Occupational Task-Inputs and the Wage Structure. Evidence from German Survey Data Working Paper

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Abstract

In recent years many economists used the task-based approach to examine various phenomena in the labour market and the wage structure. The basic idea behind this is that different people perform different tasks which are not uniformly awarded across occupations. Furthermore, new technology potentially increases the productivity of certain tasks, but substitutes others. In this paper I use survey data of roughly 25'000 German employees collected in the years 2006 and 2012 to assign a well-defined individual five-pillar task profile to each of the respondents. This time-variant individual task profiles allow to investigate on task prices across occupations and link them with changes in occupational wage structures. Preliminary results show for the relatively short time-span between 2006 and 2012 rising wage dispersion in occupations where prices for analytical and – to some extend – interactive tasks increase.

Keywords: labour market; task-based approach; wage inequality; digital revolution

1 Introduction

When questioning the impacts of the ongoing digital revolution on the labour market the so-called task-based approach is quick to hand. An approach how goes beyond – as a classical Mincer approach – skills is appealing when workers and occupations are affected so differently by technological change as it is the case for many today. There are high skilled workers who are digital pioneers working in occupations that just came into existence within in the context of digitalization. Meanwhile, there are workers with an equally high degree who work much less in synergy with new technologies. Similar interrelations are observable at the bottom of the skill distribution: some low-skill occupations are not replaceable and productivity remains low, e.g gastronomy. Where machines replace most workers in other occupations or off-shoring shifts their plant as a whole away. These examples demonstrate a world where not primarily the (observed and unobserved) skills of someone determine her or his labour market outcome, but how her or his occupations – or more precise: what she or he does – relates to new (digital) technologies. One can perform occupational tasks in synergy with digital technology and thus augment the productivity when doing so. Or tasks are unaffected, demand for them remains high, but wages for people performing them low. Other tasks simply disappear due to automation or off-shoring. These examples show there is an extensive margin – how many people work in an occupation bundling certain tasks – and an intensive margin – how intense they perform a certain task within a certain occupation. Thus, tasks allow to relate within occupation changes in task composition and prices to broader labour market phenomena, in the case of this paper: wage polarization.

Though, the new insights such a task based approach promises, it remains hard to isolate the precise impact of individually performed tasks, e.g. returns to tasks. And disentangle tasks from other labour market relevant characteristics, most notably observed and unobserved skills, is nearly impossible. Just think of skills (e.g. education) leading to a diploma allowing someone to get an occupation that bundles certain tasks. It is quiet easy to see that any observed changes in task prices could source in underlying changes in returns to skills (e.g. rise in college premium). This is the technical reason why I occupations form in most of the forthcoming analysis my examination unit. The other – related – reason is the above set out concrete interest in the contribution of within occupational changes in task prices to overall wage polarization. Using the 2006 and 2012 German BIBB-BAuA Labour Force Survey individual wage informations and assigning five task inputs to each individual based on seventeen surveyed task items I am able to estimate changes in task prices between 2006 and 2012 for 76 occupations. This changes I then relate to occupational wage dispersion. Results show higher growth rates for wages at the top of the occupational wage distribution in occupations where task prices for analytical and – to some extend – interactive tasks rose. This is in line with the contemporary task based literature on technological change.

The paper is structured as follows. The background section introduces again the literature on the task based approach and shows its close link to the wage structure as one labour market outcome. Section 3 introduces the German Labour Force Survey and presents some descriptive statistics on the relevant variables, most notable the surveyed task items and wages. Next, section 4 highlights some basic insight on wages and task, such as task prices and bundling of tasks within occupations. The main analysis connecting occupational task prices and wage dispersion is explained in section 5 and results are shown in section 6. A conclusion follows in section 7.

2 Background

[to be done]

3 Data

The BIBB-BAuA Labour Force Surveys 2006 and 2012 asks the respondents how intense (never=0, seldom=1, often=2) they perform seventeen different tasks. Following closely Spitz-Oener (2006) I assign these task items in five task categories (task inputs): analytical and interactive non-routine, cognitive and manual non-routine, and manual non-routine (see Appendix for detailed classification). Based on this classification I perform a Principal-Component-Analysis. After normalizing the first component to mean zero and a standard deviation of one in the first wave (year 2006) this forms my individual task input in the respective task category (similar to Autor and Handel 2013). This first components account between 0.41 (interactive non-routine) and 0.64 (analytical non-routine) of the variations in the underlying task items.

My sample extracted from the BIBB-BAuA Labour Force Surveys 2006 and 2012 contains personal labour market relevant informations such as sex, age, firm tenure, and education. The educational categories I refer to are compulsory schooling only, VET,[1] Tertiary-B (continuing and specialized education following VET), and Tertiary-A (bachelor or master degree at a university or university of applied science). Most important both waves contain monthly salary informations. From this I derive the log hourly wage per person. For occupational analysis we rely on the three-digit classification of German occupations. This classification includes 354 different occupations.[2] In some of the following occupation-by-occupation analysis this number can decline due to few observations in some occupations. Whenever I base analysis on two-digit level of occupations it is clearly indicated and occupational categories diminish to roughly seventy.

