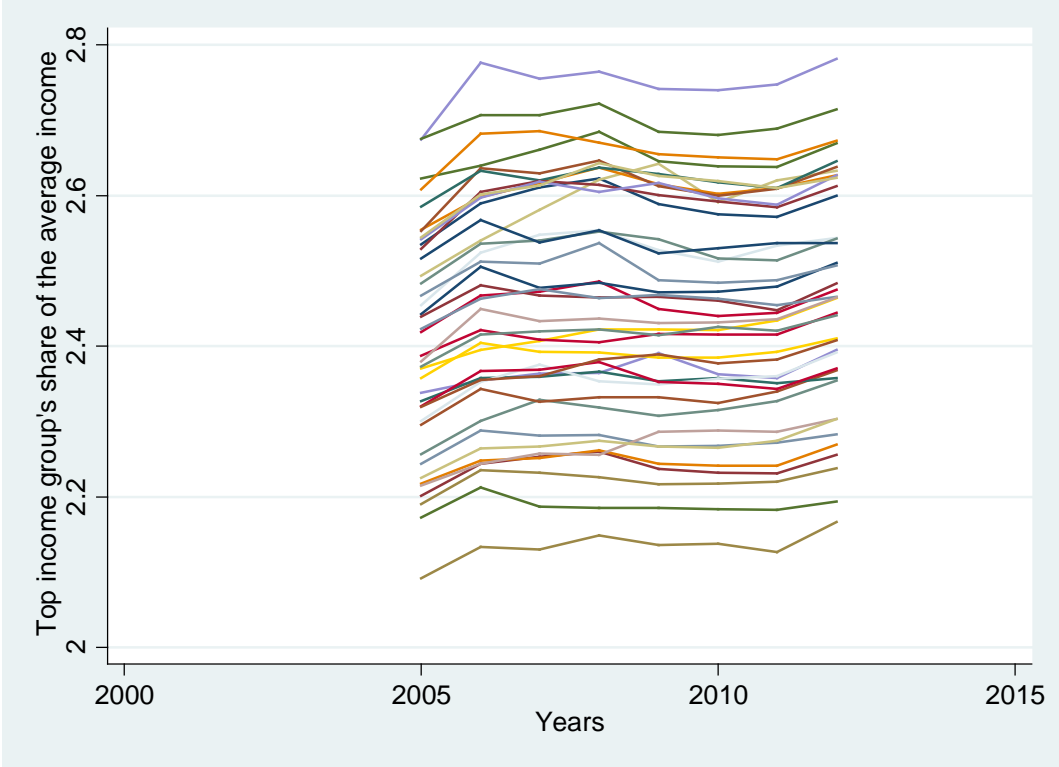


Figure 7: Evolution of the median income of the top 10th percentile income group per COROP region as a share of average incomes across regions, 2005-2013 (Source: CBS)

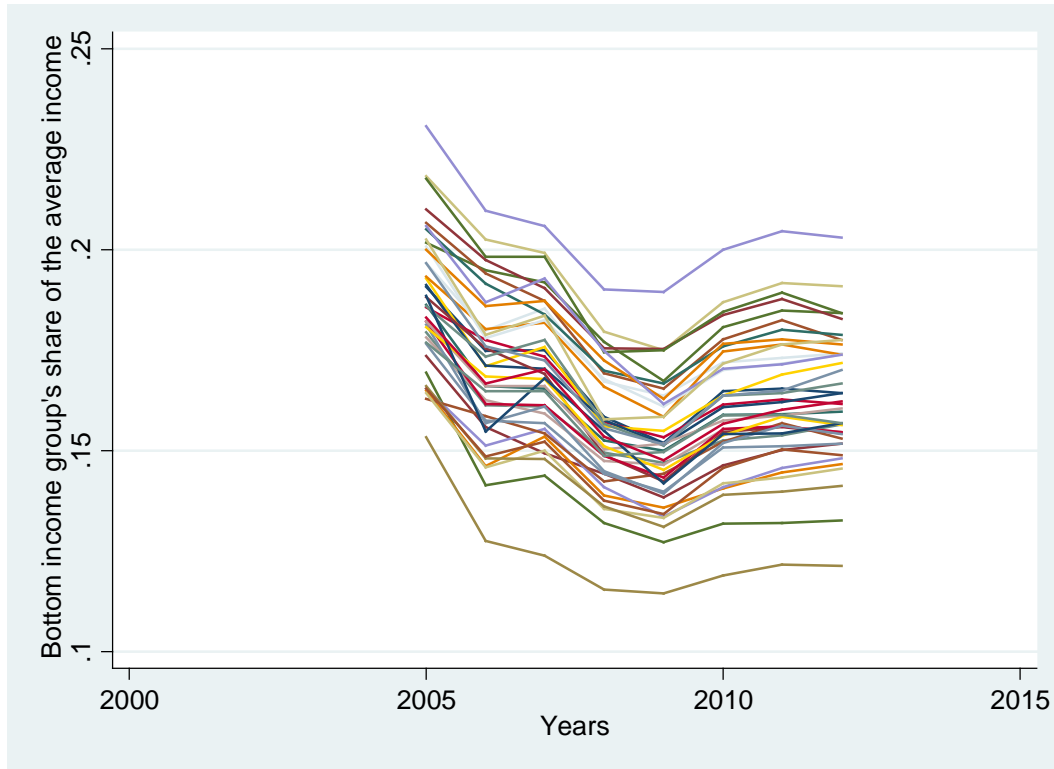


Figure 8: Evolution of the median income of the bottom 10th percentile income group per COROP region as a share of average incomes across regions, 2005-2013 (Source: CBS)

3.7 Relationship Between High-Skilled Employment and Low-Skilled Unemployment

A regression of all observations in the sample shows a positive relationship, also observed in other studies, between the share of high-skilled workers in the workforce and the unemployment rate among the lowest skilled (See Figure 9). This relationship is not indicative of any causation, however. The intrinsic characteristics of a region's economy and the composition of the workforce could have created this relationship.

What can be said with certainty at this point is that an increase in the number of high-skilled workers has not benefited everyone equally. With further analysis, it is possible to show this is not a "spurious relationship," but that there is a link between decreases in the incomes of those with low skills and increases in the number of high-skilled workers.

