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Is there job polarization in developing economies? A review and outlook

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Abstract

This paper analyses the evidence of job polarization in developing countries. We carry out an extensive review of the existing empirical literature and examine the primary data sources and measures of routine intensity. The synthesis of results suggests that job polarization in emerging economies is only incipient compared to other advanced economies. We then examine the possible moderating aspects preventing job polarization, discussing the main theoretical channels and the existing empirical literature. Overall, the literature relates the lack of polarization as a natural consequence of limited technology adoption and the offshoring of routine, middle-earning jobs to some host developing economies. In turn, the limited technology adoption results from sub-optimal capabilities in those economies, including the insufficient supply of educated workers. Finally, we present the main gaps in the literature in developing economies and point to the need for more micro-level studies focusing on the impacts of technology adoption on workers' careers and studies exploring the adoption and use of technologies at the firm level.

JEL: J24, J63, O33, E24

Keywords: Job polarization; Routine intensity; Skills; Developing countries

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1 Introduction

The economic discipline has dedicated a great deal to the possible harmful effects of technological progress on the labor market (Card and DiNardo, 2002; Katz and Murphy, 1992; Katz and Summers, 1989; Levy and Murnane, 1992). Throughout recent history, and more famously after the Luddite movement, "technological unemployment" has been a persistent debate topic among economists, which have constantly been deliberating whether massive waves of unemployment could be around the corner. Already in 1930, Keynes (2010, p.325) famously stressed that "we are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come — namely, technological unemployment."

Indeed, Keynes was correct in pointing out that we would frequently hear about technological unemployment in the years to come. As new waves of technological change hit the global economy, the fear of massive waves of unemployment also took place. However, the pessimistic predictions of technological unemployment have yet to come about. Technical progress didn't pave its way through unemployment but rather through changes in the demand and composition of employment. Technological advancement has modified the way we produce, causing significant changes in the labor market. Throughout history, technology appears to have impacted different types of labor differently, as it creates new jobs, eliminates old ones, and changes the composition of existing occupations (Buyst et al., 2018; Chin et al., 2006; Katz and Murphy, 1992; O'Rourke et al., 2013). The Second Industrial Revolution, especially the invention of steam power and electricity, led to a significant substitution of artisans for unskilled workers, favoring the transition of low-skilled workers moving out of the farms to better-paid jobs in the cities (Buyst et al., 2018).[1] In contrast, subsequent technological waves were skill-using rather than skill-saving. The Digital Revolution in the early 1980s disproportionately and positively impacted the need for skilled workers, increasing the

[1] Chin et al. (2006) show that, in addition to skill-replacing dynamics, steam power also had some elements that were skill-biased, causing a rise in the demand for engineers. Nevertheless, as pointed out by O'Rourke et al. (2013), novel technologies were on average skill-saving in the early nineteenth century.

ratio of skilled to unskilled labor in most industries (Katz and Murphy, 1992).

Not surprisingly, when most developed countries experienced increasing wage inequality in the past 40 years (Alvaredo et al., 2018), technology-related arguments were at the forefront of explaining these labor market dynamics. The skill-biased technological change (SBTC) hypothesis suggested that technology, precisely the widespread adoption of Information and Communication Technologies (ICT), increased the demand for skilled workers, as those are more capable of using these new technologies (see the review by Card and DiNardo, 2002). According to such framework, given the complementary nature of technology adoption and skilled labor, the relative demand for high-skilled workers is expected to increase, causing earnings inequality to rise (Acemoglu and Autor, 2011; Goos and Manning, 2007).

For a couple of decades, the SBTC hypothesis worked well in explaining the patterns observed in the data (Machin and Van Reenen, 1998). However, it failed to explain another important labor market dynamic: in recent years, the share of high-skill, high-wage, and low-skill, low-wage occupations grew relative to those in the middle of the distribution, resulting in "polarized" economies (Goos et al., 2009). To account for the "hollowing out" of the occupational distribution, a more nuanced analysis focused on the tasks commonly performed by each occupation to explain job polarization and inequality in developed economies. The routine-biased technological change (RBTC) hypothesis argues that computers and robots have diminished the demand for routine, repetitive tasks in production, which are more commonly concentrated among middle-earning workers. On the other hand, tasks performed by unskilled workers, such as waiters or cleaners, and skilled workers, such as managers, are not easily codified and performed by computers (Autor and Dorn, 2013; Goos et al., 2014).

Evidence of job polarization has been extensively portrayed in developed economies. For example, using harmonized data from the European Union Labour Force Survey (ELFS), Goos et al. (2009) show a disproportionate increase in high-paid and low-paid employment relative to middle-paid jobs over the period 1993–2006. In the U.S., similar results were first observed in Acemoglu (1999) and later rigorously analyzed in Autor et al. (2003).

Following Autor et al. (2003) and Acemoglu and Autor (2011), the literature moved to a more detailed analysis of workers' tasks, exploring differences between routine- and cognitive-intensive occupations. For instance, Autor and Dorn (2013) find that wages and employment in the U.S. grew mainly for low-skilled workers performing manual, non-routine tasks, and high-skilled workers in cognitive-intensive occupations. In contrast, low-skilled workers in routine occupations faced a significant decline in wages and employment share. In addition to Michaels et al. (2014) and Goos et al. (2009, 2014), who find evidence of polarization for several OECD and European countries, similar results have also been individually estimated for Germany (Dustmann et al., 2009; Spitz-Oener, 2006), the UK (Montresor, 2019; Salvatori, 2018), Portugal (Fonseca et al., 2018), and Japan (Ikenaga and Kambayashi, 2016).

However, outside of this group of developed economies, the literature on RBTC and its consequences on labor outcomes is only incipient. In fact, it is rather unclear whether developing and emerging economies are facing similar trends, as evidence of job polarization is considerably weaker (Das and Hilgenstock, 2018; Gasparini et al., 2021; Maloney and Molina, 2019). This paper attempts to provide a broad survey of job polarization in these countries, giving special attention on the one hand to the particular challenges in measuring job polarization in such contexts, and on the other hand exploring the theoretical channels that could prevent or slow down job polarization in developing and emerging economies. Finally, we highlight some of the gaps and policy implications that arise throughout the discussion. We restrict our analysis to the impacts of digital technologies and automation (robots) on the labor market. Automation refers to computer-assisted machines, robotics, and artificial intelligence, such that robots are a sub-set of automation. Recent developments in artificial intelligence (AI) make it likely that they will replace more tasks in production, with estimations suggesting that high-paying, non-routine occupations are at particular risk of displacement (Webb, 2019). Yet, due to the short evaluation time, we do not discuss the possible implications of the more recent and advanced technologies such as AI and the internet of things (IoT).

The rest of this paper is organized as follows. Section 2 describes the empirical literature on job polarization in developing economies. Next, Section 3 explores the main resources and challenges when measuring job polarization in developing economies. Section 4 describes possible factors moderating the effect of automation in developing economies and investigates the interactions between technology adoption in advanced economies and the labor market implications in emerging countries. Section 5 discusses policy implications of job polarization in developing countries. The last section concludes.

2 Labor market effects of technology adoption in developing economies

The literature on job polarization in developing economies is gaining momentum. Focusing on different regions and countries, as well as various measures of tasks and skills, a number of topics have been explored (see Table 1 for a detailed summary of this literature). But before assessing whether we observe job polarization in developing and emerging economies (section 2.2), we first need to understand the link between technology and labor market outcomes, as well as how it depends on the local context (section 2.1). Understanding the relation between firms' technology adoption and labor market dynamics not only facilitates the review of the empirical findings but also helps us later in assessing the main differences between emerging and advanced economies (see section 4).

