Jobquality Determinants of Relative Employment Growth

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Abstract

In this paper I investigate developments in relative employment in relation to general jobquality, to ascertain the validity of the polarization hypothesis, introduced by Goos and Manning (2007), in a compressed wage regime. There is a general agreement that Skill Biased Technological Change has not affected labor market outcomes in the same magnitude in the Scandinavian countries as it has in comparable economies. While this may be true with respect to wages and unemployment, relative employment changes (of occupations) were remarkably similar to the US and the UK. While the share of low educated workers in the employed population dropped considerably, occupations that were formerly intensive in low skilled work grew in relative importance. Analogously, occupations formerly intensive in medium skilled workers lost in importance despite seemingly unchanged employment opportunities for medium skilled workers. By linking employment growth and task content of occupations, I show that initial task content is well able to explain changes in relative employment, with a high initial routine task content being a good predictor for joboutflow and a high nonroutine, interactive and manual task content bein associated with positive job growth.

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1 Introduction and Motivation

Skill Biased Technological Change (SBTC) has in recent years served as a popular explanation for wage and unemployment developments as well as employment growth experienced by most industrialized countries, though the exact mechanism have been a subject to debate, as have been the empirical measures for SBTC. Card and Di Nardo (2003) identify two main approaches: the computer-skill -complementarity hypothesis, introduced by Autor, Levy and Murnane (2003) and the rising-skill-price hypothesis, introduced by John, Murphy and Pierce (1991,1993). In their paper Card and Di Nardo find that the two competing theories have quite different implications for wage developments of different demographic groups. It is therefore crucial, when assessing the validity of the SBTC approach, to be explicit which theoretical framework is used.

The rising-skill-price hypothesis assumes that computers have changed relative productivity of high skilled workers (relative to low skilled workers), which increases their relative wage. In contrast, the computer-skill-complementarity hypothesis, instead of assuming that computers increase productivity as such, claims that computers are q-complements to certain *tasks* (which in this framework are considered nonroutine analytical and manual tasks) and substitutes to certain other tasks (routine tasks). Therefore wage and employment implications result from the occupational task content. Most people that actually use computers at the worplace do not have specialized knowledge in computers, but only use simple programs such as word and excel, especially since computers have become increasingly user friendly. Teaching someone to use these simple programs is more a matter of weeks than of a lengthy education, but still wage differentials and differences in unemployment rates between high and low skilled workers are persistent and even increasing. Therefore it is reasonable to look for a more nuanced way of modeling the exact mechanism in which computers could have an impact on the wage and employment structure.

In the task framework used by Autor et.al.(2003) nonroutine tasks such as researching, interpreting rules, planning and organizing etc. are complements to computer technology, i.e. workers who perform these tasks are made more productive using computers. Conversely, there are tasks that are substitutes to computer technology, because of their repetetive and foreseeable nature, such as accounting, registering etc. In the past this framework has been mainly used to explain within occupational task changes and to estimate the demand/demand changes for individual tasks. In this paper I assess the importance and relationship between initial occupational task content and changes in relative employment in the context of a compressed wage regime that has not witnessed the large rise in wage inequality and low skilled unemployment as most other industrialized countries.

Computer capital (in efficiency units) and human routine task input are perfect substitutes, while the two educational levels are imperfect substitutes. This ensures that the changing task composition translates into observable labor market outcomes (unemployment, wages etc.).

Relation to Polarization Much of the political and public debate focuses on falling demand for low skilled workers as a scapegoat for widening wage differentials, with all the associated policy initiatives. However, occupations with a high intensity in routine cognitive tasks are mainly clerical jobs such as filing and registration jobs, which are not the type of occupations one usually associates with low skilled workers, but by medium educated workers. If we translate the three assumed implications of increased computerization on labor demand, we receive (roughly) an increased demand for high skilled workers, a decreased demand for medium skilled workers and an unchanged demand for low educated workers. If this is indeed the case, a reduced demand for medium educated workers will lead ceteris paribus to a higher wage differential between low skilled/high skilled jobs, under the assumption that medium educated workers turn to the low skill labor market. This would then lead to a polarization of the labor market with a lot of workers at the top and at the bottom of the (initial) wage distribution (as the term polarization first defined by Goos&Manning (2007)).

