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Occupations and the wage structure: The role of occupational tasks in Britain

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ABSTRACT

Occupations are central to the stratification system, including the stratification of wages. One compelling explanation for how occupations relate to the wage structure is through their task content. We consider the relationships between occupational tasks and the wage structure directly using unconditional quantile regression methods, examining a broader range of occupational tasks than normally considered. We find that occupational tasks have varied implications for the wage structure in ways not always consistent with dominant technology-based explanations. We conclude that the task-based approach to conceptualising how occupations determine the wage structure is a promising avenue for future research and outline some recommendations on how to proceed.

1. Introduction

Occupations have long been viewed as central to the stratification system. This view has been reinforced by more recent research which shows that occupations play a key role in accounting for the long-term growth in wage inequality through a polarization of the occupational structure and growing variation in mean wages between occupations (Williams, 2013; Williams, 2017a).[1] Whilst debate exists on why occupations are so central (e.g., Tåhlin, 2007), an important sociological literature has begun to focus on the task dimension of occupations in understanding the co-evolution between the occupational structure and growing inequality (e.g., Liu and Grusky, 2013), as has a burgeoning economics literature (e.g., Acemoglu and Autor, 2011; Goos and Manning, 2007).

Although the variance in occupational mean wages appears to be relatively well-explained by the types of tasks they involve in recent sociological research (e.g., Liu and Grusky, 2013; Zhou, 2015), we still know little about how occupational tasks structure wage inequality, which is a substantively different though equally important question. Although the job polarization literature in economics has examined the relationship between the changing occupational structure and changes in the wage structure through the types of tasks performed across occupations (Firpo, Fortin, & Lemieux, 2013), it has tended to focus on a rather narrow set of tasks relating to the rapid pace of technological change during the 1980s to 1990s. Not only has the pace of technological change slowed in recent years, it is not known how other sorts of tasks previously highlighted in prior sociological research—-whose relationships with developments in technology are more ambiguous—relate to the wage structure.

In this article we make three contributions to understanding the relevance of occupational tasks for the wage structure. First, we show how examining the relationship between occupational tasks and wages across the entire wage distribution is revealing in understanding how occupational tasks relate to wage inequality through their differential influences across the wage structure. Although our study is largely a descriptive exploration of how occupational tasks deemed to be important in previous research relate to the wage structure, we believe this exercise to have theoretical as well as applied implications given the centrality of occupations in stratification research.

Second, we focus on a broader range of tasks than is normally examined by the technological change literature in economics, including for example, emotional and aesthetic tasks. Previous sociological research has long highlighted a broader range of tasks mattering for occupational stratification than those that have featured in the recent empirical work in economics which largely focus on how easily substitutable certain tasks are by technology. Examining a broader range of tasks helps to understand the extent to which the relationship between occupational tasks and the wage structure can be interpreted as the effect of technology on labour demand, or whether further theorising is needed.

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[1] Trends average wages attached to occupations for growing American inequality are more ambiguous than in Britain (i.e. between-occupation inequality) partly because of how imputed wages are treated in the Current Population Survey, see Mouw and Kalleberg (2010) c.f. Kim and Sakamoto (2008).

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Finally, we also present an analysis of tasks both at the occupational and the more disaggregated (individual) job level. Recent theory and evidence in both sociology and economics have predominantly considered tasks as occupational-level constructs (e.g., Autor and Dorn, 2013; Firpo et al., 2013; Liu and Grusky, 2013), largely owing to data limitations. However, this implicitly assumes that variation in task profiles within occupations are of lesser importance than variation between them, despite theoretical accounts underpinning the relevance of tasks potentially implying both should be important. We explicitly test if this is the case by examining the influence of between-job within-occupation differences in task use on the wage structure to more robustly conclude as to the role of occupational tasks in stratifying the wage structure.

For our analyses we use British Skills and Employment Surveys (BSES), which contain detailed information on a range of tasks individuals use during their work recorded at the individual-level. We examine 11 task indicators across six task domains—cognitive, analytical, manual, interactive, organisational, and affective—pertinent to various task-focused literatures, and test the distributional implications of these dimensions using recently developed unconditional quantile regression methods (Firpo, Fortin, & Lemieux, 2009).

2. Occupations and wage inequality

Sociologists have long placed occupations at the centre of the stratification system. Occupations are not only supposed to describe the structure of inequality but they also proxy for the generative processes by which inequality patterns are produced and reproduced. Explanations for why occupations are so central are quite varied, ranging from theories of workplace authority (Wright, 2000), to the differentiation of employment relations (Goldthorpe, 2007), to skill requirements (Tåhlin, 2007), to the relative wage payoffs certain tasks command in the labour market (Liu and Grusky, 2013). In various ways, variation in characteristics of work grouped according to occupations underlies all these explanations. For instance, in Goldthorpe, 2007 theory of social class, employers offer different kinds of employment relations to their employees depending on the type of work they are doing. Work involving complex and analytical tasks is higher-paid to encourage investment in specific skills, whereas work involving simpler tasks is lower-paid as less is to be gained from forming longer-term employment relations (Williams, 2017b).

Although some research has recently begun to examine the extent to which different types of occupational tasks explain the variance in mean wages across occupations (Liu and Grusky, 2013; Bol and Weeden, 2015; Zhou, 2015) these only give limited insight into how occupational tasks structure wage inequality since the variance is ultimately a composite inequality measure. In stratification research, the relationship between occupations and overall wage inequality is often studied by decomposing the overall variance in wages into the variance in wages between workers in the same occupation (within-occupation inequality) and the variance between mean occupational wages (between-occupation inequality). Studies in Britain (Bol and Weeden, 2015; Williams, 2013, 2017a; Zhou, 2015), the US (Mouw and Kalleberg, 2010; Weeden, Kim, Carlo, & Grusky, 2007), and Germany (Bol and Weeden, 2015) generally find that the majority of the overall variance in wages is between individuals within occupations, not the variance in mean wages across occupations.[2] There could be substantively important differences in the influence of occupational tasks across the wage structure, depending on differential task-use across occupations and also in differing payoffs to occupational tasks across the wage distribution (conventionally thought of as within-occupation wage inequality). Very little is yet known about the extent to which occupational tasks are relevant for wage inequality beyond apportioning amounts of between-occupation inequality to particular kinds of tasks.

