# TASKS, OCCUPATIONS AND WAGES IN OECD COUNTRIES

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THIS VERSION: 11 March 2020

ABSTRACT

This paper investigates the relationships between earnings, human capital, and job tasks, exploiting internationally comparable information from the OECD Survey of Adult Skills. We use the theoretical framework presented in Autor and Handel (2013) and extend their empirical results to 20 OECD countries. Our data allow for a richer characterisation of worker's human capital, by including both educational attainment and a measure of cognitive skills. We are able to confirm the predictive power of job tasks in explaining wage differences both between and within occupations, and to provide empirical support for the model's prediction in the vast majority of countries.

Keywords: earnings, occupations, skills, tasks
JEL Classifications: J24, J31

Without implication, we acknowledge useful comments by Steve McIntosh on an earlier draft. We are also grateful to the Editor and two anonymous reviewers for their valuable suggestions on a previous version of the manuscript. Usual disclaimers apply.

## 1. Introduction

The skills and competencies of the labour force are widely held to be the key to productivity growth and consequent prosperity in a modern economy. Evaluating the returns to these skills has unsurprisingly therefore been a longstanding focal point for the interest of labour economists.

The lessons learned from the enormous received literature on the determinants of earnings can be grouped into three broad categories. First, some exogenous individual characteristics such as gender, ethnicity, immigrant status, or family background, are associated with lower salaries, all else equal. Second, workers with higher levels of human capital generally obtain higher earnings, holding other individual characteristics constant. Third, mostly unobservable workers' characteristics determine workers' self-selection into different jobs, occupations, industries, locations, each of them offering different wage structures (e.g. in terms of the mean and variance of earnings.

While the traditional literature grounded on the Mincerian framework is mainly based on a supply-side perspective, by which wages are essentially determined by the skills individuals are endowed with and decide to supply to the market, a more recent approach has tried to incorporate a demand-side perspective by analysing the role of job tasks, i.e. the set of activities that workers are required to undertake as part of their job. Autor and Handel (2013) – AH from now on – show that, within broad occupational categories, different workers perform different sets of tasks, and this can potentially be reflected in their wages. Additionally, these authors provide a conceptual model for analysing the relationship between wages, job tasks and human capital, and employ it to show that within-occupation variation in tasks performed is indeed important in the determination of earnings.

In this paper, we adopt the same conceptual framework as in AH and we extend their empirical investigation of the wage returns to tasks using data from the OECD Programme for the International Assessment of Adult Competencies (PIAAC). PIAAC was designed to provide internationally comparable data on the information-processing skills of the adult population in a large number of OECD countries. To analyse the role such skills play in determining labour market outcomes better, PIAAC also collects a wealth of information on survey participants, including wages, formal education, and tasks performed on the job. One important advantage of PIAAC is that it provides information on the task content of jobs at the individual level, while most papers that have investigated the role of tasks have had to content themselves with measures of tasks that only vary at the occupation level. As most datasets do not contain individual information on the tasks performed on the job, researchers have had to infer this by using information on occupation, thus disregarding both the fact that tasks might vary within occupation, and the fact that different occupations might require workers to perform similar tasks.

One important exception in this regard is based on the data from the Princeton Data Improvement Initiative (PDII), used by AH but only available for the United States. With PIAAC data we are therefore able to test the predictions of the AH model on some 20 countries, enriching at the same time the empirical analysis by including more precise measures of workers' human capital, i.e. the cognitive skills assessed by PIAAC. By sticking as much as possible to the same methodology used by AH in constructing scales to measure the abstract, manual, and routine content of jobs, we allow our results to be directly comparable to previous results in the literature, while at the same time enriching the empirical specification by taking explicitly into account a direct measure of cognitive skills. Indeed, Autor (2013), in surveying the literature on the "task approach" to the labour market, noted the vast heterogeneity across studies in the way tasks measures are defined and constructed, and urged researchers to replicate the construction of existing task measures in order to converge to a shared and standardised set of measures and definitions.

Replicating the findings of AH to a broader sample of countries is relevant and important for a number of reasons. From a scholarly viewpoint, the exercise provides empirical cross-validation. Moreover, the analysis allows discussion of whether and how the theoretical predictions formulated by AH can be considered valid in countries with a different labour framework and heterogenous market mechanisms. From a policy perspective, it is crucial to investigate whether the relationship between tasks, activities and salaries as discovered in the USA by AH is also a feature of the labour market in other countries. To anticipate our main findings, the results presented in this paper confirm the finding of AH and provide strong support for the underlying theory across the countries we analyse.

The paper is organised as follows. Section 2 briefly reviews the relevant literature. Section 3 sketches the theoretical framework presented in AH. Section 4 describes the data we use, and Section 5 presents the results of the empirical analysis. Section 6 concludes.

## 2. Literature review

In this section, we briefly review the literature that deals with the effects of tasks on wages. Within the human capital approach, this literature advances the study of the determinants of earnings based on skills and occupations, describing how specific tasks and activities are carried out by workers, and how their wages are influenced by differences in the tasks that they perform, after controlling for other differences in individual characteristics and occupations. More comprehensive reviews can be found in Acemoglu and Autor (2011) and Autor (2013). We do not cover the seminal paper by Autor and Handel (2013) in this section, as we will extensively describe (and draw upon) it throughout the rest of the paper.

Autor, Levy and Murnane (2003) is often identified as the seminal paper in the literature on the "task approach" to labour markets. In order to explain the observed polarisation of wages, that paper argued that technological change tends to substitute routine task at the middle of the wage distribution and complement non-routine cognitive and manual tasks at the top and at the bottom of the wage distribution. SThis hypothesis is usually labelled as the "routine-biased technological change" (RBTC). Similar changes in demand for tasks, leading to job polarisation, were documented by Spitz-Oener (2006) and Dustmann, Ludsteck and Schonberg (2009) for Germany, and by Goos, Manning and Salomons (2009) for a broader set of European countries. Goos, Manning and Salomons (2014) then show how RBTC and the offshorability of tasks can explain the job polarisation observed in European countries.

A few recent papers have used PIAAC data to look at the role of job tasks. De La Rica and Gortazar (2016) construct an index of routine intensity following an approach very similar to the one we adopt in this paper.[1] They interpret country differences in this index as a measure of de-routinisation (although note that PIAAC is a cross-sectional study, from which nothing can be inferred about the evolution of tasks intensity over time), and assess both the extent to which computer adoption is able to explain this de-routinisation, and the link between computer adoption and wage inequality. A similar approach is taken by Marcolin, Miroudot and Squicciarini (2016a). They construct a new measure of 'routine intensity' for various occupations and focus on exploring the correlation between the skill content and the routine-intensity of occupations. They demonstrate that while there is indeed negative correlation between skill and routine-intensity, this varies across countries. Marcolin, Miroudot and Squicciarini (2016b) then investigate the role played by global value chains in explaining employment levels in different occupations characterised by different levels of routine intensity.

[1] Essentially, they first construct indexes of Abstract, Routine and Manual tasks, as we do, and then combine them to derive a summary measure of Routine task-intensity, following Autor and Dorn (2013).

Borelli (2016) describes how the task composition of different occupations varies across countries, and then performs (on US data) a thorough comparison between the information collected in PIAAC and the information available in the O*NET data, which is the most common data source on job content used in the "task approach" literature. She finds a strong correlation between O*NET and PIAAC measures, which she interprets as supporting evidence of the validity of the information contained in PIAAC to describe the task content of occupations. An important advantage of PIAAC, which we exploit in this paper, is the availability of information on tasks at the individual level, whereas the information contained in O*NET only varies at the occupation level.

Quintini (2014) adopts a slightly different interpretation of the information on job tasks contained in PIAAC. In particular, she interprets tasks as the extent to which specific skills are used in the workplace. Tasks are categorised according to whether they call upon "information-processing skills" (which have a parallel with the skills actually measured in PIAAC through a direct assessment, i.e. literacy and numeracy) and "generic" skills (such as non-cognitive or interpersonal skills). She finds that skill-use indicators are only poorly correlated with individuals' proficiency in these latter skills, and points out the relevance of such mismatch between skills' ability and use, as well as the possible relationship between skills use and productivity. She also provides evidence that generic skills are used more often than information-processing skills.

While PIAAC offers the considerable advantage of providing data on numerous countries, thereby allowing a comparative exercise of the kind undertaken in the present paper, it remains the case that it is in essence a cross-section data set. A small number of recent studies has made use of panel data including the Outgoing Rotation Group data from the Current Population Survey (Gottschalk et al., 2015) and also the National Longitudinal Survey of Youth (Bohm, 2017) in the United States, and the British Household Panel Survey and the German Socio-economic Panel (Cavaglia and Etheridge, 2017) in other countries. The opportunity afforded by panel data to allow for unobserved heterogeneity across workers means that these studies can correct for selection effects whereby individuals choose occupations in which the mix of tasks undertaken best rewards their skills. The longitudinal structure of these data sets also allows analysis of changes in the returns to tasks over time, with the evidence suggesting that widening gaps in these returns play a major role in explaining increased job polarisation.

**3. Theoretical framework**

Our empirical analysis is informed by the conceptual model presented in AH, a Roy model describing the allocation of workers to job tasks. We sketch the main features and empirical implications of the model here, referring the reader to the original paper for a more in-depth presentation.

Workers' human capital is denoted by a vector of task-specific abilities $\Phi_i$, denoting the efficiency in performing task *k*. A crucial difference with respect to the standard Mincerian framework is the assumption that the productive value of the various tasks is occupation-specific. The output of worker *i* in occupation *j* can therefore be written as

$$y_i = e^{a_j + \sum_K \lambda_{jk}\varphi_{ik} + \mu_i} \qquad (1)$$

where $\lambda_{jk}$ is the productive value of task *k* in occupation *j* (assumed ≥0 for all *j,k*) and $\mu_i$is a worker-specific error term. Assuming workers are paid their marginal product, log wages can be written

$$w_i = a_j + \sum_K \lambda_{jk}\varphi_{ik} + \mu_i \qquad (2)$$

Workers will self-select into occupations to maximise earnings, so that, in equilibrium, marginal workers are indifferent between their current occupation and the next best alternative. Returns to tasks are occupation-specific: workers choose the occupation where they can maximise earnings, given their bundle of task-specific abilities, but this does not imply that they necessarily receive the maximum market reward to each element of their skills vector.

