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Bachelors thesis in Economics

Is technology driving the increase in wage inequality in modern day Sweden?

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Abstract: During the last couple of decades the spread of wages has increased throughout the western world. Sweden is no exception from this trend, and the increased wage inequality in Sweden can be traced back 1980. This thesis aims to answer whether technology driven changes in demand for labor can explain changes in relative wage, and if increased foreign competition can explain increasing wage inequality. It can be concluded that employment is affected in the directions predicted by the theory of Task Biased Technological Change, but that these effects are not carried on to further effects on wage change in Sweden during the studied period. Low wage is instead being found to be the best predictor of poor wage development.

Key words: Wage inequality, task biased technological change, offshorability

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1 Introduction

Since 1980 there has been an increase in wage inequality in Sweden, the aim of this thesis is to investigate some of the potential causes for this change. My hypothesis is that technological change has changed the demand structure on the labor market causing an upwards pressure on the wages for some occupations, and a downwards pressure on others. Part of the hypothesis is also that these changes are biased so that the upwards pressure is mostly affecting high income jobs and vice versa. The original theoretical form of this hypothesis is the theory of Skill Biased Technology change, a theory developed from the 1970s. The basic idea is that technological change, mostly computerization, makes it possible to robotize jobs with lower skill requirements, reducing demand for such jobs, while demand for jobs requiring advanced skills, for instance in computer science, will increase (Acemoglu and Autor, 2011)

Autor et al (2003) developed a more sophisticated theory stating that it is not the level of skill that responds differently to technical change, but rather the task content of jobs. The hypothesis is that computerization will decrease the demand for routine tasks while increasing demand for non-routine, mainly qualified tasks. Any job task that could be performed by a computer or robot following a set program was defined as a routine task. This was the advent of the theory of Task Biased Technology Change. The important difference between Skill Biased Technology Change and Task Biased Technology Change is that TBTC considers some low skill jobs, like janitors or cleaning staff, really difficult to replace by machines. The authors made an index of routine task contents in jobs centered at zero, with positive values indicating routine tasks, more routine the higher the value, and negative values indicating non routine tasks. Non routine tasks are in this context tasks not understood well enough to translate into computer programming. Notable is that they exemplify with driving a car through city traffic, a task performed quite well by experimental vehicles made by a number of car manufacturers, Google and Apple only ten years after their paper was published. The realm of routine tasks is obviously shrinking over time.

A further theoretical development was made by Goos et al (2009). Like Autor et al (2003) they made an index for routine task contents in jobs, but they also made indexes for abstract task contents and the “offhorability” of tasks. Abstract task contents are characterized by “critical thinking”, “judgment and decision making”, “complex problem solving”, “interacting with computers” and “thinking creatively” (Goos et al, 2009). The offshorability index is based on

European Restructuring Monitor (ERM) of the European Monitoring Centre on Change (EMCC) statistics of European companies offshoring production processes.

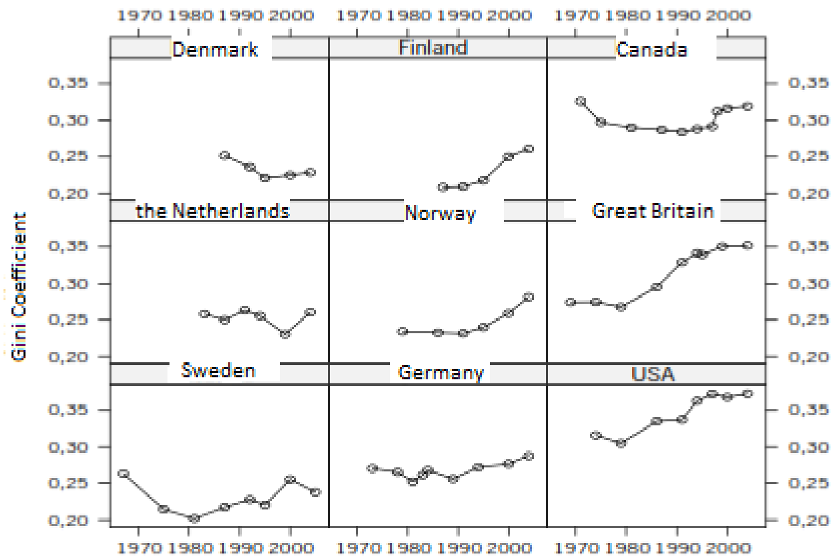
In this thesis I will apply the Goos et al three index model on the Swedish labor market. I will more specifically study a panel of 246 occupations in Sweden in order to try to find econometric links between wage change, changes in the employment in those 246 occupations and the indexes for abstract, routine and offshorable tasks borrowed from Goos et al. The period I will be studying is 2005 to 2013 and my method will be to calculate the average change in wage and employment in the period for all my 246 occupations and run these changes against the three indexes I have borrowed from Goos et al. I expect that changes in technology has increased the demand for abstract abilities while demand for routine labor has decreased. I also expect that native demand for jobs that may easily be offshored would have decreased. I further expect that these probable changes in demand will have had a negative effect on wage change for jobs with high routine contents and offshorable jobs, and that abstract contents in jobs will have a positive effect on wage change.