3. Occupational tasks and wage inequality

While sociologists are beginning to examine task-based explanations with respect to wages, perhaps the most influential theoretical account for the relevance of occupational tasks to wage inequality is that of “job polarization” or “routine-biased technological change” (Goos and Manning, 2007; Goos, Manning, & Salomons, 2014), mostly from economics. An explanation for the evolution of wage inequality since the 1970s and 80s, the main argument is that technology can increasingly substitute for occupations with a high concentration of routine tasks (manufacturing and clerical occupations) but not for those with a high concentration of nonroutine ones (including professional and lower service occupations), which it complements. Many studies show that the interaction between technology and the occupational tasks has polarized the employment structure into high and low-wage occupations across countries (e.g., Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2014; Oesch, 2013) and that wage growth across occupational task types has been uneven. In a sociological contribution, Liu and Grusky (2013) show that there was an increase in the returns to occupational-level analytical tasks over time in the US, and that this explains a substantial portion of the growth in between-occupation inequality there. Other research has shown falling wage returns to routine occupations have been important for growing inequality there too (e.g., Firpo et al., 2013).

The main weakness with the recent applied work in economics is that it has focused on a rather narrow set of tasks. Even though the types of tasks or “skills” it has focused on has broadened over time—-from a simplistic two-factor theory of skill (degree-level vs. non-degree-level qualifications) to one focusing on the substitutability/complementarity with technology in terms of how routine occupational tasks are—the underlying explanation has stayed more or less constant. The relationship between certain other occupational tasks highlighted in previous sociological work whose substitutability with technology is more ambiguous and have been examined much less (Autor, 2013). This is something of a glaring omission, especially when we begin to unpack the potentially very broad and varied tasks within the “non-routine” category, which includes various kinds of interactive, organisational, and affective tasks—all of which are known to be growing in a service-dominated economy—and all of which are all likely to have quite varied implications for the wage structure.

4. Types of occupational tasks

Although the technology-based accounts have tried to hone in on the exact mechanisms linking technological change to growing wage inequality by focusing on the demand for a specific tasks in a more precise way than the coarse two-factor model of skill in earlier research, stratification research has long highlighted the role of a broader range of occupational tasks for understanding inequality, even if not always in a systematic way. We briefly review the types of tasks we examine in this article.

We are able to examine 11 task types derived via factor analysis from 42 detailed tasks recorded in the BSES (more details below). We group the 11 task types into six task domains relating to various task-based accounts: cognitive tasks, analytical tasks, manual tasks, interactive tasks, organisational tasks, and affective tasks. The first three have featured in the technological change accounts and have been examined more extensively in that literature, whereas the latter three types have been cited as important for stratification research but have more ambiguous relationships with technology. While technological change theories largely provide an over-time narrative, in our analyses we do not attempt to examine wage inequality trends since trends were

[2] It is important to note relative magnitudes of these two components depend on the level of detail of the specific occupational classification scheme and its operational basis.

flat in this period (2006–2012). Instead, our analyses will provide a first—but important—description of how a broader range of occupational tasks than is normally studied relate to the wage structure in cross-section.

The first type of tasks we consider are *cognitive tasks*. These are related to the general cognitive demands that are required within the job. It is often measured by survey items on numerical or verbal tasks (OECD, 2013), and in virtually all studies are related to higher wages. Earlier technology-based accounts focused on the complementarity between cognitive skills and technology (e.g., Katz and Murphy, 1992). Given earlier economic studies, we expect these tasks to increase wage inequality as they are a staple feature of generally higher-paid occupations.

Analytical tasks, second, are closely related to the cognitive domain but are more practical in nature. Examples of analytical tasks include solving complex problems and the intensity of computing tasks. These emerged as explanations in later technology-based accounts which sought to explain not only the declining share of employment in lower-skilled occupations, but the faster growth in wages for higher-skilled ones which became more productive with developments in computing. Similarly, the demand for and wages attached to computing tasks in general have also been increasing (Autor et al., 2006; Green, Felstead, Gallie, & Zhou, 2007) as computers become more useful for more types of work. Given there complementarity with technology, we expect analytical tasks to positively affect wage inequality, as has been demonstrated in a cross-temporal study in the US (Liu and Grusky, 2013).

Manual tasks, third, are physical tasks such as pushing heavy objects or short repetitive tasks on a production line. Over the past decades, technological innovations are said to have automatized a large share of routine physical work, depressing their wages. Dock workers, for instance, used to be hired for their physical strength, and their ability to lift cargo from ships. Nowadays this lifting is done by automated equipment and dock workers are hired for their ability to operate machines rather than their physical strength. Similarly, manufacturing production lines are increasingly fully automated, overseen by operatives, depressing the wages of production line workers. The implications of this for the wage structure are less clear: physical tasks might decrease cross-sectional wage inequality by lifting the wages of those at the lower tail since employers now only demand more difficult to automate physical tasks. Nonetheless, perhaps occupations involving a great deal of physical tasks also make much less use of other tasks that are deemed to be more rewarding in terms of wages such as cognitive and analytical tasks.

Whereas developments in technology directly complement occupations involving a high degree of cognitive, analytical, or in the case of physical tasks, directly substitute them, its relationships with other types of tasks falling within the rather heterogeneous “nonroutine” category are more less clear (Autor, 2013). Sociologists have tended to highlight a broad range of “nonroutine” tasks as being important to occupational stratification and the quality of work more generally. Accounts range from growing types of service work whose main tasks involve caring or customer services, to other accounts highlighting tasks central to maintaining and directing organisations. We distinguish between three further types of tasks whose relationship with technology is more ambiguous: Interactive tasks, organisational tasks, and affective tasks.

Interactive tasks represent personal communication ranging from communicating information such as teaching or training, to interacting with co-workers, as well as selling products directly to customers. By and large, interactive tasks are (still) very difficult to automate and perhaps technology may make them more productive, thereby still being in demand and so should be positively related to wages. Evidence for this claim is, however, mixed: several studies show that the wages for interactive tasks are rather segmented. Those interactive tasks that are related to care work are negatively associated with wages (England, Budig, & Folbre, 2002; Liu and Grusky, 2013), and used more often by workers in the lower part of the wage distribution. Part of the reason for mixed results are likely due to inadequate distinctions between such tasks: care work involves a combination of physical, interactive, and affective tasks, which we are able separate out. More generally, interactive tasks are quite a broad category: occupations involving a high degree of client communication (such as care work) are generally low-paid, whereas those involving a higher degree of other forms of interactive tasks (such as professional communication) can yield higher returns. The implications of interactive tasks for the wage structure are therefore not straightforward.

Organisational tasks include all tasks that are related to the running of the organisation, including the managing of one’s own work but also that of others. These have long been highlighted by sociological and management studies as important for stratification (Hedström, 1991; Wright, 2000). An important type of organisational task is related to managing. Managers must be able to plan work for the employees they supervise as well as being able to coordinate tasks in their department or company. Similarly, workers often manage and plan their own activities in addition to being directed by a superior. Wages attached to organisational tasks tend to be relatively high (Liu and Grusky, 2013). As is the case with analytical and interactive tasks, organisational tasks are said to be increasingly in demand, but their direct relationship with technological developments are less clear, especially once other types of tasks such as interactive or analytical tasks are controlled. Nonetheless, given previous sociological research findings, we expect organisational tasks to have inequality-increasing influence on the wage structure because these they are used more intensely by workers further up wage distribution relative to those further down.

