Firm Size and the Task Content of Jobs: Evidence from 46 Countries*

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Abstract

Using a mix of household- and employer-based survey data from 46 countries, we provide novel evidence that workers in larger firms perform more non-routine analytical and routine cognitive tasks, even within narrowly defined occupations. Moreover, workers in larger firms rely more on the use of information and communication technologies (ICT) to perform these tasks. We also document a 10–20% wage premium that workers in larger firms enjoy relative to their counterparts in smaller firms. A mediation analysis shows that our novel empirical facts on the task content of jobs are able to explain between 5–20% of the large firm wage premium, a similar fraction to what can be explained by selection of workers on education, gender, and age.

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1 Introduction

Empirical studies show that the task composition of jobs can explain a large share of the dispersion of wages across occupations and time (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Handel, 2013; Goos et al., 2014; Acemoglu and Restrepo, 2021). Most studies are, however, constrained by the fact that direct measures of the task content of jobs are not available in standard data sets. To overcome this limitation, authors typically resort to imputing the task content of occupations by means of alternative data sets such as the Occupation Information Network (O*NET) or the European Working Conditions Survey (EWCS). The use of these general task classifications relies on the implied assumption that the task composition of jobs under the same occupation is homogeneous. This strategy therefore rules out the possibility that heterogeneity in tasks drives within-occupation wage differences.

In this paper, we explore whether the assumption of homogeneity in the task composition of jobs within occupations holds empirically. To do this, we focus on a natural and relevant dimension along which the task content of a given occupation might vary: firm size. Firm size is meaningful because it is a simple statistic that strongly correlates with total factor productivity and managerial quality both theoretically (Lucas, 1978) and empirically (Bloom and Van Reenen, 2007). Larger firms also tend to use more automation and offshoring (Alekseeva et al., 2021). Given this gradient in how production is organized, the task content of jobs in firms of different sizes is likely to also differ (Ocampo, 2022). These differences in the task content of jobs have concrete implications on the compensation of workers and may explain part of the so-called large-firm wage premium.

Our main result is that the assumption of homogeneity in the task composition of jobs within occupations does not hold empirically. In particular, we find that, even *within* narrowly defined occupations, there are systematic differences in the task intensities performed by workers employed by firms of different sizes. We document that the intensity of non-routine analytical and routine cognitive tasks of workers in larger firms are, on average, 5–15% of a standard deviation higher. The size of this gap is comparable in magnitude to the gap present between the countries at the two extremes of the development spectrum, as documented by Caunedo et al. (2023). Moreover, we find that, to undertake these tasks, workers in larger firms rely significantly more on information and communication technologies (ICT). We interpret this result as indicative that workers in larger firms perform more non-routine analytical and routine cognitive tasks through increased use in ICT. These empirical patterns are robust to using both employer- and employee-based responses and are widely present across the comprehensive set of 46 high-, middle-, and low-income countries that we study after combining two large and representative data sets: the OECD Survey of Adult Skills and the World Bank Skills Measurement Surveys. Furthermore, we provide evidence that our finding is not only true for the average worker: the distributions of the intensity of performed tasks in larger firms are also horizontally shifted relative to smaller firms.

Though we acknowledge that we cannot rule out that the estimated gaps are partly confounded by selection of workers into firms of different sizes, it is reassuring that our main results hold after controlling for a rich set of observable worker characteristics including education, cognitive and non-cognitive skills, and industry of employment. Moreover, following Oster (2019), we find that selection on unobservables would have to be *at least* as large as selection on observables for our estimated firm size gradients in task content to be statistically indistinguishable from zero.

To the best of our knowledge, this is the first paper to highlight that tasks performed by workers in the same occupation differ according to whether they are employed by a large or a small firm. This result contributes to the recent literature documenting the heterogeneity in task content within occupations (e.g., Deming and Kahn, 2018; Stinebrickner et al., 2019), which has emphasized the role of dimensions other than firm size. Atalay et al. (2021) show that the variation in tasks is correlated with city size such that larger cities have higher intensity of analytical and interactive tasks, more technological requirements, and increased task specialization. Additionally, a number of papers report that occupational task content varies across countries (Dicarlo et al., 2016; Lewandowski et al., 2019; De La Rica et al., 2020; Caunedo et al., 2023).

Our results on the firm-size heterogeneity of tasks provide novel foundations to understand firm productivity and its dynamics. Our findings are consistent with the implications of static models that endogenize the firms' decisions on how to allocate tasks for production (Ocampo, 2022; Adenbaum, 2022). For instance, Ocampo (2022) shows that automation may affect the task composition of occupations. Along with finding that workers in larger firms use more ICT, we also document that they perform more non-routine analytical and routine cognitive tasks compared to workers in smaller firms. The mechanisms by which these task differences in the content of jobs across firm size emerge in a dynamic economy remain unknown. It may be that as firms grow larger, they accumulate more capital, automate, and offshore jobs which leads to changes in the task requirements of production. In particular, jobs may evolve to focus on non-routine analytical or routine cognitive tasks and to use more ICT so as to complement the processes that aim to replace routine tasks. This is consistent not only with our results, but also with the static theoretical framework of Ocampo (2022) and additional empirical evidence that de-routinization of jobs is driven by larger incumbent firms (Jaimovich et al., 2023). Future work exploring this mechanism may provide novel insights to understand the drivers of firm dynamics.

Moreover, the uncovered patterns on task heterogeneity connect naturally with the literature exploring the determinants of within-occupation wage dispersion and provide a plausible novel driver of the large firm wage premium (LFWP) — the empirical fact that larger firms tend to pay their workers more for doing the same occupation. We explore the implications of the firm-size gradient in occupational task intensities on wage determination in two steps. First, we document that, on average, workers in larger firms earn about 10–20% more than their counterparts in smaller firms, after controlling for 2-digit occupation codes. Our measured large firm wage premium is consistent with the existence of a large and economically significant LFWP found in other studies employing alternative data sets (Velenchik, 1997; Gerlach and Hübler, 1998; Schaffner, 1998; Troske, 1999; Winter-Ebmer, 2001; Dobbelaere, 2004; Söderbom et al., 2005; Lehmer and Möller, 2010; Bloom et al., 2018; Colonnelli et al., 2018; Reed and Thu, 2019; Lochner et al., 2020; Porcher et al., 2021). Moreover, we extend previous analyses to show that this is not driven exclusively by a few workers in larger firms that are paid disproportionately more. Rather, the distribution of wages in larger firms is shifted to the right compared to the distribution of wages in smaller firms.

Second, we conduct a mediation analysis to provide suggestive evidence on the sources of this large firm wage premium, including our novel finding that task composition varies across firms of differing sizes. A number of explanations for the existence of the LFWP have been proposed (Brown and Medoff, 1989; Oi and Idson, 1999): (i) large firms hire more skilled workers (worker selection); (ii) large firms have worse working conditions (compensating differentials); (iii) large firms have market power and share rents with workers (productivity); (iv) large firms have higher costs of monitoring and pay efficiency wages; and (v) large firms pay higher because of threat of unionization. In this paper, we explore the firm size gradient in occupational task intensities as a complementary source of the LFWP. We find that this mechanism is able to explain over 10% of the raw LFWP. This proportion ranges from 5 to 20% across the countries in our sample. Our novel empirical pattern therefore accounts for an economically significant fraction of the LFWP that is comparable to the share explained by the sorting of higher educated individuals into larger firms.

These results open an exciting research avenue to explore the consequences of the firm size gradient in the task content of jobs on dynamic wage determination. Recent evidence indicates that early-career experience in large firms has dynamic rewards in future worker outcomes (Arellano-Bover, 2020). Our results suggest a compelling mechanism to rationalize this — the experience in performing non-routine analytical and in using ICT accumulated by younger workers in larger firms is rewarded with better future earnings prospects (Stinebrickner et al., 2019). We urge future research to probe along these lines.

Outline of the paper. The remainder of this paper proceeds as follows. In Section 2, we describe the main data sets and detail the measures of task content used in the analysis. In Section 3, we document novel facts on the heterogeneity of occupational task contents across firms of differing sizes. In Section 4, we measure the large-firm wage premium and study a number of explanations for its existence, including the firm-size gradient in task intensity. Finally, in Section 5, we conclude with a summary of the findings and a discussion of future directions of work. An appendix contains additional results.

2 Data and measurement

2.1 Data sources

We take advantage of the availability of cross-country harmonized surveys reporting the tasks performed by individuals in their work to construct a rich dataset covering working (not self-employed) individuals aged 16–65 across 46 countries at various stages of economic development. We combine two main data sets.

OECD Survey of Adult Skills. The Survey of Adult Skills is a cross-sectional, cross-country survey conducted under the OECD's Programme for International Assessment of Adult Competencies (PIAAC). This survey aims to measure cognitive skills (literacy, numeracy, and problem solving in technology-rich environments), as well as skills used both at work and in other contexts. It is representative of the country's adult population aged 16–65, with around 5,000 individuals participating in each country.[1] There have been three rounds of data collection (2008–2013, 2012–2016, and 2016–2019). We focus on the surveys collected from the following 30 countries: Belgium, Chile, Cyprus, Czech Republic, Denmark, Ecuador, France, Greece, Hungary, Ireland, Israel, Italy, Japan, Kazakhstan, South Korea,

[1]The United States conducted a second round of data collection to get more reliable estimates for certain subgroups.

Lithuania, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Russian Federation, Singapore, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom, and United States.[2]

Full earnings information are not available in the public-use files of New Zealand, Peru, Singapore, and USA. Instead, earnings are only reported in deciles.[3] These countries are still employed in the quantification of the gradient in task intensity by firm size.

World Bank Skills Measurement Surveys. Our second main data source is the World Bank's STEP Skills Measurement Program surveys. They also are cross-sectional surveys that aim at measuring the demand and supply of skills in urban areas of low- and middle-income countries, which allows us to complement the set of high- and middle-income countries available in the OECD's Survey of Adult Skills under PIAAC. There are two types of surveys in the program: household-based and employer-based.

The household-based surveys interview a randomly-selected household member (aged 15 to 64) about their personal education and training history, work status and history, skills used in their jobs, earnings, individual competencies, and non-cognitive traits and abilities (e.g., personality, behavior, risk preferences). Sample sizes varied from 3,000 to 4,000 individuals. We focus on the surveys that contain consistent questions regarding tasks and skills, corresponding to the following 11 countries: Armenia, Bolivia, China (Yunnan Province), Colombia, Georgia, Kenya, Laos, Macedonia, Sri Lanka, Ukraine, and Vietnam.[4]

Additionally, in some countries, firms were also surveyed using an employer-based questionnaire. In this module, an informed respondent from around 300 to 500 firms per country reported the worker composition of the firm, the skills required from workers in different occupations, and the amount of in-firm training provided. We use the employer-based survey

[2]We exclude Turkey because we cannot construct our measure of non-cognitive skills of the worker. We confirm that the results from specifications that do not control for this variable are similar when including Turkey.

[3]Peru lacks this information as well.

[4]Though Ghana has a household-based survey that contains the relevant variables, we exclude it because of the small sample size that remains after sample selection. The Philippines was also a survey country but a different questionnaire was used.

of the following 9 countries: Albania, Armenia, Azerbaijan, Bosnia-Herzegovina, Georgia, Kenya, Kosovo, Serbia, and Vietnam. Note that 4 of these countries have also conducted the household-based survey, which allows us to document consistent evidence of within-occupation task heterogeneity both from the employer and the employees' perspective.

Strengths and limitations of data used. The main virtue of these datasets is the availability of information about the tasks performed by individuals in their own work that are comparable across a wide range of countries. The main limitation is that they are cross-sectional. In particular, note that although both STEP and PIAAC were conducted over multiple rounds across years, only one country (the U.S.) was surveyed twice with different sets of respondents. In the absence of a panel, we are limited in the mechanisms that we explore. For instance, we cannot control for additional individual heterogeneity outside the characteristics we observe nor can we speak to the dynamics of tasks requirements and wages.

2.2 Measuring firm size, occupational task content, and wages

Firm size and the presence of large firm gaps. Both datasets provide a measure of firm size based on the number of employees, reported in bins. The survey questions refer more precisely to workplace or establishment but we follow the past literature and use the term "firm" interchangeably. We define firms that have at least 50 employees as large.[5] We mainly report large firm gaps that compare workers in firms that have at least 50 employees to workers in firms with less than 50 employees, but the qualitative results are robust to the use of alternative cutoffs for the definition of large firms.

Task content of occupations. We follow the approach in Caunedo et al. (2023) to construct task measures that are comparable to well-established definitions in the literature (e.g., Autor

[5]The OECD classifies micro enterprises as those with fewer than 10 employees, small enterprises as those with 10 to 49 employees, medium-sized enterprises as those with 50 to 249 employees, and large enterprises as those with 250 or more workers. See https://data.oecd.org/entrepreneur/enterprises-by-business-size.htm.

et al., 2003; Acemoglu and Autor, 2011). We distinguish five task components of occupations: non-routine analytical (NRA), non-routine interpersonal (NRI), routine cognitive (RC), routine manual (RM), and non-routine manual (NRM). Non-routine analytical tasks involve reading and thinking creatively. Non-routine interpersonal tasks require interacting with others (e.g., through advising, negotiating, teaching). Routine cognitive tasks require structured repetition of activity planning and time management. Routine manual tasks involve physically demanding activities. Finally, non-routine manual tasks involve manual dexterity. The exact variables employed are listed in Appendix Table A1.

We create an individual index measuring the intensity of a particular task category in two steps. First, we standardize the responses to each task variable to have a within-country mean of zero and standard deviation of unity. Second, to obtain the index for a skill category, we add the standardized responses to the task variables and re-standardize the result to again have a within-country mean of zero and a standard deviation of one. By construction, these measures are interpreted as intensities in units of standard deviations relative to the country mean. In Appendix C.1, we consider an alternative construction of task intensity indices using multiple correspondence analysis.

Usage of ICT. A particular focus of our paper is also on documenting the intensity with which workers use technologies such as computers and specific software as part of their work. Though we report results relating to the usage of ICT alongside the task dimensions above, we do not consider it mutually exclusive to the task dimensions mentioned above. Rather, *we interpret the use of ICT as a means through which the above task dimensions are performed.* In Table A1, we show the questions in the surveys that are relevant to measure the use of ICT. We create an index in a similar manner as for the above measures of task content.

Wages. To quantify the large firm wage gap, we focus on hourly wages in non-self-employment work. We deflate the values to 2018 local currency and use 2018 exchange rates to US dollar to convert earnings to real 2018 USD. In Section 4, we show that the gap remains even after accounting for worker sorting, a leading explanation put forward in the literature, and we then explore the sources of the LFWP.

Demographics and additional controls. To increase the comparability of demographic variables across surveys, we first consider the following standard controls: gender, age block (10-year groups starting from age 16 and ending at 65), and three education categories based on ISCED 2008 — (i) primary education or less (ISCED 1); (ii) up to a professional tertiary education degree (ISCED 5), and (iii) bachelor's degree and above (ISCED 5A and beyond).

We further aim to better account for the potential sorting of workers with higher ability or higher non-cognitive skills into larger firms. In terms of cognition, for STEP countries we standardize, at the country level, the proportion of correct responses over the total number of questions in three different linguistic tests (vocabulary, sentence, and passage). For PIAAC countries, we use the first imputation in both the numeracy and literacy competences, and we verify that the results hold employing item response theory over the ten imputations available in the survey (Khorramdel et al., 2020). In terms of non-cognitive abilities, STEP provides pre-constructed measures for the following traits: openness, stability, agreeableness, and grit. We employ the (standardized) first principal component from these four dimensions. Though PIAAC is known for being less well-equipped for measuring individual non-cognitive traits, we still use a number of measures that have previously been shown to predict earnings. In particular, we follow Anghel and Balart (2017) in using measures of cultural engagement, social trust, and political efficacy, and we follow Cabrales et al. (2014) in employing a measure of motivation for learning. We combine these four measures by taking their first principal component, which we take as a proxy of the respondent's non-cognitive skills.

We consider the following sectoral classification for STEP countries: (i) agriculture, fishing, mining; (ii) manufacturing and construction; (iii) commerce; and (iv) other services in STEP countries. For PIAAC, we use more detailed information encompassing twenty-one different industries.

Finally, in order to account for regional variation in industrial and demographic composition, we employ regional fixed effects, which are always available in STEP but are missing for a subset of PIAAC countries (Italy, Norway, and United States). Importantly, the nature of these regions changes across countries, even within the same survey. For instance, among STEP countries, regions refer to metropolitan areas in Colombia while in China (Yunnan) they pertain to census enumeration areas. In PIAAC countries, the geographical information corresponds to OECD TL-2 territorial levels (representing the first administrative tier of sub-national government), which are politically defined. Given that this hinders the interpretation of these fixed effects and that they are only available for a subset of countries, we consider the inclusion of regional controls as a robustness check, rather than as part of our main specification.

2.3 Summary statistics

Appendix Table A2 reports summary statistics for the 36 countries for which we have a continuous measure of wages. To ensure that our results are not driven by extrapolation, we also impose that each firm size and 2-digit occupation code cell has at least 5 observations. The number of observations after focusing on working-age individuals that are not self-employed varies from 857 (Greece) to 3,984 (United Kingdom) among PIAAC countries and from 360 (Laos) to 1,289 (Vietnam) among STEP countries. In general, small firms are more prevalent but there is significant cross-country variation. For instance, in Belgium and the Netherlands 50% of the firms are large, while the share is around 20% in Ecuador and Greece.

