Is There Job Polarization in Developing Economies? A Review and Outlook

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In this paper we analyze the evidence of job polarization—the relative decline of mid-wage jobs—in developing and emerging economies. We carry out an extensive literature review, revealing that job polarization in these countries is only incipient compared to advanced economies. We then examine the possible moderating aspects explaining this lack of job polarization. We distinguish three groups of explanations: Limited technology adoption; structural change; and changes in the global value chains. Finally, we suggest new microeconomic data and empirical analyses that should be developed in order to guide evidence-based policy-making addressing those issues in developing and emerging economies.

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Introduction

The economic discipline has dedicated a great deal to the possible harmful effects of technological progress on the labor market (Katz and Summers 1989; Katz and Murphy 1992; Levy and Murnane 1992; Card and DiNardo 2002). Throughout recent history, and more famously after the Luddite movement, "technological unemployment" has been a persistent debate topic among economists, who have constantly deliberated whether massive waves of unemployment could be around the corner.

However, the pessimistic predictions of technological unemployment have yet to be fulfilled. Technical progress did not pave its way through unemployment but rather through changes in the demand and composition of employment. For instance, steam power significantly favored unskilled workers to the detriment of skilled artisans, accelerating 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

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disproportionately and positively impacted the need for skilled workers, increasing the ratio of skilled to unskilled labor in most industries (Katz and Murphy 1992).

Not surprisingly, when most developed countries have experienced increasing wage inequality in the past 40 years (Alvaredo et al. 2018), technology-related arguments have been 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 they are more capable of using these new technologies (see the review by Card and DiNardo 2002), and thereby causing earnings inequality to rise (Goos and Manning 2007; Acemoglu and Autor 2011).

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 so-called job polarization (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 the so-called job polarization 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. In the United States, it was first observed by Acemoglu (1999) and later rigorously analyzed by Autor et al. (2003). Beyond this first application, 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 for 16 European countries, using harmonized data from the European Union Labour Force Survey (ELFS). Moreover, 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 (Spitz-Oener 2006; Dustmann et al. 2009), the United Kingdom (Salvatori 2018; Montresor 2019), Portugal (Fonseca et al. 2018), and Japan (Ikenaga and Kambayashi 2016).

The observed trends in advanced economies indicate that although technological change has not induced a surge in unemployment, it threatens to raise inequality and displace routine workers. However, beyond the context of developed economies, the literature on RBTC and its consequences on labor outcomes remain relatively limited. Understanding the labor market effects of technological change in emerging and developing economies is also important, as inequality and unemployment are already exceptionally high in these contexts.

The displacement of routine workers would be particularly harmful to less-educated and vulnerable groups who face more difficulties in finding another job and are more likely to transition towards low-stability, low-wage, and high-turnover occupations (Autor and Dorn 2013; Zago 2020). Furthermore, a growing demand for non-routine cognitive tasks would put further pressure on educational systems. In addition to fostering educational attainment, policy-makers in developing and emerging economies would need to respond quickly to the rapid changes in the demand for skills.[2]

This paper attempts to provide a broad survey of job polarization in emerging and developing countries, giving special attention to the theoretical channels that could prevent or slow down job polarization dynamics. Specifically, we stress the roles of technology adoption, structural change, and global value chain (GVCs) participation in explaining differences across countries. Finally, we highlight policy implications that arise throughout the discussion, particularly the need for better data and empirical evidence to support policy design.[3] Our review suggests a slower pace of job polarization in most developing and emerging economies, likely related to a significant gap in technology adoption and (or) different paths of structural change. Nevertheless, most of the literature also finds a decline in routine intensity in developing economies (a precondition for job polarization), thus indicating relevant changes in the demand for skills. In addition, we find substantial gaps in the literature, especially micro-level studies, that could significantly improve our understanding of the subject and facilitate the implementation of evidence-based policies.

The rest of this paper is organized as follows. Section 2 describes the empirical literature on job polarization in developing economies. Next, Section 3 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 4 explores the need for more micro-level studies and discusses the policy implications of job polarization in developing countries. The last section concludes.

Is There Job Polarization in Developing Economies?