The final type of task we distinguish are *affective tasks*. Several streams of research in sociology and management studies have long highlighted these sorts of tasks as an important element of stratification. Occupations differ in the extent to which one has to manage one’s feeling and appearance, as well of inducing certain feelings and affective states in co-workers or clients. Following the publication of Hochschild (2003), with its vivid portrayals of the emotional labour done by flight attendants in particular, a growing body of sociological work has studied labour where the main product or service is essentially an affective display. Just as with the other social tasks, emotional and aesthetic labour cannot easily be automatized or substituted by technology. It therefore seems plausible to expect positive returns to emotional tasks given the difficulty of automating them, although existing research tends to show the opposite (Bhave and Glomb 2009; Liu and Grusky 2013). Thus the likely relationship between affective tasks and the wage structure is unclear, especially once other types of tasks are taken into account.

5. The British skills and employment surveys

Data come from the British Skills Surveys (BSES) (Felstead, Gallie, Inanc, & Green, 2014). The BSES contains rich information on the importance of a plethora of tasks used at work. Whilst much US-focused research makes use of the Occupational Information Network (O*NET) database (Tippins and Hilton, 2010), which shares a similar purpose to BSES, one important difference is that the analytical output of O*NET consists of average tasks at the detailed occupational-level—not the individual-level (job-level) as is the case with the BSES (Felstead, Gallie, Green, & Zhou, 2007: 10–13). Therefore research examining the O*NET data pertains to occupational-level, not individual-level tasks (e.g., Liu and Grusky, 2013). Only few surveys in the world contain job-level tasks data (Autor, 2013).

We pool the latest two waves of the BSES (2006 and 2012) to obtain a large enough sample size to define occupations at a detailed (4-digit) level, resulting in a total sample size of 6910 observations. The BSES uses random probability sampling methods, so with weights, provides a nationally-representative portrait of the employed British population aged 20–65. Respondents in the BSES were asked to rate the importance of 39 specific tasks in their job on a five-point scale with the possible responses "essential", "very important", "fairly important", "not very important", and "not at all important/does not apply". The exception is an item on the complexity of computer-use. For this item, respondents reporting using a computer in their job were asked to place the way they use computers on one of four levels, ranging from "straightforward" to "advanced", with examples being given to anchor each levels. Responses across these items are coded from 0 ("not at all important/does not apply") to 4 ("essential"). For the complexity of computer-use item, responses are similarly coded 0 (not using a computer) to 4 ("advanced") forming a similar five-point scale.

We reduce these specific task items to a smaller number of tasks scales using exploratory factor analysis, revealing 11 unique factors.[3] These are identical to those identified elsewhere using the same data so we do not report the analyses in detail here (see Green, 2012). For each task factor identified, we construct simple scales averaging across items pertaining to a particular type of tasks ranging from 0 to 4 rather than using factor scores. All scales have high Cronbach's alphas (α) indicating high internal consistency. Descriptions of the items and scales as well as their pairwise correlations are listed in Tables 1 and 2.

Table 1 reports the mean task scores for each tasks scale and the items comprising each one separately for the 2006 and 2012 sample. Simple *t*-tests reveal that the means of the tasks scales are broadly stable across surveys although we do find some small but statistically significant changes with respect to the computing and physical tasks. There was no significant change in overall wage inequality between the 2006 and 2012 with essentially flat wage growth across the whole distribution (Gregg, Machin, & Fernández-Salgado, 2014). An advantage of examining the latest two waves is that it allows for the inclusion of a broader range of tasks (specifically, managerial, aesthetic, and emotional tasks) which are unavailable in earlier waves of the BSES.

6. Analytical strategy

The analysis proceeds in three steps. In the first step, we examine the relationship between occupational tasks and the wage structure descriptively, examining occupational-tasks by wage decile. In the second step, we shift to a multivariate approach and estimate the influence of occupational tasks on the wage structure. In our main analyses, our focus is on occupational-level tasks since stratification research highlights tasks at this level as being important. We calculate occupational-level mean tasks scores using a slightly modified version of the 4-digit SOC 2000 (most detailed) classification of occupations.[4] We standardise occupational task scores in the multivariate analyses to have a mean of 0 and standard deviation of 1. In all multivariate analyses, we include a full set of controls for female, non-white, married, degree-level qualification or higher, experience (five dummies: < 10, 10–19, 20–29, 30–39, and 40+ years), whether covered by a union, part-time, and a survey dummy. We use sampling weights throughout to account for sampling design.

For this second step, we first estimate multivariate wage equations at the mean using simple OLS with log real wages as the dependent variable. To gauge the effect of occupational tasks across the wage structure to make inferences about how the relate to wage inequality, we then implement the unconditional quantile regression (UQR) methods proposed by Firpo et al. (2009).[5] Quantile regression

Table 1
Description of job-level tasks.

	Task domains, scales, and items I. Cognitive tasks	2006	2012	Diff.
1	*Verbal*	*2.63*	*2.64*	*0.01*
	Reading written information, e.g., forms, notices, or signs	3.05	3.06	0.01
	Reading short documents e.g., letters, or memos	2.93	2.93	0.00
	Reading long documents e.g., long reports, manuals, etc.	2.42	2.42	0.00
	Writing material such as forms, notices or signs	2.45	2.45	0.00
	Writing short documents, e.g., letters or memos	2.47	2.49	0.02
	Writing long documents with correct spelling/grammar	2.00	1.99	−0.01
2	*Numeracy*	*1.88*	*1.92*	*0.04*
	Adding, subtracting, multiplying or dividing numbers	2.33	2.36	0.02
	Calculations using decimals, percentages or fractions	1.93	1.94	0.01
	More advanced mathematical or statistical procedures	1.46	1.54	0.08**
	II. Analytical tasks			
3	*Problem-solving*	*2.82*	*2.79*	*−0.03*
	Spotting problems or faults	3.12	3.06	−0.06**
	Working out the cause of problems or faults	2.87	2.79	−0.09***
	Thinking of solutions to problems	2.95	2.90	−0.05*
	Analysing complex problems in depth	2.32	2.35	0.02
4	*Computer-use*	*2.12*	*2.23*	*0.12****
	Using a computer, PC, or other types of computerised equipment	2.61	2.74	0.13***
	Complexity of computer-use	1.62	1.73	0.11***
5	III. Manual tasks	*1.92*	*1.87*	*−0.06***
	Physical strength e.g., carry, push, or pull heavy objects	1.65	1.65	0.00
	Work for long periods on physical activities	1.90	1.85	−0.05
	Skill or accuracy in using your hands or fingers	1.94	1.82	−0.12***
	Knowledge of use or operation of tools	2.20	2.15	0.05
IV. Interactive tasks				
6	*Professional*	*2.28*	*2.31*	*0.03*
	Instructing, training, or teaching people	2.55	2.68	0.13***
	Persuading or influencing others	2.33	2.31	−0.02
	Making speeches or presentations	1.42	1.47	0.05
	Planning the activities of others	1.90	1.88	−0.02
	Listening carefully to colleagues	3.22	3.23	0.01
7	*Client-communication*	*2.63*	*2.68*	*0.05***
	Knowledge of particular products or services	2.85	2.86	0.01
	Selling a product or service.	1.64	1.66	0.03
	Counselling, advising, or caring for customers or clients	2.57	2.64	0.07**
	Dealing with people	3.45	3.57	0.12***
	V. Organisational tasks			
8	*Self-planning*	*3.03*	*3.02*	*−0.01*
	Planning your own activities	2.90	2.85	−0.05*
	Organizing your own time	3.04	3.04	0.01
	Thinking ahead	3.14	3.17	0.03
9	*Managerial*	*1.19*	*1.10*	*−0.08***
	Motivating staff	3.36	3.30	−0.05*
	Keeping close control over resources	2.98	2.95	−0.03
	Coaching staff	3.02	2.95	−0.08**
	Making strategic decisions about future	1.94	1.91	−0.03
	VI. Affective tasks			
10	*Aesthetic*	*2.64*	*2.66*	*0.02*
	Looking the part	2.49	2.54	0.05*
	Sounding the part	2.80	2.79	−0.01
11	*Emotional*	*2.96*	*2.91*	*−0.04***
	Managing own feelings	2.98	2.92	−0.06**
	Handling feelings of others	2.94	2.90	−0.03