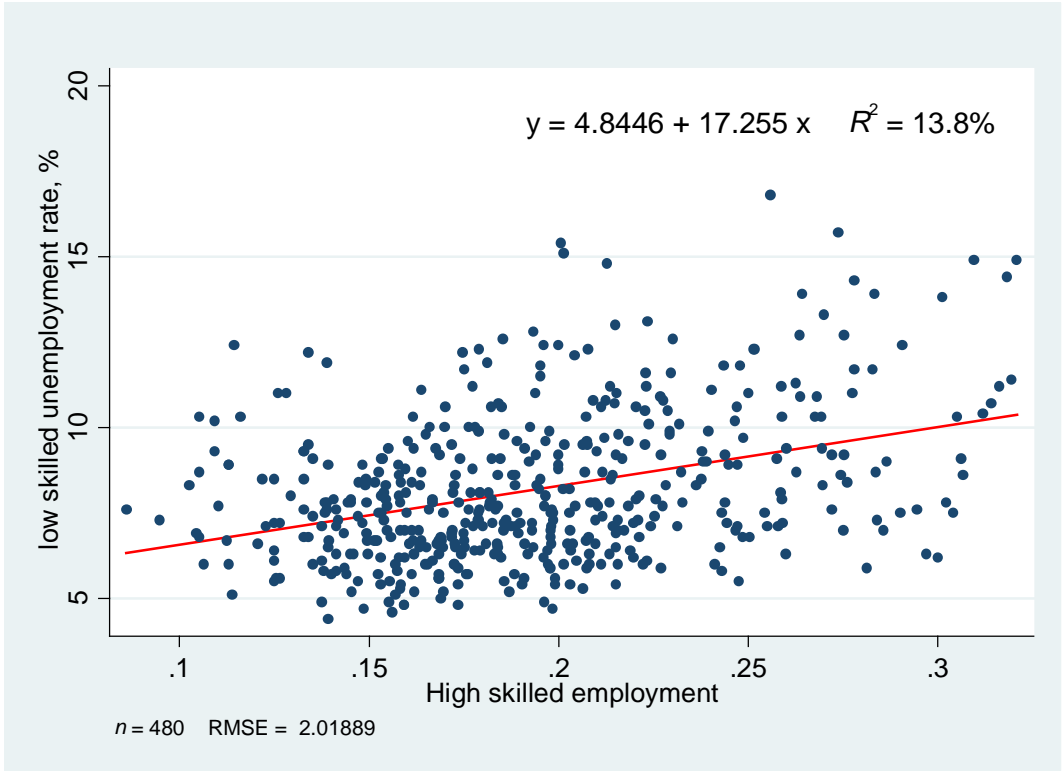


Figure 9: The relationship between high-skilled employment and low-skilled unemployment for each COROP region in the Netherlands

4. Data Analysis

To prove a more robust relationship between the share of high-skilled workers in the workforce and the incomes of as well as employment among the lowest skilled, this chapter uses a panel data fixed effects set-up.

The equation for the fixed effects model is:

$$Y_{it} = \beta_1 X_{it} + \alpha_i + u_{it}$$

Where:

- α_i (i=1....40) is the unknown intercept for each COROP region (40 region-specific intercepts);
- Y_{it} is the dependent variable, where i = entity and t = time. The dependent variable will be the characteristic that is affected by the rise in high-skilled workers;
- X_{it} represents the independent variable. This is the variable that is causing variation in the variable of interest (dependent variable);
- β_1 is the coefficient for the independent variable, showing the magnitude and direction of the effect of the independent variable on the variable of interest; and
- u_{it} is the error term, which should absorb variations across different regions and years that do not need to be accounted for.

4.1 Effect on Low-Skilled Incomes

I initially tested the effect of an increase in the absolute number of high-skilled workers on the median income for each group. The results were inconclusive. Coefficients on the high-skilled workers were small, positive and insignificant for lower income groups. This may have been due to the use of raw numbers. In any case, adding workers to the population from the high-income end would automatically shift workers from higher to lower percentiles. Because these workers have higher salaries than those in the lower percentiles, the median incomes would appear to rise – without there actually having been a rise in incomes.

Therefore, I used the share of high-skilled workers relative to the total working population. For incomes, instead of absolute numbers, I used the ratio of the median income in the group to the average income in the whole region. This should reveal the effect the composition of the workforce has on income inequality. I ran four specifications for each income group, using the share of the high-skilled workers in the working population and the share of the level 4 jobs in all the employment, both using random and fixed-effect regression.

The findings show a strong and highly significant effect on the income groups. The bottom 60 percent is affected negatively, with the lowest tenth percentile being affected the most. While the negative effect on low incomes is more or less spread out, the effect on top incomes is large and concentrated. The top second and third income groups benefit the

most from an increase in the high-skilled share of the workforce (See Figure 10). (See Appendix 3.1 for STATA output)