Workers who are particularly efficient in some tasks will self-select into occupations where those tasks have high rewards, implying that a regression of wages on tasks will not uncover the average return to tasks over all occupations. Our empirical analysis will therefore be mostly descriptive in nature; however, we see it as a valuable contribution, in that we provide a rich characterisation of the relationship between earnings, human capital and job tasks across a large set of countries. Furthermore, our data allow us to test, as in AH, two predictions from the model, both deriving from the assumption that workers self-select into occupations that guarantee the highest monetary returns. The first prediction is that returns to tasks must negatively co-vary within the set of occupations with positive employment. This is a necessary, although not sufficient, condition for self-selection, as it states that occupations with positive employment are preferred by some, but not all, workers, depending upon their skill endowments. A second prediction derives from the assumption that self-selection into occupations is based on absolute or comparative advantage, whereby workers with higher efficiency in a given task should choose occupations with high returns to that given task. One way to test this empirically is to augment a Mincerian wage equation for tasks (where log wages are regressed on the tasks they perform on the job) with a set of interaction terms between occupational task means and worker-level task inputs. A positive coefficient of the interaction term indicates a positive covariance between occupation-level task returns and the task endowments of workers who self-select into that occupation. Positive estimated coefficients for the entire set of tasks would indicate selection based on comparative advantage, which would occur if the correlation between worker abilities across tasks is low. If instead selection is based on absolute advantage (meaning that workers who excel in one task also excel in other tasks) the test would be less restrictive, requiring at least one of the interaction terms to be positive.

## 4. Data

We use data from the Programme for the International Assessment of Adult Competencies (PIAAC), an international survey of adult skills run by the OECD. The survey is based on the computer-assisted interview of around 5000 respondents aged between 16 and 65 in each participating country. The survey assesses respondents' literacy, numeracy, and problem-solving skills, as well as collecting a wealth of education and labour market related information, notably educational attainment, wage, occupation, and tasks performed on the job. In this paper, we use data from the first (and largest) round of data collection, conducted in 2011/12 in 21 OECD member countries.[2]

The PIAAC data contain a huge amount of personal information, including age, gender, nationality, education, work experience, earnings, and occupation. The distinctive feature of PIAAC is the availability of direct measures of information-processing skills (literacy and numeracy), collected through cognitive tests conducted as part of the survey process. We focus on literacy skills, which we see as a foundation cognitive skill that is also at the basis of performance in numeracy assessments. Previous research found that numeracy skills usually command a higher wage premium, but the qualitative results about the importance of cognitive skills for labour market outcomes do not usually change significantly with the chosen measure

[2] We exclude Cyprus and the Russian Federation, as they are not OECD member countries. Furthermore, the data for the Russian Federation do not include the region of Moscow. We also exclude Australia, as information is not available at the 3-digit occupational level. The analysis is based on the full files for scientific use, which include some data (e.g. on earnings) that are not available for all countries in the public use files.

of cognitive skills (Hanushek et al, 2015). Indeed, we have (in work not reported here for reasons of space) undertaken our analysis using numeracy scores rather than literacy scores and find near identical results.
Importantly, PIAAC contains a range of questions on the actual tasks performed on the job by the individual respondent. Our measures of task intensity are standardised indices of routine, manual, and abstract tasks performed, based on the first principal component of a set of underlying Likert-type questions.
To be specific, the index of Manual tasks is constructed from two underlying items:

- "How often does your job involve working physically for a long period?"
- "How often does your job involve using skill or accuracy with your hands or fingers?"

Six items were used in constructing the index of Abstract tasks:

- "How often does your job involve persuading or influencing people?"
- "How often does your job involve negotiating with people either inside or outside your firm or organisation?"
- "How often does your job involve persuading or influencing people?"
- "How often are you usually faced by problems that take at least 30 minutes to find a good solution?"
- "In your job, how often do you usually read diagrams, maps or schematics?"
- "In your job, how often do you usually use more advanced math or statistics such as calculus, complex algebra trigonometry or use of regression techniques?"

Finally, the index of Routine tasks is based on five items:

- "To what extent can you choose or change the sequence of your tasks?"
- "To what extent can you choose or change how do you work?"
- "To what extent can you choose or change the speed or rate at which you work?"
- "To what extent can you choose or change your working hours?"
- "In your job, how often did you usually read directions or instructions?"

In each case the first principal component has a high eigenvalue (2 or more) and accounts for a high proportion of the variance.

Table 1 reports average values of the three synthetic task variables for workers by single digit occupation categories in the pooled sample, which contains more than 65,000 observations. A similar pattern holds in each of the individual countries. As expected, abstract tasks are more frequently performed by managers and professionals than by other workers. Managers have also very low scores on the manual task index, which is highest among craft and related trade workers.

[TABLE 1] around here

In the rest of the paper we will look at more detailed occupational classifications, at the 3-digit ISCO classification. Prior to undertaking that analysis, we have cleaned the dataset to ensure that we have at least 5 observations in each country-occupation cell. We are then able to work with more than 70 occupations in each country, from a minimum of 71 in Norway to a maximum of 109 in Canada. The pooled sample contains 113 distinct occupational categories.

**5. Empirical Analysis**

This section is conceptually divided in three different parts. First, we investigate the correlates of job tasks, asking in particular how individual differences in education and skills contribute to explain individual differences in tasks. Importantly, we are able to perform this exercise controlling at the same time for occupation (dummies), exploiting a key peculiar feature of the PIAAC dataset, i.e. the availability of measures of tasks at the individual level. Second, we look at the predictive validity of job tasks in explaining wages, augmenting a classic Mincerian wage equation with our tasks indices. Finally, we perform two empirical tests in order to provide empirical support to the conceptual framework outlined in AH.

*5.1 The correlates of tasks*

Table 2 reports, for the pooled set of countries, the results of the first exercise, in which we regress, in turn, each task index on a variety of personal characteristics. Results for individual countries are in the Tables A1-3. Final sample weighting and jackknife replicate standard errors are used throughout. The first specification controls for gender, immigrant status, a quadratic polynomial in age and in tenure on the current job, dummies for three levels of educational attainment (less than high school, high school, above high school), and the score in the PIAAC literacy assessment. The score on the literacy assessment is on a 0-500 points scale. In the estimation sample, the average score is 278.63 points, with a standard deviation of 46.84. In the second specification, we add a set of 113 occupation dummies at the 3-digits level, to control for structural heterogeneity across jobs. All specifications include country dummies and use final survey weights. To take into account the complex survey design, standard errors are computed using 80 jackknife replicate weights. We also use the full set of plausible values for the PIAAC literacy score, properly to take into account the uncertainty associated with the estimation of latent proficiency in item response theory (IRT) models.[3]

[TABLE 2] around here

Higher levels of skills and education are positively associated with performance of abstract and routine tasks, and negatively associated with performance of manual tasks. Women are less likely to perform both abstracts and manual tasks, and migrants are less likely to perform abstract tasks. Tenure on the job is positively associated with performing abstract tasks; the introduction of tenure has also the effect of making the coefficient on age not statistically significant. [4]

The introduction of occupation fixed effects reduces the magnitude of the other estimated coefficients, which however remain statistically significant (in particular those associated with skills and education), indicating a significant degree of sorting within-occupations. The explanatory power of the regressions also increases significantly with the introduction of occupational dummies, with R-squared moving from 23% to 35% in the case of Abstract tasks and from 22% to 38% in the case of Manual tasks. In the case of Routine tasks, however, the R-squared stays as low as 8%. Such results are broadly in line with the AH findings for the US. In their data occupation dummies added greater explanatory power, probably because they are able to use a much finer disaggregation of occupation (with 240 occupation dummies).

The picture that emerges from the pooled data is broadly confirmed in analyses conducted for each country separately (see Tables A1-A3). In particular, skills and education are in all countries strong predictors of task allocation, especially as far as abstract and manual tasks are concerned. The variance explained by the model is similar across all countries. Partial exceptions are the United States (with an R-squared of only 29% in the regression explaining Abstract tasks intensity), and Korea (with an R-squared of only 13% in the regression explaining Manual tasks intensity).

[3] We use the `repest` Stata routine developed by Avvisati and Keslair (2014).

Notice that since we have a measure of tenure on the job (and not of potential or generic labour market experience), tenure and age are not collinear (the coefficient of correlation being equal to 0.48, which is about the same as the correlation between years of schooling and literacy skills).

*5.2 Wage "returns" to tasks*

The results of the second exercise, in which we investigate the predictive power of tasks measures in wage regressions, are reported in Table 3 (for the pooled sample) and in Table A4 in the Annex (for each country). Following again AH, we report various specifications of a classic Mincerian wage equation. The wage is evaluated as the hourly wage (based on monthly earnings and usual hours of work), converted to US dollars using PPP exchange rates, and logged. In column 1 of Table 3 we only include human capital and other socio-demographic variables. In column 2 we only include tasks measures, and in column 3 we only include the full set of occupation dummies. Column 4 combines human capital and socio-demographic variable with tasks measures, and column 5 further adds occupation dummies. As in Table 2, all specifications include country fixed effects, all employ sampling weights, and standard errors are computed using 80 jackknife-replicate weights to account for the complex design of the survey. Of course, we cannot give a causal interpretation to the "returns" we estimate. However, we think it is useful to provide descriptive evidence about the strength of the association between tasks and wages, as well as the explanatory power of tasks indexes in wage regressions.