Focusing on different regions and countries, as well as various measures of tasks and skills, the literature on job polarization in developing economies is gaining momentum (see table 1 for a detailed summary of this literature).[4] 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, except for Mexico and China. Das and Hilgenstock (2022) use data on 85 countries since 1990 and observe similar results. In addition, the authors propose a measure of exposure to routinization based on

Table 1. Summary of the Existing Literature on Job Polarization in Developing and Emerging Economies

Level of analysis (1)	Dataset (2)	Country (3)	Task (4)	Result (5)	Reference (6)
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 (2022)
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)
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)
Country	European Union Labour Force Survey	Central and Eastern European countries	Occupations	(-)	Nchor and Rozmahel (2020)
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)

Source: Author's elaboration.

Note: The table is separated into groups of papers according to the primary dependent variable in the analyses. 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. 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 measurement of tasks used. Column (5) indicates the sign of the significant relationship tested in each paper, that is, the existence of job polarization (in the impact on job polarization studies), or on the intensity of routine tasks (in the impact on the task content studies).

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 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) employ the Skills Toward Employment and Productivity (STEP) Surveys conducted in Bolivia and Colombia as a proxy to measure the task content of jobs in Chile and Mexico. They find few signs of job polarization, except for Chile. In fact, Brazil, Mexico, and Peru present positive growth rates for workers in the middle of the wage distribution. Beylis et al. (2020) study the labor market of 11 Latin American countries (LAC) from 2000 to 2014. Applying 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, these changes in the labor composition have not resulted in polarized markets. In Central and Eastern European economies, Nchor and Rozmahel (2020) find that despite an increase in the demand for high-skill workers and a decline in middle-skill employment, the rise in low-skill employment is minimal to lead to a U-shape employment distribution which indicates labor polarization.

Even among developing and emerging economies, the evidence is not homogeneous. 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, with a decline of 5.9 percent in the share of employment of middle-skilled occupations compared to a growth of 4.5 percent and 1.4 percent for low- and high-skilled occupations. 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. 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. In the period 1984–94, the author finds an up-grading pattern, with a substantial increase in the employment of high-skilled occupations. In contrast, the following periods show a polarized U-shaped employment growth, with a decline of almost 20 percent for occupations in the 40th percentile of the skill distribution.

Table 1 summarizes the main findings of this section, highlighting the context of the studies: the unit of analysis, the data sources, the countries, the task measurements, and the impact of technological change on two outcomes of interest, the existence or not of job polarization and the increase of decline in the intensity of routine tasks. Except for the cases of India, the Arab Republic of Egypt, and China, most papers fail to observe job polarization in emerging and developing economies. However, as previously discussed, many articles already observe a decline in the routine intensity across low- and middle-income countries—a precondition for job polarization. For the group of papers exploring the impact on task content, all results are negative, suggesting that developing countries are less intensive in non-routine cognitive skills than advanced economies. We will explore these differences in more detail in subsection 4.2 and highlight the need for better measures of tasks across occupations in emerging and developing economies.

The Missing Job Polarization

The literature has identified three main channels driving job polarization: Technology adoption; structural change; and participation in global value chains (GVCs). This section discusses how developing economies may differ from advanced ones in each of these aspects and, in turn, how that difference may explain the absence of job polarization in developing and emerging economies. For each channel, we first present the general theoretical mechanisms and then discuss the main differences observed in developing and emerging economies vis-à-vis advanced ones.

We begin by examining the role of technology adoption, focusing on why firms may have lower rates of adoption and exploring potential explanations for differences in technology choice. We then move from a micro-level to a macro-level discussion, illustrating the role of structural change and regional differences as key drivers of job polarization. Finally, we open our economy to international trade and discuss how both the micro and macro aspects of a given economy are affected by a country's participation in GVCs. Although we present each mechanism separately for the sake of simplicity, we emphasize that all of them are interacting forces. For instance, structural change and differences across sectors and regions are to a large extent a combination of firms' decisions either at the local level or a result of a country's participation in GVCs.

