Comparative Evidence on the Returns to Tasks in Developing Countries

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Abstract

I analyze the prevalence and the returns to routine and non-routine tasks in developing countries. I take advantage of worker-level data from the STEP survey, which collects data on wages and task content across a diverse set of countries. Educational attainment is a strong predictor of within-occupation non-routine task content in developing countries. Moreover, non-routine analytic and interpersonal tasks are associated with sizable wage premiums, even within narrowly-defined occupations. I further document important cross-country differences in wage task premia. Lastly, Autor and Handel (2013)'s conceptual framework indicates that individuals tend to sort into tasks on absolute advantage. Workers in high non-routine analytic occupations who perform additional analytic tasks themselves earn higher wages.

Keywords: Sorting into Tasks, Returns to Tasks, Comparative Analysis.

JEL Codes: J01, J21, J24, J62, O57.

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1 Introduction

In this paper, I analyze the prevalence and the returns to tasks in developing countries. The task framework introduced in Autor et al. (2003), which classifies jobs by their core activities, can offer important insights for examining the impacts of technological change on labor market outcomes. Yet the empirical evidence on the importance of tasks, which relies on occupational dictionaries to classify jobs by their task content, has largely come from developed countries. Since such data sources are rarely available in developing countries, previous work in this setting has often relied on occupational crosswalks to assign task averages from developed countries. Nonetheless, this analysis fails to consider cross-country heterogeneity in task content, as the tasks performed by a cashier in Uganda may differ significantly from those of her German counterpart. Furthermore, since occupation-level task averages overlook individual-level heterogeneity in task assignment (Autor and Handel, 2013), creating occupational dictionaries in developing countries may not suffice for accurately capturing country-specific task content.

In this context, I overcome existing data limitations by taking advantage of worker-level task information from the Skills Toward Employability and Productivity (STEP) survey, which surveys workers in nine low- and middle-income countries, including Armenia, Bolivia, China, Colombia, Georgia, Ghana, Kenya, Macedonia and Vietnam. STEP data includes extensive information on workers' employment outcomes, including wages, occupations and a set of harmonized questions about the tasks performed on the job. I follow Autor and Handel (2013), Dicarlo et al. (2016) and Lo Bello et al. (2019) and construct four indices capturing the prevalence of non-routine analytic, non-routine interpersonal, routine and manual tasks for each worker in the sample. Moreover, STEP surveys include extensive harmonized information on respondents' demographic characteristics, educational attainment and test score performance, which allow me to examine how workers' characteristics shape task assignment. Moreover, I take advantage of information on hourly wages to analyze how tasks are rewarded in developing countries.

I first examine the extent of worker sorting into tasks, finding that more educated workers are more likely to work in jobs with a higher non-routine analytic and interpersonal task content across all STEP countries. These results remain robust to the inclusion of occupation fixed effects, such that an additional year of education is associated with a 0.065 and 0.045 standard deviation (σ) increase in within-occupation non-routine analytic and interpersonal task content, respectively. On the other hand, less educated workers perform a higher share of within-occupation routine tasks. A variance decomposition exercise shows that while occupations remain strong determinants of task content in all countries, workers' observables explain a sizable share of the variance in tasks, both separately and through the positive covariance in workers' qualifications and occupation-level non-routine task content. These results highlight the importance of creating surveys in developing countries which go beyond occupational-averages, as these would miss an important source of heterogeneity in workers' tasks.

To understand how tasks are rewarded in developing countries, I first estimate Mincerian wage regressions aimed at providing exploratory evidence on the returns to tasks in these countries. First, in an OLS regression which controls for workers' educational attainment and test performance, a one standard deviation increase in non-routine analytic and interpersonal content is associated with a wage premium of 10.8% and 7.8%. Importantly, these results remain significant after including occupation fixed effects, thus reflecting sizable wage premiums for non-routine task content in developing countries. These results fit in with findings by Autor and Handel (2013) and Stinebrickner et al. (2018, 2019), who similarly document a positive wage premium for non-routine tasks in the United States. On the other hand, I find a significant wage penalty, in the range of 5%, for workers who perform additional routine tasks, even within occupations. Moreover, I separately estimate the Mincerian wage equations for each country in the STEP sample, finding that while there are some differences in the estimated task-wage-premia across countries, these are not strongly correlated with GDP per capita. As such, cross-country variation in task premia is likely driven by country-specific labor market idiosyncrasies instead (Almeida and Carneiro, 2012; Poschke, 2019).

While these results suggest that performing additional non-routine tasks leds to higher wages in developing countries, Mincerian wage regressions cannot recover the returns to tasks, as workers constantly self-select into jobs by their task content. The causal identification of these returns ideally requires information on pre-labor market skill measures (Saltiel et al., 2017; Böhm, 2020), which are unavailable in STEP data. I explore the returns to tasks by following a Roy (1951)-based framework introduced in Autor and Handel (2013), in which task prices are determined by the extent of workers' self-selection into occupations. In this framework, in order for task assignment to be determined in a competitive equilibrium, the covariance of the returns to tasks within occupations cannot be uniformly positive.[1] I present supportive evidence for this proposition in all countries in the sample, finding that occupations with high returns to analytic tasks tend to offer low returns to interpersonal activities. To further examine whether workers sort into tasks based on their comparative advantage, I estimate a wage regression in which occupational task means are interacted with worker-level task content.[2] I find evidence of sorting on absolute advantage in most countries in the sample, including Bolivia, China, Colombia, Georgia, Ghana and Vietnam. In fact, workers in non-routine analytic occupations who perform additional analytic tasks themselves tend to earn higher wages in most STEP countries, yet this is not the case in the United States (Autor and Handel, 2013).

All in all, these findings indicate that workers self-select into tasks, which in turn play an important role in determining labor market outcomes in developing countries. Nonetheless, there is significant heterogeneity in the importance of different task measures, and additional differences across developing countries which would not be captured by mapping occupation-level job activities from developed countries.

This paper makes various contributions to the existing literature on the importance of tasks in shaping labor market outcomes. To the best of my knowledge, this is the first paper to consider the

[1] Otherwise, workers could be made better off by switching to occupations offering higher returns.

[2] As noted by the authors, a positive coefficient on all of the interaction terms offers evidence for sorting on comparative advantage. Meanwhile, sorting on absolute advantage, where skills across tasks are positively correlated, will arise if the coefficients are positive on at least one of the interaction terms.

returns to worker-level task measures in developing countries. At the same time, I present novel comparative evidence on cross-country differences in the wage premia associated with worker-level measures of non-routine, routine and manual tasks. As such, this paper fits in with a nascent literature exploring the returns to tasks using information on worker-level task inputs, building on previous work relying on occupation-level task measures.[3] Autor and Handel (2013) use Princeton Data Improvement Initiative data to examine the factors driving sorting into abstract, routine and manual tasks in the United States and estimate the return to these measures under a Roy model of selection into tasks. Stinebrickner et al. (2018, 2019) rely on data from the Berea Panel Study, which elicits individual-level task measures, to examine the contribution of task content to wage growth in the early career and to analyze how differences in task content and experience contribute to the gender wage gap among college graduates, respectively.

Second, I contribute to a growing literature analyzing the factors driving differences in task content across developing countries. I provide extensive evidence on the individual-level characteristics which drive sorting into non-routine, routine and manual tasks, both at the individual and occupational level. Moreover, I present comparative analysis across countries and considering how the extent of sorting into tasks may vary across levels of economic development. Various papers, such as Aedo et al. (2013), Arias et al. (2014), Handel et al. (2016) and Apella and Zunino (2018), rely on O*NET data to document task content differences across developing countries, yet these papers assume that task content in the United States can be directly mapped into developing countries. At the same time, three recent papers have relied on STEP data (and other surveys) to consider cross-country differences in task content using worker-level data.[4] Lewandowski et al. (2019) combine STEP data along with two other data sources with information on worker-level tasks and show that workers in developed economies perform more non-routine analytical and interpersonal tasks and fewer routine tasks. Dicarlo et al. (2016) find significant differences in task content across occupations in developing countries, yet these patterns are remarkably similar in all STEP countries. De La Rica et al. (2020) present similar evidence for developed countries using worker-level data from the PIAAC. Lastly, Lo Bello et al. (2019) document similarities between STEP and O*NET task measures in non-routine analytical and interpersonal tasks, but not for routine cognitive and non-routine manual tasks.

The rest of the paper proceeds as follows. In Section 2, I introduce data sources and present summary statistics. In Section 3, I present evidence on the worker-level characteristics which predict worker-level task content. In Section 4, I present cursory evidence on the returns to tasks and examine differences across countries. In Section 5, I introduce a conceptual framework based on Autor and Handel (2013) which considers sorting into tasks. I also present empirical evidence on the extent to which workers sort into tasks. In Section 6, I discuss the results and conclude.

[3] For papers examining the importance of tasks in the labor market using occupation-level measures, see Autor et al. (2003), Autor et al. (2006), Acemoglu and Autor (2011), Firpo et al. (2011), Yamaguchi (2012), Gottschalk et al. (2015), Cortes (2016), Yamaguchi (2018), Jaume (2018) and Böhm (2020) among others.

[4] A parallel strand of the literature has relied on STEP data to analyze other topics, including labor market mismatch (Handel et al., 2016), the returns to skills (Acosta et al., 2015; Valerio et al., 2016) and gender wage gaps (Tognatta et al., 2016; Gunewardena et al., 2018), among others.

2 Data Sources and Summary Statistics

2.1 Data Sources

This paper uses data from the first two waves of the Skills Toward Employment and Productivity (STEP) household survey, conducted by the World Bank in urban areas of twelve low- and middle-income countries (Armenia, Bolivia, Yunnan Province in China, Colombia, Georgia, Ghana, Kenya, Lao PDR, FYR Macedonia, Sri Lanka, Ukraine and Vietnam) between 2012 and 2013.[5] STEP surveys collect demographic and educational information for all individuals in the household, and additional detailed information on skills, education and employment outcomes for a randomly-selected 15-64 year old in the household.