Notes: N = 6910.
Statistical significance: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

[3] Available on request from the first author.

[4] The BSES contains 210 unique 4-digit SOC 2000 occupations, but several have small cell sizes, even when pooling the 2006 and 2012 waves. Small occupations (those with fewer than 20 cases with non-missing data) are merged into other occupations codes in a meaningful way to form a modified classification of some 156 occupations (which is more detailed than the 82 categories at the 3-digit level of aggregation). Code available on request from the first author.

[5] Specifically we use the user-written "-rifreg-" procedure for Stata available in the Boston College Statistical Software Components (SSC) archive.

Table 2
Descriptive statistics of job-level task scales.

		Mean	S.D.	α	Correlations											
					[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
[1]	Verbal	2.63	1.10	0.87	1											
[2]	Numeracy	1.89	1.32	0.83	0.45	1										
[3]	Problem-solving	2.80	0.98	0.86	0.55	0.42	1									
[4]	Computer-use	2.15	1.30	0.84	0.51	0.48	0.39	1								
[5]	Professional	2.29	0.94	0.80	0.63	0.38	0.52	0.40	1							
[6]	Client	2.65	0.93	0.65	0.40	0.27	0.36	0.27	0.52	1						
[7]	Self-planning	3.02	0.93	0.84	0.59	0.35	0.49	0.39	0.59	0.37	1					
[8]	Managerial	1.16	1.46	0.72	0.37	0.31	0.36	0.29	0.59	0.32	0.39	1				
[9]	Aesthetic	2.65	1.03	0.77	0.39	0.17	0.24	0.18	0.40	0.50	0.36	0.20	1			
[10]	Emotional	2.94	0.91	0.76	0.39	0.11	0.28	0.13	0.43	0.40	0.40	0.21	0.49	1		
[11]	Manual	1.91	1.18	0.82	−0.11	−0.08	0.12	−0.37	−0.04	0.03	−0.07	−0.05	0.01	0.05	1	
[12]	Hourly pay (log)	2.45	0.51	–	0.41	0.32	0.34	0.48	0.41	0.12	0.37	0.41	0.06	0.07	−0.29	1

Notes: N = 6910.

techniques allow us to estimate the effect of occupational tasks on wages beyond the mean. This is particularly important for our purposes as their effects may vary between the upper or lower tails of the wage distribution, for instance, and so their effects on the wage structure. The advantage of UQR over previous conditional quantile regression (CQR) methods is that their estimated coefficients have an unconditional (i.e. marginal) interpretation (see Killewald and Bearak, 2014 for a non-technical introduction to the method).

UQR involves calculating a recentered influence function (RIF) for each wage quantile of interest and substituting these as dependent variables in linear regressions. In this way, the coefficients from RIF-regressions can be interpreted as the influence of a unit change in a particular occupational task for that particular point in the wage distribution. This is particularly useful for our purposes as it allows direct inferences about differences in occupational task-use on more nuanced indicators of wage inequality i.e. the P90-P10 differential (overall inequality), the P50-P10 differential (lower-tail inequality), and the P90-P50 differential (upper-tail inequality). Occupational tasks can affect the wage structure by giving both different wage returns and penalties at different points in the distribution.

In the third and final step, we directly examine the often implicit assumption that tasks influence the wage structure largely at the occupational instead of the job-level. This analysis simultaneously models the influence of occupational-level and job-level tasks by including both in a multivariate analyses. If tasks within occupations is more influential for the wage structure than variation between occupations we may call into the question the focus on occupational-level tasks which has been the norm in much of the literature.

7. Occupational task-use across the wage structure

To help form clearer expectations to how occupational tasks relate to the wage structure, we first analyse occupational task scores by wage decile in Fig. 1. Examining these first is useful because when we examine unconditional quantile regression (UQR) coefficients for occupational tasks in the next section as they will provide a useful benchmark in understanding the influence in specific occupational tasks at points in the wage distribution when other factors are controlled.

The bivariate patterns largely confirm our general expectations outlined earlier. Occupational tasks highlighted as benefiting from technology (cognitive and analytical) show a fairly clear monotonic pattern across deciles: individuals in higher deciles generally work in occupations that involve more intense use of these tasks as compared to those in the lower deciles. The same is also true for those integrative and organisational tasks that are generally associated with managerial and professional occupations (professional communication, self-planning, and managerial occupational tasks) which are also higher-paying occupations. The importance of manual occupational tasks—tasks said to be depressed by technology—decrease as on moves up wage deciles. Interestingly, no clear pattern emerges with respect to client communication, aesthetic, and emotional occupational tasks. There appears to be little difference in the intensity of these across wage deciles for these tasks.