2.1 Why should ICT and robots impact the occupational structure of the workforce? The routinization hypothesis

The "routinization" hypothesis argues that firms combine a continuum of tasks to produce, which can be performed either by capital or labor (Acemoglu and Autor, 2011; Autor et al., 2003). Firms will allocate more capital or labor in a given task depending on their relative cost and the degree to which tasks can be automated (repetitive and replaceable by code and machines). In the past decades, not only did the quality-adjusted ICT and robots prices fall considerably, but these technologies have been particularly successful in carrying tasks that follow explicit rules (routines) (Graetz and Michaels, 2018; Michaels et al., 2014). As a result, firms spurred the substitution of labor in routine tasks, such that workers in routine-intensive occupations were suddenly at high risk of displacement (Acemoglu and Autor, 2011; Autor et al., 2003). Traditionally, many routine tasks concentrated in middle-wage, middle-skill white-collar jobs such as bank clerks, or are carried out by blue-collar less-educated workers, performing for example assembly tasks. As firms increase the share of capital in production, the demand for middle-earning jobs should contract, and the labor market should polarize.

Most of the literature that we shall discuss takes this relationship as a given and focuses on describing changes in the structure of the labor markets (see section 2.2). Yet, though largely studied in the case of advanced economies,[2] the causal impact of ICT and robots on the occupational structure of the workforce has been the topic of analysis of only a handful of studies in the context of developing economies.

First, the labor market impact of ICT and internet adoption has been studied in the case of Latin America (Almeida et al., 2017; Iacovone and Pereira Lopez, 2018) and Africa (Hjort and Poulsen, 2019). They jointly corroborate the expected impact, with an increase in the relative demand for high-skilled occupations. Almeida et al. (2017) explore the association between digital technologies and employment in Brazil and find that digital technology adoption has led to a reduction in jobs in Brazil's local labor markets between 1996 and 2006 and that the effects were particularly harmful to workers in routine tasks. Iacovone and Pereira Lopez (2018) explore ICT adoption in Mexico and find that it leads to increasing demand for high-skilled relative to low-skilled labor. In addition, Hjort and Poulsen (2019) study the impact of fast internet adoption in a sample of 12 African countries and find strong

[2] Michaels et al. (2014) test this hypothesis for 11 advanced economies using the EU-KLEMS database from 1980 to 2004 and show that industries with faster ICT growth shifted demand from middle-educated workers to highly educated workers.

and positive effects on employment, driven mainly by increased employment in high-skilled occupations. In addition, Lo Bello et al. (2019) explore the association between ICT adoption and employment rates, finding that countries with a larger stock of occupations intensive in routine tasks face lower employment growth rates - an increase of 10 percentage points in internet penetration is associated with a 2 percentage points lower employment rate growth in a country with a relatively higher level of routine labor.

For what concerns a more specific type of technology, robots, the results are more mixed. The expected relationship is found in the case of China (Giuntella and Wang, 2019) and Latin American countries (Brambilla et al., 2021), but not in a larger panel of countries (de Vries et al., 2020). Giuntella and Wang (2019) explore robot adoption in China and see a substantial and negative impact of robot exposure on jobs and wages. The consequences are especially harmful to low-skilled male workers and are concentrated in cities with a relatively larger industrial sector. Similarly, Brambilla et al. (2021) explore robot adoption in Argentina, Brazil, and Mexico and find evidence of a decline in employment in industries more exposed to robot adoption, especially in the middle of the wage distribution. The findings also show a significant increase in a number of outcomes such as unemployment, informality, poverty, and inequality. Studying 37 countries from 2005 to 2015, de Vries et al. (2020) point that industries with faster robot growth shifted demand from middle-educated workers to highly educated workers in high-income countries, but not in emerging market and transition economies. So, when we can relate labor market outcomes to the adoption of digital technologies (a "precursor" to automation according to Shapiro and Mandelman, 2021), the expected relation is observed; however, the labor impact of robot adoption is less ubiquitous.

2.2 Is there job polarization in developing economies?

Building upon these expected mechanisms and relying on the empirical findings for advanced economies, a sub-set of the literature has more heavily explored the occupational structure of the workforce and the extent of job polarization in developing economies. Yet, if ICT and other automated technologies are expected to be widespread in advanced economies, lower adoption rates can be found in developing and emerging economies. Therefore, the impact of such technologies may not have reached large shares of the employed population.

For instance, Maloney and Molina (2019) use global census data for 67 developing countries and 13 developed economies and, although the results corroborate labor market polarization and labor-displacing automation in developed economies, the authors find little evidence of either effect on developing economies. Das and Hilgenstock (2018) use data on 85 countries since 1990 and observe similar results. In addition, the authors propose a measure of exposure to routinization based on occupations' risk of displacement by information technologies. Using this measure, the authors show that developing economies are significantly less exposed to routinization and that initial exposure to routinization is a strong predictor of the long-run exposure.

The lack of polarization is further corroborated in Gasparini et al. (2021), who find similar conclusions for Latin America's six largest economies (Argentina, Brazil, Chile, Colombia, Mexico, and Peru), arguing that although automation has largely impacted workers in routine-intensive occupations, there is no evidence for polarization in the labor market. Messina et al. (2016) explore the Skills Toward Employment and Productivity (STEP) Surveys conducted in Bolivia and Colombia as a proxy for the routine/abstract/manual content of jobs in Chile and Mexico and find few indications of job polarization. Beylis et al. (2020) explore the labor market of 11 Latin American countries (LAC) from 2000 to 2014. Using the methodology proposed by Autor et al. (2003) and Acemoglu and Autor (2011), the analysis shows substantial changes in the composition of occupations. Although at a different intensity, the demand for routine manual intensive tasks has declined for the entire sample, coupled with a clear and marked increase in the demand for non-routine intensive occupations. Yet, the trends in labor composition haven't resulted in polarized markets.

Even among developing and emerging economies, the evidence is not homogenous. Hardy et al. (2016) study 10 Central and Eastern European (CEE) countries and point to an increase in non-routine cognitive tasks and a decrease in manual tasks. Nevertheless, contrary to other developed countries and at odds with RBTC, the authors also find that routine cognitive tasks increased in six CEE countries, remained stable in two, and declined in the remaining countries. Helmy (2015) studies the Egyptian labor market over the period 2000–2009 and finds suggestive evidence of job polarization. Ge et al. (2021) use census data from China and find that the share of employment in routine manual occupations declined by 25 percentage points from 1990 to 2015. Maloney and Molina (2019) also finds signs of incipient polarization in Mexico and Brazil. Similarly, Firpo et al. (2021) find evidence of wage polarization in Brazil, but not with respect to employment. In contrast, Fleisher et al. (2018) show that middle-skilled jobs are increasingly transitioning to work in the unskilled and self-employment job categories in China, consistent with the RBTC hypothesis. Similarly, using data from the National Sample Survey Organization from India, Sarkar (2019) also observes increasing job polarization during the 1990s and 2000s.

