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The Impact of Technology on Migration to the United States from Central America and the Dominican Republic

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Abstract

Labor markets in Central America and the Dominican Republic face limited direct impacts from technological advancements compared to developed countries. However, substantial migration flows to high-income countries, particularly the United States, mean that the impacts of technological change do not stop at country borders. During the past 50 years, recent migrants from both Central America and the Dominican Republic and other countries, like US nonmigrant workers, have shifted out of production jobs requiring (automatable) routine manual and cognitive skills. Although recent non–Central America and the Dominican Republic migrants and US nonmigrants transitioned to higher-skilled work intensive in nonroutine cognitive and interpersonal tasks (for example, management), recent migrants from Central America and the Dominican Republic shifted toward jobs intensive in nonroutine manual tasks (for example, construction) and, to a lesser extent, in nonroutine interpersonal tasks (for example, serving). In essence, migrants from other middle- and high-income countries have benefited from the same technology-skill complementarity as nonmigrant US workers, whereas migrants from Central America and the Dominican Republic seem to have filled the lower-skilled jobs created alongside technological advancement. The low-skill bias of migrants from Central America and the Dominican Republic suggests greater vulnerability to disruption from artificial intelligence and mobile robotics, but less from language models like ChatGPT. Closer analysis of US robot adoption between 2000 and 2019 shows no effect on total migration flows from Central America and the Dominican Republic but impacts on high-skilled flows between 2010 and 2019. US robot adoption in the early 2000s improved labor market outcomes for high-skilled migrants from Central America and the Dominican Republic but in low-skilled, nonroutine occupations. Between 2010 and 2019, the demand expansion effect that seems to explain this improvement weakened. Robot adoption led to less demand for high-educated migrants from Central America and the Dominican Republic during this latter decade.

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The Impact of Technology on Migration to the United States from Central America and the Dominican Republic[1]

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1. Introduction

Labor markets in Central America[2] and the Dominican Republic (CADR) are experiencing muted impacts from the technological advancements that are causing profound shifts in developed countries. Technological advancements are shifting work away from routine tasks and toward jobs requiring sophisticated technical and socioemotional skills in developed countries (Acemoglu and Autor 2011; World Bank 2019). They are also causing a reorganization of working arrangements that incorporate remote work and outsourcing of individual tasks to platform or gig workers (Datta and Chen 2023). CADR countries, which are all middle-income with the exception of high-income Panama, have begun to experience some of these changes recently, but at a much slower pace: jobs involving nonroutine knowledge and people-oriented work are much less common in CADR countries than in the United States (Moroz and Viollaz 2024). Alternative working arrangements like work-from-home face significant challenges in the region, including a large share of employment in occupations that cannot be done from home and lack of access to information and communications technologies.

However, the substantial flow of migrant workers from CADR countries to high-income countries means that the impacts of technological change do not stop at country borders. Migration flows from CADR countries are substantial. In a region of about 60 million people, 6.6 million people are migrants. All countries in the region except for Costa Rica and Panama are net senders of migrants. The United States is the most common destination for all CADR migrants except for those from Nicaragua. Other common destinations for CADR migrants are high-income Canada and Spain.

Technological advances in developed countries could reduce the demand for migrant workers from CADR countries. Migrant workers might experience a decline in demand if they are employed in industries where automation is occurring, which may lead to a smaller inflow of migrants. For instance, the end of the *bracero* agreements that had allowed agricultural workers from Mexico to work in the United States did not increase domestic employment or wages in part because employers changed production technology or production levels (Clemens, Lewis, and Postel 2018; Lewis 2011). Other instances of increased immigration enforcement that have reduced the supply of migrant workers have also been shown to lead to shifts to automation (Ifft and Jodlowski 2022; Kostandini, Mykerezi, and Escalante 2014; Charlton 2023).

On the other hand, technological advances may alter the type of migrants demanded without reducing the level of migrant flows or perhaps even increasing them. Far from being a purely destructive force, technological progress and automation can also be job-creating. Where markets are competitive, automation can create jobs as price declines linked to productivity improvements generate higher demand. New technologies can also generate entirely new tasks, new types of jobs, and even new industries. Migrants may be beneficiaries of this increased employment if it is concentrated in sectors demanding the skills in which migrants tend to specialize. For instance, migrants in the United States tend to specialize in manual-intensive jobs that are in relatively higher demand as routine tasks are automated. Evidence from the United States and Germany shows that the spread of PCs, robots, and artificial intelligence either do not decrease immigration inflows or lead to more immigration, in part as a result of migrants specializing in certain (manual-intensive) tasks (Basso, Peri, and Rahman 2020; Giesing and Rude 2022; Mandelman and Zlate 2022).

Understanding how technological progress affects migration is critical for policy makers in both countries of origin and countries of destination. Building on this literature, we investigate how technological advancements are affecting employment prospects in an important migration corridor.

[2] Central America includes Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, and Panama.

We study how advances in the United States first in computers and then in artificial intelligence have altered the employment of migrants from Central America and the Dominican Republic. This is an important setting to study given the large migration flows, the skew of these flows toward lower skill levels, the proximity of the countries of origin to the country of destination, which lowers migration costs, and the high level of technological advancement of the country of destination. Our findings have important implications for understanding how technologies that are often thought of as labor-saving affect both the level and the type of demand for migrant workers.

The paper shows that technological developments in the United States have altered the labor market experience of migrants from CADR countries in distinct ways from other migrants and US nonmigrant workers. The paper draws on data from the American Community Survey, the United States Census, and labor force surveys to examine the employment, wages, unemployment, and labor force participation of migrants in the United States in during the last 50 years. Migrants from CADR and non-CADR countries, like US nonmigrant workers, all shifted out of production jobs that require the use of (automatable) routine manual and cognitive skills during the last 50 years. Non-CADR migrants and US nonmigrants shifted strongly into higher-skilled work intensive in nonroutine cognitive and nonroutine interpersonal tasks like management. CADR migrants, in contrast, shifted into work intensive in nonroutine manual tasks like construction and, more subtly, nonroutine interpersonal tasks like serving. In essence, migrants from other middle- and high-income countries have benefited from the same complementarity between technology and skills that nonmigrant US workers have enjoyed while CADR migrants seem to have benefited from the (lower-skilled) jobs created alongside technological progress. We also study the impact of robot adoption in the United States more closely. We show that robot adoption did not affect the total flow of CADR migrants during two ten-year periods between 2000 and 2019 but did impact the flow of high-skilled migrants between 2010 and 2019. Adoption had different positive impacts on labor market outcomes in the early 2000s, but negative ones between 2010 and 2019. The analysis focuses on recent migrants who have come to the US in the last 3 or 10 years, and so our findings relate more to recent flows than to changes in the stock of existing migrants.

The paper begins with a brief overview of migration from CADR countries before reviewing the literature on how technological progress affects labor markets. The paper then provides descriptive analysis of how first computers and then artificial intelligence and robots have affected CADR migrants in the United States. The paper concludes with a more rigorous evaluation of the impact of robot adoption in the United States on CADR migrants.

2. Migration from CADR Countries

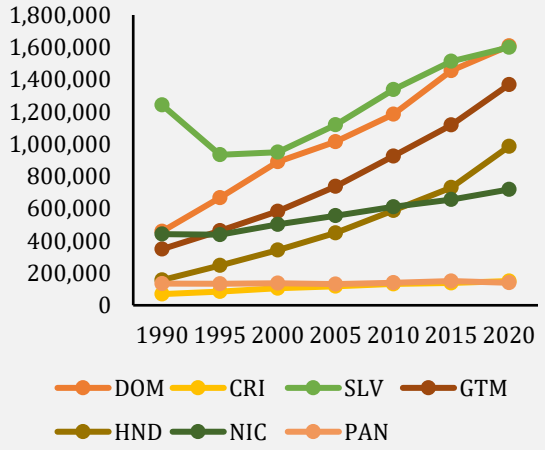
Migration abroad is a key aspect of labor markets in most CADR countries. This paper focuses on migration from CADR countries to countries outside the region.[3] The number of migrants abroad has increased since 1990 in all CADR countries except Panama (**Figure 1**). Four CADR countries – the Dominican Republic, El Salvador, Guatemala, and Honduras – have 1 million or more migrants abroad. The Dominican Republic, El Salvador, Guatemala, Honduras, and Nicaragua are all net senders of migrants (**Figure 2**). Only Panama and Costa Rica – the two highest-income countries in the region – are net receivers. On net, El Salvador sends the most people abroad as a share of its

[3] For discussions of CADR countries as destinations for migrants, see Voorend, Alvarado, and Oviedo (2021) and Blyde (2020) for Costa Rica; OECD (2018) and Hiller and Chatruc (2020) for the Dominican Republic; and OECD (2017) and Hausmann, Espinoza, and Santos (2017) for Panama.

population: 40 of every 10,000 people from El Salvador are migrants. This is more than twice as many as Guatemala, which sends 13 per 10,000 people.

Figure 1: Global Migrant Stock from CADR Countries, 1990–2020

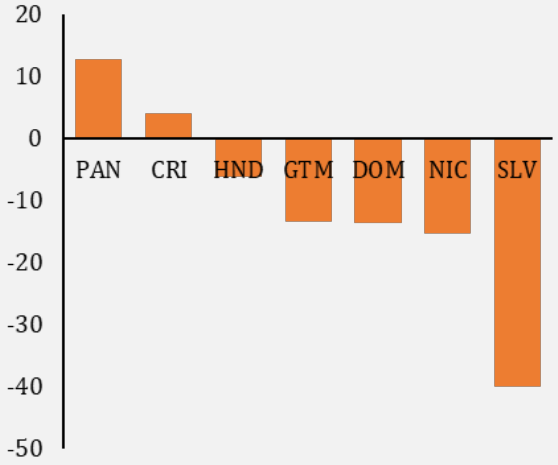
Number



Source: United Nations.
Note: CRI=Costa Rica; DOM=Dominican Republic; GTM=Guatemala; HND=Honduras; NIC=Nicaragua; PAN=Panama; SLV=El Salvador.

Figure 2: Net Migration Rate of CADR Countries, 2020

Number of migrants per 10,000 people

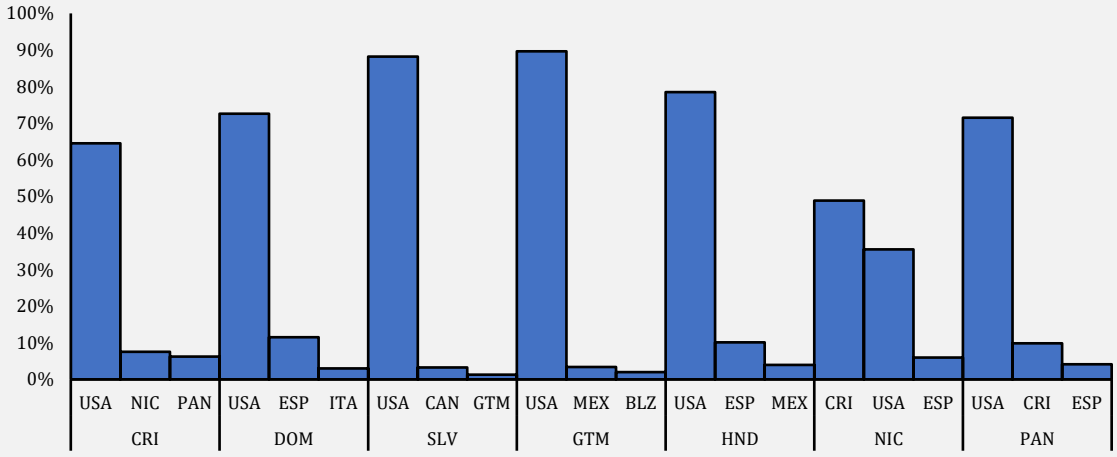


Source: United Nations.
Note: CRI=Costa Rica; DOM=Dominican Republic; GTM=Guatemala; HND=Honduras; NIC=Nicaragua; PAN=Panama; SLV=El Salvador.

The United States is the most common destination for all CADR migrants except for those from Nicaragua. The shares of total migrants going to the United States are very high and range from 49 percent in Nicaragua to 90 percent in Guatemala (**Figure 3**). Nicaragua sends about half of its migrants to neighboring Costa Rica. Other common destinations for CADR migrants are Canada and Spain.

Figure 3: Share of Out-migrants from CADR Countries, 2020

Percentage of migrants by country of destination



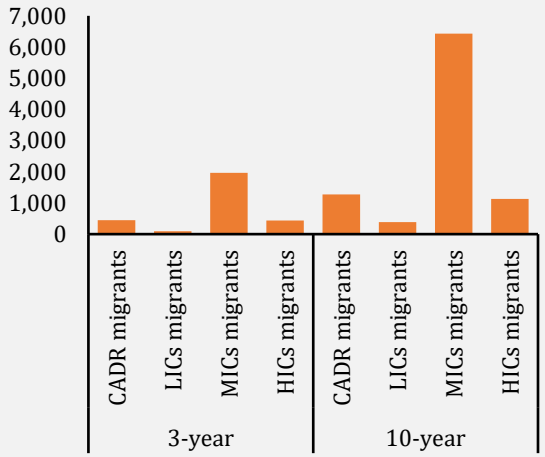
Source: United Nations.
Note: BLZ=Belize; CAN=Canada; CRI=Costa Rica; DOM=Dominican Republic; ESP=Spain; GTM=Guatemala; HND=Honduras; ITA=Italy; MEX=Mexico; NIC=Nicaragua; PAN=Panama; SLV=El Salvador; USA=United States of America.