Technology Adoption

The "routinization" hypothesis argues that firms combine a continuum of tasks to produce, which can be performed either by capital or labor (Autor et al. 2003; Acemoglu and Autor 2011). 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 past decades, not only did the quality-adjusted ICT and robot prices fall considerably, but these technologies have been particularly successful in carrying out tasks that follow explicit rules (routines) (Michaels et al. 2014; Graetz and Michaels 2018). As a result, firms accelerated the substitution of labor in routine tasks, so workers in routine-intensive occupations were suddenly at high risk of displacement. Traditionally, many routine tasks are 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. Yet, while ICT and other automated technologies are expected to be widespread in advanced economies, lower adoption rates can be found in developing and emerging economies. The slow pace of technological adoption in these economies may reflect many aspects, including firms' capabilities, the extent of informality, and countries' human capital endowments.

Firm 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). However, rather than a sign of backwardness, firms' decision to not adopt more advanced technologies may be an optimal response to their small scale, local competition, and the relative price of labor and capital. Labor is substantially cheaper in developing economies, and the number of small and informal establishments with a small production scale is larger (we discuss the role of informality below). As Banerjee and Duflo (2005) point out, one reason for the lag in technology adoption could be that the firms are too small to profit from the best technologies.

Similarly, when wages are low, the relative price of investment is relatively higher (Hsieh and Klenow 2007) and deters technology adoption. In the context of developed economies, Shim and Yang (2018) show that, in the United States, in high-paying sectors (where therefore, the relative cost of wages compared to capital is higher), there are incentives to replace routine employment. This is confirmed by Lordan and Neumark (2018), who show that minimum wage increases are associated with a higher probability of replacing routine occupations. In other words, lower wages disincentivize firms in developing countries to adopt more sophisticated technologies.

Yet, decisions are not always optimal, and firms may simply not be aware of the available technologies. Due to restricted technological diffusion, advanced technologies have limited diffusion in developing economies—a classic example of information failure. Acquiring this knowledge can be very costly, and companies may think that adopting new practices would not 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."

Technology adoption also depends on firms' dynamic capabilities (Teece et al. 1997), that is, their ability to "integrate, build and reconfigure internal and external competencies to address rapidly changing environments." Therefore, the diffusion of (foreign) new technologies within developing economies also relates to firms' absorptive capacity (Cohen et al. 1990) and can explain differences in knowledge spillovers and adoption behavior in firms (Fagerberg 1994). Because of institutional and resource constraints in developing economies, firms' low absorptive capacity could be critical to explaining limited technology adoption.

Informal Sector

The sizeable informal sector in emerging and developing economies could also impact the patterns of job polarization. The informal sector, which accounts for 90 percent of the economy in developing (low-income) countries and 67 percent in emerging (upper-middle and lower-middle) countries (Bonnet et al. 2019), typically lags in adopting the latest technologies (Cirera et al. 2021), is labor-intensive and has lower productivity compared to the formal sector (La Porta and Shleifer 2014), and most of its workers are engaged in low-skilled services and artisanal production (Falco et al. 2015). Therefore, the potential of technology-driven job displacement is likely less severe in countries with a proportionally large informal economy.[5] Moreover, technology adoption in the formal sector displaces workers toward the informal sector and, through this channel, may also affect wages there (Chacaltana Janampa et al. 2018). Using a general equilibrium model, Gomez (2021) finds that an increase in technology adoption in the formal sector results in a larger informal sector and lower wage inequality at the bottom of the skill distribution.

Availability of Human Capital

Human capital is an essential factor in explaining the adoption of advanced technologies within firms. For instance, using a large cross-country sample of developed and developing economies, Benhabib and Spiegel (1994) show that human capital affects the speed at which countries absorb technological developments. Comin and Hobijn (2004) examine the diffusion of more than 20 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 literature has largely stressed the lack of managerial capabilities (Bloom and Van Reenen 2010) and workers' skills in developing economies, which in turn are a critical constraint to innovation and technology adoption (Cirera and Maloney 2017). Educated managers may have a greater understanding of sophisticated technologies and be favorably disposed to adopt them. For instance, 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.