Table 1: Summary of the existing literature on job polarization in developing and emerging economies

Level of analysis	**Dataset**	**Country**	**Task**	**Reference**
Impact on employment				
Local Labor Markets	Employee data (RAIS)	Brazil	O*NET	Almeida et al. (2017)
Local Labor Markets	Economic Censuses (INEGI)	Mexico	Occupations	Iacovone and Pereira Lopez (2018)
Country	Household surveys	12 African countries	Occupations	Hjort and Poulsen (2019)
Country	Labor force surveys	37 advanced and emerging countries	Occupations	Reijnders and de Vries (2018)
Local Labor Markets	Labor force surveys	China	Occupations	Giuntella and Wang (2019)
Local Labor Markets	Labor force surveys	Argentina, Brazil, and Mexico	Occupations	Brambilla et al. (2021)
Impact on job polarization				
Country	Global Census Data (IPUMS)	80 developed and developing countries	Occupations	Maloney and Molina (2019)
Country	IPUMS, EULFS, household surveys	85 developed and developing countries	O*NET	Das and Hilgenstock (2018)
Country	Household surveys	Argentina, Brazil, Chile, Colombia, Mexico, and Peru	PIAAC	Gasparini et al. (2021)
Country	Household surveys	Chile and Mexico	STEP	Messina et al. (2016)
Country	Household surveys	10 Central and Eastern European countries	O*NET	Hardy et al. (2016)
Country	Household surveys	11 LAC countries	O*NET	Beylis et al. (2020)
Sectors	Egyptian Central Agency for Public Mobilization and Statistics	Egypt	Occupations	Helmy (2015)

Note: The table is separated into groups of papers according to the primary dependent variable in the analyses. *Impact on employment* refers to studies exploring the impact of digital technologies on employment without further exploring the implications on job polarization. In contrast, *impact on job polarization* refers to studies examining the extent of job polarization and, in most cases, without a clear chain of causality between technology adoption and polarization. Lastly, *impact on task content* refers to papers focusing primarily on the differences in the task content of occupations across developed and developing economies. In addition, column 2 refers to the primary occupational dataset, while column 4 describes the measure of tasks used.

Level of analysis	**Dataset**	**Country**	**Task**	**Reference**
Impact on job polarization (cont.)				
Country	Census data	China	O*NET	Ge et al. (2021)
Country	Household surveys	Brazil	O*NET	Firpo et al. (2021)
Local Labor Markets	CHIP surveys	China	O*NET	Fleisher et al. (2018)
Sectors	National Sample Survey Organization	India	Occupations	Sarkar (2019)
Country	Household surveys	70 countries	O*NET	World Bank (2016)
Country	Household surveys	70 countries	O*NET	Aedo et al. (2013)
Country	Household surveys	70 countries	O*NET	Arias et al. (2014)
Impact on task content				
Country	STEP	10 countries	STEP	Dicarlo et al. (2016)
Country	Household surveys	86 countries	STEP/O*NET	Lo Bello et al. (2019)
Country	STEP and PIAAC	42 countries	STEP/PIAAC	Lewandowski et al. (2019)
Country	Household surveys	87 countries	STEP	Lewandowski et al. (2020)
Country	STEP and PIAAC	35 countries	STEP/PIAAC	Caunedo et al. (2021)
Country	STEP	10 countries	STEP	Saltiel (2019)

Note: The table is separated into groups of papers according to the primary dependent variable in the analyses. *Impact on employment* refers to studies exploring the impact of digital technologies on employment without further exploring the implications on job polarization. In contrast, *impact on job polarization* refers to studies examining the extent of job polarization and, in most cases, without a clear chain of causality between technology adoption and polarization. Lastly, *impact on task content* refers to papers focusing primarily on the differences in the task content of occupations across developed and developing economies. In addition, column 2 refers to the primary occupational dataset, while column 4 describes the measure of tasks used.

3 The missing job polarization paradox - measurement issues

The previous section has shown that job polarization is not observed in most studies focusing on developing and emerging economies. In what follows, we shall explore more in-depth the reasons for this paradox. The first question we explore here is whether the method and data structure used for advanced economies can be reproduced in different contexts. Critical to measuring job polarization in developing economies is the appropriate definition of skills and tasks, and in particular, whether the task intensity (and in our context, the routine-task intensity) of occupations is similar across countries.

3.1 Measuring the task content of jobs across countries

While the initial discussions surrounding SBTC focused primarily on the differences between low- and high-skilled workers, the literature on RBTC explicitly explores differences in the task composition across occupations to study the labor market consequences of technological development. Within this approach, two main methods were developed, as also illustrated in column 4 of Table 1: the first one using the O*NET database, and the second one building on information about tasks from the PIAAC and/or STEP surveys (see Table 2 for a comparison of these measures).

*Measuring job polarization with the O*NET database*

The first approach focuses on occupational level tasks, which provide information on job characteristics only at the occupational level but not at the worker level. In doing so, the literature has relied on skill measures tailored for the U.S. economy. Specifically, authors have used the Dictionary of Occupational Titles (DOT) survey and its updated version, the O*NET. The O*NET database covers nearly 1,000 occupations in the United States and provides occupational level task indexes estimated by experts, who rank occupations based on workers' interviews. Using the O*NET dataset, Autor et al. (2003) developed a "routine task intensity" index based on the routine, abstract, and manual task content for each occupation.[3] The use of the O*NET database allowed for a significant transition in the literature, as we are now able to measure the tasks performed in jobs rather than simply the educational level of workers performing them.[4]

This measure has been adopted also in the case of studies on developing countries, under the assumption that the task content across occupations is similar across countries. For example, World Bank (2016) and Maloney and Molina (2019) follow Autor and Dorn (2013)'s classification and define 9 groups of occupations coded according to the major categories in the International Standard Classification of Occupations (ISCO) to study job polarization (see also Aedo et al., 2013 and Arias et al., 2014).[5] However, the assumption that the task content of occupations is similar between countries is obviously a strong one. Differences in technology use are likely to result in different job tasks performed by a machine operator in the U.S. and those performed by a machine operator in a low-income country.

[3] Autor et al. (2003) selected a number of relevant variables for each of the five conceptual categories: non-routine analytic tasks, non-routine interactive tasks, routine cognitive tasks, routine manual tasks, and non-routine manual tasks. For instance, in measuring routine manual activity, the authors use the variable FINGDEX, an abbreviation of Finger Dextery.

[4] The literature on developed economies has also explored the survey of employees carried out by the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung; BIBB) and the Research Institute of the Federal Employment Service (Institut für Arbeitsmarkt- und Berufsforschung; IAB) (see, for instance, Spitz-Oener, 2006, for additional details). However, the database only includes binary information on whether the worker either performs a specific task or not, and aggregate measures are based on the share of each category of tasks (abstract, routine and manual). In our review, the authors have opted for using the O*NET database when studying job polarization in developing economies.

[5] The 9 categories are: Legislators, Senior Officials, and Managers; Professionals; Technicians and Associated Professionals; Clerks, Service Workers, and Shop and Market Sales; Skilled Agricultural and Fishery Workers; Crafts and Related Trades Workers; Plant and Machine Operators and Assemblers; Elementary Occupations.