[Summary Statistics around here]

I do not consider observations with missing values for any of the above described characteristics. Furthermore, I restrict the analysis to West-Germany and exclude people with a reported salary per hour below 2.5 Euro. This diminish my sample down to 13'197 observations in 2006 and 11'901 observations in 2012.
Table **??** shows the task inputs for various sub-samples. As described in the data section the task inputs are normalized to mean zero and a standard deviation in 2006. The variation between male and female and between educational groups is substantially. Men perform more analytical non-routine but little less interactive non-routine tasks. Little surprisingly men perform almost half a standard deviation more manual routine tasks (typically blue-collar workers), where contrary women perform 0.34 standard deviation more manual non-routine work (typically gastronomy, cleaning, or care professions). Remarkable is difference of 0.47 standard deviation in cognitive routine tasks. It is attributable to the task item of "performing work that is prescribed in detail" that is more mentioned by women. Even more pronounced than the gender differences appear the difference between people with a VET diploma and a Tertiary-A

[1]Vocational Education and Training is a two to four year training for youngsters completed in firms and partly in VET schools. The aim is to qualify for an specific occupation.

[2]The Classification of German Occupation 1992 I use is coded both survey waves.

diploma. Tertiary-A people perform much more analytical and considerable more interactive non-routine tasks, where VET people perform more routine tasks and to same extend more manual non-routine tasks. The time variation is not as large as those witnessed differences in characteristics which is little surprising taken into account the short timespan of six years between the two survey waves. Nevertheless, as many others [Lit. here] I find increases in analytical, interactive, and non-routine manual task inputs, but decreasing routine manual and – of smaller magnitude – cognitive task inputs (last column).[3]

Table 1: Descriptive Statistics of Task Inputs

Tasks	**all(2006)**	**Male**	**Female**	**VET**	**Tertiary-A**	**all(2012)**
Analytical	0	0.122	-0.131	-0.209	0.602	0.141
	(1.000)	(0.971)	(1.014)	(0.957)	(0.790)	(0.950)
Interactive	0	-0.027	0.029	-0.153	0.427	0.042
	(1.000)	(0.992)	(1.008)	(0.985)	(0.859)	(0.990)
Routine	0	-0.227	0.244	0.149	-0.367	-0.011
cognitive	(1.000)	(0.948)	(0.997)	(0.969)	(0.978)	(0.988)
Routine	0	0.226	-0.243	0.148	-0.408	-0.042
manual	(1.000)	(1.066)	(0.860)	(1.025)	(0.786)	(0.994)
Non-routine	0	-0.164	0.176	0.099	-0.213	0.029
manual	(1.000)	(0.821)	(1.136)	(1.038)	(0.912)	(1.048)
N	13’197	6’837	6’360	7’764	3’465	11’901

4 Task-Inputs: Tasks, Wages and Occupational Bundling

Task Prices

The previous description of variant task inputs over time and sub-samples showed heterogeneously performed tasks among labour market participants. I now link task inputs with observed wages. A OLS standard Mincer regression of log hourly wages on various personal labour market relevant characteristics forms the starting point for this. I then run the same regression on task-inputs and 354 occupational dummies. Model (4) to (7) show again OLS regressions with step-by-step inclusion of those three subsets of explanatory variables. Note, that I do not suggest any causality in the regression estimates presented in table ??. This is not only due to the – almost inherent – bias of unobservable ability in the standard Mincer

[3]The almost stagnating input of routine cognitive task inputs is puzzling as thus far such tasks were considered to be the first victims of an on-going computerization by many experts (see Osborne and Frey 2013). On the other hand there is recently collected survey evidence in line with not less but more repetitive and in detail prescribed work (see for an example (Eurofound 2012 and 2017).

equation but sources additionally in the inclusion of task inputs and occupational dummy which are both likely to partly depend on the personal characteristics themselves (see **?** which makes them classical examples of "bad controls" (see Angrist and Pischke 2009). In the following discussion of table **??** I will therefore emphasise primary on explanatory power of task inputs with respect to varying inclusion of subsets of personal and occupational controls (see Autor and Handel 2013 for a similar discussion). This allows to gain further insights on task inputs and their relevance for labour market outcomes.