Human capital variables, as expected, have a strong influence on wages, and are able to explain (together with demographic variables), 43% of the variation in hourly wages. However, tasks measures also have a large impact, and, by themselves, explain 32% of the variance. Occupation dummies have a very similar explanatory power (as can be seen in column 3); however, after adjusting the degrees of freedom of the test statistic to account for the complex design of the survey, we are not able to reject the hypothesis that the estimated coefficients on occupation dummies are jointly equal to zero. Columns 4 and 5 show that tasks measures remain significant even when added in conjunction with human capital variables and occupation dummies, and that they are able to provide significant additional explanatory power. In particular, a one-standard deviation increase in the Abstract task index is associated with a 7% increase in hourly wage, an effect larger than that associated to a one-standard deviation increase in literacy skills (about 5%, given a standard deviation of literacy proficiency of 46.84). While performance of Routine tasks is not significantly associated with wages (after controlling for human capital variables), performance of Manual tasks carries a wage penalty of about 5%.

[TABLE 3] around here

Table A4 shows that the results reported above generally hold across all participating countries. The richest specification (equivalent to column 5 of Table 3) is able to explain between 39% (in Korea) and 57% (in England and Northern Ireland) of the variation in hourly wages. Returns to Abstract tasks are positive and statistically significant in all countries. However, the magnitude of estimated coefficients varies greatly, ranging from 2.5% in Sweden to 10.0% in Slovakia. Returns to Routine tasks are not statistically different from zero in most countries. Exceptions are Austria and the Nordic economiies, where small negative returns are detected. Returns to Manual tasks are negative and statistically significant everywhere, ranging from -2.4% in Sweden to -6.9% in Austria.

It is instructive to investigate what might drive the pronounced variation, noted above, across countries in the returns to Abstract tasks. We consider the results of a cross-country regression in which the dependent variable is the coefficient on the interaction between abstract tasks and country obtained from the final model of Table 3 augmented by these interaction terms. The explanatory variables are the respective country's Gini coefficient and the rate of collective bargaining coverage, obtained from the online OECD data set. The inverse standard errors of the dependent variable are used as weights. We hypothesise that, in comparison to other countries, the returns to Abstract tasks are higher in countries that have a wider income distribution, and lower in countries where unionisation is strong. The results, reported in Table 4, strongly support both hypotheses.

[TABLE 4] around here

*5.3 Testing the theoretical framework*

Our final empirical exercise involves replicating two tests proposed by AH. The first of these analyses the prediction that returns to tasks should be negatively correlated within occupations. The economic rationale is that, for example, occupations that have high returns to Abstract tasks should have low returns to Manual and Routine tasks. In other words, occupations have different levels (intensity of use) of tasks, so that the wage returns to specific tasks should be negatively related each other. Econometrically, the test is implemented in two steps. First, for each occupation separately, the wage of the worker is regressed on the task intensity. Next, the estimated coefficients (including the intercept) from the first step are regressed on one another. The model predicts that at least one estimated parameter from such second-stage, bivariate regression will be negative. The results obtained through this analysis are reported in Table 5, and indeed all estimated coefficients involving the intercepts have a negative sign. The predictions of the model are also confirmed in all participating countries (see Annex, table A5). Notice that, in the case of the United States, the signs of the various regression coefficients are the same as in AH, with the exception of the relationship between the intercept and returns to Routine tasks, which is negative in our data and positive in theirs.

[TABLE 5] around here

The second test conducted by AH (and replicated here) focuses on the hypothesis that workers positively self-select into occupations along at least one task dimension. The economic intuition is that workers select into occupations involving high intensity of tasks in which they are relatively able. The test is conducted by augmenting the Mincerian wage regression with interaction terms between individual task intensity and average task intensity at the occupation level. If is there positive self-selection (of the kind described above), then at least one of these interaction terms should be positive. The results are reported in Table 6, and they confirm that the predictions hold – see the strong, and statistically significant coefficient for the interactions presented in columns, without and with individual-level controls, respectively. The positive interaction terms reported here indicate (in accordance with theory) that workers who are more skilled at a given set of tasks do indeed self-select in occupations with high rewards for these tasks. Very similar results are obtained for all the countries individually, as reported in the Annex, Table A6.

[TABLE 6] around here

## 6. Conclusion

This paper extends and confirms the empirical results provided in Autor and Handel (2013) to a large set of 21 OECD countries that participated in the Survey of Adult Skills (PIAAC). The qualitative nature of the results proves to be remarkably similar across countries, thus lending considerable support to Autor and Handel's findings. Synthetic measures of tasks performed on the job (which can be interpreted as proxies for labour demand) have explanatory power and are significantly associated with earnings in traditional Mincerian wage regressions. This is true even after controlling for a wide set of individual control variables, including education, a measure of cognitive skills (literacy), and over a hundred occupation dummies, recorded at the three-digit ISCO level. There is a substantive wage premium associated with performing Abstract tasks, and a substantial wage penalty associated with performing Manual tasks; the association between wages and Routine tasks, on the other hand, is in most cases very close to zero and imprecisely estimated. The data also support two predictions of the theoretical framework illustrated in AH, namely a negative correlation of "returns" to tasks within occupations and a positive self-selection of workers into occupation that rewards differently the tasks in which workers have a comparative advantage. While the magnitude of estimated returns to tasks naturally varies across different countries, the qualitative picture is remarkably similar across all countries in our sample.

Our estimated returns to tasks cannot be given a causal interpretation; while the multi-country nature of the PIAAC data set offers considerable advantages, its cross-section nature precludes analysis of the kind undertaken on single countries (by Gottschalk et al. (2015) amongst others) that allows for comparison over time while also accommodating selection effects. However, the fact that we are able to confirm the results presented in AH using different data for a wide set of countries adds further empirical support to the usefulness of the so-called "task framework" in the analysis of labour markets. Future cycles of PIAAC will hopefully provide further data allowing the investigation of a broader set of issues, such as the evolution over time of the wage structure and how this relates to changing tasks compositions of jobs.

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**Table 1 Mean value of tasks measures, by occupation**

| | Abstract | Routine | Manual |
|---|---|---|---|
| Managers | 0.905 | -0.183 | -0.633 |
| Professionals | 0.494 | 0.142 | -0.433 |
| Technicians and associated professionals | 0.322 | 0.065 | -0.277 |
| Clerical support workers | -0.130 | 0.038 | -0.361 |
| Service and sales workers | -0.258 | 0.012 | 0.330 |
| Craft and related trade workers | -0.246 | 0.031 | 0.760 |
| Plant and machine operators, assemblers | -0.645 | -0.198 | 0.476 |
| Elementary occupations | -1.010 | -0.223 | 0.573 |

**Table 2 – Individual level correlates of tasks intensity**

| | Abstract | | Routine | | Manual | |
|---|---|---|---|---|---|---|
| Literacy | 0.003*** | 0.001*** | 0.001*** | 0.001*** | -0.004*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| High School | 0.390*** | 0.239*** | 0.171*** | 0.140*** | -0.133*** | -0.011 |
| | (0.027) | (0.024) | (0.037) | (0.037) | (0.022) | (0.021) |
| Above High School | 0.800*** | 0.378*** | 0.219*** | 0.161*** | -0.520*** | -0.175*** |
| | (0.028) | (0.028) | (0.034) | (0.038) | (0.022) | (0.025) |
| Female | -0.338*** | -0.325*** | 0.009 | -0.043* | -0.088*** | -0.029 |
| | (0.017) | (0.018) | (0.015) | (0.021) | (0.014) | (0.016) |
| Foreign-born | -0.219*** | -0.170*** | -0.074* | -0.059 | 0.003 | -0.023 |
| | (0.031) | (0.028) | (0.036) | (0.035) | (0.028) | (0.024) |
| Tenure | 0.017*** | 0.011*** | 0.005 | 0.004 | 0.004 | 0.006** |
| | (0.003) | (0.002) | (0.003) | (0.003) | (0.002) | (0.002) |
| $Tenure^2$ | -0.000** | -0.000*** | 0.000 | 0.000 | -0.000** | -0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Age | 0.009 | 0.003 | -0.007 | -0.003 | -0.005 | 0.002 |
| | (0.006) | (0.005) | (0.007) | (0.007) | (0.005) | (0.005) |
| $Age^2$ | -0.000* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Country FE | Y | Y | Y | Y | Y | Y |
| 113 Occupation FE | N | Y | N | Y | N | Y |
| $R^2$ | 0.226 | 0.349 | 0.050 | 0.077 | 0.216 | 0.384 |
| N | 64,352 | 64,352 | 64,352 | 64,352 | 64,352 | 64,352 |

Note: Jackknife-replicate standard errors in parentheses. All specifications include a constant and are weighted by final sampling weights. *: p-value<0.1, **: p-value<0.05, ***: p-value<0.01

**Table 3 – Augmented Mincerian wage regressions**

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Abstract tasks index | | 0.188*** | | 0.107*** | 0.070*** |
| | | (0.005) | | (0.004) | (0.004) |
| Routine tasks index | | 0.009* | | 0.001 | 0.002 |
| | | (0.004) | | (0.004) | (0.004) |
| Manual tasks index | | -0.125*** | | -0.075*** | -0.046*** |
| | | (0.005) | | (0.004) | (0.005) |
| Literacy | 0.003*** | | | 0.002*** | 0.001*** |
| | (0.000) | | | (0.000) | (0.000) |
| High school | 0.097*** | | | 0.046*** | 0.044*** |
| | (0.011) | | | (0.011) | (0.012) |
| Above high school | 0.402*** | | | 0.278*** | 0.171*** |
| | (0.014) | | | (0.014) | (0.014) |
| Female | -0.219*** | | | -0.189*** | -0.145*** |
| | (0.008) | | | (0.008) | (0.010) |
| Foreign-born | -0.024 | | | -0.001 | -0.007 |
| | (0.015) | | | (0.014) | (0.013) |
| Tenure | 0.024*** | | | 0.022*** | 0.020*** |
| | (0.001) | | | (0.001) | (0.001) |
| Tenure$^2$ | -0.000*** | | | -0.000*** | -0.000*** |
| | (0.000) | | | (0.000) | (0.000) |
| Age | 0.038*** | | | 0.037*** | 0.031*** |
| | (0.004) | | | (0.004) | (0.004) |
| Age$^2$ | -0.000*** | | | -0.000*** | -0.000*** |
| | (0.000) | | | (0.000) | (0.000) |
| | | | | | |
| F (task measures) | | 924.17 | | 392.89 | 135.07 |
| p-value | | (0.000) | | (0.000) | (0.000) |
| F (occupation dummies) | | | 8.90 | | 3.06 |
| p-value | | | (0.261) | | (0.431) |
| | | | | | |
| $R^2$ | 0.432 | 0.318 | 0.320 | 0.473 | 0.542 |
| N | 64,352 | 64,396 | 64,396 | 64,352 | 64,352 |