3 Firm size gradient in the task content of jobs

In this section, we document from various perspectives our novel stylized fact that, even within narrowly defined occupation groups, there are significant differences in the task composition of jobs across workers of firms of different sizes. To quantify such gradient we estimate versions of the following regression:

$$T_i = \beta \times \mathrm{LF}_{j(i)} + X_i'\gamma + \delta^o_{o(i)} + \delta^c_{c(i)} + \varepsilon_i, \tag{1}$$

where T_i is the measure of task content of the job of worker i, $\mathrm{LF}_{j(i)}$ is an indicator of whether the firm $j(i)$ of individual i has at least 50 employees, X is a vector of individual- and firm-level characteristics, and δ^o and δ^c are occupation-code and country fixed effects, respectively. We focus on our five main task categories (NRA, NRI, RC, RM, NRM) as well as the use of ICT as outcomes. Our coefficient of interest is β, which captures the average difference in intensity in doing task T between two observably equivalent workers in the same country and occupation who differ in that one is employed by a large firm and the other by a small one.[6] We report standard errors clustered at the country level.

In Table 1's panels (a) and (b), we report estimates of β in Equation 1 using the pooled samples of PIAAC and STEP countries, respectively, with varying specificities of additional controls. In column (1), we present the firm-size gradient in task intensity only controlling for occupation and country fixed effects. Qualitatively, we find that workers in larger firms perform more non-routine analytical tasks and make more intensive use of information and communication technologies. We also find suggestive evidence that workers in larger firms perform more routine cognitive tasks, a pattern that is more evident in the STEP pooled sample than in the PIAAC one. We do not find a difference in the intensity with which manual tasks,

[6] Throughout the paper, in the pooled regressions, we use probability weights, adjusted based on the population of the various countries in 2018 (with the exception of China, for which we use the population of Yunnan – the only province of the country that was surveyed). Intuitively, this weighting approach places more weight on observations from large-population countries.

Table 1: Pooled estimates of firm size gradient in the task content of jobs

Outcome variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): PIAAC						
Non-routine analytical	0.155	0.159	0.127	0.117	0.115	0.111
	(0.019)	(0.019)	(0.016)	(0.017)	(0.017)	(0.017)
Non-routine interpersonal	0.074	0.086	0.064	0.055	0.051	0.048
	(0.022)	(0.023)	(0.022)	(0.022)	(0.023)	(0.022)
Routine cognitive	0.008	0.006	0.024	0.035	0.041	0.039
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.015)
Routine manual	-0.006	-0.000	0.006	0.011	0.001	0.008
	(0.015)	(0.014)	(0.011)	(0.010)	(0.010)	(0.011)
Non-routine manual	-0.007	-0.008	-0.001	0.001	-0.009	-0.005
	(0.017)	(0.017)	(0.015)	(0.014)	(0.012)	(0.013)
Use of ICT	0.156	0.164	0.140	0.132	0.127	0.121
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
Sample size	65,151	65,151	65,151	65,151	65,151	65,151
Panel (b): STEP						
Non-routine analytical	0.125	0.129	0.069	0.066	0.082	0.081
	(0.032)	(0.030)	(0.024)	(0.023)	(0.023)	(0.029)
Non-routine interpersonal	-0.015	-0.003	-0.033	-0.034	-0.020	-0.039
	(0.030)	(0.033)	(0.037)	(0.034)	(0.028)	(0.028)
Routine cognitive	0.169	0.162	0.188	0.191	0.157	0.194
	(0.067)	(0.066)	(0.064)	(0.060)	(0.054)	(0.053)
Routine manual	-0.020	-0.019	0.007	0.007	0.021	0.022
	(0.034)	(0.035)	(0.032)	(0.033)	(0.033)	(0.028)
Non-routine manual	-0.048	-0.042	-0.060	-0.060	-0.065	-0.086
	(0.038)	(0.038)	(0.037)	(0.035)	(0.035)	(0.031)
Use of ICT	0.194	0.201	0.126	0.125	0.126	0.102
	(0.057)	(0.056)	(0.043)	(0.043)	(0.042)	(0.043)
Sample size	8,339	8,339	8,339	8,339	8,339	8,339
Controls:						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
2-d Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes	Yes	Yes	Yes	Yes
Individual demographics			Yes	Yes	Yes	Yes
Individual cognition/noncog.				Yes	Yes	Yes
Country interactions					Yes	Yes
Region FE						Yes

Notes: Regressions of task requirement intensity on an indicator of large firm (at least 50 employees) for the STEP and PIAAC pooled samples (separately). Additional controls are indicated in the lower part of the table. Individual demographics include education, gender, and age. Standard errors are reported in parenthesis and clustered at the country level.

either routine or non-routine, are performed between workers in larger and smaller firms. The firm size gradient in non-routine interpersonal tasks is less clear comparing the PIAAC sample with the STEP sample (we return to this later when we document that the gradients for these tasks appear to be more country-specific). Note that, by controlling for occupation fixed effects at the 2-digit level based on the ISCO-08 classification, we account for the possibility that the occupational structure of large and small firms differs in a way that could explain these patterns. In Appendix Table B2, we find the same qualitative patterns employing 3-digit occupation fixed effects instead.[7]

In columns (2)–(6), we build upon our baseline results from column (1) and incrementally account for potential confounders of the firm-size gradient. Column (2) features industry fixed effects to rule out the possibility that the gaps are driven by larger firms disproportionally concentrating in industries that use certain tasks more intensively, or have firms that are more productive. Column (3) introduces individual controls for education, gender, and age to account for the most salient sources of worker selection into firms that are typically recorded in standard datasets. In column (4), we take advantage of the availability of measures of cognitive and non-cognitive skills in the surveys we use to show that the task gap barely changes after their inclusion, which reinforces the idea that worker selection cannot fully explain the gradient in task requirements. In column (5), we saturate the regression with the interactions of all our controls with country fixed effects to allow the returns to such controls to vary across countries. Finally, column (6) introduces regional fixed effects to account for spatial differences in the presence of large and small firms and in tasks and occupations.[8] Our estimates of the gradients are fairly stable across specifications.

In terms of economic magnitude, focusing on column (5)[9], we find that the average worker

[7]Our preferred specification controls for 2-digit ISCO-08 occupation codes, which balances the trade-off between the specificity of the occupations and sample size.

[8]In Appendix Table B3 we report the results from the PIAAC sample when we do not discard countries with missing regional information. We do not identify any substantial differences.

[9]We use the specification without region fixed effects as our preferred specification given that the results are similar with and without them. The number of regions in some countries is substantial so a fixed effect specification may be demanding given the number of observations we are working with.

in a large firm performs around 11.1% and 8.1% of a standard deviation more non-routine analytical tasks than a worker in a small firm in the PIAAC and STEP countries, respectively. We interpret this standard deviation as relative to the country-specific distribution of performed tasks. The average worker in the large firm also uses 12.1% and 10.2% of a standard deviation more ICT compared to the average worker in smaller firms in STEP and PIAAC countries, respectively. In terms of routine cognitive tasks, the average large-firm worker in PIAAC countries performs 3.9% of a standard deviation more than their counterparts in smaller firms; the difference is larger at 19.4% of a standard deviation in the STEP sample. The size of these gaps is comparable to the one present between the countries at the two extremes of the development spectrum, as measured by GDP per capita (Caunedo et al., 2023).

Robustness to selection on unobservables. The results above show that the gaps in skill use persist after the inclusion of a rich set of observable covariates. Still, the cross-sectional nature of the data limits the amount of unobserved individual heterogeneity that we can control for. To show that the facts that we uncover are unlikely to be driven by unobservables, we follow Oster (2019). At the core of her approach is the idea that, when one aims at exploring the stability of a coefficient of interest upon the inclusion of additional controls, care should be paid to how the R^2 changes as those additional controls are introduced. Intuitively, if the R^2 does not change much, then the fact that your estimated coefficient of interest is not affected by their inclusion may not be enough to conclude that you are unlikely to suffer from an omitted-variable bias.

In practical terms, Oster (2019) suggests estimating the value of a parameter, denoted as δ, telling us how stronger/weaker selection on unobservables would have to be, relative to selection on observables, so as to render the coefficient of interest statistically indistinguishible from zero. A value of δ of 1 indicates that selection on unobservables would have to be as large as selection on observables to make the coefficient of interest be zero. Since one would typically believe that the included controls are capable of explaining a large fraction of the variation in the outcome, Oster (2019) suggests that a δ of 1 or higher is a good rule-of-thumb value to be confident that selection on unobservables is not a large issue. In Appendix Table B1, we replicate Table 1 including in brackets the adjusted R^2 for each of the estimated regressions, and we add a final column reporting the estimated δ for each of the tasks and the use of ICT. We find that the estimated δ's for the tasks for which we identified quantitatively significant gaps comfortably satisfy the proposed rule-of-thumb.

Alternative treatment of occupations. Our main interest is in documenting within-occupation heterogeneity in task composition. While we have demonstrated the robustness of our results to the use of various degrees of specificity in the occupation codes (2-digit and 3-digit), in Appendix Tables B4 and B5 we take an even more flexible approach. In particular, we estimate regressions such as Table 1's column (5) separately for subsamples defined by 1-digit occupation codes, while still controlling for dummies of 2-digit occupation codes. We find that workers in larger firms across virtually all 1-digit occupation codes perform more non-routine analytical tasks and use more ICT in their work, both within PIAAC and STEP countries, as consistent with the strong effects we found in the pooled results. Not surprisingly, there are differences in the magnitude of the firm size gradient depending on which 1-digit occupation code we focus on. The largest gaps in the performance of non-routine analytical tasks are seen among services and sales workers while the largest gaps in the use of ICT are seen among managers. Looking at the undertaking of routine cognitive tasks, we find that that the firm size gradient in tasks is driven by basic occupations (craftsmen, plant and machine operators, elementary occupations, as well as by clerical support workers) in the PIAAC sample. In STEP countries, these differences extend to managers and professionals as well. Finally, for most 1-digit occupation categories, in both the PIAAC and STEP samples, we find small firm size differences in the performance of routine and non-routine manual tasks – as we found in our main specification.

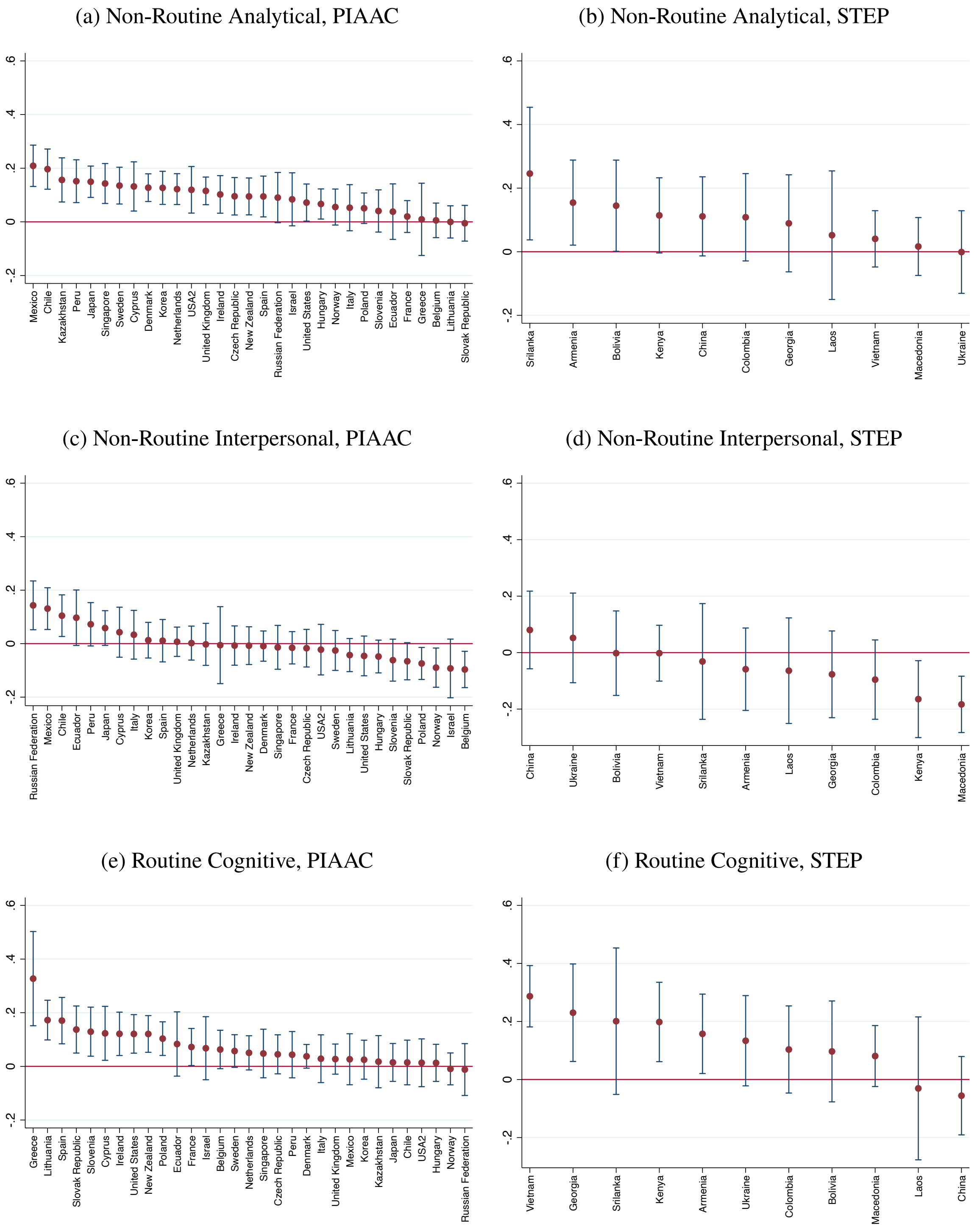
When does the gradient arise? These systematic differences in the task intensity across firm sizes could either be present at the beginning of the job spell or arise as larger firms assign more non-routine analytical and less routine cognitive, routine manual and non-routine manual tasks to workers with longer tenure in the firm. In Appendix Table B6, we show that these differences are already present at the beginning of the job tenure and early in the workers' career. In particular, we re-estimate Table 1's column (5) conditioning first on workers having been in their current job for a short period of time (up to 2 years) and then additionally on being young (less than 25 years) to discard cases of workers that have adopted more task-intensive work as they progressed in their careers. Among these young workers with short tenure, we find firm size gradients in non-routine analytical tasks and the use of ICT that are of the same sign and comparable in magnitude to the full sample. Overall, these results suggest that the patterns documented in this paper do not arise from firms requiring workers to change their task mixture, or to use more ICT over their tenure in the firm. Rather, these differences are already present at the start of performing the job. This is consistent with results, discussed below, based on demand-side information where we show that firms already expect their new hires to perform more non-routine analytical tasks and use more ICT.

Cross-country comparisons. The analyses in columns (5) and (6) of Table 1, which allow for country-specific returns to our controls, suggest that our pooled results are a fairly systematic pattern rather than being driven by a subset of countries. In Figure 1, we further support this claim by estimating our main specification separately for each country. What we find aligns well with our previous results: (i) the larger reliance on non-routine analytical and the use of information and communication technologies is present in virtually all countries in our sample; (ii) the higher intensity on routine cognitive tasks, while prevalent throughout many countries, also features a subset of countries for which the effects are not distinguishable from zero; and (iii) differences in the performance of routine and non-routine tasks are mostly indistinguishable from zero and, if any, are negative.

Although the qualitative patterns uncovered above are fairly similar across countries, quantitatively some differences arise. There are several reasons why this might be the case: (1) differences in labor market institutions, and (2) differences in the relevance of firms with at least 50 employees. We explore whether these differences can be explained by the level of development across countries, focusing on two indicators: log GDP per capita and the proportion of the population that has completed at least tertiary-level education. In Appendix Figures B1 and B2, we plot the firm size gradients in the task content of jobs against log GDP per capita and fraction of population with at least tertiary education, respectively. We highlight two empirical patterns. First, the firm size differences in the use of non-routine analytical tasks is uncorrelated with log GDP per capita and only slightly positively correlated with the proportion of the population that is at least tertiary educated. This suggests that this pattern is not driven by economic development. In contrast, the firm size gradient in the performance of routine cognitive and the use of ICT is negatively correlated with economic development—in richer countries and countries with a more educated population, the firm size differences in the task content of jobs are smaller.

