Does Skill Abundance Still Matter?
The Evolution of Comparative Advantage in the 21st Century*

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Abstract

This paper documents that skill-abundant countries no longer have a comparative advantage in skill-intensive sectors. While this empirical relationship was strong in the 1980s, it weakened in the 1990s and disappeared by the 2000s. The decline is more pronounced in countries and sectors with higher automation. I find no such heterogeneous effects among countries and sectors more exposed to offshoring. Using a quantitative trade model incorporating automation and offshoring, I confirm that the observed changes in automation can account for the evolution of comparative advantage while observed changes in offshoring cannot. I conclude by revisiting the relationships between globalization, technology, and inequality through this model. Automation increases skill premia in developed countries with high automation and also raises welfare globally, whereas offshoring leads to smaller, more evenly distributed welfare gains.

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1 Introduction

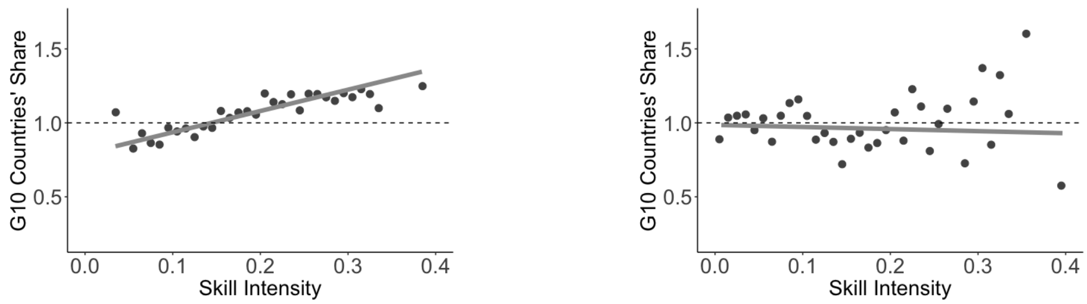
One of the most influential ideas in international economics is the idea, developed by Eli Heckscher and Bertil Ohlin and later formalized by Paul Samuelson, that a country's skill abundance may shape its pattern of comparative advantage in skill-intensive sectors. Throughout the 20th century, it has played a central role in shaping classical debates on various topics ranging from the origins of growth miracles (Young, 1995; Ventura, 1997) to the relationship between globalization, technology, and inequality (Wood, 1994; Berman et al., 1998; Krugman, 2000; Leamer, 2000). Has the emergence of China and other developing countries made the previous patterns of comparative advantage more salient? Or, has the 21st century brought new technologies, such as automation, that reverse these patterns and make them less relevant?

In the first half of the paper, I document that skill-abundant countries no longer have a comparative advantage in skill-intensive sectors. Figure 1 illustrates this finding succinctly by showing the share of G10 countries in world exports across sectors of different skill intensity. These shares are normalized to sum to one across all sectors, and skill intensity is measured using US data as the share of non-production worker's payroll in value added. If skill-abundant countries have a comparative advantage in skill-intensive sectors, they should tend to export more in these sectors. Since G10 countries are skill-abundant, we should therefore observe an upward-sloping relationship between skill intensity and their export shares. Panel 1a shows that this indeed is the case in 1980. By 2015, however, this relationship had entirely disappeared. The first empirical contribution of my paper is to show more systematically that while skill-abundant countries exhibited a comparative advantage pre-2000s (as documented by Romalis (2004); Morrow (2010); Chor (2010) and others), it disappeared afterwards. The second empirical contribution is to show that the previous decline is more pronounced among groups of countries and sectors with higher exposure to automation.

In the second half of the paper, I quantify the mechanisms and draw macroeconomic implications. I develop a multi-sector quantitative trade model, in which both automation and offshoring affect the costs of production and, in turn, the relationship between the country's skill abundance and its exports in skill-intensive sectors. I find that only automation can quantitatively account for the evolution of comparative advantage. Through the lens of the same model, I draw implications for inequality within and across countries. Automation increases skill premia only in developed countries with high automation and welfare in all countries. In contrast, the consequences of offshoring, bott for skill premia and welfare, tend to be smaller around the world.

Figure 1: Share of G10 Countries in Skill-Intensive Sectors (Normalized)

(a) 1980 (b) 2015



Notes: The figures show binned scatterplots of the share of G10 countries in world exports across 397 4-digit sectors of different skill intensity. These shares are normalized to sum to one across all sectors. Skill intensity is measured using US data as the share of non-production worker's payroll in value added. See Appendix B for details.

Does Skill Abundance Still Matter? Expanding on the findings in Figure 1, Section 2 examines the importance of the country's skill abundance for comparative advantage in skill-intensive sectors in a more systematic manner. For every five years from 1980 to 2015, I regress bilateral trade flows at the exporter-importer-sector level on the interaction of an exporter's characteristic, skill abundance, and sector's characteristic, skill intensity. This specification follows the papers, such as Chor (2010), Costinot et al. (2012), and Levchenko and Zhang (2016), which reveal comparative advantage using bilateral trade flow data.[1] My main variable of interest is the interaction between an exporter's skill abundance and a sector's skill intensity. If the coefficient in front of this interaction term is positive, skill-abundant countries export relatively more in skill-intensive sectors, i.e., they are revealed to have a comparative advantage in these sectors.

I find that, until the 1990s, skill-abundant countries used to specialize in skill-intensive sectors. This aligns with the papers that have found a positive coefficient and interpreted it as supportive of the Heckscher-Ohlin Theory (Romalis, 2004; Levchenko, 2007; Nunn, 2007; Morrow, 2010; Chor, 2010). The novel finding is that the importance of skill abundance in comparative advantage weakened over time and eventually disappeared post-2000. This empirical finding is robust across the range of the specifications previously used in the literature, the measures of countries' skill abundance and sectors' skill intensity in 1980 for entire periods, or the data sources for trade flow.

[1] Following Costinot et al. (2012), I include the exporter-importer and importer-sector fixed effects, which control for the trade pattern determinants specific to exporter-importer pairs, such as distance or trade agreements, as well as those specific to importer-sector pairs, such as tariffs or expenditure shares.

A First Look at Mechanisms. Automation and offshoring have been two major technological trends in recent decades. Both of these trends have the potential to undo the relationship between a country's skill abundance and a sector's skill intensity in trade patterns. This is because they replace low-skill workers with machines or foreign intermediates, thus reducing the role of domestic low-skill workers in production (Grossman and Rossi-Hansberg, 2008; Acemoglu and Restrepo, 2022b). The previous changes may, in turn, blur the mapping from skill abundance to relative costs and relative exports across sectors with different skill intensities.

Section 3 empirically investigates these two specific channels–the rise of automation and offshoring–as potential mechanisms behind the decline in skill-abundance-driven comparative advantage. Using data on robot adoption, intermediate imports, and factor payment shares, I construct measures of the automation share, defined as the share of factor payments to machines, and the offshoring share, defined as the share of foreign intermediates in total intermediates, by country, sector, and year. I then examine the heterogeneity in changes in comparative advantage across groups of countries and sectors that vary in terms of their exposure to automation and offshoring.

First, I find that the decline in the importance of a country's skill abundance in comparative advantage in a skill-intensive sector is more pronounced among countries and sectors with higher levels of automation, such as the automobile sectors in Germany and Japan.[2] Second, among countries and sectors where automation levels are below the global median, such as the textile sectors in developing countries, skill abundance remains as important in 2015 as it was in the 1990s. Finally, there is little heterogeneity of the decline across countries and sectors with different degrees of offshoring and, what heterogeneity there is suggests that offshoring has strengthened, not weakened, the mapping from skill abundance to comparative advantage.

Theoretical Framework. The heterogeneity in Section 3 is suggestive of automation, rather than offshoring, having caused the decline in the importance of skill abundance in comparative advantage. In Section 4, I develop a model to quantify the effects of automation and offshoring on the evolution of comparative advantage. I start from a multi-sector, multi-factor Eaton-Kortum model that incorporates a task framework for automation (Acemoglu and Restrepo, 2022b) and offshoring (Grossman and Rossi-Hansberg, 2008).

[2] The automobile sector is not skill-intensive. For example, the share of payroll allocated to skilled labor as a percentage of value added was 8%, placing it around the bottom 10th percentile in 1980, based on the Japanese Census of Manufacturers. The same is true for the US, where the share of payroll allocated to skilled labor as a percentage of value added was 11%, placing it around the bottom 25th percentile in 1980, based on the NBER CES Manufacturing Database.

In the model, exogenous increases in automation and offshoring decrease demand for low-skill labor given output, reducing the importance of the country's skill abundance in the production processes. Intuitively, this task displacement makes low-skill-scarce countries such as Germany or Japan remain competitive in low-skill-intensive sectors. For example, Germany automates or offshores its production processes in the automobile sector, allowing it to rely on machines or foreign intermediates instead of its relatively scarce production workers. This shift in production technology enables Germany to gain a comparative advantage in the automobile sector, making it harder for countries like Vietnam or Malaysia to compete even with their relatively abundant production workers.

Quantitative Relevance. Using the model developed in Section 4, Section 5 quantifies the roles of automation and offshoring in the evolution of comparative advantage. To do so, I first calibrate the model to the economy in 1995 and simulate the model under counterfactual scenarios, using the exact hat algebra (Dekle et al., 2008).[3] Using the observed changes in the measures of automation and offshoring, I consider the following two counterfactual scenarios: (a) only automation change from 1995 to 2008 and (b) only offshoring change from 1995 to 2008. Other parameters, such as trade costs or final goods sectoral expenditure shares, are held constant at their levels in 1995.

Then, I estimate the same regression as in Section 2 using the model-generated data for each counterfactual scenario and compare the coefficients for the importance of skill abundance to those obtained from the actual data.

My key finding is that the model, incorporating automation shocks, can explain around 90% of the decline in the importance of skill abundance for comparative advantage observed in the data as found in Section 2. Also, observed changes in offshoring cannot account for the changes in comparative advantage. This implies that automation, rather than offshoring, is the primary driver behind the decline. Specifically, without the advancements in automation since 1995, skill abundance would have remained important for comparative advantage in 2008.

Macro Implications. Having quantified the roles of automation and offshoring in the evolution of comparative advantage, I conclude my paper by using the same model to revisit the relationship between technology, globalization, and inequality. To do so, I simulate the model under the same counterfactual scenarios, with and without automation and offshoring shocks, keeping other parameters and exogenous variables constant.

[3] My initial year is 1995 because the World Input-Output Database with multiple labor types, which I use, is only available from 1995.

First, automation shifts tasks from low-skilled labor worldwide to high-skilled labor in high-income countries, relocating manufacturing production from low-automation countries to high-automation, high-income countries. As a result, skill premia increase in high-automation countries, while they decrease in low-automation countries because of further specialization in more low-skill intensive sectors, increasing demand for low-skill labor. The welfare effects are positive across all countries but are more pronounced in high-automation countries, such as Germany and Japan.

Second, offshoring shifts tasks from low-skilled labor in skill-abundant countries to those in skill-scarce countries. The effects on the manufacturing shares, skill premia, and welfare are smaller and more equally spread across countries compared to automation. This is because offshoring tends to occur more uniformly across countries.

I conclude by exploring how the documented changes in comparative advantage shape the previous conclusions. To this end, I consider the same changes in automation and offshoring as before, but in a counterfactual economy with lower trade elasticity and, in turn, muted declines in comparative advantage. Under low trade elasticity, where changes in comparative advantage are more limited, skill premia rise across all countries because low-automation, skill-scarce countries do not specialize in low-skill-intensive sectors as much as they do in the baseline counterfactual case. Additionally, welfare gains become smaller across all countries. This findings suggest that incorporating changes in comparative advantage and sectoral reallocation is crucial when analyzing the effects of automation on skill premia and welfare.

Literature. First, this paper contributes to the large literature that empirically investigates the sources of comparative advantage (Leamer, 1984; Bowen et al., 1987; Trefler, 1993, 1995; Davis and Weinstein, 2001; Yeaple, 2003; Romalis, 2004; Schott, 2004; Nunn, 2007; Levchenko, 2007; Costinot, 2009; Morrow, 2010; Chor, 2010; Costinot et al., 2012; Davis and Dingel, 2020). These papers stress the importance of the Ricardian or Heckscher-Ohlin sources of comparative advantage in the 20th century, and almost none study how comparative advantage evolves over time.[4] My paper offers a new fact that a country's skill abundance has become less important in comparative advantage in skill-intensive sectors after 1990 and no longer matters by 2005. My paper also shows that

[4]Some exceptions are Hanson et al. (2015) and Levchenko and Zhang (2016), which find the mean reversion or convergence of comparative advantage over time. My results show that the pattern of comparative advantage has not changed much for countries and sectors with lower levels of automation. Thus, unless mean reversion is systematically correlated with automation, it cannot explain my empirical facts entirely, and my results are complementary to the findings in Hanson et al. (2015) and Levchenko and Zhang (2016). Another related stream of the literature focusing on the changes in comparative advantage is the theoretical literature that studies endogenous comparative advantage, including Redding (1999).

automation is the most plausible explanation for this decline in the role of a country's skill abundance.

Second, this paper contributes to the large literature on the interaction between technology, globalization, and inequality, including Wood (1994), Berman et al. (1998), Krugman (2000), Leamer (2000), and Matsuyama (2007).[5,6] More specifically, my paper relates to work that embeds high- and low-skilled labor into multi-sector quantitative trade models to study the implications of trade and technology on the skill premium (Parro, 2013; Burstein et al., 2013; Caron et al., 2014; Burstein and Vogel, 2017; Burstein et al., 2019; Morrow and Trefler, 2022; Furusawa et al., 2022; Adão et al., 2022).[7] While I demonstrate the implications of changes in trade and technology for the skill premium as well, my main focus is on the changes in trade patterns over time. Moreover, I show that the implication of technology for the skill premium depends on the degree of changes in comparative advantage, which highlights the importance of international trade in analyzing the effects of technology on the skill premium.

The closest paper is Morrow and Trefler (2022), which provide a model-based decomposition of how the differences in skill abundance across countries are absorbed into different factors in trade patterns. They find that within-industry skill intensities are more important than between-industry output mixes in 2006. I empirically confirm this finding and also highlight that the relationship between skill abundance and skill intensity was important before 2000. Moreover, my empirical and quantitative results suggest that automation is a plausible explanation for why differences in within-industry skill intensities across countries are important.

Finally, this paper relates to the recent literature that studies the relationship between automation and trade, such as Wang (2021), Krenz et al. (2021), Artuc et al. (2023), and Fontagné et al. (2024). They focus on how automation affects trade volumes. My paper shows that automation changes the patterns of comparative advantage, which, in turn, affect inequality within and across countries.

[5]Earlier studies focus on the impact of trade on the rate of technological growth (e.g. Krugman (1979) and Grossman and Helpman (1991)).

[6]For empirical studies on how globalization affects inequality, see for example Feenstra and Hanson (1996), Autor et al. (2013), and Boehm et al. (2020). For empirical studies on how automation affects inequality, see for example Graetz and Michaels (2018) and Acemoglu and Restrepo (2022b). A more closely related paper is Galle and Lorentzen (2024), which compare the effects of globalization and automation.

[7]While I assume that automation is exogenous, there are several papers that discuss the roles of trade in the direction of technology, such as Wood (1994), Acemoglu and Zilibotti (2001), Acemoglu (2003), Thoenig and Verdier (2003), Epifani and Gancia (2008), and Loebbing (2022).

2 Skill Abundance as a Source of Comparative Advantage?

In this section, I examine how the interaction between skill abundance across countries and skill intensity across sectors shapes comparative advantages from 1980 to 2015.

2.1 Baseline Specification

Theoretical Motivation To motivate my main regression, I present a quick review of the multi-sector Eaton Kortum (Eaton and Kortum, 2002) model that theoretically motivates the specification linking the comparative advantage of countries with different skill abundance and the sector's skill intensity, following Chor (2010) and Costinot et al. (2012).