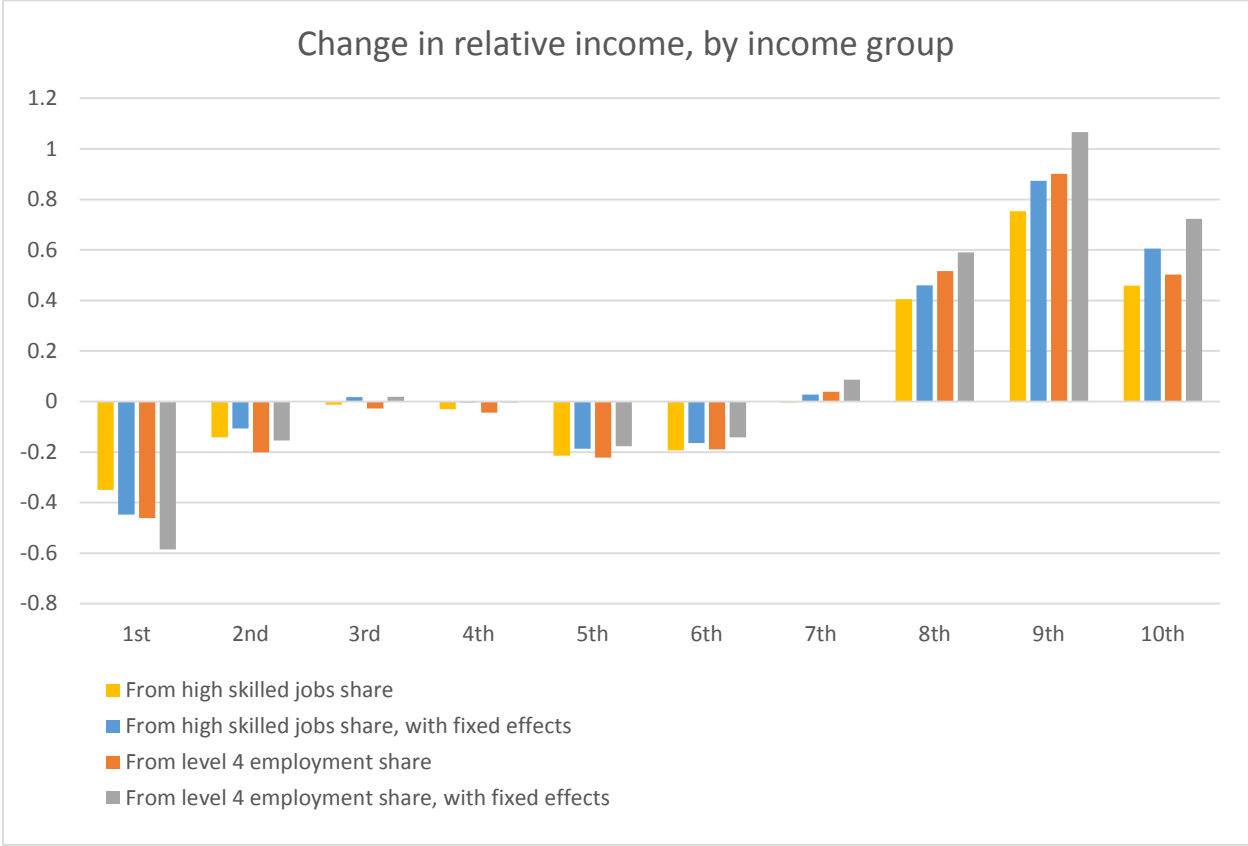


Figure 10: The effect of an increase in the share of high-skilled workers on the median incomes of the ten income groups.

It is difficult to discern the effect an increase in the share of high-skilled workers has on the livelihoods and opportunities from the income share alone. It might be that even though the income share has fallen, the absolute incomes have increased. This would create some positive effect on the bottom earners. Some might be “poor” relative to incomes in their region but “rich” compared to workers in less affluent regions. The wealthier region might also provide job opportunities and services that are unavailable in other places. For example, a poor family in New York City earns very little compared to their middle- and upper-class counterparts, but they will earn more than lower-class families in poorer cities. Living in New York probably also gives them more access to jobs and services, such as better public transport.

In any case, the rise in incomes of top earners in the Netherlands is much higher than the fall in incomes at the bottom of the scale. This raises income inequality and can have an effect on many other social aspect of living in the region.

4.2 Effect on Low-Skilled Employment

Expanding on Ponds, Marlet and Van Woerkens,¹¹ this section will map out effect of a rise in the number of high-skilled workers on the employment of other skills groups, especially medium- and low-skilled workers.

The hypothesis is that when the number of high-skilled workers increases, they lower the incomes of medium- and low-skilled workers by pushing them out of higher paying jobs.

Another relevant factor could be the effect of job level reclassifications. Some positions that did not require a degree before may now. Because of changes in the labor market and an oversupply in some degrees, low-skilled and low-paying positions are being filled by graduates. Think of baristas and shop floor assistants. Because of the change in requirements, they technically move up in job classifications. The impact on incomes is ambiguous. Here, it is assumed that jobs are classified into levels based on real skill requirements and filled by appropriately skilled labor.

Because the Dutch statistics divide jobs into four skill levels, it is possible to see the effect on each skill group in each job level by regressing it on the number of high-skilled workers. Total employment is taken into account to control for economic growth in the region.

The results are telling and confirm the hypothesis (See Table 1). The numbers represent the number of jobs gained or lost by workers with a particular skill level in a specific job level, from an increase in one high-skilled worker in the region (top number), or an increase in one job in total in the region (bottom number) (See Appendix 3.2 for STATA output).

		Level of employment			
		1	2	3	4
Education level	Low	-.0734449*** .0769625***	-.417537*** .3060678***	-.0355564*** .0353168***	-.000978 .0108889***
	Med	.089289*** -.0553944***	-.1488305*** .2239873***	-.2617844*** .2403881***	.0662876*** -.0041572
	High	.0119585*** .0002573	.1720861*** -.0250036***	.1580593*** .0092481	.4408134*** .1535873***

Table 1: The effect on the employment level (1-4) from an overall increase in employment.

First we should analyze the effect of economic growth in the region (in yellow, second line). As the number of jobs rises, the number of low-skilled workers rises across job levels, but

¹¹ Ponds, Marlet and Van Woerkens, "Trickle down in the stad"

mostly in level 2. There is a very small, but significant rise in jobs at level 4. This is consistent with the logic that workers will take up jobs that are most consistent with their skills. For medium-skilled workers, as jobs increase, there is a rise in employment in level 2 and 3. But there is also a small if significant decrease in level 1 jobs. Because the economy is growing, medium-level workers leave level 1 jobs for better-paying jobs in level 2 and 3. Something similar happens for high-skilled workers. Workers leave level 2 jobs and enter more lucrative level 4 jobs. These findings are consistent with our understanding of the labor market and support the validity of the data and model.

The interesting part is the effect of a rise in only high-skilled workers (See Table 2). For each additional high-skilled worker, there is an increase in the employment of high-skilled workers in each job level, with the highest in level 4 and moderate gains in levels 2 and 3. As high-skilled workers take up jobs that do not actually require their high skills, they push out relatively less skilled workers into lower-paying positions.

There is a large decrease in employment of medium-skilled workers in level 3 and 2 jobs, and an increase in level 1 and 4 jobs. The increase in level 1 jobs must be associated with workers taking up any job they can find, even if it requires no skills. A small uptake in level 4 jobs may be attributed to the complementarity of medium- and high-skilled workers. But this is uncertain.

Low-skilled workers suffer if the number of high-skilled workers in their region increases. Their employment decreases across all job levels. If there are no additional job opportunities for these workers, or if these opportunities are not sufficient enough to counter their displacement, then they become unemployed or are forced to relocate. Regressing unemployment for low-skilled labor directly on the share of high-skilled employment shows a significant, albeit small positive relationship. Regressing a number of low skilled workers on the number of high skilled workers shows a significant negative relationship, which points to relocation (See Appendix 3.3 for STATA output).