Denmark has seen relatively little of the wage inequality developments compared to those observed in other countries, even though this arguably depends on the method and measurement for inequality. Or as in Jensen, Fosgerau, Sørensen (2002b) "... that relative wages in Denmark have been roughly constant over the data period [1980-1998]". Why would that present a challenge to SBTC theories? As in Berman et.al (1998): ..."pervasiveness is important for two reasons: firstly, at the current level of international communication and trade it is hard to imagine major productive technological changes ocurring in one country without rapid adoption by the same industries in countries at the same technological level." ... " If we did not observe evidence of SBTC throughout the OECD, we would be forced to doubt it ocurred in any OECD country." It is of course possible to assume that governmental intervention prevented wage or unemployment effects to appear, but I would argue that the spread of computer technology can hardly be said to be less pronounced in Denmark than in comparable economies. Essentially this means that the effects of computerization should be its effects should be visible somewhere in the employment and wage distribution.

The aim of this paper is not to evaluate possible policy interventions that could have suppressed the effects of SBTC, but to document that SBTC did have an effect on the Danish labor market despite seemingly unchanged wage and employment opportunities. [1] Denmark is arguably well suited for this particular type of analysis, since in contrast to other countries with compressed wage distibutions (for example Germany or Sweden), hiring and firing laws are extremely flexible, so that we can reasonably assume that firms adjust own employment according to their labor demand at given prices.

In this paper I present evidence that patterns in employment growth (in relation to jobquality) were similar to those observed in the US and the UK, despite stable wage differentials. I further show that employment of medium skilled workers was significantly affected and by using the NAK work environment, I can link employment growth to the in-

[1] Also Autor et.al.(2006) stress the fact that there is observed polarization with different implications for employment and wages that are most likely due to institutional factors that influence wage bargaining and hiring and firing.

tial task composition of the occupation; a high routine task content has had a marked negative effect on relative employment growth, while a high nonroutine, interactive and manual task content imply positive job growth.

The remainder of the paper is organized as follows: In section (1.1) I review some of the evidence on inequality and skill biased technological change in Denmark and the task-skill/polarization hypothesis literature. In section (2) I sketch some of the key features of the underlying task and production model and talk about the empirical implications of the model. In section (4.1) and section (4.2) I present the empirical evidence on employment growth and the relation to the occupational task compsition. Section (5) concludes.

1.1 Literature Review

There exists a very extensive literature on Skill Biased Technological Change (SBTC) and wage inequality. For a recent overview about methods and empirical evidence see for example Machin (2008) on wage inequality, or Sanders and Ter Weel (2000) for a comprehensive paper summing up research results on Skill Biased Technological Change up to this point. Here I will only present a few core papers that are of immediate importance for my analysis, i.e. that are directly related to the task computerization hypothesis and/or polarization. The first ones to model the mechanism of skill biased technologcial change as computers increasing productivity of certain job *tasks* were Autor, Levy and Murnane (2002) .They argue that the notion that computers per se increase productivity is misleading, since computers became increasingly user friendly; learning basic computer skills is not something that requires very high innate abilities and/or a long education. This leads to the argument that since people's wages seem to be related to computerization, it must be the case that what these people *do* with computers, that causes higher wages/lower unemployment. They model an economy where the falling price of computers causes computerization at the workplace to increase, which consequently leads to a higher productivity in performing certain tasks. Using the Dictionary of Occupational Titles (DOT) and micro cencus data from 1960 until 1998, they find that computerization has had a significant effect on the increase of nonroutine analytic task content and decrease of routine cognitive and routine manual task content. Furthermore, shifts away from routine tasks towards nonroutine tasks can not be accounted for by shifts in the educational compostion, but are pervasive across all educational groups. In a paper that is based on this general Computer/Task-complementarity approach, Autor, Katz and Kearny (2006) show how their theoretical model can account both for a linear rise in skill demand (that happened during the 1980's in the US) and polarization, which they document happened during the 1990's.

Empirically they find substantial and pervasive evidence for a polarization of the US Labor market linked to a decrease in routine task content of occupations. They find that over the 1990's, upper half wage inequality grew substantially, while lower half wage inequality stagnated (actually it even contracted over the period 1987-2004). They group occupations into percentiles and depict average log wage growth over the entire period. They find an almost linear spreading of the wage distribution before 1988 and a polarization of the wage distribution, with the lowest quartile growing faster, than then the two middle quartiles. Using different specifications to measure job quality (initial median wages, average years of schooling, routine task content) they find that job growth has polarized over the 1990's.