Suppose that bilateral exports from i to j in sector s can be expressed as

$$X_{i,j,s} = \frac{(c_{i,s}\tau_{i,j,s})^{-\theta}}{\sum_l (c_{l,s}\tau_{l,j,s})^{-\theta}} X_{j,s} \tag{1}$$

where $c_{i,s}$ is the unit production cost in country i in sector s, $\tau_{i,j,s}$ is the bilateral trade cost, $X_{j,s}$ is the total expenditure of country j in sector s, and $\theta > 0$ is the trade elasticity.

Following Costinot et al. (2012), assume that the trade cost takes the form of $\tau_{i,j,s} = \tau_{i,j} \cdot \tau_{j,s}$. The first part $\tau_{i,j}$ measures the trade costs specific to countries i and j, such as physical distance, use of common language, historical ties, or common membership in organizations. The second part $\tau_{j,s}$ measures the trade costs specific to destination j in sector s, such as tariffs imposed by country j on s.

Now, let's consider the unit production cost $c_{i,s}$, which takes the following form

$$c_{i,s} = (w_i^H)^{\alpha_s^H}(w_i^L)^{1-\alpha_s^H}$$

where w_i^H and w_i^L are wages of high-skill and low-skill workers, and α_s^H is the share of high-skill workers' payroll in value-added, which I call the sector's skill intensity.[8]

Then, combining this unit cost function with equation (1) after taking the log, the bilateral trade flows can be written as follows:

$$\ln X_{i,j,s} = -\theta \ln\left(\alpha_s^H \times \ln\left(\frac{w_i^H}{w_i^L}\right)\right) + \eta_{i,j} + \eta_{j,s}, \tag{2}$$

[8]The results are the same if I use total cost instead of value-added for the denominator. The Cobb-Douglas assumption is for simplicity, and up to the first-order, the resulting equation (2).

where $\eta_{i,j}$ and $\eta_{j,s}$ are defined as follows:

$$\eta_{i,j} = -\theta \ln w_i^L - \theta \ln \tau_{i,j}, \quad \eta_{j,s} = -\theta \ln \tau_{j,s} - \ln \left(\sum_l (c_{l,s} \tau_{l,j,s})^{-\theta} \right) + \ln X_{j,s}.$$

The specification (2) reveals the comparative advantage of countries with different relative skill premia, w_i^H / w_i^L, across sectors with different skill intensities, α_s^H. In particular, a country with a lower skill premium has higher exports in a sector with higher skill intensity, which is the classic prediction of the Factor Proportions Theory.

In a typical cross-country dataset, it is rare to observe skill prices. Thus, the previous studies in the literature (e.g. Romalis (2004); Chor (2010)) use the relative skill abundance H_i / L_i, instead of skill premia, w_i^H / w_i^L and assume the negative relationship,

$$\ln \left(\frac{w_i^H}{w_i^L} \right) = -\gamma_{HL} \ln \left(\frac{H_i}{L_i} \right) + \nu_i, \tag{3}$$

where $\gamma_{HL} > 0$ and ν_i is an error term. This negative relationship means that skill-abundant countries have lower relative wages of skilled labor–skill premia. [9]

Then, the specification (2) becomes as follows:

$$\ln X_{i,j,s} = \beta \ln \left(\alpha_s^H \times \ln \left(\frac{H_i}{L_i} \right) \right) + \eta_{i,j} + \eta_{j,s}, , \tag{4}$$

where

$$\beta = \theta \gamma > 0.$$

This is the standard specification to reveal the comparative advantage of countries with different relative skill abundance, H_i / L_i, across sectors with different skill intensities, α_s^H.[10] We expect $\beta > 0$ because skill-abundant (higher H_i / L_i) countries have lower skill premia (lower w_i^H / w_i^L), leading to lower unit costs and larger exports in skill-intensive (higher α_s^H) sectors. As an illustration, compare two countries, the US and Bangladesh. We naturally expect that the US has a comparative advantage in more skill-intensive goods, for example, computers. This is because producing computers requires skilled designers or engineers and thus the computer sector has higher skill intensity α_s^H. This relationship between the country's skill abundance and the sectors' skill intensity means the US, with higher H_i / L_i, has lower unit production costs and larger exports in

[9] Figure C.2 in Appendix C shows that this negative relationship between skill abundance and relative wages of skilled workers across countries holds in data.

[10] See Romalis (2004); Chor (2010) for example.

sectors with higher α_s^H, which implies that $\beta > 0$.

Specification Building on the specification (4), my estimation equation takes as follows

$$X_{i,j,s,t} = \exp\left[\beta_t \left(\alpha_{s,t}^H \times \ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right) + \eta_{i,j,t} + \eta_{j,s,t}\right] + \varepsilon_{i,j,s,t}, \tag{5}$$

where $X_{i,j,s,t}$ is the bilateral trade flow from country i to j in sector s at time t, $\alpha_{s,t}^H$ is the skill intensity in sector s at time t, $H_{i,t}$ and $L_{i,t}$ are the numbers of high-skilled workers and low-skilled workers in country i at time t, respectively, $\eta_{i,j,t}$ and $\eta_{j,s,t}$ are the origin-destination and destination-sector fixed effects, and $\varepsilon_{i,j,s,t}$ is an error term. Following the literature pioneered by Silva and Tenreyro (2006) and is now standard in the gravity literature, I use the coefficients using the Poisson Pseudo Maximum Likelihood (PPML) to account for the fact that the bilateral trade flows across sectors contain many zeros.

2.2 Data

My baseline empirical analysis uses bilateral trade flow data combined with sector-level factor intensity data and country-level factor endowment data.

Bilateral Trade Flows Bilateral trade flow data come from the UN Comtrade database. The data contains annual imports and exports by detailed product code. I focus on manufacturing sectors because service trade data are available only after 2000.[11] To merge with the factor intensity measures documented below, I convert SITC Rev.2 manufacturing products into US SIC 4-digit industry. I summarize the steps to construct the final dataset in Appendix A.

Skill Abundance Skill abundance across countries comes from the Barro-Lee Educational Attainment Dataset (Barro and Lee, 2013), which is commonly used in previous studies, including Hall and Jones (1999) and Romalis (2004). I compute a relative skill endowment, the ratio of college-educated people aged 25-64 relative to non-college-educated people aged 25-64 to obtain a measure of skill abundance across countries.[12]

[11] Previous papers also focus on manufacturing sectors. Nevertheless, I show in Figure 6 in Section 5 that the main result holds when including service sectors, using the World Input-Output Database.

[12] While the original data were up to 2010, the extended data to 2015, which I use, is available in their web page here.

Skill Intensities Skill intensities across sectors come from the NBER-CES Manufacturing Industry Database (Becker et al., 2021).[13] The data contains sector-level data on output, employment, and input costs. I compute the factor payment shares of non-production workers out of total wage payments to obtain a measure of skill intensity across 397 4-digit manufacturing sectors for each year.

Sample Since factor endowment data from the Barro-Lee Dataset are available only every five years, I use data from every 5 years from 1980 to 2015. This leaves me with 8 time periods in total. For the trade flow data, to eliminate fluctuations and to focus on long-run trends, I take a 3-year moving average around each year.

For countries, first, I restrict samples of countries to those that have trade and factor endowment data covering all the periods from 1980 to 2015. Second, I restrict samples to those that have ever had imports and exports of more than 100 million USD (in 2015 value) at least once from 1980 to 2015 as in Atkin et al. (2021) to ensure that the smallest countries do not drive results. These restrictions led to 52 countries, and these 52 countries accounted for more than 98% of the world exports in 1990.

For sectors, I use all 397 sectors (in the SIC 4 digits) available in the NBER-CES Manufacturing Industry Database (Becker et al., 2021).

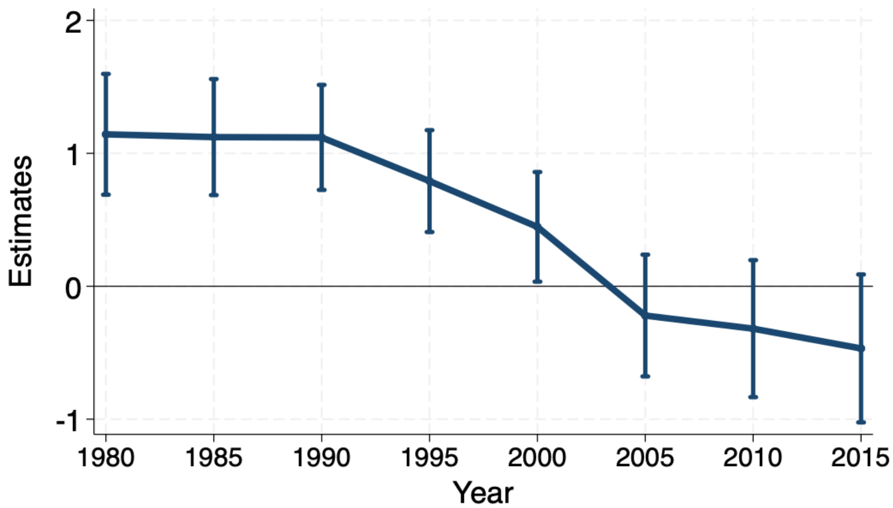
2.3 Main Results: Declining Importance of Skill Abundance

Baseline Result Figure 2 shows the estimates of β_t and its 95% confidence intervals based on heteroskedasticity robust standard errors clustered at the origin-sector level. The first finding is that estimates are positive and significant until 1995. This means that the country-level skill endowments were the source of comparative advantage in skill-intensive sectors and that developing countries specialize in low-skill-intensive sectors while developed countries specialize in skill-intensive sectors. This result is consistent with the previous literature, which finds that more skill-abundant countries specialize in skill-intensive sectors, including Chor (2010) using data from the 1980s, Morrow (2010) using data from 1985 to 1995, and Romalis (2004), Nunn (2007), and Levchenko (2007) using data from the 1990s.

The second, and new, finding is that the estimates of β_t decrease over time and become insignificant by 2000. This suggests that a country's skill abundance, at least as measured

[13] I use the US data following the literature (Romalis, 2004; Nunn, 2007; Chor, 2010) because the results can be comparable with them and because the data are comparable across different periods within my paper. This is vital as my focus is on the changes in the coefficients over time.

Figure 2: Estimates of Importance of Skill Abundance in Comparative Advantage



Note: The figures show the estimates of coefficients β_t in equation (5) in each point time separately. The bars indicate 95% confidence intervals based on heteroskedasticity-robust standard errors, clustered at the origin-sector level.

by the ratio of college-educated workers to non-college-educated workers, becomes increasingly less important as a driver of comparative advantage in skill-intensive sectors and now no longer matters at all.

Alternative Specifications from Previous Papers While this paper is the first to show the evolution of comparative advantage over time by running the same specification (5) over time, several papers have used similar specifications at the cross-section level using data from the 1980s or 1990s (e.g. Chor (2010); Morrow (2010); Romalis (2004); Nunn (2007); Levchenko (2007)). Consistent with my findings for these periods, all these papers find that skill abundance matters for comparative advantage in skill intensive sectors. I now briefly review this literature and show mu findings for most recent decades replicates with their specifications.

My specification is almost identical to the one in Chor (2010), differing only in two small ways. First, Chor (2010) does not partial out the exporter-importer fixed effects and instead includes several exporter-importer (i, j) level variables, such as physical distance, common languages, or trade agreements, because his goal is to explore broader sources of comparative advantage. My specification of Equation (5) nonparametrically controls these exporter-importer (i, j) level variables by the fixed effects, $\eta_{i,j,t}$, and focuses only on the variation at exporter-sector (i, s) level, that is relevant for my focus on comparative advantage of skill-abundant countries in skill-intensive sectors. Second, Chor (2010) uses the log of the ratio of non-production workers in sector $\ln(H_s/L_s)$ instead of skill intensity α_s^H despite deriving a specification that calls for the skill intensity is α_s^H. Nevertheless, my results are robust to using the same variable as Chor (2010). Figure C.3 in Appendix C shows the result using the factor intensity definition of Chor (2010) and confirms that the coefficient decreases in the same manner.

Other papers which adopt related specifications include Davis and Weinstein (2001), Romalis (2004), Nunn (2007), or Levchenko (2007).[14] They aggregate bilateral trade flows to total exports at the exporter-sector level and regress these aggregate exports on different potential sources of comparative advantages. They also find that skill-abundant countries or regions have relatively larger exports in skill-intensive sectors at each point in their sample periods. Conceptually, their specifications and the specification in (5) are similar in that both focus on the variation at the origin-sector (i, s) level. Importantly, however, the specification (5) allows me to include the origin-destination fixed effects, $\eta_{i,j,t}$, and the destination-sector fixed effects, $\eta_{j,s,t}$. These fixed effects can isolate the effect of having neighborhood countries with particular sectoral preferences or policies.[15] Nevertheless, the result that a country's skill abundance becomes less important for comparative advantage in skill-intensive sectors is robust to using the specification using the total exports as the dependent variable. Figure C.4 in Appendix C shows the result using the total exports at the origin-sector level as outcome variables as in Romalis (2004) and others and confirms that the coefficient decreases in the same manner.

Some Alternative Explanations Before exploring my main candidate hypotheses behind the decreases in $\widehat{\beta}_t$, which is the rise of automation and offshoring, in Section C, I show that the decline in $\widehat{\beta}_t$ is robust across different specifications and is inconsistent with several more mechanical explanations. Figure 3 shows these results.

Additional Sources of Comparative Advantage One concern is that my main specification only includes the interaction of a country's skill abundance and a sector's skill intensity, and thus, some other sources of comparative advantage, omitted from the specification, may cause biases. Figure 3a adds another term to consider capital intensity and capital endowment across countries as follows.

[14] For Nunn (2007) and Levchenko (2007), the importance of skill abundance is not their main subject of interest. However, they include the interaction between the country's skill abundance and the sector's skill intensity as a covariate and show the importance of skill abundance in comparative advantage.

[15] Note that collapsing to the exporter-sector level aggregates *after* taking the log of trade flows at the exporter-importer-sector level becomes almost identical to my specification, only differing in using the PPML to deal with zero trade flow.

$$X_{i,j,s,t} = \exp\left[\beta_t \cdot \left(\alpha^H_{s,t} \times \ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right) + \beta^K_t \left(\alpha^K_{s,t} \times \ln\left(\frac{K_{i,t}}{L_{i,t}}\right)\right) + \eta_{i,j,t} + \eta_{j,s,t}\right] + \varepsilon_{i,j,s,t}, \quad (6)$$

In this specification, I use measures of skill intensity, $\alpha^H_{s,t}$, and capital intensity, $\alpha^K_{s,t}$, from a value-added share of production labor and a value-added share of capital, both from the NBER-CES Manufacturing Industry Database (Becker et al., 2021). I use a measure of capital abundance relative to labor, $K_{i,t}/L_{i,t}$, from the capital-to-low-skilled-labor ratio using data of the real capital stock and employment Penn World Table (PWT) data (Feenstra et al., 2015).[16] Figure 3b further adds the interaction of the importance of institutions across sectors and rules of law across countries, following Nunn (2007). The patterns in Figure 3a and 3b are similar to the one in Figure 2 in that the key coefficient β_t on becomes increasingly smaller over the years and that the estimate has become insignificant after 2000.

Weights Another concern is that some small countries drive the results and do not describe trade patterns in the world. Figure 3c weights each observation by the total volume of exports for that country-year pair. Results are unchanged.

Unobserved Heterogeneity at Exporter-Sector Level Figure 3d pools the samples for all the years and includes fixed effects at the exporter-sector level. This specification controls for unobserved heterogeneity at the exporter-sector level and focuses on the variations over time. The pattern is still unaffected.

Fixing Factor Endowment and/or Intensity Data in 1980 One may think that decreasing $\widehat{\beta_t}$ may just be the result of increasing measurement errors in the running variable. For example, as the cohort size of the college-educated increases, unobserved heterogeneity, such as school quality, can become more heterogeneous within the college-educated, and this mechanically attenuates the estimate toward zero. To address this concern, I replace a country's skill abundance in each year, $H_{i,t}/L_{i,t}$, with the one in 1980, $H_{i,1980}/L_{i,1980}$, and/or a sector's skill intensity in each year, $\alpha^H_{s,t}$, with the one in 1980, $\alpha^H_{s,1980}$. Figure 3e uses a country's skill abundance in 1980 for the entire sample period, and Figure 3f uses a sector's skill intensity in 1980 for the entire sample period. Figure 3g uses both measures in 1980 for the entire sample period. The decreasing pattern of β_t holds.