Structural Explanations: Sectors, Regions, and Demographic Change

Job polarization is a combination of within-industry and between-industry changes in employment shares, which are, in turn, affected by demographic changes and their effect on the demand for goods and services across firms, sectors and regions. In what follows, we detail how the characteristics of developing and emerging economies in terms of these different dimensions may affect their employment structure and dynamics.

Structural Change

On the one hand, as technological change replaces routine tasks, a given industry will use less routine employment even while maintaining the same output levels. On the other hand, occupations' intensity in such routine tasks differs across industries, such that sectoral employment shifts also explain aggregate occupational share changes (Goos et al. 2014). In fact, Foster-McGregor et al. (2021) suggest that the risk of automation (or routine intensity) shows only modest variation within sectors and between countries, but a considerably greater variation between industries within countries. Specifically, manufacturing sectors generally demand relatively larger shares of middle-skilled, routine occupations than agriculture and services. For example, Lee and Shin (2019) find that polarization is faster in manufacturing than in services, and Bárány and Siegel (2018) indicate that job polarization in the United States is directly linked to the decline of manufacturing employment since the early 1950–1960s. Therefore, the level of aggregate routine intensity depends on the sectoral structure of employment—for example, we may expect that the higher the share of manufacturing, the higher the routine intensity for a given country.

What do these findings imply regarding employment dynamics in developing and emerging economies? The answer lies in the countries' trajectories. Often, low-income countries have a significant share of employment in agriculture and a small percentage of workers engaged in routine tasks in the first place. As countries become more productive in agriculture and start industrializing, they also increase their share of routine occupations. As clearly stated in Das and Hilgenstock (2022, p.100), "the observed increase in the exposure of routinization in developing economies indicates that structural transformation was greater than the offsetting impact from the declining in the price of ICT capital." Industrialization thus moderates the effects of technological change on the demand for routine labor. Overall, Das and Hilgenstock (2022) show that labor markets in low- and middle-income countries are significantly less exposed to routinization (lower share of routine-intensive occupations), reflecting the larger share of agriculture in developing economies. In contrast, at more advanced stages of development, countries transition from manufacturing to services and job polarization accelerates.[6]

Heterogeneity Across Sectors and Regions

Much of the literature presented above has relied primarily on aggregate measures, and thus somewhat overlooked job polarization's regional and sectoral heterogeneities. It remains unclear if the slow pace of polarization in most developing and emerging economies is a general trend or is confined to a few sectors or regions within countries. Some related evidence can be found for developed economies. Using individual-level data from Statistics Sweden from 2002 to 2012, Henning and Eriksson (2020) find that the decline in manufacturing employment in clusters of previously manufacturing-dominated municipalities drives polarization in the country. In contrast, areas with fast-growing firms in sectors with larger shares of routine workers (extraction industries and lower manufacturing) exhibit the opposite patterns, indicating a greater tendency towards job upgrading.

Regional and sectoral differences, and more specifically, the role of extractive industries, could therefore help to explain the modest evidence of job polarization in some emerging economies.[7] The commodity boom in the early 2000s led to a significant expansion of the extractive sector in many countries, which is likely to offset the decline in middle-earning jobs across other sectors. Indeed, in many Latin American and African economies, the commodity boom experienced during the 2000s mainly favored low-skilled workers, potentially overshadowing the impacts of ICT adoption (Maloney and Molina 2019).

Demography

Finally, differences in demographic dynamics across developed and developing economies affect changes in the demand for goods and services as well as the supply of work, therefore resulting in diverging patterns of overall employment. Moreno-Galbis and Sopraseuth (2014) show that population aging in developed economies leads to a rise in the demand for personal services, causing an increase in the employment share of low-paid positions. For instance, population aging leads to a rise in the demand for jobs such as cleaners, transportation services in the health industry, and housework employees in private homes. In addition, Acemoglu and Restrepo (2021) find that population aging results in a shortage of middle-skilled workers, thus increasing the adoption of automation technologies. However, this pattern contrasts with the demography of most emerging economies. Especially in Africa, countries are experiencing significant growth in the working-age population, resulting in a less intense demand for low-paid occupations and an abundance of middle-skilled workers.