Spitz-Oener (2006) finds similar results for Germany, but instead of administrative data she uses microsurvey data on computerization and job tasks. She constructs a scalar task index, where she groups occupations into 10 different groups: Occupations with values in the lowest decile of the skill index of 1979 form the first group, occupations with values in the second decile form the second group, and so on. She claims that this occupational skill distribution represents closely skill requirements that existed in the Pre-computer era. She finds that routine task values are relatively high in all deciles, but routine manual tasks are more pronounced for lower deciles and routine cognitive scores are more pronounced for higher deciles. One implication of this approach concerns medium skilled workers that very often perform jobs that require classical routine cognitive tasks. This consequently leads to an increased polarization of the labor market. Autor, Katz and Kearny (2006) demonstrate that employment growth that was triggered by education during the 1980's shifted to rapid growth in the top and the bottom of the wage distribution.

Goos and Manning (2007) show that for the period 1975-1999 this growth of "Lovely and Lousy jobs" also characterized the british labor market. They conclude that the hypothesis of Autor et.al. (2002) is broadly consistent with empirical evidence in the UK. They document that educational upgrading is a good predictor for he rise of "lovely jobs" but not for "lousy jobs". Card and Di Nardo (2002) offer some general critique on the SBTC hypothesis: they emphasize especially, as previously mentioned, that the theoretical framework and the measure for skill biased technologcial change is especially important in explaining the data. They present cases in which the predictions of the model (s) fall short in explaining several empirical facts, especially in the timing of wage changes, but also with regard to the hypothesis' predictions for specific demographic groups (by gender, race, age+interactions) and conclude that real wage decrease during the 1980's and a decrease in union coverage were the main driving forces behind higher wage inequality.

2 The Model

The underlying production model from where my empirical predictions are derived was developed by Autor et.al. (2003) and Autor et.al. (2007). Their model only includes two distinct types of workers, low and high skilled; low skilled workers differ from each other by their varying degrees of routine skill endowment. Extending the model to three different educational groups is non-trivial and requires many (strong)assumptions which is why I explore these questions empirically at this point.

What are routine tasks? It is important to stress again the particular nature of routine tasks in this context. Routine here does not mean that the task is boring or monotonous (even though it could certainly also be boring). A routine task here is only a routine task, if it can be performed by a computer. Truckdriving for example is by most people seen as routine and not exactly stimulating, but in our context it is not routine, because it can not (yet) be performed by a computer.

2.1 Empirical Implications of the model

There are structural implications for medium skilled workers, even though they are not explicitly modeled (in the model there are only two types of workers, college and high school workers). The implications for medium educated workers result by endowing high school workers with a continuum of routine abilities. Those that posess more routine abilities are ex-ante more likely to perform jobs that contain a high routine task set. These workers can be interpreted as being medium skilled workers. The (empirical) magnitude of the effect of this task based skill biased technical change approach depends largely on institutional factors such as wage rigdity, employment protection laws etc. Roughly the empirical implications are threefold, even though in this paper I mainly focus on the implications for relative employment changes:

2.1.1 Implications for Employment Changes

Employment growth should be lowest in occupations with a high share of medium educated workers, which according to the theoretical framework indicates a high routine task content. The implications for employment growth are twofold as there are two different "margins" with which task change induced by computerization influences the labor market: Workers can be laid off and the position is not refilled, which leads to changes in the relative employement of this occupation (changes in the "extensive margin"), or: changes in the task composition of jobs (changes in the "intensive margin" of occupations. In the latter case there is either skill upgrading involved (lower skilled workers are replaced by higher skilled workers, accounting for the fact that performing nonroutine tasks requires abstract skills) or workers that already posess abstract skills receive higher wages. It is quite likely that both effects were at work: the number of workers in occupations characterized by high routine task content were reduced, while the the task content of these occupations also change. The implications for employment growth are therefore unclear: If task content is held constant then we should expect a large negative employment growth in those occupations that were dominated by medium educated workers. If task content within occupations changed, then we should also observe skill upgrading within these occupations.