I observe the main respondent's gender, age, educational attainment, potential experience, and employment status, selected among four options, including unemployment, unpaid family work, self-employment and working as an employee. As the goal of this paper is to understand sorting into occupations as well as the returns to tasks, I restrict my attention to individuals working as employees for whom I observe hourly wages (reported in constant 2010 US dollars).[6] STEP surveys additionally include information on employed workers' occupations, harmonized at the 3-digit level under the ISCO-08 classification.[7] Lastly, the main respondent in each country completed a standardized reading proficiency test developed by the Educational Testing Service (ETS). Moreover, respondents answered 24 survey items capturing socio-emotional skills, which can be mapped to the Big Five (agreeableness, conscientiousness, emotional stability, extraversion and openness to experience), grit, hostile attribution bias and coping strategies (Acosta et al., 2015).[8]

As noted above, the literature on the importance of tasks in the labor market has largely relied on dictionaries mapping occupations to tasks. Nonetheless, two recent surveys in the United States (STAMP and PDII) have spearheaded the analysis of worker-level task content by eliciting information on job activities across various domains, including cognitive, interactive and physical tasks. The STEP survey was in fact designed with the explicit goal of following the STAMP survey to capture worker-level job activities, such that a number of questions in STEP map directly into the O*NET (Pierre et al., 2014). As a result, STEP includes various questions regarding workers' tasks, such as the share of time spent thinking on the job, the frequency of presentations, and whether they operate heavy machinery, among others.

Given the large number of questions regarding respondents' job activities, I follow two other papers analyzing tasks in the STEP survey (Dicarlo et al., 2016; Lo Bello et al., 2019), as well as Autor and Handel (2013), and map these questions into specific skill categories as outlined in

[5]While STEP is representative of urban areas in these countries, the surveys in Lao PDR and Sri Lanka covered individuals in rural areas, as well (Pierre et al., 2014). To ensure comparability with the rest of the surveys, I follow Handel et al. (2016) and restrict the analysis to individuals in urban areas. I remove Sri Lanka from the analysis as the vast majority of respondents reside in rural areas.

[6]I remove Lao PDR from the sample as fewer than one-fourth of respondents report working as employees.

[7]The Ukraine survey only reports occupations at the two-digit level. Since the empirical strategy outlined in Section 3 requires information on three-digit occupations, I exclude Ukraine from the sample, as well.

[8]I additionally drop individuals with missing educational attainment, test score information, wage observations, as well as those working in the armed forces or in agricultural occupations.

Autor et al. (2003). I classify tasks into four categories, including abstract thinking and problem-solving tasks (non-routine analytic), tasks requiring interacting and managing people and clients (non-routine interpersonal), tasks which follow explicit procedures (routine) and tasks requiring physical movements (manual).[9]

I follow Dicarlo et al. (2016) and Lo Bello et al. (2019) in mapping job activities into task categories by assigning specific questions to each category and then applying principal component analysis (PCA) to calculate a standardized task index in each country.[10] To construct the non-routine analytic index, I rely on five STEP questions, which capture the length of the longest document read at work, the types of documents read, the length of the longest document written, whether the job requires basic, advanced or no math skills, and whether thinking for 30 minutes is required at work. For the non-routine interpersonal index, I use three questions: whether the job requires supervising co-workers, making formal presentations and spending time with customers. Three STEP items include information about the routine nature of the job, including whether the job involves learning new things, the repetitive nature of the job is and the level of autonomy the worker has. Lastly, the manual index is estimated from three questions regarding whether the job requires driving, operating heavy machinery, repairing items/instruments along with a categorical variable measuring the physical intensity of the job. I standardize the four task categories in each country to have mean zero and standard deviation one. The empirical analysis includes sample weights to represent the working-age (15-64 year old) population in each country. To carry out cross-country comparisons in the prevalence and determinants of tasks (De La Rica et al., 2020), I follow the PCA procedure outlined above for the full STEP sample, and weigh all countries equally.

2.2 Summary Statistics

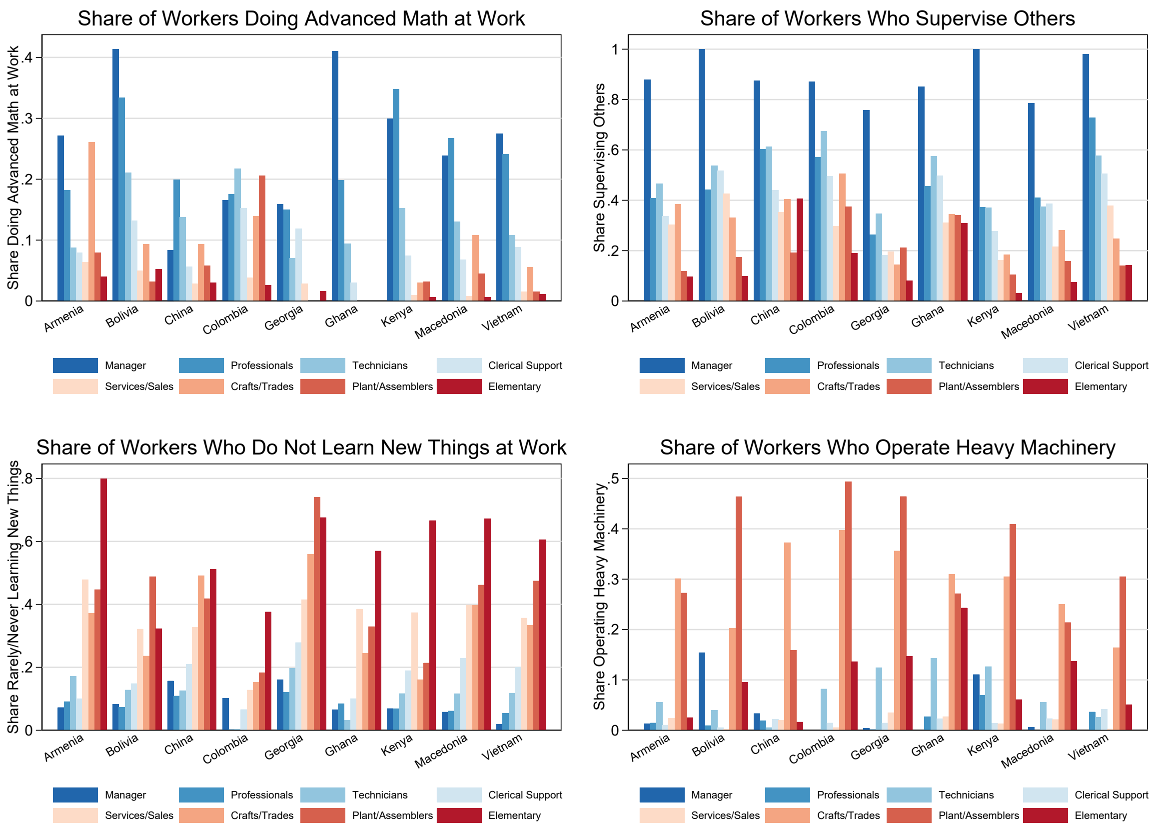
Table A1 presents summary statistics for the sample considered in this paper. The overall sample size exceeds 8,600 respondents, while varying across countries, from 515 respondents in Ghana to 1,435 in Macedonia. STEP covers low- and middle-income countries, yet there is a wide range in countries' GDP PPP per capita, from US$2,500 in Kenya to upwards of US$12,000 in Colombia. The average respondent in the sample has completed upwards of 12 years of education, and the differences in education across countries are positively correlated with GDP. The occupational composition indicates that one-fourth of the sample work as professionals, about 20% are in services and sales, and the rest of the sample is largely evenly-split across the other six one-digit occupations, notwithstanding small differences across countries. Lastly, differences in task prevalence across countries are also positively correlated with income per capita (Lewandowski et al., 2019), as, for

[9]Since STEP surveys only include three questions about the routine nature of the job, I cannot distinguish between routine manual and routine cognitive tasks, as in Autor et al. (2003). Autor and Handel (2013) deal with similar data limitations, as they classify routine tasks in one category and group non-routine analytic and interpersonal tasks into one category. The questions available in STEP allow me to extend their work by separately considering the importance of non-routine analytic and interpersonal tasks, which carry relevance in the context of the growing importance of social skills in the labor market (Kuhn and Weinberger, 2005; Deming, 2017).

[10]I pursue the PCA approach for comparability with Autor and Handel (2013). The empirical results are similar when I create the task indices averaging across the relevant questions. These results are available upon request.

instance, 14.6% of Bolivians report using advanced math at work, compared to 9% of Kenyans.

Figure 1: Share of Workers Performing Tasks by Occupations Across STEP Countries



Source: Skills Toward Employability and Productivity (STEP) Survey. Note: Figure 1 shows the share of workers across one-digit occupations in the nine STEP countries who perform different tasks.

Figure 1 further documents differences in the prevalence of tasks across occupations in each STEP country. The first panel shows that across all STEP countries, managers and professionals are far more likely to use advanced math at work vis-à-vis workers in other occupations. Similarly, while the vast majority of managers in the STEP sample supervise others, this is not the case for all managers, indicating the importance of considering within-occupation differences in the prevalence of tasks. At the same time, the third panel shows that individuals working in plants, crafts and trades, as well as those in elementary occupations are least likely to learn new things on the job and most likely to operate heavy machinery, remarking the routine and manual nature of these occupations in developing countries. Nonetheless, there are sizable differences in the prevalence of workers performing these tasks both across countries, but also across and within occupations.[11]

Figure A1 extends the analysis by considering the prevalence of task indices in different occupa-

[11]The difference in the prevalence of tasks remain even within three-digit occupational groups, fitting in with evidence in Autor and Handel (2013) showing significant differences in the task content of jobs within six-digit occupations in the United States.

tions in the STEP sample. Unsurprisingly, the first two panels show that managers and professionals have the highest non-routine analytic and interpersonal content in all countries, followed by technicians and those in clerical jobs. The third panel shows that differences in the routine content of jobs across occupations are less clear, as both the absolute difference in occupation-averages in the highest- and lowest-ranked occupation is far lower than for both non-routine indices, but also the ranking of occupations varies across countries. For instance, workers in elementary occupations have the highest routine content in Armenia, Kenya and Macedonia, compared to plant workers in Georgia and clerical support workers in Ghana. The last panel shows similar differences in the manual content of jobs across occupations, with craftsmen and plant workers leading the way. In light of important differences in the prevalence of tasks across and within occupations, I next consider the extent to which there is sorting into occupations and into within-occupation task content for each country in the STEP survey.