		Level of employment			
		1	2	3	4
Education level	Low	-.0734449*** .0769625***	-.417537*** .3060678***	-.0355564*** .0353168***	-.000978 .0108889***
	Med	.089289*** -.0553944***	-.1488305*** .2239873***	-.2617844*** .2403881***	.0662876*** -.0041572
	High	.0119585*** .0002573	.1720861*** -.0250036***	.1580593*** .0092481	.4408134*** .1535873***

Table 2: The effect on the employment level (1-4) of an increase in high-skilled workers.

If all the coefficients for the effect of an increase in high-skilled workers are put together, the overall impact is 0.0003627 – which is almost zero. This makes sense, because as more workers are added to a set number of jobs, the combined changes in all jobs must amount to zero.

Adding all the coefficients of the effect of growth in employment, the overall impact is 0.972149 – which is also consistent with the understanding that if only one more job is added to the economy, only one more person across all levels of education will get an additional job.

In the context of policies that incentivize the creation of high-skilled jobs, these two effects come together. There is an increase in the total labor force, but also a redistribution of jobs among medium- and low-skilled workers. A hypothetical net effect (combining the effect from jobs increases with the increase due to a high-skilled worker) is presented below:

		Level of employment			
		1	2	3	4
Education level	Low	0.0035176	-0.111469	-0.00024	0.009911
	Med	0.0338946	0.0751568	-0.021396	0.06213
	High	0.0122158	0.1470825	0.1673074	0.594401

Table 3: The combined effect of an increase in total employment and an increase in high-skilled workers.

High-skilled workers still benefit overall. Medium- and low-skilled workers, however, are pushed out of higher-level jobs into lower ones, something that is usually accompanied by a loss of income. This finding gives an alternative view on the effect on bottom earners. Even if their incomes go up in absolute terms, they are now earning less not only relative to everyone else, but relative to what they used to earn as well.

5. Conclusion

Using data from the country's National Bureau of Statistics (CBS), this paper has measured the impact of increases in high-skilled labor in the Netherlands on the relative income share and unemployment opportunities of medium- and low-skilled workers. The data reveals a significant negative effect on the bottom 60 percent of earners and a disproportionate increase in the earnings share of the top 30 percent. This development can be explained by job market dynamics. Every high-skilled worker that enters the labor market displaces medium- and low-skilled workers into lower paid positions.

Although high skills and high value-added industries are important to developed countries competing in a global economy, policies that incentivize companies and workers to invest in high skills will not on themselves bring about balanced growth. There is no positive trickle-down effect. Dutch policies that promote the country's "top sectors" and encourage students to get the highest possible degree, preferably in fields that should lead directly to employment in the top sectors, harm those with less skills and less training. Subsidizing higher education and giving tax breaks to companies that hire researchers and scientists may be a net positive for the Dutch economy, but this study has shown there are workers who lose out as well – or are even directly hurt by this approach – and there is far less political interest in them.

This relationship is present in the current year of the policy. Long-term effects are not evaluated. Specific policies that incentivize education choices today will have an effect only several years after graduates enter the workforce. The total impact of a better-educated workforce on society at large can take even longer to materialize. There is no doubt in the long run that developed countries like the Netherlands will need more high-skilled workers to compete in the modern global economy. There is also little doubt that society benefits from more cultured, civilized and intelligent people. Getting more citizens educated is generally a good thing. But if there are negative short-term effects, they should be properly understood and, where possible, offset with policies that run parallel to those that are designed to raise high-skilled employment.

By overlooking the damage the emphasis on top performers is doing to workers with limited abilities, Dutch policy is inadvertently causing income inequality to widen and that could undermine social cohesion.

Rising inequality is especially important at a time of economic downturns. As this study shows, if there is no growth, new high-skilled workers are putting pressure on the lower-skilled ones. When the economy contracts and unemployment rises, the bottom earners are hit the most. Looking at the data for low-skilled unemployment, we can see the number has risen dramatically, much higher than the national average, right after the onset of the European sovereign debt crisis in 2010. Since then, the economy has turned around, the national unemployment figures have dropped, but the unemployment of the low-skilled has stayed high. In times like this, governments should implement policies that alleviate the

pain of the most vulnerable in society. Because the sample includes those turbulent years, it is possible that the effect on the livelihoods of low-skilled workers has been overstated. But the cross-sectional set-up and the inclusion of the pre-financial crisis years (2003-2007) should balance out the data.

Other developed nations can take a lesson from this. They might aspire to create an extremely high-skilled workforce, but there will still be need for low-skilled labor. They could end up with university graduates pushing lower-skilled workers into unemployment by taking up menial jobs. Already, we see law graduates serving coffee at Starbucks.

There is a negative financial impact as well. In a country that publicly finances education, like the Netherlands, resources are wasted when graduates can't find employment in the industries that require their high skills and instead take up low-paid jobs. Low-skilled workers, in turn, would go on unemployment benefits, putting more stress on public finances.

Appendix 1: Dutch Education System

The Dutch education system is divided into three levels:

1. Primary education (*basisschool*) for children between the ages of 4 and 12.
2. Secondary education (*voortgezet onderwijs*), which is compulsory for students up to the age of either 16 or 18, depending on which of the three levels they attend:
 - a. VMBO (*Voorbereidend Middelbaar BeroepsOnderwijs*, literally, “preparatory middle-level applied education”) takes four years and combines theoretical education in arts, history, languages, mathematics and science with vocational training. It grants access to tertiary education at the MBO level.
 - b. HAVO (*Hoger Algemeen Voortgezet Onderwijs*, literally, “higher general advanced education”) takes five years and combines three years of theoretical education in arts, history, languages, mathematics and science with a two-year specialization in one of four course profiles. It grants access to an HBO professional education.
 - c. VWO (*Voortgezet Wetenschappelijk Onderwijs*, literally, “advanced scientific education”) takes six years and combines three years of theoretical education in arts, history, languages, mathematics and science with a three-year specialization in one of four course profiles. It grants access to university.
3. Tertiary education falls into three levels that correspond with the three levels of secondary education:
 - a. MBO (*Middelbaar BeroepsOnderwijs*, literally, “middle-level applied education”) takes one to four years and prepares students for a concrete profession. It is composed of four levels:
 - i. MBO Level 1: Assistant training. Lasts one year and focuses on simple executive tasks.
 - ii. MBO Level 2: Basic vocational education. Lasts two to three years and focuses on executive tasks.
 - iii. MBO Level 3: Lasts three to four years and teaches students to achieve their tasks independently.
 - iv. MBO Level 4: Middle management. Lasts four years and prepares students for jobs with higher responsibility. Also grants access to a HBO program.
 - b. HBO (*Hoger BeroepsOnderwijs*, literally, “higher professional education”) typically takes four years and prepares students for a concrete higher profession, such as business or water management. A HBO degree grants access to the WO level.
 - c. WO (*Wetenschappelijk Onderwijs*, literally, “scientific education”) is the Netherlands’ university education. It has adopted the Bachelor-Master system with the former degree typically taking three years and the later one or two. Academic programs are less job-specific than training at the HBO level, although there are specialized and technical universities.