Measuring job polarization with the PIAAC and STEP surveys

In response to this caveat, a second approach has used worker-level information provided by new household surveys such as the Program for International Assessment of Adult Competencies (PIAAC) by the Organisation for Economic Co-operation and Development (OECD) and the Skills Toward Employment and Productivity (STEP) by the World Bank. Both surveys attempt to measure tasks and skills across the developing world.[6]

Dicarlo et al. (2016) construct a measure of the skill content of occupations for ten low and middle-income countries using the STEP skill measurement surveys and compare it with that of the United States. A number of exciting facts result from this comparison: (i) first, along the skill dimension, occupations are ranked similarly across countries; (i) second, workers in higher-income countries use analytical and interpersonal skills more frequently; (iii) lastly, there are significant differences in the skill content across countries, so that assuming that the U.S. skill content is a good proxy for developing countries is wrong and likely to impact the estimates. Messina et al. (2016) also explore the STEP Surveys conducted in Bolivia and Colombia as a proxy for the routine/abstract/manual content of jobs in Latin America. They show that Latin American occupations exhibit a higher manual content than similar occupations in the United States. Similar results are discussed in Lo Bello et al. (2019), who apply the STEP survey for a more significant number of developing countries. The authors argue that indexes based on U.S. data do not provide a fair approximation of routine cognitive and non-routine manual skill content of jobs in developing countries. Although both indexes are primarily correlated with respect to non-routine analytical, non-routine interpersonal, and routine manual task contents, occupations relatively intensive in routine cognitive and non-routine manual tasks are not necessarily the same according to O*NET and STEP. Lo Bello et al. (2019) also point out two caveats in using the STEP Surveys. First, given that estimates are based on workers' responses, we assume that workers do not differ in their

[6] The use of direct worker-level information on the specific tasks performed on the job was pioneered by Handel (2008), who developed the STAMP survey.

view of tasks performed at work. Given that most questions are quite subjective, this is unlikely to be the case. Second, the survey focuses on urban areas, thus under-representing the agricultural sector.

Lewandowski et al. (2019) combine the STEP and PIAAC surveys and develop a harmonized measure of the task content of occupations based on Acemoglu and Autor (2011).[7] The cross-country measure allows a detailed analysis of differences in the task content of workers in similar occupations, but in different countries. As a result, the authors find that workers in developed economies perform mostly non-routine cognitive analytical and non-routine cognitive interpersonal tasks. In contrast, workers in developing economies perform routine tasks more intensively. Following this analysis, Lewandowski et al. (2020) explore the PIAAC survey for 46 low-, middle-, and high-income countries and develop a regression-based methodology to predict the country-specific routine task intensity of occupations. Using regression-based measures allows overcoming the lack of available survey data for several large emerging economies, such as Brazil and India. In addition, to corroborate that occupations in developing countries are more routine intensive, the authors also find that from 2000 to 2017, the gap in average routine-task intensity with respect to developed countries has increased. In contrast, Gasparini et al. (2021) use harmonized national household surveys for Latin America's six largest economies combined with task content based on information from the PIAAC surveys conducted in Chile, Mexico, Peru, and Ecuador. Applying the mean results derived from these four economies, the authors find a strong linear correlation between their measure of routine intensity and the routine task index developed by Autor and Dorn (2013). However, unlike the previous studies, Gasparini et al. (2021) do not consider the different types of occupations when exploring the correlation between the two indexes. Finally, Caunedo et al. (2021) construct a measure of occupational task content using the PIAAC and STEP surveys from 2006 to 2015 and find that developed countries use

[7] Figure 1 and Figure 2 describe how to map skills in the STEP and PIAAC surveys according to Lo Bello et al. (2019) and Lewandowski et al. (2019). Lewandowski et al. (2020) also present different task measures based on STEP and PIAAC data from other authors.

non-routine analytical and interpersonal tasks more intensively than developing countries. In contrast, developing countries use routine cognitive and routine-manual tasks more intensively. In addition, the authors show that countries are converging to similar task intensities over this period.

The discussion above on comparing O*NET vs. PIAAC or STEP data highlights the difficulty of standardized measures across countries. Rather harmonized categories (e.g., the international classification of occupations) may have a very different meaning in different parts of the world. This can be explained both by the relative availability of skilled or educated workers and the heterogeneity of market needs, sectoral specializations, and technological content of capital. An Egyptian engineer may use more routinized tasks than her American counterpart, not only because her competencies may differ but also because the product she works on may not require the same level of cognitive effort or creativity.

3.2 Remaining challenges: heterogeneity within occupations and over time

Within-occupations variance

Another related important aspect in discussing task intensity across occupations is the extent of within-occupations variance. As discussed above, both DOT and O*NET provide information only at the level of occupations, not workers. Therefore, the implementation of worker-level surveys, including the PIAAC and STEP surveys discussed above, allow us to study within-occupations differences. For example, Autor and Handel (2013) explore data from the Princeton Data Improvement Initiative (PDII) survey (former STAMP) and document that tasks vary substantially within occupations in the U.S. More specifically, the authors find that Spanish-language speakers perform fewer analytical and interpersonal tasks and female workers perform substantially fewer analytical tasks than other workers in the same occupation. Stinebrickner et al. (2019) take advantage of data from the Berea Panel Study and explore the contribution of task content to wage growth, finding that high-skilled tasks pay substantially more than low-skilled tasks. In the context of developing economies and to the best of our knowledge, Saltiel (2019) is the only paper to consider the returns to worker-level task measures. The author explores work-level data from the STEP survey for 10 low- and middle-income countries, finding substantial variance in task intensity within occupations and suggesting that non-routine analytic and interpersonal tasks are associated with sizable wage premiums. In addition, the empirical findings suggest that more educated workers sort into occupations with higher non-routine task content.

Evolution of tasks over time

Despite the recent development in task measurement across the developing world, the literature still lacks information on the evolution of tasks. Not only do occupations differ across countries, but they also evolve over time. For instance, using data from job ads from the Boston Globe, the New York Times, and The Wall Street Journal, Atalay et al. (2020) demonstrate that words related to routine tasks have declined in frequency over the period from 1950 to 2000 in the U.S. Furthermore, Garcia-Couto (2020) harmonizes data from three different rounds of the Dictionary of Occupation Title (DOT) and the Occupational Information Network (O*NET) and finds that the cognitive intensity of occupations has increased during the last decades and that a significant share of wage changes is due to increases in the return and the intensity of cognitive tasks. Similar trends are also observed by Cassidy (2017) and Spitz-Oener (2006), who use the German Qualification and Career Survey conducted by Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment (IAB).

In contrast, there is no evidence of the evolution of tasks within occupations in developing countries. Thus, although the evidence of job polarization in emerging economies is only incipient, it remains unclear whether we observe changes in tasks within occupations similar to what we observe in other advanced economies. Most analyses still rely on occupational and sector composition information to determine the extent of polarization in emerging economies without watching changes in task requirements over time. An obvious reason for this gap in the literature is a lack of longitudinal data sources, which subsequent rounds of the STEP and PIAAC surveys could overcome. Thus, in addition to expanding the number of countries covered in the study, especially the large emerging economies mentioned above, it is also critical to expand the survey to gather information on worker-level tasks within countries over time. Another way forward would be to use job ads from job platforms to study the demand for digital skills and non-routine tasks in developing countries. Following the methodology proposed by Atalay et al. (2020), researchers could explore other platforms to study the evolution in task demand in some emerging economies. Yet, researchers should also be aware of some issues in using job ads data, particularly that they under-represent construction occupations and occupations related to the production and transportation of goods. In addition, these job ads would not include any positions from the informal sector (by definition), which represents a significant share of the workforce in developing and emerging economies (La Porta and Shleifer, 2014).[8]

[8] Note however that some statistical offices from these countries make an important effort to record informal work and the related occupations. For instance, Firpo et al. (2021) explores Brazil's formal and informal sector when discussing job polarization.