2 Background

During the past decades, wage inequality has increased throughout the western world. During the 20th century income inequality was steadily declining in Europe until around 1980, then the trend changed and the increases in income inequality has been going on since then (Piketty, 2014). This is to a larger or smaller degree considered a problem in the political sphere, depending on where you are on the political scale. However, there seems to be a consensus in the view that more equality is preferable to less.

Though the recent historical pattern in the western world has been largely common there are differences when you break it down to specific countries. Figure 1 displays the Gini coefficients, the most common measurement of equality/inequality, for nine countries. A high Gini coefficient means an unequal society. Figure 1 displays coefficients for wage inequality.

Figure 1. Gini coefficient 1967-2005 (source Björklund and Jäntti)



As we can see in figure 1, Denmark has actually become more equal during the displayed period, and the Netherlands has not had much change at all. Sweden displays a rather typical pattern with the lowest Gini coefficient in 1980, and an increase since then. However, the increase is quite moderate, and the coefficient was still low by international standards in 2005 and it had barely reached the levels of the late 60s (Björklund and Jäntti, 2011).

Before the First World War wage inequality in Sweden measured as the percentage of income for the top decentile was around 45 percent, which was normal for Europe at the time, the US was slightly more equal with an income percentage of around 40 percent for the top decentile. In the 1920s the situation reversed and the US became less equal than Western Europe while inequality in Sweden dropped significantly to circa 35 percent of income for the top decentile. From 1930 equality started to increase in the US as well as in Europe and in the 1950s and 1960s the US, UK, Sweden, France and Germany were all quite similar with percentages for the top decentile between 30 and 35 percent. In 1970 the trend reversed in the US and UK an inequality increased, Sweden however continued to become ever more equal until 1980 when the percentage for Sweden was a very low 23 percent, by the European countries including the UK remained between 30 and 35 percent, and the US was between 35 and 40 percent. Since 1980 Inequality in Sweden has increased to just below 30 percent, while the US has increased to very high levels near 50 percent, the UK has increased to above 40 percent which is 1920s levels for the UK, and France and Germany remains between 30 and 35 percent. In other words, Sweden has become less equal since 1980, but it remains equal in a historical comparison as well as compared to other countries (Piketty, 2014)

If other incomes such as returns on capital and benefits from the welfare state are included the increase in the Swedish Gini coefficient during the period gets substantially larger, and I believe that the intense political debate during the last couple of years about increasing inequality in Sweden gives the impression that wage inequality has increased severely, an impression that I would claim to be false. It is however wage/salaries that is the topic of this thesis, and an increase in inequality in that has indeed occurred. I will hereafter use the word wage for all income from labor.

3 Previous research

Using a human capital based framework Juhn et al (1993) finds that increased wage inequality among males was consistent with increased returns to education. Changes in the structure of the global economy, but especially skill biased technical change. They found a steady increase in the demand for skilled labor in the 1960s, 1970s as well as in the 1980s, but somehow this change in demand only seems to translate into an increase into an increase in wages of skilled personnel from 1970 and onwards.

Borjas and Ramey (1995) explained differences in returns to schooling by foreign competition affecting some markets but not others. Labor with poor returns on their schooling are working in industries under heavy foreign competition, those in industries not affected by foreign competition can benefit from higher returns on their education. They also observed declining employment in industries of high international competition. These results are in a way corroborated by Bergh and Nilsson (2010). In a study of Gini coefficients in 37 countries they found that the freedom to trade internationally as indicated by the economic freedom index correlates with income inequality. Beyer et al (1999) finds evidence for Chile that an increase in the supply of college educated reduces the education premium and thus inequality, and that trade liberalization increased those variables.

Topel (1997) also studied increased international competition as an explanation for increasing wage inequality. According to Topel's findings the American industry are substituting towards higher skilled labor in spite of the increasing cost of such labor that is one of the corner stones of these studies. Topel claims that the depreciations of low skill wages caused by increasing international competition from countries with low costs and abundance of low skill labor would cause American industries to cease the opportunity to employ all of this cheap labor. That has not occurred, and Topel claims that that falsifies the hypothesis of increased competition causing the changes in the wage structure. Topel also found that the effects of immigration were moderate at best.

Topel further reports that returns to schooling dropped in Sweden and the United States during the decades leading up to the 1970s, this could plausibly be due to a rapidly increasing supply of the highly educated, but the direction of change has since reversed because demand is catching up with the higher levels of supply, a finding supporting the notion of skill biased technical change. Another change that can be observed on the labor market during that period is the increase of working women. Highly educated women had lower pay than men in the United States in the period, and Topel found that women's labor market entry put a lot of pressure on many categories of men, and decreases in the relative wages of some male labor could be observed as women moved into the market. This may be a contributor to the increased wage inequality among men (Ibid).