Employment Dynamics in Open Economies

Most of the literature on job polarization in developing countries has relied on isolated analysis at the country level without considering possible effects stemming from changes in global value chains. The effects of GVCs on job polarization in developing economies are not straightforward. 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 (Acemoglu and Autor 2011; Blinder and Krueger 2013; Goos et al. 2014). In turn, the inflow of routine jobs from advanced countries has likely reduced polarization forces in some host countries (Maloney and Molina 2019).

At the same time, new advancements in robotics have reduced the prices of these technologies substantially, resulting in developed economies re-shoring part of their production. The rapid spread of robots in advanced economies could thus have the opposite effect, likely reducing the share of routine workers and accelerating job polarization in developing economies. Krenz et al. (2021) develop a theoretical model to account for these interactions in which automation in advanced countries increases productivity and reduces the costs of producing in-shore. As a result, part of the production that was previously off-shored to host areas in developing regions may return, although not leading to an improvement in wages for low-skilled workers or the creation of new jobs in the receiving economies.

Below, we examine these two contrasting forces affecting job polarization in developing economies. We first highlight the initial findings pointing to the role of offshoring in mitigating job polarization in developing economies. We then point to more recent evidence about the effects of re-shoring and conclude by discussing the specific case of multinationals (MNEs).

Global Value Chains and the Routinization of Tasks

Early studies on the interactions between global value chains (GVCs) and job polarization pointed to different trajectories between developed and developing economies. For instance, Das and Hilgenstock (2022) show that participation in GVCs might have played a role in the rising number of routine jobs in developing economies, while reducing them in advanced economies. Similarly, Reijnders and de Vries (2018) explore the impacts of both technological change and offshoring on the labor market for several developed 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 decline in routine jobs for advanced economies and mitigates it for developing countries. 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 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. Finally, 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 in developing economies.

New Trends: Reshoring, Robot Adoption, and Job Polarization

Recent findings show that automation may be linked to reshoring or decreased offshoring, implying decreasing employment in developing economies.[8] 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.

Without focusing on offshoring per se, a recent strand of the literature also 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 of robot adoption 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 United States lowers growth in exports per worker from Mexico to the United States by 6.7 percent. However, the authors did not find evidence of an impact on wage employment or manufacturing wage employment. Kugler et al. (2020) use data from the International Federation of Robotics (IFR) to measure automation in the United States and microdata from the Colombian Social Security records to examine the effects of robot adoption in the United States on 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]

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 Tag (2017) examine the impacts of private equity acquisition on the employment composition of recently acquired firms in Sweden and find that workers in less productive firms in routine-intensive occupations are twice as likely to be displaced after buyouts. In the specific case of FDI, Hakkala et al. (2014) rely on Swedish data 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-Paterno-Castello (2018) use data on greenfield FDI for several European economies to examine the extent to which different types of FDI are related to job polarization. They find that low-skill FDI investments are associated with skill down-grading, while 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 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.

Tacking Stock

Our literature review indicated a significant decline in routine intensity in many developing economies, although with little evidence of job polarization. In addition, section 3 has explored the reasons for such a lack of polarization in (most) emerging and developing economies and has highlighted some of the main gaps in the literature. We have stressed the need to empirically examine the main drivers of the slow pace of polarization, including countries' participation in GVCs.

A critical argument in our discussion is that structural change and GVC participation can counterbalance the effects of technology adoption on labor demand for routine tasks in emerging and developing countries. Yet, we do not have empirical evidence on this particular process. Also, the observed differences across countries, also at a similar level of income or technological knowledge, raise many questions and suggest that further evidence should explore more disaggregated information. For instance, is there within-sector polarization in low- and middle-income countries? Has the process of industrialization curbed the aggregate routine intensity among those economies? Did occupations become less intense in routine tasks over time? Lastly, has the falling demand for routine tasks negatively impacted workers?

Answering these questions (and many others) can significantly impact the development of better-adapted technological, educational, and labor market policies. The following section discusses the opportunities and challenges associated with technology policies in developing and emerging economies and the implications in terms of employment patterns and policies.