8. Multivariate analyses of occupational tasks and the wage structure

We begin by presenting results on estimates for the coefficients of occupational tasks with a conventional OLS regression along with estimates from RIF-regressions for the P10, P50, and the P90 in Table 3. Our OLS findings (Column 1) are partially consistent with the previous section. We find that verbal, problem-solving, professional, managerial, and aesthetic occupational tasks are all associated with higher wages. Our results show the strongest wage effects are found for problem solving tasks, with a one standard deviation above average in these occupational tasks being associated with 32% ($e^{0.277}$) higher wages. On the other hand, numerical, client communication, emotional, and manual occupational tasks are all be associated with substantively lower pay. The negative association between emotional occupational tasks and wages is strongest: occupations involving a one standard deviation above average emotional tasks are associated with 16% lower wages ($1 - e^{-0.175}$). Interestingly, occupational-level computer-use and self-planning appear to have no statistically significant association with pay at the mean.

Turning to the results from the unconditional quantile regressions for key quantiles (P10, P50, and P90) in Table 3 Columns 2–4, it is evident that the influence of occupational tasks are not constant across the wage distribution. This supports our broad expectation that wage effects at the mean may give a somewhat partial picture when attempting to make inferences about influences along the wage structure. To better interpret the relationship between occupational tasks and the whole wage structure, we graph results from RIF-regressions for each fifth percentile in Fig. 2. To get a handle on what these predicted influences imply for wage inequality, Table 4 shows the differentials between the influence of occupational tasks for the P90–P10 (overall inequality), the P90–P50 (upper tail inequality), and the P50–P10 (lower-tail inequality). Fig. 2 and Table 4 essentially present the same results: the differentials are presented in graphical form in Fig. 2 and in numeric form in Table 4.

Taking cognitive tasks first, as with the OLS estimates, we find that they have substantively small implications for inequality compared to the other types of tasks we consider next. Interestingly, verbal tasks are found to be slightly inequality-increasing, whereas numerical tasks are slightly inequality-reducing, generally being associated with a pay

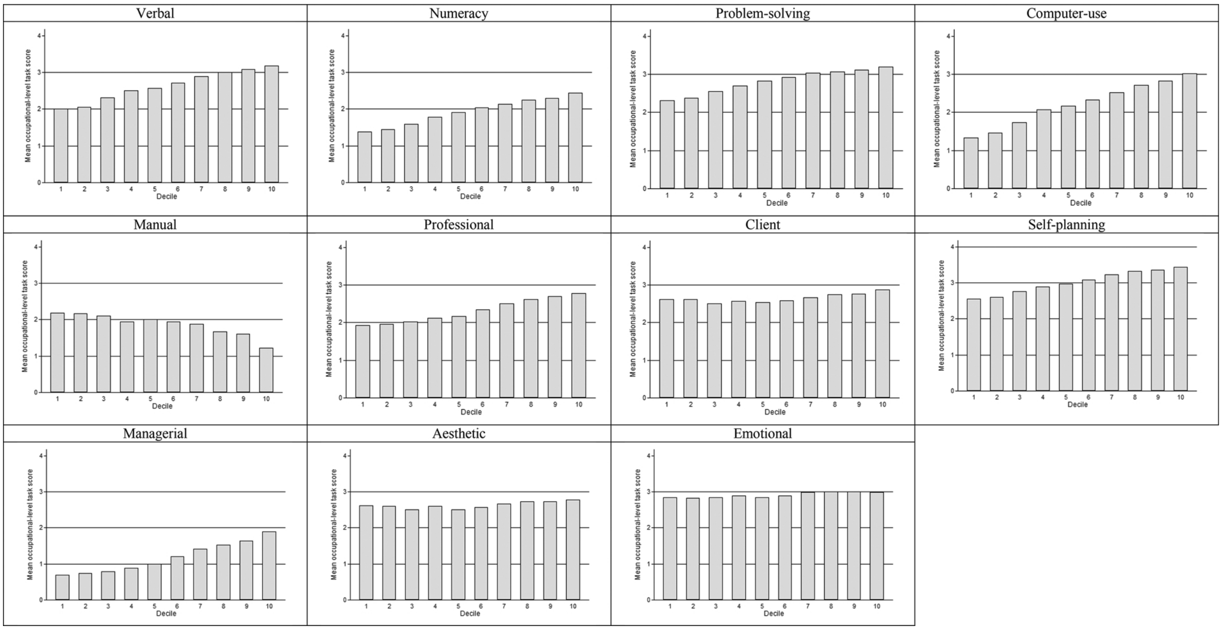

Fig. 1. Occupational-level task-use by wage decile.

penalty. On the other hand, the bivariate analysis in Fig. 1 demonstrated a clear relationship between position in the wage structure and intensity of numerical occupational task-use. This is perhaps not surprising, given they are quite general tasks and other more specific tasks are controlled.

The two types of analytical tasks we consider appear to have countervailing influences on the wage structure. Problem-solving tasks increase inequality as they have a large influence on wages that increases in magnitude higher up the wage structure. Interestingly, their inequality-increasing effects are generally much larger for lower-tail inequality rather than upper-tail inequality (Table 4). Computing tasks, on the other hand, are found to actually be inequality-reducing, especially at the upper-tail because they raise wages around the median relative to higher up the wage structure.

Turning to manual tasks, these are found to be strongly inequality-reducing (Table 4). They have virtually no influence on pay at the lower-tail but a very strong negative penalty which increases in magnitude the further one moves up the wage distribution (Fig. 2). Manual tasks reduce inequality at the lower-tail through a larger negative influence at the median relative to lower quantiles, and reduce upper-tail

Table 3
OLS and unconditional quantile regression coefficients of occupational-level tasks on log wages.