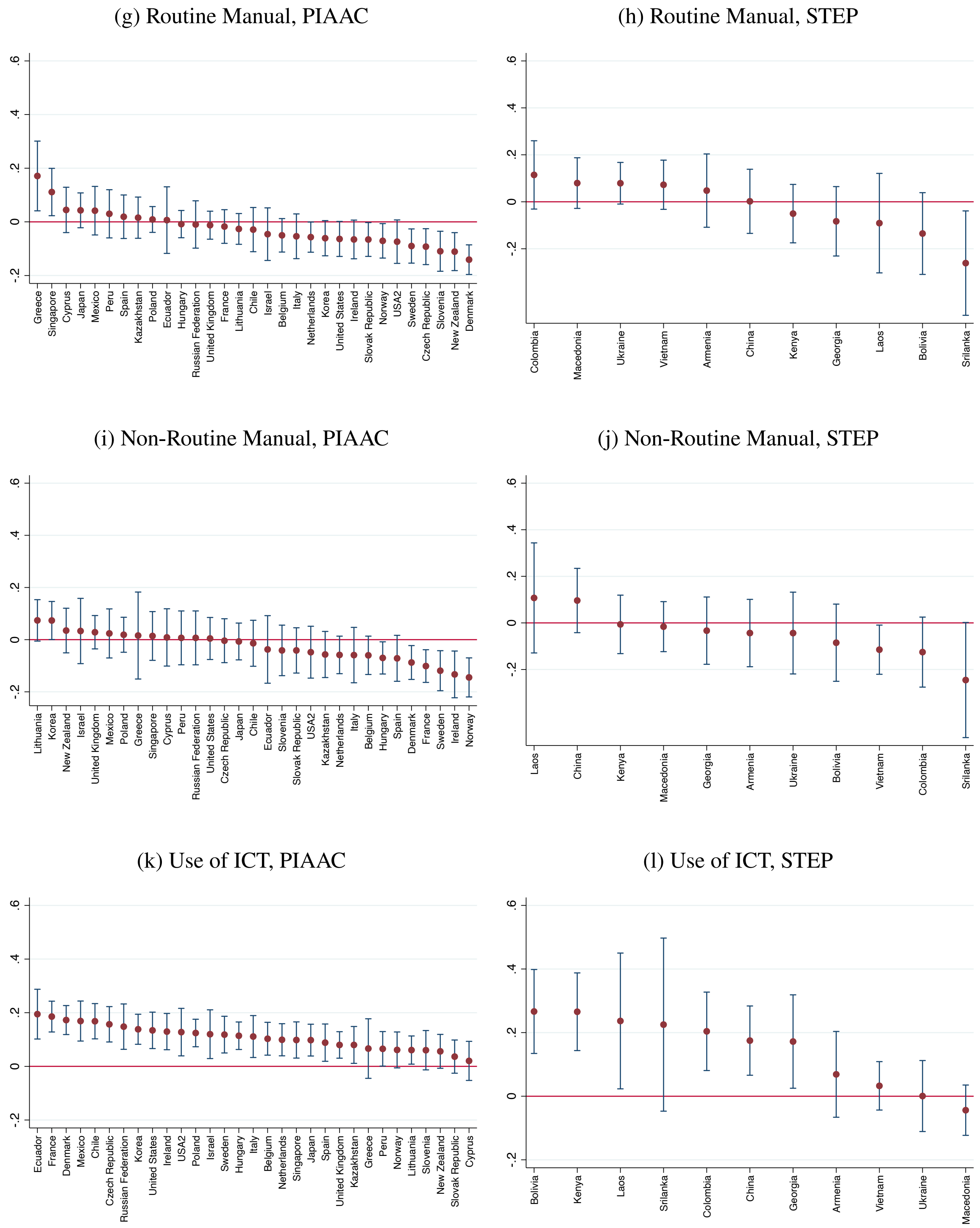
Differences in the distribution of task intensity by firm size. So far our results document average differences in task composition of occupations between firms of different sizes. In Appendix C.2, we extend our analysis by also exploring the differences in the distribution of task intensity. For this, we employ distributional regressions in the spirit of Chernozhukov et al. (2013) and show that the large firm differences in non-routine analytical, routine-cognitive, and in the use of ICT are present at multiple thresholds throughout the support of the distribution. This demonstrates that the mean differences we find are not driven solely by discrepancies in the upper tail of the distribution of tasks performed. Instead, the distributions of the intensity of performed tasks in larger firms are all shifted to the right compared to the distribution in smaller firms. For the case of routine and non-routine manual tasks, the

Figure 1: Firm size gradient in the task content of jobs by country, within 2-digit occupations



Notes: Baseline sample. Coefficient of an indicator for large firm in a regression of task content intensity on indicator of large firm (at least 50 employees) and the full set of controls as in Table 1's column (5). Countries ordered by decreasing point estimates. Regressions done for each country separately. Reported confidence intervals at 95% confidence level computed using heteroskedasticity-robust standard errors.

Figure 1: Firm size gradient in the task content of jobs by country, within 2-digit occupations



Notes: Baseline sample. Coefficient of an indicator for large firm in a regression of task content intensity on indicator of large firm (at least 50 employees) and the full set of controls as in Table 1's column (5). Countries ordered by decreasing point estimates. Regressions done for each country separately. Reported confidence intervals at 95% confidence level computed using heteroskedasticity-robust standard errors.

insignificant differences are seen throughout the intensity distribution, except for the case of routine manual tasks for large firms where there is suggestive evidence of a widening of the intensity distribution in larger firms.

Evidence from the demand side. We complement the above evidence, which was based on workers' self-reported task intensity, by performing a demand-side analysis using the employer surveys from the World Bank STEP Skill Surveys program.[10] In these surveys, firms answer a limited set of questions on the skill requirements of occupations within the firm. Based on the questions asked in the survey, we are only able to identify skills that pertain to the following categories: (1) non-routine analytical and (2) use of ICT, which fortunately are the task categories for which we found clear patterns based on worker-level information. To limit the burden on the survey respondent, STEP only elicits two occupations (randomly selected out of nine categories), so we do not have access to these responses across multiple occupations within a given firm. Table 2 reports estimates of average differences in task requirements between large and small firms, within occupation categories, for the pooled sample of nine countries where the STEP Employer Survey is available. We again find that large firms require more non-routine analytical tasks and use more ICT.

Table 2: Evidence from the demand side

(a) Task requirements

Task category	LF estimate	# Obs.
Non-routine analytical	0.197 (0.004)	8,222
Use of ICT	0.184 (0.004)	8,212

Notes: Pooled sample, STEP employer surveys. Coefficient in a regression of task measure on an indicator of large firm and fixed effects for sector, country, and the occupation asked at random by the survey. In parenthesis, we report the p-values of the test that the effects are null using wild-bootstrapped standard errors clustered at the country level.

[10] We acknowledge that the results in this subsection are based on a small number of low- and middle-income countries so external validity is limited.

4 Large firm wage premium and the role of individual selection, sectors, and tasks

In this section, we first document the presence of a large firm wage premium — both on average and throughout the wage distribution — using the pooled PIAAC and STEP samples separately (Subsection 4.1). We then explore in Subsection 4.2 how much of this raw gap can be linearly explained by various mechanisms, including selection of individuals into occupations and differences in the task composition of occupations.

4.1 Large firm wage premium: Cross-country evidence

Similarly to how we documented the large firm gap in the task content of jobs in Section 3, in this subsection we explore the large firm gap in wages. We estimate the following regression:

$$\ln w_i = \beta \times \mathrm{LF}_{j(i)} + X_i' \gamma + \delta^o_{o(i)} + \delta^c_{c(i)} + \varepsilon_i, \tag{2}$$

where $\ln w_i$ is log real hourly wages in 2018 USD of individual i, $\mathrm{LF}_{j(i)}$ is an indicator of whether the firm $j(i)$ of individual i has at least 50 employees, X is a vector of individual and firm controls, δ^o are occupation-code fixed effects, and δ^c are country fixed effects. We interpret β as a measure of the LFWP, which is how much more workers with similar observables in firms with at least 50 employees are paid (in log-points) relative to those in smaller firms within the same occupation and country.

In the first column of Table 3's panel (a), we report the coefficient β controlling for country and for 2-digit ISCO-08 occupation codes fixed effects. The estimated raw LFWP is 0.153 and 0.229 for PIAAC and STEP countries, respectively, which means that an average worker in a large firm earns about 16.5% and 25.7% more than an average worker in a small firm.[11] These results show that the firm-size wage gaps are not explained by differences in

[11] Note that $\exp(0.153) - 1 \approx 0.165$.

Table 3: Pooled estimates of the large firm wage premium

(a) Mean regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PIAAC							
LFWP	0.153	0.132	0.129	0.114	0.111	0.110	0.095
	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)	(0.009)	(0.014)
	[0.787]	[0.793]	[0.794]	[0.801]	[0.802]	[0.812]	[0.820]
Sample size	54,782	54,782	54,782	54,782	54,782	54,782	54,782
STEP							
LFWP	0.229	0.213	0.210	0.185	0.185	0.166	0.139
	(0.028)	(0.023)	(0.023)	(0.024)	(0.025)	(0.023)	(0.029)
	[0.761]	[0.765]	[0.765]	[0.766]	[0.766]	[0.775]	[0.819]
Sample size	8,339	8,339	8,339	8,339	8,339	8,339	8,339
Controls:							
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-d Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tasks		Yes	Yes	Yes	Yes	Yes	Yes
Industry FE			Yes	Yes	Yes	Yes	Yes
Individual demographics				Yes	Yes	Yes	Yes
Individual cognition/noncog.					Yes	Yes	Yes
Country interactions						Yes	Yes
Region FE							Yes

(b) Quantile regressions

	(1) p10	(2) p25	(3) p50	(4) p75	(5) p90
PIAAC	0.117	0.102	0.106	0.103	0.085
	(0.010)	(0.009)	(0.010)	(0.011)	(0.012)
Sample Size	54,782	54,782	54,782	54,782	54,782
STEP	0.216	0.194	0.143	0.109	0.056
	(0.034)	(0.027)	(0.022)	(0.029)	(0.030)
Sample Size	8,339	8,339	8,339	8,339	8,339

Notes: Panel (a) shows regressions of log hourly wages (in 2018 USD) on an indicator of large firm (at least 50 employees) and various specifications as noted on the Table. Countries for which continuous wage data are not available are excluded. Table B7 in the Appendix reports the point estimates and standard errors for the various tasks and computer use. Panel (b) shows results from quantile regressions under the specification in panel (a)'s column (5). Standard errors are reported in parenthesis and clustered at the country level. Adjusted R^2 is reported in brackets.

the occupational structure of firms. Similarly to Table 1, our estimates decrease in size but remain strongly significant as we saturate the regression across columns. Note that for the last four columns we also control for the task composition of jobs.[12] In the most saturated regression including region fixed effects, in Column (7), we still find a LFWP of 0.10 and 0.14 log points in PIAAC and STEP countries, suggesting that the controls we include are unable to fully explain the raw LFWP we estimated. In the next section, we will quantify the importance of the task composition in determining the size of the LFWP. For now, we highlight that, while our estimates of the LFWP are not readily comparable to estimates in the literature (which are usually reported as elasticities), their magnitudes are reasonable based on existing estimates (Reed and Thu, 2019).

Similarly to our analysis for the gradient in the task content of jobs, Appendix Tables B8 and B9 show that the presence of a sizable LFWP remains when we employ 3-digit occupational fixed effects and when we expand the sample to include the PIAAC countries that lack regional information. Moreover, in Appendix Tables B10 and B11, we again account for occupations more flexibly by estimating Equation 2 conditioning on workers being in specific 1-digit occupation codes, and controlling for 2-digit occupation codes. Both in PIAAC and STEP countries we find a comparatively large LFWP among workers in service and sales (0.178 and 0.191 log points, respectively), with clerical and support workers, managers, and professionals also commanding a large wage premium.

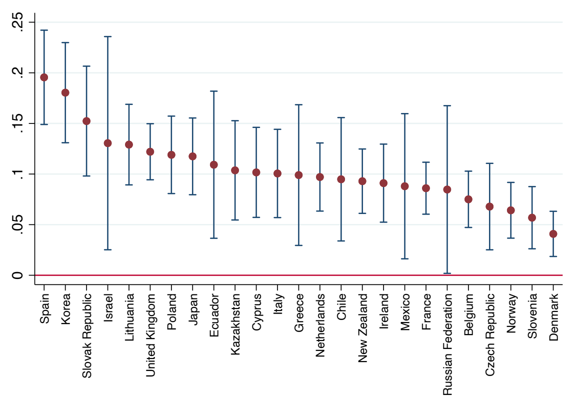
Distributional differences. Our wage analysis contributes to providing harmonized evidence on the presence of the LFWP across a large set of diverse countries. We now expand on the existing literature by extending the exploration of the LFWP beyond the comparison of average wages between large and small firms, as has been done so far in the literature. We document that the entire wage distribution of large firms is shifted to the right compared to smaller firms, even within occupations. Panel (b) in Table 3 reports the β coefficients

[12]To complement the present analysis and the decomposition provided later in the text, we document the coefficients associated to the task measures and the use of ICT in Appendix Table B7.

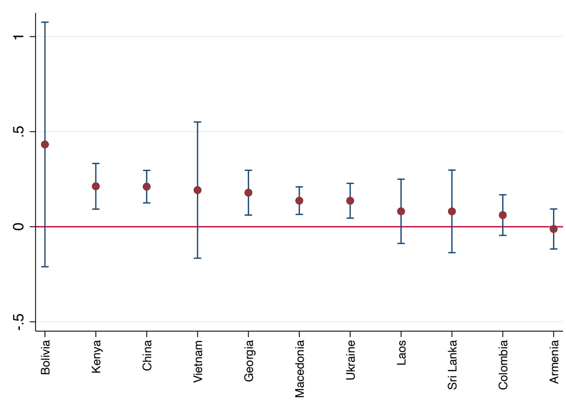
in a quantile regression version of Equation 2 for various quantiles, additionally controlling for tasks, industry fixed effects, and individual controls. These results compare the wage distribution of larger and smaller firms. We find that the worker at the 10th percentile in larger firms is paid 0.117 and 0.216 log-points more than the worker at the 10th percentile in smaller firms in PIAAC and STEP, respectively. For the median worker, the difference is about 0.106 and 0.143 log-points and it is 0.085 and 0.056 log-points at the 90th percentile.

Figure 2: Estimated average large firm wage premium by country

(a) PIAAC, no region FE



(b) STEP, no region FE



Notes: Regressions of log wages on an indicator of large firm (at least 50 employees), by country. In (a) and (b) with the controls in column (6) in Table 3's panel (a). Reported confidence intervals at 95% confidence level computed using heteroskedasticity-robust standard errors.

Cross-country comparisons. We find that the pooled estimates are reflective of fairly universal patterns at the country level. In Figure 2, we report the estimates of the LFWP by country. Most of the country-specific LFWP estimates under our main specification (column (6) of Table 3) lie between 0.05 and 0.20 log points, corresponding to approximately 5–22% average real hourly wage differences between workers in larger firms relative to those in smaller firms. In Appendix Figure B3, we additionally adjust for region fixed effects and find that the LFWP remains almost unchanged. In Appendix Figure B4, we report the differences in the distribution of wages across firm size by country. We find that in almost all of the countries we study, the wage distribution of workers in larger firms is shifted to the right relative to the wage distribution of workers in smaller firms. These results echo the qualitative results we obtained using the pooled data.

For privacy reasons, not all countries in PIAAC report information on hourly wages in the public use files. In such cases, only the decile of the wage distribution the person is located in is provided. We utilize this information and estimate linear probability models where the outcome is an indicator taking the value of 1 if the worker is *at least* in a certain wage decile. Appendix Figure B5 reports the coefficient of this linear probability model controlling for the full set of controls in column (6) of Table 3's panel (a). The results complement what we learn from the quantile regressions: not only are workers in larger firms more likely to have wages in the last decile, but these workers are also more likely to have wages that are at least above the second and fifth decile. This is further evidence towards the wage distribution of large firms being shifted to the right compared to smaller firms, even within narrowly-defined occupation groups.

4.2 Sources of the large firm wage premium

There are a number of plausible reasons for the existence of the large firm wage premium. In this subsection, we explore the role in wage determination of (1) sorting by individual characteristics, (2) industry characteristics, and (3) differential task content of jobs. To quantify their relative importance, we conduct a simple mediation analysis adopting the two-step conditional decomposition developed in Gelbach (2016). A desirable feature of his approach is that the results from the decomposition are independent of the order in which the mediators are introduced in the regression. A limitation, however, is that we require measurement of the key mediators to avoid omitted-variable biases. The decomposition begins with a raw estimate of the LFWP, β^{raw}, from the regression:

$$\ln w_i = \beta^{\text{raw}} \times \text{LF}_{j(i)} + \delta^{o,\text{raw}}_{o(i)} + \delta^{c,\text{raw}}_{c(i)} + \varepsilon^{\text{raw}}_i, \tag{3}$$

where $\ln w_i$ is log real hourly wages, $\text{LF}_{j(i)}$ is the indicator for worker i being in a large firm, δ^o are occupation fixed effects (2-digit ISCO code), and δ^c are country fixed effects. This raw LWFP estimate coincides with the estimate in column (1) of Table 3's panel (a). The second step of the decomposition consists of re-estimating the above equation after the inclusion of a set of individual controls X_i that are believed to mediate the LFWP:

$$\ln w_i = \beta^{\text{full}} \times \text{LF}_{j(i)} + X_i'\gamma + \delta^{o,\text{full}}_{o(i)} + \delta^{c,\text{full}}_{c(i)} + \varepsilon^{\text{full}}_i. \tag{4}$$

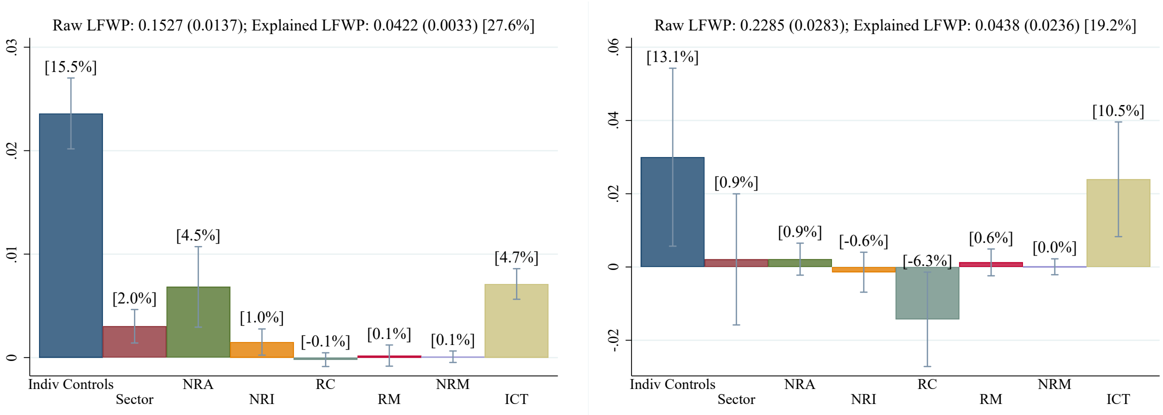
In our case, the variables incorporated in X are (1) individual characteristics including sex, age and education, (2) sector dummies, and (3) the task content of jobs and usage of ICT reported by workers. In other words, this regression replicates the specification in Table 3's column (5). The difference $\beta^{\text{raw}} - \beta^{\text{full}}$ is interpreted as the part of the LFWP that we are able to explain by controlling for X. Gelbach (2016) then proposes a methodology to apportion the explained part of the LFWP to each of the component variables of X.