Table 2: Comparing the different measures of tasks

	O*NET	**STEP**	**PIAAC**
Countries	United States	Albania, Armenia, Azerbaijan, Bolivia, Bosnia & Herzegovina, Colombia, Georgia, Ghana, Kenya, Kosovo, Lao PDR, Macedonia, Serbia, Sri Lanka, Ukraine, Vietnam, and the Yunnan Province in China. The third wave of the China Urban Labor Survey (CULS) includes a section based on the STEP survey. It includes information on Guangzhou, Shanghai, and Fuzhou on the coast, Shenyang in the northeast, Xian in the northwest, and Wuhan in central China;	Australia, Austria, Belgium (Flanders), Canada, Chile, Czech Republic, Denmark, Ecuador, Estonia, Finland, France, Germany, Greece, Hungary, Indonesia, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Latvia, Lithuania, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Russian Federation, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Turkey, United Kingdom (England and Northern Ireland), and the United States;
Measure	Composite measures of O*NET work activities and work context importance scales. For each occupation, experts assign a score—between 1 and 5 to the 44 existing tasks;	Workers are asked about specific tasks. STEP questions typically refer to whether workers perform a specific task as part of their job or not;	Workers are asked about specific tasks. Often, the PIAAC questions refer to the frequency of performing a task (five categories ranging from "never" to "every day");
Caveats	• Assumption that the task content of occupations is similar across countries and constant over time; • Includes "numerous potential task scales, and it is rarely obvious which measure (if any) best represents a given task construct" (Acemoglu and Autor, 2011, p.1078); • No variation in the task scores within occupations;	• Only covers urban areas; • Doesn't cover large developing economies, including, for instance, Argentina, Brazil, Bangladesh, India, Nigeria, and South Africa; • The mapping between tasks and skills isn't trivial; • Subject bias in workers' response, especially given that most questions are subjective. • Sample size isn't large enough to develop disaggregated classifications at the country level;	• Doesn't cover large developing economies, including, for instance, Argentina, Brazil, Bangladesh, India, Nigeria, and South Africa; • The mapping between tasks and skills isn't trivial; • Subject bias in workers' response, especially given that most questions are subjective; • Sample size isn't large enough to develop disaggregated classifications at the country level;
Advantages	• Offers tasks content of occupations at disaggregated levels and with easily-available crosswalks to most classifications;	• Variation in the tasks scores within occupations; • Estimation for a number of developing countries, including low-income economies;	• Variation in the tasks scores within occupations; • Estimation for a number of developing countries;

Source: Own elaboration. STEP and PIAAC also present differences in the way the data is collected and in the way the proficiency of respondents is estimated (see Keslair and Paccagnella, 2020).

4 The missing job polarization paradox - conceptual issues

Besides issues related to measurement as described above, the lack of observed job polarization in developing and emerging economies could be explained by differences in the economic structures, the level of technology adoption, and the interactions with other economies. Therefore, after discussing the factors affecting technology diffusion and adoption processes (see section 4.1) and how structural characteristics of the economy (sectors, wages, and firms) explain the employment distribution (section 4.2), we investigate whether the labor market effects of such technology adoption are expected to align with the RBTC hypothesis in countries positioned differently within Global Value Chains (see section 4.3).

4.1 Local challenges to technology adoption

The overall extent of polarization in developing economies is still incipient compared to developed economies, making us wonder what possible mechanisms could prevent it. Several factors could explain these different dynamics. First, the time and degree of technology adoption may differ across industries and countries. For instance, relative to the Anglo-Saxon countries, other European countries experienced a decade-long lag regarding their labor market trends (Dustmann et al., 2009; Fonseca et al., 2018; Spitz-Oener, 2006). Therefore, the lack of polarization could be simply related to a significant lag in technology adoption. In turn, the slow pace of technological adoption may be related to countries' business environments, firms' capabilities, and human capital endowments. We discuss some of these factors below.

Firms' behavior and capabilities

Firms' ability and willingness to adopt digital technologies are heterogeneous across and within countries. For instance, in the specific cases of Brazil and Vietnam, recent evidence suggests that most firms still rely on pre-digital technologies to perform daily tasks (Cirera et al., 2021a,b). Therefore, the significant share of small and technologically-lagged firms in developing countries could also help to explain the few signs of polarization. For one, firms may simply not be aware of the available technologies. Due to restricted technological diffusion, advanced technologies have limited dissemination in developing economies - a classic example of information failure. Acquiring this knowledge can be very costly, and companies may think adopting new practices wouldn't be profitable (Jensen, 1988). Finally, even when managers are aware of best practices, there is a final process of acceptance and implementation. As once stated by Rosenberg (1972, p.191), "in the history of diffusion of many innovations, one cannot help being struck by two characteristics of the diffusion process: its apparent overall slowness on the one hand, and the wide variations in the rates of acceptance of different inventions, on the other".

Availability of human capital

Building upon Nelson and Phelps (1966)'s ideas, a range of empirical evidence suggests that human capital is an important factor in explaining the adoption of advanced technologies within firms. For instance, Benhabib and Spiegel (1994) shows that human capital affects the speed at which countries absorb technological developments. Comin and Hobijn (2004) examine the diffusion of more than twenty technologies across developed economies and find that countries' human capital endowment is the most crucial determinant of the pace of technology adoption. As clearly stated by Boothby et al. (2010, p.621), "firms embracing new technology have to obtain new skills and/or to upgrade the skill level of their existing workforce because the attributes of new technology could be significantly different from old technologies". The recent literature has largely stressed the lack of managerial and workers' skills in developing economies as a critical constraint to innovation and technology adoption. Educated managers may have more information about more sophisticated technologies and be favorably disposed to adopt them. More recently, using data on digital technology usage, Nicoletti et al. (2020) find empirical evidence that low managerial quality and the lack of ICT skills are negatively associated with technological adoption in 25 European economies.

4.2 Structural explanations: sectors, wages and firms

Notwithstanding a generally lower level of technology adoption in developing and emerging economies, the economy's composition in terms of sectors, wages, and firms is an essential part of the missing job polarization paradox.

Within-country heterogeneity: sectors and regions

Given that the literature on emerging economies presented above has relied primarily on aggregate measures, it has somewhat overlooked job polarization's regional and sectoral heterogeneities. For instance, it is somewhat unclear if the slow pace of polarization in most developing and emerging economies is a general trend or restricted to a few sectors or regions within countries. Using individual-level data from Statistics Sweden from 2002 to 2012, Henning and Eriksson (2020) find that clusters of previously manufacturing-dominated municipalities drive polarization in the country. In contrast, areas with fast-growing industries (higher shares of extraction industries and lower manufacturing industries) share opposite patterns, showing more tendencies towards job upgrading. These regional and sectoral differences, and more specifically the role of extractive industries, could help to explain the slight evidence of job polarization in some emerging economies, especially in Latin American Countries (LAC). The commodity boom in the early 2000s led to a significant expansion of the extractive sector in LAC, which is likely to offset the decline in middle-earning jobs across other sectors. In many Latin American economies, the commodity boom experienced in the region during the 2000s mainly favored low-skilled workers, likely overcoming the impacts of ICT adoption (Maloney and Molina, 2019).