Note: In all specifications, the dependent variable is log hourly wage. Jackknife-replicate standard errors in parentheses. The F-statistics for the joint significance of subset of regressors are also adjusted to take into account the complex survey design. All specifications include a constant and are weighted by final sampling weights. *: p-value<0.1, **: p-value<0.05, ***: p-value<0.01

**Table 4 - Country-level institutional factors affecting returns to Abstract tasks**

| | Coeff. | St.Err. | t | P>t | Conf95% | |
|---|---|---|---|---|---|---|
| gini | 0.275 | 0.015 | 18.370 | 0.000 | 0.246 | 0.304 |
| collbar | -0.001 | 0.000 | -60.280 | 0.000 | -0.001 | -0.001 |
| constant | 0.013 | 0.005 | 2.490 | 0.013 | 0.003 | 0.023 |
| $R^2$ | 0.729 | | | | | |

Notes: **gini** is the specific country's Gini coefficient, while **collbar** is the rate of collective bargaining coverage. This is a cross-country regression in which the dependent variable is the coefficient of the return to abstract tasks (by country), and we include the interaction between abstract tasks and country obtained from the final model of Table 3 augmented by interaction terms.

**Table 5 - Co-variation of returns to tasks within occupations**

| | | dependent variable | |
|---|---|---|---|
| | b(Abstract) | b(Routine) | Intercept |
| b(Abstract) | | | -5.553*** |
| | | | (0.057) |
| *$R^2$* | | | *0.211* |
| b(Routine) | 0.106*** | | -14.885*** |
| | (0.008) | | (0.072) |
| *$R^2$* | *0.347* | | *0.466* |
| b(Manual) | 0.078*** | 0.181*** | -4.623*** |
| | (0.002) | (0.001) | (0.035) |
| *$R^2$* | *0.019* | *0.326* | *0.447* |

Note: N=113 in all specifications. Each regression is weighed by the sum of sampling weights in each occupation, and includes a constant (not reported). Standard errors in parentheses, $R^2$ in italics. *: p-value<0.1, **: p-value<0.05, ***: p-value<0.01

**Table 6 – Mincerian wage regressions augmented with interaction terms**

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Abstract tasks (individual) | 0.073*** | 0.073*** | 0.046*** | 0.047*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Routine tasks (individual) | 0.005* | 0.007** | 0.003 | 0.004 |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Manual tasks (individual) | -0.060*** | -0.052*** | -0.043*** | -0.037*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Abstract tasks (occupation mean) | 0.322*** | 0.307*** | 0.210*** | 0.201*** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| Routine tasks (occupation mean) | -0.302*** | -0.212*** | -0.161*** | -0.088* |
| | (0.042) | (0.047) | (0.041) | (0.045) |
| Manual tasks (occupation mean) | 0.035*** | 0.013 | -0.013 | -0.029*** |
| | (0.011) | (0.010) | (0.011) | (0.011) |
| Abstract tasks interaction | | 0.018*** | | 0.015*** |
| | | (0.005) | | (0.005) |
| Routine tasks interaction | | 0.058*** | | 0.045*** |
| | | (0.018) | | (0.017) |
| Manual tasks interaction | | 0.077*** | | 0.059*** |
| | | (0.007) | | (0.007) |
| Individual-level controls | N | N | Y | Y |
| Country FE | Y | Y | Y | Y |
| $R^2$ | 0.392 | 0.398 | 0.480 | 0.484 |
| N | 65,217 | 65,217 | 65,217 | 65,217 |

Note: The dependent variable is log hourly wage. Jackknife-replicate standard errors in parentheses. The F-statistics for the joint significance of interaction terms are also adjusted to take into account the complex survey design. The specification includes a constant (not reported here) and is weighted by final sampling weights. Individual level controls include: gender, immigrant status, and quadratic polynomials in age and in tenure on the job. *: p-value<0.1, **: p-value<0.05, ***: p-value<0.01

Table A1. Individual-level correlates of Abstract tasks intensity

| | Austria | Belgium | Canada | Czech Republic | Germany | Denmark | Spain | Estonia | Finland | France |
|---|---|---|---|---|---|---|---|---|---|---|
| Literacy | 0.002*** | 0.002** | 0.002*** | 0.002*** | 0.003*** | 0.002*** | 0.001** | 0.000 | 0.001** | 0.002*** |
| | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| High school | 0.184** | 0.118 | 0.096 | 0.042 | 0.116 | 0.150*** | 0.215*** | 0.207*** | 0.240*** | 0.158*** |
| | 0.063 | 0.061 | 0.050 | 0.102 | 0.075 | 0.043 | 0.055 | 0.048 | 0.065 | 0.041 |
| Above High School | 0.383*** | 0.371*** | 0.190*** | 0.235 | 0.351*** | 0.432*** | 0.380*** | 0.331*** | 0.312*** | 0.382*** |
| | 0.091 | 0.070 | 0.050 | 0.134 | 0.089 | 0.045 | 0.068 | 0.052 | 0.070 | 0.057 |
| Female | -0.406*** | -0.404*** | -0.293*** | -0.382*** | -0.339*** | -0.294*** | -0.311*** | -0.333*** | -0.261*** | -0.289*** |
| | 0.050 | 0.044 | 0.029 | 0.073 | 0.050 | 0.033 | 0.050 | 0.032 | 0.038 | 0.033 |
| Foreign-born | -0.024 | -0.063 | -0.105*** | -0.050 | -0.174*** | -0.122** | -0.130* | 0.071 | -0.034 | -0.146** |
| | 0.055 | 0.071 | 0.029 | 0.141 | 0.052 | 0.047 | 0.056 | 0.038 | 0.103 | 0.045 |
| Tenure | 0.007 | 0.015* | 0.009* | 0.014 | 0.013* | 0.003 | 0.015* | 0.002 | 0.005 | 0.005 |
| | 0.005 | 0.006 | 0.004 | 0.010 | 0.005 | 0.004 | 0.006 | 0.005 | 0.005 | 0.004 |
| $Tenure^2$ | -0.000 | -0.000* | -0.000 | -0.000 | -0.000 | 0.000 | -0.000 | 0.000 | -0.000 | 0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Age | 0.032* | 0.004 | 0.040*** | 0.012 | 0.022 | 0.041** | 0.017 | 0.015 | 0.024* | 0.028* |
| | 0.015 | 0.014 | 0.010 | 0.023 | 0.016 | 0.013 | 0.017 | 0.011 | 0.012 | 0.013 |
| $Age^2$ | -0.000** | -0.000 | -0.000*** | -0.000 | -0.000* | -0.000*** | -0.000 | -0.000** | -0.000* | -0.000** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Constant | -1.311*** | -0.566 | -1.144*** | -0.735 | -1.046** | -1.434*** | -1.072** | -0.364 | -0.663* | -1.232*** |
| | 0.357 | 0.326 | 0.263 | 0.505 | 0.402 | 0.315 | 0.340 | 0.250 | 0.277 | 0.300 |
| N | 2,358 | 2,304 | 13,001 | 2,103 | 2,548 | 3,705 | 2,110 | 3,354 | 2,710 | 2,924 |
| $R^2$ | 0.43 | 0.43 | 0.32 | 0.48 | 0.43 | 0.43 | 0.41 | 0.43 | 0.37 | 0.43 |

Table A1 (continued) Individual-level correlates of Abstract tasks intensity

| | United Kingdom | Ireland | Italy | Japan | Korea | Netherlands | Norway | Poland | Slovak Republic | Sweden | United States |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Literacy | 0.002*** | 0.002*** | 0.002** | 0.001** | 0.001 | 0.002*** | 0.002*** | 0.002** | 0.002*** | 0.002*** | 0.000 |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 |
| High school | 0.241*** | 0.169* | 0.218*** | 0.125* | 0.157** | 0.238*** | 0.140*** | 0.192* | 0.181*** | 0.170** | 0.393*** |
| | 0.062 | 0.069 | 0.056 | 0.058 | 0.059 | 0.049 | 0.037 | 0.075 | 0.047 | 0.058 | 0.097 |
| Above High School | 0.399*** | 0.465*** | 0.433*** | 0.287*** | 0.332*** | 0.476*** | 0.319*** | 0.541*** | 0.534*** | 0.211*** | 0.409*** |
| | 0.064 | 0.078 | 0.100 | 0.067 | 0.067 | 0.061 | 0.047 | 0.093 | 0.085 | 0.064 | 0.116 |
| Female | -0.203*** | -0.248*** | -0.223*** | -0.459*** | -0.300*** | -0.280*** | -0.369*** | -0.307*** | -0.269*** | -0.202*** | -0.278*** |
| | 0.047 | 0.046 | 0.057 | 0.045 | 0.047 | 0.038 | 0.033 | 0.051 | 0.050 | 0.038 | 0.045 |
| Foreign-born | -0.175** | -0.203*** | -0.182** | 0.682*** | -0.184 | -0.075 | -0.083 | -0.785 | 0.099 | -0.024 | -0.179** |
| | 0.067 | 0.052 | 0.069 | 0.164 | 0.116 | 0.075 | 0.049 | 0.448 | 0.118 | 0.062 | 0.066 |
| Tenure | 0.016* | 0.012 | -0.003 | 0.022*** | 0.004 | 0.008 | 0.016*** | 0.006 | 0.019** | -0.001 | 0.002 |
| | 0.007 | 0.007 | 0.008 | 0.005 | 0.006 | 0.005 | 0.005 | 0.006 | 0.006 | 0.005 | 0.006 |
| Tenure$^2$ | -0.000 | -0.000 | 0.000 | -0.000** | 0.000 | -0.000 | -0.001*** | -0.000 | -0.000* | 0.000 | -0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Age | 0.011 | 0.062*** | -0.003 | -0.002 | 0.023* | 0.049*** | 0.049*** | 0.004 | 0.053*** | 0.013 | -0.011 |
| | 0.016 | 0.016 | 0.022 | 0.011 | 0.012 | 0.013 | 0.010 | 0.014 | 0.015 | 0.012 | 0.013 |
| Age$^2$ | -0.000 | -0.001*** | 0.000 | -0.000 | -0.000** | -0.001*** | -0.001*** | -0.000 | -0.001*** | -0.000 | 0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Constant | -0.685 | -1.863*** | -0.799 | -0.464 | -0.839** | -1.836*** | -1.401*** | -0.885** | -2.253*** | -0.769** | 0.229 |
| | 0.365 | 0.378 | 0.503 | 0.288 | 0.281 | 0.323 | 0.254 | 0.341 | 0.346 | 0.295 | 0.304 |
| N | 4,018 | 2,350 | 1,533 | 2,764 | 2,557 | 2,496 | 2,544 | 2,224 | 2,115 | 2,365 | 2,269 |
| $R^2$ | 0.41 | 0.35 | 0.42 | 0.41 | 0.38 | 0.40 | 0.36 | 0.43 | 0.44 | 0.37 | 0.29 |