[16] I divide real capital stock by the number of non-college-educated people, which is computed from employment in PWT multiplied by the share of non-college-educated people in the Barro-Lee Dataset.

Alternative Skill Endowment Measures Figure 3h uses high school graduates to others for skilled to non-skilled labor ratio, using the same data source (Barro and Lee, 2013). Figure 3i replaces $H_{i,t}/L_{i,t}$ with the old-to-middle workers ratio, the ratio of workers aged above 55 to those aged 25 to 54, Acemoglu and Restrepo (2022a). The patterns of β_t hold with these alternative measures.

3 Potential Hypotheses: Automation and Offshoring

The result in Figure 2 suggests that in recent decades skill endowments have become less important as a source of comparative advantage. In this section, I investigate the potential forces driving this shift, focusing on two major trends that have reshaped the global economy in recent decades: automation and offshoring.[17] While I present a formal analysis in Section 4, I briefly explain why automation and offshoring can potentially change the roles of skill abundance in comparative advantage. Automation replaces low-skilled workers who complete routine tasks with machines. This task displacement allows firms to rely on machines instead of low-skilled workers, and domestic abundance of low-skilled workers can become less important for comparative advantage. Similarly, offshoring replaces domestic factors, including labor, with foreign factors. This displacement allows firms to rely on foreign factors, and domestic factor abundance becomes less relevant in production.

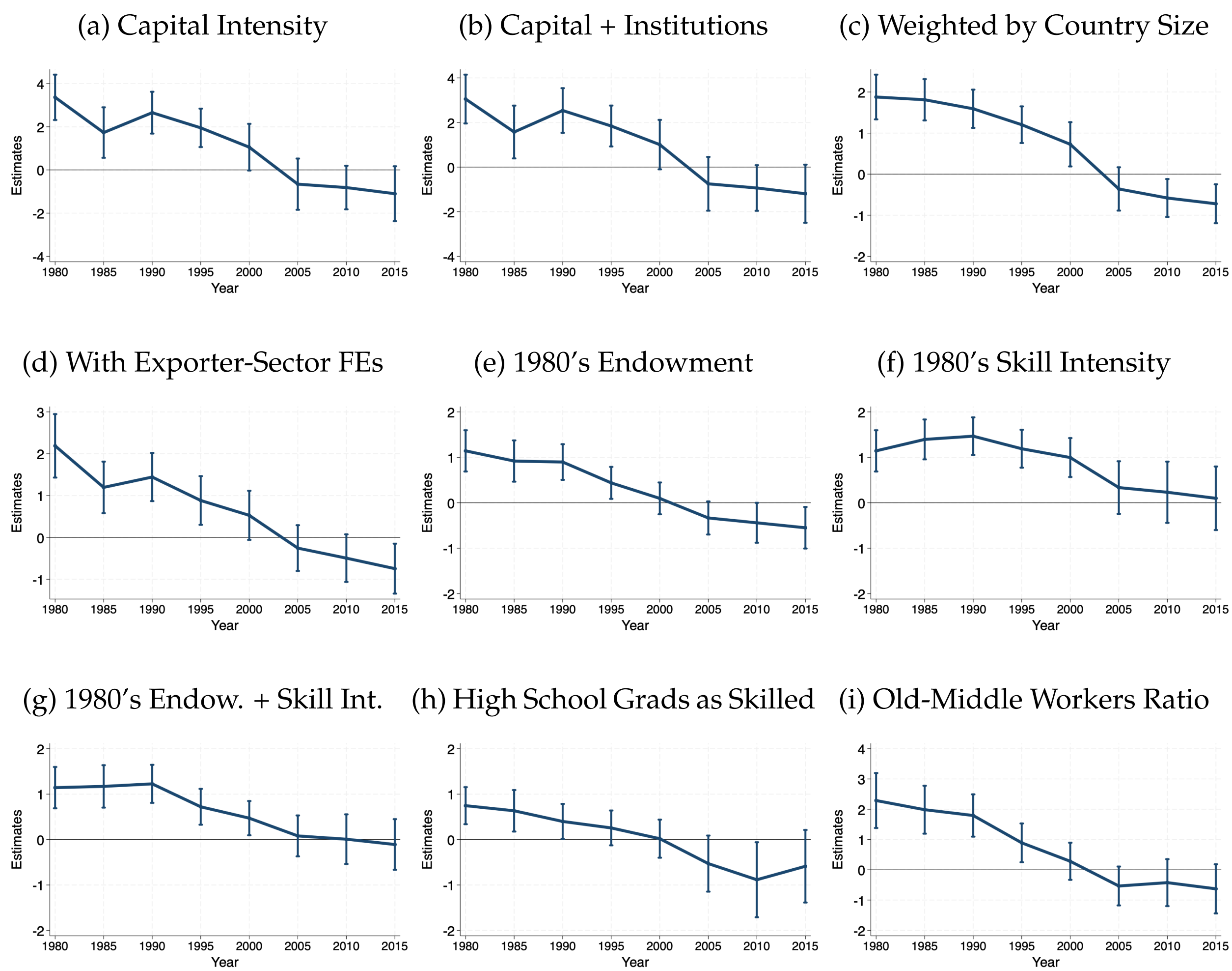
3.1 Rises of Automation and Offshoring

Before going into the analyses, I provide a quick overview of the trends in automation and offshoring during the period. Figure 4 shows the trends in automation and offshoring since 1995. Panel 4a shows the robots per thousand industry workers, which is a typical measure of automation in the literature (e.g. Acemoglu and Restrepo (2020)). I plot the average number of robots per thousands industry workers for G10 and non-G10 countries, using data from the IFR data. The degrees of automation, measured by robots per thousand workers, increase for both groups, and the level is higher for G10 countries with around 10 robots per one thousand workers, compared to 2 robots per thousand workers for non-G10 countries.

Panel 4b shows the share of imports in total intermediate uses, which is a typical measure of offshoring in the literature (e.g. Feenstra and Hanson (1996); Hanson and Harrison

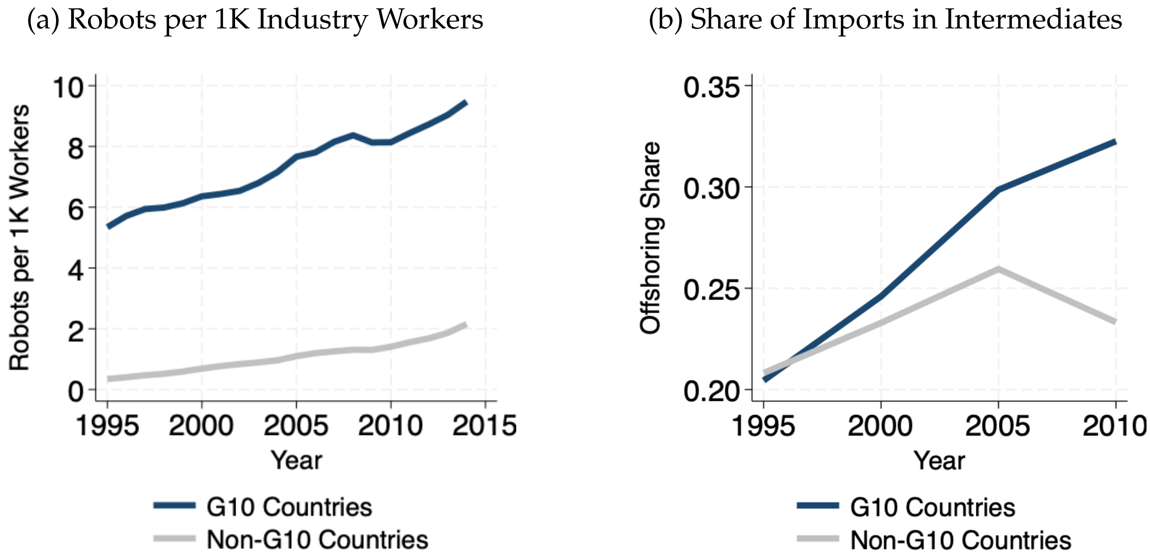
[17]Several papers argue that automation or offshoring changes the patterns of trade. For example, Artuc et al. (2023) show that automation spurs trade between the North and South. Yi (2003) shows that vertical specialization, which is closely connected to offshoring, incrases trade volumes.

Figure 3: Importance of Skill Abundance in Comparative Advantage: Robustness Check



Notes: The figures show the estimates of coefficients β_t in equation (5) in each point time separately under various specifications. The bars indicate 95% confidence intervals based on heteroskedasticity-robust standard errors, clustered at the origin-sector level. Figure 3a adds the interaction of capital intensity and capital endowments as an additional control. Figure 3b further adds institution intensity and institution endowment terms as in Nunn (2007). Figure 3c weighs counties by total exports in each year. Figure 3d pools the samples for all the years and includes fixed effects at the exporter-sector level. Figure 3e uses a country's skill abundance in 1980 for the entire sample period, and Figure 3f uses a sector's skill intensity in 1980 for the entire sample period. Figure 3g uses both measures in 1980 for the entire sample period. Figure 3h replaces skill endowments based on college graduation with those based on high school graduates. Figure 3i replaces $H_{i,t}/L_{i,t}$ with the old-to-middle workers ratio, the ratio of workers aged above 55 to those aged 25 to 54, Acemoglu and Restrepo (2022a).

Figure 4: Automation and Offshoring



Notes: The figures show the trends in automation and offshoring. The left panel shows the number of robots per thousand industry workers from Acemoglu and Restrepo (2022a). The data is originally from the IFR (for robot data) and the ILO (for worker data). The right panel shows the share of imports in intermediates from the World Input-Output Database Release (Timmer et al., 2015). Both measures are the weighted average of the countries in each group, using a country's real GDP in Penn World Table Feenstra et al. (2015) as weights.

(1999)). I plot the average offshoring shares for G10 and non-G10 countries, using data from the World Input-Output Database (Timmer et al., 2015). While both groups start with 20% in 1995, G10 countries increase the offshoring share to 32% in 2010 while non-G10 countries increase the offshoring share only to 23%.

3.2 Specifications for Heterogeneity

With the measures of automation and offshoring above, I now study if the changes in comparative advantage in 2 are different across countries and sectors with differential exposures to automation and offshoring.

Discrete Measures The first specification is to define groups of countries and sectors with high degrees of automation or offshoring and to let the importance of skill abundance in comparative advantage depend on automation or offshoring. Specifically, for automation, I estimate the following:

$$X_{i,j,s,t} = \exp\left[\beta_t^0\left(1+\beta_t^A HA_{i,s}\right)\cdot\left(\alpha_{s,t}^H \times \ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right) + \eta_{i,j,t} + \eta_{j,s,t}\right] + \varepsilon_{i,j,s,t}, \qquad (7)$$

where $HA_{i,s}$ is a dummy variable that takes one if the number of robots per workers in 2015 is in the top 33% of the all pairs of countries and sectors and zero otherwise. Compared to the baseline specification (5), I have an additional term, $\beta_t^A HA_{i,s}$. The interpretation of β_t^0 is the importance of a country's skill abundance in comparative advantage in skill-intensive sectors for low-automation groups while the interpretation of $\beta_t^0\left(1+\beta_t^A\right)$ is the one for high-automation groups.

For offshoring, the specification is equivalent as follows:

$$X_{i,j,s,t} = \exp\left[\beta_t^0\left(1+\beta_t^O HO_{i,s}\right)\cdot\left(\alpha_{s,t}^H \times \ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right) + \eta_{i,j,t} + \eta_{j,s,t}\right] + \varepsilon_{i,j,s,t}, \qquad (8)$$

where $HO_{i,s}$ is a dummy variable that takes one if the offshoring share in 2015 is in the top 33% of the all pairs of countries and sectors and zero otherwise.

Figure 5 shows the results. Panel 5 plots the estimates of β_t^0 and $\beta_t^0(1+\beta_t^A)$ in the gray and navy lines, respectively. The bars are the 95% confidence intervals based on the standard errors clustered at the exporter-sector level and computed using the delta method. While $\widehat{\beta_t^0}$ is still positive and significant in 2015, $\widehat{\beta_t^0}(1+\widehat{\beta_t^A})$ becomes negative after 2000. This means that the a country abundance no longer matters for comparative advantage only in countries and sectors with high automation. Similarly, Figure 5b plots the estimates of β_t^0 and $\beta_t^0(1+\beta_t^O)$. Both estimates decrease similarly, and there is no clear heterogeneity across countries and sectors with different levels of offshoring.

These results are robust across different specifications, such as defining the high-groups below and above the median, using the different measures of skill intensity α_s^H, or normalizing the offshoring measures by a country's import penetration ratio.[18]

Continuous Measures The previous specifications using the discrete measures of automation and offshoring are simple and transparent but ignore the more granular heterogeneity within the high groups or a potential correlation between automation and offshoring. To supplement the results based on the discrete measures, I now show the results using the continuous measures. In particular, my estimation equation is as follows:

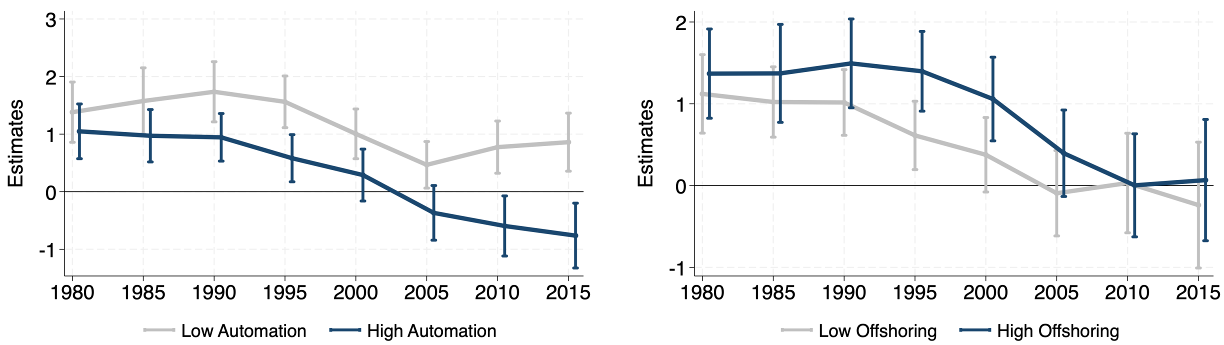
$$X_{i,j,s,t} = \exp\left[\beta_t^0\left(1+\beta_t^A \text{Auto}_{i,s} + \beta_t^O \text{Ofs}_{i,s}\right)\cdot\left(\alpha_{s,t}^H \times \ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right) + \eta_{i,j,t} + \eta_{j,s,t}\right] + \varepsilon_{i,j,s,t}, \qquad (9)$$

[18] See Appendix D for details.

Figure 5: Estimates of Importance of Skill Abundance in Comparative Advantage: Trends by Groups using Time-Invariant Dummy Variables

(a) Automation

(b) Offshoring



Notes: The figures show the estimates of the importance of skill abundance in comparative advantage in skill-intensive sectors. Panel 5a plots the estimates of β_t^0 and $\beta_t^0(1+\beta_t^A)$ in the gray and navy lines, respectively. Panel 5b plots the estimates of β_t^0 and $\beta_t^0(1+\beta_t^O)$ in the gray and navy lines, respectively. In both panels, The bars are the 95% confidence intervals based on the standard errors clustered at the exporter-sector level and computed using the delta method.

where $\text{Auto}_{i,s}$ is the log robot stocks in 2015 for country i and sector s, and $\text{Ofs}_{i,s}$ is the offshoring share in 2010 for country i and sector s.

Table 1 shows the results on how skill abundance influences comparative advantage, accounting for automation and offshoring. Columns (1), (3), (5), and (7) show the estimates of the interaction between the exporter's skill abundance and the sector's skill intensity. These estimates represent the time-varying coefficient β_t, which captures the strength of this relationship. In 1995, the estimate is positive and statistically significant, but it becomes negative and statistically insignificant after 2000. This trend reflects a weakening relationship between skill abundance and comparative advantage over time, consistent with what is shown in Figure 2.