Another moderating mechanism relates to differences in the economic structure, especially developing countries' significant share of employment in agriculture and the small percentage of workers engaged in codified tasks in the first place. Recent literature has suggested that the sectoral structure is a critical component to explain differences in automation risk across countries (Foster-McGregor et al., 2021). For example, Lee and Shin (2019) find that horizontal and vertical polarization is faster in manufacturing than in services. Using a novel dataset spanning 91 countries, Peña and Siegel (2021) explore cross-country differences in employment structures and find that average income is positively associated with abstract employment share and negatively associated with manual and routine occupations. In addition, the authors show that countries with higher labor productivity tend to have technologies that are more biased against routine workers. What do these findings imply in terms of dynamics when developing and emerging economies move away from a more traditional sectoral specialization and increase their level of industrialization? Bárány and Siegel (2018) discuss the association between job polarization and structural change, arguing that as relative labor productivity in manufacturing increases, labor has to shift to low- and high-skilled services sectors, which in turn need to increase wages to attract more workers. As a relatively larger share of middle-earning jobs is concentrated in manufacturing, this dynamic leads to job polarization.

Industrial dynamics

Besides differences across sectors, firms of the same industry also present considerable differences in their employment and wage structures (see Helpman et al. (2017) for Brazil and Domini et al., ming in the case of France). Therefore, changes in the shares of firms with different types of occupation affect the aggregate distribution of jobs and wages. Harrigan et al. (2020) suggest that firms with a more significant percentage of technology-related occupations grew faster from 1994 to 2007, responding to a sizable share of job polarization in France. As firms with a larger share of technology-related occupations grow faster, job polarization rises due to reallocation processes between firms rather than substitution across workers within firms. The results are related to the recent literature describing the importance of larger and more capital-intensive firms in explaining the drop in the labor share in the US (Autor et al., 2020). In the context of developing countries, it could be the case that there is a polarization process within firms, but it is compensated by the fact that larger and growing firms are more intensive in middle-earning occupations. As a consequence, occupational shares at the aggregate level do not change.

Wage level and distribution

A third explanation for the slow pace of polarization in developing and emerging economies, although not examined rigorously, is the natural consequence of lower wages and the wage distribution. Indeed, the structure of wages matters on the firm (employer) side because it affects their choice of technology (whom to hire and whom to replace by capital) and the prices of consumption goods via the demand channel. When wages are low, or when the share of low-wage workers increases, this puts downward pressure on the prices of consumption goods and increases the relative price of investment (Hsieh and Klenow, 2007). In this context, as observed by Shim and Yang (2018) in the U.S., in high-paying sectors (where therefore the relative cost of wages compared to capital is higher), there are more incentives to replace routine employment. This is confirmed by Lordan and Neumark (2018) who show, in the same context, that minimum wage increases are associated with a higher probability of replacing routine occupations.

A similar explanation relates to the wage structure. The decline in the demand for routine-intensive occupations only leads to job polarization if these occupations are in the middle of the wage distribution and if the wage distribution reflects the skills structure. Nevertheless, routine occupations in emerging economies could be ranked differently given the different levels of development and wage-setting institutions. For example, in the last twenty years, Brazil has seen a joint growth of its minimum wage and of its supply of more educated, more qualified workers. This dual process has resulted in lower relative returns to skills (Firpo and Portella, 2019), and a compression of the wage distribution. In addition, using data from 10 OECD countries, Haslberger (2021) documents that RBTC can lead to occupational upgrading rather than polarization, as countries differ in terms of the occupational routine-wage hierarchies.

Demand and demography

Furthermore, Comin et al. (2019) put forward the non-homotheticity of demand as another potential explanation of the low polarization in developing economies. They observe a positive association between the sectoral intensity of high- and low-skill occupations and the income elasticity of sectoral value-added. Consequently, as aggregate expenditure grows, demand shifts towards sectors concentrated in high- and low-skill occupations, hence polarizing workers' earnings. Similar to this argument, Moreno-Galbis and Sopraseuth (2014) show that goods and personal services are complementary for seniors. As a result, population aging leads to a rise in the demand for personal services, causing an increase in the employment share of low-paid positions. However, both patterns contrast with the demography in most emerging economies. On the one hand, especially across African economies, developing economies are experiencing significant growth in the working-age population, resulting in a less intense demand for low-paid occupations. On the other hand, most developing countries are in the early stages of economic development, where the share of income spent on manufacturing goods is still rising.

4.3 Employment dynamics in open economies

Most of the literature on job polarization in developing countries has relied on isolated analysis of job polarization at the country level, without considering possible effects stemming from changes in global value chains. We explore below the employment implications of the positioning of developing and emerging economies in international flows of goods and tasks.

Global Value Chains and the routinization of tasks

Local employment dynamics are exposed to external pressures, such as job polarization in advanced economies. The inflow of routine jobs from advanced countries is then likely to offset polarization forces in some host countries (Maloney and Molina, 2019). Das and Hilgenstock (2018) indeed show that the participation in global value chains might have played a role in the rising routine exposures in developing economies while reducing exposure in advanced economies. In addition, Lewandowski et al. (2019) test the association between the routine-intensity of occupations and technology (computer use), globalization (specialization in global value chains), structural change, and supply of skills in 42 countries at different stages of development. The results generally corroborate the main drivers of job polarization. On the one hand, technology, structural change, and the supply of skilled workers are positively correlated with the routine intensity. On the other hand, globalization is positively associated with routine intensity in developing countries and negatively in developed countries, reinforcing the argument that developed countries are offshoring routine occupations to host countries. Lo Bello et al. (2019) study both supply (e.g., education, age, and age structure) and demand (growth, sector structure, technology, and trade) factors in explaining differences in the skill content of jobs and find that technology adoption is related to de-routinization and trade is an offsetting force. Furthermore, while controlling for different characteristics, they find no association between non-routine cognitive skills and GDP growth or levels.

Technological change, offshoring and reshoring of tasks

The literature has focused on the impacts of offshoring in explaining job polarization in developed economies. Technological development has drastically reduced the costs of offshoring jobs to locations with lower labor costs, such that firms in developed economies have off-shored routine-intensive occupations, especially those concentrated among middle-earning workers (Acemoglu and Autor, 2011; Blinder and Krueger, 2013; Goos et al., 2014). Reijnders and de Vries (2018) explore the impacts of both technological change and offshoring on the labor market for several advanced and emerging economies. Although the results corroborate an increasing share of non-routine occupations in the labor market of both groups, the authors find that the effect of task reallocation (via offshoring) reinforces the trend for advanced economies and mitigates it for developing countries.

There are also second-order effects from technological change and offshoring on wages and productivity, which affect the employment allocation decisions of firms in advanced economies. The increased "routinization" of jobs in host economies can be later offset by capital accumulation in the host economy or labor-saving technology advances in the domestic economy. Capital accumulation leads to rising wages in the host economy and thus reduces the incentives for domestic firms to offshore. As a result, firms start to move their production back to the domestic economy, and routine jobs begin to disappear in the host economy (Chu et al., 2013). A recent strand of the literature already shows that robot adoption in developed economies negatively impacts wages and employment in developing economies. Using data from Mexican local labor markets between 1990 and 2015 and the International Federation of Robotics (IFR), Faber (2020) shows a negative impact on Mexican employment, with a more substantial effect for women and low-educated machine operators in the manufacturing sector. Also exploring the Mexican labor market, Artuc et al. (2019) show that an increase of one robot per thousand workers in the U.S. lowers growth in exports per worker from Mexico to the U.S. by 6.7 percent. However, the authors didn't find evidence of an impact of wage employment, nor manufacturing wage employment. Kugler et al. (2020) use data from the International Federation of Robotics (IFR) to measure automation in the U.S. and microdata from the Colombian Social Security records to examine the effects of robot adoption in the U.S. in the Colombian labor market. The results indicate a negative impact on the employment and wages of Colombian workers, especially for women, older and middle-aged workers, and workers employed by SMEs.[9]

In contrast, the rapid spread of robots in developed economies could also accelerate job polarization in developing economies. Krenz et al. (2021) develop a theoretical model to account for these interactions. Since automation in advanced countries increases productivity and reduces the costs of producing in-shore, part of the production once off-shored to host areas in developing regions returns, although not improving low-skilled wages and without creating jobs for low-skilled workers in the receiving economies. Although some evidence suggests that automation in advanced economies is yet to impact FDI flows (Hallward-Driemeier and Nayyar, 2019), recent findings already show some negative impacts in terms of increasing reshoring and decreasing employment in developing economies. Krenz et al. (2021) explore 43 countries and nine manufacturing sectors and provide evidence that robot adoption increases re-shoring activity. Similarly, Kinkel et al. (2015) analyze 3,313 manufacturing firms in seven European countries and find empirical evidence that firms using industrial robots are less likely to off-shore their production outside the region.