3 Prelimenaries and Definitions

3.1 Employment Growth

For the results on employment growth I use the data provided by the registry data from the IDA[2] Database from Statistics Denmarks, containing observations for the years 1995 and 2005 as a cross section in november for each year for the entire population.Even though the panel structure of the data would allow for it, I do not track individuals, but aggregate within occupations The database includes information on gender, age, education, employment history, labor and nonlabor income and civil status for all individuals in Denmark that were aged between 14-74 in the respective years. In this analysis I include individuals that were aged 25-54 and were employed in a fulltime position of the respective year. The lower age restriction was set to include university graduates, the upper age bound to avoid a selective sample due to early retirement schemes. After these reductions we are left with about 700.000 observations for each year. The occupation is coded according to the DISCO (**D**anish **I**nternational **S**tandard **C**lassification of **O**ccupations) occupational code, which is comparable to the ISCO classification that is widely used in the international literature. For the results on employment growth and wages/educational level I use the 4 digit classification which results in about 400 distinct occupations. For the results on task composition and employment growth I use the 3 digit DISCO code, which results in about 90 different occupations (in both years), which

[2] Integreret Database for Arbejdsmarkeds-forskning

is due to the size of the survey. I sort workers into three educational categories: Low, medium and high:

Educational Category	Definition
Low	"Normal" everyone with highest 11 years of general schooling, some prepatory vocational courses
Medium	Gymnasium, vocational training short further education
High	Bachelor, long further education

Definition Relative Employment Growth The outcome variable I investigate in this paper is changes in relative employment Δ_i:

$$\Delta_i = \frac{E_i^{2005}}{E^{2005}} - \frac{E_i^{95}}{E^{95}} \tag{1}$$

where E_i^{95} is employment in occupation i in 1995, E^{95} is total employment in 1995 (E_i^{2005} and E^{2005} are defined analogously). This means that

$$\sum_{i=1}^{I} \frac{E_i^{95}}{E^{95}} = \sum_{i=1}^{I} \frac{E_i^{2005}}{E^{2005}} = 1 \tag{2}$$

$$\sum_{i=1}^{I} \Delta_i = 0 \tag{3}$$

Thus, relative employment is constructed such that an inflow of n workers will result in the same increase in relative employment, regardless of initial cell size[3].

3.2 Task Data:

Determining the task content of an occupation requires more effort and we must necessarily rely on more imprecise measures than for registry

[3] A numerical example to demonstrate this point: Scenario A: $E_i^{95} = 10$, $E^{95} = 10.000$, $E_i^{2005} = 20$, $E^{2005} = 10.000 \mapsto \Delta_i^A = \frac{1}{1000}$ Scenario B: $E_i^{95} = 100$, $E^{95} = 10.000$, $E_i^{2005} = 110$, $E^{2005} = 10.000 \mapsto \Delta_i^B = \frac{1}{1000}$

data on wages and educational level of an occupation. Autor, Levy, Murnane (2003) and Autor, Katz, Kearny (2007) and Goos and Manning use task descriptions from the Dictionary of Occupational Titles (DOT). The drawback with this is clear, as this is administrative information.

Spitz-Oener (2006) uses survey data which was collected by the IAB/ BIBB employment survey and covers about 30.000 individuals in each year (both men and women), the sample size is further reduced by excluding East Germans and non-native Germans, age restrictrions and restricting the sample to fulltime workers. Arguably Germany is because of rigid hiring and firing rules not ideal to assess the determinants of relative employment growth, as this depends largely on external factors and not on job characteristics

Furthermore, both the DOT and the IAB survey data fail to provide information on task intensity, i.e. whether a task is performed is merely reported as a dummy variable.

In contrast task measure that I use here i derived from survey data , where work tasks are ranked according to how often they are performed during the work time. I use the NAK Work Environment Survey[4], conducted by the National Research Center for the Working Environment[5]. In the full survey 27133 workers were asked various questions about their work environment and their work tasks (For example "Do you have contact with clients, customers, students etc. during you working time") the answers were given in discreet categories ranging from "always" to "never/very rarely". I calculate the occupation means for these task scores and match them with relative emploment changes from derived from the registry data. When calculating these occupation means I only consider individuals that match the population criteria as outlined above (fulltime workers, 25-55 years).

Task Score Construction For a more detailed analysis of the relationship between initial task composition and employment growth I

[4]Den Nationale Arbejdsmiljøkohorte

[5]Det Nationale Forskningscenter for Arbejdsmiljø

construct task scores $Task_{ij}$, as the occupation mean from the questions of the NAK survey (see section (3.2). I construct task scores for four different tasks: Nonroutine tasks, routine tasks, interactive tasks and manual tasks. Table (1) shows which questions were used for the task scores[6]. Routine, interactive and physical task content are derived using a single question, while the nonroutine task content is a combination of three questions which all relate to the degree as to which the worker has to make personal decisions about her work that were not predetermined. Table (2) and table (3) report the correlation between the three questions on an individual level. for 1995 and 2005 respectively. They are strongly, positively correlated and the correlation is highly significant in both years.