Table A2. Individual-level correlates of Routine tasks intensity

| | Austria | Belgium | Canada | Czech | Germany | Denmark | Spain | Estonia | Finland | France |
|---|---|---|---|---|---|---|---|---|---|---|
| Literacy | 0.002** | 0.001* | 0.001 | 0.001 | 0.001 | 0.001 | 0.002** | 0.001 | 0.001 | 0.002*** |
| | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 |
| High school | -0.053 | -0.018 | 0.123 | 0.135 | 0.118 | -0.008 | 0.011 | 0.111* | 0.200*** | 0.020 |
| | 0.083 | 0.070 | 0.072 | 0.109 | 0.106 | 0.052 | 0.056 | 0.054 | 0.058 | 0.048 |
| Above High School | -0.004 | -0.098 | 0.143* | 0.154 | 0.214 | 0.057 | 0.246*** | 0.091 | 0.272*** | 0.145* |
| | 0.095 | 0.082 | 0.071 | 0.127 | 0.121 | 0.070 | 0.066 | 0.062 | 0.071 | 0.070 |
| Female | -0.054 | -0.030 | -0.082* | -0.114 | -0.118* | 0.012 | -0.168*** | 0.004 | 0.046 | -0.151*** |
| | 0.051 | 0.051 | 0.033 | 0.076 | 0.059 | 0.048 | 0.046 | 0.042 | 0.040 | 0.035 |
| Foreign-born | 0.063 | -0.004 | 0.015 | 0.031 | 0.007 | -0.038 | -0.048 | -0.151** | -0.026 | -0.098 |
| | 0.064 | 0.090 | 0.040 | 0.147 | 0.064 | 0.048 | 0.066 | 0.059 | 0.102 | 0.056 |
| Tenure | 0.005 | 0.019** | 0.002 | 0.001 | 0.010 | -0.009 | -0.002 | 0.006 | 0.002 | 0.009 |
| | 0.008 | 0.007 | 0.005 | 0.009 | 0.008 | 0.006 | 0.008 | 0.005 | 0.007 | 0.005 |
| Tenure$^2$ | 0.000 | -0.000* | -0.000 | -0.000 | -0.000 | 0.000 | 0.000 | -0.000 | 0.000 | -0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Age | -0.012 | -0.016 | 0.011 | -0.009 | -0.024 | 0.014 | 0.010 | -0.013 | 0.015 | 0.005 |
| | 0.020 | 0.017 | 0.012 | 0.024 | 0.018 | 0.014 | 0.021 | 0.011 | 0.015 | 0.016 |
| Age$^2$ | 0.000 | 0.000 | -0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.000 | -0.000 | -0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Constant | -0.448 | -0.013 | -0.342 | -0.416 | 0.277 | -0.484 | -0.912* | 0.198 | -0.923* | -0.701 |
| | 0.472 | 0.376 | 0.256 | 0.548 | 0.437 | 0.352 | 0.445 | 0.258 | 0.386 | 0.362 |
| N | 2,358 | 2,304 | 13,001 | 2,103 | 2,548 | 3,705 | 2,110 | 3,354 | 2,710 | 2,924 |
| $R^2$ | 0.09 | 0.10 | 0.04 | 0.13 | 0.09 | 0.10 | 0.13 | 0.06 | 0.08 | 0.09 |

Table A2 (continued) Individual-level correlates of Routine tasks intensity

| | United Kingdom | Ireland | Italy | Japan | Korea | Netherlands | Norway | Poland | Slovak Republic | Sweden | United States |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Literacy | 0.002** | 0.002*** | 0.001 | 0.001 | 0.001 | 0.002** | -0.001 | 0.000 | 0.001 | 0.002*** | 0.001* |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| High school | 0.090 | 0.048 | 0.083 | 0.033 | 0.154 | 0.203*** | 0.063 | 0.086 | 0.321*** | -0.019 | 0.236* |
| | 0.075 | 0.088 | 0.068 | 0.080 | 0.095 | 0.059 | 0.051 | 0.125 | 0.086 | 0.066 | 0.109 |
| Above High School | 0.180* | 0.087 | 0.242* | 0.038 | 0.235* | 0.167* | 0.216*** | 0.108 | 0.357** | 0.066 | 0.163 |
| | 0.086 | 0.080 | 0.098 | 0.080 | 0.119 | 0.067 | 0.064 | 0.152 | 0.115 | 0.085 | 0.123 |
| Female | 0.044 | -0.123* | -0.036 | -0.025 | -0.125* | 0.033 | 0.032 | -0.172* | 0.001 | 0.064 | -0.002 |
| | 0.049 | 0.053 | 0.066 | 0.047 | 0.054 | 0.043 | 0.043 | 0.071 | 0.061 | 0.049 | 0.047 |
| Foreign-born | -0.049 | -0.053 | -0.106 | -0.595 | -0.388* | -0.092 | -0.122 | -0.151 | -0.139 | 0.009 | -0.039 |
| | 0.073 | 0.058 | 0.113 | 0.323 | 0.172 | 0.066 | 0.062 | 0.481 | 0.137 | 0.057 | 0.079 |
| Tenure | 0.014* | 0.029*** | 0.024* | -0.013* | 0.003 | 0.003 | 0.006 | 0.001 | 0.009 | -0.008 | 0.000 |
| | 0.007 | 0.007 | 0.011 | 0.005 | 0.011 | 0.006 | 0.007 | 0.007 | 0.008 | 0.006 | 0.008 |
| Tenure$^2$ | -0.000 | -0.001** | -0.001* | 0.000* | -0.000 | 0.000 | -0.000 | 0.000 | -0.000 | 0.000 | 0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Age | -0.012 | 0.010 | -0.004 | -0.018 | 0.030 | 0.020 | -0.020 | -0.002 | -0.017 | -0.006 | 0.002 |
| | 0.018 | 0.019 | 0.025 | 0.015 | 0.018 | 0.016 | 0.014 | 0.016 | 0.022 | 0.015 | 0.018 |
| Age$^2$ | 0.000 | -0.000 | -0.000 | 0.000 | -0.001* | -0.000 | 0.000 | -0.000 | 0.000 | 0.000 | -0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Constant | -0.247 | -0.595 | -0.441 | 0.330 | -0.686 | -0.960* | 0.678 | 0.017 | -0.180 | -0.441 | -0.383 |
| | 0.417 | 0.397 | 0.589 | 0.353 | 0.490 | 0.384 | 0.365 | 0.392 | 0.503 | 0.347 | 0.410 |
| N | 4,018 | 2,350 | 1,533 | 2,764 | 2,557 | 2,496 | 2,544 | 2,224 | 2,115 | 2,365 | 2,269 |
| $R^2$ | 0.09 | 0.12 | 0.17 | 0.10 | 0.13 | 0.10 | 0.11 | 0.11 | 0.14 | 0.10 | 0.09 |

Table A3. Individual-level correlates of Manual tasks intensity

| | Austria | Belgium | Canada | Czech | Germany | Denmark | Spain | Estonia | Finland | France |
|---|---|---|---|---|---|---|---|---|---|---|
| Literacy | -0.003*** | -0.003*** | -0.001*** | -0.000 | -0.002*** | -0.002*** | -0.002* | -0.001 | -0.002*** | -0.002*** |
| | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 |
| High school | -0.088 | -0.157** | 0.034 | -0.072 | 0.065 | 0.002 | -0.072 | -0.035 | 0.139 | -0.009 |
| | 0.056 | 0.054 | 0.047 | 0.085 | 0.067 | 0.051 | 0.058 | 0.049 | 0.075 | 0.042 |
| Above High School | -0.397*** | -0.452*** | -0.136** | -0.372*** | -0.122 | -0.254*** | -0.231*** | -0.197*** | -0.043 | -0.289*** |
| | 0.084 | 0.069 | 0.049 | 0.109 | 0.082 | 0.061 | 0.060 | 0.055 | 0.087 | 0.060 |
| Female | -0.004 | 0.039 | -0.037 | 0.180** | 0.013 | 0.019 | -0.059 | -0.024 | 0.110** | -0.080* |
| | 0.053 | 0.045 | 0.026 | 0.059 | 0.039 | 0.039 | 0.054 | 0.033 | 0.043 | 0.040 |
| Foreign-born | -0.041 | -0.081 | 0.070** | 0.178 | 0.015 | 0.015 | 0.043 | 0.022 | 0.087 | -0.061 |
| | 0.061 | 0.075 | 0.027 | 0.139 | 0.056 | 0.052 | 0.062 | 0.042 | 0.093 | 0.050 |
| Tenure | 0.005 | 0.000 | 0.004 | 0.001 | 0.006 | 0.000 | 0.014 | -0.002 | 0.007 | 0.004 |
| | 0.006 | 0.006 | 0.003 | 0.008 | 0.005 | 0.005 | 0.007 | 0.004 | 0.005 | 0.005 |
| $Tenure^2$ | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | 0.000 | -0.000 | -0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Age | -0.013 | 0.014 | 0.014 | 0.029 | -0.014 | -0.000 | 0.016 | 0.035*** | -0.002 | 0.000 |
| | 0.016 | 0.016 | 0.009 | 0.019 | 0.012 | 0.014 | 0.020 | 0.010 | 0.014 | 0.011 |
| $Age^2$ | 0.000 | -0.000 | -0.000 | -0.000 | 0.000 | 0.000 | -0.000 | -0.000*** | -0.000 | -0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Constant | 1.295*** | 0.732* | 0.263 | -0.420 | 0.882** | 0.794* | 0.209 | -0.329 | 0.316 | 0.517 |
| | 0.364 | 0.370 | 0.221 | 0.458 | 0.298 | 0.334 | 0.420 | 0.260 | 0.327 | 0.264 |
| N | 2,358 | 2,304 | 13,001 | 2,103 | 2,548 | 3,705 | 2,110 | 3,354 | 2,710 | 2,924 |
| $R^2$ | 0.44 | 0.48 | 0.37 | 0.43 | 0.48 | 0.36 | 0.37 | 0.39 | 0.44 | 0.44 |