Heckman et al (1998) used long term American micro data with overlapping generations. Like Juhn et al and Topel they found a pattern where skilled biased technological change created an increase in high education earnings followed by a surge in education investments by the upcoming new generation eventually leading to a reversal of the initial effect leading to a cyclic pattern of wage inequality. They also tried to find out if immigration had any effect in their model, but found that the magnitude of empirical immigration was too small to have any explanatory power.

Card (2002) on the other hand claims that the decline in real minimum wage explains as much as 90 percent of the increase in 90-10 inequality. He admits that other explanatory factors are needed, such as declining unionization, and that the effect of declining minimum wage should not be exaggerated, but the support for the hypothesis at hand, skill biased technology change, he finds surprisingly weak.

In a study of 16 countries Martins and Pereira (2004) found that the returns on investments in human capital are higher in the higher income strata. They hypothesize that it is due to skill bias, meaning that individuals that are inherently more skilled can make more of their education, and that incomes for the highly educated are hence not equal. A logical consequence of this is that increased spending on higher education increasing the supply of high educated labor would not increase equality since the high skilled would still be in scarce supply.

Autor et al (2003) tested their theory of Task Biased Technology Change using the Dictionary of Occupational Titles and found good support for it, especially since the observed changes tasks was evident within educational groups as well as between them, as well as within occupational and gender divisions. Goos et al (2009) found that the occupational structure of Western Europe in later years has seen an increase in tasks identified as abstract, while routine tasks has declined in demand. They found that the increase in jobs that where not characterized by routine was across all income levels. They also found that offshoring was prevalent in both industrial labor and office work, mainly in routine tasks. The relative importance of this was however found to be smaller than the impact of new technology. They found no support for an impact of institutional change or a reversed causality with an effect of income changes on employment.

Adermon and Gustavsson (2015) in a very recent study for Sweden based on Goos et al's method found that as much as 44 percent of the 1990 to 2005 job polarization can be explained by routine task contents. They however fail to find between occupation support for an effect of task biased change on wages. In order to find such, support the authors needed to go to within occupational effects. This casts some doubt over the hypothesis in the view of the authors. Kampelmann and Rycx (2011) made a similar study for Germany and found similar results. They also found a very weak link between changes in employment and wage.

3.1 Summary of previous research

The support for international competition being a factor in explaining the increased wage spreads in the western world seems to have good support in the literature. Another picture that emerges is that of increases in educational capacity from the 1950s and onwards increasing wage equality through the vast increase in supply of highly skilled labor. This effect seems to have reversed after a couple of decades when the expansion of higher education came to a halt and increases I demand for high skilled labor wasn't as easily met by increases in supply. Women's entry into the labor market also seems to have put supply pressure on some occupations reducing the relative wages of the men employed in those trades.

Research in the field of Task Biased Technology Change has found support for the theory within occupations but it has been a lot harder to find support between occupations. Occupations with high abstract contents has however been found to be in increasing demand while routine occupations are showing a downward trend. Support can be found for the hypothesis of offshoring reducing demand for offshorable occupations. The link between these changes in demand and wage trends is found to be weak at best.

4 Theoretical framework

Skill Biased Technological Change is a theory of technological change affecting the demand for labor in such a way that the less skilled are in ever decreasing demand due to automation, while those with high levels of human capital, especially technically skilled labor is in ever increasing demand due to society becoming ever more technically complicated. This will obviously increase the demand for workers with higher levels of human capital, and their returns to the human capital will increase since the increasing demand for their ability will raise their wages in accordance with the general economic laws of supply and demand (Welsh, 1973. Tinbergen, 1974. Topel, 1997. Galor and Moav, 2000).

Task Biased Technological Change is a Ricardian model of the labor market, e g a model with comparative advantages and it was introduced by Autor, Levy and Murnane (2003). The first step of development from the simpler Skill Biased Technology Change model mentioned above is to introduce a distinction between skills and work tasks. A skill is a feature of the individual combining innate ability with the fruits of education, whereas a task is a component of work needed in production. A certain task would require a certain set of skills, and a certain occupation would consist of a certain set of tasks.

A further development is to expand the two skill levels in the previous model to three, High, Low, and a medium level.

A single task has the following production function

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

where A is technology that affects productivity in the different categories, α is a productivity term for each category, l, m, and h are the quantities used in low, medium and high skill labor respectively, and finally we have added a capital category K or quantitatively k, e g the opportunity of replacing labor with machines (Acemoglu and Autor, 2011).