Migration from CADR to the United States is a longstanding phenomenon. Military dictatorships, civil wars and economic instability led people from CADR to move north in the 1980s and 1990s in large numbers. Migration to the United States had occurred for generations, dating back to at least the 1800s, but the scale changed dramatically in this period. Much migration has been and continues to be without documentation.

Migrants from CADR countries make up about 15 percent of all recent migrants to the United States.[4] In 2021, there were nearly 450,000 migrants from CADR countries in the United States who had arrived in the last 3 years and around 1.3 million who had arrived in the last decade (**Figure 4**). CADR migrants make up about 0.2 percent of the working age population in the United States versus 0.04 percent for migrants from low-income countries, 0.9 percent for migrants from middle-income countries, and 0.2 percent for migrants from high-income countries (**Figure 5**).

Figure 4: Migrant Stock in the United States, 2021

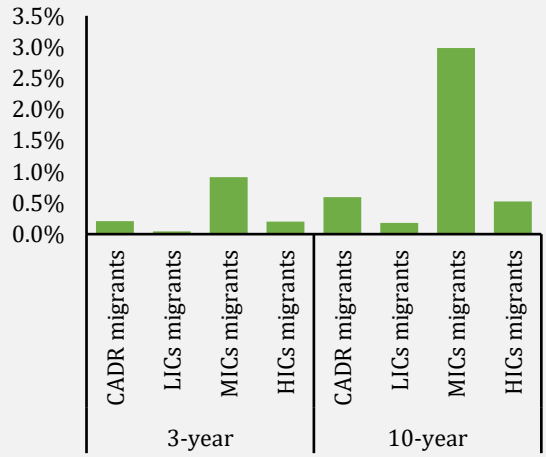
1,000s of migrants



Source: ACS 2021.
Note: CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

Figure 5: Migrant Stock in the United States as a Share of the Working Age Population, 2021

Percentage of working age population



Source: ACS 2021.
Note: CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

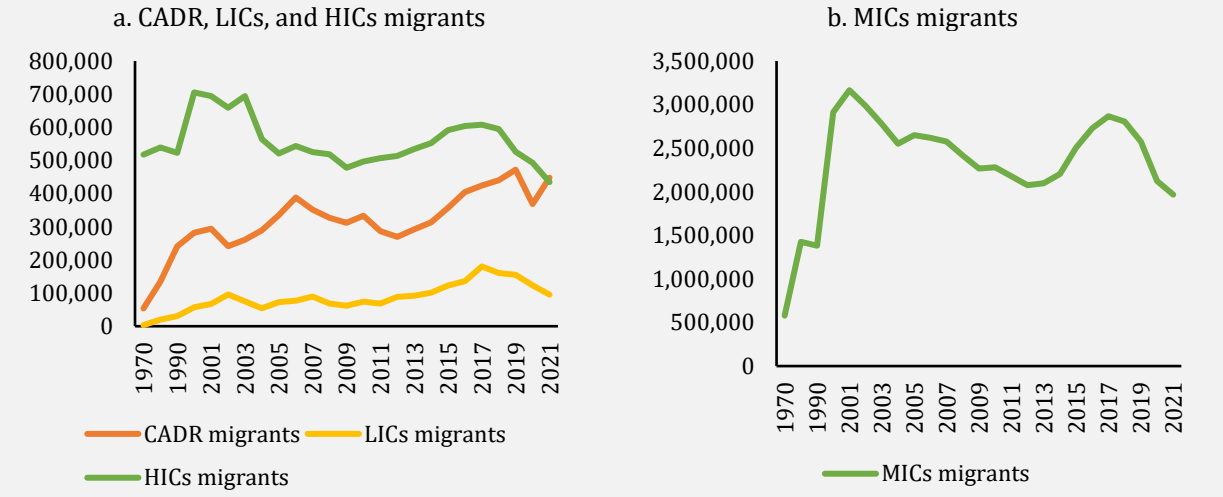
Migration to the United States from CADR countries has risen over time, including a steady increase since the early 2010s that contrasts with declines for other global regions. Between 1970 and 2000 there was a sharp increase in 3-year migrants to the United States from all countries including CADR countries (**Figure 6**). This trend was less pronounced for high-income countries, which experienced little growth or decline until the 1990s when migration from these countries increased. Since the 2000s, migration from low-income countries generally increased until 2017 after which migration declined, while migration from middle- and high-income countries declined during most of this period. Migration from CADR countries, which are all either middle- or upper-income, did not follow

[4] Data on CADR migrants in the United States is taken from the American Community Survey 1-year estimates for 2000 to 2021, from the United States Census 1 percent sample for 1970, and from the United States Census 5 percent sample for 1980 and 1990. The three-year cohort migrants are foreign-born individuals who moved to the United States in the three years prior to the survey. Due to data limitations, for 1970 and 1980 this group includes foreign-born individuals who moved to the United States five years prior to the survey. The ten-year cohort migrants are foreign-born individuals who moved to the United States in the ten years prior to the survey.

this pattern. Migration increased sharply throughout the entire 2010s and, except for a drop in 2020 during the COVID-19 pandemic, did not experience a decline after 2017 as occurred in every other country group. Migration of 10-year migrants follows the same general patterns, though changes over time are less pronounced (**Figure 7**). One notable difference between 3- and 10-year migrants from CADR countries is that the 10-year migrant share remained fairly steady during the early 2010s reflecting the decline in 3-year migrants during the 2000s.

Figure 6: 3-year Migrants in the United States, 1970–2021

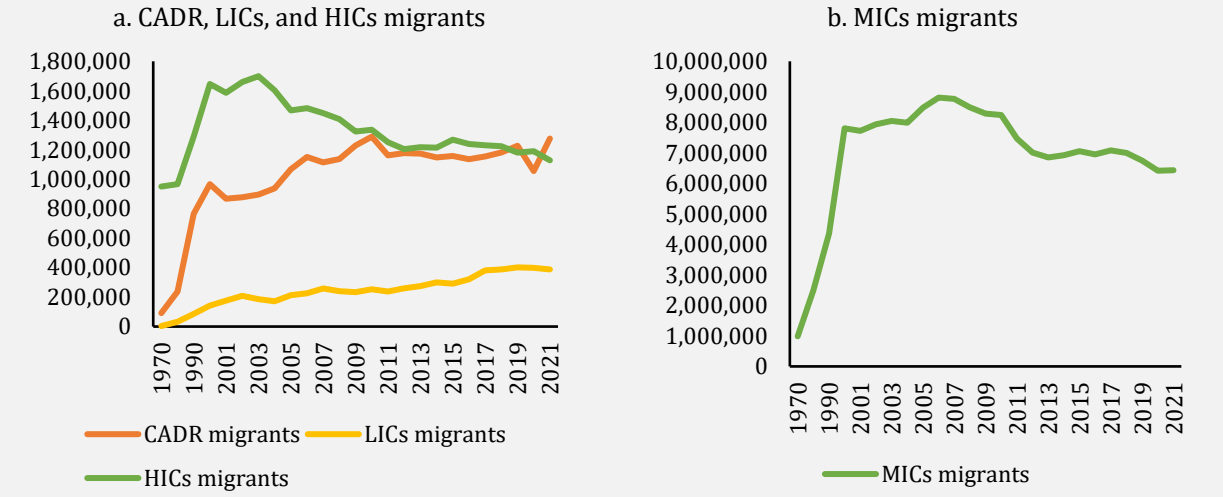
Number of migrants



Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

Figure 7: 10-year Migrants in the United States, 1970–2021

Number of migrants



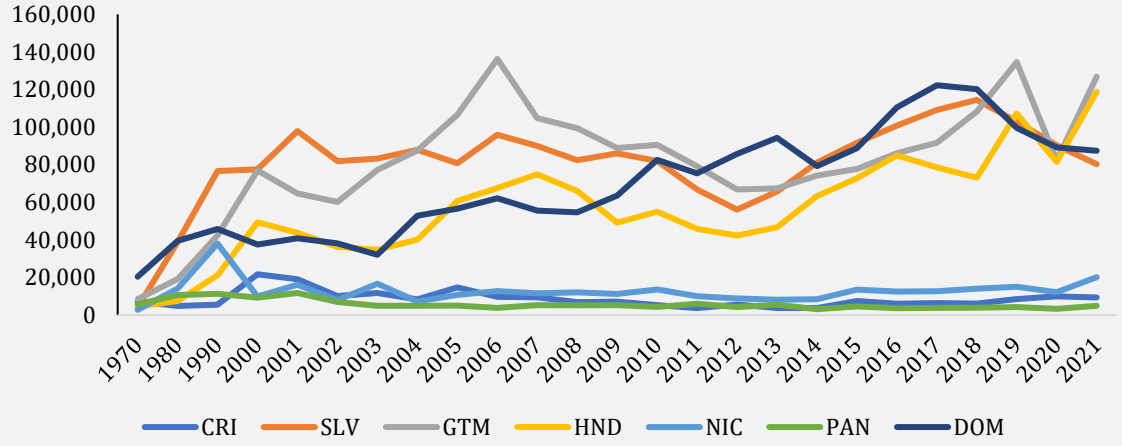
Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

El Salvador, Guatemala, Honduras, and the Dominican Republic are the main senders of migrants to the United States among CADR countries. These four countries have been responsible for more than 90 percent of the migrants from CADR countries since the early 2000s. During this period, migration

from all four countries generally increased particularly for 3-year migrants and with more stability for 10-year migrants (**Figure 8** and **Figure 9**). During the 1970s and 1980s, the Dominican Republic sent the most migrants followed by El Salvador in the 1990s and early 2000s, Guatemala in the late 2000s, and an unstable pattern in the 2010s. The predominance of El Salvador is notable given that its population is a third of the size of Guatemala's and half of the size of the Dominican Republic's.

Figure 8: 3-year CADR Migrants in the United States, 1970–2021

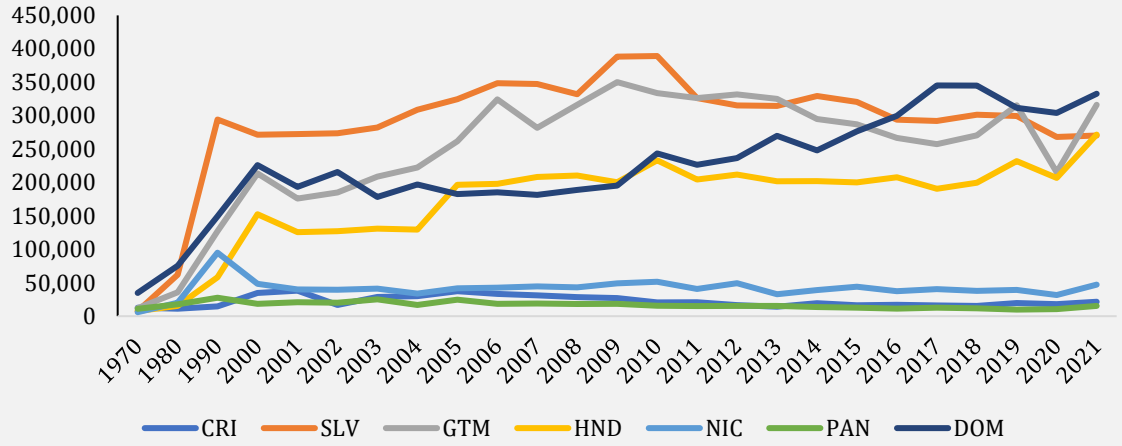
Number



Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: CRI=Costa Rica; DOM=Dominican Republic; GTM=Guatemala; HND=Honduras; NIC=Nicaragua; PAN=Panama; SLV=El Salvador.

Figure 9: 10-year CADR Migrants in the United States, 1970–2021

Number



Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: CRI=Costa Rica; DOM=Dominican Republic; GTM=Guatemala; HND=Honduras; NIC=Nicaragua; PAN=Panama; SLV=El Salvador.

CADR migrants are different in age, location in the United States, and, particularly, educational attainment from other country income groups, including those from other middle-income countries. Migrants from all other countries are better educated than CADR migrants. Their education levels have also improved in the last thirty years. This descriptive statistic is key to understanding how CADR migrants, versus migrants from other countries, have responded to changes in technology in the United States. CADR migrants are also younger and more concentrated in the southern part of the

United States. Unless otherwise noted, the remainder of the paper refers to 3-year migrants as trends are very similar between 3- and 10-year migrants.

- *Gender*. Women make up about half of all migrants from CADR and non-CADR countries (**Figure 10**). The female share exhibits a U-shaped pattern since 1970 for CADR migrants with the share declining from a high of 60 percent in 1970 to a low of 39 percent in 2000 before increasing to 47 percent in 2021. Migrants from lower-income countries and middle-income countries exhibit a similar pattern, while the female share of migrants from high-income countries shows a decline since 1970 with a slight recovery in 2010.

- *Age*. The average age of migrants from CADR countries is 30 years old, an increase of around two years since 2000 (**Figure 11**). This makes CADR migrants younger than those from other countries who have an average age in the mid-30s. Migrants from high-income countries, in particular, have become older with the average age increasing four years to 34 between 2000 and 2021.