The first column of table **??** shows a standard cross-sectional Mincer equation of log hourly wages on personal characteristics. All coefficients have the expected sign and are statistically significant. The R-squared is 0.31. Column 2 displays an OLS regression of log hourly wages on the five task inputs. The signs are as expected and indicate a positive association between analytical and interactive non-routine and wages and a negative association between manual non-routine and routine tasks in general and wages. The R-squared drops to 0.21 but the reported p-value of a joint F-test on all task inputs indicates high statistically significance. The predict wage differentials by task inputs range from a 16.2% when performing one standard deviation more analytical non-routine tasks to -12.5% hourly wage when performing one standard deviation more non-routine manual tasks. This patter remains generally robust when adding personal characteristics (Model 4), occupational dummies (Model 6), or both together (Model 7). Though the coefficients are of smaller magnitude when including covariates. P-values of zero for a joint F-test on all task inputs indicate nevertheless remaining prediction power of task inputs for wages.
Table **??** shows again models (2), (4), (6), and (7) but adds an 2012-dummy and interacts the task inputs with this dummy. Thus, the estimates in row 5 to 9 display changes in task prices. Only two task prices changed statistically significant between 2006 and 2012: in line with the literature in prices for analytical tasks augmented. Presumably due to growing productivity related to their complementary character to new technologies. The negative sign for non-routine manual task may surprise since table **?** displayed growing inputs of these tasks. Though, the literature exactly predicts this: growing inputs because non-routine manual tasks, e.g. gastronomy or care-taking, do not fear automation what leads to a constant demand. Meanwhile,

Table 2: OLS Wage Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sex	-0.210***			-0.181***	-0.181***		-0.161***
	(0.005)			(0.005)	(0.006)		(0.006)
Age	0.030***			0.029***	0.028***		0.027***
	(0.002)			(0.002)	(0.002)		(0.002)
Age(^{2})/1000	-0.330***			-0.301***	-0.293***		-0.271***
	(0.022)			(0.021)	(0.020)		(0.020)
comp.School	-0.179***			-0.126***	-0.103***		-0.088***
	(0.009)			(0.009)	(0.009)		(0.009)
Tertiray-B	0.169***			0.089***	0.094***		0.064***
	(0.009)			(0.009)	(0.009)		(0.009)
Tertiray-A	0.378***			0.225***	0.201***		0.164***
	(0.006)			(0.006)	(0.007)		(0.007)
Tenure	0.027***			0.025***	0.024***		0.023***
	(0.001)			(0.001)	(0.001)		(0.001)
Tenure(^{2})/1000	-0.418***			-0.412***	-0.397***		-0.384***
	(0.022)			(0.021)	(0.020)		(0.020)
T:analytical		0.149***		0.104***		0.059***	0.051***
		(0.003)		(0.003)		(0.004)	(0.003)
T:interactive		0.050***		0.035***		0.059***	0.038***
		(0.003)		(0.003)		(0.003)	(0.003)
T:Routine cog.		-0.053***		-0.023***		-0.028***	-0.020***
		(0.003)		(0.003)		(0.003)	(0.003)
T:Routine man.		-0.017***		-0.024***		-0.020***	-0.018***
		(0.003)		(0.003)		(0.003)	(0.003)
T:Nonroutine man.		-0.113***		-0.063***		-0.055***	-0.037***
		(0.003)		(0.003)		(0.004)	(0.003)
N	25098	25098	25098	25098	25098	25098	25098
R^2	0.341	0.223	0.341	0.408	0.478	0.376	0.496
p-value		0.000		0.000		0.000	0.000

Standard errors in parentheses

Models (3),(5),(6), and (7) include 354 occupation dummies; all models include a Wave-Dummy.

The p-value reports on a F-Test for all 5 Task-Variables.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: OLS Wage Regression with Year-Interaction

	(1)	(2)	(3)	(4)
T:analytical	0.143***	0.099***	0.055***	0.047***
	(0.005)	(0.004)	(0.004)	(0.004)
T:interactive	0.048***	0.033***	0.058***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)
T:Routine cog.	-0.057***	-0.024***	-0.031***	-0.020***
	(0.004)	(0.004)	(0.004)	(0.003)
T:Routine man.	-0.018***	-0.022***	-0.021***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)
T:Nonroutine man.	-0.105***	-0.058***	-0.050***	-0.032***
	(0.004)	(0.004)	(0.004)	(0.004)
d_2012(analytical)	0.020**	0.016**	0.020***	0.016**
	(0.007)	(0.006)	(0.006)	(0.005)
d_2012(interactive)	0.003	0.003	-0.000	0.003
	(0.007)	(0.006)	(0.006)	(0.005)
d_2012(Routine cog.)	0.011+	0.002	0.006	-0.001
	(0.006)	(0.005)	(0.005)	(0.005)
d_2012(Routine man.)	0.001	-0.004	0.001	-0.002
	(0.006)	(0.005)	(0.005)	(0.005)
d_2012(Non-R.manual)	-0.016**	-0.011*	-0.013**	-0.011*
	(0.006)	(0.005)	(0.005)	(0.005)
N	25098	25098	25098	25098
R^2	0.220	0.408	0.370	0.495
p-value	0.001	0.002	0.001	0.001

Standard errors in parentheses

Models (3),(5),(6), and (7) include 354 occupation dummies; all models include a Wave-Dummy.

The p-value reports on a F-Test for all 5 Task-Variables.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

they do not witness productivity increase and thus no increases in prices since new technology is rarely supportive when performing them.