The decomposition results are graphically summarized in Figure 3. We find that the mediators that we consider are able to explain 27.6% of the raw LFWP in PIAAC and 19.2% in STEP. Individual characteristics (age, sex, and education) explain a significant portion of the LFWP, around 15.5% and 13.1%. This suggests that large firms pay more on average because they hire workers who are older, more educated, and better skilled. This sorting pattern of workers to larger firms has been recently documented by Arellano-Bover (2021). Importantly, though human capital sorting (by occupation or education) explains a large portion, it is unable to fully explain the existence of the LFWP.

The third to eighth bars in both panels of Figure 3 report the fractions of the raw LFWP that are explained by the differences in the tasks performed and in ICT use by the workers which we document in Section 3. To help us better interpret the results, in Appendix Table

Figure 3: Gelbach decomposition of LFWP, pooled

(a) PIAAC (b) STEP



Notes: Pooled PIAAC and STEP samples. Raw LFWP refers to the estimate in Table 3's column (1). Explained LFWP is the difference in the estimate between columns (1) and (5) in that Table. The y-axis is the amount of the LFWP explained by the corresponding component. Numbers in brackets indicate percentages of the raw LFWP. Reported confidence intervals at 95% confidence level. Standard errors are clustered at the country level.

B7, we report the coefficients of the tasks on log wages in the regressions of Table 3. In particular, we document that non-routine analytical, non-routine interpersonal, and the use of ICT have positive returns on wages, whereas routine cognitive and routine manual have negative returns. Something important to notice is that Gelbach (2016)'s decomposition estimates the contribution of each mediator *keeping* the other mediators constant. Hence, while the different task components may be predictive of wages, the variation that explains the LFWP is largely mediated by the variation in the usage of ICT rather than variation in the task content. The impact of non-routine manual tasks is close to zero.

We find that the firm size gradient in the performance of non-routine analytical tasks explains about 4.5% of the raw large firm wage premium in PIAAC. Moreover, differences in the use of ICT explain an additional 4.7% of the raw LFWP in PIAAC and 10.5% in STEP. Non-routine interpersonal tasks, which are performed more by large firm workers in PIAAC countries and have positive returns for wages, also contribute to explaining the wage gap significantly but modestly (1% in PIAAC countries). In PIAAC countries, RC tasks are undertaken disproportionally more often in larger firms, but the returns to these tasks are negative and small, which leads to this task explaining -0.1% of the gap, which is not statistically significant. Finally, also in PIAAC countries, manual tasks (both routine and non-routine), for which a firm-size gradient is absent, contribute little to explaining the gap.

In STEP countries, apart from the large role of ICT, we find that RC tasks, which are disproportionately undertaken by workers in large firms but have sizable negative returns on wages, explain -6.3% of the gap.

Overall, we take these results to reflect not only the disproportionately higher intensity with which workers perform various tasks and use ICT in larger firms, but also the growing importance of computer skills (Alekseeva et al., 2021) in the labor market.[13] Combined, these task components and the use of ICT explain more than 10% of the raw LFWP, a magnitude comparable to that explained jointly by education, age and sex.[14]

The main concern in the performed decomposition analysis is omitted variables. While we do have a rich set of worker controls, including cognitive and non-cognitive skills that should reduce the potential for the presence of unobserved determinants of worker selection into firms, not observing firm characteristics, in particular firm performance, is potentially a concern. The LFWP may be partially driven by differences in firm productivity—in many models of the labor market, including rent-sharing models or search and matching models, more productive firms pay higher wages to its workers. Unfortunately, we do not observe measures of firm productivity. To partially address this issue, we control for the sector in which the worker works with the aim of accounting for aggregate productivity differences

[13] A concern is that ICT, which explains a large fraction of the LFWP in both samples is itself a mediator of the role of tasks, i.e., after tasks are assigned to workers, ICT use is decided as a function of the tasks. In Appendix Figure B6 we replicate the same analysis excluding ICT as a potential mediator. We find that the fraction of the LFWP that tasks can explain is mostly unaffected. This suggests that ICT use is an independent mechanism in itself.

[14] In STEP countries, routine cognitive tasks explain 6% of the closing of the gap in wages between workers in larger and smaller firms. This is on top of the differences in the use of ICT explaining 10% of the widening gap in wages between workers in larger and smaller firms.

across sectors. We find that the sectoral membership of the worker only partly explains the existence of the LWFP, about 2.3% of the raw LFWP in PIAAC countries.

Another concern is that the LFWP may be driven by spatial differences in wages. In an attempt to capture within-country spatial differences in wages, we repeat the decomposition including regional fixed effects as was done in Tables 1 and 3.[15] When we include regional fixed effects in the decomposition exercise, whose results are reported in Appendix Figure B7, we find that the regional dummies are able to explain a non-neglible fraction of the LFWP (around 9% and 20% in PIAAC and STEP countries, respectively). Importantly, we show that this does not come at the expense of shifting the importance of the tasks performed, as their importance in the decompositions remain of about the same size.

Cross-country comparisons. The results of the decomposition exercise by country are graphically summarized in Appendix Figure B8, focusing on countries for which both the LFWP and the explained portion of the LFWP are statistically significant. We find that the proportion of the raw LFWP explained by the controls that we consider varies between 20% and 40%. In terms of broad patterns, basic individual characteristics such as age, sex, and education consistently explain a significant portion of the raw LFWP (between 10–30%). Sectoral membership is intermittently statistically and economically significant in a handful of countries. In countries where this component accounts for a statistically significant portion, sectors explain around 5–20% of the raw LFWP.

The firm size gradient in the performance of non-routine analytical tasks and the use of ICT explain, in general, a total of about 5–20% of the raw LFWP. The firm size gradient in the performance of non-routine analytical tasks explains, between 5–8% of the raw large firm wage premium whenever it contributes to a statistically significant share of the LFWP. Among the countries for which the ICT component is statistically significant, the estimates lie mostly between 3–9% of the raw LFWP, with a couple of countries where the use of ICT

[15] We note that in STEP, only urban areas are surveyed which partially alleviates the urban-rural differences we might expect in wages.

contributes more substantially to the LFWP.[16]

5 Conclusion

In this paper, we document novel stylized facts about the heterogeneity in occupational task intensity across firms. We find that individuals working in larger firms report that they perform non-routine analytical and routine cognitive tasks more frequently and use ICTs more intensively, even within narrowly-defined occupations. We complement these empirical facts with demand-side information confirming that larger firms indeed require workers to perform more non-routine analytical and ICT-intensive tasks.

Moreover, we document the existence of an economically significant large firm wage premium of about 10–20%. We provide suggestive evidence on the role of task heterogeneity in explaining this LFWP. By controlling for individual characteristics (age, gender, education, cognition, and non-cognition) of the workers, sector, and the task content of jobs, we are able to explain about 28% of the raw LFWP in PIAAC countries and 19% in STEP countries. Differences in the task content of jobs are able to account for over 10% of the raw LFWP.

We consider that our work opens two natural avenues for future research. First, an unresolved question is how these task differences arise in a dynamic economy. In the introduction, we suggested that as firms grow larger, they invest in automation or conduct more off-shoring which transforms the organization of production. These larger firms focus workers towards complementary tasks such as non-routine analytical and routine cognitive tasks. Moreover, these tasks are performed with more ICT. While our results are consistent with this micro-founded mechanism of firm dynamics, it is difficult to establish its consistency with reality in the absence of panel data of firms and tasks.

Second, we leave for further study other implications of the firm size gradient in occu-

[16] We also report the version of the decomposition where we also include regional fixed effects as mediators, both in the pooled case and on a country basis (Appendix Tables B7 and B9.) The qualitative results remain and region emerges as a contributor of its own to the LFWP for PIAAC countries.

pational content on labor markets. We have suggestive evidence of its role in static wage determination but lack exogenous identifying conditions to argue their causal nature. The implications of our results on dynamic wage determination remain unexplored. More specifically, our results may serve as a nexus between two seemingly parallel strands of the literature. First, a number of studies shows that having experience in certain tasks has different returns in the market: analytical tasks and use of ICT have been found to have high market returns, especially in recent years (Stinebrickner et al., 2019; Alekseeva et al., 2021). Second, there is evidence that experience in large firms also has higher returns in the market (Arellano-Bover, 2020). Our results suggest a plausible mechanism for the bigger dynamic returns to working in larger firms — workers in larger firms gain more experience in performing non-routine analytical tasks and the use of ICT, which are highly valued in the labor market.

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A Appendix: Data measurement and summary statistics

Table A1 summarizes the mapping, following Caunedo et al. (2023), of the questions in PIAAC and STEP to the different dimensions of work we are interested in: non-routine analytical, non-routine interpersonal, routine cognitive, routine manual, non-routine manual, and the usage of ICT.

Construction of task content measures using employer-based surveys. In the employers questionnaire, a knowledgeable person within the firm was asked about the task needs from two randomly selected occupations. One of them would be chosen among the following ones: manager/professional/technician while the second one would be selected from: clerk/services/sales/crafting/operator/elementary occupation. We are able to obtain a measure of firm's demand that closely matches the construction of our non-routine analytical and ICT use measures from the workers' survey. In particular, we construct firm requirements as the standardized sum of the standardized score in each of the following questions (possible answers were yes/no):

- Non-routine analytical: (a) does the job involve reading?; (b) does the job involve writing; (c) does the job involve math?; (d) does the job involve problem solving?, and (e) does the job involve speaking other languages?
- ICT: (a) what is the highest level of computer use in the job? (possible responses were: none, straightforward, moderate, complex, and specialized).

Table A1: Mapping of survey questionnaires to task categories

	STEP surveys		PIAAC surveys	
Task category	Item description	Item nos.	Item description	Item nos.
Non-routine analytical	Type of documents read and frequency	A-4, A-5-(1-6)	Type of documents read and frequency	G_Q01(a-h)
	Think creatively	B-10	Think creatively	F_Q05b
Non-routine interpersonal	Personal relationship	B-5, B-6	Personal relationship	F_Q02a, F_Q02d, FQ_04a, FQ_04b
	Guiding/coaching	B-13	Guiding/coaching	F_Q02b, F_Q02e, F_Q03b
Routine cognitive	Freedom how to decide work	B-14	Planning activities	FQ_03a
	Presence of short, repetitive tasks	B-16	Organizing own time	FQ_03c
	Learning new things	B-17		
Routine manual	Physical demand	B-3	Long physical work	FQ_06b
Non-routine manual	Driving car. truck, three-wheeler	B-7	Use/accuracy hand/fingers	FQ_06c
	Repair/maintain electronic equip.	B-8		
Use of ICT	Used a computer	B-18	Used a computer	G_Q04

Notes: For STEP countries, we diverge from Caunedo et al. (2023) in constructing our measure of routine manual tasks by not including the category of operating heavy machinery, which does not have a clear counterpart in PIAAC.

Table A2: Summary Statistics

Variable	New Zealand	United Kingdom	Slovak Republic	Russia	Czech Republic	Mexico	Lithuania	Kazakhstan	Israel
Large Firm	0.368 (0.482)	0.499 (0.5)	0.434 (0.496)	0.466 (0.499)	0.376 (0.484)	0.318 (0.466)	0.456 (0.498)	0.364 (0.481)	0.369 (0.483)
Log Earnings	2.812 (0.509)	2.772 (0.566)	1.579 (0.672)	0.693 (0.775)	1.703 (0.578)	0.811 (0.874)	2.595 (0.597)	0.288 (0.593)	2.492 (0.809)
	-0.223 - 10.675	0.387 - 6.784	0.209 - 7.617	-3.63 - 5.49	-2.573 - 6.793	-2.051 - 5.01	0.334 - 9.092	-3.185 - 4.362	-0.498 - 8.849
Female	0.576 (0.494)	0.592 (0.491)	0.507 (0.5)	0.637 (0.481)	0.513 (0.5)	0.386 (0.487)	0.608 (0.488)	0.568 (0.495)	0.522 (0.5)
Age (16-24)	0.204 (0.403)	0.128 (0.334)	0.093 (0.291)	0.220 (0.415)	0.147 (0.354)	0.216 (0.412)	0.088 (0.283)	0.106 (0.307)	0.280 (0.449)
Age (25-34)	0.191 (0.393)	0.237 (0.426)	0.254 (0.435)	0.278 (0.448)	0.292 (0.455)	0.267 (0.442)	0.209 (0.407)	0.317 (0.466)	0.328 (0.47)
Age (35-44)	0.223 (0.416)	0.254 (0.435)	0.251 (0.433)	0.200 (0.400)	0.233 (0.423)	0.257 (0.437)	0.234 (0.423)	0.287 (0.452)	0.239 (0.427)
Age (45-54)	0.199 (0.399)	0.229 (0.421)	0.257 (0.437)	0.195 (0.396)	0.188 (0.391)	0.166 (0.372)	0.273 (0.446)	0.208 (0.406)	0.104 (0.305)
Age (above 55)	0.183 (0.387)	0.152 (0.359)	0.145 (0.352)	0.106 (0.308)	0.140 (0.347)	0.094 (0.291)	0.196 (0.397)	0.082 (0.275)	0.048 (0.214)
Education (Primary or less)	0.013 (0.113)	0.078 (0.268)	0.002 (0.041)	0.006 (0.075)	0.001 (0.029)	0.22 (0.415)	0.004 (0.065)	0.003 (0.056)	0.048 (0.214)
Education (up to professional tertiary education degree)	0.578 (0.494)	0.493 (0.5)	0.766 (0.423)	0.235 (0.424)	0.752 (0.432)	0.614 (0.487)	0.605 (.489)	0.534 (0.499)	0.470 (0.499)
Education (bachelor and above)	0.409 (0.492)	0.429 (0.495)	0.232 (0.422)	0.758 (0.428)	0.247 (0.431)	0.166 (0.372)	0.391 (0.488)	0.463 (0.499)	0.481 (0.5)
Observations	2,461	3,984	2,355	1,412	2,412	2,241	2,564	2,265	1,182

Variable	Greece	Ecuador	Chile	Spain	Slovenia	Poland	Norway	Netherlands	Korea
Large Firm	0.223 (0.416)	0.248 (0.432)	0.361 (0.48)	0.348 (0.476)	0.526 (0.499)	0.375 (0.484)	0.446 (0.497)	0.483 (0.5)	0.378 (0.485)
Log Earnings	2.058 (0.524)	1.117 (0.651)	1.518 (0.783)	2.518 (0.566)	2.223 (0.427)	1.335 (0.604)	3.381 (0.429)	3.057 (0.616)	4.779 (0.733)
	0.324 - 3.892	-0.002 - 4.066	-0.397 - 6.467	0.392 - 9.418	0.967 - 4.277	-1.148 - 10.1	0.495 - 6.559	0.46 - 12.948	2.331 - 8.332
Female	0.567 (0.496)	0.389 (0.488)	0.493 (0.5)	0.486 (0.5)	0.516 (0.5)	0.446 (0.497)	0.518 (0.5)	0.506 (0.5)	0.46 (0.498)
Age (16-24)	0.077 (0.267)	0.207 (0.405)	0.154 (0.362)	0.075 (0.264)	0.042 (0.201)	0.396 (0.489)	0.169 (0.375)	0.173 (0.378)	0.096 (0.294)
Age (25-34)	0.258 (0.438)	0.313 (0.464)	0.284 (0.451)	0.248 (0.432)	0.246 (0.431)	0.313 (0.464)	0.193 (0.395)	0.185 (0.388)	0.265 (0.441)
Age (35-44)	0.324 (0.468)	0.235 (0.424)	0.207 (0.405)	0.305 (0.461)	0.295 (0.456)	0.119 (0.324)	0.246 (0.431)	0.232 (0.422)	0.286 (0.452)
Age (45-54)	0.277 (0.448)	0.156 (0.363)	0.226 (0.418)	0.261 (0.439)	0.329 (0.47)	0.119 (0.313)	0.232 (0.422)	0.249 (0.432)	0.239 (0.427)
Age (above 55)	0.064 (0.245)	0.089 (0.285)	0.129 (0.335)	0.111 (0.314)	0.088 (0.284)	0.062 (0.240)	0.16 (0.367)	0.162 (0.368)	0.115 (0.319)
Education (Primary or less)	0.054 (0.226)	0.304 (0.460)	0.076 (0.266)	0.132 (0.339)	0.004 (0.067)	0.009 (0.095)	0.001 (0.028)	0.05 (0.219)	0.05 (0.217)
Education (up to professional tertiary education degree)	0.534 (0.499)	0.536 (0.499)	0.624 (0.484)	0.424 (0.494)	0.608 (0.488)	0.67 (0.47)	0.555 (0.497)	0.606 (0.489)	0.463 (0.499)
Education (bachelor and above)	0.412 (0.492)	0.160 (0.367)	0.3 (0.458)	0.444 (0.497)	0.388 (0.487)	0.321 (0.467)	0.444 (0.497)	0.344 (0.475)	0.487 (0.5)
Observations	857	1,502	2,149	2,023	1,786	3,821	2,569	2,860	3,008

Notes: Baseline sample. All variables except log earnings are binary. Means are reported with standard deviations in parentheses. For log earnings, the min and max are reported on a separate row.