Task	**Question**	**Scale**	# Obs.
Nonroutine Tasks	1. Is there a possibility to learn sth. new	0-3	90
	2. Do you have and Influence on how to conduct your work	0-3	90
	3. Is your Work varying?	0-3	90
Routine Tasks	Do you repeat the same task many times an hour?	0-5	77
Interactive Tasks	Do you deal with clients,. Students etc	0-5	90
Physical Tasks	Is your work physically straining?	0-3	90

Table 1: Construction of Task Scores from NAK Survey

I standardized the variables to (0,1) and then rescaled them to mean

[6]In the original survey the answers were scaled in reverse order (1 "always", 6/4 "never"). I reversed the order from 0 "never" to 3/5 "always" to make the empirical results more intuitively interpretable.

1995	**nonroutine 1**	**nonroutine 2**	**nonroutine 3**
non routine 1	1		
nonroutine 2	0.2642 ***	1	
nonroutine 3	0.3721***	0.4060***	1

Table 2: Correlation between measures for nonroutine task content, 1995

2005	**nonroutine 1**	**nonroutine 2**	**nonroutine 3**
non routine 1	1		
nonroutine 2	0.1863 ***	1	
nonroutine 3	0.4154 ***	0.3117 ***	1

Table 3: Correlation between measures for nonroutine task content, 2005

10 to avoid having to work with negative values of the task score. From the survey I constructed task scores for each task j (T_j) and occupation i (as the occupation mean). I sum up the task scores of all workers in occupation i and divide by the number of workers in occupation i[7]:

$$Task_{ij} = \frac{1}{n_i}\sum_{1}^{n_i} T_j \tag{4}$$

Note on the the Concept of Occupations One possible weakness of an analysis that considers relative employment growth on the occupational level is that it is possible that the concept of occupations is not very meaningful. It is of course possible and even likely that at least to some degree the classification is arbitrary. I argue that in the present case this is not such a relevant problem, since it is reasonable to assume that occupations that are vey similar (also in task content) are more subject to arbitrary classification. The growth in relative employment in these occupations is arguably also more likely to be influenced by the same characteristics. By not focusing on individual occupations but aggregating by some measure of job quality (share of low educated

[7] I only divide by the number of workers where the task question is nonmissing

workers, initial median wage, initial routine task content) I can avoid the arbitrariness in classification.

3.3 Outline and summary of the results section

In the first part of the result section I examine relative employment growth and its relation to initial jobquality conditions such as initial median wage, initial share of medium and low educated workers. In the second part, section (4.2) I introduce my measures for task content of occupations and look at the relationship between *initial* task content and employment growth. In the concluding part of the results section I replicate part of the analysis conducted by Autor et.al. (2003) and Spitz-Oener (2006) on whether changes in task content can be explained by changes in computerization of occupations.

4 Empirical Results

4.1 Relative Employment Growth

4.1.1 Educational Group Distribution

Table (4) depicts the development of the share of the three educational groups among the employed, decomposed into within and across industry changes (from 1995-to 2005). Employment of low skilled workers has dropped significantly, while employment of medium skilled workers remained roughly constant. This seems to confirm the traditional notion that demand for skills has decreased almost linearly by educational level. Furthermore it is interesting to note that the growth in medium skilled workers within industries is almost completely offset by a decrease between industries. This could suggest that trends in skill demand were not uniform across and within industries, which is not in line with the theoretical model of Autor et.al. (2003) In table (5) I report the ten occupations where relative employment decreased the most over the period. Almost none of these occupations seem traditionally "low skilled". Indeed many of these occupations are precisely the types of jobs (i.e. clerical and secretarial jobs) that would be easily substituted by computers in the theoretical set up outlined in section (2).