The Need for More Studies Based on Microdata to Guide Policymaking

As mentioned by Case and Deaton (2020, p.261), "[G]lobalization and automation are ultimately beneficial, but they create disruption, especially in the short run, and many less skilled workers lose out." This conflicting impact of technology poses additional challenges to policy-makers, 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 workers with low job mobility, especially more disadvantaged groups. For instance, Lewandowski et al. (2017) study the intergenerational disparities in the de-routinization of jobs in 12 European countries and find a significant relationship between age groups and shifts in task composition. The decreasing demand for routine occupations also challenges existing education and training systems to respond to changing skill demands, especially given the fact that low-educated workers are commonly more affected by the routinization process (Martins-Neto et al. 2022). 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 United Kingdom).

Ultimately, designing better-fitted policies for skill development, such as programs up-scaling digital skills, vocational training, and better-adapted social protection systems, requires detailed microeconomic studies. Researchers 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 in different institutional contexts. This calls for more systematic and frequent micro-level data collection in developing economies to better understand the task content of occupations specific to each country as well as constraints and patterns of technology adoption at the firm level.

The remainder of this section presents the main shortcomings that limit a more detailed overview of the effects of technology adoption in low- and middle-income countries. First, we discuss the available measures of technology adoption (section 4.1) and tasks (section 4.2) and highlight the need for longitudinal and micro-level data. Following this discussion, we point out some of the main gaps in the (empirical) literature, focusing on those that could vastly improve our understanding and facilitate the development of appropriate public policies (section 4.3).

Measuring Firm-level Technology Adoption

Emerging and developing economies lack information on technology adoption at disaggregated levels. Efforts to expand our knowledge in this direction would facilitate a finer understanding of the composition effects of technology adoption and expand our knowledge of the main barriers preventing the adoption of more advanced technologies among those economies. Some recent efforts have provided new evidence and data in this direction. For instance, a new survey by the World Bank offers granular information on the adoption (*extensive margin*) and use (*intensive margin*) of technologies for both general business functions and sector-specific business functions for several emerging and developing economies. Even though there is significant heterogeneity across firms, the results indicate that, on average, firms are adopting manual, pre-digital technologies (Cirera et al. 2021b). In addition, a novel database from UNIDO offers detailed information on the adoption of production technology in developing economies (see, for instance, Delera et al. 2022). The results also point to few firms adopting very advanced technologies and large heterogeneity among firms.

However, the continuous evolution of technologies (Dosi 1982) makes it challenging to measure their adoption. Indeed, firms may need to maintain, upgrade or adapt the technologies embedded in their production processes over time—then, which of these decisions should be considered as technology adoption *per se*? The study of such dynamic systems, i.e., how technologies and their adoption evolve and how firms, workers and their skills co-evolve, requires longitudinal data that tracks firms over time. Further data and research on this would improve our understanding of the relation between firm characteristics, local availability of skills, and technological paradigms in emerging and developing economies.

Measuring the Task Content of Jobs Across Countries

Data collection and integration at a decentralized level with a detailed skill mapping system will help local economies to shape policies to foster skill upgrading and place themselves in a better position to respond to the threats and opportunities brought by technological change.

*Measuring Tasks with the O*NET Database*

The literature on RBTC explicitly explores differences in task composition across occupations to study the labor market consequences of technological development. Within this approach, two main methods have been developed, as also illustrated in column 4 of table A1: 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 also table A1 for a general comparison of these measures). 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. Specifically, authors have used the Dictionary of Occupational Titles (DOT) survey and its updated version, the O*NET. 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.[10] 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.[11]

This measure has also been adopted in the case of studies on developing countries, under the assumption that the task content across occupations is similar across countries.[12] 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 United States and those performed by a machine operator in a low-income country.