Occupational Bundling

Table **??** shows generally declining prediction power of task inputs when controlling for personal characteristics (Model 4), occupational dummies (Model 6), or both (Model 7). This is little surprising when understanding personal characteristics (e.g. education), occupations, and task inputs as different ways of segregating a labour market and understand the present mechanisms of reward in it. Or, so to speak on an individual level, different types of persons regarding their education bundle in different occupations, which bundle a specific set of tasks (see also Autor and Handel 2013). The differences in the magnitude of such changes in the respective task coefficients hints towards heterogeneous bundling among task inputs. To detect such differences in bundling in personal characteristics and occupations among task inputs I perform simple OLS regressions of the five task inputs separately on three categories of educational achievement (VET is omitted; Models 1-5) and 354 occupational dummies (Models 6-10). Table **??** displays the results for the educational dummies and, more importantly, the corresponding R-squares. The regressions on the educational dummies yield R-squares between 0.17 (analytical task, model 1) and 0.03 (non-routine manual task, model 5). The relatively high R-square for analytical and, to some extend, for interactive (model 2) tasks together with the substantially positive association of tertiary education in these two task categories suggest that mostly higher education allows people to sort in job-profiles demanding these tasks inputs mainly. When turning to the prediction power of occupations for individual task inputs the picture changes. Manual tasks are relatively strongly bundled within occupations (R-squares: 0.41 for routine manual and 0.53 for non-routine manual tasks), where the three other task inputs are less bundles.

Table 4: Bundling of Task Inputs

	(1) analytical	(2) interactive	(3) R.cognitive	(4) R.manual	(5) Non-R.manual	(6) analytical	(7) interactive	(8) R.cognitive	(9) R.manual	(10) Non-R.manual
comp.School	-0.431***	-0.393***	0.157***	-0.084***	-0.020					
	(0.021)	(0.022)	(0.022)	(0.022)	(0.023)					
Tertiray-B	0.457***	0.439***	-0.349***	0.054*	-0.269***					
	(0.022)	(0.023)	(0.023)	(0.023)	(0.024)					
Tertiray-A	0.807***	0.586***	-0.526***	-0.552***	-0.369***					
	(0.013)	(0.014)	(0.014)	(0.014)	(0.015)					
N	25962	25962	25962	25962	25962	25962	25962	25962	25962	25962
R^2	0.167	0.094	0.061	0.059	0.026	0.365	0.340	0.230	0.414	0.531

Standard errors in parentheses

OLS Wage Regression, dependent variable: Task Inputs.

Models (6)-(10) include 354 occupation dummies. All models include a Wave-Dummy.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Graphically I illustrate this stronger cross-sectional character of analytical, interactive, and routine cognitive task inputs with a Lorenz-curve shown in figure ??. The Lorenz-curve plots the cumulative share of each task input within 354 occupations (y-axis) on the the cumulative share of occupations weighted with the number of observations per occupation.