Columns (2), (4), (6), and (8) include additional interaction terms to account for automation and offshoring. Specifically, these columns use measures of automation, represented by the log of robot stock in 2015, and offshoring, represented by the offshoring share in 2010 (multiplied by 100). The coefficient $\widehat{\beta_t^0}$, which represents the baseline impact of skill abundance on comparative advantage in sectors with minimal automation and offshoring, remains positive and fairly stable from 2005 to 2010, indicating that skill abundance is still relevant for sectors with limited exposure to these technologies.

The coefficient $\widehat{\beta_t^A}$, which captures how automation affects the importance of skill abundance, is negative and statistically significant. This suggests that in sectors with

Table 1: Importance of Skill Abundance in Comparative Advantage: Roles of Automation and Offshoring, Continuous Measures

	Dep. Var. Bilateral Trade Flow							
	1995	1995	2000	2000	2005	2005	2010	2010
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Int. x Abd.	1.26	3.00	0.79	2.26	-0.04	2.85	-0.33	3.49
	(0.23)	(0.41)	(0.26)	(0.46)	(0.28)	(0.47)	(0.28)	(0.57)
x Automation		-0.19		-0.14		-0.26		-0.35
		(0.05)		(0.05)		(0.05)		(0.06)
x Offshoring		0.04		0.04		0.03		0.05
		(0.05)		(0.06)		(0.06)		(0.07)
Observations	419,398	419,398	422,059	422,059	422,756	422,756	420,603	420,603
Exp.-Imp. FE	✓	✓	✓	✓	✓	✓	✓	✓
Imp.-Sec. FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table shows the results for the importance of skill abundance in comparative advantage, estimated based on equation (9). The dependent variable is the bilateral trade flow. Columns (1) and (2), (3) and (4), (5) and (6), and (7) and (8) use the data for 1995, 2000, 2005, and 2010 respectively. All columns include (a) the interaction between the exporter's skill abundance and the sector's skill intensity as the running variable, (b) the interaction of (a) with log robot stock in 2015, and (c) the interaction of (a) with offshoring shares in 2010 (multiplied by 100). All columns include exporter-importer fixed effects and importer-sector fixed effects. The standard errors are in parentheses and clustered at the exporter-sector level.

higher levels of automation, skill abundance is progressively less important for comparative advantage. The values of $\widehat{\beta_t^A}$ become more negative over time, indicating an increasing effect of automation on diminishing the role of skill abundance.

The coefficient $\widehat{\beta_t^O}$, which measures the impact of offshoring on skill abundance's relevance, is statistically insignificant across all specifications. This implies that offshoring does not associate with the importance of skill abundance for comparative advantage.

To quantify the impact of automation, consider the example of the German automobile sector, which has a high log robot stock of 12.2. In this sector, the relationship between skill abundance and trade flows becomes negative, as shown by the calculation $\widehat{\beta_t^0}(1 + \beta_t^A \times \text{Auto}_{i,s}) = 3.49 - 0.35 \times 12.2 = -0.78$. By contrast, in the Indian textile sector, which has a much lower log robot stock of 2.3, skill abundance still has a positive relationship with trade flows: $\widehat{\beta_t^0}(1 + \beta_t^A \times \text{Auto}_{i,s}) = 3.49 - 0.35 \times 2.3 = 2.69$. This example illustrates how automation can reduce the relevance of skill abundance in predicting trade flows.[19]

[19]Table D.1 shows the results when I define the skill intensity as the value-added share of skilled labor's payroll, instead of the payroll share, and the results are robust.

4 Trade Model with Automation and Offshoring

In this section, I develop a quantitative trade model with automation and offshoring to quantify the mechanisms and to draw implications for macroeconomic outcomes, such as manufacturing shares, skill premia, and welfare. The model embeds the task framework of Acemoglu and Restrepo (2018) and Acemoglu and Restrepo (2022a) into a multi-sector, multi-factor Eaton-Kortum model with input-output linkages.

4.1 The Model

There are I countries and S sectors. I denote countries by i and j and sectors by r and s. Countries differ in primary factor endowments—high-skilled H_i and low-skilled labor L_i. These labor endowments are the only primary factors in this model. Sectors differ in factor shares as explained later. All markets are perfectly competitive and both types of labor are freely mobile across sectors but not across countries.

Compared to the standard multi-sector Eaton-Kortum model, the key difference is the unit production cost $c_{i,s}$, incorporating automation and offshoring. Specifically, the production side follows the task framework developed by Acemoglu and Restrepo (2018), extended to incorporate two types of labor by Acemoglu and Restrepo (2022a), and generalized to include multiple factors within the task framework by Acemoglu and Restrepo (2022b).

Technology: Final Goods Gross output in sector s in country i is produced by combining high-skilled labor $H_{i,s}$ and production task composites $T_{i,s}$ produced by low-skilled labor, machines, domestic intermediates, and foreign intermediates. Here, machines include equipment and exclude structures, such as buildings.

The gross production function of a variety $\omega \in \Omega \equiv \{1, ..., +\infty\}$ is

$$Y_{i,s} = z_{i,s}(\omega) \cdot (H_{i,s}(\omega))^{\alpha_s^H} \cdot (T_{i,s}(\omega))^{1-\alpha_s^H}, \tag{10}$$

where $z_{i,s}(\omega)$ is the productivity for the ωth variety of country i and sector s, α_s^H is the factor share of high-skilled labor. [20]

As in Eaton and Kortum (2002), for all countries i, sectors s, and varieties ω, I assume that the productivity $z_{i,s}(\omega)$ is a random variable drawn independently for each

[20]This unitary elasticity of substitution across high-skilled labor and task composites follows Acemoglu and Restrepo (2022a). This is for simplicity and to highlight the substitution across low-skilled labor and automation or offshoring.

pair (i, s, ω) from a Fréchet distribution $F_{i,s}(\cdot)$ such that $F_{i,s}(\cdot) = \exp[-(z/z_{i,s})^{-\theta}]$ for all $z \geq 0$, where $z_{i,s} > 0$ and $\theta > 1$. Final goods can be used as final consumption, intermediate, or machines.

Technology: Production Task Following Acemoglu and Restrepo (2022b), tasks are combined as follows:

$$T_{i,s}(\omega) = \exp\left(\int_0^1 \ln T_{i,s}(\omega, x)dx\right).$$

Task $T_{i,s}(\omega, x)$ can be produced either by low-skill labor, machines, or intermediates:

$$\begin{aligned} T_{i,s}(\omega, x) = {} & A^M \psi_{i,s}^M(x) M_{i,s}(\omega, x) + A^L \psi_{i,s}^L(x) L_{i,s}(\omega, x) \\ & + A^{XD} \psi_{i,s}^{XD}(x) XD_{i,s}(\omega, x) + A^{XF} \psi_{i,s}^{XF}(x) XF_{i,s}(\omega, x), \end{aligned} \tag{11}$$

where $M_{i,s}(\omega, x), L_{i,s}(\omega, x), XD_{i,s}(\omega, x), XF_{i,s}(\omega, x)$ are machines, low-skill labor, domestic intermediates, and foreign intermediates. A^M, A^L, A^{XD}, and A^{XF} are factor-augmented technology, which makes each factor more productive equally across tasks. $\psi_{i,s}^M(x)$, $\psi_{i,s}^L(x)$, $\psi_{i,s}^{XD}(x)$. and $\psi_{i,s}^{XF}(x)$ are task-specific productivity components, which determine the specialization patterns of each factor across tasks. This becomes zero for factors that cannot perform a task. For example, if $\psi_{i,s}^M(x_1) = 0$ for the task $x = x_1$, this means that machines cannot do the task $x = x_1$.

Demand for machines, low-skilled labor, and intermediates across tasks within a country-sector pair (i, s) add up to aggregate factor inputs at the country-sector level,

$$\int_0^1 L_{i,s}(\omega, x)dxd\omega = L_{i,s}, \quad \int_0^1 M_{i,s}(\omega, x)dxd\omega = M_{i,s},$$

$$\int_0^1 XD_{i,s}(\omega, x)dxd\omega = XD_{i,s}, \quad \int_0^1 XF_{i,s}(\omega, x)dxd\omega = XF_{i,s}.$$

Task Share One of the most important objects in this theoretical framework is task share, which represents task allocation across factors. Cost minimization leads to the following allocation:

$$\mathcal{T}_{i,s}^{PF} = \left\{z : \frac{w_i^{PF}}{\psi_{i,s}^{PF}(z) \cdot A^{PF}} = \min_{PF' \in \{L,M,XD,XF\}} \frac{w_i^{PF'}}{\psi_{i,s}^{PF'}(z) \cdot A^{PF'}}\right\}$$

for each production factor $PF \in \{L, M, XD, XF\}$, where $\mathcal{T}_{i,s}^{PF}$ are sets of tasks allocated to factor PF.

Tasks are allocated to the factor, which is the most efficient to complete the task. As in Acemoglu and Restrepo (2022b), when a task can be produced at the same unit cost by different factors, I assume it is allocated to labor, machines, and then domestic intermediates as a tie-breaking rule.[21]

Given these task allocation rules, I define the task share as follows

$$\Gamma^{L}_{i,s} = \int_{\mathcal{T}^{L}_{i,s}} dx, \quad \Gamma^{M}_{i,s} = \int_{\mathcal{T}^{M}_{i,s}} dx, \quad \Gamma^{XD}_{i,s} = \int_{\mathcal{T}^{XD}_{i,s}} dx, \quad \Gamma^{XF}_{i,s} = \int_{\mathcal{T}^{XF}_{i,s}} dx,$$

where these quantities are the measures of the sets, $\mathcal{T}^{L}_{i,s}$, $\mathcal{T}^{M}_{i,s}$, $\mathcal{T}^{XD}_{i,s}$, $\mathcal{T}^{XF}_{i,s}$.

In this theoretical framework, automation and offshoring are isomorphic and captured by increases in $\Gamma^{M}_{i,s}$ and $\Gamma^{XF}_{i,s}$, respectively. These changes in task share decrease the task share of low-skilled workers, $\Gamma^{L}_{i,s}$.

This framework nests the previous papers in the task framework. The papers on automation literature, such as Acemoglu and Restrepo (2020) or Acemoglu and Restrepo (2022b), assume that there is no intermediate, $\Gamma^{XD}_{i,s} = \Gamma^{XF}_{i,s} = 0$, and focus on task allocations across labor (potentially multi types) and machines. Grossman and Rossi-Hansberg (2008), which studies the effects of offshoring on factor prices, assumes that there is no capital and that intermediates are supplied only from abroad, $\Gamma^{M}_{i,s} = \Gamma^{XD}_{i,s} = 0$, and the foreign intermediates are produced only using foreign labor.

Consequently, the unit production cost in country i sector s can be written as follows:

$$c_{i,s} = \Lambda_s \cdot (w^{H}_{i})^{\alpha^{H}_{s}} \cdot \left[\left(\frac{w^{M}_{i,s}}{\Gamma^{M}_{i,s}}\right)^{\Gamma^{M}_{i,s}} \cdot \left(\frac{w^{L}_{i}}{\Gamma^{L}_{i,s}}\right)^{\Gamma^{L}_{i,s}} \cdot \left(\frac{w^{XD}_{i,s}}{\Gamma^{XD}_{i,s}}\right)^{\Gamma^{XD}_{i,s}} \cdot \left(\frac{w^{XF}_{i,s}}{\Gamma^{XF}_{i,s}}\right)^{\Gamma^{XF}_{i,s}} \right]^{1-\alpha^{H}_{s}} \tag{12}$$

where Λ_s is

$$\Lambda_s = (\alpha^{H}_{s})^{-\alpha^{H}_{s}} (1-\alpha^{H}_{s})^{\alpha^{H}_{s}-1}.$$

Input-Output Linkages Machines and intermediates used in country i and sector s are sourced by different sectors $r \in \mathcal{S}$. In particular,

$$M_{i,s}(\omega, x) = \prod_{r \in \mathcal{S}} [M_{i,r,s}(\omega, x)]^{\alpha^{M}_{i,rs}},$$

$$XD_{i,s}(\omega, x) = \prod_{r \in \mathcal{S}} [XD_{i,r,s}(\omega, x)]^{\alpha^{X}_{i,rs}}, \quad XF_{i,s}(\omega, x) = \prod_{r \in \mathcal{S}} [XF_{i,r,s}(\omega, x)]^{\alpha^{X}_{i,rs}},$$

[21] This simplifies the exposition and has no substantial consequences.

where $\alpha^M_{i,rs}$ and $\alpha^X_{i,rs}$ are the shares of materials from sector r used in the production of machines and intermediate goods respectively, with

$$\sum_{r\in\mathcal{S}} \alpha^M_{i,rs} = \sum_{r\in\mathcal{S}} \alpha^X_{i,rs} = 1.$$

This leads to the following expression for factor price:

$$w^u_{i,s} = \prod_r \left(\frac{w^u_{i,rs}}{\alpha^u_{i,rs}}\right)^{\alpha^u_{i,rs}}, \tag{13}$$

where $w^u_{i,rs}$ is the price of goods in country i, sector s, and usage $u = \{M, XD, XF\}$ sourced from r.

Market Structure The market structure is standard as in Eaton and Kortum (2002) and Costinot et al. (2012). I assume that markets for final goods, machines, and intermediates are perfectly competitive. With constant returns to scale in production, this implies that in any country i and sector s, for a usage $u \in \{F, M, X\}$ (F : final consumption, M : machine, X : intermediate), the price $p^u_{i,s}(\omega)$ paid by buyers of variety ω is

$$p^u_{i,s}(\omega) = \min_{i\in\mathcal{I}^u_i}[c^u_{i,k}(\omega)] \tag{14}$$

where $\mathcal{I}^u_i = \mathcal{I}$ for $u = F, M$, $\mathcal{I}^u_i = \mathcal{I}/i$ for $u = XF$. The unit cost for each variety ω is given as follows:

$$c^u_{i,k}(\omega) = (\tau^u_{i,j,k} \cdot c_{i,k})/z_{i,k} > 0,$$

and $\tau^u_{i,j,k}$ is the iceberg trade cost that satisfies

$$\tau^u_{i,i,k} = 1, \quad \tau^u_{i,l,k} < \tau^u_{i,j,k} \cdot \tau^u_{j,l,k}.$$

The second assumption simply rules out cross-country arbitrage opportunities.

Preference for Final Goods Consumption In each country, there is a representative household with a two-tier utility function consuming final goods. The upper tier utility function across sectors is the Cobb-Douglas with the expenditure share $\mu_{j,s}$ where $\sum_{s\in\mathcal{S}} \mu_{j,s} = 1$. The lower tier utility function across varieties within each sector is CES. Thus, in country j, total expenditure on variety ω in sector s as final goods consumption is

$$X^F_{j,s}(\omega) = [p^F_{j,s}(\omega)/p^F_{j,s}]^{1-\sigma} \cdot \mu_{j,s} \cdot \left(w^L_j L_j + w^H_j H_j\right)$$

where $\sigma < 1+\theta$, $p^F_{j,s} \equiv \left[\sum_{\omega' \in \Omega} (p^F_{j,s})^{1-\sigma}\right]^{1/(1-\sigma)}$, and w^L_j and w^H_j are wages for low-skilled and high-skilled workers in country j, respectively.

This leads to the following expression of the trade share for final consumption goods:

$$\pi^F_{ij,s} = \frac{(c_{i,s}\tau^F_{ij,s})^{-\theta}}{\sum_l (c_{l,s}\tau^F_{lj,s})^{-\theta}}. \tag{15}$$

Souring of Machines and Foreign Intermediates Similarly, machines and intermediates are sourced from different varieties ω within each country-sector.[22] Then, in country j, total expenditure on variety ω in sector s as a usage $u \in \{M, XF\}$ is

$$X^u_{j,s}(\omega) = [p^u_{j,s}(\omega)/p^u_{j,s}]^{1-\sigma} \cdot X^u_{j,s}$$

where $p^u_{j,s} \equiv \left[\sum_{\omega' \in \Omega} (p^u_{j,s})^{1-\sigma}\right]^{1/(1-\sigma)}$ and $X^u_{j,s}$ is the total expenditure in country j and sector s for a usage $u \in \{M, XF\}$.