Table A3 (continued) Individual-level correlates of Manual tasks intensity

| | United Kingdom | Ireland | Italy | Japan | Korea | Netherlands | Norway | Poland | Slovak Republic | Sweden | United States |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Literacy | -0.002** | -0.002*** | -0.000 | -0.002*** | 0.001 | -0.004*** | -0.002*** | -0.001*** | 0.000 | -0.002*** | -0.002*** |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 | 0.000 | 0.000 |
| High school | 0.080 | -0.022 | -0.133* | 0.003 | -0.121 | -0.050 | -0.078 | -0.018 | -0.028 | 0.017 | 0.031 |
| | 0.060 | 0.060 | 0.066 | 0.065 | 0.066 | 0.054 | 0.058 | 0.065 | 0.052 | 0.053 | 0.071 |
| Above High School | 0.004 | -0.177* | -0.447*** | -0.056 | -0.154* | -0.347*** | -0.321*** | -0.385*** | -0.358*** | -0.085 | -0.118 |
| | 0.077 | 0.071 | 0.090 | 0.065 | 0.073 | 0.061 | 0.071 | 0.094 | 0.080 | 0.072 | 0.076 |
| Female | 0.057 | -0.005 | -0.003 | -0.104* | 0.084 | 0.032 | 0.041 | -0.034 | 0.067 | 0.147*** | -0.041 |
| | 0.042 | 0.042 | 0.061 | 0.048 | 0.045 | 0.047 | 0.040 | 0.058 | 0.047 | 0.040 | 0.036 |
| Foreign-born | 0.064 | 0.105** | -0.040 | -0.878*** | -0.133 | -0.071 | 0.017 | -0.146 | 0.009 | 0.075 | -0.067 |
| | 0.056 | 0.040 | 0.076 | 0.178 | 0.105 | 0.071 | 0.052 | 0.245 | 0.122 | 0.048 | 0.051 |
| Tenure | 0.008 | -0.002 | 0.003 | 0.010* | -0.007 | -0.002 | 0.000 | -0.001 | -0.019** | -0.004 | 0.001 |
| | 0.007 | 0.007 | 0.011 | 0.005 | 0.007 | 0.006 | 0.006 | 0.005 | 0.006 | 0.005 | 0.006 |
| Tenure$^2$ | -0.000 | 0.000 | -0.000 | -0.000 | 0.000 | 0.000 | 0.000 | -0.000 | 0.001** | 0.000 | 0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Age | 0.005 | 0.015 | -0.040 | 0.016 | 0.010 | 0.003 | 0.010 | 0.022 | 0.019 | 0.004 | -0.004 |
| | 0.015 | 0.013 | 0.025 | 0.014 | 0.016 | 0.016 | 0.013 | 0.013 | 0.016 | 0.013 | 0.012 |
| Age$^2$ | -0.000 | -0.000 | 0.000 | -0.000* | -0.000 | -0.000 | -0.000 | -0.000* | -0.000 | -0.000 | 0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Constant | 0.314 | 0.687* | 1.077* | 0.042 | -0.426 | 0.967** | 0.300 | 0.429 | -0.183 | 0.312 | 0.935** |
| | 0.358 | 0.331 | 0.495 | 0.381 | 0.348 | 0.353 | 0.305 | 0.283 | 0.369 | 0.337 | 0.307 |
| N | 4,018 | 2,350 | 1,533 | 2,764 | 2,557 | 2,496 | 2,544 | 2,224 | 2,115 | 2,365 | 2,269 |
| $R^2$ | 0.29 | 0.32 | 0.40 | 0.32 | 0.14 | 0.40 | 0.45 | 0.56 | 0.42 | 0.52 | 0.37 |

Table A4. Augmented Mincerian wage regressions

| | Austria | Belgium | Canada | Czech | Germany | Denmark | Spain | Estonia | Finland | France |
|---|---|---|---|---|---|---|---|---|---|---|
| Abstract tasks | 0.053*** | 0.032*** | 0.063*** | 0.058*** | 0.062*** | 0.043*** | 0.063*** | 0.095*** | 0.058*** | 0.030*** |
| | 0.009 | 0.007 | 0.006 | 0.015 | 0.009 | 0.006 | 0.011 | 0.010 | 0.006 | 0.006 |
| Manual tasks | -0.072*** | -0.034*** | -0.046*** | -0.059*** | -0.065*** | -0.040*** | -0.051*** | -0.044*** | -0.038*** | -0.035*** |
| | 0.008 | 0.009 | 0.006 | 0.012 | 0.011 | 0.006 | 0.011 | 0.008 | 0.006 | 0.006 |
| Routine tasks | -0.020** | 0.002 | 0.000 | -0.006 | -0.002 | -0.011** | -0.005 | -0.003 | -0.014** | 0.004 |
| | 0.007 | 0.006 | 0.006 | 0.012 | 0.010 | 0.004 | 0.009 | 0.008 | 0.005 | 0.004 |
| Literacy | 0.001*** | 0.001*** | 0.001*** | 0.001* | 0.001*** | 0.001*** | 0.001* | 0.001** | 0.000** | 0.001*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| High School | 0.088*** | 0.037* | 0.015 | 0.056 | 0.032 | 0.020 | 0.094*** | -0.023 | 0.018 | 0.063*** |
| | 0.023 | 0.018 | 0.019 | 0.042 | 0.043 | 0.017 | 0.024 | 0.029 | 0.020 | 0.014 |
| Above high school | 0.187*** | 0.157*** | 0.118*** | 0.224*** | 0.114* | 0.082*** | 0.192*** | 0.076* | 0.057** | 0.139*** |
| | 0.032 | 0.024 | 0.023 | 0.053 | 0.046 | 0.019 | 0.027 | 0.030 | 0.022 | 0.019 |
| Female | -0.132*** | -0.056*** | -0.114*** | -0.150*** | -0.117*** | -0.048*** | -0.124*** | -0.227*** | -0.094*** | -0.080*** |
| | 0.017 | 0.014 | 0.012 | 0.026 | 0.018 | 0.011 | 0.021 | 0.022 | 0.011 | 0.013 |
| Foreign-born | -0.062** | -0.041 | -0.024 | -0.005 | 0.002 | -0.056*** | -0.068* | -0.082** | -0.018 | -0.024 |
| | 0.021 | 0.024 | 0.014 | 0.055 | 0.024 | 0.014 | 0.027 | 0.030 | 0.036 | 0.015 |
| Tenure | 0.007** | 0.012*** | 0.018*** | 0.015*** | 0.021*** | 0.008*** | 0.015*** | 0.003 | 0.007*** | 0.006*** |
| | 0.002 | 0.002 | 0.002 | 0.003 | 0.002 | 0.001 | 0.003 | 0.003 | 0.002 | 0.001 |
| $Tenure^2$ | 0.000 | -0.000** | -0.000*** | -0.000* | -0.000*** | -0.000*** | -0.000 | -0.000 | -0.000* | -0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Age | 0.018** | 0.023*** | 0.031*** | 0.001 | 0.031*** | 0.027*** | 0.033*** | 0.008 | 0.029*** | 0.018*** |
| | 0.007 | 0.006 | 0.005 | 0.008 | 0.007 | 0.003 | 0.010 | 0.006 | 0.004 | 0.005 |
| $Age^2$ | -0.000* | -0.000** | -0.000*** | -0.000 | -0.000*** | -0.000*** | -0.000** | -0.000* | -0.000*** | -0.000** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Constant | 2.088*** | 2.066*** | 1.800*** | 1.827*** | 1.767*** | 2.311*** | 1.569*** | 1.959*** | 2.109*** | 1.968*** |
| | 0.155 | 0.126 | 0.112 | 0.197 | 0.167 | 0.081 | 0.199 | 0.136 | 0.101 | 0.095 |
| N | 2,358 | 2,304 | 13,001 | 2,103 | 2,548 | 3,705 | 2,110 | 3,354 | 2,710 | 2,924 |
| $R^2$ | 0.52 | 0.43 | 0.51 | 0.47 | 0.53 | 0.43 | 0.50 | 0.45 | 0.56 | 0.50 |