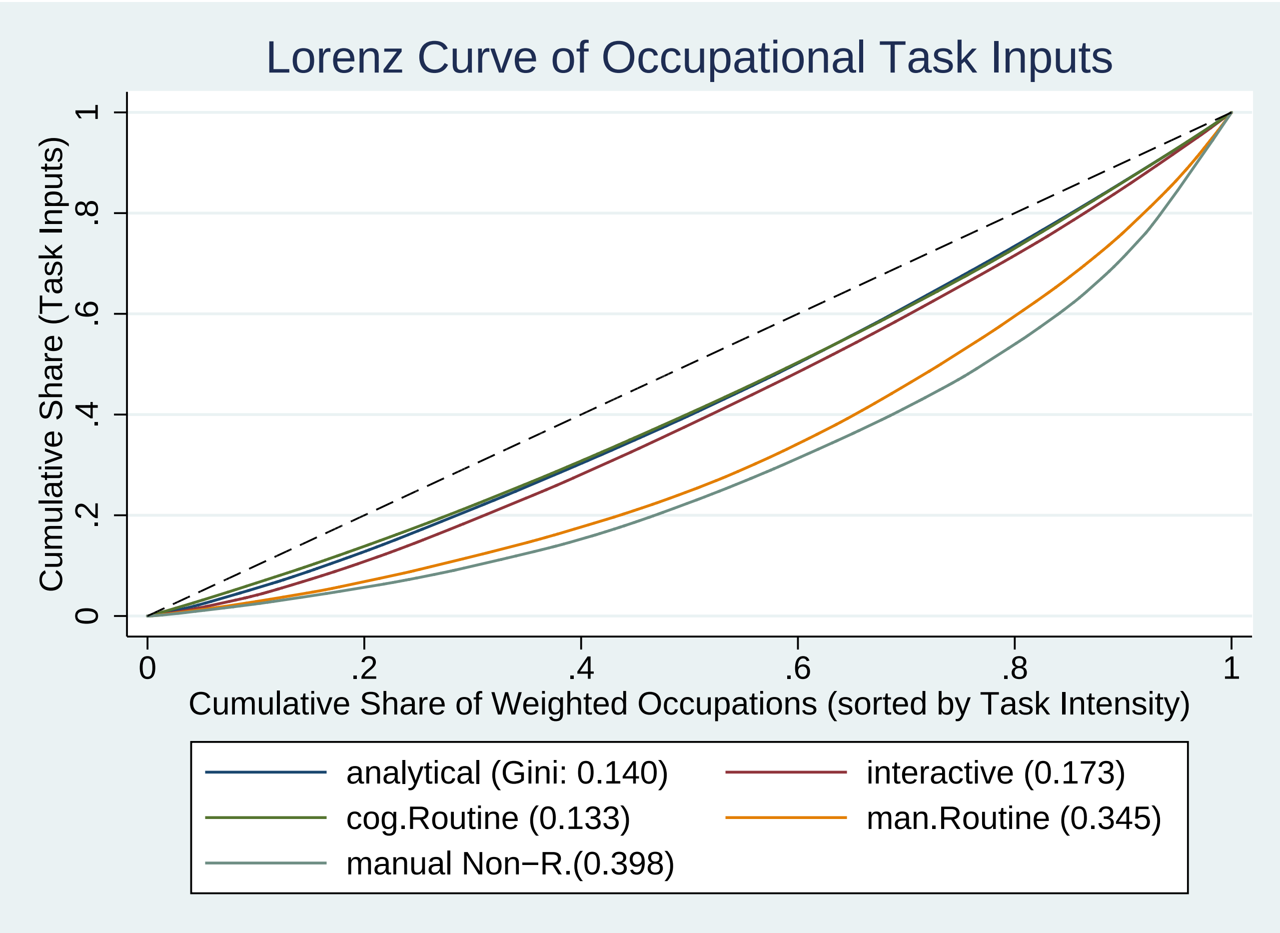

Figure 1: TASK INPUT COEFFICIENTS OVER THE WAGE DISTRIBUTION 2006/2012 USING QUANTILE REGRESSION. Source: BIBB-BAuA 2006/2012.

5 Task Inputs within Occupations

The previous chapters showed that a) tasks can not be analysed isolated from other labour market relevant characteristics (e.g. occupations and education) and b) their variation within such characteristics is remarkable. Though a third feature is yet hidden: the task composition of occupations is changing. This is best illustrated by simply disentangle changes task input (measured in full time equivalent FTE) attributable to changes employment shares of occupations (extensive margin) and changes of task composition within occupation (intensive margin). Hence, I split FTE worked in occupations 2006 and 2012 among occupational task inputs. The difference yields the overall change in task inputs. The change on the the extensive margin is calculated by keeping every occupational task profile constant but allow for changes in worked FTE between occupations. The intensive margin is the simply the difference between the overall effect and the extensive margin.[4]