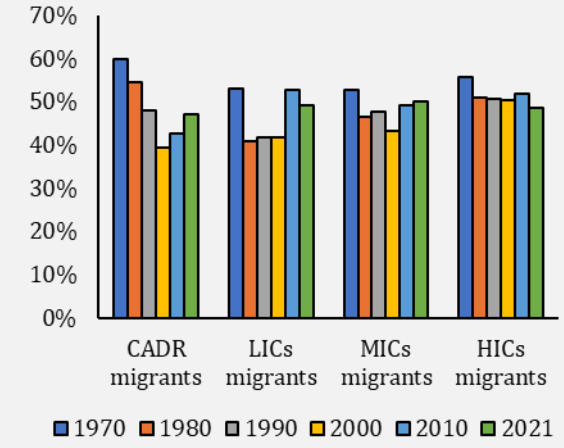
- *Geography*. Half of recent CADR migrants are in the southern part of the United States, which is the region closest to CADR countries (**Appendix Figure 1**). This concentration is unique: migrants from all other country income groups are more evenly distributed across the United States. The concentration has grown stronger in the last decade.

- *Educational attainment*. Most migrants from CADR countries have less than secondary education (**Figure 12**). This pattern has been fairly stable over time, though the share of migrants with at least secondary education has increased slightly. In contrast, the skill level of migrants from other countries has increased significantly over time and about half now have complete tertiary education.[5]

[5] There are some differences in the changes in education levels of CADR migrants when looking at individual countries. Costa Rica experienced an important increase in the share of migrants with tertiary education accompanied with a decrease in the share with secondary education. The Dominican Republic and El Salvador also exhibited improvements in migrants' level of education, primarily at the secondary level, with a reduction in the share with primary education. The remaining countries showed more modest shifts in the educational composition of their migrant workers (Figure **2** in Appendix 1).

Figure 10: Share of 3-year Female Migrants in the United States, 1970–2021

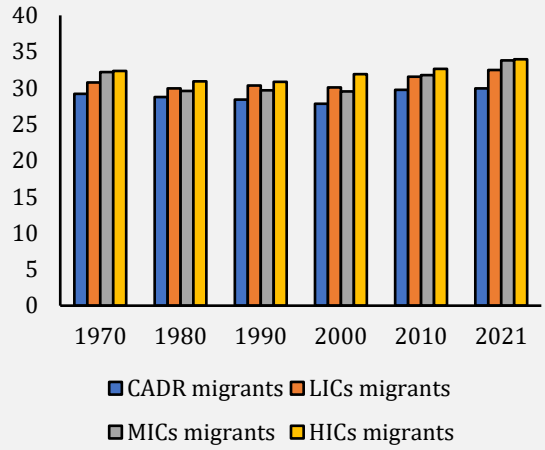
Percentage of migrant stock



Source: ACS 2000, 2010, 2021; US Census 1970, 1980, 1990.
Note: CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

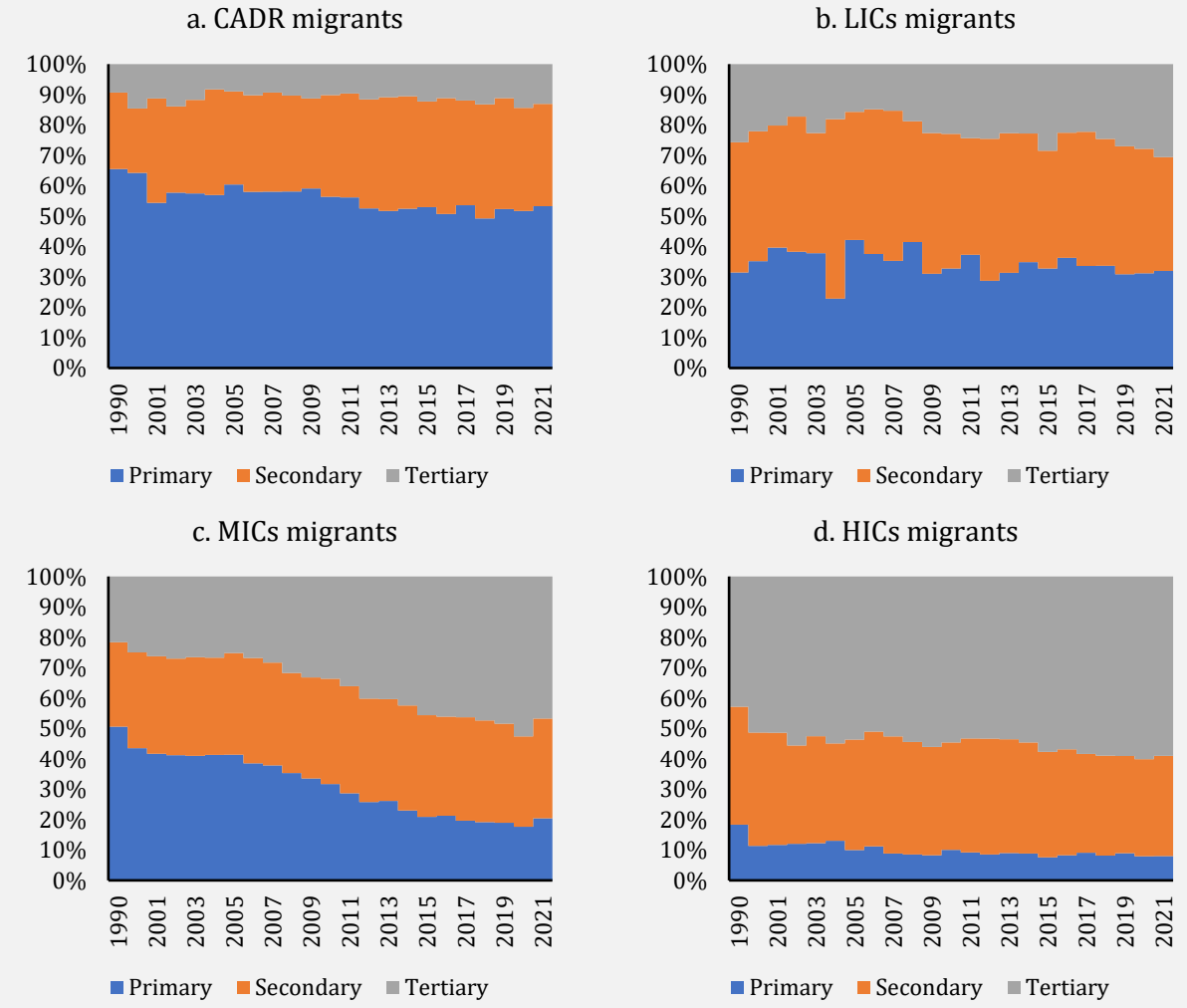
Figure 11: Average Age of 3-year Migrants in the United States, 1970–2021

Years of age



Source: ACS 2000, 2010, 2021; US Census 1970, 1980, 1990.
Note: The population considered is between the ages of 16 and 64. CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

Figure 12: Educational Level of 3-year Migrants in the United States, 1990–2021
Percentage of migrant stock



Source: ACS 2000-2021; US Census 1990.
Note: Primary is incomplete secondary education and less. Secondary is complete secondary and incomplete tertiary. Tertiary is complete tertiary. Data on tertiary education is not available for 1970 and 1980. CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

3. Literature review

In a first stage of digitally enabled automation, computers facilitated the automation of routine tasks. Certain types of tasks—routine ones—are more susceptible to automation by computers (Acemoglu and Autor 2011; Autor, Levy, and Murnane 2003). These routine tasks might be either cognitive (that is, involving thinking or analysis) or manual (that is, involving physical labor) but are suitable for automation because they "follow explicit programmed rules" and "can be exhaustively specified with programmed instructions and performed by machines." Routine manual tasks can be thought of as repetitive hands-on work like packaging and assembly that requires recurring actions in circumstances that do not change much. Routine cognitive tasks consist of administrative work like data entry that do not involve much problem solving or critical thinking. Nonroutine tasks, in contrast, "cannot at present be described in terms of a set of programmable rules" and so are less susceptible to automation (Autor, Levy, and Murnane 2003). Again, these could be higher-skilled cognitive or lower-skilled manual tasks. Nonroutine manual tasks involve flexible hands-on work like

groundskeeping and maintenance that requires physical labor in varying settings. Nonroutine cognitive tasks may be either analytical, involving knowledge work like strategic planning or risk assessment, or interpersonal, involving people-oriented work like client relations or counseling. This model of routine-biased technological change predicts that as the costs of computing decline, repetitive hands-on and administrative jobs—that is, jobs that involve lots of routine manual and routine cognitive tasks—will decline as well.[6]

A second stage of digitally enabled automation raises concerns about displacement of the nonroutine tasks once thought safe from automation. This second stage, driven by AI and mobile robotics,[7] has the potential to automate nonroutine tasks including high-skilled knowledge work like forecasting and high-skilled people-oriented work like counseling (Brynjolfsson and Mitchell 2017). For instance, large language models like GPT-4, Claude, and Gemini allow users to make requests in natural language. Automation of these tasks need not involve the explicit programmed rules that constrain automation under the traditional routine-biased task model. To acknowledge the expansion in computer capacity to undertake more complex tasks, Frey and Osborne (2017) created a new framework to evaluate the impact of technological progress in which only "engineering bottlenecks to computerization" hold back automation. These bottlenecks are tasks involving perception and manipulation (that robots struggle to undertake) and tasks involving creative and social intelligence (that computers struggle to undertake).

In advanced economies, there is evidence of both job losses and jobs gains from these waves of technological progress. The process of routine-biased technological change described above is associated with job loss as automation replaces jobs and job gains as price declines linked to lower capital costs induce additional product demand and, in turn, additional labor demand (Autor 2022; Montobbio et al. 2022; Gregory, Salomons, and Zierahn 2022). A recent review of the empirical literature uncovers several themes (Montobbio et al. 2022).[8] First, a set of studies finds that technological change has been associated with job loss in some areas, particularly in traditional manufacturing in the case of process innovations, but job gains in others, particularly in high-tech and knowledge-intensive industries where product innovations are more frequent. Second, recent research on the impact of robots finds that firms adopting robots tend to increase employment, but primarily by expanding at the expense of smaller and less innovative firms. This explains in part why, at the aggregate level, some studies find negative impacts of robots on employment (for example, Acemoglu and Restrepo 2020) while others find no negative impacts (for example, Graetz and Michaels 2018). Again, where negative impacts are found, they tend to be present in manufacturing. Third and finally, the firm and its level of innovation plays an important role in mediating the impacts of technological change. In general, more innovative firms that invest in new technologies tend to increase employment (Bessen, Denk, and Meng 2022; Hirvonen, Stenhammer, and Tuhkuri 2022).

The negative labor market impacts of technological change are felt most by less-skilled workers. Across different technologies and different measures of technological progress, high-skilled workers are found to benefit from technological change while less-skilled workers are found to lose out

[6] Routine-biased technological change is a more sophisticated version of skill-biased technological change. Skill-biased technological change posits that technological change augments the productivity (and wages) of high-skilled workers relative to less-skilled workers and so favors higher-skilled employment growth (Mondolo 2021; Katz and Murphy 1992; Sebastian and Biagi 2018).

[7] Mobile robots use sensors, artificial intelligence, and other technology to maneuver in order to perform nonroutine manual tasks (Frey and Osborne 2017).

[8] Mondolo (2021) and Hötte, Somers, and Theodorakopoulos (2023) are also recent literature reviews of the links between technological change and labor markets.

(Hötte, Somers, and Theodorakopoulos 2023). For instance, in many but not all developed countries, routine-biased technological change has led to employment polarization, which is a hollowing out of middle-skill jobs. Computers replace (low- and mid-skilled) jobs intensive in routine cognitive and manual tasks, complement (high-skilled) jobs intensive in more advanced nonroutine cognitive (analytical and interpersonal) tasks like problem solving and coordination, and in some countries, increase (low-skilled services) jobs intensive in basic nonroutine manual and cognitive tasks like dexterity and interpersonal communication (Autor and Dorn 2013; Autor et al. 2022; Autor, Levy, and Murnane 2003). While other factors, such as offshoring that moves routine (industrial) jobs abroad, have played a role, automation has generally been found to be dominant (Autor and Dorn 2013; Goos, Manning, and Salomons 2009; Goos, Manning, and Salomons 2014; Michaels, Natraj, and Van Reenen 2014).

However, the latest advancements in AI may have different impacts across the skills distribution, including benefiting less-skilled workers. AI-linked technological changes may have more disruptive effects among high-skilled occupations. Recent research estimating the exposure of tasks to disruption by AI and machine learning generally finds that exposure is higher in higher-skilled, higher-wage occupations (Eloundou et al. 2023; Felten, Raj, and Seamans 2023; Meindl, Frank, and Mendonça 2021; Tolan et al. 2021; Webb 2020).[9] Industries likely to be impacted include information processing, legal services, and securities and investments (Eloundou et al. 2023; Felten, Raj, and Seamans 2023). These sectors are typically associated with high-skilled knowledge work. Notably, recent research suggests that AI assistants increase the productivity of *less-skilled* workers within occupations, in effect substituting for worker education and experience (Agrawal, Gans, and Goldfarb 2023). This has been found in the case of customer support agents, taxi drivers, software developers, and college-educated workers completing writing tasks (Brynjolfsson, Li, and Raymond 2023; Kanazawa et al. 2022; Noy and Zhang 2023; Peng et al. 2023).