	(1)	(2)	(3)	(4)
	Mean (OLS)	P10	P50	P90
Verbal	0.052** (0.020)	0.036 (0.030)	0.046 (0.038)	0.077 (0.059)
Numeracy	−0.048*** (0.010)	−0.011 (0.012)	−0.047* (0.020)	−0.058 (0.031)
Problem-solving	0.277*** (0.022)	0.108*** (0.032)	0.310*** (0.040)	0.418*** (0.067)
Computer-use	0.013 (0.011)	0.065*** (0.016)	0.059** (0.021)	−0.200*** (0.032)
Manual	−0.105*** (0.010)	0.019 (0.012)	−0.031 (0.018)	−0.379*** (0.031)
Professional	0.133*** (0.022)	−0.103*** (0.027)	0.214*** (0.043)	0.257*** (0.063)
Client	−0.097*** (0.016)	−0.055* (0.025)	−0.147*** (0.029)	−0.026 (0.039)
Self-planning	0.000 (0.021)	0.113** (0.035)	0.098* (0.038)	−0.342*** (0.049)
Managerial	0.100*** (0.010)	0.017 (0.012)	0.089*** (0.019)	0.203*** (0.036)
Aesthetic	0.051** (0.019)	−0.023 (0.023)	0.070* (0.035)	0.105* (0.052)
Emotional	−0.175*** (0.023)	0.026 (0.027)	−0.202*** (0.042)	−0.314*** (0.079)
Sex	−0.116*** (0.010)	−0.033* (0.015)	−0.114*** (0.019)	−0.172*** (0.031)
Non-white	−0.020 (0.016)	−0.003 (0.031)	−0.015 (0.032)	−0.054 (0.045)
Married	0.065*** (0.010)	0.040*** (0.011)	0.070*** (0.017)	0.068* (0.027)
Degree	0.229*** (0.011)	0.041** (0.014)	0.227*** (0.021)	0.380*** (0.041)
< 10 years' experience	Reference			
10–19 years' experience	−0.151*** (0.015)	−0.111*** (0.021)	−0.130*** (0.028)	−0.200*** (0.042)
20–29 years' experience	0.017 (0.014)	0.011 (0.017)	0.052* (0.024)	−0.018 (0.043)
30–39 years' experience	0.006 (0.021)	0.018 (0.028)	0.055 (0.036)	−0.090 (0.059)
40+ years' experience	−0.042 (0.031)	0.058 (0.040)	0.042 (0.053)	−0.255*** (0.075)
Union contract	0.066*** (0.009)	0.102*** (0.012)	0.129*** (0.017)	−0.042 (0.026)
Part-time	−0.031** (0.012)	−0.100*** (0.020)	−0.040* (0.020)	0.078** (0.029)
Survey dummy	−0.087*** (0.009)	0.041** (0.013)	0.085*** (0.017)	0.113*** (0.026)
Constant	2.416*** (0.034)	1.865*** (0.049)	2.279*** (0.062)	2.864*** (0.090)
R^2	0.514	0.195	0.422	0.212
N	6910	6910	6910	6910

Notes: Standard errors in parentheses. Coefficients for controls omitted to save space.
Statistical significance: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

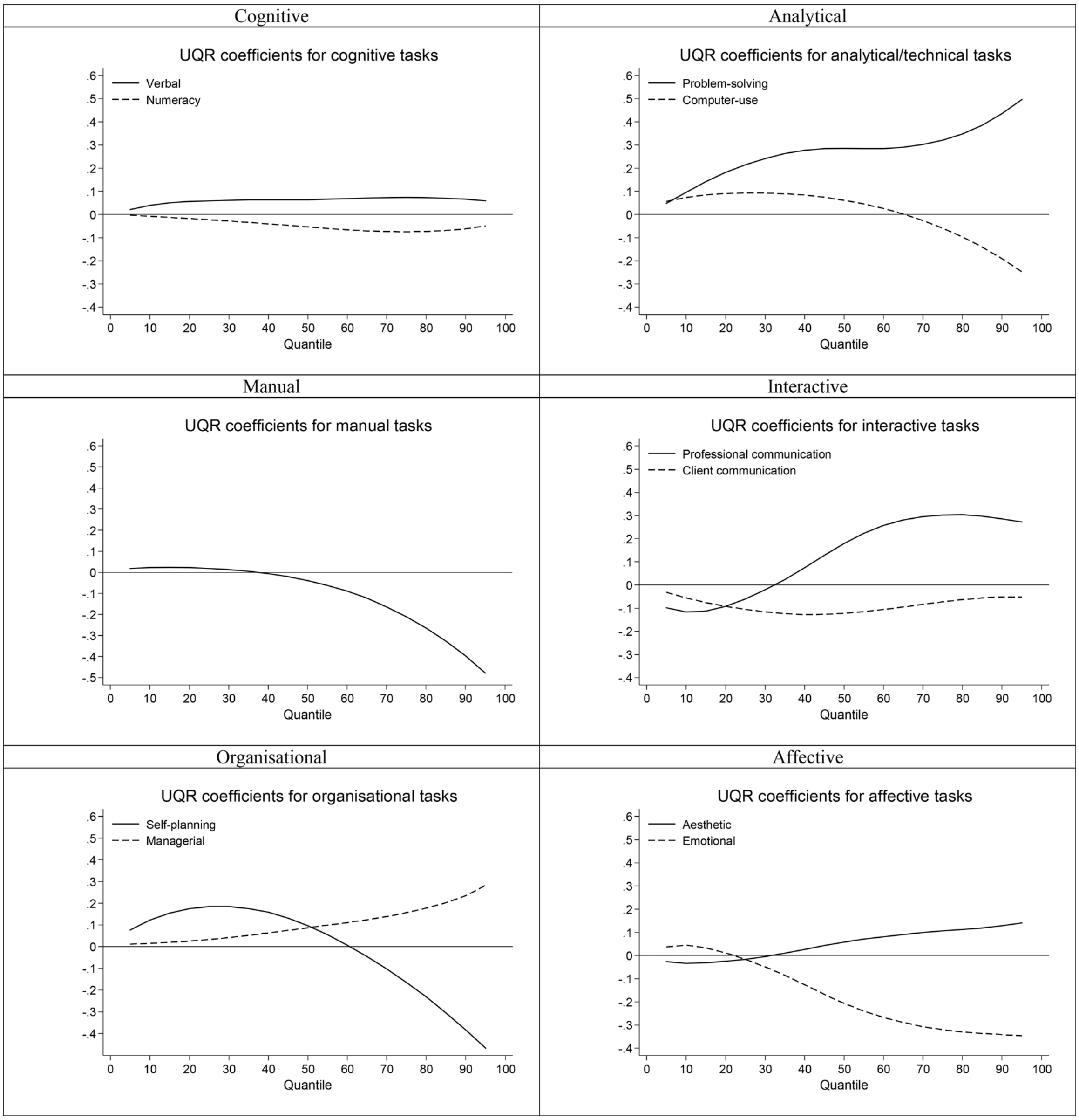

Fig. 2. Unconditional quantile regression coefficients of occupational-level tasks on log wages across the wage distribution.

Table 4
Occupational-level tasks and wage inequality.

	(1)	(2)	(3)
	90 − 10	90 − 50	50 − 10
Verbal	0.042	0.031	0.011
Numeracy	−0.047	−0.011	−0.036
Problem-solving	0.310	0.108	0.202
Computer-use	−0.265	−0.259	−0.006
Manual	−0.398	−0.348	−0.049
Professional	0.360	0.043	0.317
Client	0.029	0.121	−0.092
Self-planning	−0.455	−0.440	−0.015
Managerial	0.186	0.114	0.072
Aesthetic	0.128	0.035	0.093
Emotional	−0.341	−0.112	−0.229

Notes: N = 6910.

inequality by larger positive influence for the highest quantiles relative to the median.

Turning to the tasks with a more ambiguous relationship with technology, taking the case of interactive tasks first, again we find countervailing influences (Fig. 2). Professional communication greatly increases inequality at the lower-tail through a larger influence at the median relative to the lowest quantiles, with a much smaller influence on upper-tail inequality, where their influence flattens out. Client communication tasks, on the other hand, are generally associated with lower pay. Why a penalty exists for an occupational task which cannot seemingly be automated by technology is an open question. The penalty is more influential at the median compared to the tails such that they are found to be inequality-reducing at the lower-tail but inequality-increasing influence at the upper-tail, resulting in negligible net influence on overall inequality (Table 4).