Appendix 2: CBS Jobs Level Classification

The Netherlands' National Bureau of Statistics' (CBS) classification of professions follows the International Labor Organization's International Standard Classification of Occupations 2008 (ISCO 2008). Classifications are based on a job's complexity and the scope of the tasks it involves.

Jobs are divided into four levels, with Level 1 requiring the least amount of skill and minimal training and Level 4 requiring complex skills and specialized training or a degree:

1. Level 1 jobs involve simple routine tasks that require little more than elementary education. Examples of tasks include cleaning, lifting and moving materials, assembling goods (sometimes working with machines), operating non-motorized vehicles, fruit picking and harvesting vegetables. Examples of jobs in this category include cleaners, loaders, garbage collectors, kitchen aids and farmhands.
2. Level 2 jobs involve mildly complex tasks, requiring some secondary education. Examples of tasks include operating electronic appliances, machinery and vehicles, maintaining or repairing electrical and mechanical devices and editing, organizing and storing data. Jobs in this category require workers to understand (safety) instructions and to make simple calculations. Examples include barbers, bus drivers, clerks, dressmakers, electricians, secretaries and salespersons.
3. Level 3 jobs involve complex tasks and require secondary or higher education. Tasks require communication skills, factual knowledge and technical expertise, an understanding of procedures and written information and the ability to deal with problems. Examples of professions in this category include legal secretaries, medical laboratory technicians, IT support staff, radio engineers and sales representatives.
4. Level 4 jobs involve highly complex and specialized tasks that require a higher or academic education. Such tasks involve solving complex problems, making decisions based on practical and theoretical knowledge in a specialized field, the ability to understand complex written information as well as the ability to share such information with others in various ways. Examples include doctors, engineers, marketing managers, musicians and systems analysts.

Appendix 3.1: STATA Output for Effect on Low-Skilled Incomes

```
. xtreg share empshare, fe

Fixed-effects (within) regression      Number of obs   =       320
Group variable: regio                  Number of groups =        40

R-sq:  within = 0.2743                  Obs per group:  min =         8
        between = 0.4224                  avg =           8.0
        overall = 0.3590                  max =           8

corr(u_i, Xb) = -0.5614                  F(1,279)        =       105.46
                                          Prob > F         =        0.0000
```

```
-----+-----
      share |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
      empshare |  -0.4469428   .0435217   -10.27   0.000   -0.5326155   -0.3612701
      _cons    |   0.2518609   .0084694    29.74   0.000    0.2351889    0.2685329
-----+-----
      sigma_u  |   0.01531897
      sigma_e  |   0.00999687
      rho      |   0.70133011   (fraction of variance due to u_i)
-----+-----
F test that all u_i=0:      F(39, 279) =    12.86      Prob > F = 0.0000
```

```
. xtreg share2 empshare, fe

Fixed-effects (within) regression      Number of obs   =       320
Group variable: regio                  Number of groups =        40

R-sq:  within = 0.0604                  Obs per group:  min =         8
        between = 0.4847                  avg =           8.0
        overall = 0.4464                  max =           8

corr(u_i, Xb) = 0.5687                  F(1,279)        =        17.94
                                          Prob > F         =        0.0000
```

```
-----+-----
      share2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
      empshare |  -0.1063272   .0251047    -4.24   0.000   -0.1557459   -0.0569085
      _cons    |   0.3622865   .0048854   74.16   0.000    0.3526696    0.3719035
-----+-----
      sigma_u  |   0.02483921
      sigma_e  |   0.00576651
      rho      |   0.94886087   (fraction of variance due to u_i)
-----+-----
F test that all u_i=0:      F(39, 279) =   100.43      Prob > F = 0.0000
```

```
. xtreg share3 empshare, fe

Fixed-effects (within) regression      Number of obs   =       320
Group variable: regio                  Number of groups =        40

R-sq:  within = 0.0022                  Obs per group:  min =         8
        between = 0.5094                  avg =           8.0
        overall = 0.4593                  max =           8

corr(u_i, Xb) = -0.6930                  F(1,279)        =         0.61
                                          Prob > F         =        0.4363
```

```

      share3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
      empshare |   .0181472   .0232794     0.78   0.436   - .0276784   .0639727
      _cons   |   .4964105   .0045302    109.58  0.000   .4874928   .5053282
-----+-----
      sigma_u |   .04245408
      sigma_e |   .00534724
      rho     |   .98438349   (fraction of variance due to u_i)
-----+-----
F test that all u_i=0:      F(39, 279) =    262.08      Prob > F = 0.0000

```

```
. xtreg share4 empshare, fe
```

```

Fixed-effects (within) regression      Number of obs   =    320
Group variable: regio                  Number of groups =     40

R-sq:  within = 0.0001                  Obs per group:  min =     8
      between = 0.5316                      avg =    8.0
      overall  = 0.4843                      max =     8

corr(u_i, Xb) = 0.6976                  F(1,279)        =    0.02
                                          Prob > F         =    0.8781

```

```

      share4 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
      empshare |  -.0035862   .0233555    -0.15   0.878   - .0495616   .0423891
      _cons   |   .6218634   .004545    136.82  0.000   .6129165   .6308103
-----+-----
      sigma_u |   .0516948
      sigma_e |   .00536472
      rho     |   .98934512   (fraction of variance due to u_i)
-----+-----
F test that all u_i=0:      F(39, 279) =    381.28      Prob > F = 0.0000