The law of one price for labor implies that for each skill level using the notation for low skill as an example

$$W_L = p\,(i)\; A_L\alpha_L(i) \equiv P_L$$

And equivalently for the two higher skill levels. This implies that $l(i)=L/I_L$ where I_L is a task that requires at least low skilled labor, a so called threshold task. It also implies $m(i)=M/(I_H-I_L)$ for any $I_H > i > I_L$ and $h(i)=H/(1-I_H)$ for any $i=I_H$. Comparing high skill and medium skill labor is expressed

$$\frac{P_H}{P_M} = \left(\frac{A_H H}{1-I_H}\right)^{-1}\left(\frac{A_M M}{I_H-I_L}\right)^{-1}$$

I_H is obviously a threshold task for high skilled labor. The equivalent comparison of the medium and low skilled

$$\frac{P_M}{P_L}=\left(\frac{A_M M}{I_H-I_L}\right)^{-1}\left(\frac{A_L L}{I_L}\right)$$

Comparing wages of the different skill levels, first of all wage is given by $w_L=P_L A_L$ using low skill as an example. $P_M A_M/P_L A_L$ is a perfectly fine way of comparing medium and low skilled wage. Including our information about tasks however we obtain

$$\frac{w_H}{w_M}=\left(\frac{1-I_H}{I_H-I_L}\right)\left(\frac{H}{M}\right)^{-1}$$

And the medium to low wage comparison is

$$\frac{w_M}{w_L}=\left(\frac{I_H-I_L}{I_L}\right)\left(\frac{M}{L}\right)^{-1}$$

Focusing on the allocation of tasks rather than on the skills themselves as explanatory factors for wage provides the opportunity to model the effects of technological change in a more fruitful way, including the opportunity to allow for wages in some skill category declining due to technological change, and distinguishing between task at risk of offshoring from those that are not (Ibid).

In other words, since routine tasks performed by human labor and by computers and machines are good substitutes, and since computerization is expected to increase demand for abstract tasks needing high skilled labor, computerization is expected affect demand for different occupations and skill levels in different directions. These effects on demand can in accordance with basic economic theory be expected to affect wage, or rather wage change, in a positive direction in cases of increased demand, and a negative direction in cases of decreased demand.

5 Data and descriptive statistics

The data is obtained from Statistics Sweden (SCB). The four-digit classification of occupations (SSYK) contains a total of 249 occupations, wage and employment for those are available from 2001 to 2013. I have dropped all occupations containing three missing values or more, leaving a dataset of 249 occupations stretching from 2005 to 2013 with very few missing values. Potential problems of consistency in the data is primarily due to changes in the classifications for the local public sector in 2008, creating changes in the employment data due to this change alone. Since the changes in employment will not correlate with changes in wage, that correlation may be more difficult to find econometrically.

5.1 Variables

5.1.1 Wage

Wage is my prime dependent variable, the wage figures obtained from SCB is the mean wage for each of my 249 occupations, and they are not adjusted for inflation. The target variable I will actually be using is the percentages of the national annual mean wage. That will take care of the problem of inflation, as well as creating transparency about the relative levels of the different wages. I have also created a high income dummy for all wages that are over 120 percent of medium wage on average for the entire period, the dummy contains 25 occupations, and a low income dummy for wages that are on average under 80 percent for the period containing 23 occupations.

5.1.2 Employment

The employment statistics are simply the discrete numbers of persons employed for each occupation. There are potential problems with this measurement due to the fact that part time workers are not distinguished from full time workers. However, I do not believe that this will pose any problems since I believe, based on previous research (Goos et al, 2009) that persons employed and hours worked will vary in a similar fashion.

5.1.3 Tasks

From Goos et al (2009) I have borrowed numerical grades of an occupation's abstract content, its level of routine tasks, and the viability of sending the work abroad. The hypothesis obviously being that routine tasks are easy to transfer to computers, whereas increasing computerization are expected to increase demand for abstract tasks. The grades are based on American statistics from the Occupational Information Network (ONET). ONET is a survey of job content where employees have graded the relative importance of different contents in their daily work. Goos et al has made composites of 96 variables of the 2006 ONET that are relevant to create the grades of the different occupations. Routine tasks are characterized by cognitive skills that are not complex and that are repetitive, as well as repetitive manual work. Goos et al exemplifies the following criteria for abstract tasks "critical thinking, judgment and decision making, complex problem solving, interacting with computers and thinking creatively. The two digit occupational codes are compatible with my SCB four digit codes. Unfortunately, I could not pair three of my occupational codes with Goos indexes leaving a dataset of 246 occupations.

5.1.4 Increased competition

I will control for Increased competition on the labor market that is supposed to be in the shape of offshoring and immigration. I have chosen to use offshorability grades collected by Goos et al (2009) from the European Restructuring Monitor (ERM) of the European Monitoring Centre on Change (EMCC), containing statistics from companies all over Europe of how many jobs of what occupations has been offshored, and offshoring plans

5.2 Descriptive statistics

I have calculated the average annual change in wage and employment over the period generating slopes for my occupations. Descriptive statistics for these slopes and my three indexes borrowed from Goos et al (2009) are displayed in figure 2 below. Notable is that the indexes are not centered on zero, ant that Swedish occupations are on average on the abstract side, and not very routine.