Table A4 (continued) Augmented Mincerian wage regressions

| | United Kingdom | Ireland | Italy | Japan | Korea | Netherlands | Norway | Poland | Slovak Republic | Sweden | United States |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Abstract tasks | 0.074*** | 0.039*** | 0.059*** | 0.091*** | 0.049** | 0.054*** | 0.033*** | 0.073*** | 0.096*** | 0.025*** | 0.069*** |
| | 0.009 | 0.009 | 0.012 | 0.011 | 0.016 | 0.007 | 0.006 | 0.013 | 0.013 | 0.006 | 0.009 |
| Manual tasks | -0.040*** | -0.045*** | -0.032* | -0.037*** | -0.038*** | -0.047*** | -0.046*** | -0.070*** | -0.045*** | -0.024*** | -0.054*** |
| | 0.008 | 0.011 | 0.015 | 0.009 | 0.011 | 0.008 | 0.006 | 0.020 | 0.013 | 0.006 | 0.014 |
| Routine tasks | -0.009 | 0.011 | 0.027 | -0.004 | 0.009 | -0.008 | -0.015* | -0.015 | 0.018 | -0.011* | 0.016 |
| | 0.006 | 0.009 | 0.014 | 0.008 | 0.011 | 0.006 | 0.006 | 0.011 | 0.010 | 0.005 | 0.010 |
| Literacy | 0.001*** | 0.001** | 0.000 | 0.001*** | 0.001* | 0.001** | 0.000** | 0.001** | 0.001*** | 0.001*** | 0.001*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| High School | 0.033 | 0.042 | 0.041 | -0.032 | 0.101** | 0.032 | 0.039** | 0.050 | 0.065 | -0.001 | 0.123** |
| | 0.018 | 0.029 | 0.029 | 0.033 | 0.039 | 0.016 | 0.015 | 0.043 | 0.038 | 0.015 | 0.040 |
| Above high school | 0.160*** | 0.177*** | 0.167*** | 0.045 | 0.258*** | 0.171*** | 0.114*** | 0.215*** | 0.268*** | 0.032 | 0.281*** |
| | 0.023 | 0.032 | 0.039 | 0.036 | 0.046 | 0.024 | 0.017 | 0.054 | 0.047 | 0.019 | 0.050 |
| Female | -0.129*** | -0.056** | -0.090*** | -0.256*** | -0.180*** | -0.067*** | -0.076*** | -0.151*** | -0.191*** | -0.059*** | -0.127*** |
| | 0.018 | 0.019 | 0.025 | 0.024 | 0.035 | 0.015 | 0.013 | 0.028 | 0.023 | 0.012 | 0.027 |
| Foreign-born | 0.037 | -0.081*** | -0.064 | 0.301 | -0.165* | -0.071** | -0.062*** | 0.119 | -0.043 | 0.008 | 0.033 |
| | 0.022 | 0.022 | 0.033 | 0.203 | 0.084 | 0.024 | 0.015 | 0.142 | 0.076 | 0.014 | 0.029 |
| Tenure | 0.012*** | 0.027*** | 0.013*** | 0.024*** | 0.029*** | 0.008*** | 0.008*** | 0.010** | 0.004 | 0.003* | 0.026*** |
| | 0.003 | 0.003 | 0.004 | 0.002 | 0.004 | 0.002 | 0.002 | 0.003 | 0.003 | 0.002 | 0.003 |
| $Tenure^2$ | -0.000* | -0.000*** | -0.000 | -0.000*** | -0.000 | -0.000 | -0.000*** | -0.000 | -0.000 | -0.000 | -0.001*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Age | 0.044*** | 0.040*** | 0.044*** | 0.031*** | 0.022* | 0.040*** | 0.026*** | 0.027** | 0.012 | 0.015*** | 0.034*** |
| | 0.006 | 0.008 | 0.011 | 0.007 | 0.011 | 0.004 | 0.004 | 0.010 | 0.009 | 0.004 | 0.009 |
| $Age^2$ | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000 | -0.000*** | -0.000*** | -0.000** | -0.000 | -0.000** | -0.000** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Constant | 1.358*** | 1.651*** | 1.478*** | 1.554*** | 1.734*** | 1.817*** | 2.376*** | 1.174*** | 1.318*** | 2.321*** | 1.499*** |
| | 0.143 | 0.174 | 0.257 | 0.159 | 0.230 | 0.103 | 0.100 | 0.209 | 0.205 | 0.085 | 0.198 |
| N | 4,018 | 2,350 | 1,533 | 2,764 | 2,557 | 2,496 | 2,544 | 2,224 | 2,115 | 2,365 | 2,269 |
| $R^2$ | 0.57 | 0.50 | 0.41 | 0.54 | 0.39 | 0.49 | 0.49 | 0.45 | 0.40 | 0.48 | 0.56 |

Table A5 – Co-variation between returns to tasks within occupations

| | Austria | Belgium | Canada | Czech Republic | Germany | Denmark | Spain | Estonia | Finland | France | United Kingdom |
|---|---|---|---|---|---|---|---|---|---|---|---|
| b(Abstract)/b(Routine) | 0.499*** | 0.682*** | 0.003 | 2.507*** | 0.049 | -1.174*** | 0.487*** | -0.289*** | -1.050*** | 0.511*** | -0.516*** |
| | (0.023) | (0.012) | (0.031) | (0.070) | (0.031) | (0.026) | (0.008) | (0.022) | (0.078) | (0.014) | (0.047) |
| *$R^2$* | *0.154* | *0.291* | *0.000* | *0.434* | *0.001* | *0.383* | *0.211* | *0.050* | *0.125* | *0.264* | *0.036* |
| b(Abstract)/b(Manual) | -0.017 | -0.362*** | -0.224*** | -0.239*** | 0.124*** | -0.400*** | 0.002 | 0.120*** | -0.230*** | 0.222*** | -0.312*** |
| | (0.013) | (0.016) | (0.002) | (0.008) | (0.013) | (0.008) | (0.019) | (0.004) | (0.014) | (0.008) | (0.010) |
| *$R^2$* | *0.001* | *0.080* | *0.267* | *0.137* | *0.026* | *0.246* | *0.000* | *0.189* | *0.067* | *0.222* | *0.266* |
| b(Routine)/b(Manual) | 0.126*** | 0.138*** | 0.094*** | 0.017*** | -0.381*** | 0.056*** | -0.294*** | -0.008*** | -0.082*** | 0.333*** | 0.054*** |
| | (0.007) | (0.013) | (0.001) | (0.004) | (0.009) | (0.007) | (0.020) | (0.003) | (0.006) | (0.005) | (0.005) |
| *$R^2$* | *0.078* | *0.019* | *0.363* | *0.010* | *0.418* | *0.018* | *0.140* | *0.001* | *0.075* | *0.492* | *0.059* |
| Intercept/b(Abstract) | -1.512*** | -4.191*** | -2.929*** | -1.939*** | -1.913*** | 2.510*** | -3.051*** | 4.148*** | 5.243*** | -7.211*** | -2.037*** |
| | (0.213) | (0.067) | (0.121) | (0.169) | (0.265) | (0.080) | (0.178) | (0.122) | (0.068) | (0.197) | (0.172) |
| *$R^2$* | *0.028* | *0.737* | *0.086* | *0.082* | *0.061* | *0.183* | *0.237* | *0.261* | *0.644* | *0.416* | *0.055* |
| Intercept/b(Manual) | -3.670*** | -4.458*** | -5.750*** | -8.941*** | -3.383*** | -1.513*** | -6.168*** | -3.657*** | -2.536*** | -7.336*** | -15.150*** |
| | (0.192) | (0.057) | (0.118) | (0.581) | (0.240) | (0.183) | (0.052) | (0.170) | (0.427) | (0.168) | (0.423) |
| *$R^2$* | *0.103* | *0.521* | *0.044* | *0.120* | *0.111* | *0.018* | *0.860* | *0.121* | *0.017* | *0.436* | *0.410* |
| Intercept/b(Routine) | -4.114*** | 0.475*** | -1.163*** | -2.033*** | 0.349*** | -1.301*** | 1.859*** | -0.403*** | -3.619*** | -4.168*** | -2.290*** |
| | (0.078) | (0.116) | (0.022) | (0.078) | (0.121) | (0.065) | (0.106) | (0.037) | (0.095) | (0.038) | (0.052) |
| *$R^2$* | *0.635* | *0.006* | *0.072* | *0.215* | *0.003* | *0.114* | *0.126* | *0.032* | *0.392* | *0.625* | *0.188* |

Note: Each cell reports the results of a separate regression of estimated returns to tasks on one another. Each regression is weighted by the sum of sampling weights in each occupation, and includes a constant (not reported). Standard errors in parentheses, $R^2$ in italics. *: p-value<0.1, **: p-value<0.05, ***: p-value<0.01

Table A5 (continued) – Co-variation between returns to tasks within occupations

| | Ireland | Italy | Japan | Korea | Netherlands | Norway | Poland | Slovak Republic | Sweden | United States |
|---|---|---|---|---|---|---|---|---|---|---|
| b(Abstract)/b(Routine) | 0.766*** | -0.655*** | 0.015 | 1.679*** | -0.218*** | 0.040*** | 1.913*** | -0.258*** | 0.629*** | 0.945*** |
| | (0.015) | (0.052) | (0.042) | (0.033) | (0.019) | (0.016) | (0.060) | (0.031) | (0.023) | (0.021) |
| $R^2$ | 0.269 | 0.091 | 0.000 | 0.388 | 0.049 | 0.002 | 0.273 | 0.032 | 0.230 | 0.377 |
| b(Abstract)/b(Manual) | -0.200*** | 0.588*** | 0.056*** | -0.141*** | -0.062*** | -0.071*** | 0.257*** | -0.003 | -0.414*** | -0.042*** |
| | (0.128) | (0.020) | (0.017) | (0.021) | (0.009) | (0.010) | (0.022) | (0.035) | (0.011) | (0.008) |
| $R^2$ | 0.061 | 0.312 | 0.004 | 0.015 | 0.018 | 0.013 | 0.110 | 0.000 | 0.304 | 0.013 |
| b(Routine)/b(Manual) | -0.091*** | 0.102*** | 0.243*** | 0.053*** | 0.178*** | 0.088*** | -0.025*** | -0.200*** | 0.225*** | -0.071*** |
| | (0.011) | (0.014) | (0.008) | (0.010) | (0.007) | (0.009) | (0.003) | (0.018) | (0.007) | (0.003) |
| $R^2$ | 0.027 | 0.045 | 0.226 | 0.015 | 0.144 | 0.017 | 0.014 | 0.059 | 0.154 | 0.087 |
| Intercept/b(Abstract) | -3.827*** | 1.463*** | -4.497*** | -2.106*** | -5.418*** | 4.054*** | -4.590*** | 0.204*** | 2.129*** | -5.577*** |
| | (0.228) | (0.114) | (0.109) | (0.112) | (0.111) | (0.121) | (0.088) | (0.029) | (0.084) | (0.243) |
| $R^2$ | 0.137 | 0.057 | 0.289 | 0.214 | 0.494 | 0.282 | 0.563 | 0.004 | 0.232 | 0.212 |
| Intercept/b(Manual) | -14.029*** | -4.015*** | -2.877*** | -9.791*** | -0.412*** | -5.141*** | -10.030*** | 2.700*** | -2.554*** | 1.919*** |
| | (0.097) | (0.360) | (0.211) | (0.095) | (0.138) | (0.100) | (0.735) | (0.102) | (0.108) | (0.323) |
| $R^2$ | 0.846 | 0.091 | 0.038 | 0.635 | 0.003 | 0.552 | 0.200 | 0.295 | 0.194 | 0.011 |
| Intercept/b(Routine) | 0.729*** | -2.716*** | -5.478*** | -2.184*** | -1.747*** | -1.390*** | -1.774*** | -1.377*** | -3.126*** | -3.157*** |
| | (0.125) | (0.150) | (0.121) | (0.081) | (0.062) | (0.064) | (0.074) | (0.068) | (0.137) | (0.092) |
| $R^2$ | 0.008 | 0.178 | 0.532 | 0.170 | 0.239 | 0.087 | 0.139 | 0.113 | 0.887 | 0.496 |