3 Sorting into Tasks

To examine the extent to which workers' characteristics drive task content, in Figure A2, I first analyze differences in task content for workers across different educational categories. The average non-routine analytic task content of college graduates surpasses that of their high school dropout counterparts by upwards of a full standard deviation, with similar gaps appearing in interpersonal content. These patterns are reversed in routine and manual content, yet the magnitude of the differences in task content is smaller across educational groups. I further consider the extent to which human capital and demographic characteristics shape the tasks that workers perform on the job by estimating the following OLS regressions:

$$T^n_{ic} = \alpha_0 + \alpha_1 \boldsymbol{X_i} + \lambda_c + \varepsilon_{ic} \tag{1}$$

$$T^n_{ioc} = \beta_0 + \beta_1 \boldsymbol{X_i} + \lambda_c + \gamma_o + v_{ioc} \tag{2}$$

where for worker i residing in country c, T_{ic} captures her task n content, where n represents non-routine analytic, interpersonal, routine or manual content. $\boldsymbol{X_i}$ denotes human capital and demographic characteristics, encompassing educational attainment, potential experience, gender, as well as the reading proficiency test score and the non-cognitive measures, λ_c captures country fixed effects and γ_o is a vector of 123 three-digit occupation dummies. In equation (2), I include three-digit occupation fixed effects to examine how occupations mediate the importance of worker characteristics in determining task assignment. I estimate equations (1)-(2) both in the full sample, but also separately for each country to analyze cross-country differences in the extent of sorting-into-tasks.

The first four columns of Table 1 present the estimated results from equation (1). Columns 1 and 2 show that educational attainment remains a strong predictor of non-routine tasks, such that an additional year of education is associated with an 0.134 and 0.108 standard deviation increase in

Table 1: Determinants of Worker-Level Task Content

	Analytic (1)	Interpersonal (2)	Routine (3)	Manual (4)	Analytic (5)	Interpersonal (6)	Routine (7)	Manual (8)
Educational Attainment	0.134***	0.108***	-0.050***	-0.039***	0.065***	0.045***	-0.018***	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Experience	-0.009***	0.014***	-0.004	0.018***	-0.009***	0.014***	-0.002	0.011***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Experience^2	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.017	0.057***	-0.076***	0.573***	0.060***	0.132***	-0.070***	0.319***
	(0.017)	(0.020)	(0.021)	(0.021)	(0.018)	(0.021)	(0.025)	(0.022)
Test	0.050***	-0.015	0.019	-0.008	0.054***	-0.013	0.014	-0.016
	(0.010)	(0.012)	(0.013)	(0.012)	(0.009)	(0.011)	(0.013)	(0.011)
Non-Cognitive Test	0.136***	0.137***	-0.076***	0.024**	0.103***	0.104***	-0.060***	0.048***
	(0.009)	(0.010)	(0.011)	(0.011)	(0.008)	(0.009)	(0.011)	(0.010)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes	Yes	Yes
Adj. R^2	0.357	0.194	0.041	0.102	0.478	0.332	0.085	0.275
Within adj. R^2	0.351	0.188	0.041	0.102	0.126	0.046	0.007	0.027
Observations	8,677	8,677	8,677	8,677	8,672	8,672	8,672	8,672

Source: Skills Toward Employability and Productivity (STEP) Survey. Note: Robust standard errors in parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table 1 presents evidence on the extent to which worker characteristics drive worker-level task content. The first four columns include country fixed effects whereas the last four additionally include three-digit fixed effects.

analytic and interpersonal task content, respectively. Meanwhile, workers who received higher test scores in the reading proficiency exam perform additional analytic tasks, yet this is not the case on the interpersonal dimension. On the other hand, the non-cognitive skills measure is strongly predictive of both dimensions of non-routine task content. As such, these results indicate human capital and demographic characteristics explain a sizable share of the variation in non-routine task content: the within-country adjusted R^2 exceeds 0.35 and 0.18 in analytic and interpersonal tasks, respectively. The third and fourth columns show a different story for routine and manual tasks, as educational attainment is negatively correlated with the prevalence of such tasks. Importantly, worker characteristics explain a lower share of routine and manual content — the adjusted R^2 equals 0.041 and 0.102, respectively — exhibiting important differences on vis-à-vis the determinants of non-routine tasks in developing countries.

Column (5) presents the estimated results for equation (2) for non-routine analytic tasks. First, the increase in the adjusted R^2 from 0.357 to 0.478 indicates that an important share of analytic task content is explained by occupational assignment. As a result, since more educated individuals tend to work in occupations exhibiting a higher prevalence of analytic tasks, the estimated coefficient on education falls by 50% relative to the first column (from 0.134 to 0.065 σ). Nonetheless, educational attainment, along with other worker characteristics remain strong determinants of within-occupation analytic task content, as the within-occupation adjusted R^2 equals 0.126. I similarly find that occupations strongly shape non-routine interpersonal content, yet an additional year of schooling increases within-occupation interpersonal content by 0.045 standard deviations. The last two columns show that occupations further drive workers' routine and manual task content, as shown by the larger adjusted R^2 vis-à-vis the results of equation (1). In fact, the negative relationship between education and task content in these two dimensions is largely mediated through occupational assignment. Workers' characteristics thus play a limited role in driving within-occupation routine and manual task content, as indicated by the small within-occupation adjusted R^2, which equals 0.007 and 0.027, respectively.

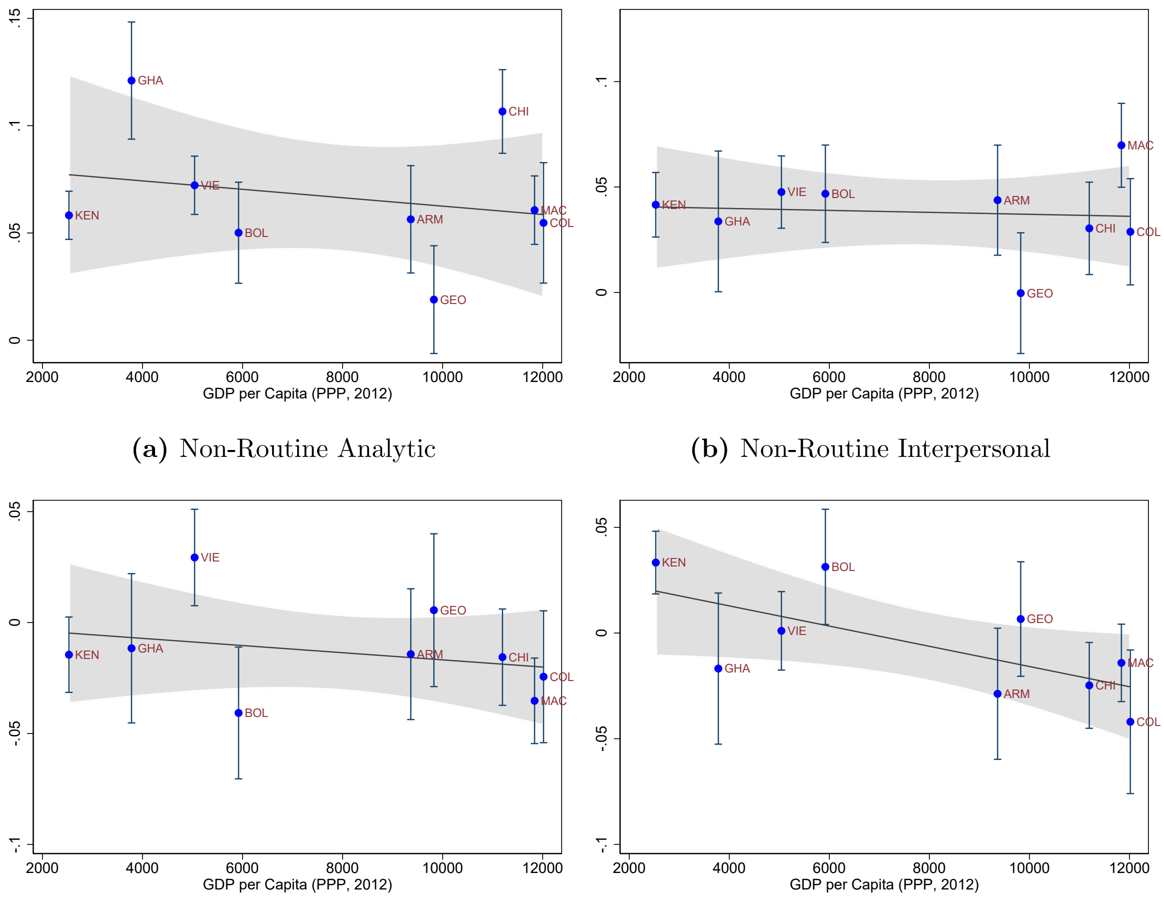
To formally explore the importance of occupations vis-à-vis individual characteristics in determining task assignment, I conduct a variance decomposition of worker-level task content in developing countries following the results of equation (2). I present the results in Table A2. First, individual characteristics and occupational assignment are strong drivers of workers' analytic task content, accounting for 13.8% and 18.1% of the variance of the task index, respectively. Moreover, individual characteristics also determine analytic task content through occupational assignment, as the covariance term accounts for 19% of the variance in such tasks. The second column shows similar findings for non-routine interpersonal task content, albeit with smaller magnitudes: worker-level characteristics account for just 4.8% of the task variance along with an additional 9.8% through the covariance term. At the same time, three-digit occupations independently account for a sizable share of the variance (20.3%) of interpersonal task content. I lastly find a negligible small contribution of workers' characteristics to the variance in routine and manual task content, whereas occupations strongly shape the prevalence of such tasks accounting for 10.9% and 24.3% of their variance, respectively.[12] While the variance decomposition exercise remarks the importance of occupations in structuring the types of tasks done at work in developing countries, there are sizable differences in *within-occupation* task content, especially in the non-routine dimension.