Figure 2

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
WSlope	246	0.0287	0.00671	0.00470	0.0601
ESlope	246	0.0217	0.0788	-0.215	0.706
Abstract	246	0.471	0.896	-1.380	1.800
Routine	246	-0.218	1.021	-1.630	1.330
Offshore	246	-0.0751	0.769	-0.640	1.630

6 Econometric methods

In order to test the theory, I have calculated the average change in wage and in employment for the 246 occupations for my 2005-2013 period, generating 246 slopes for wage change and 246 slopes for employment change. The slopes are calculated by taking the average of the yearly changes in these two key variables over the entire period as displayed for wage below.

$$\frac{\left(\frac{(w_t/w_{t-1})}{w_{t-1}}\right)}{T}$$

The slopes may be positive or negative. The reason for calculating these slopes and run OLS rather than using a panel data model is that all my explanatory variables are time invariant, and using slopes I can still correlate the explanatory variables against change over time. These wage and employment slopes are regressed against the indexes borrowed from Goos et al (2009) and my dummies for high and low income using OLS. A potential problem is that I cannot separate supply from demand, making my employment data a rather weak variable. Since theory predicts that wage will be affected by increases or decreases in demand for various occupations, the model relies on the hope that these changes in demand will dominate over changes in supply, and hence manifest themselves through changes in employment in the directions predicted by theory. The basic OLS-model can be expressed:

$$Y_i = \alpha + E\beta_1 + H\beta_2 + L\beta_3 + A\beta_4 + R\beta_5 + O\beta_6 + u_i$$

Where Y is the wage slope, α is the intercept, E is the slope of the logged employment, H is the high wage dummy, L is the low wage dummy, A is the abstract task variable, R is the routine task variable, O is the variable of offshorability, and u is the error term. The model will be modified by excluding various variables in order to avoid multicollinearity.

7 Results

7.1 Preliminary test model

First of all, I am testing the basic theoretical notion that relative wage changes are demand driven and that changes in wage should hence correlate positively with changes in employment. The method is described in the appendix. Displayed in figure 3 below are the results of random effects models testing the first year correlation between wage change and employment change, the second model is with lags and the third is with a polynomial. Due to missing values I am losing ten occupations in the models including lags. Wage is the annual change in the logarithm of the wage statistics. Employment is the annual change in the logarithm of the employment statistics, Employment 2 is the square of that, and L, L2 and L3 are the lags. The first year effect is significantly negative and that effect dominates over the two following year lags that are not statistically significant. It may seem as the causal connection between demand and pay does not dominate over the effects of supply. Using a polynomial generates at better fit, basically confirming the results.

Figure 3

	(1)	(2)	(3)
VARIABLES	Wage	Wage	Wage
Employment	-2.508***	-3.518***	-3.908***
	(0.377)	(0.635)	(0.676)
Employmen 2			-2.985*
			(1.627)
L.Employment		0.354	0.255
		(0.458)	(0.465)
L.Employment 2			0.267
			(0.452)
L2.Employment		0.439	0.597
		(0.454)	(0.462)
L2.Employment 2			-0.706
			(0.454)
L3.Employment		-1.450***	-2.202***
		(0.433)	(0.443)
L3.Employment 2			2.626***
			(0.424)
Constant	0.0410	0.0312	0.00798
	(0.0729)	(0.0802)	(0.0854)
Observations	1,846	1,074	1,074
Number	249	239	239

7.2 Tests for multicollinearity

Turning from this preliminary check to my slope regressions, first of all, I checked the correlations between my three explanatory indexes. As could be expected they are significantly correlated with positive correlation between Routine and Offshore, and negative correlation between Abstract and those two. This poses a problem of multicollinearity and it may be necessary to avoid including these variables simultaneously in my models. The results of these tests are displayed in figure 4 below.

Figure 4

	(1)	(2)	(3)	(4)
VARIABLES	Abstract	Abstract	Routine	Abstract
Routine	-0.549***			-0.444***
	(0.0438)			(0.0501)
Offshore		-0.576***	0.699***	-0.266***
		(0.0649)	(0.0723)	(0.0665)
Constant	0.352***	0.428***	-0.165***	0.355***
	(0.0457)	(0.0500)	(0.0557)	(0.0444)
Observations	246	246	246	246
R-squared	0.391	0.244	0.277	0.429

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The next step was to examine how the explanatory indexes correlate with my high and low income dummies. High is a dummy for wages over 20 percent above average, and low is a dummy for wages more than 20 percent below average. The results, displayed in figure 5 below, are encouragingly reasonable with high income having a strong positive correlation with the Abstract index, and negative correlations with Routine and Offshore, especially Routine. The low income dummy correlates only with the Abstract index, positively as can be expected. Once more I have a potential multicollinearity problem, and must probably refrain from using these dummies with my explanatory variables. The low wage dummy should work well with either Routine or Offshore however.