4.1.2 Occupations

Skill Group	Δ Employment	Between Industry	Within Industry
Low	**-7.88**	-1.22	-6.66
Medium	**-.08**	-2.10	2.03
High	**7.96**	3.32	4.64

Table 4: Changes in education groups in percent

Occupation Title	**Δ_i (in %)**
Internal Office Work, other	-2.82
Postal Service worker (Bank/Office Service Worker)	-2.76
Middle School Teacher (Folkeskole)	-1.4
Financial work on medium level (Money exchange etc.)	-1.26
Administrative work secretariat	-.89
Registering of Moneytransactions, Bankassistent	-.81
Judicialwork in Public Administration	-.75
Administrative Work in the Public Sector	-.73
Machine Precision Work with Metal	-.69
Automechanic	-.58

Table 5: 10 Occupations with most job outflow 1995-2005, 4 digit DISCO

In order to get a clearer picture on what types of jobs gained and lost in importance over the period, I sorted occupations according to their initial share of low skilled workers, the hypothesis being that the share of educational groups in the beginning of the period (with given degree of computerization) approximates for jobquality of the occupation (i.e. whether an occupation can be thought of as "typical" for low skilled workers etc.). If demand for this typical low skilled work has really decreased, we should expect occupations with a high share of low skilled workers to shrink. In figure (1) I sorted occupations into decile groups according to their 1995 share of low educated workers and mapped their relative employment growth. Contrary to the traditional reasoning, occupations that had the largest and the lowest shares of low educated workers grew. Figure (2) repeats the same exercise with medium educated workers. Here those occupations with the largest shares of medium educated workers (i.e. "typical" medium quality jobs) experience joboutflow. This suggests that even though low skilled workers left active employment, the jobs that were formerly dominated by low skilled workers, still exist.

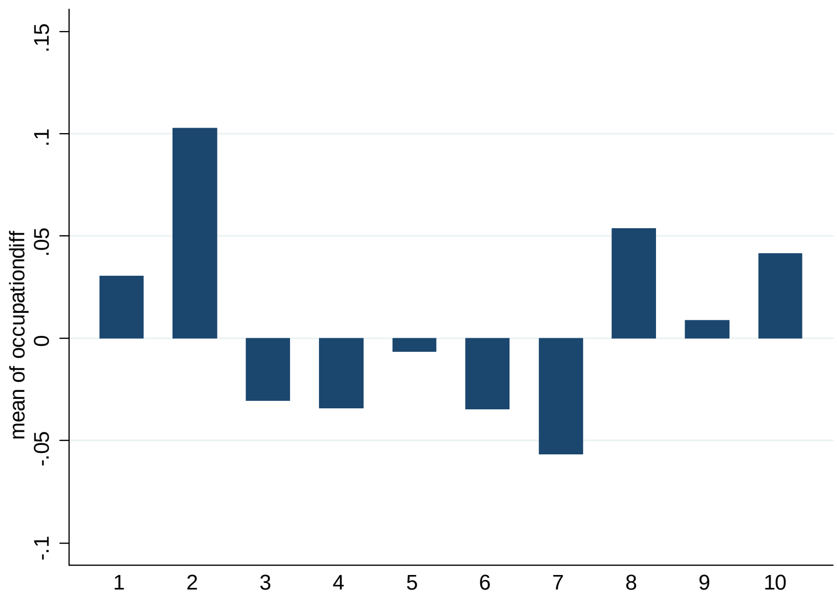

Figure 1: Jobgrowth by Jobquality Decile: Share of Low Educated Workers

As there is no clear counterfactual with three education groups, a more comprehensive jobquality indicator is the medianwage in 1995. Figure (3) shows relative employment changes for all decile groups. Employment in the lowest decile and in the three highest deciles grew, while relative employment in the middle of the initial medianwage distribution dropped. This evidence seems more in favor of polarization than a linear drop in skill demand.