```

```
. xtreg share5 empshare, fe
```

```

Fixed-effects (within) regression      Number of obs   =    320
Group variable: regio                  Number of groups =     40

R-sq:  within = 0.1298                  Obs per group:  min =     8
      between = 0.5312                      avg =    8.0
      overall  = 0.4978                      max =     8

corr(u_i, Xb) = 0.6337                  F(1,279)        =   41.61
                                          Prob > F         =    0.0000

```

```

      share5 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
      empshare |  -.1872565   .0290301    -6.45   0.000   - .2444024  -.1301107
      _cons   |   .8119997   .0056493   143.73  0.000   .800879    .8231203
-----+-----
      sigma_u |   .05958763
      sigma_e |   .00666816
      rho     |   .98763211   (fraction of variance due to u_i)
-----+-----
F test that all u_i=0:      F(39, 279) =    382.28      Prob > F = 0.0000

```

```
. xtreg share6 empshare, fe
```

```

Fixed-effects (within) regression      Number of obs   =    320

```

```

Group variable: regio                                Number of groups = 40
R-sq:  within = 0.0850                             Obs per group: min = 8
      between = 0.5285                             avg = 8.0
      overall = 0.4923                             max = 8
corr(u_i, Xb) = 0.6518                             F(1,279) = 25.91
                                                    Prob > F = 0.0000

```

share6	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
empshare	-.164092	.0322394	-5.09	0.000	-.2275554	-.1006287
_cons	.9804598	.0062738	156.28	0.000	.9681097	.9928098
sigma_u	.07452297					
sigma_e	.00740533					
rho	.99022219	(fraction of variance due to u_i)				

```

F test that all u_i=0:      F(39, 279) = 465.97          Prob > F = 0.0000

```

```
. xtreg share7 empshare, fe
```

```

Fixed-effects (within) regression                Number of obs = 320
Group variable: regio                            Number of groups = 40
R-sq:  within = 0.0023                           Obs per group: min = 8
      between = 0.5375                             avg = 8.0
      overall = 0.4896                             max = 8
corr(u_i, Xb) = -0.7083                           F(1,279) = 0.66
                                                    Prob > F = 0.4185

```

share7	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
empshare	.0271545	.0335164	0.81	0.419	-.0388227	.0931318
_cons	1.128287	.0065223	172.99	0.000	1.115447	1.141126
sigma_u	.09527596					
sigma_e	.00769867					
rho	.99351308	(fraction of variance due to u_i)				

```

F test that all u_i=0:      F(39, 279) = 610.47          Prob > F = 0.0000

```

```
. xtreg share8 empshare, fe
```

```

Fixed-effects (within) regression                Number of obs = 320
Group variable: regio                            Number of groups = 40
R-sq:  within = 0.2858                           Obs per group: min = 8
      between = 0.5344                             avg = 8.0
      overall = 0.4652                             max = 8
corr(u_i, Xb) = -0.7677                           F(1,279) = 111.62
                                                    Prob > F = 0.0000

```

share8	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
empshare	.4594078	.0434831	10.57	0.000	.3738111	.5450044
_cons	1.25163	.0084619	147.91	0.000	1.234973	1.268287

```

sigma_u | .12649763
sigma_e | .009988
rho | .99380426 (fraction of variance due to u_i)
-----
F test that all u_i=0:      F(39, 279) = 526.88      Prob > F = 0.0000

```

```
. xtreg share9 empshare, fe
```

```

Fixed-effects (within) regression      Number of obs      =      320
Group variable: regio                  Number of groups   =       40

R-sq:  within = 0.3698                  Obs per group: min =       8
      between = 0.5341                      avg =      8.0
      overall = 0.4492                      max =       8

corr(u_i, Xb) = -0.7956                  F(1,279)           =    163.71
                                          Prob > F            =     0.0000

```

```

-----
share9 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
empshare | .8737715   .0682896    12.80  0.000   .7393432   1.0082
_cons   | 1.487542   .0132893   111.94  0.000   1.461382   1.513702
-----+-----
sigma_u | .16482421
sigma_e | .01568601
rho     | .99102433 (fraction of variance due to u_i)
-----

```

```

F test that all u_i=0:      F(39, 279) = 324.25      Prob > F = 0.0000

```

```
. xtreg share10 empshare, fe
```

```

Fixed-effects (within) regression      Number of obs      =      320
Group variable: regio                  Number of groups   =       40

R-sq:  within = 0.1243                  Obs per group: min =       8
      between = 0.4536                      avg =      8.0
      overall = 0.3902                      max =       8

corr(u_i, Xb) = -0.7217                  F(1,279)           =     39.59
                                          Prob > F            =     0.0000

```

```

-----
share10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
empshare | .6055544   .0962419     6.29  0.000   .416102   .7950068
_cons   | 2.329603   .0187288   124.39  0.000   2.292735   2.366471
-----+-----
sigma_u | .17343047
sigma_e | .0221066
rho     | .98401202 (fraction of variance due to u_i)
-----

```

```

F test that all u_i=0:      F(39, 279) = 235.92      Prob > F = 0.0000

```

```
. xtreg share jobs4
```

```

Random-effects GLS regression      Number of obs      =      320
Group variable: regio              Number of groups   =       40

R-sq:  within = 0.3598                  Obs per group: min =       8
      between = 0.5160                      avg =      8.0

```

```

overall = 0.4452                                max = 8
corr(u_i, X) = 0 (assumed)                      Wald chi2(1) = 174.39
                                                Prob > chi2 = 0.0000

```

share	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
jobs4	-.4605426	.0348742	-13.21	0.000	-.5288947	-.3921905
_cons	.2403701	.0059976	40.08	0.000	.2286149	.2521253
sigma_u	.01102632					
sigma_e	.00938937					
rho	.57966847 (fraction of variance due to u_i)					

```
. xtreg share2 jobs4
```

```

Random-effects GLS regression                    Number of obs = 320
Group variable: regio                          Number of groups = 40

R-sq:  within = 0.0969                        Obs per group: min = 8
        between = 0.5802                       avg = 8.0
        overall = 0.5352                       max = 8

Wald chi2(1) = 53.38
corr(u_i, X) = 0 (assumed)                    Prob > chi2 = 0.0000