4. Results

The substantial flows of CADR migrants to advanced economies, particularly the United States, means that these migrants are exposed to the technology-linked labor market transformations that have occurred in these countries. The following sections discuss how computers, artificial intelligence, and robots have changed CADR migration to the United States and the jobs they do once there.

Computerization

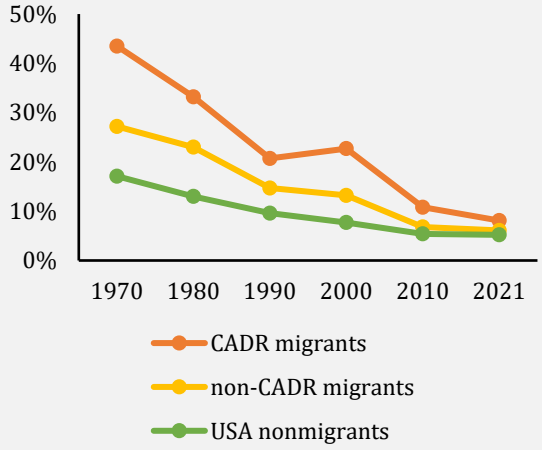
During the last 50 years, recent migrants from CADR countries have been concentrated in just a few less-skilled occupations (**Appendix Table 1**).[10] These are food preparation and serving; building and grounds cleaning; sales and related services; office and administrative support; construction; production; and transportation and material moving. Migrants from non-CADR countries, in contrast, are less concentrated and have substantial shares of workers in high-skilled jobs like management, computer and mathematical, and education jobs (**Appendix Table 2**). Nonmigrant United States workers are also less concentrated, though mid-skilled jobs in office and administrative support and sales have substantial shares of workers as do higher-skilled jobs in management, health care, and education and training (**Appendix Table 3**).

[9] Brynjolfsson, Mitchell, and Rock (2023) find that both low- and high-wage jobs are suitable for machine learning but show a negative correlation between suitability and wage.
[10] These occupations have made up 5 percent or more of employment at least once during this period.

Migrants from CADR and non-CADR countries all shifted out of production jobs that require the use of routine manual and cognitive skills during the last 50 years. Employment in production occupations, which are intensive in routine tasks, declined precipitously for CADR migrants in this period from nearly 50 percent of employment in 1970 to 8 percent in 2021, consistent with the automation of routine manual tasks (**Figure 13**). This decline also occurred among non-CADR migrants, but production jobs made up a much smaller share of jobs in 1970, meaning that the overall shift out of these jobs was less drastic. Nonmigrant United States workers also experienced a decline but started the period with an even smaller share, meaning a similarly less dramatic decline. Employment in office and administrative support jobs also declined for both CADR and non-CADR migrants, consistent with the automation of routine cognitive tasks.

Figure 13: Employment of CADR and Non-CADR Migrants and USA Nonmigrants in Production Jobs, 1970–2021

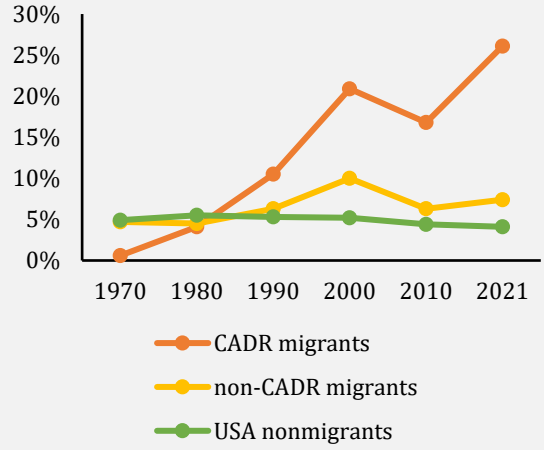
Percentage share of employment



Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: CADR=Central America and the Dominican Republic; USA=United States of America.

Figure 14: Employment of CADR and Non-CADR Migrants and USA Nonmigrants in Construction Jobs, 1970–2021

Percentage share of employment



Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: CADR=Central America and the Dominican Republic; USA=United States of America.

CADR migrants shifted into jobs intensive in nonroutine manual tasks while non-CADR migrants and United States nonmigrants shifted into higher-skilled jobs intensive in nonroutine cognitive tasks. This mirrors the decline in education levels of CADR migrants and the increase in education levels of other migrants. Employment in construction occupations, which are intensive in non-routine manual tasks, increased sharply among CADR migrants and is now the top occupational group (**Figure 14**).[11] There has been little change in employment in construction among non-CADR migrants and even a slight decline among local nonmigrants. Employment also increased for CADR migrants in several other occupations intensive in nonroutine manual tasks including food preparation and serving, building and grounds cleaning, and transportation and material. Non-CADR migrants generally saw more muted employment increases in these occupations while experiencing employment growth in higher-skilled occupations in management, computers and mathematics, and education and training.

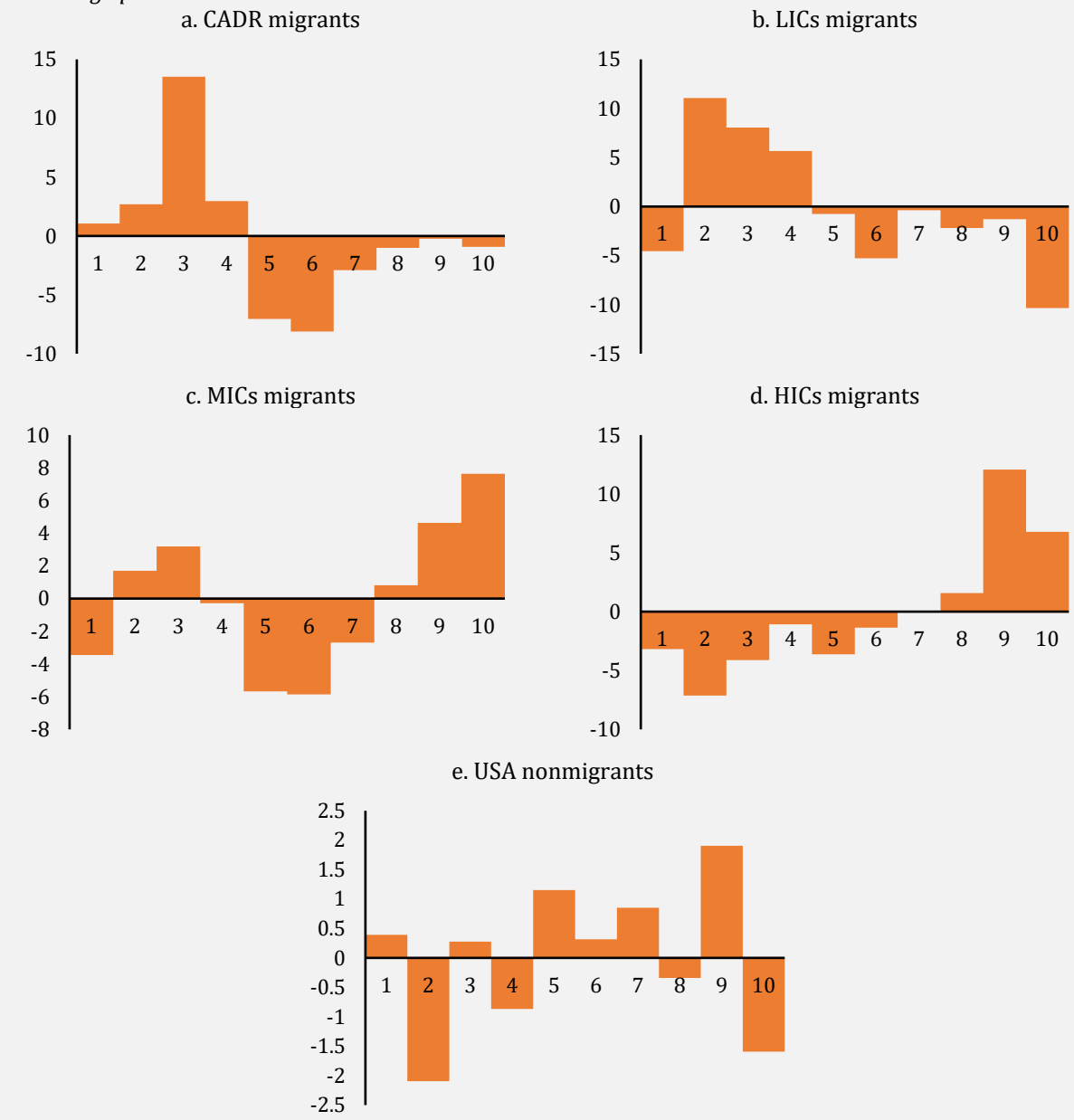
[11] A similar trend to that seen in Figures 13 and 14 occurred in most individual CADR countries, though the intensity varied. With the exception of only Panama, in all CADR countries there was a decline in the share of employment in production jobs. In Panama, the initial share of production jobs was already low, and the trend remained stable over time. Similarly, in most CADR countries, the share of employment in construction jobs increased. This shift was most pronounced in Honduras, Guatemala, El Salvador, and Nicaragua, while Panama showed no significant change in this regard over the period (Figures 3 and 4 in the Appendix 1).

Nonmigrant United States workers experienced similar increases in higher-skilled jobs in health care, management, business operations, and computers and mathematics. The trends are similar for 10-year CADR migrants, suggesting that even those with potentially more US labor market experience were not able to shift into higher-skilled jobs.

CADR migrants contributed to the expansion in low-skilled employment observed in the United States in the last several decades – one side of employment polarization – but did not contribute to the expansion in high-skilled employment – the other side of polarization. CADR migrants have shifted strongly from middle- to low-skilled jobs, where skill is measured by wage deciles (**Figure 15a**). This is distinct from the pattern observed for migrants from other middle- and high-income countries (**Figure 15b-d**). In fact, CADR migrants and migrants from lower-income countries are responsible for much of the increase in low-skilled employment observed in the United States in recent decades. This is consistent with recent research showing that offshoring and automation in the United States has increased demand for low-skilled services that are intensive in nonroutine manual tasks (Mandelman and Zlate 2022). Migrants from other middle- and high-income countries, on the other hand, have benefited from the same complementarity between technology and skills that nonmigrant United States workers have enjoyed. Notably, when focusing on nonmigrant US workers alone, the picture of routine-biased technological change becomes murkier with declines apparent at lower skill levels, small increases apparent at middle skill levels, and increases apparent at higher skill levels (**Figure 15e**).

Figure 15: Change in Employment Share by Skill Level Measured by Wages Deciles of 3-year Migrants and USA Nonmigrants, 1980-2021

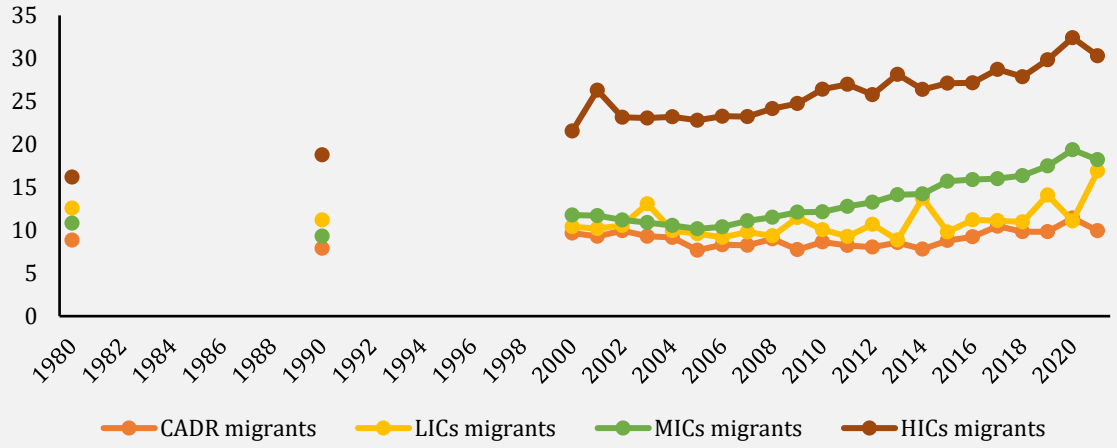
Percentage points



Source: ACS 2000-2021; US Census 1980, 1990.
Note: Employment shares are calculated for each occupation and year and then ordered in 1 percent bins by mean occupational wage. The bins are then summed to 10 percent bins. LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries; USA=United States of America.

Consistent with the growth of low-skilled employment and the stagnation of the education levels of CADR migrants, the real wages of CADR migrants have stagnated. The wages of CADR migrants are lower than those of migrants from all other country income groups (**Figure 16**). Real hourly wages for migrants from CADR countries were not substantially different in 2021 than they were in 2000 after falling somewhat in the 2000s and increasing in the 2010s. The average annual growth rate was only 0.2 percent. Real hourly wages increased sharply in the mid-2000s for migrants from non-CADR middle-income countries and steadily for those from non-CADR high-income countries.