I further examine cross-country heterogeneity in the extent to which education shapes within-occupation task content by re-estimating equation (2) separately for each country in the sample. I present the results in Figure 2. First, in all countries but Georgia, higher educational attainment is associated with a greater prevalence of within-occupation analytic tasks. While the extent of sorting-into-analytic tasks exhibits a small negative correlation with countries' GDP per capita, this relationship is not statistically significant. The second panel shows similar patters for interpersonal tasks, as more educated workers perform a higher share of such tasks within occupations in all countries — yet the extent of sorting does not vary significantly across the STEP sample. Meanwhile, educational attainment does not consistently shape workers' routine and manual tasks across STEP countries, as the estimated coefficients vary in sign and significance across the sample.

The results presented in so far show that occupations explain an important share of the variance in worker-level tasks, whereas workers' educational attainment strongly shape non-routine tasks, along with a limited impact on the prevalence of routine and manual tasks. In light of existing evidence showing the importance of education and occupations in shaping labor market outcomes, I next analyze the relationship between worker-level task content and wage outcomes in developing countries.

[12] Across all task indices, country-specific characteristics explain only a limited share of the variance in task content, as seen by the small contribution of country fixed effects along with its covariance with worker characteristics and occupations to the overall variance in analytic, interpersonal, routine and manual task content.

Figure 2: Education as a Determinant of Within-Occupation Task Content



(a) Non-Routine Analytic

(b) Non-Routine Interpersonal

(c) Routine

(d) Manual

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure 2 presents evidence of the importance of educational attainment in driving worker-level task content within three-digit occupations. The reported coefficients denote the estimated effect of an additional year of education on each of the four task indices. The vertical lines for each country represent 90% confidence intervals. The shaded area represents the 90% confidence interval from a cross-country regression of the estimated importance of education as a driver of tasks. Task indices are constructed as described in Section 2, normalized to have an average of zero and a variance of one.

4 Wages and Tasks

Given the paucity of evidence on the importance of tasks in driviing labor market outcomes in developing countries, I first consider the relationship between worker-level task content and hourly wages in the following OLS regression:

$$w_{ioc} = \eta_0 + \eta_1 \boldsymbol{T_{ioc}} + \eta_2 \boldsymbol{X_i} + \lambda_c + \gamma_o + e_{ioc} \tag{3}$$

where w_{ioc} represents hourly wages (in US Dollars) for worker i employed in occupation o in country c, $\boldsymbol{T_{ioc}}$ captures the four individual-level task measures defined above, whereas $\boldsymbol{X_i}$, λ_c and

γ_o capture worker-characteristics, country and occupation-fixed effects, respectively. I estimate equation (3) both for the full sample as well as for each country in STEP separately.

Table 2: Wage Regressions with Individual Task Content and Occupation Fixed Effects

	(1)	(2)
Worker-Level Task Content		
Non-Routine Analytic	0.108***	0.061***
	(0.017)	(0.016)
Non-Routine Interpersonal	0.078***	0.072***
	(0.014)	(0.015)
Routine	-0.055***	-0.049***
	(0.012)	(0.012)
Manual	0.033**	0.015
	(0.014)	(0.013)
Educational Attainment	0.071***	0.057***
	(0.006)	(0.007)
Experience	0.024***	0.023***
	(0.004)	(0.004)
Experience^2	-0.000***	-0.000***
	(0.000)	(0.000)
Male	0.172***	0.115***
	(0.040)	(0.025)
Test	-0.017	-0.012
	(0.014)	(0.013)
Non-Cognitive Test	0.016	0.014
	(0.012)	(0.011)
Country FE	Yes	Yes
Occupation FE	No	Yes
F (task measures)	27.88	19.04
P-value	0.000	0.000
Adj. R^2	0.277	0.333
Observations	8,362	8,355

Source: Skills Toward Employability and Productivity (STEP) Survey. Note: Standard Errors in Parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the three-digit occupation level. Table 2 presents evidence on the wage premium associated with a one standard deviation increase in each of the worker-level task measures. The first column controls for country fixed effects. The second column additionally includes three-digit occupation fixed effects. The F-statistic follows from a Wald test of the joint significance of the worker-level task measures.

I first estimate equation (3) without including occupation fixed effects and present the results in the first column of Table 2. Educational attainment is positively associated with hourly wages across all STEP countries, as the return to an additional year of schooling reaches 7.1% on average.[13] Moreover, I find evidence of a concave experience-wage profiles, fitting in with recent evidence by Lagakos et al. (2018) across developed and developing countries, along with a gender wage gap, exceeding 17 log points. Lastly, neither the reading proficiency nor the non-cognitive skill measures are predictive of hourly wages in the STEP survey countries.

At the same time, Table 2 shows the extent to which non-routine tasks shape wage outcomes in developing countries. A one standard deviation increase in the non-routine analytic index is associated with a 10.8% wage premium in the full STEP sample. In fact, the estimated analytic

[13] Psacharopoulos and Patrinos (2018) similarly document a return to schooling of 8.8% across 139 countries.

task premium is remarkably similar to the results in Autor and Handel (2013), who had found that a one standard deviation increase in abstract tasks is associated with a 12% wage premium in the United States. The interpersonal task premium is also positive and significant: a one standard deviation increase in this task measure corresponds to a 6.8% wage premium. Nonetheless, this coefficient is significantly lower than for analytic tasks, remarking the importance of separately considering these two non-routine task measures. Meanwhile, I find evidence of a large wage penalty to routine tasks, reaching 5.5%, whereas a one standard deviation increase in the manual task index is associated with a wage premium of 3.3%.

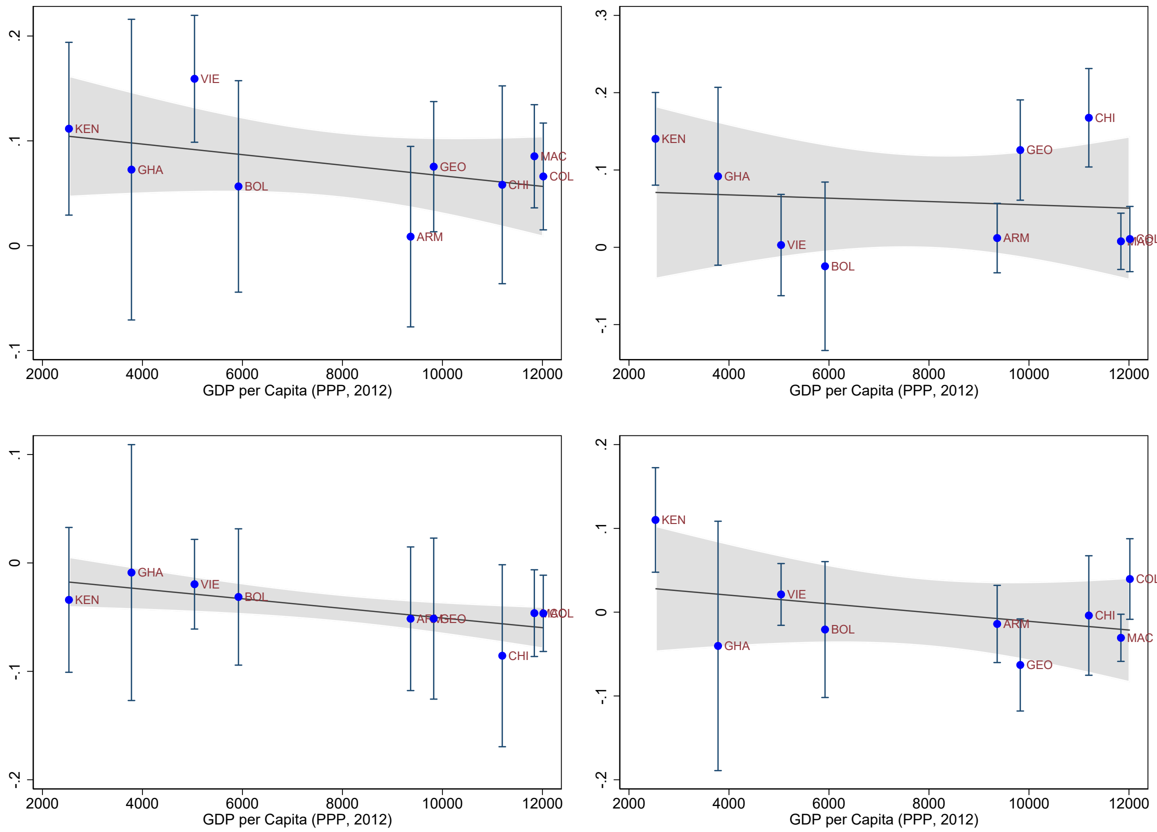
The second column of Table 2 presents the results from equation (3), which incorporates three-digit occupation fixed effects. Within occupations, a one standard deviation increase in the non-routine analytic index is associated with an average wage premium of 6.1%, whereas a corresponding increase in within-occupation interpersonal task content has a wage premium exceeding 7%. Relative to the results presented in the first column, the non-routine analytic task wage premium falls by about 40%, whereas the returns to interpersonal tasks remain remarkably stable. These results thus show that non-routine tasks remain strong predictors of labor market outcomes in developing countries, even upon controlling for occupations and educational attainment. The wage penalty associated with routine tasks remains significant within occupations, as a one standard deviation increase in this measure is associated with lower hourly wages by close to 5%. Meanwhile, the within-occupation returns to manual tasks are largely mediated by occupational assignment, as the estimated manual-task wage premium is no longer statistically significant. The statistical significance of the the Wald test on the joint significance of the individual task measures within occupations further highlights the extent to which differences in task content within occupations shape labor market outcomes in developing countries.[14]

To examine whether the estimated wage premia vary consistently with countries' levels of economic development, I re-estimate equation (3) separately for each country in the STEP sample. I present the results in Figure 3. The first panel shows the estimated returns to non-routine analytic tasks across countries. While the estimated coefficients are positive for all countries in the sample, the returns to analytic tasks are not statistically significant in Armenia, Bolivia, China and Ghana. Moreover, the estimated analytic wage premium is not strongly correlated with GDP per capita. The second panel shows similar results for interpersonal tasks, as the estimated wage premia are largely positive, yet not differentially so across countries' levels of income per capita. The last panel shows significant differences in the returns to manual tasks across countries, as the returns are positive in Colombia and negative in Macedonia, yet the task premia are not strongly correlated with GDP per capita. As such, cross-country differences in the estimated returns to tasks are not accounted for by differences in GDP per capita. Instead, these patterns may be driven by differences in countries' labor market structures, encompassing the extent of regulations and the size of the informal sector among other potential factors.[15]

[14]Controlling for three-digit occupations only leads to a small increase in the adjusted R^2, from 0.277 to 0.333, indicating that occupations separately explain a small share of the variance in wage outcomes in developing countries.