Figure 5

	(1)	(2)	(3)
VARIABLES	Abstract	Routine	Offshore
High wage	0.869***	-0.842***	-0.410**
	(0.171)	(0.211)	(0.161)
Low wage	-0.941***	-0.136	-0.210
	(0.181)	(0.223)	(0.171)
Constant	0.467***	-0.120*	-0.0146
	(0.0573)	(0.0704)	(0.0539)
Observations	246	246	246
R-squared	0.195	0.062	0.030

Standard errors in parentheses

7.3 Wage as dependent variable

Using these insights, I tried to investigate what affects the wage slopes. The results are displayed in figure 6 below. First of all, I tried a regression of only employment slope against wage slope, displayed as model 1 in figure 6. Like in the preliminary test, the employment slope correlates negatively with the wage slope, and that correlation is significant at the 5 percent level. Like the random effects model tried previously the wage slope seems to be supply driven, rather than driven by demand as I had expected. In model 2, using all my variables with the risk of multicollinearity, the only other significant variable is the dummy for low income. Low income correlates negatively with the wage slope, consistent with our previous knowledge of increasing wage gaps. Taking out the high wage dummy because of its correlation with the explanatory variables, and Abstract because of its correlations with low wage and the other variables produces the same result in model 3, as does taking out Routine as well due to its correlation with Offshore in model 4.

Figure 6

	(1)	(2)	(3)	(4)
VARIABLES	WSlope	WSlope	WSlope	WSlope
ESlope	-0.0133**	-0.0130**	-0.0131**	-0.0132**
	(0.00538)	(0.00542)	(0.00542)	(0.00541)
High wage		0.00237		
		(0.00147)		
Low wage		-0.00365**	-0.00352**	-0.00349**
		(0.00166)	(0.00148)	(0.00147)
Abstract		-0.000370		
		(0.000716)		
Routine		0.000407	0.000410	
		(0.000573)	(0.000485)	
Offshore		-0.000119	-4.92e-05	0.000235
		(0.000681)	(0.000650)	(0.000556)
Constant	0.0290***	0.0293***	0.0294***	0.0293***
	(0.000439)	(0.000563)	(0.000463)	(0.000456)
Observations	246	246	246	246
R-squared	0.024	0.061	0.051	0.048

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Since changes in employment does not have the positive correlation with changes in wage that we have expected it may cause problems of multicollinearity as well, I will hence try to exclude it. After taking the employment slope out, and once more including all the variables, the results presented in model 1 in figure 7 once more tells us that having a low wage to begin with is the only significant indicator of getting a poor wage development. Then I am excluding variables that can be suspected to cause collinearity. In model 2 I have excluded High wage and Abstract tasks since they are posing most problems with correlations with the other variables, in model 3 I am excluding Routine tasks as well, and in model 4 I am excluding Offshorability instead of Routine tasks. The results are exactly the same, only low income has a significant correlation with the wage slope at the 5 percent level, and that correlation is negative telling us that occupations with low wages has had a poor income development during the period. Trying Abstract tasks on its own, not displayed, gave no significant results.

Figure 7

	(1)	(2)	(3)	(4)
VARIABLES	WSlope	WSlope	WSlope	WSlope
High wage	0.00239			
	(0.00149)			
Low wage	-0.00364**	-0.00341**	-0.00337**	-0.00343**
	(0.00168)	(0.00149)	(0.00149)	(0.00148)
Abstract	-0.000459			
	(0.000722)			
Routine	0.000413	0.000453		0.000508
	(0.000579)	(0.000490)		(0.000415)
Offshore	4.13e-05	0.000139	0.000457	
	(0.000684)	(0.000652)	(0.000554)	
Constant	0.0291***	0.0291***	0.0290***	0.0291***
	(0.000560)	(0.000454)	(0.000446)	(0.000453)
Observations	246	246	246	246
R-squared	0.039	0.028	0.024	0.028

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

7.4 Employment as dependent variable

The theory states that abstract tasks have a positive effect on demand and should increase employment, and that routine tasks and offshorability should have a negative impact on demand, hence reducing employment. In the next step these changes are supposed to affect wages in that same direction. Since the second stage is not positively correlated as expected we need to test the first step, the correlation between our variables and employment. As displayed in model 1 in figure 8 below, I begin using all the variables, and this time I get a different result. Low wage does not correlate significantly with changes in employment, indicating that the negative correlation with wage change must work though some other mechanism. In case there is problems of multicollinearity, in model 2 I exclude the high wage dummy and Abstract tasks since they correlate with Offshore and Routine, and indeed suddenly Offshore is significant at the ten percent level. Since there is correlation between Routine and Offshore I tried them both without the other, generating two new models without multicollinearity. On its own Routine has a negative correlation with the employment change significant at the ten percent level as seen in model 3. This correlation is weak but at least in the right direction. Offshore however is significant at the five percent level while run without the problem of multicollinearity, the correlation is in the expected negative direction, and I think we have a real result displayed in model 4.