This leads to the following expression of the trade share for machines and foreign intermediates:

$$\pi^u_{ji,r} = \frac{(c_{j,r}\tau^u_{ji,r})^{-\theta}}{\sum_{l \in \mathcal{I}^u_i} (c_{l,r}\tau^u_{li,r})^{-\theta}}, \tag{16}$$

for usage $u = M, XF$.

The price in country i and sector s sourced from sector r for usage $u = M, XF$ is given by

$$w^u_{i,rs} = \left(\sum_{j \in \mathcal{I}^u_i} (c_{j,r}\tau^u_{ji,r})^{-\theta}\right)^{-1/\theta}. \tag{17}$$

Trade Balance I denote $X^u_{i,j,s} \equiv \sum_{\omega \in \Omega^u_{i,j,s}} X^u_{i,j,s}(\omega)$ the value of total exports from country i to j in sector s for usage u, where $\Omega^u_{i,j,s} \equiv \{\omega \in \Omega | c_{i,j,s}(\omega) = \min_{i' \in \mathcal{I}^u_j} c_{i',j,s}(\omega)\}$ is the set of varieties exported by country i to j in sector s. Also, I denote the trade share $\pi^u_{i,j,s} = X^u_{i,j,s} / \sum_{i' \in \mathcal{I}^u_j} X^u_{i',j,s}$ for each exporter i, importer j, sector s, and usage u. With these

[22] This structure is the same as Caliendo and Parro (2015).

notations, I assume that for any country i, trade is balanced:

$$\sum_{j\in\mathcal{I}}\sum_{s\in\mathcal{S}}\pi^F_{i,j,s}\mu_{j,s}\zeta_j=\zeta_i \tag{18}$$

where $\zeta_i \equiv (w^L_i L_i + w^H_i H_i)/\sum_{i'}(w^L_{i'}L_{i'}+w^H_{i'}H_{i'})$ is the share of country i in world income.

Goods Market Clearing Output in country i and sector s, $Y_{i,s}$, can be used as final consumption, machines service, or intermediates. Thus, the good market clearing condition is as follows

$$\begin{aligned}Y_{i,s}=&\underbrace{\sum_j \pi^F_{ij,s}\mu_{j,s}(w^L_j L_j+w^H_j H_j)}_{\text{Final Consumption in } j}+\underbrace{\sum_j\sum_r \pi^M_{ij,r}\alpha^M_{j,sr}(1-\alpha^H_r)\Gamma^M_{j,r}Y_{j,r}}_{\text{Machine Service in } j-r}\\&+\underbrace{\sum_r \alpha^X_{i,sr}(1-\alpha^H_r)\Gamma^{XD}_{i,r}Y_{i,r}}_{\text{Domestic Intermediates in } i-r}+\underbrace{\sum_j\sum_r \pi^X_{ij,r}\alpha^X_{j,sr}(1-\alpha^H_r)\Gamma^{XF}_{j,r}Y_{j,r}}_{\text{Foreign Intermediates in } j(\neq i)-r}\end{aligned} \tag{19}$$

Labor Market Clearing The labor market clearing condition is standard as follows.

$$\begin{aligned}w^L_i L_i&=\sum_s(1-\alpha^H_s)\Gamma^L_{i,s}Y_{i,s}\\w^H_i H_i&=\sum_s \alpha^H_s Y_{i,s}\end{aligned} \tag{20}$$

Equilibrium I now define formally the equilibrium in this model.

Definition 4.1. A *decentralized equilibrium* consists of a vector of wages $\{w^H_i, w^L_i\}$ that satisfies the following systems of equations for all i, j, s.

(i) Given the vector of wages, prices of machines, prices of intermediates, and unit production costs are jointly pinned down by (12), (13), and (17),

(ii) Given unit costs in each country and sector, trade shares for final goods, machines, and intermediates are determined by (15) and (16),

(iii) Trade is balanced as in (18),

(iv) Goods and labor markets clear by (19) and (20).

In the next two subsections, I examine how automation and offshoring affect comparative advantage. While the full impacts are analyzed by solving the model numerically in Section 5, the next subsections simplify the model to obtain intuitions.

4.2 Automation and Comparative Advantage

First, I study how automation affects comparative advantage. To focus on automation, assume $\Gamma_{is}^{XD} = \Gamma_{is}^{XF} = 0$.

Proposition 4.1. **(Trade Flow with Automation)** *Assume that machines are non-tradable and produced only by sector $s = R$. Also, assume that the automation share in country i and sector s satisfies $\Gamma_{i,s}^{M} = \Gamma_{i}^{M} \cdot \Gamma_{s}^{M}$ for all i, s. Then, the trade flow follows*

$$\ln X_{i,j,s} = -\theta \left(1 - \overline{\alpha_R^H} \Gamma_{i,s}^M\right) \left[\alpha_s^H \times \ln\left(\frac{w_i^H}{w_i^L}\right)\right] - \theta \overline{\alpha_R^H} \Gamma_{i,s}^M \ln\left(\frac{w_i^H}{w_i^L}\right) + \eta_{i,j} + \eta_{j,s}, \tag{21}$$

where $\overline{\alpha_R^H}$ is the skill intensity in machine-producing sector $s = R$, $\eta_{i,j}$ and $\eta_{j,s}$ are some (i, j) and (j, s) level variables, respectively.

This equation (21) extends the expression (2), which is the trade flow equation without automation. The first additional component is $-\overline{\alpha_R^H} \Gamma_{i,s}^M$ in front of the interaction term. I call this the displacement term, which is increasing in $\Gamma_{i,s}^M$. When $\Gamma_{i,s}^M$, the task share of machines (hereafter, automation share), increases, the interaction term between the sector's skill intensity and the country's relative wage (skill premium) becomes smaller. This means that automation provides countries with lower skill premia (i.e., skill-abundant countries), such as Germany, a comparative advantage in low-skill-intensive sectors, such as the automobile sector.

The second component $-\theta \overline{\alpha_R^H} \Gamma_{i,s}^M \ln\left(\frac{w_i^H}{w_i^L}\right)$ adjusts the comparative advantage of countries with lower skill premium in high automation sectors, regardless of the sector's skill intensity α_s^H.

To relate this expression to the regression, which is the comparative advantage in terms of a country's relative factor abundance, let's again assume the negative relationship between country's skill abundance and skill premia as in equation (3):

$$\ln\left(\frac{w_i^H}{w_i^L}\right) = -\gamma_{HL} \ln\left(\frac{H_i}{L_i}\right) + \nu_i,$$

where $\gamma_{HL} > 0$.[23]

Lemma 4.2. **(Trade Flow Regression with Automation)** *To simplify, further assume $\Gamma_{i,s}^M = \Gamma$*

[23] See Figure C.2 in Appendix C that this negative relationship between skill abundance and relative wages of skilled workers across countries holds in data.

for all i, s. Then, the log trade flow satisfies the following

$$\ln X_{i,j,s} = \theta \cdot (1 - \overline{\alpha_R^H}\Gamma) \cdot \gamma_{HL} \left[\alpha_s^H \times \ln\left(H_i/L_i\right) \right] + \theta \cdot \overline{\alpha_R^H}\Gamma \cdot \gamma \ln\left(H_i/L_i\right) + \eta_{i,j} + \eta_{j,s} + \varepsilon_{i,j,s}.$$

Then, the coefficient for the importance of a country's skill abundance in comparative advantage, β in the baseline specification (5) can be expressed as follows:

$$\beta = \theta \times \underbrace{(1 - \overline{\alpha_R^H}\Gamma)}_{\text{Task Displacement}} \times \underbrace{\gamma_{HL}}_{GE}. \tag{22}$$

Given the trade elasticity θ, an increase in automation Γ can affect β via two channels. The first channel is a direct task displacement effect, which increases Γ, and hence, decreases β. The intuition is that a skill-abundant (low-skill-scarce) country substitutes low-skilled labor with machines via automation to weaken the country's comparative disadvantage in low-skill-intensive sectors.

The second channel is a general equilibrium effect via the changes in skill premia across countries. In particular, if skill-abundant countries automate more and increase skill premia more, the negative relationship between countries' skill abundance and skill premia in equation (3) weakens, and γ_{HL} decreases.[24] In that case, β decreases via this channel as well.

4.3 Offshoring and Comparative Advantage

Next, I study how offshoring affects comparative advantage. To focus on offshoring, assume $\Gamma_{i,s}^M = \Gamma_{i,s}^{XD} = 0$ for all i, s. Also, assume that all countries offshore to the same, small country $i = Z$ using only low-skilled labor as inputs so that the unit cost of foreign intermediates is

$$w_{i,s}^{XF} = w_Z^L \equiv \overline{w}$$

for all i, s.

Proposition 4.3. (Trade Flow with Offshoring) *Assume that the offshoring share in country i and sector s satisfies $\Gamma_{i,s}^{XF} = \Gamma$ for all i and s. Then, the trade flow follows*

$$\ln X_{i,j,s} = -\theta \left[\alpha_s^H \times \ln\left(\frac{w_i^H}{w_i^L}\right) \right] - \theta(1 - \alpha_s^H)(1 - \Gamma)\ln w_i^L + \theta(1 - \alpha_s^H)\Gamma\overline{w} + \theta \ln w_i^L. \tag{23}$$

[24] In a closed economy setting, many papers document that automation increases skill premium or expands inequality (e.g. Acemoglu and Restrepo (2020); Dauth et al. (2021); Kikuchi (2024)).

To relate (23) to the regression (5), I assume that the negative relationship between country's skill abundance and skill premia as in equation (3) and the positive relationship between country's skill abundance and low-skilled wages:

$$\ln w_i^L = \gamma_L \ln\left(\frac{H_i}{L_i}\right) + \iota_i, \tag{24}$$

where $\gamma_L > 0$ and ι_i is an error term. This assumption means that the wages of low-skilled workers in developed countries are higher than those in developing countries. Figure E.8 in Appendix E shows that this positive relationship between skill abundance and wages of low-skilled workers across countries holds in data in 2004.

Lemma 4.4. (Trade Flow Regression with Offshoring) *The log trade flow satisfies the following equation:*

$$\ln X_{i,j,s} = \theta(\gamma_{HL} + \gamma_L(1-\Gamma))\left[\alpha_s^H \times \ln\left(H_i/L_i\right)\right] + \eta_{i,j} + \eta_{j,s} + \varepsilon_{i,j,s}.$$

Then, the coefficient for the importance of a country's skill abundance in comparative advantage, β in the baseline specification (5) *can be expressed as follows:*

$$\beta = \theta \times (\gamma_{HL} + \gamma_L(1-\Gamma)). \tag{25}$$

Equation (25) shows how offshoring Γ affects the importance of a country's skill abundance in comparative advantage β. Given the trade elasticity θ, offshoring can affect β via three channels; (1) via skill premia γ_{HL}, (2) via levels of low-skilled wage γ_L, and (3) via the direct task displacement Γ.

First, offshoring can affect the relationship between countries' skill abundance and skill premia, γ_{HL}. If offshoring increases skill premia in skill-abundant countries more, or equivalently, it increases relative low-skilled wages in skill-scarce countries more, which is intuitive, γ_{HL} increases so that β increases. In contrast, if offshoring increases skill premia in skill-scarce countries more, γ_{HL} decreases so that β decreases.

Second, offshoring can affect the relationship between countries' skill abundance and the levels of low-skilled wages, γ_L. If offshoring increases low-skilled wages in skill-scarce countries more, γ_L decreases so that β decreases. In contrast, if offshoring increases low-skilled wages in skill-abundant countries more, γ_L increases so that β increases.

Finally, offshoring can decrease β directly via the task displacement effect, which is the same effect as in the case of automation.

4.4 Changes in Skill Premium

In the previous subsections, I examine how automation and offshoring affect comparative advantage, and one of the key mechanisms, aside from direct task displacement, is the change in skill premia across countries. This section shows how automation and offshoring affect skill premia across countries.

Proposition 4.5. **(Changes in Skill Premium due to Automation and Offshoring)** Changes in the skill premium can be decomposed into task displacement and sectoral reallocation terms as follows:

$$\widehat{w_i^H} - \widehat{w_i^L} = \sum_s \left(\zeta_{i,s}^H - \zeta_{i,s}^L\right) \cdot \widehat{Y_{i,s}} + \zeta_{i,s}^L \left(1 - \widehat{\Gamma_{i,s}^L}\right) \widehat{Y_{i,s}} \tag{26}$$

where $\widehat{X} \equiv X'/X$ and $\zeta_{i,s}^H$ and $\zeta_{i,s}^L$ are sectoral share in payroll for each labor type defined as follows:

$$\zeta_{i,s}^H = \frac{\alpha_s^H Y_{i,s}}{\sum_r \alpha_r^H \cdot Y_{i,r}} = \frac{w_i^H H_{i,s}}{\sum_r w_i^H H_{i,r}}, \quad \zeta_{i,s}^L = \frac{(1-\alpha_s^H) \cdot \Gamma_{i,s}^L \cdot Y_{i,s}}{\sum_r (1-\alpha_r^H) \cdot \Gamma_{i,r}^L \cdot Y_{i,r}} = \frac{w_i^L L_{i,s}}{\sum_r w_i^L L_{i,r}}.$$

This proposition shows how skill premium changes in response to automation or offshoring, which leads to decreases in labor share, $\Gamma_{i,s}^L$. Suppose $\Gamma_{i,s}^L$ decreases and $\widehat{\Gamma_{i,s}^L} < 0$. Fixing changes in sectoral output constant, $\widehat{Y_{i,s}} = 1$, one unit of decrease in labor share increases the skill premium by $\sum_s \zeta_{i,s}^L Y_{i,s}$. In response to the decrease in labor share, sectoral outputs can also change. In particular, up to the first order ignoring the interaction between $\widehat{Y}_{i,s}$ and $\widehat{\Gamma_{i,s}^L}$, one unit of decrease in labor share changes the skill premium by $\sum_s (\zeta_{i,s}^H - \zeta_{i,s}^L) \cdot \widehat{Y_{i,s}}$ via this channel. Intuitively, if automation or offshoring increases outputs in sectors, which are important for high-skilled rather than low-skilled workers, the skill premium increases. Importantly, this also means that automation can even decrease the skill premium, which is opposite to the conventional wisdom, if automation is so productive that the sectors exposed to automation expand substantially.

5 Quantitative Analysis

In this section, I study the quantitative importance of automation and offshoring for changes in comparative advantage and the implications for structural change and welfare. First, I explain the data, the calibration strategy, and the counterfactual exercises I run. Second, I show how much automation and offshoring affect comparative advantage by running the same regression (5) in Section 2 using the data generated under counterfactual scenarios. Finally, I explore the quantitative implications for skill premia, manufacturing shares, and welfare across countries.

5.1 Data and Calibration

Data My main dataset for the quantitative analysis is the WIOD data (Timmer et al., 2015). I use 36 countries, plus the rest of the world and 18 2-digit sectors. Note that in this exercise, the sectoral coverage differs from the analysis in Section 2. I used 396 4-digit sic manufacturing sectors in Section 2 while I use 18 sectors, including service sectors here.[25] Since the WIOD with labor compensation by multiple labor types is only available between 1995 and 2008, I choose 1995 as the benchmark year, t_0.

Exact Hat Algebra I avoid explicitly calibrating the factor-specific productivity, A^F, exporter-sector-factor-task specific productivity, $\psi^F_{i,s}(z)$, and trade costs $\tau^F_{ij,s}, \tau^M_{ij,s}, \tau^X_{ij,s}$, by solving the model in percent changes from the observed equilibrium in 1995 using the exact hat algebra method pioneered by Dekle et al. (2008). This method implicitly calibrates those parameters to exactly match the factor payments in each country and trade shares. Details are in Appendix F. The only parameter I need to calibrate is the trade elasticity, θ, and I set it to be 4, which is the standard value estimated in the literature (Anderson and Van Wincoop, 2004; Simonovska and Waugh, 2014).