[15]See Almeida and Carneiro (2012), Poschke (2019) and Rucci et al. (2020) for a discussion of the interaction of

Figure 3: Estimated Within-Occupation Task Wage Premiums in Developing Countries



Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure 3 presents evidence of the the estimated wage premium associated with each task measure within three-digit occupations occupations in the STEP survey. denote the estimated premium associated with a one standard deviation increase in each task measure, controlling for workers' observable characteristics along with three-digit occupation fixed effects. The vertical lines for each country represent 90% confidence intervals. The shaded area represents the 90% confidence interval from a cross-country regression of the estimated importance of education as a driver of tasks. Task indices are constructed as described in Section 2, normalized to have an average of zero and a variance of one.

Two additional results confirm the importance of individual-level tasks in shaping wage outcomes in developing countries. First, in Table A3, I present results from a regression which includes both individual and occupation-level task measures.[16] The estimated returns to the worker-level measures largely follow those in Table 2, with positive returns in the two non-routine measures along with a wage penalty for routine tasks. In fact, the F-statistic for the joint significance of the individual tasks remains statistically significant. Furthermore, to assess the robustness of the estimated task wage premiums to selection on unobservables (Altonji et al., 2005), I re-estimate equation (3) removing different covariates and compare the estimated task wage premiums to the main sample results. The first column of Table A4 shows that upon removing test scores from $\boldsymbol{X_i}$, the estimated task-wage premiums are largely in line with those shown in Table 2. The second column further removes educational attainment as a control variable. Fitting in with the importance

regulations and labor market outcomes in developing countries.

[16]For each worker i, the average occupation-level task indices do not include her task content.

of education as a determinant of task content presented in Section 3, the estimated non-routine task premiums are larger than in Table 2. At the same time, these results indicate that the non-routine analytic task premium would remain significantly different from zero even with selection on unobservables as large as that on observed characteristics.

While the evidence presented in this section indicates a positive wage premium for jobs with a greater non-routine task content, the fact that workers continuously sort into tasks implies these premiums cannot be interpreted as causal. I next present a framework which accounts for self-selection into task content to analyze the returns to tasks.

5 Estimating the Returns to Tasks

5.1 Conceptual Framework

The existing literature has presented different models to identify the returns to tasks while correcting for self-selection. Nonetheless, these models are not estimable with cross-sectional STEP data. For instance, Saltiel et al. (2017) and Böhm (2020) present empirical strategies which require information on workers' pre-labor market skills for identification, Yamaguchi (2012) follows a structural approach which requires longitudinal data on workers' labor market outcomes, Cortes (2016) and Stinebrickner et al. (2018, 2019) take advantage of panel data to estimate task prices, and Acemoglu and Autor (2011), Firpo et al. (2011) and Gottschalk et al. (2015) pursue different empirical strategies, while relying on data from repeated cross-sections to estimate changing task prices. In this section, I briefly present a model introduced in Autor and Handel (2013), which accounts for Roy-like selection into tasks in the cross-section, and allows me to examine the returns to tasks in developing countries.[17]

Let $\Phi_i = \{\phi_{i1}, ..., \phi_{iK}\}$ represent the vector of workers' task efficiencies, where ϕ_{ik} denotes the efficiency of worker i at performing task k. Assuming that occupations in the economy produce output using the vector of K tasks to varying degrees, the output of worker i in occupation o can be expressed as:

$$Y_{io} = e^{\alpha_o + \sum_K \lambda_{ok}\phi_{ik} + \mu_i} \tag{4}$$

where α_o captures occupation-specific productivity, which may be negative if worker i does not have the relevant skills for the occupation, λ_o defines the prevalence of tasks $k \in K$ in occupation o and μ_i is a worker-specific error term. Assuming that workers are paid their marginal product, log wages can be expressed as:

$$w_{io} = \alpha_o + \sum_K \lambda_{ok}\phi_{ik} + \mu_i \tag{5}$$

[17]The presentation of the model follows directly from Autor and Handel (2013). I introduce their model to fix ideas about the extent of workers' self-selection into tasks.

In a context of self-selection, workers select the occupation which maximizes their expected earnings, such that

$$w_i = \max_o w_{io} = \max_o \{\alpha_o + \sum_K \lambda_{ok}\phi_{ik} + \mu_i\} \tag{6}$$

Task returns in this context are given by λ_{ok}, which captures the relative reward to performing task k in occupation o, and as such, the returns to tasks are occupation-specific.

As noted by Autor and Handel (2013), in an economy characterized by self-selection, workers are assigned into occupations by their comparative advantage. Two empirical propositions follow from their model. The first indicates that for any occupation o to have positive employment, it must offer either a higher returns relative to an occupation o' in at least one task k, as otherwise workers would prefer to switch to a different occupation.[18] As a result, the returns to at least one task-pair $\{k,k'\}$ must negatively covary across occupations $\{o,o'\}$ for both occupations to have positive employment: $Cov(\lambda_k, \lambda_{k'}) \leq 0$. This test of self-selection can implemented by estimating the task returns within occupations in the following OLS regression:

$$w_{io} = \alpha_o + \beta_{1o}Analytic_i + \beta_{2o}Interpersonal_i + \beta_{3o}Routine_i + \beta_{4o}Manual_i + \varepsilon_{io} \tag{7}$$

I estimate equation (7) separately by three-digit occupation in each country.[19] The proposition can be thus tested empirically by estimating bivariate regressions using the five estimated parameters in equation (7) $\{\hat{\alpha_o}, \hat{\beta_{1o}}, \hat{\beta_{2o}}, \hat{\beta_{3o}}, \hat{\beta_{4o}}\}$ and for self-selection to take place in this economy these coefficients cannot be uniformly positive.

While the first test provides suggestive evidence of self-selection taking place in an economy, it is silent about whether workers with a particular high task efficiency sort into those tasks. In this context, Autor and Handel (2013) show that if the correlation of workers' efficiencies across tasks is not too high, then workers will sort into tasks based on their comparative advantage. In this context, they note that self-selection implies a positive covariance between occupation-level task returns and the individual-task content of workers' occupations. As a result, an augmented wage regression in which individual- and occupation-task averages are interacted can recover the patterns of self-selection as follows:

$$w_{io} = \alpha + \sum_{n=1}^{N} \beta_n T_i^n + \sum_{n=1}^{N} \gamma_n \overline{T_o^n} + \sum_{n=1}^{N} \eta_n \times T_i^n \times \overline{T_o^n} + \varepsilon_{io} \tag{8}$$

where T_i^n indicates worker i's task n content, and T_o^n captures occupation-averages in the four task measures. In the context of equation (8), comparative advantage takes place if workers with high

[18]This condition is also satisfied if the intercept for occupation o is higher than for occupation o'. Throughout this sub-section, any reference to the negative covariance across task returns also considers the occupation-specific intercept as a 'task'.

[19]Equation (7) requires five parameters to be estimated, so at least six observations per occupation are required for inference.

efficiency in a particular task are employed in an occupation which values this task. As a result, comparative advantage will take place if $\{\eta_1, ..., \eta_N\} > 0$. On the other hand, if workers are highly efficient across more than one task, then a set of occupations will employ less-efficient workers, potentially yielding negative returns. In this setting, the economy exhibits sorting on absolute advantage if at least one of the interaction terms is positive, making it a weaker restriction than in the comparative advantage case.

I implement these two tests in each of the nine STEP countries separately. A sizable share of employment in these countries is in self-employment or in unpaid family work. As a result, there may be an additional margin through which workers self-select into tasks. Due to the lack of information on wages and tasks for workers in these sectors, I do not include them in my analysis, and note that the empirical evidence in this section is valid only for workers in paid employment.[20]

5.2 Empirical Evidence

Table 3 presents evidence on the bivariate regressions for within-occupation task returns (equation 7) for the nine countries in the STEP sample. I first note that there is at least one statistically significant negative relationship between the coefficients in each country, which is consistent with the conceptual framework presented above. There is sizable heterogeneity in the within-occupation task returns across countries, as for instance, occupations which offer a high return to manual tasks have low returns to routine tasks in Colombia and Georgia, yet the relationship is reversed in Armenia, Ghana and Vietnam. The most consistent pattern which emerges indicates that occupations with a high return to analytic tasks in turn offer low returns to interpersonal tasks. The bivariate interpersonal-analytic regression coefficients are negative in all countries (except for Colombia) and significant in Armenia, Ghana, Kenya, Macedonia and Vietnam. The negative relationship in the within-occupation returns to analytic and interpersonal tasks further highlights the importance of considering both margins of non-routine task content, especially in the context of growing returns to social skills in the labor market (Deming, 2017). Lastly, the heterogeneity in the estimated returns across countries indicates that tasks are rewarded differentially in various settings, and these patterns are not necessarily related to a country's level of economic development, thus likely reflecting country-specific labor market idiosyncrasies.

In Table 4, I present the estimated results from equation (8). The conceptual model presented above indicates that self-selection takes place as long as at least one of the interaction terms is positive in each country. The results in Table 4 generally lend support to that prediction, as at least one interaction term is significant in Bolivia, China, Colombia, Georgia, Ghana and Vietnam.[21] The interaction terms for the non-routine analytic tasks are significant in China, Colombia, Ghana

[20] In Table A5, I examine the worker-level characteristics associated with paid employment. Educational attainment is a strong predictor of working as an employee for all countries in the sample, which suggests the analysis presented so far is relevant for more educated individuals.