Table A2: Summary Statistics (cont.)

Variable	Japan	Italy	Ireland	France	Denmark	Cyprus	Belgium	Vietnam	Ukraine
Large Firm	0.428 (0.495)	0.376 (0.485)	0.405 (0.491)	0.45 (0.498)	0.458 (0.498)	0.310 (0.463)	0.532 (0.499)	0.416 (0.493)	0.564 (0.496)
Log Earnings	2.638 (0.631)	2.714 (0.516)	3.051 (0.566)	2.782 (0.445)	3.408 (0.439)	2.544 (0.574)	3.122 (0.42)	-6.890 (3.133)	-0.002 (0.612)
	-3.016 - 7.841	0.743 - 5.607	0.179 - 7.333	0.4 - 5.747	0.125 - 6.604	0.683 - 5.836	0.565 - 6.895	-60.477 - -0.61	-4.089 - 3.012
Female	0.489 (0.5)	0.48 (0.5)	0.586 (0.493)	0.499 (0.5)	0.506 (0.5)	0.603 (0.490)	0.496 (0.5)	0.541 (0.499)	0.626 (0.484)
Age (16-24)	0.109 (0.312)	0.051 (0.22)	0.088 (0.283)	0.089 (0.285)	0.119 (0.324)	0.081 (0.274)	0.098 (0.297)	0.117 (0.322)	0.063 (0.244)
Age (25-34)	0.203 (0.402)	0.203 (0.402)	0.266 (0.442)	0.229 (0.42)	0.129 (0.336)	0.325 (0.469)	0.248 (0.432)	0.31 (0.463)	0.263 (0.441)
Age (35-44)	0.268 (0.443)	0.345 (0.475)	0.304 (0.46)	0.263 (0.44)	0.207 (0.405)	0.257 (0.437)	0.245 (0.43)	0.293 (0.455)	0.23 (0.421)
Age (45-54)	0.224 (0.417)	0.278 (0.448)	0.204 (0.403)	0.278 (0.448)	0.231 (0.421)	0.215 (0.411)	0.296 (0.456)	0.202 (0.401)	0.265 (0.442)
Age (above 55)	0.197 (0.397)	0.124 (0.329)	0.139 (0.346)	0.143 (0.35)	0.314 (0.464)	0.121 (0.326)	0.113 (0.317)	0.078 (0.268)	0.179 (0.383)
Education (Primary or less)	0 (0.018)	0.033 (0.179)	0.035 (0.183)	0.029 (0.167)	0.004 (0.06)	0.048 (0.214)	0.02 (0.141)	0.133 (0.34)	0.002 (0.044)
Education (up to professional tertiary education degree)	0.480 (0.5)	0.743 (0.437)	0.487 (0.5)	0.573 (0.495)	0.538 (0.499)	0.386 (0.487)	0.54 (0.499)	0.433 (0.496)	0.453 (0.498)
Education (bachelor and above)	0.520 (0.5)	0.223 (0.417)	0.478 (0.5)	0.399 (0.49)	0.458 (0.498)	0.567 (0.496)	0.44 (0.496)	0.434 (0.496)	0.545 (0.498)
Observations	3,149	1,535	2,227	2,993	3,607	1,608	2,470	1,289	521

Variable	Sri Lanka	Macedonia	Laos	Kenya	Georgia	Colombia	China	Bolivia	Armenia
Large Firm	0.367 (0.483)	0.421 (0.494)	0.289 (0.454)	0.229 (0.420)	0.387 (0.488)	0.347 (0.476)	0.397 (0.49)	0.270 (0.444)	0.407 (0.492)
Log Earnings	-0.016 (0.949)	0.505 (1.63)	-0.173 (0.766)	0.045 (1.079)	0.122 (0.822)	0.487 (0.838)	0.494 (0.689)	0.618 (2.335)	-6.83 (0.745)
	-2.205 - 3.835	-54,59 - 3.924	-3.488 - 3.958	-4.427 - 4.417	-2.744 - 3.296	-7.503 - 4.517	-2.638 - 3.747	-52.352 - 4.324	-8.545 - 0.690
Female	0.422 (0.495)	0.464 (0.499)	0.408 (0.492)	0.385 (0.487)	0.688 (0.464)	0.430 (0.495)	0.499 (0.5)	0.491 (0.5)	0.664 (0.473)
Age (16-24)	0.098 (0.297)	0.044 (0.205)	0.128 (0.334)	0.248 (0.432)	0.085 (0.280)	0.183 (0.387)	0.067 (0.25)	0.207 (0.406)	0.105 (0.307)
Age (25-34)	0.25 (0.434)	0.275 (0.447)	0.336 (0.473)	0.454 (0.498)	0.213 (0.410)	0.357 (0.48)	0.26 (0.439)	0.345 (0.476)	0.228 (0.42)
Age (35-44)	0.348 (0.477)	0.285 (0.451)	0.303 (0.46)	0.184 (0.388)	0.287 (0.453)	0.235 (0.424)	0.384 (0.487)	0.26 (0.439)	0.221 (0.415)
Age (45-54)	0.199 (0.4)	0.235 (0.424)	0.175 (0.38)	0.083 (0.276)	0.246 (0.431)	0.168 (0.374)	0.235 (0.424)	0.123 (0.328)	0.246 (0.431)
Age (above 55)	0.105 (0.308)	0.162 (0.369)	0.058 (0.235)	0.031 (0.173)	0.169 (0.375)	0.057 (0.231)	0.054 (0.226)	0.065 (0.246)	0.2 (0.401)
Education (Primary or less)	0.098 (0.297)	0.008 (0.087)	0.15 (0.358)	0.271 (0.444)	0 (0)	0.209 (0.407)	0.058 (0.233)	0.091 (0.288)	0.003 (0.056)
Education (up to professional tertiary education degree)	0.715 (0.452)	0.653 (0.476)	0.3489 (0.501)	0.559 (0.497)	0.213 (0.41)	0.442 (0.497)	0.556 (0.497)	0.426 (0.495)	0.263 (0.441)
Education (bachelor and above)	0.888 (0.391)	0.34 (0.474)	0.361 (0.481)	0.171 (0.376)	0.787 (0.41)	0.35 (0.477)	0.386 (0.487)	0.483 (0.5)	0.734 (0.442)
Observations	256	1,325	360	1,131	586	761	868	603	639

Notes: Baseline sample. All variables except log earnings are binary. Means are reported with standard deviations in parentheses. For log earnings, the min and max are reported on a separate row.

B Appendix: Additional tables and figures

Table B1: Pooled estimates of firm size gradient in the task content of jobs – Robustness to Selection on Unobservables (Oster, 2019)

Outcome variable	(1)	(2)	(3)	(4)	(5)	(6)	(7) δ
Panel (a): PIAAC							
Non-routine analytical	0.155	0.159	0.127	0.117	0.115	0.111	1.590
	(0.019)	(0.019)	(0.016)	(0.017)	(0.017)	(0.017)	
	[0.296]	[0.297]	[0.334]	[0.350]	[0.365]	[0.379]	
Non-routine interpersonal	0.074	0.086	0.064	0.055	0.051	0.048	2.037
	(0.022)	(0.023)	(0.022)	(0.022)	(0.023)	(0.022)	
	[0.241]	[0.247]	[0.272]	[0.286]	[0.308]	[0.320]	
Routine cognitive	0.008	0.006	0.024	0.035	0.041	0.039	-0.986
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.015)	
	[0.134]	[0.135]	[0.146]	[0.159]	[0.176]	[0.185]	
Routine manual	-0.006	-0.000	0.006	0.011	0.001	0.008	-0.409
	(0.015)	(0.014)	(0.011)	(0.010)	(0.010)	(0.011)	
	[0.245]	[0.249]	[0.259]	[0.263]	[0.297]	[0.312]	
Non-routine manual	-0.007	-0.008	-0.001	0.001	-0.009	-0.005	-0.432
	(0.017)	(0.017)	(0.015)	(0.014)	(0.012)	(0.013)	
	[0.084]	[0.085]	[0.089]	[0.092]	[0.138]	[0.164]	
Use of ICT	0.156	0.164	0.140	0.132	0.127	0.121	1.905
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	
	[0.360]	[0.361]	[0.389]	[0.396]	[0.419]	[0.424]	
Sample size	65,151	65,151	65,151	65,151	65,151	65,151	65,151
Panel (b): STEP							
Non-routine analytical	0.125	0.129	0.069	0.066	0.082	0.081	0.550
	(0.032)	(0.030)	(0.024)	(0.023)	(0.023)	(0.029)	
	[0.376]	[0.376]	[0.413]	[0.421]	[0.430]	[0.483]	
Non-routine interpersonal	-0.015	-0.003	-0.033	-0.034	-0.020	-0.039	-1.469
	(0.030)	(0.033)	(0.037)	(0.034)	(0.028)	(0.028)	
	[0.264]	[0.270]	[0.287]	[0.293]	[0.303]	[0.354]	
Routine cognitive	0.169	0.162	0.188	0.191	0.157	0.194	-7.175
	(0.067)	(0.066)	(0.064)	(0.060)	(0.054)	(0.053)	
	[0.149]	[0.150]	[0.162]	[0.171]	[0.187]	[0.265]	
Routine manual	-0.020	-0.019	0.007	0.007	0.021	0.022	-0.262
	(0.034)	(0.035)	(0.032)	(0.033)	(0.033)	(0.028)	
	[0.211]	[0.213]	[0.229]	[0.229]	[0.236]	[0.297]	
Non-routine manual	-0.048	-0.042	-0.060	-0.060	-0.065	-0.086	-2.571
	(0.038)	(0.038)	(0.037)	(0.035)	(0.035)	(0.031)	
	[0.159]	[0.161]	[0.212]	[0.213]	[0.240]	[0.267]	
Use of ICT	0.194	0.201	0.126	0.125	0.126	0.102	0.817
	(0.057)	(0.056)	(0.043)	(0.043)	(0.042)	(0.043)	
	[0.435]	[0.436]	[0.491]	[0.493]	[0.511]	[0.542]	
Sample size	8,339	8,339	8,339	8,339	8,339	8,339	8,339
Controls:							
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	
2-d Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	
Industry FE		Yes	Yes	Yes	Yes	Yes	
Individual demographics			Yes	Yes	Yes	Yes	
Individual cognition/noncog.				Yes	Yes	Yes	
Country interactions					Yes	Yes	
Region FE						Yes	

Notes: This table replicates Table B1 with the inclusion of (1) adjusted R^2 in brackets and (2) the estimated δ following Oster (2019) in column (7). The larger the values of δ (in absolute terms), the stronger the selection on unobservables would have to be for the estimated coefficient of interest to be zero.

Table B2: Pooled estimates of firm size gradient in the task content of jobs when controlling for 3-digit occupations

Outcome variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): PIAAC						
Non-routine analytical	0.155	0.157	0.131	0.122	0.120	0.115
	(0.020)	(0.021)	(0.019)	(0.019)	(0.020)	(0.020)
	[0.299]	[0.300]	[0.336]	[0.351]	[0.367]	[0.382]
Non-routine interpersonal	0.082	0.092	0.072	0.064	0.060	0.055
	(0.023)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)
	[0.272]	[0.274]	[0.298]	[0.311]	[0.336]	[0.348]
Routine cognitive	-0.002	-0.001	0.014	0.024	0.021	0.020
	(0.023)	(0.024)	(0.024)	(0.023)	(0.025)	(0.025)
	[0.140]	[0.140]	[0.152]	[0.163]	[0.179]	[0.190]
Routine manual	0.007	0.014	0.018	0.022	0.019	0.025
	(0.019)	(0.019)	(0.016)	(0.016)	(0.016)	(0.019)
	[0.285]	[0.288]	[0.295]	[0.298]	[0.328]	[0.341]
Non-routine manual	0.013	0.016	0.020	0.022	0.016	0.020
	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
	[0.100]	[0.101]	[0.104]	[0.107]	[0.151]	[0.180]
Use of ICT	0.146	0.150	0.129	0.122	0.112	0.103
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.007)
	[0.374]	[0.375]	[0.400]	[0.407]	[0.433]	[0.439]
Sample size	47,905	47,905	47,905	47,905	47,905	47,905
Panel (b): STEP						
Non-routine analytical	0.132	0.130	0.074	0.072	0.081	0.106
	(0.030)	(0.029)	(0.024)	(0.021)	(0.020)	(0.037)
	[0.355]	[0.355]	[0.388]	[0.397]	[0.399]	[0.449]
Non-routine interpersonal	-0.006	-0.003	-0.032	-0.034	-0.019	-0.027
	(0.035)	(0.037)	(0.042)	(0.041)	(0.033)	(0.040)
	[0.248]	[0.253]	[0.268]	[0.273]	[0.277]	[0.313]
Routine cognitive	0.127	0.126	0.157	0.159	0.137	0.152
	(0.062)	(0.059)	(0.055)	(0.049)	(0.048)	(0.066)
	[0.120]	[0.120]	[0.129]	[0.142]	[0.149]	[0.206]
Routine manual	-0.016	-0.016	0.011	0.012	0.019	0.006
	(0.038)	(0.037)	(0.033)	(0.034)	(0.032)	(0.022)
	[0.195]	[0.197]	[0.208]	[0.208]	[0.203]	[0.267]
Non-routine manual	-0.014	-0.013	-0.007	-0.004	-0.003	-0.003
	(0.038)	(0.037)	(0.033)	(0.034)	(0.032)	(0.022)
	[0.165]	[0.165]	[0.215]	[0.217]	[0.223]	[0.252]
Use of ICT	0.211	0.218	0.136	0.135	0.122	0.084
	(0.064)	(0.064)	(0.054)	(0.052)	(0.054)	(0.056)
	[0.422]	[0.424]	[0.485]	[0.487]	[0.499]	[0.537]
Sample size	4,664	4,664	4,664	4,664	4,664	4,664
Controls:						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
3-d Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes	Yes	Yes	Yes	Yes
Individual demographics			Yes	Yes	Yes	Yes
Individual cognition/noncog.				Yes	Yes	Yes
Country interactions					Yes	Yes
Region FE						Yes

Notes: Replication of Table 1 substituting 2-digit occupation fixed effects by 3-digit ones. The unavailability of this finer degree of information for some countries explains the difference in observations with respect to the main table.

Table B3: Pooled estimates of firm size gradient in the task content of jobs when not discarding countries without region

Outcome variable	(1)	(2)	(3)	(4)	(5)
Non-routine analytical	0.143	0.145	0.117	0.109	0.105
	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)
	[0.290]	[0.291]	[0.320]	[0.333]	[0.348]
Non-routine interpersonal	0.045	0.054	0.036	0.029	0.025
	(0.023)	(0.025)	(0.023)	(0.022)	(0.023)
	[0.221]	[0.226]	[0.245]	[0.257]	[0.279]
Routine cognitive	0.015	0.013	0.036	0.046	0.051
	(0.016)	(0.016)	(0.018)	(0.017)	(0.016)
	[0.145]	[0.146]	[0.159]	[0.172]	[0.187]
Routine manual	-0.034	-0.030	-0.019	-0.013	-0.021
	(0.018)	(0.019)	(0.016)	(0.015)	(0.013)
	[0.276]	[0.280]	[0.290]	[0.296]	[0.327]
Non-routine manual	-0.022	-0.022	-0.013	-0.010	-0.014
	(0.014)	(0.014)	(0.013)	(0.012)	(0.010)
	[0.073]	[0.073]	[0.077]	[0.081]	[0.122]
Use of ICT	0.155	0.162	0.141	0.133	0.128
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
	[0.334]	[0.337]	[0.358]	[0.367]	[0.393]
Sample size	73,292	73,292	73,292	73,292	73,292
Controls:					
Country FE	Yes	Yes	Yes	Yes	Yes
2-d Occupation FE	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes	Yes	Yes	Yes
Individual demographics			Yes	Yes	Yes
Individual cognition/noncog.				Yes	Yes
Country interactions					Yes

Notes: Replication of Table 1 when not discarding PIAAC countries without regional information (Italy, Norway, and United States). This explains the increase in available observations.

Table B4: Firm size gradient in the task content of jobs, by occupation, PIAAC pooled estimates

1-digit ISCO-08 Category	Task Category NRA	NRI	RC	RM	NRM	ICT	# Obs.
Managers	0.087	-0.003	-0.010	-0.020	0.021	0.36	4,157
	(0.052)	(0.042)	(0.024)	(0.047)	(0.060)	(0.033)	
Professionals	0.088	0.051	-0.045	-0.016	-0.082	0.085	13,472
	(0.026)	(0.024)	(0.020)	(0.040)	(0.063)	(0.014)	
Technicians & associate professionals	0.132	-0.036	0.021	-0.035	0.059	0.086	9,601
	(0.027)	(0.025)	(0.025)	(0.038)	(0.038)	(0.027)	
Clerical support workers	0.050	0.040	0.112	-0.111	0.011	0.096	7,503
	(0.044)	(0.035)	(0.040)	(0.050)	(0.040)	(0.025)	
Services & sales workers	0.167	0.157	-0.022	0.103	0.069	0.223	12,175
	(0.031)	(0.061)	(0.059)	(0.042)	(0.035)	(0.030)	
Craft & related trade workers	0.076	-0.022	0.087	-0.032	-0.084	0.190	6,344
	(0.093)	(0.072)	(0.109)	(0.039)	(0.040)	(0.064)	
Plant & machine operators, & assemblers	0.163	0.060	0.051	-0.022	0.021	0.179	5,244
	(0.080)	(0.067)	(0.108)	(0.024)	(0.041)	(0.028)	
Elementary occupations	0.113	0.131	0.124	0.120	0.027	0.200	6,132
	(0.023)	(0.043)	(0.039)	(0.042)	(0.056)	(0.038)	

Notes: PIAAC pooled sample. Coefficient of an indicator for large firm in a regression of task content intensity on indicator of large firm (at least 50 employees) by 1-digit ISCO-08 occupation codes and the full set of controls as in Table 1's column (5). We do not report the 1-digit categories corresponding to armed forced occupations and skilled agricultural, forestry and fishery workers due to small sample size. Reported standard errors clustered at the country-level.