Figure 16: Average Hourly Wage of 3-year Migrants, 1980–2021
Real 2010 $US

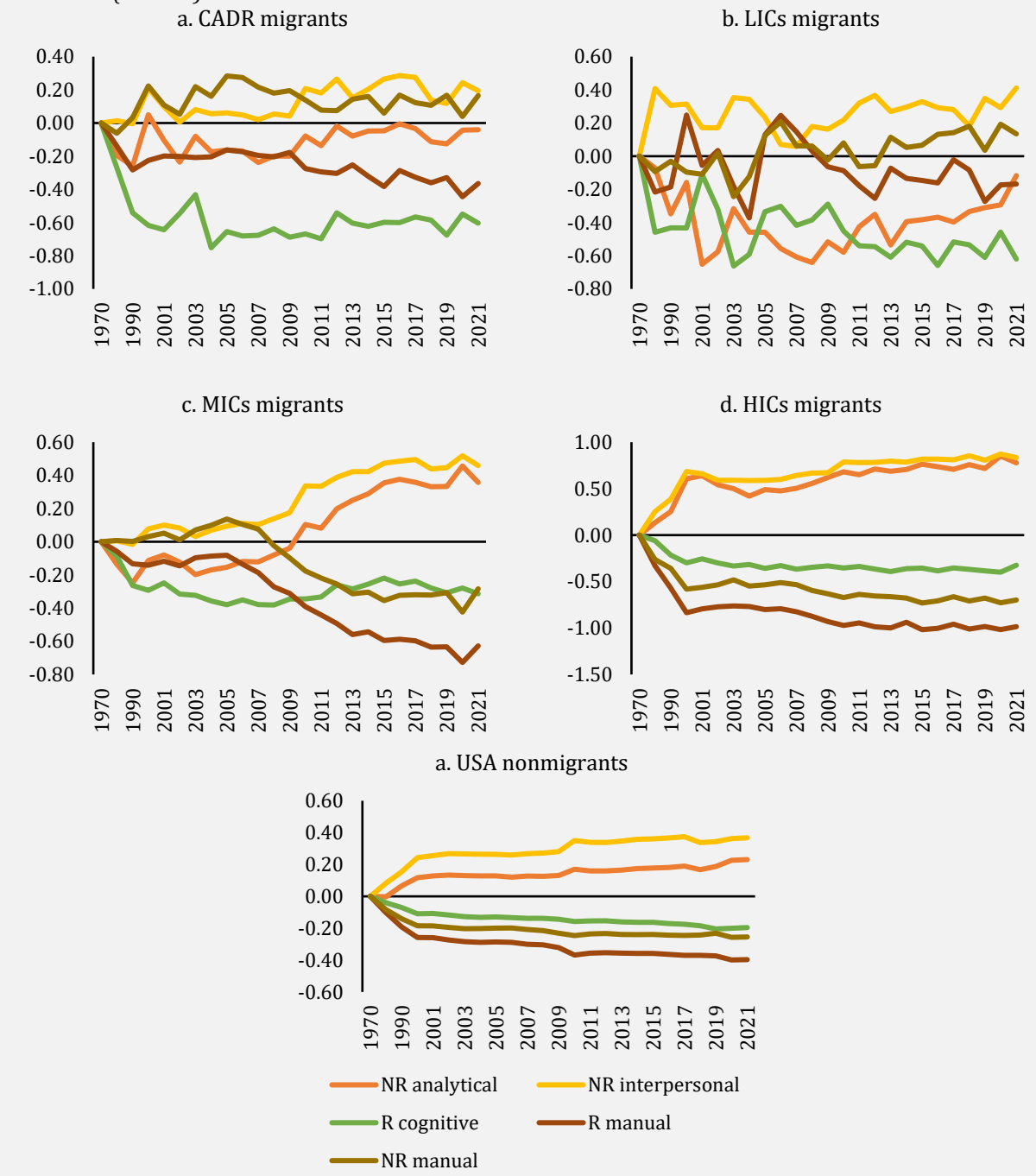


Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: Wage information is not available for 1970. CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

Since 1970 the employment of nonmigrant US workers and migrants from high- and middle-income countries has become more intensive in nonroutine interpersonal and nonroutine analytical tasks and less intensive in routine cognitive and manual and nonroutine manual tasks (**Figure 17c-e**). The employment of migrants from CADR countries (and from low-income countries), in contrast, has become *more* intensive in nonroutine manual tasks (**Figure 17a-b**). This provides further evidence that technological progress in the United States is changing the composition of the employment of CADR workers towards less-skilled services and construction sector jobs where nonroutine manual and interpersonal tasks dominate. Again, the trends for 10-year migrants are similar, providing further suggestive evidence that additional experience in the United States does not translate into more opportunities to shift to (higher-skilled) work that is more complementary with technology.

Figure 17: Evolution of the Task Content of 3-year Migrants and USA Nonmigrants, 1970-2021

Task index (1970=0)

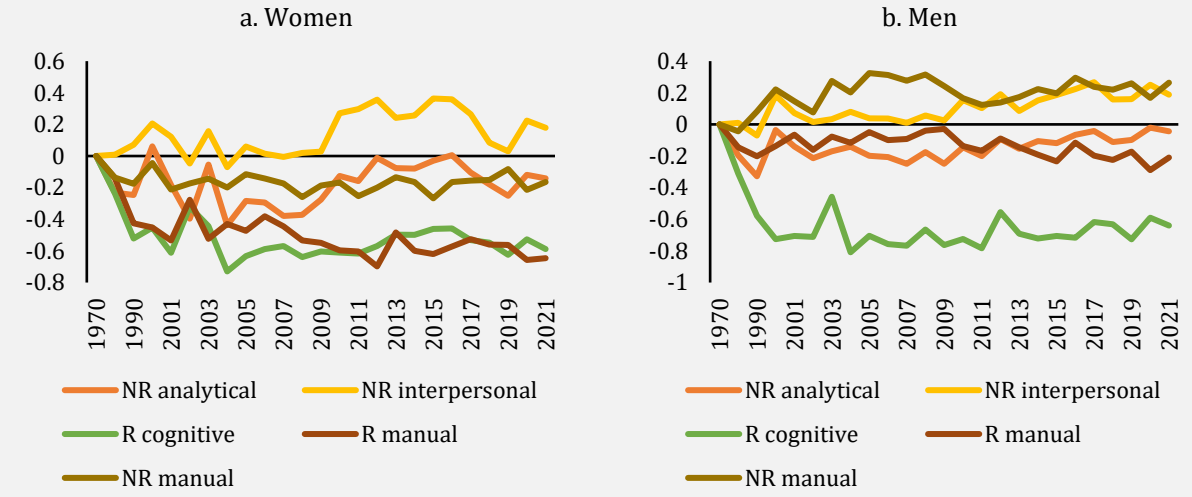


Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries; USA=United States of America. NR=nonroutine; R=routine.

Patterns are similar across gender and country of origin with a few notable exceptions. The increase in nonroutine manual tasks is only apparent for male migrants from CADR: women have only experienced an increase in the intensity of employment in nonroutine interpersonal tasks (**Figure 18**). This is consistent with the growth in construction employment among CADR workers being

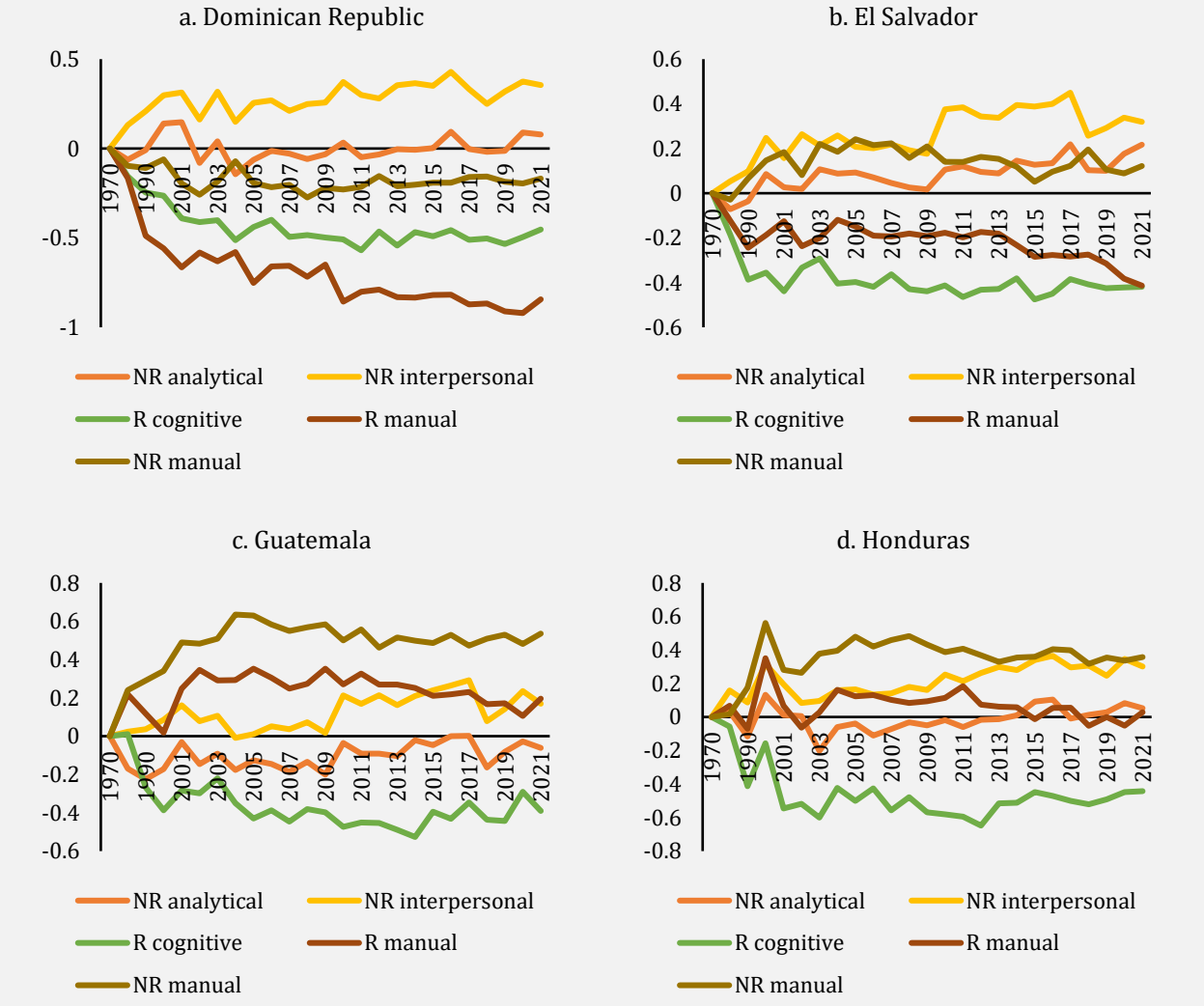
heavily biased towards men. Focusing on the four CADR countries with the most migrants in the United States, employment has become more intensive in nonroutine interpersonal tasks among migrants from all of them and in nonroutine manual tasks among migrants from all except the Dominican Republic (**Figure 19**). Nonroutine analytical skills have become more important for migrants from El Salvador, while routine manual skills have become more important for migrants from Guatemala. In the case of El Salvador, these changes relate to growth in occupations like education and training, management, and business, and a related increase in migrants with tertiary education. Guatemala shows nearly the opposite picture: employment increased in construction occupations while the educational level of migrants from Guatemala declined.

Figure 18: Evolution of the Task Content of 3-year CADR Migrants by Gender, 1970-2021
Task index (1970=0)



Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: NR=nonroutine; R=routine.

Figure 19: Evolution of the Task Content of 10-year CADR Migrants by Country, 1970-2021
Task index (1970=0)



Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: NR=nonroutine; R=routine. We focus on 10-year migrants to take advantage of the larger sample size provided by this group.

Artificial intelligence and mobile robotics

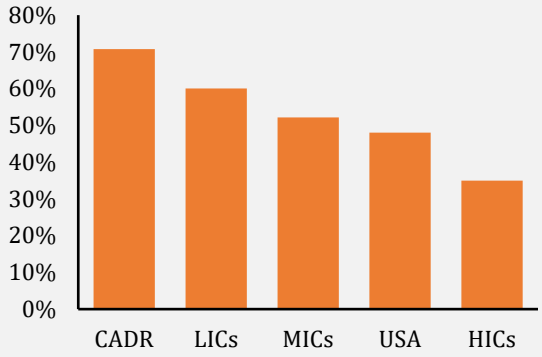
We calculate the probability that an occupation will be automated using the occupation-based measure proposed in Frey and Osborne (2017).[12] To do so, we assign each worker a probability of automation according to the five-digit SOC-2010 occupation reported in the ACS. Next, we compute the average probability of automation for each two-digit SOC category and weigh them by the share of that category in total employment. We apply this procedure to each wave of the ACS between 2000 and 2021 and to the US Census samples for 1970, 1980, and 1990. To understand if the most recent advancement in technology – large language models – are having different effects from those anticipated by Frey and Osborne's (2017) methodology, we apply an experimental measure of

[12] The probability of automation calculated here is the occupation-based measure proposed in Frey and Osborne (2017). The task-based methodology for estimating automation probabilities cannot be used because of the small sample sizes of migrants in the Program for the International Assessment of Adult Competencies (PIAAC) data that is typically used for this analysis.

exposure to generative pretrained transformers (GPTs) like ChatGPT used by Eloundou et al. (2023). The authors use manual coders and GPT-4 to classify the exposure of occupations to GPTs.