[21] The F-statistic on the joint significance of the interaction terms is significant in all countries in the sample, except for Armenia and Macedonia.

Table 3: Bivariate Relationships Across Task Occupation-Level Task Coefficients

	Armenia (1)	Bolivia (2)	China (3)	Colombia (4)	Georgia (5)	Ghana (6)	Kenya (7)	Macedonia (8)	Vietnam (9)
Analytic v. Routine	0.262	0.260	0.107	0.226	0.120	-0.295	0.065	-0.059	0.224
	(0.102)***	(0.093)***	(0.201)	(0.221)	(0.112)	(0.192)	(0.130)	(0.102)	(0.111)**
Interpersonal v. Analytic	-0.191	-0.069	-0.181	0.088	-0.002	-0.415	-0.135	-0.746	-0.310
	(0.094)**	(0.116)	(0.122)	(0.113)	(0.132)	(0.134)***	(0.059)**	(0.121)***	(0.144)**
Interpersonal v. Routine	-0.442	0.361	0.536	-0.035	-0.360	0.822	-0.381	0.292	-0.383
	(0.303)	(0.178)**	(0.099)***	(0.114)	(0.213)*	(0.177)***	(0.318)	(0.112)***	(0.116)***
Intercept v. Analytic	-0.437	-0.522	0.097	-0.864	0.221	-0.161	2.936	-0.043	-0.555
	(0.237)*	(0.175)***	(0.186)	(0.245)***	(0.193)	(0.269)	(0.684)***	(0.154)	(0.112)***
Intercept v. Interpersonal	0.607	0.403	-0.028	-0.448	0.584	0.160	-1.501	0.008	-0.141
	(0.134)***	(0.161)**	(0.158)	(0.210)**	(0.151)***	(0.215)	(0.290)***	(0.192)	(0.153)
Intercept v. Routine	0.338	0.119	0.163	0.319	-0.029	-0.053	0.933	0.237	0.039
	(0.333)	(0.242)	(0.134)	(0.189)*	(0.253)	(0.265)	(0.781)	(0.182)	(0.149)
Manual v. Analytic	0.323	-0.098	-0.033	-0.074	-0.207	0.387	2.882	-0.239	0.259
	(0.166)**	(0.082)	(0.144)	(0.239)	(0.275)	(0.246)	(0.906)***	(0.103)**	(0.107)**
Manual v. Interpersonal	-0.320	-0.208	-0.335	0.192	0.681	-0.092	0.298	0.065	-0.150
	(0.103)***	(0.070)***	(0.112)***	(0.189)	(0.224)***	(0.206)	(0.441)	(0.132)	(0.128)
Manual v. Intercept	-0.029	-0.019	0.029	-0.386	0.575	0.271	0.859	0.003	0.178
	(0.105)	(0.056)	(0.114)	(0.112)***	(0.192)***	(0.179)	(0.124)***	(0.085)	(0.106)*
Manual v. Routine	0.555	0.164	-0.135	-0.701	-0.761	0.497	0.246	0.187	0.405
	(0.221)**	(0.105)	(0.104)	(0.116)***	(0.344)**	(0.232)**	(1.039)	(0.125)	(0.114)***
Observations	47	63	48	51	47	28	55	69	62

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Standard Errors in Parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Each row corresponds to a separate bivariate OLS regression of the two coefficients for each country plus a constant coefficient (not reported). The task coefficients are recovered from a worker-level regression of log hourly wages on the four task inputs and an intercept separately for each three-digit occupation by country. Each regression needs to include at least six observations.

and Vietnam, which suggests that workers who are productive in analytic tasks are more likely to self-select into occupations with high returns for those tasks in these countries. At the same time, the interaction term for the interpersonal task is significant in just two countries in the sample (Colombia and Georgia), indicating that workers in these countries in occupations with a high interpersonal content who perform additional interpersonal tasks themselves tend to earn higher wages. Furthermore, the interaction term for routine tasks is significant in Bolivia, China and Ghana, while the manual task interaction term is positive and significant in Colombia, Georgia and Vietnam.

These results are consistent with sorting on absolute advantage, as there are no countries in which all four interaction terms are positive and significant. Nonetheless, in Colombia three of these terms are significant, indicating that Colombian workers may be more likely to self-select into tasks according to their comparative advantage. Lastly, there is no evidence of self-selection into task content in Armenia, Ghana and Macedonia. While this result may be explained by differential self-selection into paid employment in these two countries, the results presented in Table A5 do not indicate differential sorting patterns into paid employment across STEP countries. As a result, it is possible that the extent of worker sorting-into-task content is simply less prevalent in these countries.

The results presented in Table 4 differ from those in Autor and Handel (2013), who had found a positive interaction term for routine and manual tasks along with an insignificant coefficient on

Table 4: Wage Regressions with Individual-Occupation Task Content Interactions

	Armenia	Bolivia	China	Colombia	Georgia	Ghana	Kenya	Macedonia	Vietnam
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Worker-Level Task Content									
Non-Routine Analytic	-0.001	0.075*	0.069***	0.047	0.064	0.049	0.073*	0.084***	0.152***
	(0.038)	(0.039)	(0.026)	(0.036)	(0.041)	(0.073)	(0.042)	(0.021)	(0.038)
Non-Routine Interpersonal	0.010	-0.064	0.009	0.166***	0.108***	0.119*	0.123***	-0.000	-0.000
	(0.033)	(0.042)	(0.023)	(0.034)	(0.039)	(0.063)	(0.035)	(0.019)	(0.031)
Routine	-0.053*	-0.064**	-0.049**	-0.095***	-0.053*	0.029	-0.041	-0.041**	-0.027
	(0.031)	(0.030)	(0.022)	(0.026)	(0.028)	(0.053)	(0.030)	(0.016)	(0.024)
Manual	-0.011	-0.002	0.037	0.004	-0.136***	-0.067	0.152***	-0.042**	-0.002
	(0.033)	(0.033)	(0.024)	(0.032)	(0.043)	(0.072)	(0.037)	(0.017)	(0.029)
Occupation-Level Task Content									
Non-Routine Analytic	0.044	0.032	0.017	0.031	0.054	0.106	0.238***	0.098***	-0.027
	(0.054)	(0.071)	(0.029)	(0.062)	(0.051)	(0.092)	(0.066)	(0.034)	(0.050)
Non-Routine Interpersonal	-0.053	0.216***	0.004	-0.025	-0.054	-0.009	0.036	0.045	0.035
	(0.041)	(0.073)	(0.029)	(0.058)	(0.047)	(0.087)	(0.060)	(0.029)	(0.045)
Routine	-0.091*	-0.041	-0.077***	0.017	-0.029	0.092	-0.030	-0.032	0.056**
	(0.047)	(0.039)	(0.029)	(0.029)	(0.031)	(0.058)	(0.047)	(0.027)	(0.024)
Manual	0.009	0.054	0.047*	0.020	-0.060	0.298***	0.034	0.050**	-0.025
	(0.040)	(0.038)	(0.027)	(0.037)	(0.045)	(0.071)	(0.039)	(0.021)	(0.032)
Task Content: Interaction									
Non-Routine Analytic	0.002	0.049	0.032*	0.073**	0.030	0.148***	0.021	-0.017	0.061**
	(0.030)	(0.033)	(0.019)	(0.029)	(0.027)	(0.053)	(0.031)	(0.017)	(0.028)
Non-Routine Interpersonal	0.039	0.006	-0.001	0.113***	0.094***	0.023	0.015	0.012	-0.005
	(0.030)	(0.032)	(0.020)	(0.032)	(0.029)	(0.053)	(0.028)	(0.016)	(0.028)
Routine	0.017	0.087***	0.034*	0.015	0.006	0.064**	-0.036*	0.020	-0.009
	(0.027)	(0.020)	(0.018)	(0.020)	(0.021)	(0.031)	(0.021)	(0.014)	(0.021)
Manual	0.007	-0.008	0.002	0.067***	0.080***	-0.028	-0.040**	0.009	0.031*
	(0.015)	(0.017)	(0.011)	(0.020)	(0.019)	(0.036)	(0.017)	(0.011)	(0.018)
Educational Attainment	0.032***	0.049***	0.064***	0.071***	0.051***	0.106***	0.041***	0.048***	0.073***
	(0.011)	(0.010)	(0.008)	(0.010)	(0.012)	(0.021)	(0.008)	(0.006)	(0.009)
Experience	0.012*	0.027***	0.007	0.018***	0.015*	0.064***	0.033***	0.009**	0.027***
	(0.007)	(0.007)	(0.005)	(0.006)	(0.008)	(0.014)	(0.007)	(0.004)	(0.007)
Experience^2	-0.000*	-0.000*	-0.000	-0.000**	-0.000**	-0.001***	-0.000***	0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.297***	0.152***	0.076**	0.205***	0.421***	0.051	-0.062	0.140***	0.186***
	(0.058)	(0.056)	(0.038)	(0.051)	(0.063)	(0.102)	(0.049)	(0.028)	(0.049)
F (interaction terms)	0.761	5.979	2.549	11.137	7.825	3.914	2.187	1.279	1.945
P-value	0.551	0.000	0.038	0.000	0.000	0.004	0.068	0.276	0.101
R^2	0.120	0.308	0.268	0.313	0.272	0.321	0.400	0.370	0.228
Observations	761	860	1,011	898	648	497	1,126	1,298	1,263

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Standard Errors in Parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table 4 presents evidence from an augmented OLS regression (equation (8)), which interacts worker-level task content by three-digit occupational task averages. This regression examines the extent of worker sorting into tasks across the nine STEP countries. The F-statistic follows from a Wald test of the joint significance of the interaction terms.

the analytic task interaction in the United States. These differences may arise due to the different countries being considered in the analysis, as most developing countries in the STEP sample have large informal sectors. While the difference in the questions included in the STEP survey compared to those in STAMP may also explain part of the difference in results, I note that the importance of tasks may truly vary across countries, given the heterogeneous results across STEP-survey countries presented in Sections 4 and 5. While this paper has taken an important first step to understand cross-country differences in the importance of tasks, further work is needed to better discern the extent to which workers sort into tasks based on their underlying skills and how these patterns vary across developed and developing countries.