Table B5: Firm size gradient in the task content of jobs, by occupation, STEP pooled estimates

	Task Category						
1-digit ISCO-08 Category	NRA	NRI	RC	RM	NRM	ICT	# Obs.
Managers	0.150	-0.015	0.369	-0.170	-0.128	0.260	451
	(0.131)	(0.152)	(0.142)	(0.150)	(0.160)	(0.202)	
Professionals	0.017	0.068	0.074	-0.046	-0.095	0.177	2,142
	(0.032)	(0.062)	(0.048)	(0.055)	(0.038)	(0.085)	
Technicians & associate professionals	0.149	0.271	0.058	0.150	-0.027	-0.052	788
	(0.079)	(0.126)	(0.123)	(0.060)	(0.096)	(0.067)	
Clerical support workers	0.035	-0.126	0.059	0.069	0.088	0.198	895
	(0.067)	(0.098)	(0.101)	(0.038)	(0.131)	(0.038)	
Services & sales workers	0.202	0.047	0.223	-0.117	0.009	0.218	1,847
	(0.062)	(0.080)	(0.065)	(0.075)	(0.084)	(0.106)	
Craft & related trade workers	0.107	-0.214	0.275	0.135	0.121	0.093	687
	(0.122)	(0.105)	(0.092)	(0.104)	(0.095)	(0.119)	
Plant & machine operators, & assemblers	0.286	-0.122	0.194	-0.024	-0.295	0.139	588
	(0.108)	(0.068)	(0.111)	(0.075)	(0.120)	(0.075)	
Elementary occupations	0.087	0.204	0.150	0.042	-0.064	0.010	941
	(0.064)	(0.102)	(0.150)	(0.107)	(0.018)	(0.049)	

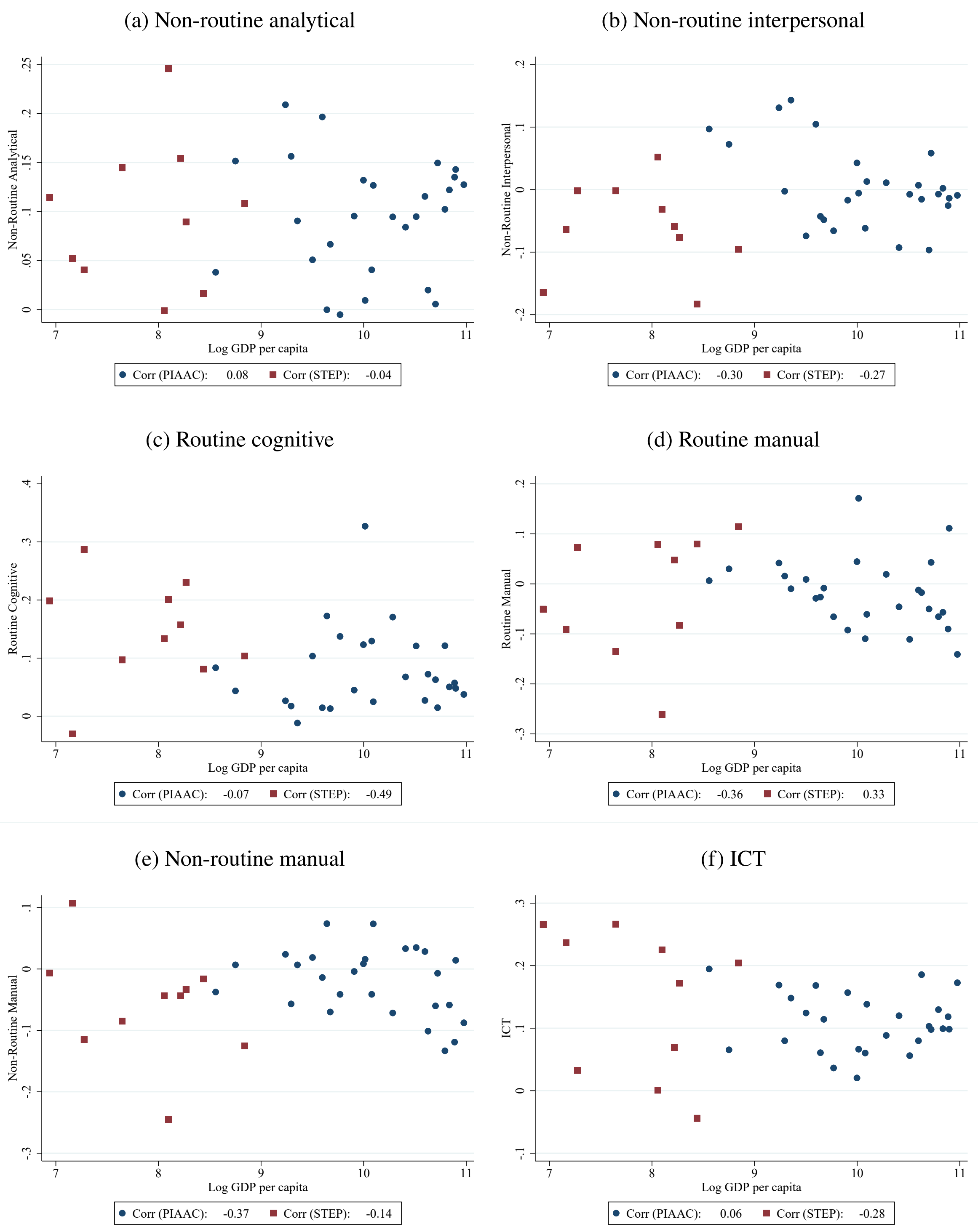
Notes: STEP pooled sample. Coefficient of an indicator for large firm in a regression of task content intensity on indicator of large firm (at least 50 employees) by 1-digit ISCO-08 occupation codes and the full set of controls as in Table 1's column (5). We do not report the 1-digit categories corresponding to armed forced occupations and skilled agricultural, forestry and fishery workers due to small sample size. Reported standard errors clustered at the country-level.

Table B6: Firm size gradient in the task content of jobs, young workers with short tenure, pooled estimates

	PIAAC		STEP	
Task Category	Short Tenure	+ Age < 25	Short Tenure	+ Age < 25
NRA	0.115	0.096	0.070	0.135
	(0.015)	(0.020)	(0.054)	(0.064)
NRI	0.041	0.084	-0.109	-0.166
	(0.031)	(0.058)	(0.045)	(0.100)
RC	0.029	-0.030	0.168	0.221
	(0.031)	(0.086)	(0.059)	(0.046)
RM	-0.010	0.033	0.017	0.219
	(0.018)	(0.032)	(0.037)	(0.025)
NRM	-0.003	0.128	-0.025	0.120
	(0.017)	(0.045)	(0.011)	(0.069)
Use of ICT	0.230	0.183	0.221	0.145
	(0.013)	(0.030)	(0.076)	(0.088)
# of Observations	28,220	5,716	2,656	810

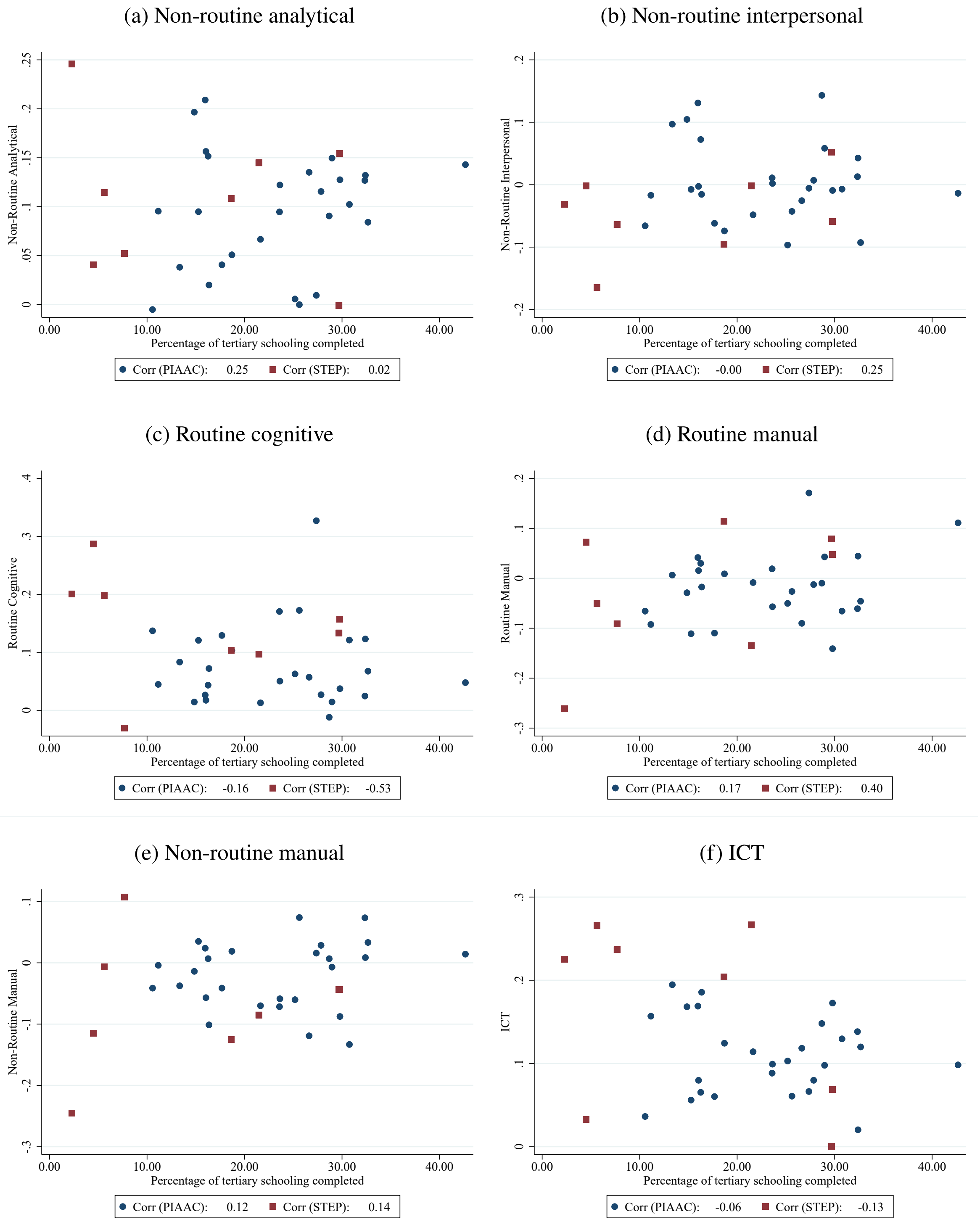
Notes: Pooled PIAAC and STEP samples. Coefficient of an indicator for large firm in a regression of task content intensity on indicator of large firm (at least 50 employees) controlling for the full set of controls as in Table 1's column (5). The first and third columns restrict the sample to workers with short tenure. In PIAAC there is no direct question about tenure, so we proxy short-tenure by an individual having worked for multiple firms in the last five years. STEP does provide information on the months that the individual has worked for the firm. We are therefore able to define short tenure in a more demanding manner: having worked for the current employer for up to 24 months. The second and fourth columns additionally require the worker to be up to 25 years of age. Reported standard errors clustered at the country-level.

Figure B1: Correlations of the firm size gradient in task content with log GDP per capita



Notes: Correlations of the firm size gradient in task content (obtained from column (5) in Table 1) with country-level log GDP per capita. Correlations weighted by estimated precision of estimated firm size gradients.

Figure B2: Correlations of the firm size gradient in task content with fraction of population with at least tertiary education



Notes: Correlations of the firm size gradient in task content (obtained from column (5) in Table 1) with country-level proportion of population with at least tertiary-level education (as measured using Barro and Lee (2013) methodology on 2015 data). Correlations weighted by estimated precision of estimated firm size gradients.

Table B7: Pooled estimates of the large firm wage premium, explicitely documenting the returns on tasks

(a) Mean regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PIAAC							
LFWP	0.153	0.132	0.129	0.114	0.111	0.110	0.095
	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)	(0.009)	(0.014)
Non-routine analytical		0.067	0.066	0.048	0.044		
		(0.010)	(0.008)	(0.008)	(0.007)		
Non-routine interpersonal		0.022	0.024	0.021	0.020		
		(0.010)	(0.010)	(0.008)	(0.008)		
Routine cognitive		-0.029	-0.029	-0.026	-0.022		
		(0.006)	(0.006)	(0.008)	(0.007)		
Routine manual		-0.039	-0.037	-0.036	-0.033		
		(0.007)	(0.007)	(0.006)	(0.006)		
Non-routine manual		-0.025	-0.025	-0.017	-0.016		
		(0.007)	(0.007)	(0.007)	(0.007)		
Use of ICT		0.052	0.052	0.049	0.045		
		(0.006)	(0.006)	(0.004)	(0.004)		
Sample size	54,782	54,782	54,782	54,782	54,782	54,782	54,782
STEP							
LFWP	0.229	0.213	0.210	0.185	0.185	0.166	0.139
	(0.028)	(0.023)	(0.023)	(0.024)	(0.025)	(0.023)	(0.029)
Non-routine analytical		0.038	0.038	0.016	0.017		
		(0.022)	(0.021)	(0.019)	(0.016)		
Non-routine interpersonal		0.105	0.107	0.094	0.095		
		(0.040)	(0.040)	(0.034)	(0.035)		
Routine cognitive		-0.090	-0.089	-0.084	-0.085		
		(0.017)	(0.017)	(0.016)	(0.016)		
Routine manual		-0.057	-0.057	-0.062	-0.062		
		(0.015)	(0.015)	(0.017)	(0.016)		
Non-routine manual		0.019	0.018	-0.001	-0.001		
		(0.020)	(0.020)	(0.023)	(0.023)		
Use of ICT		0.141	0.140	0.123	0.124		
		(0.023)	(0.022)	(0.025)	(0.026)		
Sample size	8,339	8,339	8,339	8,339	8,339	8,339	8,339
Controls:							
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-d Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tasks		Yes	Yes	Yes	Yes	Yes	Yes
Industry FE			Yes	Yes	Yes	Yes	Yes
Individual demographics				Yes	Yes	Yes	Yes
Individual cognition/noncog.					Yes	Yes	Yes
Country interactions						Yes	Yes
Region FE							Yes

Notes: Replication of Table 3 where we additionally report the results on the returns of tasks on wages. Column (1) does not report results since tasks are not part of that specification. Columns (6) and (7) do not report them because tasks are interacted with country fixed effects, so the level effect of the task lacks a meaningful interpretation. Reported standard errors are clustered at the country level.

Table B8: Pooled estimates of the large firm wage premium when using 3-digit occupations (mean regressions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel (a): PIAAC							
LFWP	0.158	0.138	0.135	0.126	0.123	0.118	0.101
	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
	[0.802]	[0.809]	[0.809])	[0.815]	[0.816])	[0.824]	[0.833]
Sample size	42,945	42,945	42,945	42,945	42,945	42,945	42,945
Panel (b): STEP							
LFWP	0.242	0.219	0.226	0.205	0.0206	0.159	0.075
	(0.060)	(0.054)	(0.061)	(0.062)	(0.064)	(0.039)	(0.032)
	[0.675]	[0.678]	[0.678])	[0.679]	[0.679])	[0.709]	[0.639]
Sample size	4,664	4,664	4,664	4,664	4,664	4,664	4,664
Controls:							
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3-d Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tasks		Yes	Yes	Yes	Yes	Yes	Yes
Industry FE			Yes	Yes	Yes	Yes	Yes
Individual demographics				Yes	Yes	Yes	Yes
Individual cognition/noncog.					Yes	Yes	Yes
Country interactions						Yes	Yes
Region FE							Yes

Notes: Replication of Table 3's panel (a) substituting 2-digit occupation fixed effects by 3-digit ones. The unavailability of this finer degree of information for some countries explains the difference in observations with respect to the main table.