The role of MNEs

The literature has yet to examine the role of MNEs as drivers of job polarization in emerging economies. An extensive literature has already provided evidence that MNEs are more productive (Helpman et al., 2004), pay higher wages (Hijzen et al., 2013), and employ a higher share of non-routine jobs (Hakkala et al., 2014). In this context, an increase in foreign direct investment (FDI) could have implications for job polarization in host economies. For instance, Olsson and Tåg (2017) examine the impacts of private equity acquisition on the employment composition of recently acquired firms in Sweden and finds that workers in less productive firms in routine-intensive occupations are twice more likely to be displaced after buyouts. In the specific case of FDI, Hakkala et al. (2014) rely on Swedish data

[9] In addition to changes in world trade, the COVID-19 pandemic could also change the pace of digital adoption in developing economies. Initial evidence suggests that the pandemic has accelerated digital adoption (Apedo et al., 2020; Cirera et al., 2020), which could result in higher job polarization and inequality.

to study changes in firms' ownership and find that MNEs demand more non-routine tasks or tasks requiring personal interactions compared to their local counterparts. In addition, Amoroso and Moncada-Paternò-Castello (2018) use data on greenfield FDI for several European economies to examine the extent to which different types of FDI are responsive for job polarization. While low-skill FDI investments lead to skill downgrading, skill-intensive FDI is more commonly associated with skill upgrading. Only investments in ICT are related to job polarization.

Yet, as for developing economies, the overall impact on the labor market will depend on many factors. In addition to the current economic structure and the target sectors (either low-skill or skill-intensive), the impacts of FDI also rely on foreign firms' ability to spur technology adoption. Changes in ownership and the increasing share of MNEs in already established sectors could have different impacts. For instance, extensive literature has pointed out to MNEs' role in transferring technology and managerial skills (for example, Teece, 1977). In this context, if MNEs catalyze technology adoption across local firms, job polarization could emerge as an overall effect of more extensive technology diffusion. In contrast, a different strand of the literature stresses that MNEs are more likely to crowd out local firms, use technology that is inappropriate for local circumstances, and limit technology transfer (Oetzel and Doh, 2009). As a result, job polarization would be limited to a few MNEs, and the extent of polarization would depend on MNEs' share in total employment.

5 Discussion and policy implications

This section discusses the opportunities and challenges associated with technology policies in developing and emerging economies, and the implications in terms of employment patterns and labor policies. On the one hand, we briefly stress the need to adopt and use more advanced technologies in developing countries. But, on the other hand, we point to the need for better-adapted policies to cope with the changing nature of work in developing countries' unique contexts. In addition, we discuss the main gaps in the (empirical) literature, focusing on those that could vastly improve our knowledge and facilitate the development of adapted public policies.

5.1 Technology and labor policies

Targeting the adoption of more sophisticated technologies is uncontested, as technology adoption can facilitate firms' competitiveness, generate more and better-quality jobs, and substantially improve living standards (Comin and Hobijn, 2004). Waves of new technologies, especially the fast-growing adoption of robots and the increasing penetration of ICT technologies, bring additional challenges and opportunities for developing economies. On the one hand, emerging economies are at risk of lagging further behind, widening the productivity gap to advanced economies. On the other hand, as most emerging economies aren't locked into existing technologies, the possibility of "leapfrogging" towards these more advanced technologies and skipping the traditional development path could engender great benefits (Lee, 2013; Soto, 2020).

The second, and preferred scenario, requires countries to overcome many barriers. As discussed in section 4, several factors could prevent the adoption of more sophisticated technologies, including the lack of firms' capabilities and the insufficient supply of educated workers. In addition, other mechanisms are also likely to impact technology adoption in emerging economies, including the absence of finance and firms' information on existing technologies. In this context, policymakers can play a crucial role in applying several policy instruments to advance technology adoption, facilitating access to finance, reducing information asymmetries, and improving workers' and managers' capabilities (see Cirera et al., 2020, for a discussion on policies to facilitate technology adoption in developing countries).

On the other hand, however, technology adoption can also be linked to widening income inequality and the polarization of the labor market (Acemoglu and Autor, 2011). New production methods are associated with the displacement of workers in more routine occupations, threatening to push up the unemployment rates and increase inequality. Although the potential labor market disruptions are similar to those observed in other advanced economies, they can be more severe in emerging economies, where social protection systems are considerably weaker, and the educational system lacks the necessary capacity to respond to changes in the nature of work quickly.

This conflicting impact of technology poses additional challenges to policymakers, highlighting the need for complementarity in public policies. For instance, while encouraging and facilitating technology adoption, labor market de-routinization calls for robust social protection systems to help the transition of workers with low job mobility in finding a new job, especially more disadvantaged groups. For instance, Lewandowski et al. (2017) study the intergenerational disparities in the de-routinization of jobs and find a significant relationship between age groups and shifts in the task composition. The decreasing demand for routine occupations also challenges existing education and training systems to respond to changing skill demands. It is crucial to adequately equip the labor force with the necessary skills to guarantee maximum benefits from recent technological advancements, stimulating the development of competencies with increasing demand - an excellent example of this is the soft-skills training for employees in the hotels and accommodation industry (for instance, the training from Quality Assurance Agency, 2015 in the UK).

5.2 The need for evidence-based policymaking

Ultimately, designing better-fitted policies for skills development, such as programs upscaling digital skills and vocational training and better-adapted social protection systems, requires detailed studies. Researchers will need to move from aggregate measurements of polarization into micro-level information to examine differences across firms and workers, including assessing workers' ability to transition from displacement to re-employment in high-paying jobs. This calls for more systematic and frequent micro-level data collection in developing economies to better understand the task content of occupations that are specific to each country and technology adoption at the firm level.[10] Data collection and integration at a decentralized level with a detailed skill mapping system will help local economies to resolve skills mismatch and place themselves in a better position to respond to the threats and opportunities brought by technological change. In turn, data on technology adoption at the firm level will help understand the barriers to technology diffusion in different contexts and understand which policies could address them.

For instance, the literature has not explored the extent to which the declining demand for routine occupations takes place within worker categories or through changes in the composition of workers. If workers can easily transition between routine and non-routine occupations, unemployment becomes less of an issue. In contrast, public policies can play a crucial role if job polarization occurs through workers' composition changes. For instance, Cortes et al. (2020) show that most of the decline in routine occupations in the U.S. is linked to the inflow rates to routine employment (from unemployment and non-participation) rather than the outflow rates. Maczulskij (2019) explores the occupational mobility of routine workers using the Finnish Longitudinal Employer-Employee Data (FLEED) from Statistics Finland. The results show that most of the relative increase in non-routine occupations compared to mid-level routine occupations is a within-worker phenomenon in the decomposition analysis. In contrast, the share of low-skilled non-routine manual tasks has increased mainly through entry dynamics.