Figure 8

	(1)	(2)	(3)	(4)
VARIABLES	ESlope	ESlope	ESlope	ESlope
High wage	-0.00152			
	(0.0175)			
Low wage	-0.00117	-0.00862	-0.00649	-0.00886
	(0.0198)	(0.0175)	(0.0175)	(0.0175)
Abstract	0.00690			
	(0.00851)			
Routine	-0.000449	-0.00335	-0.00904*	
	(0.00683)	(0.00575)	(0.00491)	
Offshore	-0.0123	-0.0144*		-0.0167**
	(0.00807)	(0.00765)		(0.00650)
Constant	0.0177***	0.0207***	0.0203***	0.0213***
	(0.00661)	(0.00533)	(0.00535)	(0.00523)
Observations	246	246	246	246
R-squared	0.031	0.028	0.014	0.027

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Finally, I need to test abstract tasks. It is problematic since it correlates with everything, hence I need to run it alone. The correlation with employment change, displayed in figure 9 below, is positive, confirming the theoretical expectation that demand for abstract tasks should have increased. Including Routine tasks as well, not displayed, provides no significant effect of either Abstract tasks nor Routine tasks on employment.

Figure 9

	(1)
VARIABLES	ESlope
Abstract	0.0124**
	(0.00557)
Constant	0.0159***
	(0.00563)
Observations	246
R-squared	0.020

7.4 Summary of findings

Since Task Biased Technology Change theory predicts that task contents affects wage through effects on employment, we would have expected that occupations with increasing employment driven by rising demand for Abstract tasks would have a better wage development, and that occupations with decreasing employment due to a decreasing demand for Routine and Offshorable tasks would have a negative wage development. The correlation between employment change and wage change in the preliminary test model was however negative, posing a real problem for the theory. Since effects of my variables are obviously not carried on from employment to wage it is hardly surprising that they are found to have no significant effect on wage in the slope models with wage as dependent variable. Only the dummy for low wage has a significant effect on wage change. The effect is negative, consistent with our point of departure that the gap between high and low wages has increased during the period.

Moving on to the models with employment as the dependent variable, we discover that the dummy for Low wage occupations employment has not changed during the period, indicating that some other mechanism than Task Biased Technology Change is causing the negative wage effects on Low wage occupations discovered in the previous models. Running models with the explanatory variables isolated in order to avoid multicollinearity we find that all three task indexes have significant effects on employment in the direction that we are expecting from theory, e g positive for abstract tasks, and negative for routine tasks and tasks that are easily offshorable. The largest, and as it seems most important effect is the offshorability effect.

8 Conclusions

First of all, there seems to be some merit to the theory of Task Biased Technology Change since I have found that occupations dominated by abstract tasks have actually increased in employment as predicted, and routine and offshorable task occupations have decreased. The demand-effects of Tasks Biased Technology Change seem to have been moving employment creating the changes we have observed in the data. This has not, however, translated into effects on wage change in the equivalent directions. On the contrary, the effect of employment change on wage change is negative. My first interpretation of this initial result would be that supply has dominated over demand in employment, thus falsifying my entire model and making some other factors the prime movers in the developments on the Swedish labor market in later years. Some modeling of changes in supply might have been appropriate, but that was not easy to do for 246 occupational codes given that data at hand.

The model is to some extent saved by the fact that employment is actually changing in the directions predicted, meaning an increase in occupations dominated by Abstract tasks, and a decrease in occupations dominated by Routine tasks, and especially Offshorability. The fact that this does not translate into an equivalent change in wages could be due to one of two possible factors. Even larger changes in supply than the changes in demand that we must assume to be present could dominate over the demand effects that are the subject of interest for this thesis, cancelling out the wage effects of Task Biased Technology Change. This would however make it really hard to explain the increasing wage gap since there actually is a higher increase in the higher wages, typically associated with abstract tasks. On the other hand, a decreasing interest among the young for easily offshorable occupations might overcompensate for the significant decrease in demand for such tasks that we need to assume is associated with the significant decrease in employment for such occupations. Exactly the same might be said for routine occupations, and besides, those two categories are largely overlapping.

An important difference between Skill Biased Technological Change theory and the theory of Task Biased Technology Change is that SBTC assumes that the low paying jobs will decrease in demand, whereas TBTC assumes that many of the very lowest paid jobs are hard to automate or substitute with computers, whereas the jobs that could easily be made superfluous are predominately in the midlevel. My model confirms the latter, more sophisticated TBTC theory since it actually is the routine dominated and easily offshorable occupations that have been decreasing in employment, while there is no significant such effect for the lowest paying jobs.

The lowest paying jobs are however the only category that has any significant effect on wage change. Since this does not seem to be due to any change in demand as could be expected by SBTC, some other factor is needed to explain it. There could for instance have been a surge in low skilled labor, possibly due to immigration, or to decreased demand for higher paid routine jobs “pushing down” individuals that would previously have been employed in such occupations to seek low wage sector jobs instead. This would be due to a lack of skills for higher paying jobs dominated by abstract tasks.

Summing these hypotheses up, changes in demand are as predicted by the TBTC theory, but met by changes in supply where declining interest in routine tasks reduces supply even further than the reduction in demand. This labor supply is predominately shifted to abstract task jobs, annihilating the increase in wages that would otherwise have occurred, and at the same time the lower skilled labor is pushed down to low wage occupations. This would indicate that the wage gap in Sweden is smaller than it might have been, and it is indeed smaller than in many other countries. A further explanation for this might be that Sweden’s generous educational policies easily translates a declining interest in routine jobs into effective supply of abstract task skilled labor.