As for organisational tasks, self-planning tasks have similar influence on the P50 and the P10, having a slight inequality-reducing influence for the lower-tail. However, they are associated with a lower wages above about the P60, which has the influence of strongly reducing upper-tail inequality (Table 4). The net effect of both of these is a substantively large inequality-reducing influence on overall inequality (P90–P10). As to why self-planning is associated with a pay penalty beyond a certain point, we expect this might be due to diminishing marginal returns to productivity of this task. Occupations with large amounts of self-planning may involve this task at the expense of other revenue-generating tasks. Managerial tasks on the other hand are straightforwardly inequality-producing with a greater influence on pay differentials the further one moves up the wage distribution.

In terms of affective tasks, occupations high in emotional tasks are found to generally be associated with lower pay and have very large inequality-reducing influence, compressing the wage structure the most at both the lower and upper-tails. Aesthetic tasks, on the other hand, generally increase inequality, having greatest influence on upper tail inequality. The implications of aesthetic tasks for the wage structure are therefore different to emotional ones implying the underlying mechanisms may be different.

Taking the results together, we find varied influence of occupational tasks across the wage structure. Some occupational tasks straightforwardly increase inequality by having larger influence on wage differentials amongst higher earners, for instance problem-solving, professional communication, and managerial tasks fall into this category, with substantively large influences on overall inequality. We find other occupational tasks are more straightforwardly inequality-reducing, with wage penalties that have a larger influences the further one moves up the distribution. Computing, manual, self-planning, and emotional tasks fall into this category. Whereas arguments can be made about the depressing wage influence of technology automating physical and possibly self-planning tasks too, the large penalties for occupations involving emotional tasks are not easily explained by technology. Whereas computing-use increases the further one moves up the distribution and so this could potentially explain why differentials become negative after a certain point, the intensity of emotional tasks are fairly evenly distributed across the wage distribution, making this result is even more intriguing.

9. Occupational tasks, job tasks, and the wage structure

So far we have examined the relationship between *occupational*-level tasks and the wage structure, as stratification theory has emphasised inequality-producing processes at the occupational, not job-level. As of yet, we have not examined what the implications of ignoring within-occupation heterogeneity in understanding their relationship with the wage structure, whilst previous research indicates that such within-occupation differences exist (Autor and Handel, 2013; Carbonaro, 2005). We next provide a robustness check on this assumption. We first examine the correlations between the aggregated mean tasks scores used in the previous analyses and job-level ones in Table 5.

Table 5
Correlation between occupational-level tasks and job-level tasks.

	Occupational tasks		Correlation with job scores
	Mean	S.D.	
Verbal	2.64	0.65	0.58
Numeracy	1.94	0.73	0.55
Problem-solving	2.82	0.48	0.46
Computer-use	2.23	0.97	0.74
Manual	1.86	0.79	0.65
Professional	2.32	0.56	0.59
Client	2.66	0.51	0.52
Self-planning	3.03	0.50	0.51
Managerial	1.19	0.80	0.53
Aesthetic	2.64	0.49	0.45
Emotional	2.91	0.41	0.43

Notes: N = 6910.

We find moderate correlations between the occupational and job-level tasks we consider. This implies that the occupational classification system does distinguish between occupations on the basis of their task-content to a varying degree. Job-level computing tasks, for instance, are very strongly correlated with those at the occupational-level (R = 0.74). This high correlation implies that most people that work in an occupation that scores high on computer task-use do so to a similar degree within that occupation. However, this does not yet rule out the role for between-job within-occupation tasks as being influential for wage inequality, especially since the correlations for several task domains are not as strong (e.g., problem-solving, aesthetic, and emotional).

We repeat the analyses of Fig. 2 in Fig. 3, incorporating job-level tasks with both occupational-tasks into the RIF-regressions, controlling for the same covariates as before. This exercise should indicate whether assuming constant task profiles within occupations is adequate when mapping the relationships between the task and wage structures, as is often made in the previous literature given the lack of job-level task information typically available. We find the wage structure is more sensitive to differences in occupational-level tasks and not job-level tasks: the influence of job-level tasks within occupations are generally much smaller in comparison to those between occupations at all points in the wage distribution. Moreover, the influence of within-occupation tasks scores are reasonably flat across the wage distribution. Reassuringly, the results in Fig. 3 generally support the notion that it is task content at the *occupational*-level instead of the *job*-level that explain how tasks relate to the wage structure. The implications of this finding for future research are discussed in the concluding section.

10. Conclusions

Sociological work has long documented that occupations matter tremendously for wage inequality. Recent work, both in sociology and economics, focuses on the task-content of occupations. Although very revealing, the sociological literature has not yet examined how occupational tasks relate to the wage structure, which is a substantively different question to the more commonly-studied variance in occupational mean wages. While research in economics has addressed this question to an extent, it has focused on a rather limited set of tasks. We have investigated these two gaps in current literatures using data from Britain containing information on 11 types of task.

Several key findings emerge. First, our article has demonstrated that occupational tasks do matter for the structuring of wage inequality. Some occupational tasks increase inequality by having larger influence higher up the distribution, particularly those that have said to have been complemented by technological change such as problem-solving and managerial tasks. On the other hand, some technology-related occupational tasks tend to compress the wage structure by having larger depressing influences higher up the distribution, such as computing and physical tasks. Other occupational tasks that are often neglected and whose relationship with technology is less clear are found to have substantively important and often countervailing influences across the wage structure. Self-planning and emotional occupational tasks, for instance, have a very large inequality-reducing influence. Other neglected tasks such as professional communication tasks, on the other hand, have a very strong inequality-increasing influence. Taken together, our results demonstrate that occupational tasks structure wage inequality in quite varied ways and that certain “nonroutine” tasks need to be further investigated.