Note: Each cell reports the results of a separate regression of estimated returns to tasks on one another. Each regression is weighted by the sum of sampling weights in each occupation, and includes a constant (not reported). Standard errors in parentheses, $R^2$ in italics. *: p-value<0.1, **: p-value<0.05, ***: p-value<0.01

Table A6 – Mincerian wage regressions augmented with interaction terms

| | Austria | Belgium | Canada | Czech Republic | Germany | Denmark | Spain | Estonia | Finland | France | United Kingdom |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Abstract tasks (individual) | 0.066*** | 0.031*** | 0.071*** | 0.063*** | 0.079*** | 0.053*** | 0.078*** | 0.110*** | 0.047*** | 0.034*** | 0.073*** |
| | (0.006) | (0.005) | (0.004) | (0.010) | (0.007) | (0.004) | (0.008) | (0.007) | (0.006) | (0.005) | (0.006) |
| Routine tasks (individual) | -0.001 | 0.001 | -0.003 | -0.010 | 0.009 | -0.004 | 0.008 | 0.021 | -0.014** | 0.003 | -0.001 |
| | (0.010) | (0.006) | (0.007) | (0.025) | (0.008) | (0.004) | (0.009) | (0.013) | (0.007) | (0.006) | (0.007) |
| Manual tasks (individual) | -0.069*** | -0.034*** | -0.057*** | -0.071*** | -0.061*** | -0.050*** | -0.044*** | -0.052*** | -0.033*** | -0.013** | -0.070*** |
| | (0.007) | (0.007) | (0.006) | (0.014) | (0.009) | (0.005) | (0.010) | (0.010) | (0.006) | (0.006) | (0.010) |
| Abstract tasks (occupation mean) | 0.128*** | 0.121*** | 0.263*** | 0.217*** | 0.226*** | 0.082*** | 0.333*** | 0.303*** | 0.107*** | 0.243*** | 0.292*** |
| | (0.019) | (0.018) | (0.016) | (0.027) | (0.029) | (0.014) | (0.040) | (0.027) | (0.014) | (0.015) | (0.022) |
| Routine tasks (occupation mean) | 0.301*** | -0.009 | 0.025 | 0.087 | -0.017 | -0.062** | -0.228** | 0.022 | -0.355*** | -0.256*** | -0.304*** |
| | (0.061) | (0.052) | (0.054) | (0.099) | (0.057) | (0.029) | (0.094) | (0.093) | (0.053) | (0.048) | (0.069) |
| Manual tasks (occupation mean) | -0.067*** | -0.007 | 0.014 | 0.183*** | 0.016 | -0.026 | 0.090*** | 0.195*** | -0.051*** | 0.025* | -0.058* |
| | (0.025) | (0.022) | (0.021) | (0.045) | (0.032) | (0.021) | (0.028) | (0.037) | (0.015) | (0.015) | (0.034) |
| Abstract tasks interaction | 0.026*** | -0.015** | 0.004 | 0.022** | 0.024*** | 0.020*** | 0.008 | 0.033*** | 0.028*** | 0.002 | 0.026*** |
| | (0.008) | (0.007) | (0.007) | (0.010) | (0.009) | (0.006) | (0.010) | (0.010) | (0.033) | (0.005) | (0.007) |
| Routine tasks interaction | 0.026 | 0.011 | 0.042 | -0.040 | -0.007 | 0.021 | -0.023 | -0.064 | -0.024 | -0.016 | 0.009 |
| | (0.034) | (0.026) | (0.028) | (0.053) | (0.032) | (0.019) | (0.027) | (0.046) | (0.032) | (0.015) | (0.026) |
| Manual tasks interaction | 0.034*** | 0.017 | 0.067*** | 0.057** | 0.033** | 0.037*** | 0.029** | 0.139*** | 0.046*** | 0.046*** | 0.113*** |
| | (0.012) | (0.011) | (0.013) | (0.027) | (0.013) | (0.011) | (0.015) | (0.018) | (0.010) | (0.008) | (0.026) |
| $R^2$ | 0.352 | 0.2275 | 0.2889 | 0.2821 | 0.333 | 0.252 | 0.293 | 0.254 | 0.376 | 0.334 | 0.390 |
| N | 2371 | 2315 | 13236 | 2123 | 2555 | 3757 | 2113 | 3375 | 2723 | 3150 | 4041 |

Note: In all specifications, the dependent variable is log hourly wage. Jackknife-replicate standard errors in parentheses. All specifications include a constant and are weighted by final sampling weights. Individual level controls include: gender, immigrant status, and quadratic polynomials in age and in tenure on the job. *: p-value<0.1, **: p-value<0.05, ***: p-value<0.01

Table A6 (continued) – Mincerian wage regressions augmented with interaction terms

| | Ireland | Italy | Japan | Korea | Netherlands | Norway | Poland | Slovak Republic | Sweden | United States |
|---|---|---|---|---|---|---|---|---|---|---|
| Abstract tasks (individual) | 0.053*** | 0.061*** | 0.114*** | 0.090*** | 0.055*** | 0.053*** | 0.084*** | 0.101*** | 0.030*** | 0.055*** |
| | (0.007) | (0.010) | (0.008) | (0.010) | (0.005) | (0.005) | (0.010) | (0.010) | (0.005) | (0.009) |
| Routine tasks (individual) | 0.027*** | 0.025** | -0.000 | 0.006 | -0.007 | -0.008 | -0.017 | 0.019** | -0.013*** | 0.001 |
| | (0.009) | (0.013) | (0.015) | (0.009) | (0.006) | (0.005) | (0.014) | (0.008) | (0.005) | (0.014) |
| Manual tasks (individual) | -0.081*** | -0.037*** | -0.004 | -0.076*** | -0.039*** | -0.028*** | -0.081*** | -0.085*** | -0.026*** | -0.148*** |
| | (0.012) | (0.012) | (0.016) | (0.021) | (0.007) | (0.007) | (0.015) | (0.012) | (0.006) | (0.015) |
| Abstract tasks (occupation mean) | 0.094** | 0.382*** | 0.299*** | 0.600*** | 0.158*** | 0.179*** | 0.132*** | 0.147*** | 0.225*** | 0.283*** |
| | (0.038) | (0.047) | (0.018) | (0.044) | (0.017) | (0.017) | (0.042) | (0.035) | (0.024) | (0.029) |
| Routine tasks (occupation mean) | 0.498*** | -0.533*** | -0.239*** | -0.633*** | 0.014 | -0.005 | -0.265* | -0.209*** | -0.210*** | 0.022 |
| | (0.089) | (0.092) | (0.068) | (0.080) | (0.047) | (0.030) | (0.139) | (0.064) | (0.047) | (0.069) |
| Manual tasks (occupation mean) | 0.093** | -0.001 | 0.148*** | 0.189*** | -0.045** | 0.012 | -0.125** | -0.074 | 0.108*** | -0.302*** |
| | (0.041) | (0.037) | (0.027) | (0.056) | (0.020) | (0.015) | (0.054) | (0.057) | (0.024) | (0.048) |
| Abstract tasks interaction | 0.023** | 0.018 | 0.011 | -0.024 | -0.000 | 0.015* | 0.007 | 0.002 | 0.018** | 0.028** |
| | (0.010) | (0.012) | (0.012) | (0.017) | (0.008) | (0.009) | (0.013) | (0.011) | (0.007) | (0.013) |
| Routine tasks interaction | -0.050** | 0.014 | 0.019 | 0.016 | 0.036 | -0.033* | -0.056 | 0.006 | -0.030 | 0.051 |
| | (0.025) | (0.030) | (0.038) | (0.020) | (0.028) | (0.019) | (0.060) | (0.022) | (0.022) | (0.044) |
| Manual tasks interaction | 0.009 | 0.040** | 0.058*** | 0.000 | 0.049*** | 0.041*** | 0.118*** | 0.116*** | 0.046*** | 0.210*** |
| | (0.032) | (0.018) | (0.019) | (0.051) | (0.011) | (0.009) | (0.024) | (0.023) | (0.008) | (0.031) |
| $R^2$ | 0.294 | 0.0223 | 0.332 | 0.205 | 0.335 | 0.298 | 0.289 | 0.243 | 0.294 | 0.332 |
| N | 2356 | 1534 | 2766 | 2681 | 2519 | 2551 | 2247 | 2128 | 2403 | 2273 |

Note: In all specifications, the dependent variable is log hourly wage. Jackknife-replicate standard errors in parentheses. All specifications include a constant and are weighted by final sampling weights. Individual level controls include: gender, immigrant status, and quadratic polynomials in age and in tenure on the job. *: p-value<0.1, **: p-value<0.05, ***: p-value<0.01