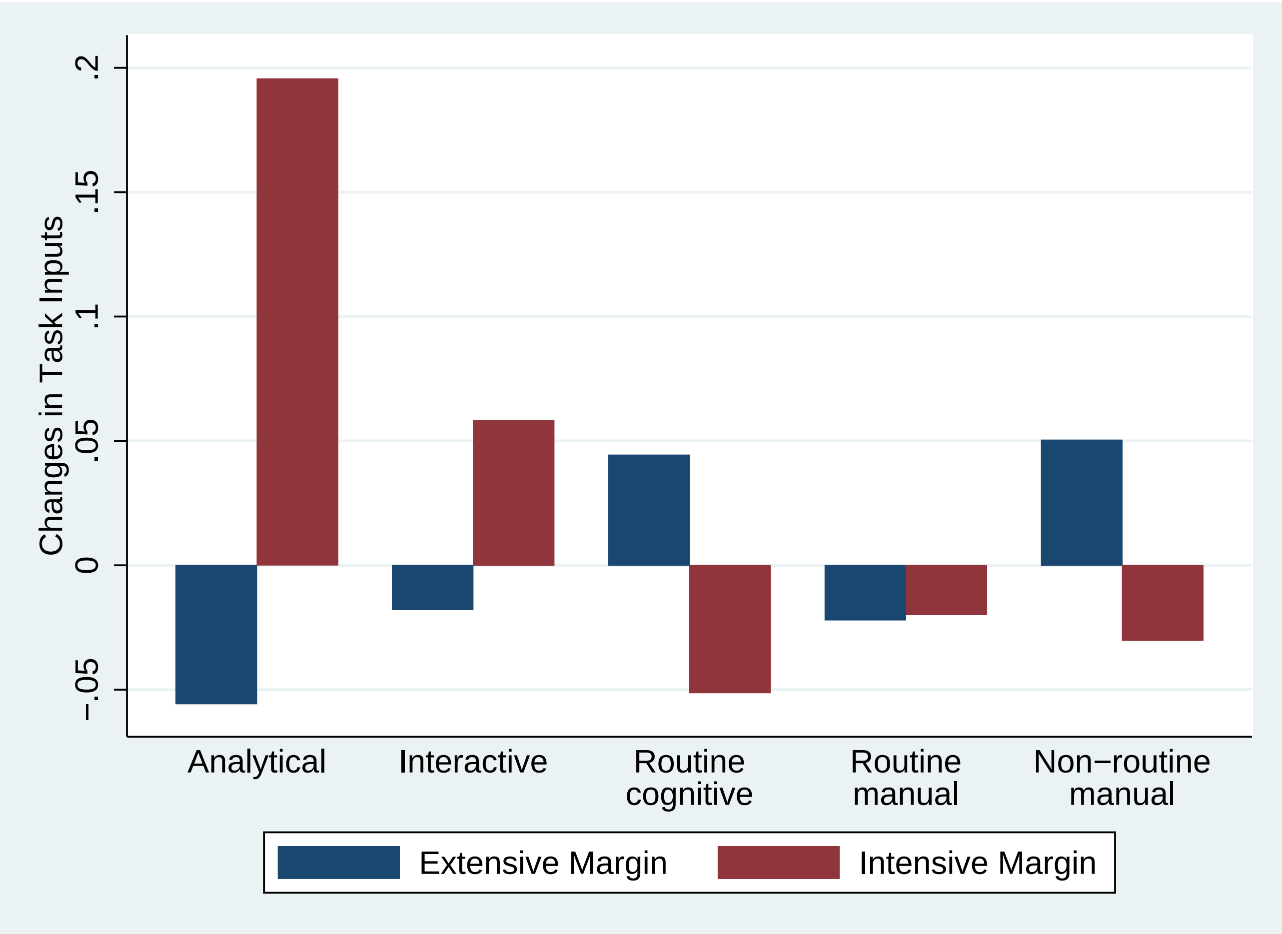

Figure 2: DECOMPOSITION OF CHANGES IN TASK INPUTS 2006 AND 2012 Source: BIBB-BAuA 2006/2012.

Figure ?? displays the results of this decomposition and highlighting some of them is particular worthwhile. The overall gain of analytical tasks of roughly 14 percent (see table ?? is even bigger within occupations. The same – on smaller magnitude – is true for interactive tasks. Routine manual task loose on both scales. Generally occupations consist of less non-routine manual tasks, but occupations relying heavily on such tasks seem to witness employment grow. Again, this hints towards employment growth in low-skill service occupations (e.g. gastron-

[4]Alternatively the intensive margin can be calculated by keeping the worked FTE per occupation between 2006 and 2012 constant but let the occupational task compositions float.

omy and caring). Overall figure **??** confirms that intra-occupational changes are at least as important as inter-occupational in task composition between 2006 and 2012. To explain wage polarization with the skill content of an occupation may thus fall short or be incomplete. If new digital technology augments let's say the productivity of analytical tasks this – in line with the "classical" polarization hypothesis – favours high skill occupations and leads to the well-known convex form of wage growth in the upper tail of the wage distribution. But meanwhile, this mechanism potentially leads to within occupation wage dispersion. A prerequisite for this are uneven distributed task inputs within occupations. Or, to come back to figure **??**, the large increase of analytical tasks on the intensive margin must spread dissimilarly on workers within the same occupation. This section aims thus to demonstrate the importance of changes in occupational task price inputs for a phenomena revealed by the data even over the relatively short time span of six years: wage polarization.

Figure 3: LOG WAGE CHANGE PER PERCENTILE 2006-2012 Source: BIBB-BAuA 2006/2012.

Figure **??** plots the log wage changes between 2006 and 2012 against the percentiles of the wage distribution in 2006. One can see a remarkable U-shaped pattern: wage growth occurred pronounced at the lower and upper tail of the wage distribution with higher average growth rates at lower percentiles.

Occupational Wage Profiles and Task Prices

When arranging a similar plot for the top-20 (in terms of workers) occupations I exploit a similar – also arguably less clear-cut – picture (figure **??**).