```

share2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
jobs4	-.200794	.0274823	-7.31	0.000	-.2546583	-.1469297
_cons	.3744685	.0054018	69.32	0.000	.3638811	.385056
sigma_u	.01817636					
sigma_e	.00565332					
rho	.91179547 (fraction of variance due to u_i)					

```
. xtreg share3 jobs4
```

```

Random-effects GLS regression                    Number of obs = 320
Group variable: regio                          Number of groups = 40

R-sq:  within = 0.0018                        Obs per group: min = 8
        between = 0.6093                       avg = 8.0
        overall = 0.5461                       max = 8

Wald chi2(1) = 0.91
corr(u_i, X) = 0 (assumed)                    Prob > chi2 = 0.3388

```

share3	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
jobs4	-.0269372	.028164	-0.96	0.339	-.0821377	.0282632
_cons	.5043383	.006479	77.84	0.000	.4916398	.5170368
sigma_u	.02645386					
sigma_e	.00534821					
rho	.96073177 (fraction of variance due to u_i)					


```
-----+-----
sigma_u | .04911219
sigma_e | .00755019
rho     | .97691168 (fraction of variance due to u_i)
-----+-----
```

```
. xtreg share7 jobs4
```

```
Random-effects GLS regression           Number of obs   =       320
Group variable: regio                   Number of groups =        40

R-sq:  within = 0.0182                   Obs per group:  min =         8
        between = 0.6373                  avg =           8.0
        overall = 0.5738                  max =           8

corr(u_i, X) = 0 (assumed)                Wald chi2(1)    =         0.86
                                           Prob > chi2     =         0.3546
```

```
-----+-----
share7 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
jobs4  |   .0383872   .0414672     0.93  0.355    -0.0428869   .1196614
_cons  |   1.127283   .0121292    92.94  0.000     1.10351     1.151056
-----+-----
sigma_u | .05753023
sigma_e | .0076372
rho     | .98268235 (fraction of variance due to u_i)
-----+-----
```

```
. xtreg share8 jobs4
```

```
Random-effects GLS regression           Number of obs   =       320
Group variable: regio                   Number of groups =        40

R-sq:  within = 0.3616                   Obs per group:  min =         8
        between = 0.6341                  avg =           8.0
        overall = 0.5465                  max =           8

corr(u_i, X) = 0 (assumed)                Wald chi2(1)    =        94.72
                                           Prob > chi2     =         0.0000
```

```
-----+-----
share8 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
jobs4  |   .5166487   .0530854     9.73  0.000     .4126032     .6206943
_cons  |   1.256368   .0150669    83.39  0.000     1.226838     1.285899
-----+-----
sigma_u | .06796102
sigma_e | .00944283
rho     | .98105999 (fraction of variance due to u_i)
-----+-----
```

```
. xtreg share9 jobs4
```

```
Random-effects GLS regression           Number of obs   =       320
Group variable: regio                   Number of groups =        40

R-sq:  within = 0.4218                   Obs per group:  min =         8
        between = 0.6341                  avg =           8.0
        overall = 0.5290                  max =           8

corr(u_i, X) = 0 (assumed)                Wald chi2(1)    =       110.86
                                           Prob > chi2     =         0.0000
```


Appendix 3.2: STATA Output for Effect of Increase in High-Skilled Workers on Number of Workers in Groups by Skill and Job Level

```
. xtreg row25 row52 row5, fe
```

```
Fixed-effects (within) regression      Number of obs   =       480
Group variable: regio                  Number of groups =       40

R-sq:  within = 0.3087                  Obs per group:  min =       12
        between = 0.9763                  avg =          12.0
        overall = 0.9669                  max =          12

corr(u_i, Xb) = -0.9621                  F(2,438)        =       97.79
                                          Prob > F         =       0.0000
```

row25	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
row52	-.0880864	.0068889	-12.79	0.000	-.1016258	-.074547
row5	.1088434	.0078615	13.85	0.000	.0933925	.1242944
_cons	-5.376931	1.240563	-4.33	0.000	-7.815126	-2.938736
sigma_u	4.3895326					
sigma_e	.77053188					
rho	.97010735	(fraction of variance due to u_i)				

```
F test that all u_i=0:      F(39, 438) =    19.84      Prob > F = 0.0000
```

```
. xtreg row26 row52 row5, fe
```

```
Fixed-effects (within) regression      Number of obs   =       480
Group variable: regio                  Number of groups =       40

R-sq:  within = 0.6961                  Obs per group:  min =       12
        between = 0.9802                  avg =          12.0
        overall = 0.9729                  max =          12

corr(u_i, Xb) = -0.6285                  F(2,438)        =      501.52
                                          Prob > F         =       0.0000
```

row26	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
row52	-.5422238	.0190393	-28.48	0.000	-.5796436	-.504804
row5	.3652661	.0217274	16.81	0.000	.3225632	.4079689
_cons	-6.034722	3.428634	-1.76	0.079	-12.77334	.7038965
sigma_u	4.2390304					
sigma_e	2.1295754					
rho	.79848041	(fraction of variance due to u_i)				

```
F test that all u_i=0:      F(39, 438) =    10.61      Prob > F = 0.0000
```

```
. xtreg row27 row52 row5, fe
```

```
Fixed-effects (within) regression      Number of obs   =       480
Group variable: regio                  Number of groups =       40

R-sq:  within = 0.1237                  Obs per group:  min =       12
        between = 0.9827                  avg =          12.0
        overall = 0.9506                  max =          12
```



```

sigma_e | .81263572
rho | .98725376 (fraction of variance due to u_i)
-----
F test that all u_i=0: F(39, 438) = 11.80 Prob > F = 0.0000

```

```
. xtreg row42 row52 row5, fe
```

```

Fixed-effects (within) regression      Number of obs   =    480
Group variable: regio                  Number of groups =    40

R-sq:  within = 0.1949                  Obs per group:  min =    12
      between = 0.9921                      avg =    12.0
      overall = 0.9883                      max =    12

corr(u_i, Xb) = 0.9284                  F(2,438)        =    53.02
                                          Prob > F         =    0.0000