Measuring Tasks 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 Skills Toward Employment and Productivity (STEP) by the World Bank. Both surveys attempt to measure tasks and skills across the developing world.[13]

Dicarlo et al. (2016) construct a measure of the skill content of occupations for 10 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: (a) first, along the skill dimension, occupations are ranked similarly across countries; (b) second, workers in higher-income countries use analytical and interpersonal skills more frequently; (c) lastly, there are significant differences in the skill content across countries, so that assuming that the US skill content is a good proxy for developing countries is wrong and likely to impact the estimates. Messina et al. (2016) also employ 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 US data do not provide a fair approximation of routine cognitive and non-routine manual skill content of jobs in developing countries. Lo Bello et al. (2019) also point out two caveats in using the STEP Surveys. First, as estimates are based on workers' responses, it is assumed that workers do not differ in their view of tasks performed at work. However, this assumption may not hold as most questions are subjective. 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).[14] 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. Moreover, Lewandowski et al. (2020) explore the PIAAC survey for several countries and develop a regression-based methodology to predict the country-specific routine task intensity of occupations, thus overcoming the lack of survey data for several large developing economies, such as Brazil and India. Besides corroborating 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). 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 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.

Within-occupations Variance

Another important aspect besides differences in task intensity across occupations is the extent of within-occupations variance in tasks. 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-occupation differences. For example, Autor and Handel (2013) explore data from the Princeton Data Improvement Initiative (PDII) survey (formerly STAMP) and document that tasks vary substantially within occupations in the United States. 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's (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 developments 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 United States. 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 recent decades and that a significant share of changes in wages 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).

As for developing economies, it remains unclear whether (and to what extent) changes in tasks within occupations are similar to what we observe in advanced economies. Most analyses still rely on occupational and sector composition information to determine the extent of polarization without a clear understanding of changes in task requirements over time. An obvious reason for this gap is the 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 emerging economies, it is also critical 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 of tasks demanded in some emerging economies. Yet, researchers should also be aware of some issues in using job ads data, particularly that they under-represent certain sectors and occupations, for instance, the construction sector and occupations related to the production and transportation of goods. In addition, these job ads might not capture jobs from the informal sector, which represents a significant share of the workforce in developing and emerging economies.

Future Research Directions

As discussed in section 3, there is little evidence of the underlying mechanisms explaining the slow polarization pace in low- and middle-income countries. Geographical, sectoral, and firm heterogeneities have largely been overlooked, as most studies have focused on aggregate measures. In many cases, the lack of research stems from inappropriate information. In this context, firm-level details on the adoption of more advanced technologies and longitudinal measures of tasks as described above will enable a significant leap in the literature.

In addition, tracking workers' transitions across occupations and in and out of unemployment could improve public policies and help design or improve a safety net minimizing the harms of technological change. 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, technological unemployment becomes less of an issue. 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 United States is linked to the inflow rates to routine employment (from unemployment and non-participation, i.e., less workers starting a routine job) rather than the outflow rates (more routine workers losing their job). Moreover, Maczulskij (2019) explores Finnish data and shows 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.

Additionally, 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 concerns which types of workers have 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 developing 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.

In the context of advanced economies, a number of studies show that automation increases the probability of incumbent workers separating from their employers (Bessen et al. 2019), and that displaced workers in routine-intensive occupations are more likely to face long-term unemployment and a decrease in wages and number of days worked (Bessen et al. 2019; Blien et al. 2021; Goos et al. 2021). However, the literature on developing economies is much thinner. Except for Martins-Neto et al. (2022), who find that displaced individuals in routine-intensive occupations face longer unemployment rates in Brazil, no other study has sought to investigate the implications of routinization at the individual level in the context of developing countries. A detailed account of the effects of displacement on different kinds of workers could help in assessing the differential impacts on employment and income distribution. This in turn will help to categorize more disadvantaged workers, thereby formulating specific policies for various 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 worker 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.[15]

Two other dimensions that require further research are the roles of the type of technology and the way technology adoption affects firms' internal organization. First, employment dynamics depend on the nature of technologies, i.e., which skills they complement or substitute. This has been the focus of several recent works highlighting the new patterns linking digital technologies and demand for skills in advanced economies (Frey and Osborne 2017; Acemoglu and Restrepo 2020). However, such a relationship is also mediated by firms' own organizational routines and adaptations, which affect how technologies remodel production and workers' tasks within firms (Dosi and Nelson 2010; Dosi and Virgillito 2019; Ciarli et al. 2021). Firms intentionally invest in organizational arrangements, practices, and routines to create new business models in response to the changing and increasingly complex technological landscape (Colfer and Baldwin 2016). The employment effects of technology in developing and emerging economies could therefore be significantly related to the complex interplay between technologies, innovation, and skills driven by organizational restructuring, highlighting the need for urgent attention and more research in this area.