6 Conclusion

The advent of computerization has upended labor markets in both developed and developing countries. As a result, an extensive literature has examined the tasks performed by workers to better understand the potential consequences of these changes in the labor market. Nonetheless, the empirical evidence on this topic has been relatively scarce in developing countries, in part due to data limitations. In this paper, I have used worker-level data across nine developing countries to present evidence on the prevalence and the returns to tasks across a diverse set of countries. In this context, I have shown that there is extensive sorting into worker-level non-routine task content, as more educated workers are more likely to perform these tasks even within occupations. Furthermore, non-cognitive skills positively predict non-routine task content as well, with the caveat that these skills are measured in adulthood. Nonetheless, these results indicate an important role for human capital accumulation in determining labor market outcomes in developing countries, both through its direct effect on wages but also indirectly through task assignment.

Furthermore, I have shown that both within-occupation non-routine analytic and interpersonal task content are associated with sizable wage premiums. Routine tasks, on the other hand, lead to significant wage penalties across a variety of countries. To examine whether these relationships are causal, I have outlined a conceptual framework of self-selection into tasks following Autor and Handel (2013). Within this framework, I have shown that individuals in high non-routine analytic occupations who perform additional analytic tasks themselves are more likely to earn higher wages in six countries, which is not necessarily the case for other task measures. While these results offer preliminary evidence of the extent of worker sorting into non-routine analytic tasks, this analysis relies on cross-sectional data, which does not allow for a clear examination of the types of skills which drive self-selection into tasks. As a result, future work in this context should take advantage of new longitudinal data sources, such as the Young Lives Survey, which has tracked a cohort of children in developing countries through young adulthood, to better understand how tasks are rewarded in the labor market while controlling for early-life skills, as has been previously done in the developed country literature.

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Appendices

Table A1: Summary Statistics

	All (1)	Armenia (2)	Bolivia (3)	China (4)	Colombia (5)	Georgia (6)	Ghana (7)	Kenya (8)	Macedonia (9)	Vietnam (10)
Observables										
Education (Years)	12.687	14.108	12.175	12.935	10.71	15.569	13.381	10.024	13.686	12.01
Male	0.497	0.377	0.496	0.523	0.521	0.36	0.681	0.61	0.492	0.451
Age	36.46	40.1	31.4	39.5	33.5	40	32.8	31.7	41.4	36.8
Occupations										
Manager	0.04	0.053	0.049	0.038	0.021	0.097	0.035	0.022	0.03	0.023
Professional	0.241	0.372	0.16	0.164	0.091	0.379	0.41	0.16	0.234	0.272
Technician	0.102	0.13	0.123	0.069	0.073	0.091	0.092	0.083	0.155	0.097
Clerical	0.107	0.1	0.091	0.212	0.133	0.065	0.062	0.091	0.096	0.094
Services/Sales	0.209	0.132	0.201	0.255	0.263	0.173	0.181	0.315	0.175	0.181
Craft/Trades	0.102	0.069	0.137	0.073	0.086	0.065	0.08	0.103	0.131	0.158
Machine Operators	0.07	0.056	0.055	0.069	0.112	0.035	0.059	0.061	0.102	0.072
Elementary	0.128	0.087	0.185	0.12	0.22	0.095	0.081	0.164	0.077	0.102
Tasks										
Advanced Math	0.109	0.136	0.146	0.079	0.106	0.093	0.106	0.091	0.117	0.105
Supervise Others	0.368	0.375	0.391	0.45	0.391	0.275	0.429	0.219	0.311	0.457
Repair Items	0.108	0.269	0.058	0.185	0.054	0.059	0.085	0.07	0.091	0.1
Hourly Wages (USD)	4.637	6.535	4.091	3.363	5.515	3.964	3.379	3.24	5.456	5.749
GDP		9364	5921	11197	12018	9826	3781	2530	11839	5042
Observations	8,677	786	884	1,038	910	673	515	1,155	1,435	1,281

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Summary statistics reported for the full sample included in the paper as well as separately for each country. The 'Occupations' row reports the share of workers in each country who work in each of the one-digit occupations outlined above. The 'Tasks' row indicates the share of workers in each country who perform each of the three job activities at work. 2012 GDP per capita is reported in USD PPP (Source: World Bank Data).

Table A2: Variance Decomposition: Worker-Level Task Content

	Analytic (1)	Interpersonal (2)	Routine (3)	Manual (4)
Variance	1	1	1	1
$Var(X_i)$	0.138	0.054	0.029	0.023
$Var(\gamma_O)$	0.181	0.203	0.109	0.243
$Var(\lambda_c)$	0.029	0.048	0.087	0.009
$Cov(X_i, \gamma_O)$	0.189	0.098	0.046	0.035
$Cov(X_i, \lambda_c)$	-0.022	-0.018	-0.013	0.001
$Cov(\gamma_O, \lambda_c)$	-0.023	-0.027	-0.025	0.003
$Var(v_{ioc})$	0.500	0.650	0.782	0.710

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Table A2 presents a variance decomposition of worker-level analytic, interpersonal, routine and manual task content following equation (2). The 'Variance' row denotes the share of the variance in the task measures to be explained and the rows below the share explained by observables, occupations, countries, their covariances and the unexplained share captured by the error term.

Table A3: Wage Regressions with Individual and Occupation-Level Task Content

	(1)
Worker-Level Task Content	
Non-Routine Analytic	0.077***
	(0.016)
Non-Routine Interpersonal	0.061***
	(0.014)
Routine	-0.047***
	(0.013)
Manual	0.005
	(0.015)
Occupation-Level Task Content	
Non-Routine Analytic	0.086***
	(0.029)
Non-Routine Interpersonal	0.029
	(0.029)
Routine	-0.014
	(0.023)
Manual	0.072***
	(0.020)
Educational Attainment	0.064***
	(0.006)
Experience	0.023***
	(0.004)
Experience^2	-0.000***
	(0.000)
Male	0.144***
	(0.037)
Test	-0.021
	(0.014)
Non-Cognitive Test	0.016
	(0.012)
Country FE	Yes
Occupation FE	No
F (task measures)	18.42
P-value	0
F (Task occ means)	9.30
P-value	0.00
Adj. R^2	0.291
Observations	8,286

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Standard Errors in Parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the three-digit occupation level. Table A3 presents evidence on the wage premium associated with a one standard deviation increase in each of the worker-level task measures controlling for three-digit occupation-average task content. The first F-statistic follows from a Wald test of the joint significance of the worker-level task measures. The second F-statistic follows from a Wald test of the joint significance of the occupation-level measures.

Table A4: Robustness to Estimated Wage Premiums

	(1)	(2)
Worker-Level Task Content		
Non-Routine Analytic	0.073***	0.124***
	(0.013)	(0.014)
Non-Routine Interpersonal	0.056***	0.071***
	(0.012)	(0.012)
Routine	-0.045***	-0.044***
	(0.009)	(0.009)
Manual	0.013	0.013
	(0.009)	(0.009)
Educational Attainment	0.055***	
	(0.006)	
Experience	0.019***	0.017***
	(0.003)	(0.003)
Experience^2	-0.000***	-0.000***
	(0.000)	(0.000)
Male	0.115***	0.116***
	(0.019)	(0.020)
Country FE	Yes	Yes
Occupation FE	Yes	Yes
Education	Yes	No
Test Scores	No	No
F (task measures)	27.20	43.25
P-value	0.00	0.00
Adj. R^2	0.341	0.314
Observations	8,700	8,700

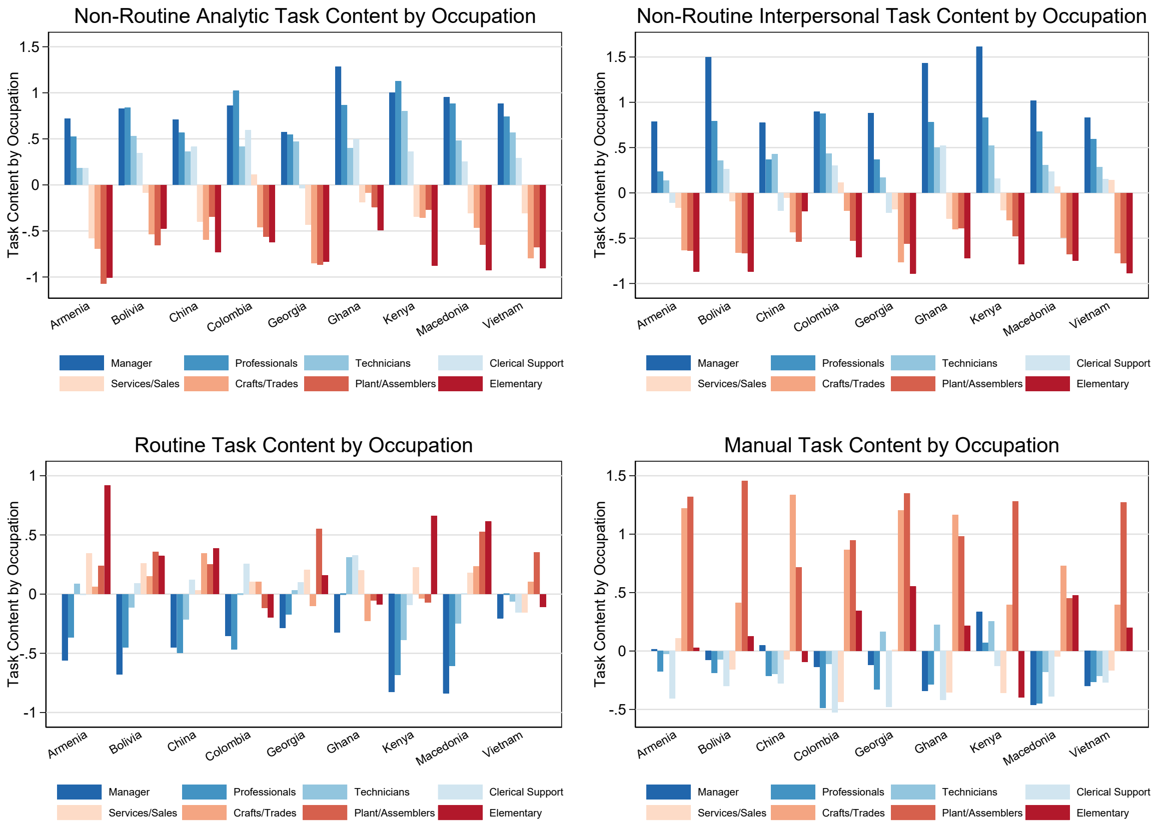
Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Standard Errors in Parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the three-digit occupation level. Table A4 presents evidence on the wage premium associated with a one standard deviation increase in each of the worker-level task measures controlling for occupation fixed effects. This table presents comparative evidence on the estimated wage premiums after removing measures of workers' test scores (first column) and educational attainment (second column).