Baseline Year: 1995 In particular, for the benchmark year t_0, I directly use the observed values of trade shares, π_{i,j,s,t_0}, expenditure shares, μ_{i,s,t_0}, factor endowments, $\{L_i, H_i\}$, factor shares, $\{\alpha^H_{s,t_0}, \Gamma^L_{i,s,t_0}, \Gamma^M_{i,s,t_0}, \Gamma^{XD}_{i,s,t_0}, \Gamma^{XF}_{i,s,t_0}\}$, and the total factor payments by labor types, $\{w^L_i L_i, w^H_i H_i\}$ from the WIOD (Timmer et al., 2015).[26] The input-output coefficients for intermediates and machines, $\alpha^X_{i,rs}$ and $\alpha^M_{i,rs}$, are from Ding (2023).[27]

[25]The original WIOD data has 35 sectors, and I aggregate service sectors into two aggregate sectors, high-skilled service and low-skilled service sectors. High-skilled service sectors consist of Post and telecommunications, Financial Intermediation, Real Estate Activities, and Renting and Other Business Activities. The remaining service sectors are categorized as low-skilled service sectors. I drop Education, Health and Social Work, Other Community, Social and Personal Services, and Private Households with Employed Persons because of missing values in many countries.

[26]The original WIOD data has three types of labor, low-skilled, middle-skilled, and high-skilled. I combine low-skilled and middle-skilled as low-skilled labor.

[27]Ding (2023) constructs a novel dataset on inter-sectoral capital service flow. I use the input-output coefficient for capital for the ones for machines in my paper. I covert the input-output coefficients at the bilateral level to the use-country level by taking the median.

Automation and Offshoring Shocks The shocks I feed are automation and offshoring shocks. I directly feed the time paths of $\{\Gamma^M_{i,s,t}, \Gamma^{XF}_{i,s,t}\}$ as explained below. I fix the share of domestic inputs Γ^{XD}_{i,s,t_0}, and the factor share of low-skilled labor, $\Gamma^L_{i,s,t}$, is the reminder in the total cost minus the factor payment to high-skilled labor.

I define the automation shock as the change in $\Gamma^M_{i,s,t}$, which is the share of automation capital, such as machines and equipment, in-country i, sector s, and year t, which is the factor payment share for automation capital to the sum of the total cost, minus the factor payment to high-skilled labor.

The challenge here is that there is no data source for payments to automation capital, $p^M_{i,s,t}M_{i,s,t}$, across countries and sectors. Therefore, I construct it by combining (1) time-*invariant* capital income $p^K_{i,s,t0}K_{i,s,t0}$ at the country-sector level from the WIOD data, (2) time-*invariant* machine-to-capital ratio at the sector level from the NBER CES data in the US, and (3) time-*variant* robot adoption data at the country-sector level from the IFR data. In particular, I construct $p^M_{i,s,t}M_{i,s,t}$ as

$$p^M_{i,s,t}M_{i,s,t} = \underbrace{p^K_{i,s,t0}K_{i,s,t0}}_{\text{Capital Income}} \cdot \underbrace{\frac{p^M_{US,s,t0}M_{US,s,t0}}{p^K_{US,s,t0}K_{US,s,t0}}}_{\text{Machine-Capital Ratio}} \cdot \underbrace{\frac{p^R_{i,s,t}R_{i,s,t}}{p^R_{i,s,t0}R_{i,s,t0}}}_{\text{Increases in Robots}} .$$

Ideally, we would have data on payments for machines (i.e., automation capital) across countries, sectors, and years. However, the available data only cover overall capital, which is broader, and robots, which are a narrower subset of machines. Given this, I assume that the growth rate of robots and machines is the same, which justifies the expression I use.

The first term (1) sets the magnitude correctly by using capital income data. The second term (2) adjusts for the broader definition of capital, which includes buildings and other non-machine assets, ensuring that my focus remains on automation capital, specifically machines. The third term (3) incorporates the growth rate of robot adoption, a specific form of automation capital, to ensure that changes in automation capital are accurately captured across countries and sectors.

I define the offshoring shock as the share of imported intermediates in total cost minus the factor payment to high-skilled labor. I follow the literature (e.g. Feenstra and Hanson (1996)) that proxies offshoring inputs by imported intermediates. I directly compute this value from the WIOD data.

5.2 Changes in Comparative Advantage

5.2.1 Overview

In this subsection, I quantify the roles of automation and offshoring in the changes in comparative advantage, observed in Section 2. To do so, I first assume that the model economy is at the level of the benchmark year, 1995. Then, using the exact hat algebra, I consider two scenarios, (1) only the path of automation share, $\Gamma^{M}_{i,s,t}$, changes over time and (2) only the path of offshoring share, $\Gamma^{XF}_{i,s,t}$, changes over time. I then, for each scenario, run the same regression as in (5) as follows:

$$\ln(X_{i,j,s,t})' = \beta_t \left[\alpha^{H}_{s,t_0} \times \ln\left(\frac{H_{i,t_0}}{L_{i,t_0}}\right)\right] + \eta_{i,j,t} + \eta_{j,s,t} + \varepsilon_{i,j,s,t}.$$

I compare the estimates of β_t under different counterfactual scenarios with the estimates obtained from the real data in the WIOD.

Note that I fix the skill intensity and factor endowments at the level of 1995 in this counterfactual exercise. Therefore, the only time-varying variable in this regression is the trade flow, $(X_{i,j,s,t})'$ which the model generates under different counterfactual scenarios.

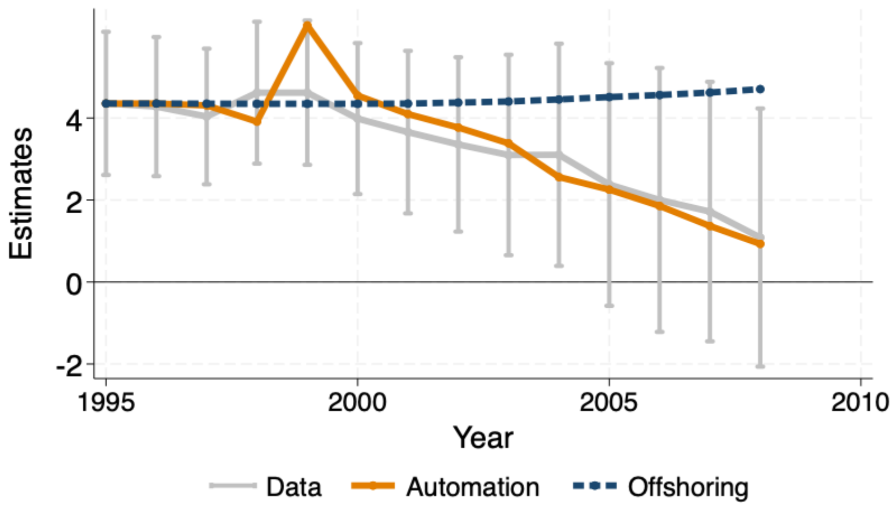
By construction, without automation and offshoring shocks, the estimate of β_t will be the constant at the level in 1995 for all the periods. Under the first counterfactual case (1) with automation shocks, the time path of the estimate of β_t will reflect how much the observed change in automation affects comparative advantage. Under the second counterfactual case (2) with offshoring shocks, the path will reflect how much the observed change in offshoring affects comparative advantage.

5.2.2 Result

Figure 6 shows the results for the importance of skill abundance in comparative advantage in the different counterfactual scenarios. To start with, the gray line shows the estimates of $\widehat{\beta}$ in the WIOD as in the data. Consistent with the findings in Section 2 where I used more detailed data from different sources, the importance of the skill abundance decreased over time.

The orange line shows the estimates based on the generated data under the counterfactual scenario where I only change the automation share over time. The time trend almost perfectly explains the path from the data, which implies that changes in automation can explain the evolution of comparative advantage well. This is surprising because I do not target any moments for automation after the benchmark year, 1995.

Figure 6: Counterfactual: Importance of Skill Abundance in Comparative Advantage



Notes: The figures show the importance of skill abundance in comparative advantage in the different counterfactual scenarios. The gray line is the path of the estimates $\widehat{\beta}$ using the WIOD with the 95% confidence interval cluster at the exporter-sector level. The orange line is the one when I only change automation share $\Gamma^M_{i,s,t}$ (and corresponding changes in $\Gamma^L_{i,s,t}$) as in the data and fix everything else at the levels in 1995. The navy line is the one when I only change offshoring share $\Gamma^{XF}_{i,s,t}$ (and corresponding changes in $\Gamma^L_{i,s,t}$) as in the data and fix everything else at the levels in 1995.

The navy dashed line shows the estimates based on the generated data under the counterfactual case where only the offshoring share changes over time. The estimates slightly increase over time and do not show any decreasing trends. This implies that offshoring cannot explain the pattern of comparative advantage over time.[28]

5.3 Macro Implications

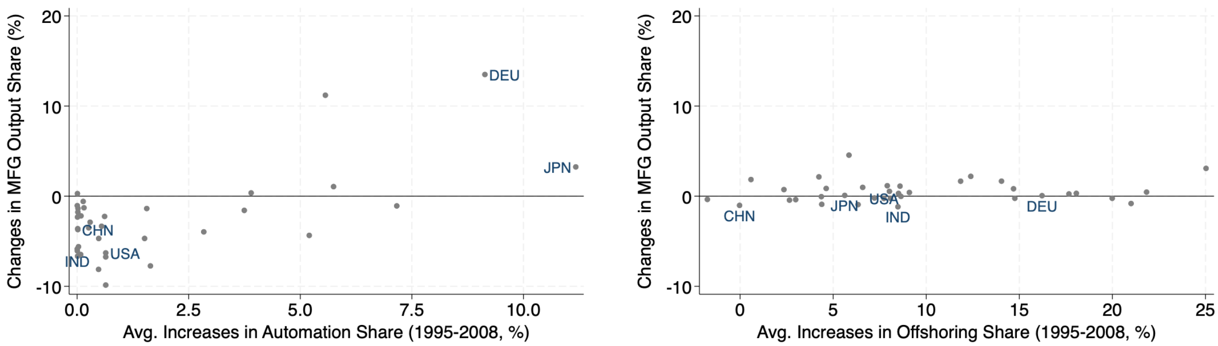
The previous subsection shows how automation and offshoring affect comparative advantage. In this subsection, I investigate the implications for macroeconomic aggregates, such as manufacturing output shares within each country, skill premia, and welfare across countries. To do so, I again assume that the model economy is at the level of the benchmark year, 1995. Then, I use the exact hat algebra to consider the following counterfactual cases, (1) automation shares are at the level of 1995 and (2) offshoring shares are at the level of 1995.

[28]Figure G.9 in Appendix shows the results when all the countries are exposed to the same magnitudes of automation shocks, $\widehat{\Gamma^L_{i,s}}$. There, I find that skill-abundant countries still have comparative advantage in skill-intensive sectors in 2008 under the counterfactual trade pattern. This implies that heterogeneous automation shocks across countries are the key to change the patterns of comparative advantage.

Figure 7: Changes in Manufacturing Output Share within Each Country

(a) Automation

(b) Offshoring



Notes:Both panels show the changes in manufacturing output share in total output in each country in response to automation (Figure 7a) and offshoring (Figure 7b) from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share (Figure 7a) or the offshoring share (Figure 7b) between 1995 and 2008. In both panels, the vertical axis shows the changes in manufacturing output share in total output in each country. Each dot represents a country.

Manufacturing Output Shares within Each Country First, I study the effect of automation and offshoring on manufacturing output shares within each country. Figure 7a shows the result for automation. The horizontal axis shows the country-level average increases in the automation share between 1995 and 2008. The vertical axis shows the country-level changes in the share of manufacturing output in total output between 1995 and 2008. Each dot represents a country. The result shows two groups of countries. The first group is a group of high-automation countries, such as Germany and Japan, which increase manufacturing output shares. For instance, Germany increases the manufacturing output share by 13% pt as it increases the automation share in each sector by 13% on average. The second group is a group of low-automation countries, such as the US, China, and India, which decrease their manufacturing shares. This indicates that automation shifts manufacturing production from low-automation countries to high-automation countries.

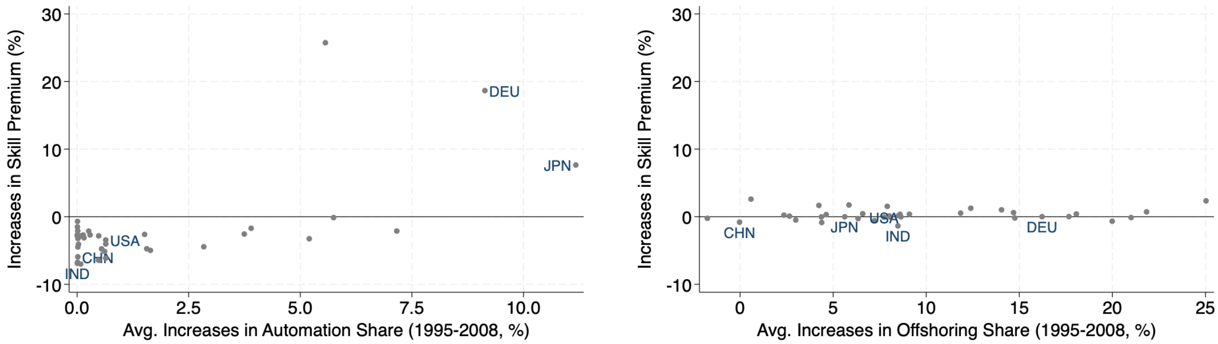
Figure 7b shows the result for offshoring. The horizontal axis now shows the country-level average increases in the offshoring share between 1995 and 2008. Compared to the results for automation, the effects of offshoring are small for most countries.

Skill Premium I then explore the implications of automation and offshoring for skill premia. Figure 8 shows the results. Figure 8a shows the changes in skill premia across countries when only automation shares changes since 1995. The horizontal axis shows the country-level average increases in the automation share between 1995 and 2008, and the

Figure 8: Changes in Skill Premia

(a) Automation

(b) Offshoring



Notes: Both panels show the changes in skill premia across countries in response to automation (Figure 8a) and offshoring (Figure 8b) from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share (Figure 8a) or the offshoring share (Figure 8b) between 1995 and 2008. In both panels, the vertical axis shows the changes in skill premia across countries. Each dot represents a country.

vertical axis shows the changes in skill premia across countries. There are two takeaways from this figure. First, there is a positive association between automation and increases in skill premia. This is consistent with the intuition that automation increases the relative demand for high-skilled labor to low-skilled labor. Second, while high-automation countries, such as Germany and Japan, increased skill premia, other countries decreased skill premia. These low-automation countries indeed reallocated resources to more low-skill-intensive sectors, and the relative demand for low-skilled workers increased, leading to declines in skill premia.

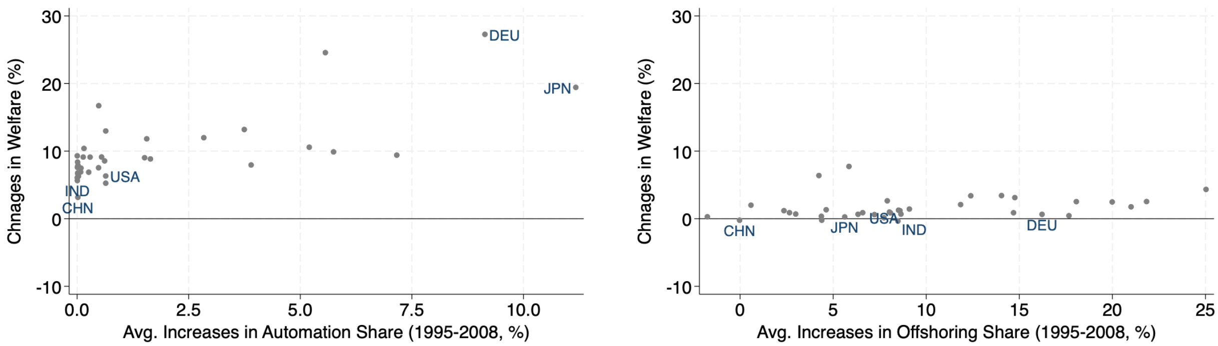
Figure 8b shows the result for offshoring. The horizontal axis shows the country-level average increases in the offshoring share between 1995 and 2008, and the vertical axis shows the changes in skill premia across countries. Compared to automation, the effect is modest, although the magnitude of the increases in offshoring shares is larger than those in automation shares.[29]

Welfare Finally, I examine the welfare effect of automation and offshoring across countries. Here, welfare change is the real consumption, which is equal to the real labor income, $(w_i^L L_i + w_i^H H_i)/P_i$ where P_i is the consumer price index for country i. Figure 9a shows the changes in welfare when only the automation shares change. All countries

[29] To investigate the roles of this sectoral reallocation, Figure G.10 in the Appendix shows the effects of automation on skill premia

Figure 9: Changes in Welfare

(a) Automation (b) Offshoring



Notes: Both panels show the changes in welfare across countries in response to automation (Figure 9a) and offshoring (Figure 9b) from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share (Figure 9a) or the offshoring share (Figure 9b) between 1995 and 2008. In both panels, the vertical axis shows the changes in welfare across countries. Each dot represents a country.

benefit from automation, and those with more automation increase welfare more. For instance, Germany with around 14% increases in automation enjoys about 30% increases in welfare. Figure 9b shows the results for offshoring. Again, all countries benefit from offshoring while there is not much heterogeneity in gains across countries.