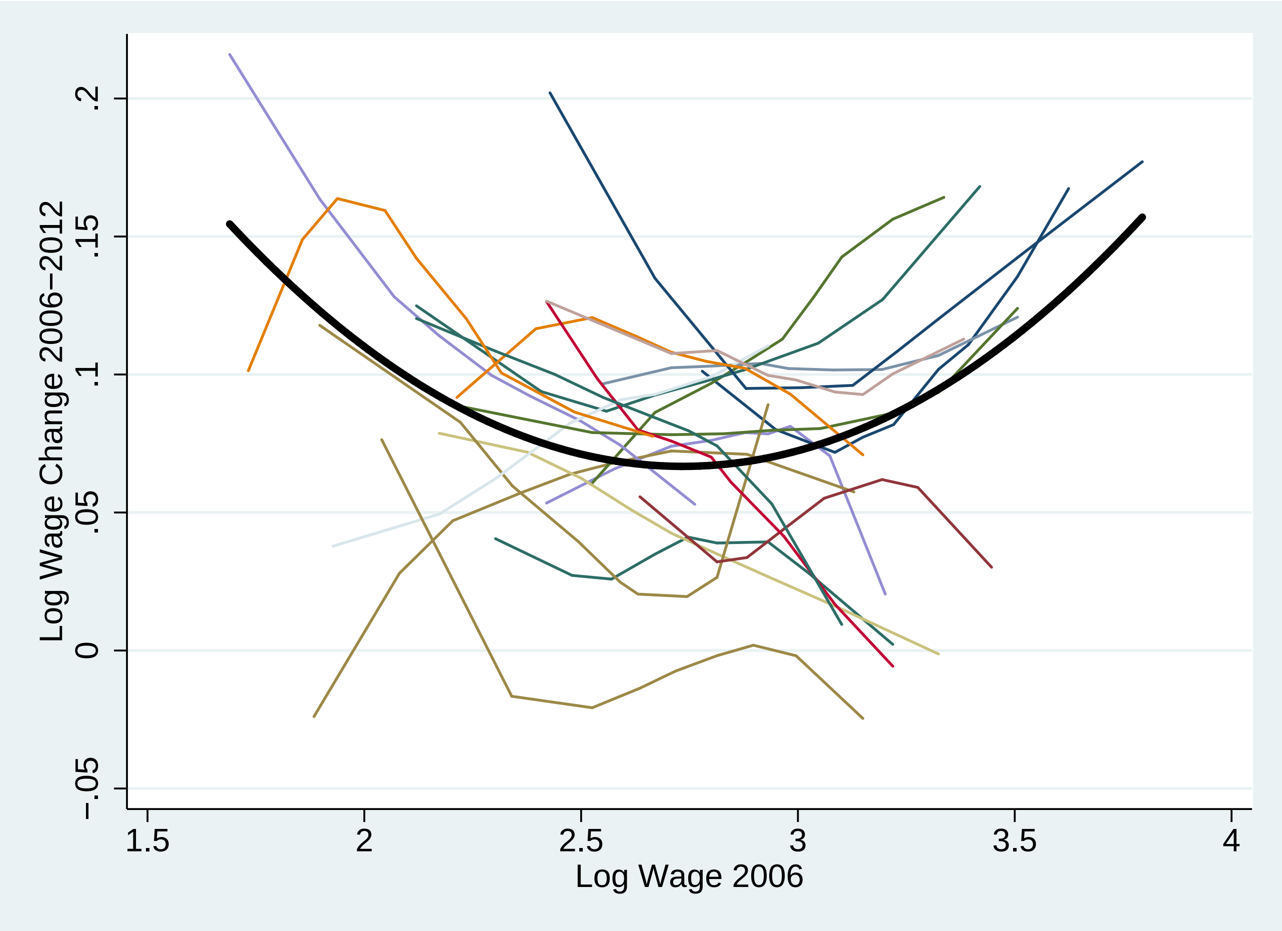

Figure 4: LOG WAGE CHANGE PER PERCENTILE 2006-2012 IN TOP-20 OCCUPATIONS
Source: BIBB-BAuA 2006/2012.

Following closely Firpo et al. (2011) and Fortin and Lemieux (2015) I estimate the slopes witnessed in figure **??** for all 76 occupation$_j$.[5] Therefore, I regress changes in log hourly wages between 2006 and 2012 per percentile$_p$ on the base-level (=2006) of log hourly wages and – to capture often non-monotonic occupational wage dispersion in a second specification – on the square-term of this base-level log hourly wage.

Formally:

[5]Two-digit level of the Classification of German Occupations.

$$\Delta w_p^j \;\; = \delta^j + \gamma_1^j w_{pj} (+\gamma_2^j w_{pj}^2) + \epsilon^j$$

for each occupation$_j$: j=1, ..., 76.

Thus, I get the estimates $\hat{\delta}^j$, $\hat{\gamma}_1^j$, and $\hat{\gamma}_2^j$ describing changes in the wage structure of each occupation$_j$ between 2006 and 2012.

In line with the (task based) literature on the digital economy I assume within occupation wage dispersion is closely related to differently developing task prices. Namely, I expect higher prices for analytical and interactive tasks to be associated with higher occupational wage dispersion at the upper tail of an occupation's wage structure, i.e. higher estimates of $\hat{\gamma}_1^j$ and – if this mechanism is non-linear – higher $\hat{\gamma}_2^j$. Changes in occupational task prices I simply get from repeating estimations displayed in table **??** for each occupation$_j$ separately. The estimates for the five interaction terms between the five task inputs and a 2012-dummy $\hat{\lambda}^j_{t=1,\ldots,5}$ yield those changes in occupational task prices. The put the assumed association of higher task prices for analytical and interactive tasks with accelerating wage dispersion along the occupational wage structure to the test, those estimated $\hat{\lambda}^j_{t=1,\ldots,5}$ serve as my independent variables in a simple OLS setting. The different measurements for the occupational wage structure form the estimates $\hat{\delta}^j$, $\hat{\gamma}_1^j$, and $\hat{\gamma}_2^j$.