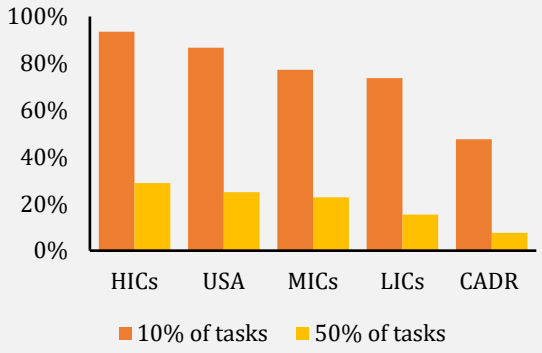
We find that CADR migrants in the United States are at greater risk of automation than nonmigrants and migrants from other country groups, but at much lower risk from the latest advances in artificial intelligence. The average probability of automation is around 70 percent for migrants from CADR countries, the highest among all migrant groups and substantially higher than the risk of US nonmigrant workers (**Figure 20**). This suggests that CADR migrants will likely continue experiencing labor market disruptions of the kind they have experienced in the last several decades in the United States. However, CADR migrants are unlikely to be as affected by the latest advances in AI. The exposure of CADR migrants to GPTs like ChatGPT is lower than that of other migrants and of nonmigrants. Unlike automatability in general, the share of the median CADR worker's tasks that are exposed to GPTs is relatively low—16 percent for CADR migrants versus 44 percent for US workers—as is the share of workers in occupations with at least 10 or 50 percent of their tasks exposed to GPTs (**Figure 21**). The low-skill bias of CADR migrants is likely to mean more labor market disruptions from certain AI and mobile robotics, but relatively less from GPTs.[13]

Figure 20: Average Probability of Automation of 3-year Migrants and USA Nonmigrants, 2021
Percentage average probability



Source: ACS 2000-2021; US Census 1970, 1980, 1990; Frey and Osborne 2017.
Note: CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries; USA=United States of America.

Figure 21: Share of Workers with at Least 10 and 50 Percent of Tasks Exposed to GPTs, 2021
Percentage



Sources: ACS 2021; Eloundou et al. 2023.
Note: CADR=Central America and the Dominican Republic; HICs=high-income countries; LICs=lower-income countries; MICs=middle-income countries; USA=United States of America.

A closer look at robots

We investigate the impact of robot adoption in the United States on recent migrants in the United States. Following the previous literature in this area, we examine the impact that adoption of robots in the United States has on inflows of CADR migrants and on the employment outcomes of these migrants. We combine two sources of data in our analysis. First, we use data from the ACS for the years 2000, 2010, and 2019. The ACS allows for the identification of migrants from CADR countries

[13] The average probability of automation for CADR migrants ranges between 35 percent in Panama and 77 percent in Guatemala. The share of workers with at least 10 percent of their tasks exposed to GPTs is lowest in Guatemala (32 percent) and highest in Panama (98 percent), while the share with at least 50 percent of exposure is lowest in Guatemala and Honduras (4 percent) and highest in Panama (29 percent).

and the commuting zone where they live. We define migrants from CADR countries as persons who live in the United States at the moment of the survey, were born in any CADR country, and migrated to the United States in the last 10 years.[14] The ACS also has information on gender, education level, labor market status, and sector of employment for those who are employed. We define our sample as working age persons (15 to 64 years old) regardless of their migration status. We collapse this information at the commuting zone and year level.

Using this information we run OLS models, one for the period 2000-2010 and another one for the period 2010-2019, where a measure of robot adoption in the United States is a determinant of the flow of CADR migrants to the United States and their labor market outcomes. Technological advances in the destination country of international migrants, i.e., the United States, can affect the demand for migrant labor depending on migrants' skill levels and the industries in which they are employed. This, in turn, can impact migration flows. We explore these relationships estimating the following model:

$$Y_c = \beta X_c + \theta R_c + \mu_s + \varepsilon_c \quad (1)$$

The outcome variables in equation (1) (Y_c) are the change in the number of CADR migrants (total and by education level), changes in the labor force participation rate, employment rate and unemployment rate of CADR migrants (total and by education level), and the logarithm of their hourly wages (total and by education level) in each commuting zone (c) between, alternatively, 2000 and 2010 and 2010 and 2019. R_c is a measure of exposure to robots in commuting zone c between 2000-2010 and 2010-2019. The control variables (X_c) include the initial share of women in the working age population, the unemployment rate, the share of the working age population with medium and high levels of education, the share of the working age to the total population, the total population, the sectoral distribution of total and female employment, and a productivity measure.[15] μ_s are state fixed effects and ε_c is an error term that we allowed to be correlated at the state level. All of the control variables correspond to the first year of data in each subperiod and are at the commuting zone level. We estimate the models for each period separately.

The measures of exposure to robots in commuting zones between 2000 and 2010 and between 2010 and 2019 (R_c in equation 1) are obtained using data on robot adoption in the United States at the sector and year level from the International Federation of Robots (IFR):

$$R_c = \sum_i l_{ci} \frac{\Delta R_i}{L_i} \quad (2)$$

R_c in equation (2) is the exposure to robots of commuting zone c during the period 2000 to 2010 or 2010 to 2019; ΔR_i is the change in the stock of robots of industry i between 2000 and 2010 or between 2010 and 2019; L_i is total employment of industry i measured in thousands of workers in the first year of each subperiod (2000 or 2010) and l_{ci} is the industrial shares of employment in commuting zone c in the first year (2000 or 2010). These measures follow Acemoglu and Restrepo (2020) and

[14] We focus on 10-year migrants to take advantage of the larger sample size provided by this group.

[15] We define low level of education as complete primary education or lower, medium education level as complete or incomplete secondary, and high level as complete or incomplete tertiary or college education. Sectors of employment include primary sector, manufacturing, services, and construction. The productivity measure is defined at the commuting zone level and calculated as the sum of change in the industrial employment in the corresponding subperiod (2000–10 or 2010–19) multiplied by the initial share of industrial employment in each commuting zone.

capture, for each commuting zone and period of analysis, the change in the sectoral stock of robots weighted by the initial participation of each sector in total employment. The analysis of these measures show that the second period (2010 to 2019) saw significantly more robot adoption than the first (2000 to 2010).[16]

The estimation of θ in equation (1) might be biased due to omitted variables or reverse causality. An example of omitted factors that has been explored in the literature is the immigration enforcement that may affect the inflow of migrants and technology adoption decisions by local firms (Ifft and Jodlowski 2022; Kostandini, Mykerezi, and Escalante 2014; Charlton 2023). Previous studies have also point out the possibility that the inflow of migrant workers affects firms' production technology (Clemens, Lewis, and Postel 2018; Lewis 2011). Because of these, we refrain from assigning a causal interpretation to our estimates.

Our results show that robot adoption in the United States did not affect the total flow of CADR migrants to the United States between 2000 and 2019 but did impact the flow of high-skilled migrants between 2010 and 2019. Our OLS estimates, where the outcome variables are the change in the number of CADR migrants (total and by education level) in each commuting zone and time period and the main regressor is the exposure to robots measure, show that the adoption of robots does not affect the overall number of migrants from CADR countries to the United States in either period (**Figure 22**). However, results by educational subgroups[17] do show impacts. During the first period between 2000 and 2010, none of the outcomes show statistically significant associations between robot adoption in the United States and the number of CADR migrants. In the second period, in contrast, adoption is associated with a reduction in the number of high-educated CADR migrants: an increase of one robot per thousand industrial workers is associated with a decline of 60 CADR migrants with a high level of education.

[16] Around 170,000 robots were adopted in the United States between 2010 and 2019 versus around 100,000 between 2000 and 2010.

[17] Low-educated migrants include up to complete primary education; medium-educated include incomplete or complete secondary education; and high-educated include incomplete or complete college or tertiary education.

Figure 22: Impact of Robot Adoption in the United States on CADR Migrants

	All		Low educated		Medium educated		High educated	
Change in number of migrants								
Change in number of robots 2000-2010	31.2		-36.68		50.6		17.28	
	[146.6]		[37.08]		[92.33]		[53.93]	
Change in number of robots 2010-2019		-91.81		12.8		-44.73		-59.88
		[100.2]		[20.41]		[102.6]		[28.49]**
Observations	741	741	741	741	741	741	741	741
R-squared	0.69	0.416	0.479	0.322	0.606	0.52	0.718	0.359
Change in LFP rate								
Change in number of robots 2000-2010	0.118		0.0333		-0.0364		0.169	
	[0.0694]*		[0.255]		[0.121]		[0.116]	
Change in number of robots 2010-2019		-0.0816		-0.124		-0.0335		-0.368
		[0.0748]		[0.219]		[0.0762]		[0.139]**
Observations	431	402	183	159	355	321	206	160
R-squared	0.339	0.312	0.296	0.328	0.242	0.292	0.415	0.52
Change in employment rate								
Change in number of robots 2000-2010	0.172		0.0481		0.0603		0.251	
	[0.0650]**		[0.323]		[0.109]		[0.127]*	
Change in number of robots 2010-2019		-0.129		-0.0751		-0.114		-0.358
		[0.0765]*		[0.205]		[0.0889]		[0.130]***
Observations	431	402	183	159	355	321	206	160
R-squared	0.366	0.289	0.34	0.432	0.262	0.311	0.446	0.535
Change in unemployment rate								
Change in number of robots 2000-2010	-0.0542		-0.0148		-0.0967		-0.0816	
	[0.0431]		[0.0963]		[0.0541]*		[0.0402]**	
Change in number of robots 2010-2019		0.047		-0.0491		0.0801		-0.0109
		[0.0297]		[0.0814]		[0.0582]		[0.0175]
Observations	431	402	183	159	355	321	206	160
R-squared	0.224	0.28	0.32	0.438	0.351	0.251	0.399	0.236
Change in log hourly wages								
Change in number of robots 2000-2010	-0.131		1.644		-0.0712		0.0423	
	[0.181]		[0.762]**		[0.149]		[0.326]	
Change in number of robots 2010-2019		-0.15		-0.879		-0.164		-0.505
		[0.187]		[0.498]*		[0.113]		[0.390]
Observations	340	309	125	105	261	215	166	125
R-squared	0.284	0.242	0.538	0.801	0.396	0.37	0.334	0.563

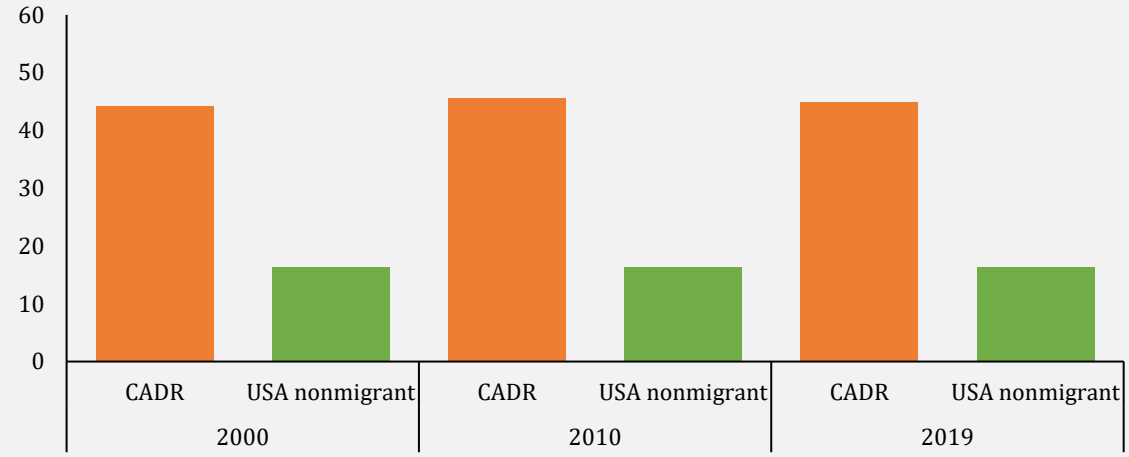
Sources: ACS 2000, 2010, and 2019; IFR.
Note: Ordinary least squares (OLS) estimation. Sample of workers 15-65 years old. All models control for initial characteristics of the community zones: share of female workers, unemployment rate, share of medium- and high-educated workers, share of working age population, total population, share of total employment, and share of female employment by sectors, and a proxy for long-run changes in labor productivity defined as a weighted average of industry-specific growth of employment. All models include state fixed effects. Regressions weighted by working age population in the first year. Robust standard errors in brackets clustered at the state level.
*** p<0.01, ** p<0.05, * p<0.1.

Robot adoption in the United States in the early 2000s seems to have increased the demand for high-skilled CADR migrants but in low-skilled nonroutine occupations. Although results on flows showed no association between robot adoption in the United States and the inflow of CADR migrants during the first period, the analysis of the association with the labor market outcomes of CADR migrants do show important results (**Figure 22**). During the first period between 2000 and 2010, an increase of one robot per thousand industrial workers is associated with a 0.25 percentage point increase in the employment rate and a 0.08 percentage point reduction in the unemployment rate for high-educated CADR migrants.

This increased demand for high-educated CADR migrants could be the result of complementarity between these workers and robots or of an increase in aggregate demand due to a surge in productivity. The evidence indicates that nearly half of highly educated CADR migrants work in occupations that only require low- to mid-skilled qualifications compared to about 20 percent of nonmigrant US workers (**Figure 23**). This mismatch increased between 2000 and 2010. We speculate that the increase in their employment rate is related to a switch to lower-skilled nonroutine manual (less automatable) jobs, particularly in food preparation and building and grounds cleaning and

maintenance, where a demand expansion linked to automation created more employment. This hypothesis is in line with the results presented in **Figure 14** for all CADR migrants.