6 Conclusion

Comparative advantage is the backbone of economics. Has the emergence of China and other developing countries made previous patterns of comparative advantage more prominent? Or has the 21st century, with new technologies such as automation, reversed these patterns, rendering them less relevant? This paper documents new evidence on the evolution of comparative advantage: skill-abundant countries no longer hold a comparative advantage in skill-intensive sectors.

First, on the empirical side, I find that a country's skill abundance was a source of comparative advantage in skill-intensive sectors during the 1980s. However, this relationship weakened in the 1990s and disappeared by the 2000s. I show that the decline is more pronounced in countries and sectors heavily exposed to automation, while no such variation exists in those more exposed to offshoring.

Second, on the quantitative side, I develop a multi-sector quantitative trade model to demonstrate that observed changes in automation largely account for this decline, whereas observed changes in offshoring do not. Using this model, I revisit the classic debate on the relationship between technology, globalization, and inequality. My findings indicate that automation in developed countries shifts manufacturing production from developing to developed economies. This shift raises skill premia in developed countries with high automation while reducing skill premia elsewhere. Welfare increases globally, but most significantly in developed countries with high automation. In contrast, offshoring redistributes manufacturing production by enabling countries to specialize in sectors where they have a comparative advantage. Consequently, offshoring has positive, albeit smaller, effects on skill premia and welfare across all countries.

In summary, this paper shows how automation and globalization expand inequality within and across countries by changing the pattern of specialization. What are the policy implications for countries with different comparative advantages as in Costinot et al. (2015)? Should policies be different in particularly for developing economies seeking to climb the technological ladder as in Atkin et al. (2021)? What are the optimal regulations on technology if governments have distributive motives as in Costinot and Werning (2023), and how might these vary across countries at different stages of development? These are open questions for future research to tackle.

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A Data Construction

In this section, I explain the data sources in this paper in detail.

A.1 Bilateral Trade Flow Data from the UN Comtrade

The main data is the bilateral trade flow data from the UN Comtrade data. First, I take the bilateral trade flow data in each year.[30] I take annual values of traded goods from 1964 to 2016 across 4-digit SITC product categories in SITC Rev. 2. I convert all trade flows into real 2015 US dollars using the US CPI from OECD (2010).

Second, using the cleaner provided by Feenstra and Romalis (2014), I construct bilateral trade flow data at the SITC Rev.2, 4-digit level across origin and destination pairs over time. This step gives primacy to importer's reports over exporter's reports where available, corrects values where UN values are known to be inaccurate, and accounts for re-exports of Chinese goods through Hong Kong.[31]

Third, I combine countries that reunify or report jointly for subsets of years in the database. I combined East and West Germany before the reunification, Belgium and Luxembourg, the islands that formed the Netherlands Antilles, North and South Yemen, and Sudan and South Sudan.

Fourth, I convert the data at the 4-digit SITC Rev.2 classification into the 4-digit SIC categories. I first map the 4-digit SITC data into the 6-digit HS 1996/2002 classification using the crosswalk provided by the United Nations. I then covert it into 4-digit SIC categories using the crosswalk by Autor et al. (2013).[32]

Finally, to remove fluctuations at annual frequency, I take moving averages over three years. For instance, to get trade flows in 2000, I take averages of the values in 1999, 2000, and 2001.

A.2 Automation and Offshoring Data

My primary measure for automation is robot adoption data from the International Federation of Robots (IFR). It is available across countries and 2-digit sectors. For country groups, I take the countries with the number of robots in 2014 above the median as high-

[30] Bulk downloads are available on their United Nation's web page here.

[31] Their cleaner is available here.

[32] The crosswalk from SITC to HS is available in the UNSD web page here. The crosswalk from HS to SIC is available on David Dorn's web page here. sic87dd is an industry classification, which Autor et al. (2013) slightly modified the SIC 4-digit code in 1987 to make the classification time-consistent. See Autor et al. (2013) for details.

automation countries and the rest as low-automation countries. These high-automation countries include Japan, the US, China, South Korea, Germany, and others and have a share of 99% of the world total. For sector groups, I take the Electronic & Other Electric Equipment sector, Transportation Equipment sector, and Plastic Chemical sector as the high-automation sectors and the rest as low-automation sectors.

My primary measure for offshoring is the share of foreign intermediate inputs, following Feenstra and Hanson (1996). For country groups, I use the data from World Input-Output Database (Timmer et al., 2015), the Long-run WIOD covering the period 1965-2000 and the Release 2016 covering the period 2000-2014. I compute the increases in the offshoring share from 1980 to 2014 and take countries above the median value of the increase in offshoring share. For sector groups, I use the US Input-Output Table as in Feenstra and Hanson (1996). I convert 6-digit sectoral categories in the IO Table into 4-digit sic codes, which I use in this paper. Since the Input-Output Table is published every five years between 1982 and 2017, I compute the increases in the offshoring share from 1982 to 2017 and take sectors above the median value of the increase in offshoring share.

B Details for Figure 1

B.1 Details on Data Construction and Definition

Data Export data is from the UN Comtrade Data. The skill intensity is defined as the share of non-production workers' payroll in total value-added in each sector in the US from the NBER CES Manufacturing Database (Becker et al., 2021).

G10 Countries G10 countries are Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, the United Kingdom, and the United States.

Definition of Revealed Comparative Advantage Following Balassa (1965), I define a revealed comparative advantage for country i, sector s, and year t as follows:

$$\mathrm{RCA}_{i,s,t} = \frac{\frac{X_{i,s,t}}{\sum_{s'} X_{i,s',t}}}{\frac{\sum_{i'} X_{i',s,t}}{\sum_{i',s'} X_{i',s',t}}}$$

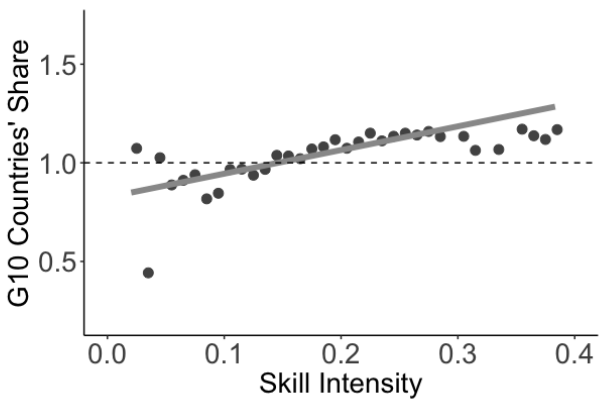
where $X_{i,s,t}$ is the total export for country i, sector s, and year t.

B.2 Robustness

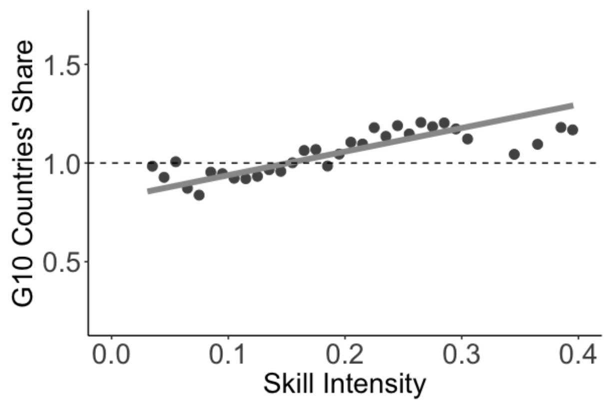
Figure B.1 shows the figures for the evolution of revealed comparative advantage of G10 countries between 1965 and 2015, for every five years. It shows that the revealed comparative advantage in skill-intensive sectors is gradually weakening but that the speed has accelerated in the 2000s.

Figure B.1: Revealed Comparative Advantage of G10 Countries in Skill-Intensive Sectors: Different Years

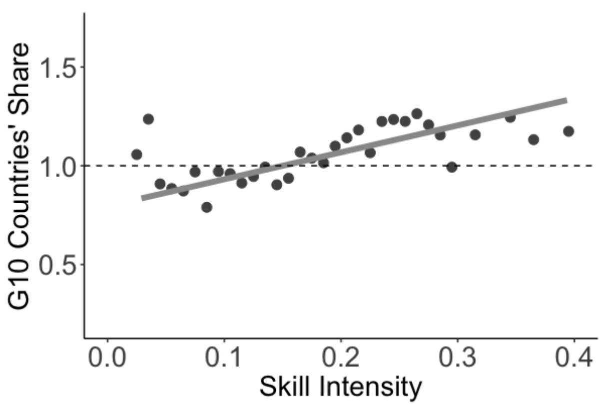
(a) 1965



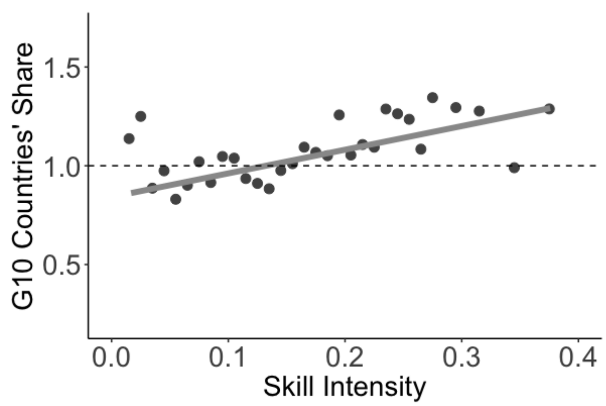
(b) 1975



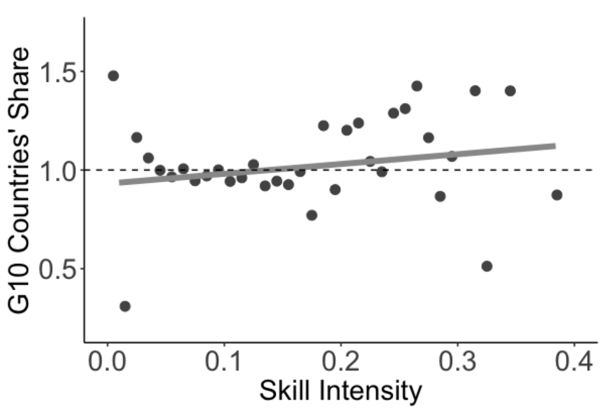
(c) 1985



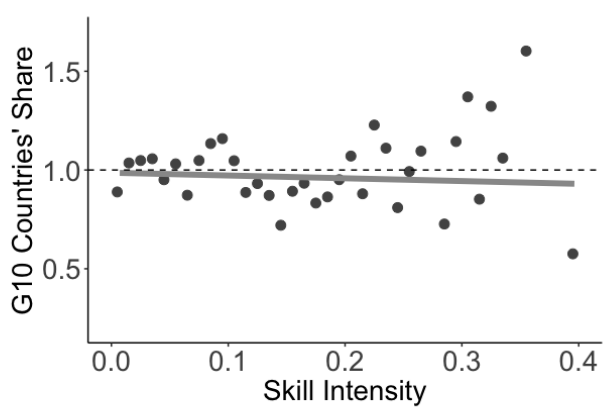
(d) 1995



(e) 2005



(f) 2015

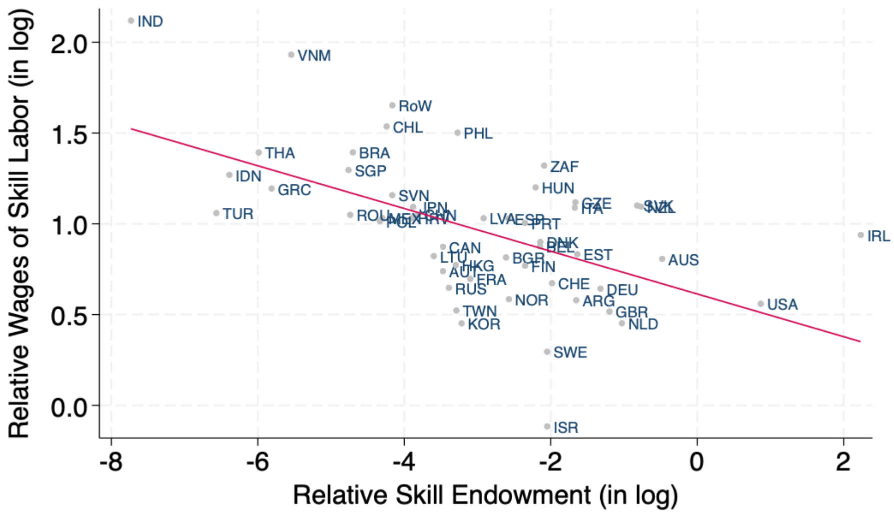


Notes: The figures show binned scatter-plots of revealed comparative advantage, a country's share of global exports in a sector divided by its share of aggregate global exports, for G10 countries across 397 four-digit sectors with different skill intensities, which I define as the share of non-production workers' payroll in value-added in the US each year. Export data is from the Comtrade database, and skill intensity data is from the US NBER CES Manufacturing Database (Becker et al., 2021). G10 countries are Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom, and the United States.

C Additional Figures and Tables for Section 2

C.1 Relative Skill Endowment and Relative Wages of Skilled Labor

Figure C.2: Relative Skill Endowment and Relative Wages of Skilled Labor

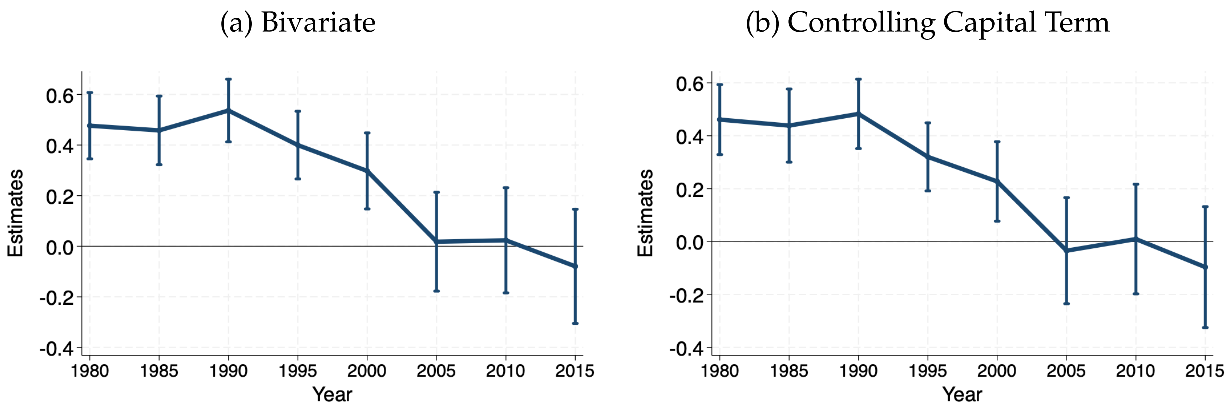


Note: The figure shows the relative skill endowment and relative wages of skilled labor across countries in 2004. Each dot represents a country, and the red line is the fitted line. Data is from The Global Trade Analysis Project (GTAP) Version 11.