The following equations capture this formally:

$$\hat{\delta}_j = \alpha + \mu_j \lambda_{j,t=1,\ldots,5} + \epsilon_j$$

$$\hat{\gamma}_{1j} = \alpha + \nu_j \lambda_{j,t=1,\ldots,5} + \epsilon_j$$

$$\hat{\gamma}_{2j} = \alpha + \upsilon_j \lambda_{j,t=1,\ldots,5} + \epsilon_j$$

When going back to figure **??** where one can see explanatory the dependant variables $\hat{\delta}^j$, $\hat{\gamma}_1^j$, and $\hat{\gamma}_2^j$ it appears clear that interpretation of OLS results from the above equations are far from simple. Naturally, the estimates for the intercept $\hat{\delta}^j$ captures the wage increase at the 10th percentile. And this is, if – and only if – the $\hat{\gamma}$-estimates are zero, equal to the median wage growth in the respective occupation. Obviously, a simple regression of $\hat{\lambda}^j_{t=1,\ldots,5}$ on the log difference of occupational mean wage 2006 to 2012 is more accurate to map changes in task prices to changes in occupational mean wages, and is suggested in further work. Let's turn to the interpretation of estimates for changing occupational task prices ($\hat{\lambda}^j_{t=1,...,5}$) on $\hat{\gamma}^j_1$. Positive (negative) values indicate hereby that occupations with increasing (decreasing) prices in the respective task$_t$ witnessed higher (lower) wage growth rates at upper parts of the occupational wage distribution. Or, if wages in the respective occupation shrank at all percentiles, that growth rates were less (more) negative at upper parts of the occupational wage distribution. The interpretation of the estimates of task prices ($\hat{\lambda}^j_{t=1,...,5}$) on the quadratic term $\hat{\gamma}^j_2$ is strongly related to linear estimate $\hat{\gamma}^j_1$[6]. It strengthens (weakens) the positive or negative association between task prices and wage growth within occupations indicated by $\hat{\gamma}^j_1$ when having the same (opposite) sign. Nevertheless, the quadratic specification tells us little on the overall association among the occupational wage structure.

6 Results

Table 5: Linear OLS estimation of occupational wage profiles on task prices

Dep. Variable:	Intercept ($\hat{\delta}$)			Slope ($\hat{\gamma}_1$)		
	(1)	(2)	(3)	(4)	(5)	(6)
Analytical	0.399	-0.029	-0.377	0.679***	0.640***	0.386**
	(0.411)	(0.180)	(1.163)	(0.211)	(0.212)	(0.209)
Interactive	-0.095	-0.166	0.086	0.455***	0.448***	0.181
	(0.383)	(0.166)	(1.160)	(0.196)	(0.195)	(0.208)
Routine	-0.105	-0.027	-0.556***	0.010	0.018	0.057
cognitive	(0.167)	(0.072)	(0.250)	(0.086)	(0.085)	(0.045)
Routine	0.565	0.435***	0.744	0.268	0.256	0.472***
manual	(0.358)	(0.155)	(0.975)	(0.184)	(0.183)	(0.175)
Non-Routine	-0.270	-0.090	-1.093	-0.079	-0.062	-0.034
manual	(0.295)	(0.128)	(0.826)	(0.152)	(0.151)	(0.148)
Base Wage (2006)	no	yes	yes	no	yes	yes
Covariates	no	no	yes	no	no	yes
N(Occupations)	76	76	74	76	76	74
Adj. R-square	0.117	0.837	0.714	0.189	0.210	0.173

[6]Note: There is no link between $\hat{\gamma}^j_1$ in the linear specification and $\hat{\gamma}^j_2$ in the quadratic specification. $\hat{\gamma}^j_2$ aims to detect any non linear association between changes in occupational task prices and wage structures but should only be interpreted together with $\hat{\gamma}^j_1$ in the quadratic specification. Together they detect possible non linear associations between task prices and wage growth within occupations.

[Interpretation on intercept coefficients follows]

Table 6: Quadratic OLS estimation of occupational wage profiles on task prices

Dep. Variable:	Slope ($\hat{\gamma}_1$)		Slope ($\hat{\gamma}_2$)	
	(1)	(2)	(3)	(4)
Analytical	4.662*	5.195*	-0.688	-0.771
	(2.762)	(2.769)	(0.493)	(0.496)
Interactive	3.974	4.062	-0.596	-0.610
	(2.569)	(2.552)	(0.459)	(0.458)
Routine	-1.454	-1.552	0.245	0.260
cognitive	(1.120)	(1.115)	(0.200)	(0.200)
Routine	0.883	1.044	-0.189	-0.214
manual	(2.404)	(2.390)	(0.430)	(0.429)
Non-Routine	1.730	1.506	-0.384	-0.349
manual	(1.981)	(1.974)	(0.354)	(0.354)
Base Wage (2006)	no	yes	no	yes
N(Occupations)	76	76	76	76
Adj. R-square	0.065	0.092	0.059	0.079

7 Conclusion

[to be done]

8 Literature

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