Table B9: Pooled estimates of the large firm wage premium when not discarding countries without region (mean regressions)

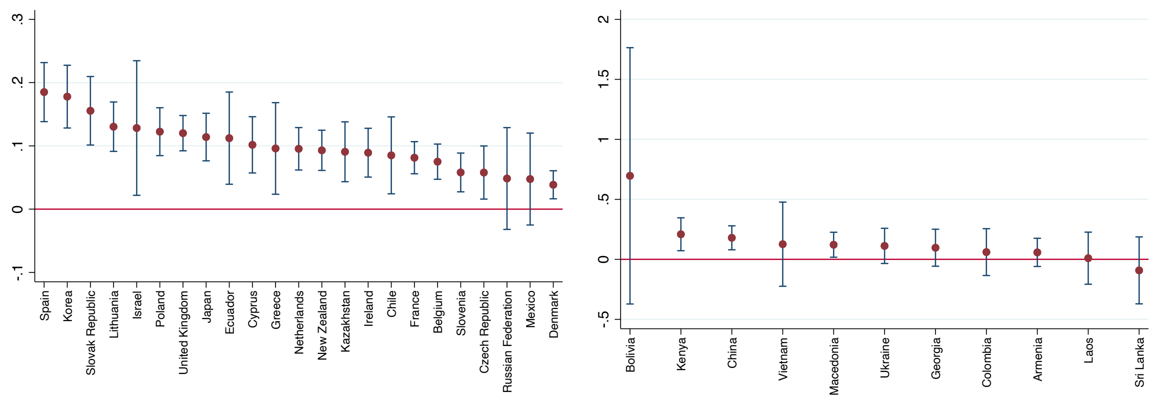
	(1)	(2)	(3)	(4)	(5)	(6)
LFWP	0.153	0.133	0.129	0.114	0.111	0.109
	(0.013)	(0.013)	(0.013)	(0.012)	(0.011)	(0.009)
Sample size	58,885	58,885	58,885	58,885	58,885	58,885
Controls:						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
2-d Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Tasks		Yes	Yes	Yes	Yes	Yes
Industry FE			Yes	Yes	Yes	Yes
Individual demographics				Yes	Yes	Yes
Individual cognition/noncog.					Yes	Yes
Country interactions						Yes

Notes: PIAAC pooled sample. Replication of Table 3 when not discarding PIAAC countries without regional information (Italy and Norway). This explains the increase in available observations.

Figure B3: Estimated average large firm wage premium by country

(a) PIAAC, with region FE

(b) STEP, with region FE



Notes: Regressions of log wages on an indicator of large firm (at least 50 employees), by country. In (a) and (b) with the controls in column (6) in Table 3's panel (a), while in (c) and (d) we feature regional fixed effects as in column (7). Countries ordered by decreasing point estimates. Reported confidence intervals at 95% confidence level computed using heteroskedasticity-robust standard errors.

Table B10: Large firm wage premium, by occupation, PIAAC pooled sample

1-digit ISCO-08 Category	LFWP	# Obs.
Managers	0.138	3,561
	(0.042)	
Professionals	0.121	11,408
	(0.017)	
Technicians & associate professionals	0.072	7,811
	(0.033)	
Clerical support workers	0.120	6,484
	(0.023)	
Services & sales workers	0.178	10,410
	(0.017)	
Craft & related trade workers	0.085	5,414
	(0.040)	
Plant & machine operators, & assemblers	0.155	4,364
	(0.028)	
Elementary occupations	0.027	4,900
	(0.044)	

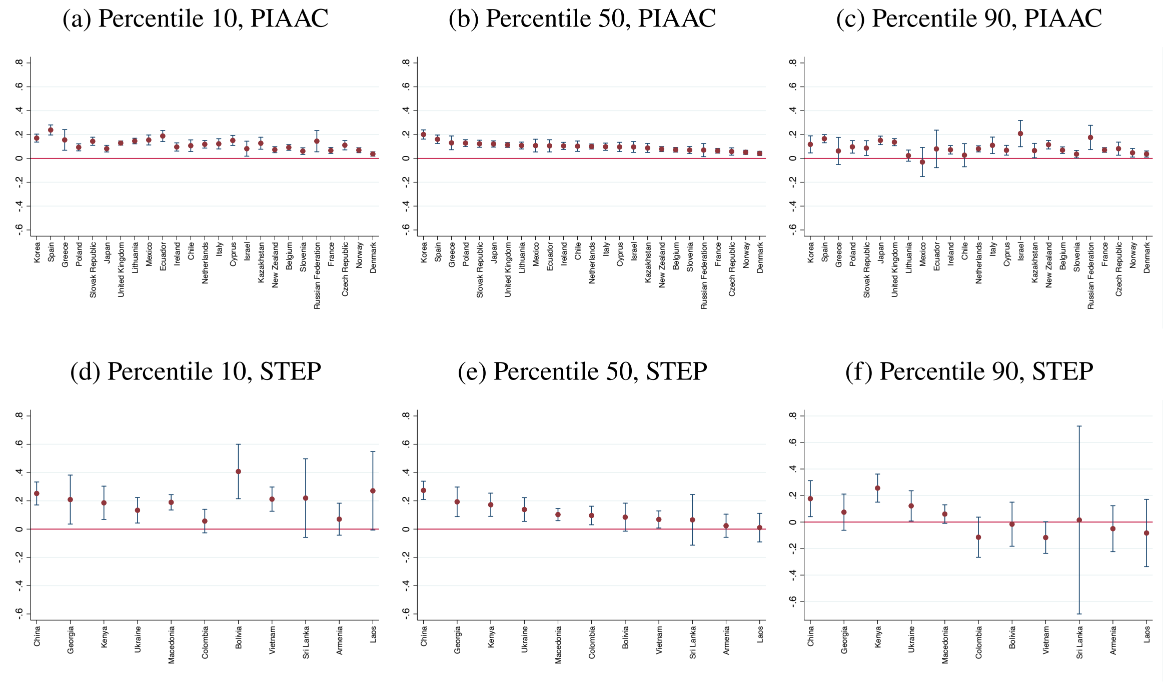
Notes: PIAAC pooled sample. Coefficient of an indicator for large firm in a regression of log real hourly wages on indicator of large firm (at least 50 employees) by 1-digit ISCO-08 occupation codes, controlling for the full set of controls as in Table 3's column 6 in panel (a). We do not report the 1-digit categories corresponding to armed forced occupations and skilled agricultural, forestry and fishery workers due to small sample size. Reported standard errors clustered at the country-level.

Table B11: Large firm wage premium, by occupation, STEP pooled sample

1-digit ISCO-08 Category	LFWP	# Obs.
Managers	1.110	451
	(0.803)	
Professionals	0.162	2,142
	(0.075)	
Technicians & associate professionals	-0.378	788
	(0.331)	
Clerical support workers	0.198	895
	(0.064)	
Services & sales workers	0.191	1,847
	(0.050)	
Craft & related trade workers	0.094	687
	(0.074)	
Plant & machine operators, & assemblers	0.010	588
	(0.093)	
Elementary occupations	0.135	941
	(0.117)	

Notes: STEP pooled sample. Coefficient of an indicator for large firm in a regression of log real hourly wages on indicator of large firm (at least 50 employees) by 1-digit ISCO-08 occupation codes, controlling for the full set of controls as in Table 3's column 6 in panel (a). We do not report the 1-digit categories corresponding to armed forced occupations and skilled agricultural, forestry and fishery workers due to small sample size. Reported standard errors clustered at the country-level.

Figure B4: Distribution of wages in large firms by country, percentiles 10, 50 and 90

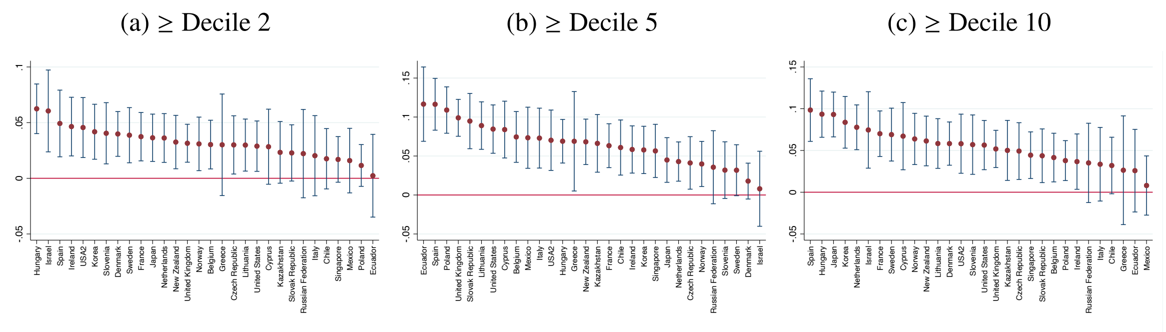


(a) Percentile 10, PIAAC (b) Percentile 50, PIAAC (c) Percentile 90, PIAAC

(d) Percentile 10, STEP (e) Percentile 50, STEP (f) Percentile 90, STEP

Notes: Coefficient of an indicator for large firm in a quantile regression of task content intensity on indicator of large firm (at least 50 employees) and the full set of controls as in column (6) in Table 3's panel (a). Countries ordered by decreasing point estimates in the median regression. Regressions estimated for each country separately. Reported confidence intervals at 95% confidence level computed using heteroskedasticity-robust standard errors.

Figure B5: LFWP based on wage deciles in PIAAC

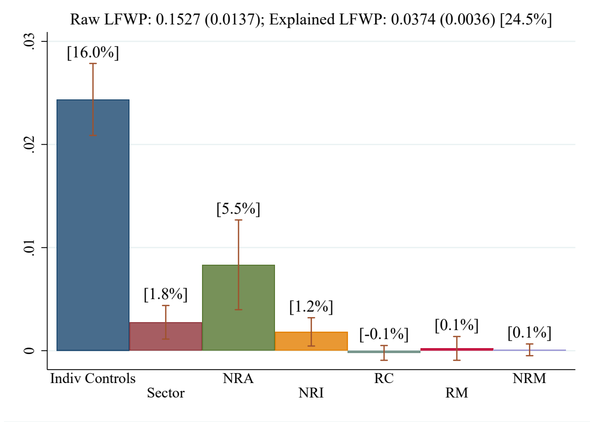


(a) ≥ Decile 2 (b) ≥ Decile 5 (c) ≥ Decile 10

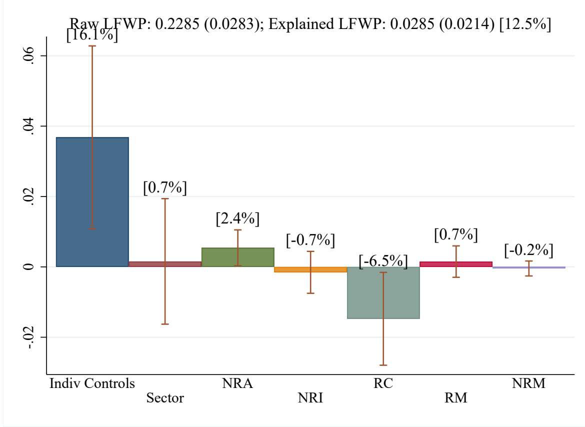
Notes: Coefficient of an indicator of being at least in a certain wage decile in linear regression on indicator of large firm (at least 50 employees) and the full set of controls as in column (6) in Table 3's panel (a). Countries ordered by decreasing point estimates. Regressions done for each country separately. Reported confidence intervals at 95% confidence level computed using heteroskedasticity-robust standard errors.

Figure B6: Gelbach decomposition of LFWP without ICT as mediator, pooled

(a) PIAAC



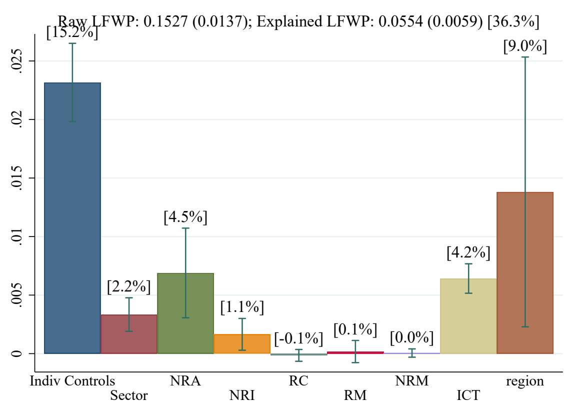
(b) STEP



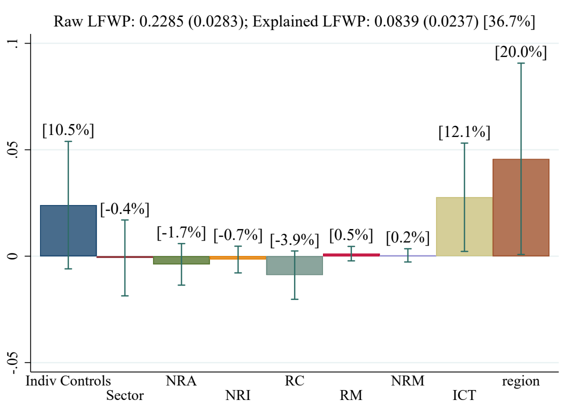
Notes: Pooled PIAAC and STEP samples. Replication of Figure 3 not allowing ICT to be an independent mediator.

Figure B7: Gelbach decomposition of LFWP with region FE as mediators, pooled

(a) PIAAC

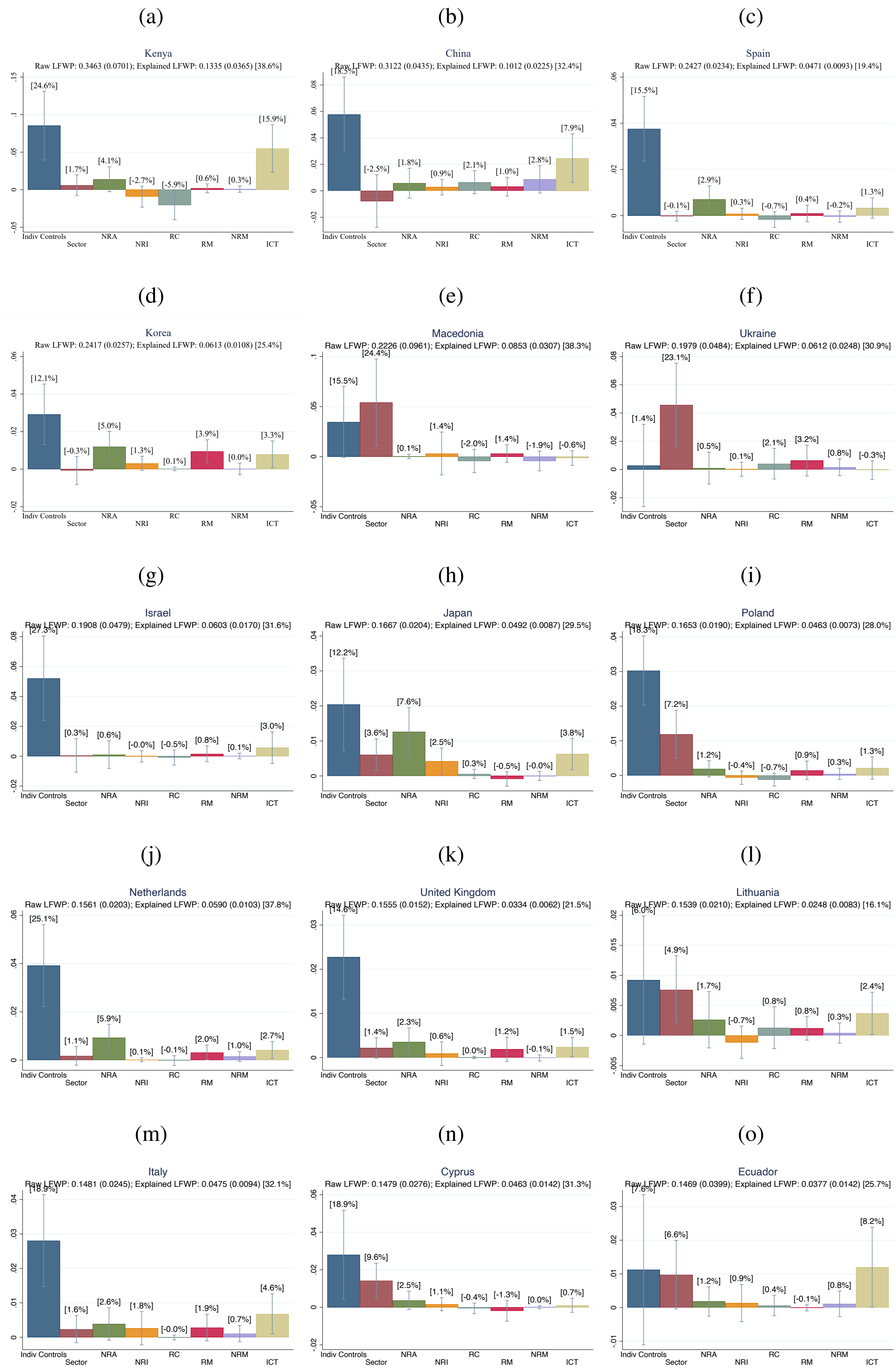


(b) STEP



Notes: Pooled PIAAC and STEP samples. Numbers in brackets indicate percentages of the raw LFWP. Reported confidence intervals at 95% confidence level. Standard errors are clustered at the country level.

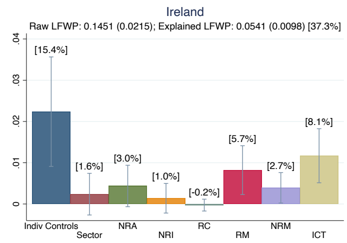
Figure B8: Gelbach decomposition of LFWP, by country, no region FE as mediators



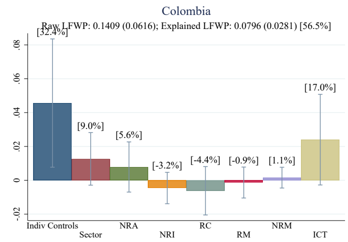
Notes: Only countries for which both the LFWP and the explained portion of the LFWP are statistically significant at the 95% confidence level are reported. Countries ordered by decreasing point estimate of the LFWP. Numbers in brackets indicate percentages of the raw LFWP.

Figure B8: Gelbach decomposition of LFWP, by country, no region FE as mediators (cont.)