A different hypothesis altogether is that the basic law of supply and demand isn't working very well on the Swedish labor market due to a large public sector and strong unions. A possible explanation for the significant negative correlation between low wage and poor wage increase could be that strong Swedish trade unions have previously imposed an upward pressure on the lowest wages due to egalitarian preferences, and what we are observing is the weakening of these union policies, either due to institutional factors, or due to the generally higher levels of unemployment in Sweden in later years. These thoughts are beyond the scope of this thesis, but a possibility that needs be mentioned alongside the supply driven explanations described above.

8.1 Comparing with previous research

Juhn et al (1993) found an increase in demand for the highly educated combined with a raise in income for that stratum after 1970 in the United States. I have with some difficulty found an increase in employment for abstract tasks, which is approximately the high educated, but I have found no significant effect on income of this change possibly due to similar increases in education used by Juhn et al to explain the decreasing relative pay for the well educated in the US before 1970. This comparison also applies to Heckman et al (1998)

My data corroborates studies saying that increased international competition has an effect (Borjas and Ramey, 1995. Bergh and Nilsson, 2010. Beyer et al, 1999) since offshorability is my largest observed effect on employment. It is however disappointing that is does not provide an explanation for the wage changes that are the actual object of interest for this thesis. Further, low income is my only variable with a significant effect on income change, and as TBTC predicts, low income does not correlate with offshorability, and low income jobs are not decreasing in employment.

Like Card (2002) I have found that the strong explanation for increasing wage inequality is the weakening of the low paying jobs, and like Card I have found no actual support for SBTC affecting wages, nor have I found such support for effects of TBTC on the wage structure.

Finally comparing with the previous TBTC studies I have unfortunately not been able to study within occupation changes, only between occupations. That is unfortunate since the most significant results in previous studies are within occupations. Like all the previous TBTC studies I have however found the expected effects of Abstract, Routine, and Offshoring on employment. For Goos et al (2009) and Kampelmann and Rycx (2011) the effects on wages was surprisingly small. Adermon and Gustavsson (2015) found no between occupations effect on wage at all, and since I have only been able to study between occupations effects, my results are the same as theirs.

8.2 Summing up

Is technology driving the increase in wage inequality in modern day Sweden? The theory of Task Biased Technology Change has been found to explain changes in employment over the studied period quite well, but this does in turn not provide any explanation for the increase in wage inequality using my data and method. The only significant factor explaining the rising wage inequality was that initially low wages has not increased as well as higher wages. The reasons for this are beyond the scope of this thesis, and open only to speculations at this point, I do however think it is an interesting topic for further study. Another interesting topic for further study would be just why the observed changes in employment due to TBTC seems to have no effect on the wage structure. Regarding my own study, I mostly regret that I had no access to individual data making within occupation comparisons, found to be more fruitful in previous studies, possible.

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Appendix

Initial test model method

The methodology for the initial test is a panel data approach using a panel of 246 occupations spanning from 2005 to 2013. Since I am using all four-digit code occupations with no more than three missing values I believe that a random effects model is appropriate, and that the cross sectional dimension is very valuable. The comparison of how various occupations have developed is more interesting than the dataset viewed as a set of 246 time series. A Hausman test confirms the presence of random effects hence I opted for a random effects model as displayed in the equation below:

$$Y_{it} = X_{it}\beta + \alpha_t + u_{it}$$

My Y variable is the percentage of wage and the X variable is the log of employment. I am actually regressing the changes in the two variables against each other in order to isolate the effect of a change in employment on the change in wage for each occupation making the model rather look like:

$$\Delta Y_{it} = \Delta X_{it}\beta + \alpha_t + u_{it}$$

It is however likely that there is some delay in the effects of employment on wages, a series of lags would take care of that problem rendering the equation:

$$\Delta Y_{it} = \Delta X_{it}\beta_1 + \Delta X_{it-1}\beta_2 + \Delta X_{it-2}\beta_2 + \Delta X_{it-3}\beta_3 + \alpha_t + u_{it}$$

Since the relation could be polynomial rather than linear I also tried a model with a polynomial X variable:

$$\Delta Y_{it} = \Delta X_{it}\beta_1 + \Delta X^2_{it}\beta_2 + \Delta X_{it-1}\beta_3 + \Delta X^2_{it-1}\beta_4 + \Delta X_{it-2}\beta_5 + \Delta X^2_{it-2}\beta_6 + \Delta X_{it-3}\beta_7 + \Delta X^2_{it-3}\beta_8 + \alpha_t + u_{it}$$

The basic assumption is that earnings are influenced by changes in supply and demand. If the observed widening of the wage gap in Sweden is really demand driven as presumed by the theory of ability biased technical change, changes in employment should be associated with changes in earnings in that same direction. Lags has been added to the X variable in order to try to find Granger causality.