Conclusions

While studying the impact of technological change on jobs and how it affects economies and societies, one must recognize the existing differences among countries that emerge from different socioeconomic systems, levels and distributions of income, institutional contexts, and industrial structures. The nature and long-term impact of technologies created and adopted in different economies very much relate to existing institutional and political contexts.

In this review, we have 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 (Spitz-Oener 2006; Acemoglu and Autor 2011). 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; Firpo et al. 2021; Gasparini et al. 2021).

In section 3, 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 accelerating job polarization.

Finally, in section 4, we have stressed the need for micro-level studies and 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.

Appendix A

Table A1. 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), 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 * Does not cover large developing economies, including, for instance, Argentina, Brazil, Bangladesh, India, Nigeria, and South Africa *The mapping between tasks and skills is not trivial *Subject bias in workers' response, especially given that most questions are subjective *Sample size is not large enough to develop disaggregated classifications at the country level	*Does not cover large developing economies, including, for instance, Argentina, Brazil, Bangladesh, India, Nigeria, and South Africa *The mapping between tasks and skills is not trivial * Subject bias in workers' response, especially given that most questions are subjective * Sample size is not large enough to develop disaggregated classifications at the country level
Advantages	* Offers task content of occupations at disaggregated levels and with easily-available crosswalks to most classifications	* Variation in the task scores within occupations * Estimation for a number of developing countries, including low-income economies	* Variation in the task scores within occupations * Estimation for a number of developing countries

Source: Authors' elaboration.

Note: 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).

Notes

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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.

2. Job polarization and the decline in the middle-class could also have important political implications. For instance, Birdsall (2010) suggests that the middle class is an "indispensable" force to achieve more sensible economic policy, robust and responsive political institutions, and thus more sustained growth.

3. 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 subset 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).

4. Despite the growing discussion around job polarization in developing economies, one of our research's main challenges was the initial search for articles on the topic. When searching on the Web of Science and on Scopus using different keywords related to job polarization and developing economies, we identified only a few articles, among which only some were actually about developing and emerging economies. To overcome this challenge, we have extensively relied on citations and Google Scholar to find additional working papers, articles, and reports, which has resulted in the identification of about 20 articles focusing on job polarization in developing and emerging economies.

5. The considerable presence of informal firms in low-income countries relates to countries' capabilities and is due to inadequate access to education but also corruption, regulation, and the lack of proactive policies to embrace the informal economy (Etim and Daramola 2020).

6. 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 sizeable informal sector and wage-setting institutions. For example, 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. In other words, given that in many developing countries, the number of workers engaged in codified tasks is small and, in some cases, concentrated in low-wage occupations, routinization could lead to occupational upgrading.

7. Besides differences across sectors, firms of the same industry also present considerable heterogeneity in their employment and wage structures (see Helpman et al. 2017 for Brazil and Harrigan et al. 2021; Domini et al. 2022 in the case of France). 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 large and growing firms are more intensive in middle-earning occupations. Therefore, reallocation dynamics (i.e., changes in the market shares of firms within sectors) among firms with different occupational structures may explain why occupational shares at the aggregate level do not change.

8. Although some evidence suggests that automation in advanced economies is yet to impact FDI flows (Hallward-Driemeier and Nayyar 2019).

9. In addition to changes in world trade, the COVID-19 pandemic may also have had an impact on the pace of digital adoption in developing economies. While initial evidence suggests that the pandemic has accelerated the digital transformation of businesses, it also indicates widening the digital divide (Avalos Almanza et al. 2023).

10. 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. 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.

11. 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 in section 2, authors have opted for using the O*NET database when studying job polarization in developing economies.

12. For example, World Bank (2016) and Maloney and Molina (2019) follow Autor and Dorn's (2013) classification and define nine 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).

13. 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.

14. Lewandowski et al. (2020) also present different task measures based on STEP and PIAAC data from other authors.

15. Such data is available in several developing economies, including Brazil, Mexico, South Africa, Morocco, and Tunisia.

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