A second important finding is that although variation in tasks *within* occupations have some independent influences on the wage structure, they are small and flat across the wage distribution, implying that job-level tasks do not add much substantively important information in understanding the relationship between tasks and the wage structure. This is a highly relevant finding for a field where job tasks often only can be assumed to be constant within occupations due to the absence of

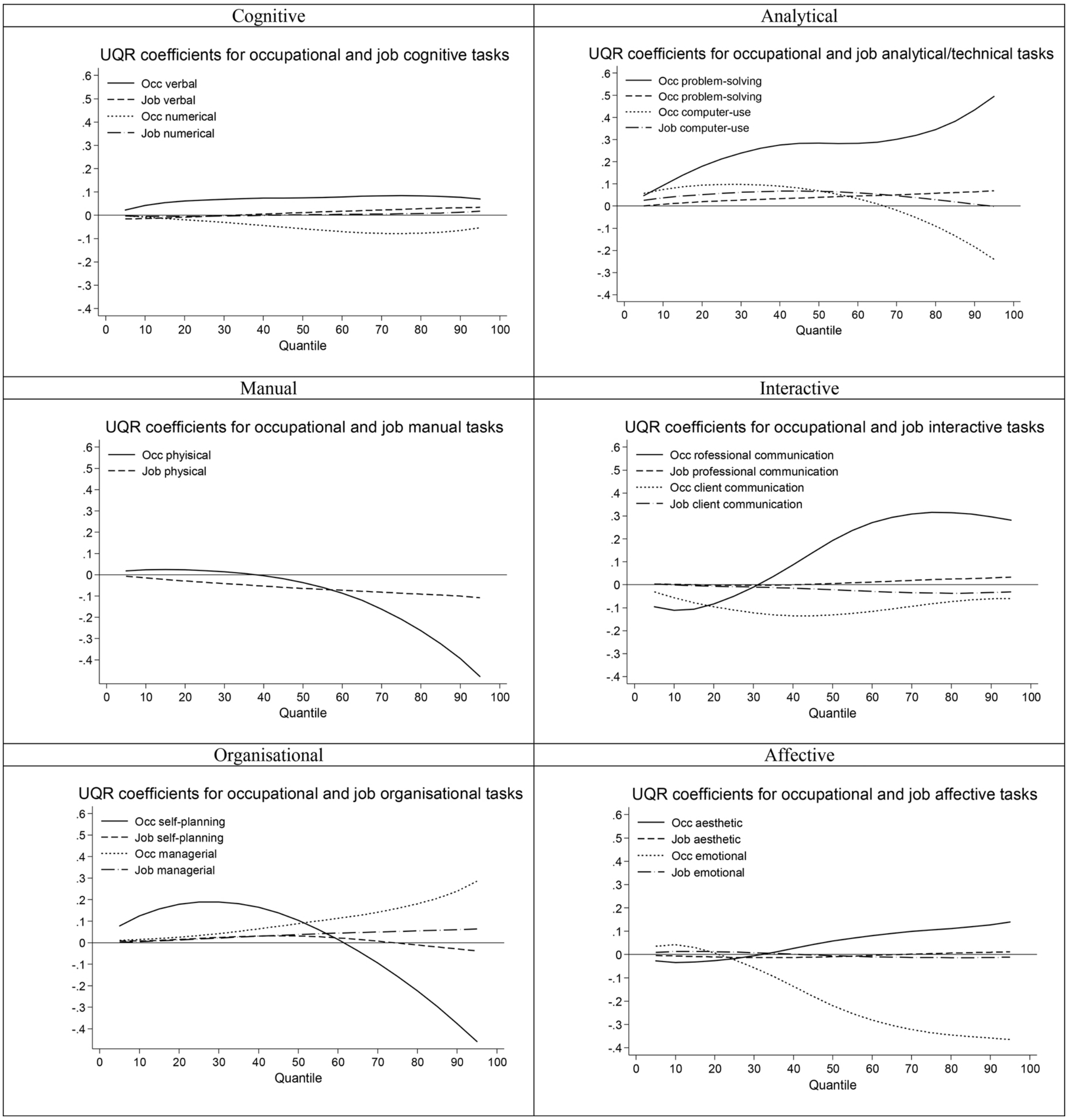

Fig. 3. Unconditional quantile regression coefficients of occupational-level and job-level tasks on log wages across the wage distribution.

good individual-level data on job task-use. More generally, it also highlights that sociologists are justified in focusing on occupational-level explanations in understanding inequality and that future theorising on the relationship between tasks and stratification should focus on understanding occupational-level processes relating to these types of tasks.

More broadly, our analyses supports current research streams that dissects occupational inequality using occupational tasks, moving beyond apportioning the overall variance in wages into between- and within-occupation variance. Such a task-based approach has advantages over other existing approaches to understanding occupational inequality, for example, relying on aggregated occupational schemas that bundle inequality-producing processes into broad analytic categories, or simply relying on occupation dummies ("micro-classes") in wage equations. An advantage of the task-based approach with UQR is that it identifies the influence of specific occupational characteristics on specific parts of the wage structure.

We have several recommendations for future research on the relationship between occupations, their characteristics, and the wage structure. First, future sociological research in this area should move beyond apportioning the overall variance in wages into between- and within-occupation components by implementing UQR methods (Firpo et al., 2009). Such methods are not only revealing to what occupational characteristics imply for the wage structure, they are also very straightforward to interpret, making it an accessible method for a large group of researchers.

Second, we have presented several findings that do not always square neatly with dominant technology-based explanations and further theorising and applied work is needed. Our findings reinforce examining alternative explanation to technology because we find substantively large and varied influences for several of these types of task whose relationship to technology is not straightforward. Indeed, in a simple OLS exercise excluding the technology-related occupational tasks (verbal, numeracy, problem-solving, computer-use, and manual) we found these accounted for 35.6% of the explained variance in log wages, while the other occupational tasks whose relationship with technology is less straightforward (professional communication, client communication, self-planning, managerial, aesthetic, and emotional) accounted for 34.1%, with the controls accounting for the remaining explained variance.[6]

A stream of sociological studies have shown that occupational-level institutions, such as occupational licencing also matter for wage differentials (Bol and Weeden, 2015; Koumenta, Humphris, Kleiner, & Pagliero, 2014; Weeden, 2002) and could help to understand why the influence of professional and managerial tasks, for instance, are more influential at the upper-tail. Although such explanations are beyond the scope of this study, future research should investigate the relative contribution to the wage structure of these sorts of explanations. Similarly, another interesting line of research is how the wage effects occupational tasks might vary by gender—an issue we have sidestepped here in order to keep our article focused.[7]

Finally, as we have shown, variation in tasks between jobs within occupations only have trivial implications for the wage structure. The influences of tasks between occupations are much greater implying that ignoring variation in tasks within-occupations because of data limitations may be permissible when job-level information is not available, as is often the case. The availability of task information is becoming increasingly available as governments, researchers, and statistical agencies are beginning to see the value in the task-based approach. Information in other surveys with tasks at the individual-level exists and is growing (for example, with the Programme for the International Assessment of Adult Competencies [PIAAC], that provides standardised cross-country measures of competencies and task-use). Our article shows that such a task-based approach to occupational stratification offers a promising avenue for, and likely the future direction of, sociological research which has always placed occupations at the centre of the stratification system.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.rssm.2017.11.003.

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[6] We thank an anonymous referee for suggesting this exercise. Full results available on request.

[7] We reran all our analyses presented here by gender and found mostly qualitatively similar results, with some interesting exceptions. See Online Supplement.