Table A5: Determinants of Working in Wage Employment in Developing Countries

	(1) All	(2) Armenia	(3) Bolivia	(4) China	(5) Colombia	(6) Georgia	(7) Ghana	(8) Kenya	(9) Macedonia	(10) Vietnam
Educational Attainment	0.018***	0.013***	0.011***	0.032***	0.009**	0.008*	0.045***	0.014***	-0.001	0.023***
	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Experience	-0.006***	-0.005*	-0.017***	-0.009***	0.009***	-0.007*	-0.012***	-0.004	-0.010***	-0.004
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Experience^2	0.000	0.000	0.000***	0.000***	-0.000***	0.000	0.000*	0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.038***	-0.061***	0.068***	-0.002	0.079***	-0.079***	0.177***	0.111***	-0.075***	0.074***
	(0.007)	(0.021)	(0.023)	(0.021)	(0.023)	(0.025)	(0.029)	(0.021)	(0.017)	(0.020)
Test	0.005	-0.007	-0.025	-0.016	-0.022	0.005	0.020	0.005	0.019	-0.011
	(0.006)	(0.014)	(0.020)	(0.015)	(0.025)	(0.017)	(0.031)	(0.012)	(0.026)	(0.014)
Non-Cognitive Test	-0.006	0.002	0.036**	-0.028**	-0.057***	0.005	-0.007	-0.044***	-0.025*	-0.003
	(0.005)	(0.014)	(0.017)	(0.013)	(0.017)	(0.017)	(0.019)	(0.015)	(0.013)	(0.017)
R^2	0.166	0.037	0.095	0.064	0.075	0.034	0.192	0.063	0.022	0.108
Observations	13,704	937	1,699	1,269	1,715	843	1,028	2,090	1,803	2,320

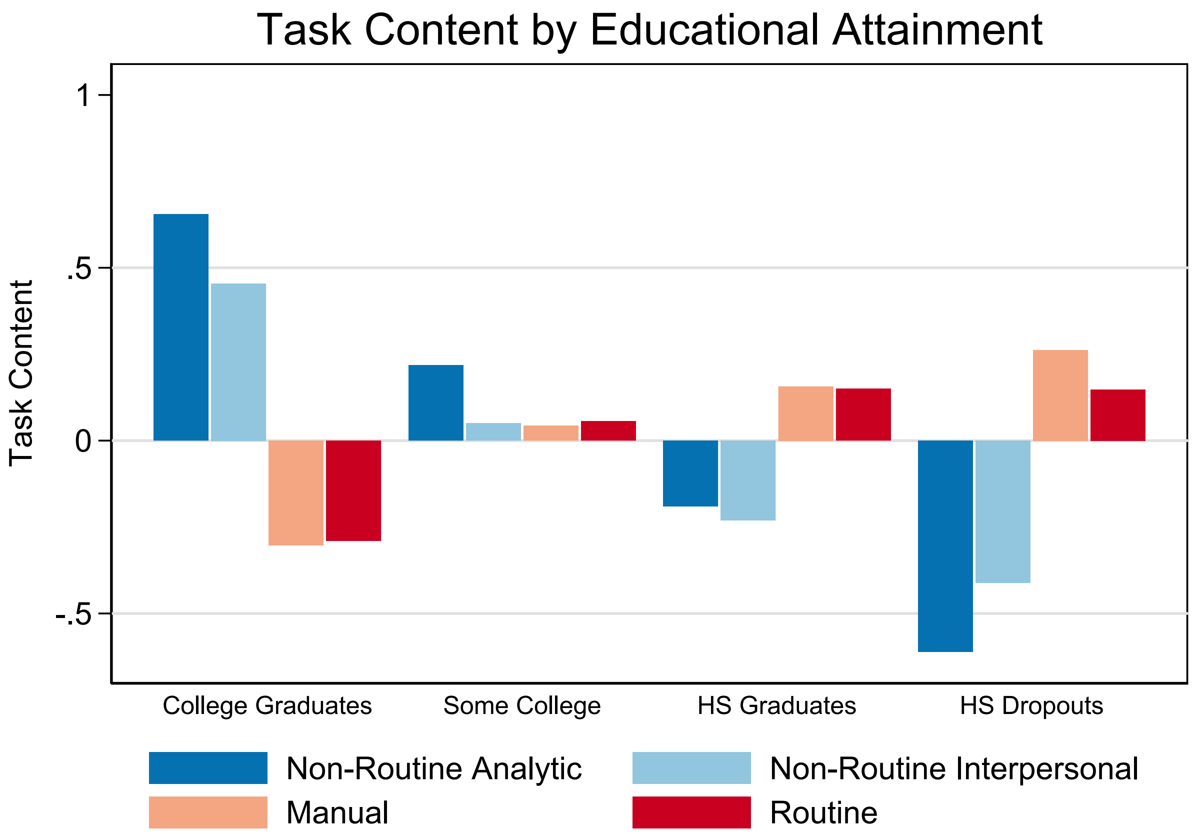
Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Standard Errors in Parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table A5 presents evidence from an OLS regression with a dummy for paid employment as the dependent variable and worker-level characteristics as explanatory variables for all countries in the STEP sample.

Figure A1: Task Content by Occupations Across STEP Countries



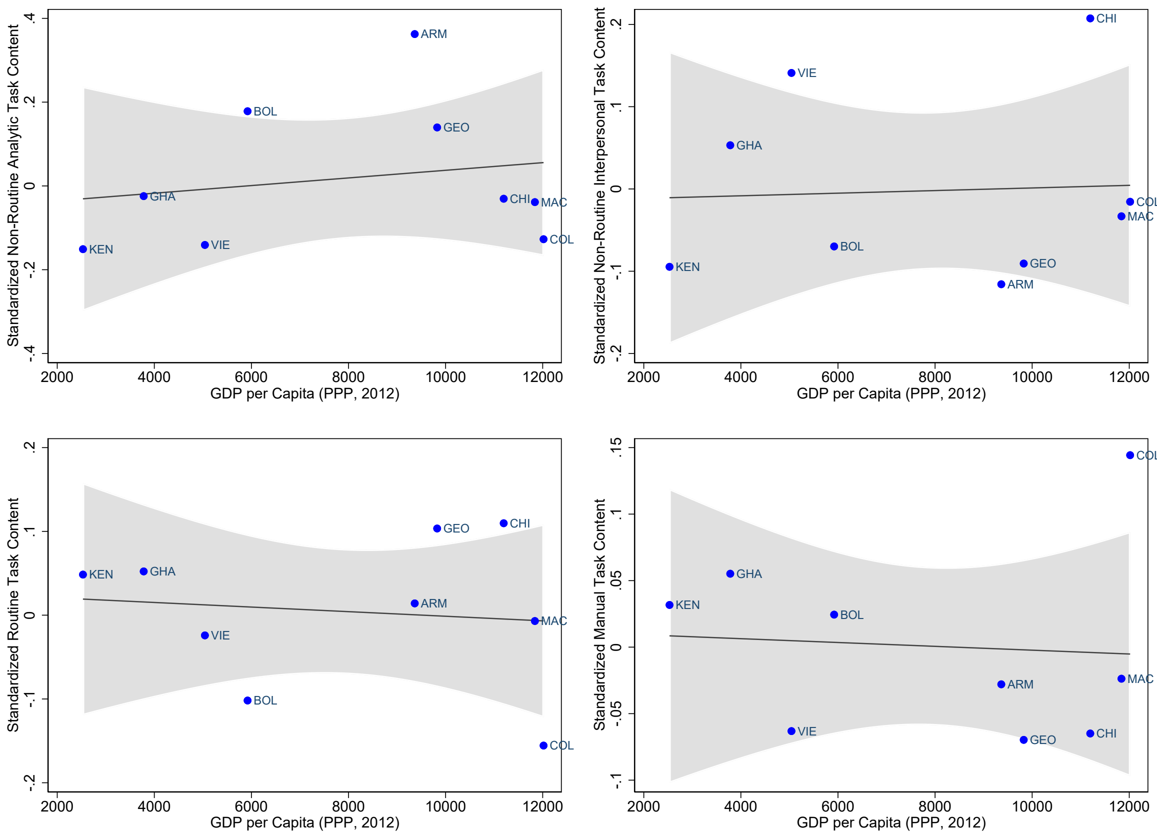
Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure A1 presents evidence of the importance of non-routine analytic, non-routine interpersonal, routine and manual tasks across one-digit occupations in the nine STEP countries included in the paper. Task indices are constructed as described in Section 2, normalized to have an average of zero and a variance of one.

Figure A2: Task Content by Educational Attainment



Note: Figure A2 presents average non-routine analytic, non-routine interpersonal, routine and manual task content for workers in the STEP sample who either completed a college degree, completed some college, graduated secondary school or failed to complete a secondary degree.

Figure A3: Cross-Country Comparison: Task Prevalence and GDP per Capita



Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure A3 presents evidence from the relationship between countries' GDP per capita and the prevalence of analytic, interpersonal, routine and manual tasks. Task measures are standardized to be mean zero with variance one in the *full sample*, thus allowing for cross-country comparisons in the prevalence of the relevant task indices.