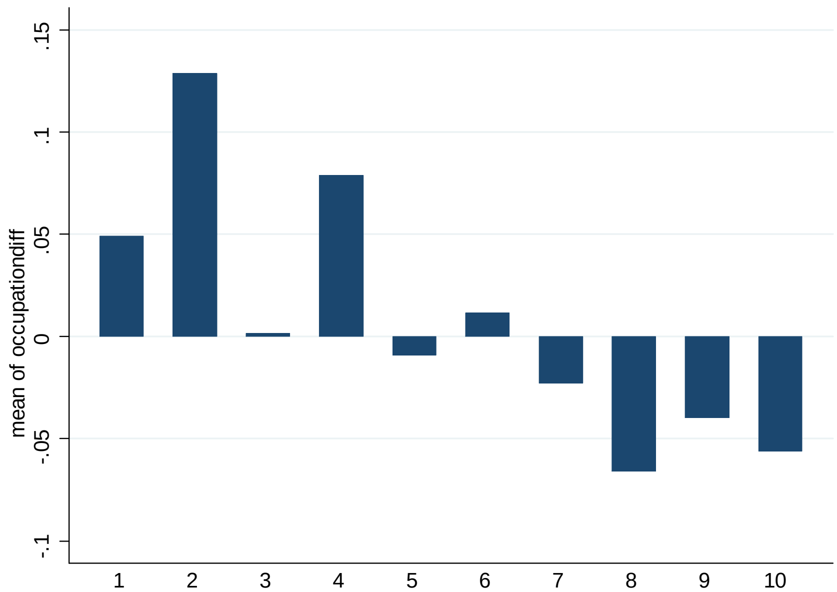

Figure 2: Jobgrowth by Jobquality Decile: Share of Medium Educated Workers

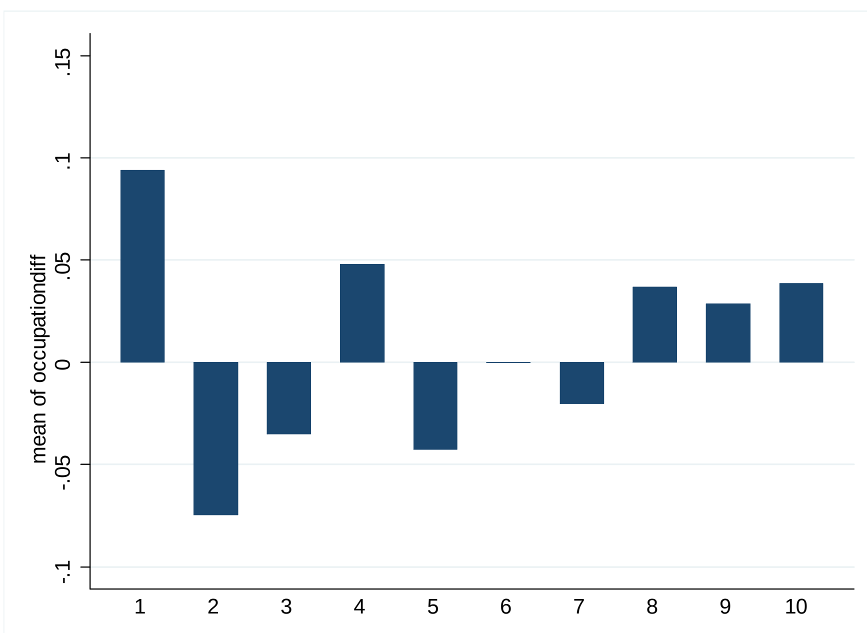

Figure 3: Jobgrowth by Jobquality Decile: Initial Medianwage

	Model Squared	**Model Linear**
β_1	-9.851 (.7138339)***	.984 (.008792)***
β_2	.436 (.0287048)***	
Constant	Yes	Yes
Adj. R^2	0.0174	0.0171
Total initial cell size	719508	719508

Table 6: Regression Results, Job growth and initial Median Wage, weighted by intial cell size

Regression Results As a next step I estimate the specification of Goos and Manning (2007) to determine the relationship between job-growth and initial medianwage. The empirical specification has the following form:

$$\Delta Job_i = \alpha + \beta_1 w^i_{1995} + \beta_2 w^i_{1995} \tag{5}$$

where ΔJob_i is the change in relative log employment of occupation i and w^i_{1995} is the log of the initial median wage of occupation i. With the assumption that job growth was especially pronounced in the bottom and the top of the jobquality distribution, we should expect the coefficent β_1 to have a negative sign and β_2 to be positive, reflecting the supposed j shape of the curve. From the more traditional literature we should expect a positive linear relationship (positive growth only in the top of the jobquality distribution), I included the estimates for the linear specification of equation (5) in table 6 (i.e. $\beta_2 = 0$). The squared model fits well with our predictions and the results confirm the u-shape of the curve. What do these results mean quantitatively? (Can I plot the regression with standard error bands?)

4.2 Task Content

Table (4.2) reports the unweighted within occupation task content changes. Routine tasks have decreased within occupations, while interactive and manual task content increased over the period. Nonroutine tasks also decreased, which is somewhat at odds with the intution of the model. Despite this, it is possible that changes in nonroutine task content have an effect on the margin and that initial nonroutine task content serves as a good indicator for jobgrowth.