Figure 23: Percentage of High-Educated Workers in Low- and Mid-Skilled Occupations



Sources: ACS 2000, 2010, 2019.
Note: Low- and mid-skilled occupations were identified calculating the distribution of nonmigrant US workers by level of education within each occupation. In all occupations the distribution is skewed towards workers of medium and high levels of education (that is, the participation of less-educated workers in total employment is always low). Low- and mid-skilled occupations are those in which at least 1 percent of workers has a low level of education and at least 50 has a medium level of education, respectively. These occupations are Food Preparation and Serving Related Occupations, Building and Grounds Cleaning and Maintenance Occupations, Farming, Fishing, and Forestry Occupations, Construction and Extraction Occupations, Production Occupations, and Transportation and Material Moving Occupations.

Robot adoption in the United States between 2010 and 2019 led to less demand for high-educated CADR migrants. The employment rate of high-educated CADR migrants declined 0.4 percentage points for each additional robot (**Figure 22**). The negative employment impact could be a direct effect of robot adoption if high-educated CADR migrants were employed in those industries more exposed to automation during this period or in the case of a weakening in the demand expansion effect that seems to have been at play in the first period. The change in the industrial distribution of employment of high-educated CADR migrants and the change in robot adoption has a correlation close to zero, providing evidence against the first explanation. On the other hand, the participation of high-educated CADR migrants in jobs requiring lower levels of education stopped increasing and even declined during this period (**Figure 23**). This provides some evidence that the labor outcomes of high-educated CADR migrants continued to be driven mainly by the aggregate demand implications of automation. High-skilled CADR migrants may have faced greater competition for less skilled jobs during this period or wages may have been too low for them to accept employment in less skilled jobs. Estimation results also show a reduction in the labor force participation rate of high-educated CADR migrants during the same period suggesting that some of these migrants lost their jobs and left the labor market.

To put our estimations in context, we run the same models but using information from non-CADR migrants. In this case, the outcome variables in equation (1) are the change in the inflow of non-CADR migrants and the change in their labor market outcomes between 2000 and 2010 and between 2010 and 2019. Our results, available in Appendix 1, show that robot adoption in the United States is not related to the inflow of migrant workers from countries different from the CADR region. We do observe some correlations with labor outcomes including a reduction in the employment rate of middle-educated migrant workers between 2000 and 2010. Considering our previous finding, it

could be that high-educated CADR migrants, whose demand increased over the same period, displaced middle-educated non-CADR migrants. We also find a reduction in the employment rate of non-CADR migrants of low level of education between 2010 and 2019. This result goes in the same direction as the change in the employment rate of high-educated CADR migrants over the same period suggesting that robot adoption displaced migrant workers of various levels of education between 2010 and 2019.

5. Conclusion

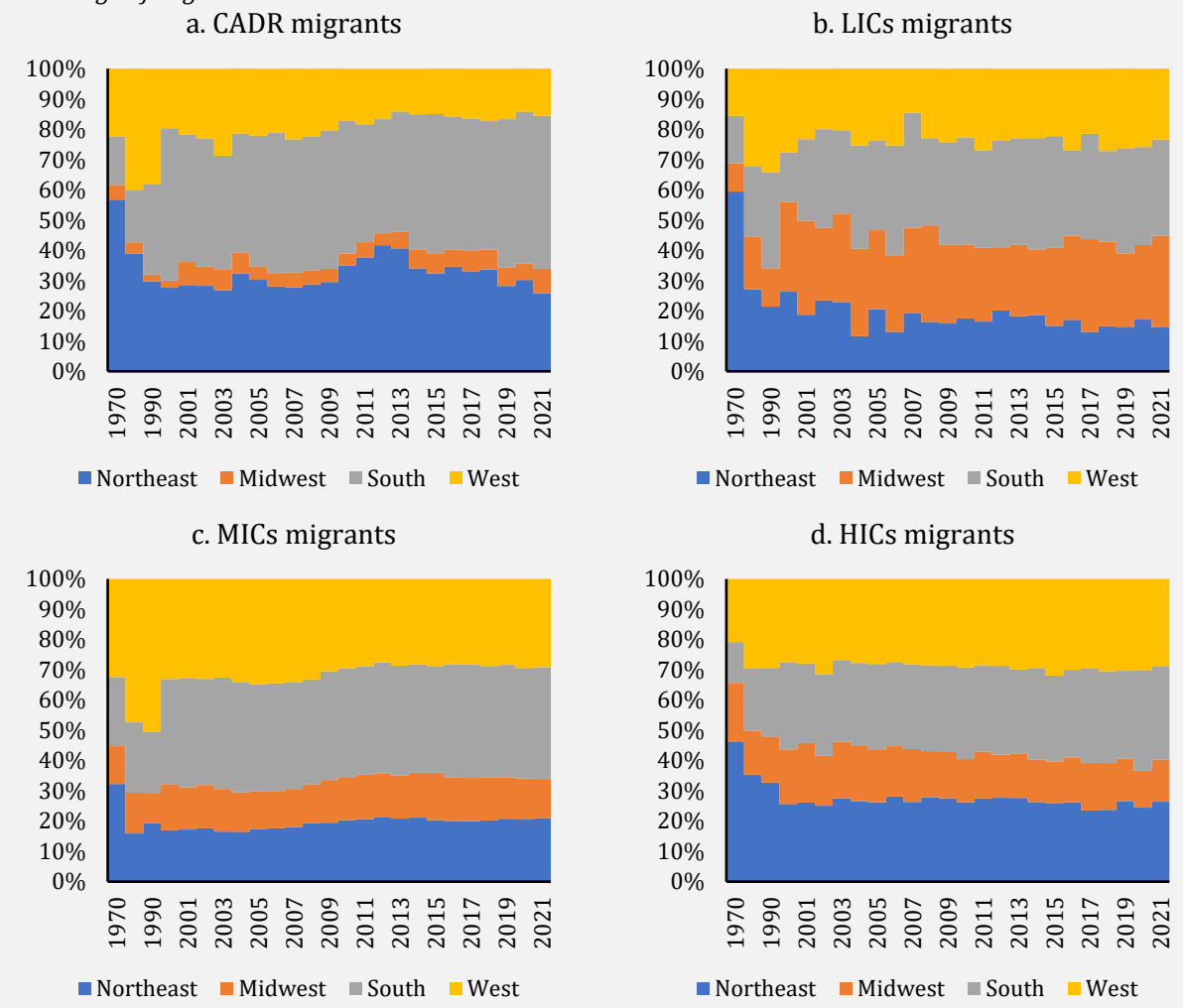
Technological developments have altered the labor market experience of recent migrants from CADR countries in distinct ways from other recent migrants and US nonmigrant workers. Recent CADR migrants to the United States, unlike other migrants and nonmigrant United States workers, shifted into work intensive in nonroutine manual tasks like construction and, more subtly, nonroutine interpersonal tasks like serving. In essence, migrants from other middle- and high-income countries have benefited from the same complementarity between technology and skills that nonmigrant US workers have enjoyed while CADR migrants seem to have benefited from the (lower-skilled) jobs created alongside technological progress. This also seems to be apparent in the impact on CADR migrants of robot adoption, which benefited high-skilled migrants in the 2000s but only by leading to a shift into (mismatched) low-skilled jobs.

These findings have important implications for policy makers. In general, recent migrants from CADR countries are benefiting from technological progress in the United States, but thus far only in low-skilled, low-quality jobs that tend to be low-wage with a history of wage stagnation. Changing this dynamic will be challenging, particularly given the types of migration flows – asylum seekers, without documentation – that characterize the corridor between CADR countries and the United States. Working without documentation can require taking less-skilled informal jobs and, despite most migrants wishing to remain in the United States, the prospect of deportation may alter decisions about the kinds of jobs to take and whether to invest in obtaining additional skills. Indeed, the analysis shows that CADR migrants who spend more time in the United States (arriving in the last 10 years rather than the last 3) are no better able to shift to higher-skilled work. This is consistent with evidence that migrants are less likely to switch sectors in response to technological developments perhaps because they face challenges accessing training and labor market institutions that can assist with such shifts (Giesing and Rude 2022). Migrants from CADR countries may face additional challenges because of the high levels of undocumented migration, which could create barriers to accessing formal training opportunities. Models of migration that emphasize pre-migration training, such as Global Skills Partnerships (GSPs) that look for areas of shared labor market demand between sending and receiving countries, are a good place for policy makers to start.

Appendix 1: Additional figures and tables

Appendix Figure 1: Region of 3-year Migrants in the United States

Percentage of migrant stock

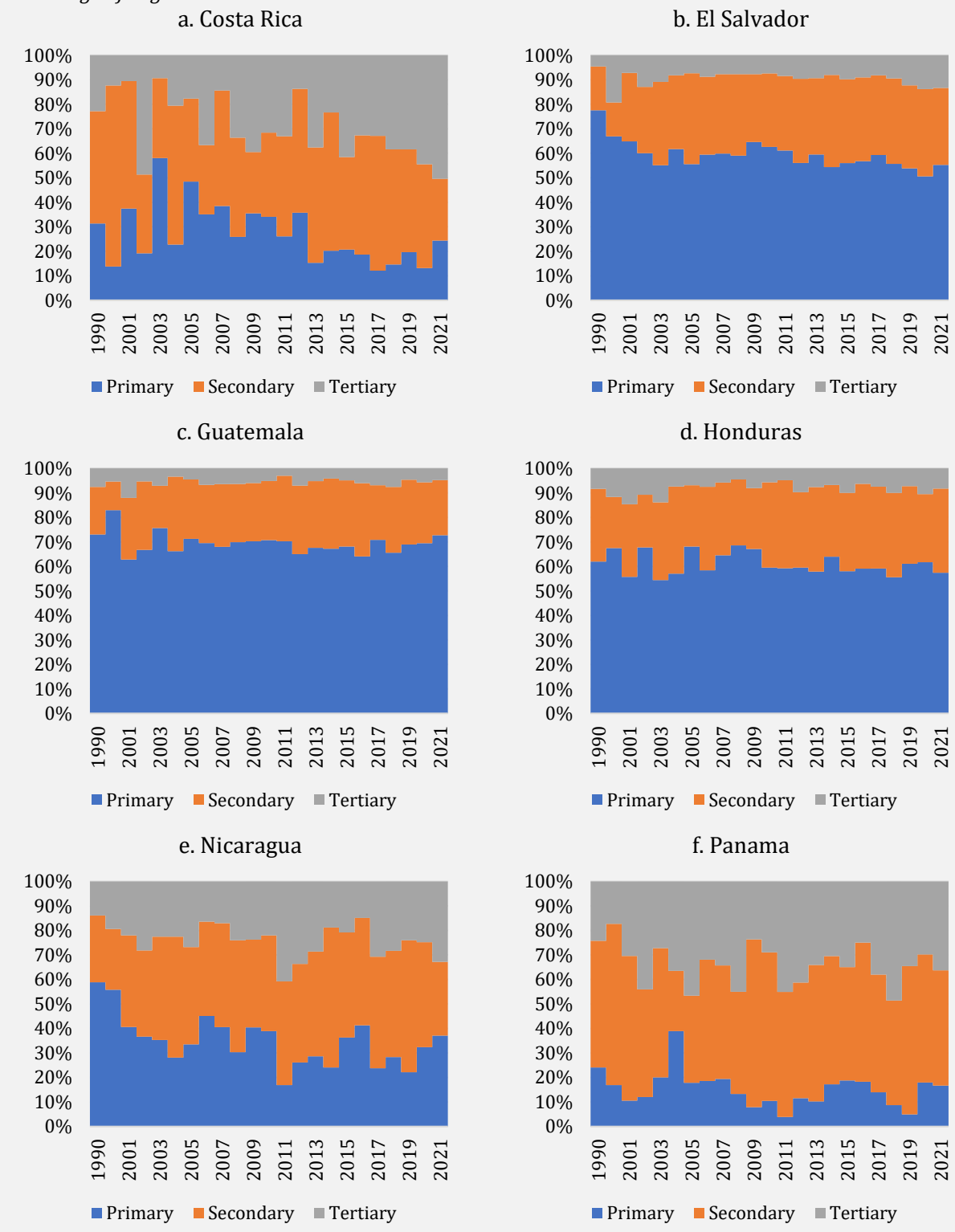


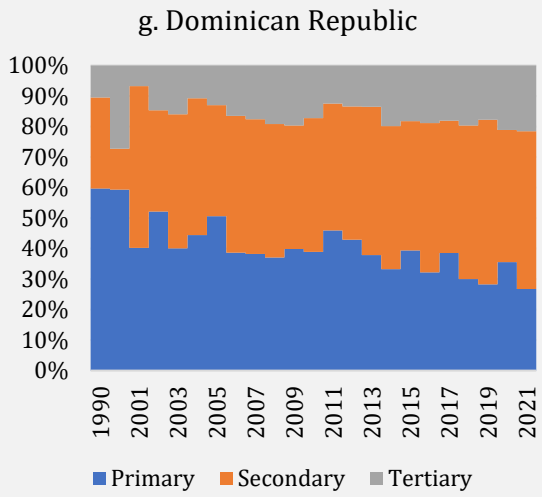
Source: ACS 2000-2021; US Census 1970, 1980, 1990.