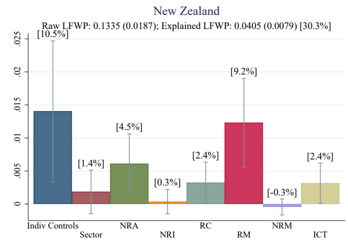
(p)



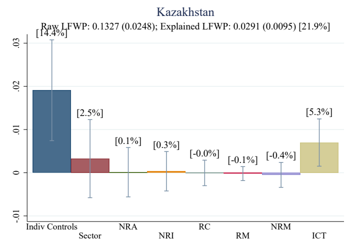
(q)



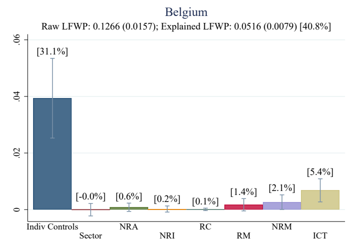
(r)



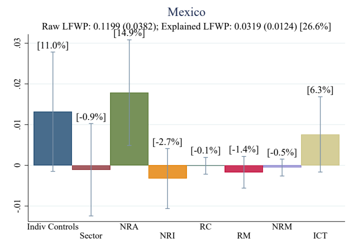
(s)



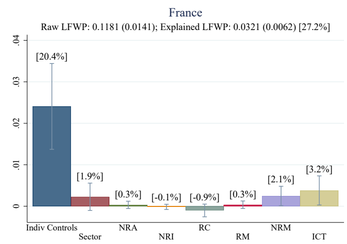
(t)



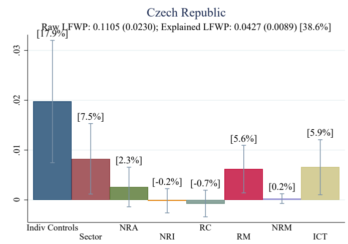
(u)



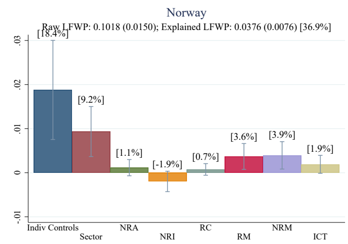
(v)



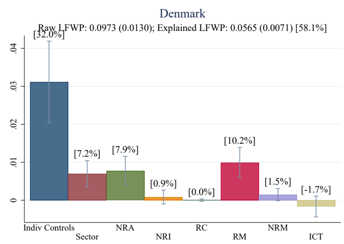
(w)



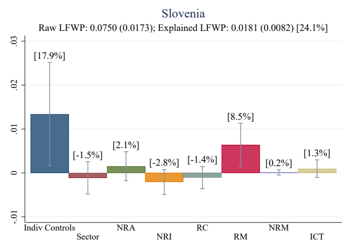
(x)



(y)

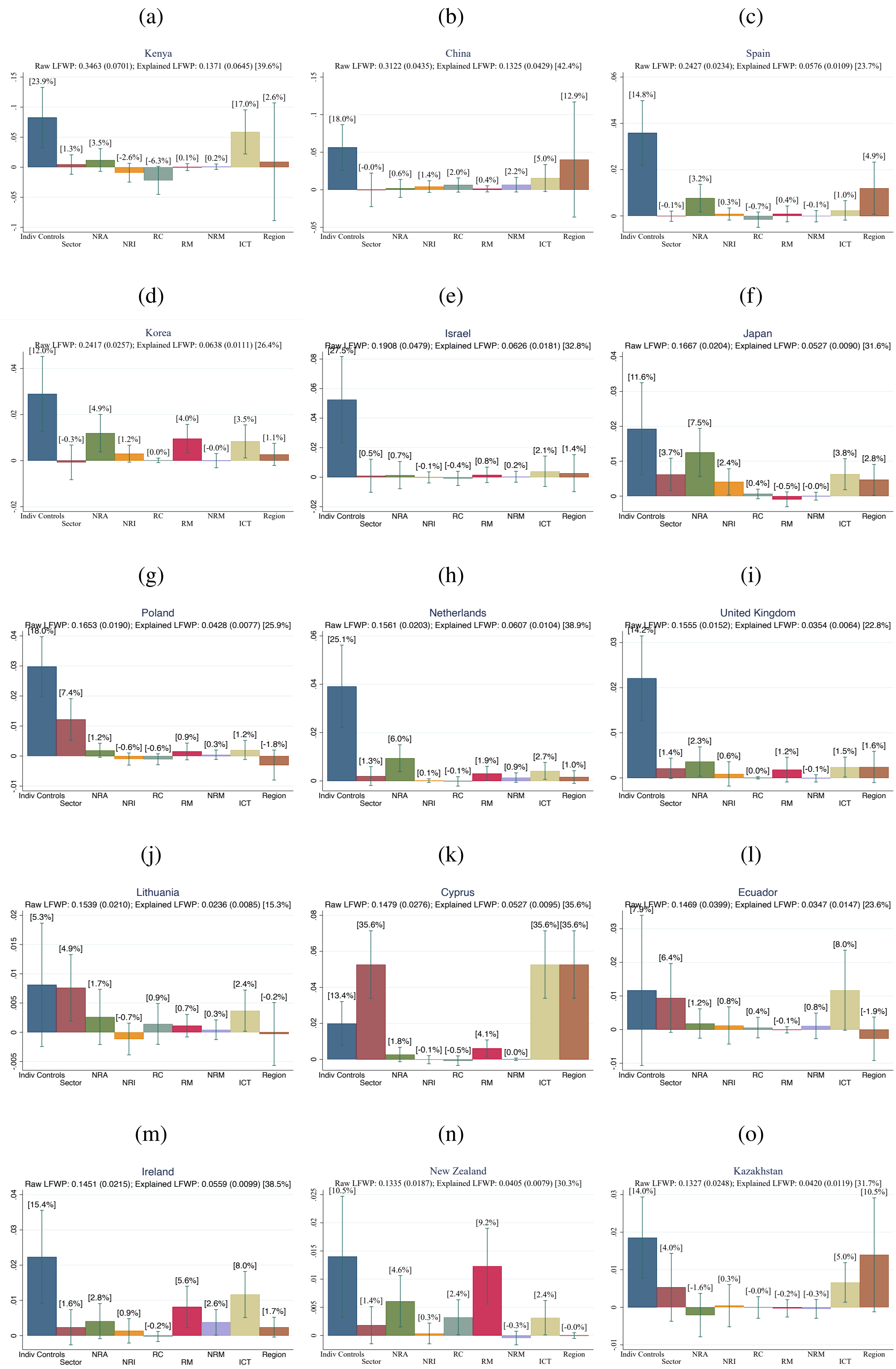


(z)



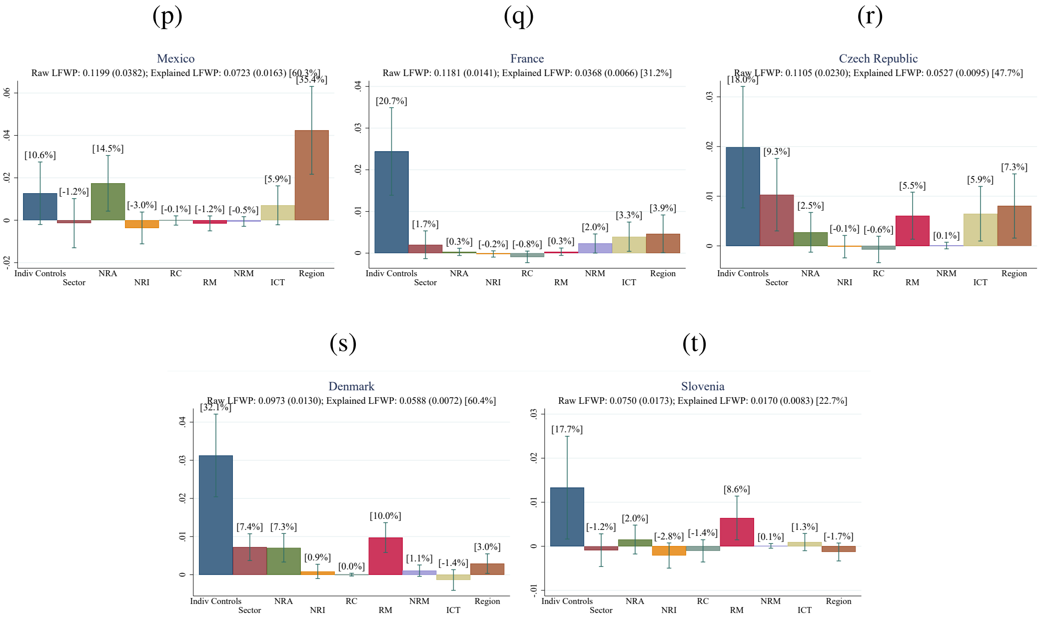
Notes: Countries ordered in decreasing point estimate of the LFWP. Numbers in brackets indicate percentages of the raw LFWP.

Figure B9: Gelbach decomposition of LFWP with region FE as mediators, by country



Notes: Only countries for which both the LFWP and the explained portion of the LFWP are statistically significant at the 95% confidence level are reported. Countries ordered by decreasing point estimate of the LFWP. Numbers in brackets indicate percentages of the raw LFWP.

Figure B9: Gelbach decomposition of LFWP with region FE as mediators, by country (cont.)



Notes: Countries ordered in decreasing point estimate of the LFWP. Numbers in brackets indicate percentages of the raw LFWP.

C Appendix: Additional analyses

C.1 Alternative construction of measures: Multiple correspondence analysis (MCA)

We assess the robustness of our qualitative results by performing some of the same analyses using a differently-constructed measure of task content. In particular, we use the same questions detailed in Appendix Table A1 but aggregate them in a different way. For this, we perform a multiple correspondence analysis (MCA) and choose the first dimension extracted, which corresponds to the dimension that explains the largest variance in the data. MCA is an attractive tool in that it can be thought of as the counterpart of principal component analysis for categorical (particularly, ordinal) data, just like the responses to the questions we have. We opt to perform the MCA by country and we standardize the resulting measure within the country. This means that they are again interpreted as standard deviations relative to the country mean.[2]

Figures available upon request summarize the proportion of total variance explained by the first dimension in the MCA. For most of the task dimensions, the MCA measures constructed explains a large proportion of the variation in the responses to the underlying questions. For example, for non-routine analytical tasks, the MCA measure explains around 70–90% of the variation, depending on the country, the fraction being larger in STEP countries. This fraction is around 60–70% for non-routine interpersonal in PIAAC countries and close to 100% for STEP ones. For routine cognitive it is 60–80% in PIAAC countries but this is reduced to 30–60% in STEP countries. Indeed, the variance explained in STEP countries by the first dimension in the MCA using the questions related to routine cognitive is relatively small — around 20–60%, depending on the country, while the second dimension in MCA

[2]Note that we are not able to construct MCA-based measures for routine manual, non-routine manual, and use of ICT since they were originally constructed out of a single variable (in the case of routine manual in STEP we have two variables but the resulting MCA-based variable perfectly correlates with the non-MCA measure).

still explains a substantial portion of the variation (20–30%). This would suggest that the questions we associate with routine cognitive tasks capture multiple dimensions that a single index could not fully capture.

Table C1: Pooled estimates of firm size gradient in the task content of jobs, MCA measure

Outcome variable	(1)	(2)	(3)	(4)	(5)	(6)
PIAAC						
Non-routine analytical	0.139	0.143	0.107	0.094	0.089	0.089
	(0.015)	(0.016)	(0.015)	(0.016)	(0.017)	(0.017)
	[0.362]	[0.364]	[0.407]	[0.429]	[0.447]	[0.459]
Non-routine interpersonal	0.090	0.101	0.075	0.066	0.060	0.059
	(0.024)	(0.024)	(0.023)	(0.022)	(0.021)	(0.022)
	[0.255]	[0.259]	[0.288]	[0.303]	[0.332]	[0.342]
Routine cognitive	0.013	0.012	0.030	0.041	0.047	0.043
	(0.017)	(0.017)	(0.016)	(0.015)	(0.013)	(0.015)
	[0.122]	[0.122]	[0.134]	[0.146]	[0.165]	[0.174]
Sample size	65,151	65,151	65,151	65,151	65,151	65,151
STEP						
Non-routine analytical	0.138	0.142	0.078	0.074	0.089	0.091
	(0.037)	(0.036)	(0.031)	(0.029)	(0.030)	(0.038)
	[0.418]	[0.419]	[0.459]	[0.466]	[0.476]	[0.525]
Non-routine interpersonal	-0.017	-0.005	-0.031	-0.032	-0.015	-0.029
	(0.032)	(0.036)	(0.039)	(0.037)	(0.031)	(0.031)
	[0.249]	[0.254]	[0.271]	[0.275]	[0.285]	[0.337]
Routine cognitive	0.045	0.037	0.020	0.020	-0.011	-0.018
	(0.070)	(0.067)	(0.064)	(0.064)	(0.051)	(0.075)
	[0.025]	[0.027]	[0.032]	[0.032]	[0.114]	[0.192]
Sample size	8,339	8,339	8,339	8,339	8,339	8,339
Controls:						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
2-d Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes	Yes	Yes	Yes	Yes
Individual demographics			Yes	Yes	Yes	Yes
Individual cognition/noncog.				Yes	Yes	Yes
Country interactions					Yes	Yes
Region FE						Yes

Notes: Replication of Table 1 where task requirement intensity is our MCA measure. Only those tasks for which an MCA measure can be computed are reported. Reported standard errors are clustered at the country level.

In Appendix Table C1, we replicate the results reported in Table 1 using the MCA measures we constructed. We find not only qualitatively but also quantitatively similar results as in the main text. The pattern is not repeated for routine cognitive in STEP countries. This is not surprising since, as we argued before, our MCA measure is likely to capture a very specific dimension of routine cognitive tasks that do not really reflect the same aspects as our original measure did.

C.2 Distributional differences in the task content of jobs by firm size

To complement our finding on the task intensity gradients by firm size, we run various distribution regressions that model the conditional distribution of the outcome (Chernozhukov et al., 2013).[3] We approximate the probability that the task intensity performed T_i is greater than a particular value $t \in \mathcal{T} \subset \text{Supp}(T_i)$ as a linear probability model:

$$\Pr(T_i > t \mid LF_{j(i)}, o(i), c(i)) = \beta \times \text{LF}_{j(i)} + X_i'\gamma + \delta^o_{o(i)} + \delta^c_{c(i)} + \varepsilon_i, \tag{5}$$

where $LF_{j(i)}$ is the indicator for worker i being in a large firm, X is a vector of individual- and firm-level characteristics, δ^o are occupation fixed effects, and δ^c are country fixed effects. We report the estimates for β for a set of support points $\mathcal{T}$. We have also used a probit specification and the qualitative results do not change.

Appendix Table C2 summarizes the estimated coefficients in the distribution regression of the task content of jobs on an indicator of being in a large firm controlling for the full set of controls in column (5) of Table 1. We consider the points on the support $\{-0.75, -0.5, 0, 0.5, 0.75\}$ as thresholds. We find that the coefficient on firm size for non-routine analytical, routine-cognitive and use of ICT all maintain the sign and the significance in all of the five support points. This suggests that our baseline result are not driven by a few workers who perform these tasks more intensively, i.e. the difference in means is not because of differences in the tails but that the entire tasks intensity distribution in large firms is shifted to the right relative to smaller firms.

[3] A complementary approach is quantile regression. However, since the task content measures inherit the discrete nature of the responses to the survey questions, quantile regressions may not be appropriate while distribution regression remains valid.

Table C2: Distribution regression estimates of firm size gradient in the task content of jobs, pooled sample

	Support points				
	(1)	(2)	(3)	(4)	(5)
Outcome variable:	−0.75	−0.50	0.00	0.50	0.75
Panel (a): PIAAC					
NRA	0.031	0.040	0.049	0.054	0.054
	(0.008)	(0.005)	(0.008)	(0.009)	(0.009)
NRI	0.031	0.028	0.023	0.011	0.007
	(0.008)	(0.009)	(0.010)	(0.010)	(0.008)
RC	–	0.012	0.014	0.017	0.010
	(–)	(0.007)	(0.005)	(0.005)	(0.007)
RM	-0.013	-0.008	0.008	0.018	0.017
	(0.004)	(0.004)	(0.004)	(0.007)	(0.006)
NRM	-0.010	-0.006	0.004	0.013	0.007
	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)
Use of ICT	0.061	0.061	0.061	0.059	0.030
	(0.005)	(0.005)	(0.005)	(0.005)	(0.012)
Sample Size	61,151	61,151	61,151	61,151	61,151
Panel (b): STEP					
NRA	0.024	0.026	0.021	0.031	0.024
	(0.005)	(0.012)	(0.017)	(0.017)	(0.010)
NRI	-0.031	-0.013	-0.008	-0.006	0.005
	(0.017)	(0.021)	(0.014)	(0.013)	(0.011)
RC	0.072	0.060	0.057	0.063	0.064
	(0.017)	(0.024)	(0.022)	(0.023)	(0.023)
RM	-0.013	-0.007	0.002	0.010	0.011
	(0.018)	(0.019)	(0.014)	(0.009)	(0.014)
NRM	–	0.003	-0.022	-0.022	-0.016
	(–)	(0.009)	(0.012)	(0.012)	(0.019)
Use of ICT	0.032	0.058	0.058	0.058	0.058
	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)
Sample Size	8,339	8,339	8,339	8,339	8,339

Notes: Pooled PIAAC and STEP samples. Coefficient of an indicator for large firm in a distribution regression of task content intensity on indicator of large firm (at least 50 employees) and the full set of controls in column (5) of Table 1 estimated as a linear probability model. "–" indicates cases where no observation is found below the threshold indicated by the relevant column. Reported standard errors are clustered at the country level.