Moreover, we need a more detailed analysis of the effects of labor-displacing automation on workers' labor prospects, especially in the context of increasing digitalization. One crucial empirical question is for what types of workers there is a more pronounced decline in wages and increase in unemployment duration following the event of displacement. Despite the long-term drop in demand for routine tasks, little is known about the short-term impacts of technological change at the individual level, and less so in the context of develop-

[10] Recent surveys, such as Cirera et al. (2021a,b), already point to a better understanding of technology adoption at the firm level in the context of developing and emerging economies.

ing countries. Although most empirical results point to a lack of polarization among those economies, it is still unclear whether workers previously employed in routine-intensive occupations are already facing the negative implications of automation. For instance, Gasparini et al. (2021) already point to a decline in job growth in routine-intensive occupations in six LAC economies. In addition, Reijnders and de Vries (2018) use a sample of 37 advanced and emerging economies and document an increasing share of non-routine occupations in the labor force.

In the context of advanced economies, Blien et al. (2021) test whether the declining demand for routine work hampers their recovery from adverse shocks. Specifically, the authors employ an event-study approach and treat firms' bankruptcy or mass layoffs as an external shock to estimate the effect of an involuntary job loss on earnings and employment prospects. Using German data from 1980 to 2010, the authors test different implications of job losses between routine and non-routine workers and find evidence that workers in routine occupations suffer more considerable and more persistent wage losses. In addition, the authors show that the difference concerning non-routine workers has increased over time. Similarly, Goos et al. (2021) explore survey data of workers previously employed in a large Belgium establishment in the automotive sector. After the plant closed and in line with the RBTC hypothesis, workers in routine-intensive occupations were less likely to find a job 1,5 years after the event. Additionally, for those workers who could find a job, the non-routine content of job tasks is higher, wages are lower, and permanent jobs are less frequent. Given that these studies rely on firms' closure or mass layoffs, neither Blien et al. (2021) nor Goos et al. (2021) can observe the direct impact of automation on workers' probability of separation. Using Dutch micro-data from 2000 to 2016, Bessen et al. (2019) employ a direct measure of automation at the firm level and find that automation increases the probability of incumbent workers separating from their employers. Furthermore, displaced workers are more likely to face long-term unemployment and decrease the number of days worked.

However, no study has sought to investigate the implications of job polarization at the individual level in the context of developing countries. A detailed account of the effects of displacement on different workers (according to their tasks) helps categorize more disadvantaged workers, thereby formulating specific policies related to particular occupational categories (including unemployment benefits). Therefore, while the literature on job polarization in developing countries is relatively new, the research agenda should concentrate on understanding the factors behind the slow pace of job polarization and examining the heterogeneities of this process, especially those related to firm-level differences in technology adoption and the adverse impacts at the work level. As discussed in this section, researchers could expand our understanding of the many heterogeneities surrounding labor market trends in emerging economies while exploring matched employer-employee databases. By identifying new trends in demand for specific jobs, this research agenda could help formulate policies to support workers, especially vulnerable groups and the youth, in building digital skills specific to newly created jobs. Indeed, an essential part of the transition is to upskill/train workers to adapt to the changing skill needs. In the end, reaping the benefits of technological progress will challenge policymakers' ability to facilitate technology adoption and cope with its adverse effects.

6 Conclusion

This literature review has highlighted the impacts of technology adoption on the labor market, focusing on the extent of job polarization in developing and emerging economies. The evidence synthesis suggests that, in advanced economies, the rapid spread of ICTs and robots has resulted in increasing inequality and the "hollowing out" of the occupational distribution, with a significant decline in the demand for routine occupations (Acemoglu and Autor, 2011; Spitz-Oener, 2006). Yet, in economies at lower levels of income per capita, the pace is considerably slower, with little evidence of labor market polarization or labor-displacing automation (Maloney and Molina, 2019). In section 3, we explored the different definitions of tasks, suggesting that future empirical work requires much better measures, taking into account differences across countries and the evolution of occupations through time.

In section section 4, we explored the possible mechanisms slowing job polarization in developing economies, suggesting the critical role of firms' and workers' capabilities in slowing technology adoption and the off-shoring of routine-intensive jobs from advanced economies to some host developing countries. Other moderating aspects include lower wages and different economic structures in emerging economies. We also highlighted the need for more research on the moderating sources, especially those associated with differences in the relative cost of inputs (lower wages in developing countries) and the role of MNEs in slowing or spurring job polarization.

Finally, in section 5, we have stressed the importance of advancing technology adoption in developing and emerging economies, underlining the need for complementary policies to spur technology adoption and protect the employment of those bearing the brunt of this process. In turn, we have discussed the need for micro-level studies and the exploration of the different mechanisms preventing job polarization in those economies. These studies would enhance our understanding of the main barriers to technology adoption and the adverse effects at the worker level, thus allowing for the development and implementation of better-adapted policies fitted to developing and emerging economies' specific contexts.

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Figure 1: Mapping skills in the STEP survey

Skill Bracket	STEP Task	Question	Corresponding O*Net Task	Coding
Non-routine Analytical	Type of document read	m5a_q05	Analyzing data/information	Summation of "Yes" (0-5)
	Length of longest document typically read	m5a_q04*m5a_q06		Categorical (0-5)
	Math tasks	m5a_q18		Summation of "Yes" (0-5)
	Thinking for at least 30 minutes to do tasks.	m5b_q10	Thinking creatively	Categorical (1-5)
Non-routine Interpersonal	Supervising coworkers	m5b_q13	Guiding subordinates	Dummy
	Contact with clients	m5b_q05*m5b_q06	Establishing personal relationships	Categorical (0-10)
Routine Cognitive	How often your work involves learning new things	m5b_q17	Importance of repeating the same task (inverse)	Categorical (0-5)
	Autonomy	m5b_q14	Structured vs unstructured work	Categorical (1-10)
	Repetitiveness	m5b_q16	Importance of repeating the same task	Categorical (1-4)
Routine Manual	Operate	m5b_q09	Controlling Machines and processes	Dummy
	Physical demanding	m5b_q03	-	Categorical (1-10)
Non-Routine Manual	Driving	m5b_q07	Operating vehicles	Dummy
	Repair	m5b_q08	Control/Feel objects; Manual dexterity	Dummy

Source: Lo Bello et al. (2019) Note: Questions codes based on STEP's second wave.

Figure 2: Mapping skills in the PIAAC survey

Task content	Non-routine cognitive analytical	Non-routine cognitive interpersonal	Routine cognitive	Manual
Task items	Solving problems Reading news (at least once a month – answers 3,4,5) Reading professional journals (at least once a month – answers 3,4,5) Programming (any frequency – answers 2,3,4,5)	Supervising others Making speeches or giving presentations (any frequency - answers 2,3,4,5)	Changing order of tasks - reversed (not able) Filling out forms (at least once a month – answers 3,4,5) Making speeches or giving presentations - reversed (never)	Physical tasks
Correlation with Acemoglu and Autor (2011) measures	0.77	0.72	0.55	0.74

Source: Lewandowski et al. (2019)