```

```

-----
row42 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
row52 |  -1.1488305   .0193325   -7.70  0.000   -1.1868265   -1.1108345
row5  |   .2239873   .0220619   10.15  0.000    .1806269    .2673477
_cons |  13.81321    3.48143    3.97  0.000    6.970823    20.65559
-----+-----
sigma_u |  8.186073
sigma_e |  2.1623682
rho | .93477485 (fraction of variance due to u_i)

```

```

-----
F test that all u_i=0: F(39, 438) = 18.64 Prob > F = 0.0000

```

```
. xtreg row43 row52 row5, fe
```

```

Fixed-effects (within) regression      Number of obs   =    480
Group variable: regio                  Number of groups =    40

R-sq:  within = 0.5790                  Obs per group:  min =    12
      between = 0.9911                      avg =    12.0
      overall = 0.9839                      max =    12

corr(u_i, Xb) = -0.9830                  F(2,438)        =   301.14
                                          Prob > F         =    0.0000

```

```

-----
row43 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
row52 |  -0.2617844   .0107028  -24.46  0.000   -0.2828196   -0.2407492
row5  |   .2403881   .0122139   19.68  0.000    .216383     .2643931
_cons | -11.79739    1.927378   -6.12  0.000  -15.58545   -8.00933
-----+-----
sigma_u |  7.8826288
sigma_e |  1.1971235
rho | .9774559 (fraction of variance due to u_i)

```

```

-----
F test that all u_i=0: F(39, 438) = 11.32 Prob > F = 0.0000

```

```
. xtreg row44 row52 row5, fe
```

```

Fixed-effects (within) regression      Number of obs   =    480
Group variable: regio                  Number of groups =    40

R-sq:  within = 0.2116                  Obs per group:  min =    12
      between = 0.9150                      avg =    12.0
      overall = 0.8914                      max =    12

```



```

sigma_e | .90042377
rho | .82604053 (fraction of variance due to u_i)
-----
F test that all u_i=0: F(39, 438) = 12.04 Prob > F = 0.0000

```

```
. xtreg row59 row52 row5, fe
```

```

Fixed-effects (within) regression      Number of obs   =      480
Group variable: regio                  Number of groups =      40

R-sq:  within = 0.8396                  Obs per group: min =      12
      between = 0.9945                  avg =           12.0
      overall = 0.9890                  max =           12

corr(u_i, Xb) = -0.9108                  F(2,438)        = 1146.04
                                          Prob > F         = 0.0000

```

row59	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
row52	.1580593	.006504	24.30	0.000	.1452764	.1708422
row5	.0092481	.0074222	1.25	0.213	-.0053395	.0238357
_cons	-1.253754	1.171248	-1.07	0.285	-3.555719	1.048211
sigma_u	1.8311391					
sigma_e	.72747963					
rho	.86368209					(fraction of variance due to u_i)

```

F test that all u_i=0: F(39, 438) = 11.75 Prob > F = 0.0000

```

```
. xtreg row60 row52 row5, fe
```

```

Fixed-effects (within) regression      Number of obs   =      480
Group variable: regio                  Number of groups =      40

R-sq:  within = 0.9309                  Obs per group: min =      12
      between = 0.9748                  avg =           12.0
      overall = 0.9733                  max =           12

corr(u_i, Xb) = -0.8401                  F(2,438)        = 2950.56
                                          Prob > F         = 0.0000

```

row60	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
row52	.4408134	.0137464	32.07	0.000	.4137964	.4678304
row5	.1535873	.0156871	9.79	0.000	.1227559	.1844187
_cons	-18.71504	2.475468	-7.56	0.000	-23.58032	-13.84977
sigma_u	12.337743					
sigma_e	1.5375503					
rho	.98470694					(fraction of variance due to u_i)

```

F test that all u_i=0: F(39, 438) = 31.15 Prob > F = 0.0000

```

Appendix 3.3: STATA Output for Effect on Low-Skilled Unemployment Rate and Employment

```
. xtreg row31 empshare, fe

Fixed-effects (within) regression      Number of obs   =      480
Group variable: regio                  Number of groups =      40

R-sq:  within = 0.2147                  Obs per group:  min =      12
      between = 0.1767                    avg =      12.0
      overall  = 0.1384                    max =      12

corr(u_i, Xb) = -0.7139                  F(1,439)        =      120.01
                                          Prob > F         =      0.0000
```

row31	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
empshare	44.93064	4.101474	10.95	0.000	36.86967	52.9916
_cons	-.4940194	.7946886	-0.62	0.534	-2.055886	1.067848
sigma_u	1.8372358					
sigma_e	1.6350458					
rho	.55803296	(fraction of variance due to u_i)				

F test that all u_i=0: F(39, 439) = 7.43 Prob > F = 0.0000

```
. xtreg row31 row52, fe

Fixed-effects (within) regression      Number of obs   =      480
Group variable: regio                  Number of groups =      40

R-sq:  within = 0.1466                  Obs per group:  min =      12
      between = 0.1985                    avg =      12.0
      overall  = 0.0925                    max =      12

corr(u_i, Xb) = -0.9469                  F(1,439)        =      75.42
                                          Prob > F         =      0.0000
```

row31	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
row52	.070119	.0080741	8.68	0.000	.0542502	.0859877
_cons	3.604145	.5318354	6.78	0.000	2.558885	4.649405
sigma_u	4.0067794					
sigma_e	1.7044337					
rho	.84677268	(fraction of variance due to u_i)				

F test that all u_i=0: F(39, 439) = 6.86 Prob > F = 0.0000

```
. xtreg row21 row51, fe

Fixed-effects (within) regression      Number of obs   =      480
Group variable: regio                  Number of groups =      40

R-sq:  within = 0.4063                  Obs per group:  min =      12
```

```

    between = 0.8249                avg =      12.0
    overall  = 0.7767                max  =      12

corr(u_i, Xb) = -0.9486              F(1,439)      = 300.47
                                         Prob > F      = 0.0000

-----
      row21 |      Coef.   Std. Err.      t    P>|t|    [95% Conf. Interval]
-----+-----
      row51 |   -0.2498258   0.0144123   -17.33   0.000   -0.2781516   -0.2215001
      _cons |    70.60614    1.140582    61.90   0.000    68.36446    72.84782
-----+-----
      sigma_u | 53.733866
      sigma_e | 3.4170978
      rho     | 0.99597222   (fraction of variance due to u_i)
-----
F test that all u_i=0:      F(39, 439) = 297.21          Prob > F = 0.0000

```