Note: CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

Appendix Figure 2: Educational Level of 3-year CADR Migrants in the United States, 1990–2021

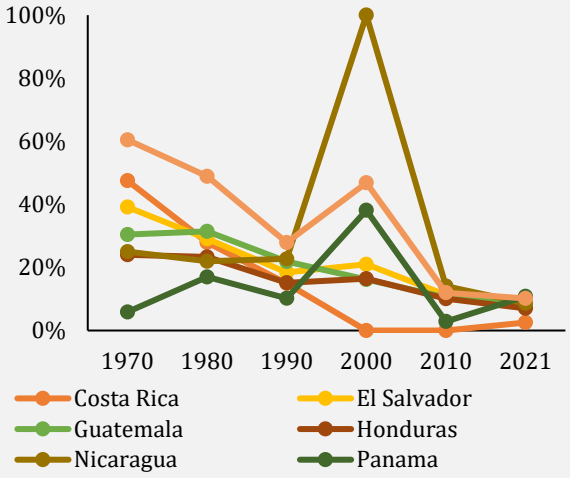
Percentage of migrant stock





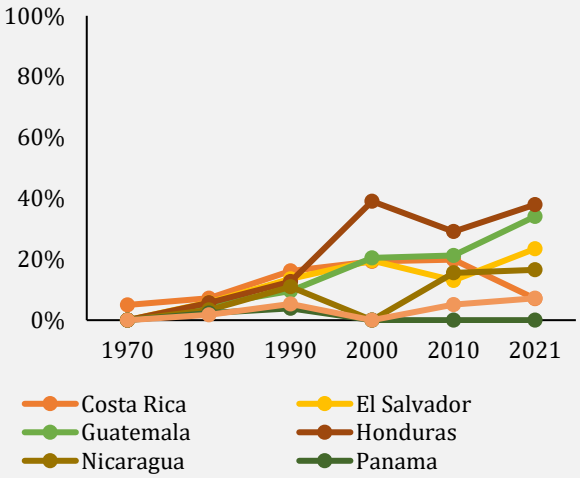
Source: ACS 2000-2021; US Census 1990.
Note: Primary is incomplete secondary education and less. Secondary is complete secondary and incomplete tertiary. Tertiary is complete tertiary. Data on tertiary education is not available for 1970 and 1980. CADR=Central America and the Dominican Republic; LICs=low-income countries; MICs=middle-income countries; HICs=high-income countries.

Figure 3: Employment of CADR Migrants in Production Jobs by Country, 1970–2021
Percentage share of employment



Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: CADR=Central America and the Dominican Republic..

Figure 4: Employment of CADR Migrants in Construction Jobs by Country, 1970–2021
Percentage share of employment



Source: ACS 2000-2021; US Census 1970, 1980, 1990.
Note: CADR=Central America and the Dominican Republic..

Appendix Table 1: Employment by Occupation of Migrants in the United States from CADR countries

Percentage of employment

	3-year migrants						10-year migrants					
Occupation	1970	1980	1990	2000	2010	2021	1970	1980	1990	2000	2010	2021
Management, Business	2%	2%	2%	2%	1%	2%	2%	2%	3%	2%	1%	3%
Business Operations	0%	0%	0%	0%	0%	1%	0%	0%	1%	0%	0%	1%
Financial Specialists	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Computer & Mathematical	0%	0%	0%	0%	0%	1%	0%	0%	0%	1%	0%	1%
Architecure & Engineering	1%	0%	0%	0%	0%	0%	1%	1%	0%	0%	0%	1%
Technicians	1%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%
Life, Physical, & Social Science	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%
Communiy & Social Services	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	1%
Legal	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Education, Training, & Library	0%	1%	1%	1%	1%	2%	0%	1%	1%	1%	1%	2%
Arts, Design, Entertainment	1%	0%	1%	0%	0%	0%	1%	1%	1%	0%	1%	1%
Healthcare Practitioners	3%	1%	1%	0%	0%	1%	3%	1%	1%	0%	1%	1%
Healthcare Support	3%	1%	2%	0%	1%	2%	3%	2%	2%	1%	2%	3%
Protective Service	0%	1%	1%	0%	0%	0%	1%	1%	1%	0%	0%	0%
Food Prep & Serving	5%	10%	12%	12%	17%	11%	6%	8%	10%	10%	15%	11%
Building & Grounds	12%	15%	17%	11%	17%	14%	11%	14%	16%	11%	18%	13%
Personal Care and Service	3%	2%	4%	3%	4%	3%	3%	2%	3%	4%	4%	3%
Sales	3%	5%	6%	9%	5%	5%	3%	5%	8%	9%	6%	6%
Office & Admin	12%	8%	6%	5%	7%	7%	16%	10%	8%	9%	6%	7%
Farming, Fishing, & Forestry	0%	0%	1%	2%	5%	2%	0%	0%	1%	1%	2%	2%
Construction	1%	4%	11%	21%	17%	26%	1%	4%	9%	16%	19%	22%
Extraction	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Installation, Maintenance	2%	3%	3%	4%	3%	3%	3%	3%	3%	3%	3%	3%
Production	44%	33%	21%	23%	11%	8%	39%	33%	20%	19%	10%	9%
Transportation & Moving	6%	10%	10%	6%	8%	8%	5%	9%	10%	10%	8%	9%
Military Specific	0%	1%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%

Source: ACS 2000, 2010, 2021; US Census 1970, 1980, 1990.
Note: CADR=Central America and the Dominican Republic.

Appendix Table 2: Employment by Occupations of Migrants in the United States from non-CADR Countries

Percentage of employment

	3-year migrants						10-year migrants					
Occupation	1970	1980	1990	2000	2010	2021	1970	1980	1990	2000	2010	2021
Management, Business	3%	5%	5%	6%	6%	10%	4%	5%	6%	5%	6%	9%
Business Operations	0%	1%	1%	1%	2%	2%	0%	1%	1%	1%	1%	3%
Financial Specialists	1%	1%	1%	1%	2%	2%	1%	1%	1%	1%	2%	2%
Computer & Mathematical	1%	1%	2%	7%	7%	8%	1%	1%	2%	5%	5%	10%
Architecure & Engineering	4%	3%	2%	1%	2%	3%	4%	3%	2%	2%	2%	3%
Technicians	1%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%
Life, Physical, & Social Science	3%	2%	3%	1%	3%	3%	3%	2%	2%	1%	2%	3%
Communiy & Social Services	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
Legal	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	1%
Education, Training, & Library	3%	3%	4%	3%	7%	7%	3%	2%	3%	3%	4%	6%
Arts, Design, Entertainment	1%	1%	2%	1%	2%	2%	1%	1%	1%	2%	1%	2%
Healthcare Practitioners	6%	4%	3%	2%	3%	4%	5%	5%	3%	3%	4%	5%
Healthcare Support	1%	2%	2%	1%	2%	2%	1%	2%	2%	2%	3%	3%
Protective Service	0%	1%	1%	1%	1%	1%	0%	1%	1%	1%	1%	1%
Food Prep & Serving	7%	9%	11%	13%	12%	6%	6%	8%	9%	11%	12%	6%
Building & Grounds	6%	6%	8%	7%	7%	5%	6%	6%	8%	7%	9%	4%
Personal Care and Service	2%	2%	3%	3%	5%	5%	2%	2%	2%	3%	4%	4%
Sales	4%	6%	9%	7%	8%	6%	5%	6%	9%	8%	8%	7%
Office & Admin	12%	11%	9%	8%	7%	7%	13%	11%	10%	9%	7%	8%
Farming, Fishing, & Forestry	3%	4%	3%	4%	4%	2%	2%	3%	3%	3%	3%	1%
Construction	5%	4%	6%	10%	6%	7%	5%	5%	7%	9%	9%	6%
Extraction	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Installation, Maintenance	4%	3%	2%	2%	2%	2%	4%	3%	3%	2%	2%	2%
Production	27%	23%	15%	13%	7%	6%	26%	23%	16%	14%	7%	6%
Transportation & Moving	5%	7%	7%	6%	6%	7%	5%	7%	7%	7%	6%	8%
Military Specific	0%	1%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%

Source: ACS 2000, 2010, 2021; US Census 1970, 1980, 1990.
Note: CADR=Central America and the Dominican Republic.

Appendix Table 3: Employment by Occupations of Nonmigrant United States workers

Percentage of employment

Occupation	1970	1980	1990	2000	2010	2021
Management, Business	9%	9%	10%	10%	10%	12%
Business Operations	1%	1%	2%	2%	3%	3%
Financial Specialists	1%	1%	2%	2%	2%	2%
Computer & Mathematical	0%	1%	1%	2%	2%	3%
Architecure & Engineering	2%	2%	2%	2%	1%	2%
Technicians	1%	0%	0%	0%	0%	0%
Life, Physical, & Social Science	1%	1%	2%	1%	1%	1%
Communiy & Social Services	1%	1%	1%	1%	2%	2%
Legal	0%	1%	1%	1%	1%	1%
Education, Training, & Library	5%	5%	5%	6%	7%	7%
Arts, Design, Entertainment	1%	1%	2%	2%	2%	2%
Healthcare Practitioners	3%	3%	4%	5%	6%	7%
Healthcare Support	1%	2%	2%	2%	2%	2%
Protective Service	1%	2%	2%	2%	3%	2%
Food Prep & Serving	4%	4%	4%	4%	5%	5%
Building & Grounds	4%	3%	3%	3%	3%	3%
Personal Care and Service	3%	2%	2%	3%	3%	3%
Sales	9%	10%	12%	11%	11%	10%
Office & Admin	17%	17%	16%	16%	15%	12%
Farming, Fishing, & Forestry	1%	1%	1%	1%	0%	0%
Construction	5%	5%	5%	5%	4%	4%
Extraction	0%	0%	0%	0%	0%	0%
Installation, Maintenance	5%	4%	4%	4%	4%	3%
Production	17%	13%	10%	8%	5%	5%
Transportation & Moving	8%	8%	7%	6%	6%	6%
Military Specific	0%	2%	0%	0%	0%	0%

Source: ACS 2000, 2010, 2021; US Census 1970, 1980, 1990.

Appendix Table 4: Impact of Robot Adoption in the United States on non-CADR Migrants

	All		Low educated		Medium educated		High educated	
Change in number of migrants								
Change in number of robots 2000-2010	581.8		96.07		205		280.8	
	[608.0]		[102.1]		[364.7]		[477.4]	
Change in number of robots 2010-2019		1,023		-8.086		688		342.6
		[1,455]		[118.7]		[1,003]		[385.5]
Observations	741	741	741	741	741	741	741	741
R-squared	0.32	0.47	0.325	0.624	0.443	0.822	0.462	0.378
Change in LFP rate								
Change in number of robots 2000-2010	-0.00943		-0.0276		-0.0872		0.0467	
	[0.0278]		[0.102]		[0.0296]***		[0.0433]	
Change in number of robots 2010-2019		0.0323		-0.0683		0.057		0.0446
		[0.0232]		[0.0621]		[0.0393]		[0.0461]
Observations	737	737	504	399	715	708	717	718
R-squared	0.232	0.256	0.294	0.292	0.237	0.278	0.192	0.213
Change in employment rate								
Change in number of robots 2000-2010	-0.02		-0.0444		-0.117		0.0361	
	[0.0317]		[0.110]		[0.0457]**		[0.0411]	
Change in number of robots 2010-2019		0.0443		-0.103		0.0771		0.0442
		[0.0281]		[0.0613]*		[0.0485]		[0.0415]
Observations	737	737	504	399	715	708	717	718
R-squared	0.269	0.262	0.28	0.298	0.265	0.255	0.219	0.231
Change in unemployment rate								
Change in number of robots 2000-2010	0.0106		0.0169		0.0299		0.0106	
	[0.0105]		[0.0829]		[0.0287]		[0.0178]	
Change in number of robots 2010-2019		-0.0119		0.0352		-0.0201		0.000422
		[0.0136]		[0.0320]		[0.0204]		[0.0133]
Observations	737	737	504	399	715	708	717	718
R-squared	0.212	0.167	0.241	0.356	0.196	0.199	0.2	0.182
Change in log hourly wages								
Change in number of robots 2000-2010	0.106		0.253		0.102		-0.0263	
	[0.105]		[0.217]		[0.147]		[0.0953]	
Change in number of robots 2010-2019		-0.028		-0.235		-0.0786		0.0729
		[0.0856]		[0.175]		[0.111]		[0.0881]
Observations	719	717	381	292	676	651	692	686
R-squared	0.149	0.146	0.201	0.42	0.162	0.239	0.193	0.124

Sources: ACS 2000, 2010, and 2019; IFR.
Note: Ordinary least squares (OLS) estimation. Sample of workers 15-65 years old. All models control for initial characteristics of the community zones: share of female workers, unemployment rate, share of medium- and high-educated workers, share of working age population, total population, share of total employment, and share of female employment by sectors, and a proxy for long-run changes in labor productivity defined as a weighted average of industry-specific growth of employment. All models include state fixed effects. Regressions weighted by working age population in the first year. Robust standard errors in brackets clustered at the state level.
*** p<0.01, ** p<0.05, * p<0.1.

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