Task	**Δ Task Intensity**
Nonroutine Tasks	-.28
Routine Tasks	-.08
Interactive Tasks	.23
Manual Tasks	1.54

Table 7: Within Occupation Task Changes, 1995-2005

From the model we should expect that high routine task content is a good predictor for joboutflow and conversely, that a high nonroutine, interactive and manual task content are associated with postive jobgrowth. I estimate equation (6) for each task seperately:

$$\Delta E_i = \beta_0 + \beta_1 Task_{ij,1995} \tag{6}$$

where ΔE_i is the change in relative employment and $Task_{ij,1995}$ is the initial task intensity of task j. The results are reported in table (8). All coefficients have the expected sign and are highly significant, suggesting that those occupations that were initially intensive in nonroutine, interactive and manual tasks grew, while occupations that were intensive in routine tasks experienced job outflow.

As demonstrated above, initial task content serves as a good predictor for occupation growth, but the question remains whether changes in the task content are related to computerization (as presented in Autor et.al [4] , Spitz-Oener). I estimate to what degree changes in task content can be attributed to changes in computerization according to the following

Task	**Nonroutine**	**Routine**	**Interactive**	**Manual**
β_1	7.8 (1.1088)***	-4.29 (.6081)***	6.12 (.5744)***	4.61 (.645)***
Adj. R^2	0.0334	0.0363	0.0741	0.0345
Constant	Yes	Yes	Yes	Yes
# Obs.	1401	1293	1401	1401

Table 8: Regression Results (weighted by initial cell size), Task Content

specification:

$$\Delta Task_{ij} = \beta_0 + \beta_1 \Delta PCUse_i \tag{7}$$

where $\Delta PCUse_i$ measures the change in computer use in occupation i Table[8] (9) reports the results[9]. It shows that changes in computerization are negatively associated with all three task changes (I omitted manual tasks from this analysis, as I have no prior hypothesis concerning the relationship between manual task changes and changes in computerization). The coefficient for changes in routine task content is large and negative and highly significant, which shows that computerization was an important factor in decreasing routine task content. The coefficients for the two other task changes, however, are somewhat puzzling. We would have expected at least nonroutine task changes to be positively associated with computerization of the workplace. This is clearly not the case. What can be an explanation for these diverging results? 1) The choice of questions from the survey is wrong: Maybe the task measure doesn't capture exactly what we would understand as nonroutine tasks. For interactive tasks this is not likely, since the question is very straightforward and can hardly be misinterpreted. For nonroutine tasks this is

[8]Results are from three seperate regressions, manual tasks were excluded as there are no predictions regarding the relationship between manual tasks and computerization of the workplace.

[9]The results reported are unweighted estimates as to make them comparable to those reported by Spitz-Oener (2006) and Autor et.al. (2003).Weightng by initial occupation cell size doesn't change the results qualitatively, but significantly reduces standard errors, such that all three coefficients are significant on the 1% level

certainly a possibilty, even though initial nonroutine task content served as a good predictor for jobgrowth in the previous analysis (i.e. was in line with our predictions). 2) Nonlinear effects/Overcomputerization: I consider a far more recent time period (all in all) than the other studies. It is possible to suppose that the effects of computerization are nonlinear and that once a certain satiation point is reached (because prices for computers drop by so much) that additional computers have only a small effect on the task composition. 3) Task changes are induced by more than one channel: In a recent paper by Rosholm et.al. (2008), they show that import competition and outsourcing to nonwestern countries can explain a large part of the within occupational "upskilling" for a more recent time period (2000-2006). Is it possible that trade is a further channel that might influence jobgrowth and changes in the task content?

Model	**ΔRoutine**	**ΔNonroutine**	**ΔInteractive**
β_1	-.97	-.27	-.705
	(.3550623)***	(.1148306)**	(.4044829)*
Adj. R^2	0.0791	0.0485	0.0223

Table 9: Changes in Task Intensity and Computerization, unweighted regression

5 Conclusions and Outlook

The results in derived in the jobgrowth section clearly indicate U-Shaped Job Growth (as taken over initial medianwage as a jobquality indicator). Furthermore, even though overall employment of low skilled workers decreased, jobs where low skilled employment was typical grew, which suggests an educational upgrading in the lower part of the jobquality distribution. This is theoretically at odds with the model's assumption with respect to manual skills, since in the model each worker is endowed with the same amount of manual skills. There is also strong evidence that initial task content was a crucial determinant for jobgrowth in the direction the model predicts. The strong increase in manual employment is especially at odds with the predictions of the rising skill price hypothesis. However, the changes in task content are not associated with computerization in the way older studies found. One possible explanation is that more recent task changes could be associated with increased international trade with middle and low wage countries, which could certainly be an avenue for further research.

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