Figure C.2 shows the relative skill endowment and relative wages of skilled labor across countries in 2004. Both are in the log unit. Each dot represents a country, and the red line is the fitted line. Data is from the Global Trade Analysis Project (GTAP) database Version 11. Following Weingarden and Tsigas (2010), I aggregate ISCO-08 one-digit occupations from 1 to 3 as the high-skilled and 4 to 9 as the low-skilled groups. The negative relationship is consistent with the assumption in equation (3).

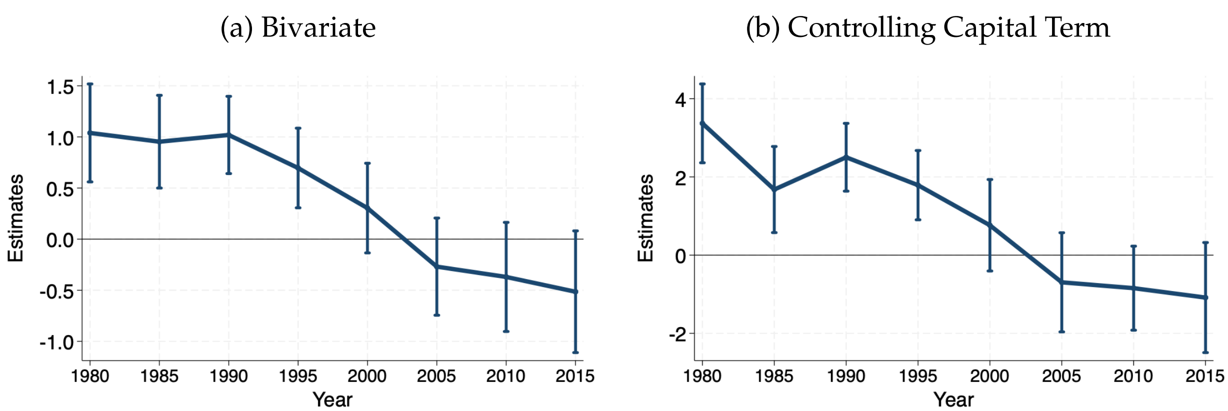
C.2 Main Results under Other Papers' Specifications

Figure C.3: Estimates of Importance of Skills in Comparative Advantage: Specification of Chor (2010)



Note: The figures show the estimates of coefficients β_t in equation (5) in each point time separately. The skill intensity measure is the log factor used in each sector in the US, $\ln(H_s/L_s)$, as in Chor (2010), instead of the skill intensity in the main specification. The bars indicate 95% confidence intervals based on heteroskedasticity-robust standard errors, clustered at the origin-sector level.

Figure C.4: Estimates of Importance of Skills in Comparative Advantage: Specification of Romalis (2004)



Note: The figures show the estimates of coefficients β_t using a total export as an outcome in each point time separately. The bars indicate 95% confidence intervals based on heteroskedasticity-robust standard errors, clustered at the origin-sector level.

D Robustness Checks for Section 3

This section shows the robustness of the result presented in Section 3.

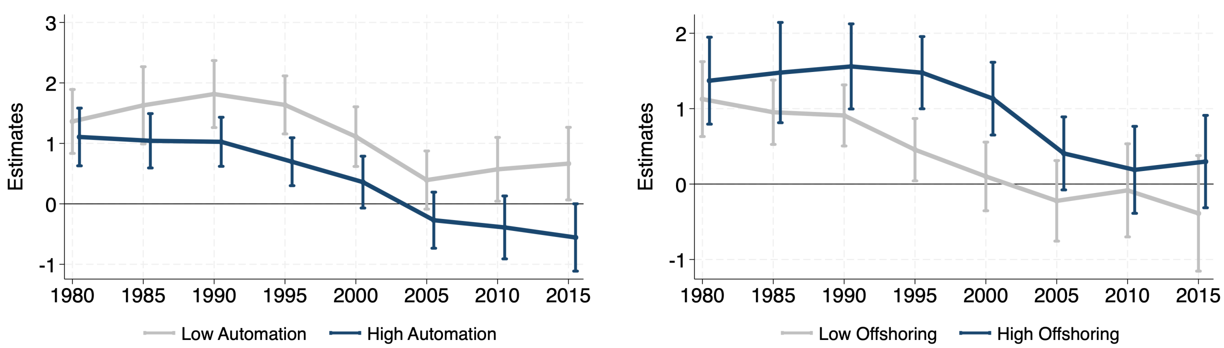
D.1 Discrete Measures

This subsection provides three versions of robustness checks for Figure 5.

First, Figure D.5 shows the results when I define a country-sector pair to be in the high automation and offshoring groups if the measure is above the median, instead of being in the top 33%. The qualitative patterns are similar.

Figure D.5: Heterogeneity in the Changes in Comparative Advantage: Discrete Measures: Below/Above Median

(a) Automation (b) Offshoring



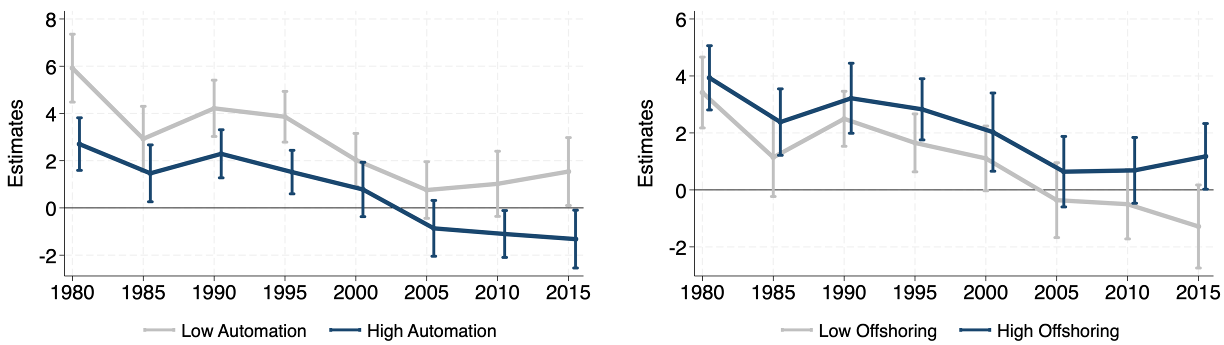
Notes: The figures show the estimates of the importance of skill abundance in comparative advantage in skill-intensive sectors. Panel D.5a plots the estimates of β_t^0 and $\beta_t^0(1+\beta_t^A)$ in the gray and navy lines, respectively. Panel D.5b plots the estimates of β_t^0 and $\beta_t^0(1+\beta_t^O)$ in the gray and navy lines, respectively. In both panels, The bars are the 95% confidence intervals based on the standard errors clustered at the exporter-sector level and computed using the delta method.

Second, Figure D.6 uses the share of skilled labor's payrolls in value-added rather the one in payroll share. The qualitative patterns are similar for automation. For offshoring, the navy line is above the gray line in 2015, and $\widehat{\beta_t^O}$ is negative and statistically significant. This implies that offshoring in this specification may have an opposite effect on the importance of skill abundance in comparative advantage by keeping it important.

Finally, Figure D.7 shows the result when I normalize the offshoring share for each country and sector. Specifically, I divide the offshoring share by the share of imports in the final consumption. This measure removes the home bias or comparative disadvantage for each country-sector pair from the measure of offshoring. The qualitative result is the same

Figure D.6: Heterogeneity in the Changes in Comparative Advantage: Discrete Measures: Value-Added Share

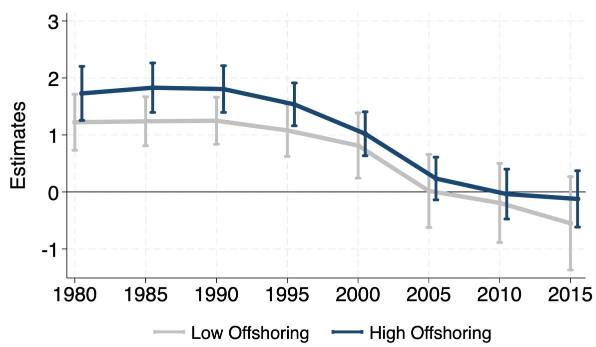
(a) Automation   (b) Offshoring



Notes: The figures show the estimates of the importance of skill abundance in comparative advantage in skill-intensive sectors. Panel D.6a plots the estimates of β_t^0 and $\beta_t^0(1+\beta_t^A)$ in the gray and navy lines, respectively. Panel D.6b plots the estimates of β_t^0 and $\beta_t^0(1+\beta_t^O)$ in the gray and navy lines, respectively. In both panels, The bars are the 95% confidence intervals based on the standard errors clustered at the exporter-sector level and computed using the delta method.

in that the high offshoring group is not necessarily the group of countries and sectors that drives the decrease in β_t.

Figure D.7: Heterogeneity in the Changes in Comparative Advantage: Discrete Measures: Normalizing Offshoring Share



Notes: The figure shows the estimates of the importance of skill abundance in comparative advantage in skill-intensive sectors. It plots the estimates of β_t^0 and $\beta_t^0(1+\beta_t^O)$ in the gray and navy lines, respectively. In both panels, The bars are the 95% confidence intervals based on the standard errors clustered at the exporter-sector level and computed using the delta method.

D.2 Continuous Measures

Table D.1 shows the results when I define the skill intensity as the value-added share, instead of the payroll share. First, the estimates for the interaction between the exporter's skill abundance and the sector's skill intensity are 3.11 in 1995 and -0.45 in 2010. This means that without controlling automation and offshoring, the importance of a country's skill abundance decreases over time. This result is the same as in Table 1.

Second, the estimates controlling automation and offshoring are positive and significant in all periods. For example, in 2010, the estimate is 4.24 with a standard error 1.47, which means that a country's skill abundance matters for comparative advantage, controlling the degrees of automation and offshoring. This also echos the finding shown in Table 1.

Third, the estimates for the interaction term with the automation measure are negative and statistically significant in 1995, 2005, and 2010 and increase in the absolute value over time. This means that automation becomes increasingly important, which is also consistent with Table 1.

Finally, the estimates for the interaction term with the offshoring measure is positive and statistically insignificant in 1995, 2000, and 2005, which is the same as the estimates in Table 1. The only difference is the positive and statistically significant estimate in Column (8), 27.83 with a standard error 12.22.[33]

[33] However, the size of the heterogeneity from offshoring is quantitatively smaller than those for automation. For instance, the top 10 and the bottom 10 percentiles of the measures of automation are 9.24 and 2.34 while those of offshoring are 0.08 and 0.004. This implies that the differences between the top and bottom 10 percentiles in automation can affect the estimates for $\beta_t^0(1 + \beta_t^A \times \text{Auto}_{i,s} + \beta_t^O \times \text{Ofs}_{i,s})$, ranging from 0.08 ($= 4.24 - 9.24 \times 0.45$) to 3.12, while those in offshoring can affect them, ranging from 4.35 to 6.47.

Table D.1: Importance of Skill Abundance in Comparative Advantage: Roles of Automation and Offshoring, Continuous Measures

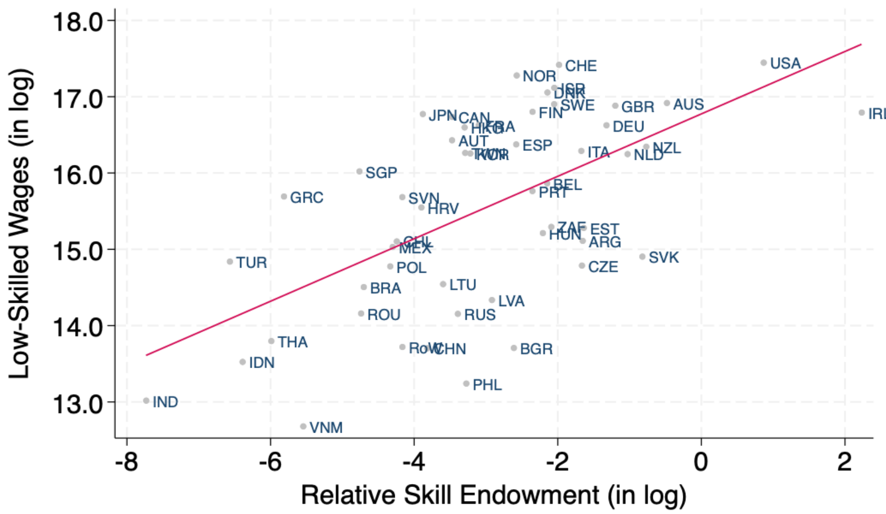
	Dep. Var. Bilateral Trade Flow							
	1995	1995	2000	2000	2005	2005	2010	2010
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Int. x Abd.	3.11	6.69	1.97	3.82	0.02	4.68	-0.45	4.24
	(0.48)	(0.93)	(0.65)	(1.11)	(0.72)	(1.20)	(0.63)	(1.47)
x Automation		-0.40		-0.18		-0.41		-0.45
		(0.10)		(0.13)		(0.11)		(0.12)
x Offshoring		0.09		0.14		0.15		0.28
		(0.12)		(0.15)		(0.12)		(0.12)
Observations	419,398	419,398	422,059	422,059	422,756	422,756	420,603	420,603
Exp.-Imp. FE	✓	✓	✓	✓	✓	✓	✓	✓
Imp.-Sec. FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table shows the results for the importance of skill abundance in comparative advantage, estimated based on equation (9). The dependent variable is the bilateral trade flow. Columns (1) and (2), (3) and (4), (5) and (6), and (7) and (8) use the data for 1995, 2000, 2005, and 2010 respectively. All columns include (a) the interaction between the exporter's skill abundance and the sector's skill intensity as the running variable, (b) the interaction of (a) with log robot stock in 2015, and (c) the interaction of (a) with offshoring shares in 2010. All columns include exporter-importer fixed effects and importer-sector fixed effects. The standard errors are in parentheses and clustered at the exporter-sector level.

E Additional Figures for Section 4

E.1 Relative Skill Endowment and Wages of Low-Skilled Labor

Figure E.8: Relative Skill Endowment and Wages of Low-Skilled Labor



Note: The figure shows the relative skill endowment and wages of low-skilled labor across countries in 2004. Each dot represents a country, and the red line is the fitted line. Data is from The Global Trade Analysis Project (GTAP) Version 11.

Figure E.8 shows the relative skill endowment and wages of low-skilled labor across countries in 2004. Both are in the log unit. Each dot represents a country, and the red line is the fitted line. Data is from the Global Trade Analysis Project (GTAP) database Version 11. Following Weingarden and Tsigas (2010), I aggregate ISCO-08 one-digit occupations from 1 to 3 as the high-skilled and 4 to 9 as the low-skilled groups. The negative relationship is consistent with the assumption in equation (24).

F Exact Hat Algebra

In this paper, I follow Dekle et al. (2008) to use the exact hat algebra to focus on changes of variables. Here I show the equilibrium conditions, in hat notations, that is $\widehat{X} = X'/X$, where X' is a new value in a counterfactual equilibrium for a variable X.

The equilibrium in changes can be characterized by the changes in wages $\{\widehat{w_i^H}, \widehat{w_i^L}\}$ where the following systems of equations holds.

Labor Demand

$$
\begin{aligned}
w_i^L L_i \widehat{w_i^L} \widehat{L_i} &= \sum_s (\Gamma_{i,s}^L)' \cdot (1-\alpha_s^H) \cdot (Y_{i,s})' \\
w_i^H H_i \widehat{w_i^H} \widehat{H_i} &= \sum_s \alpha_s^H \cdot (Y_{i,s})'
\end{aligned}
$$

Goods Market Clearing

$$
\begin{aligned}
(Y_{i,s})' = &\sum_j \pi_{ij,s}^F \widehat{\pi_{ij,s}^F} \mu_{j,s} \left(w_i^L L_i \widehat{w_i^L} \widehat{L_i} + w_i^H H_i \widehat{w_i^H} \widehat{H_i} \right) \\
&+ \sum_j \sum_r \pi_{ij,r}^M \widehat{\pi_{ij,r}^M} \alpha_{j,sr}^M (1-\alpha_r^H)(\Gamma_{j,r}^M)'(Y_{j,r})' \\
&+ \sum_r \alpha_{i,sr}^X (1-\alpha_r^H)(\Gamma_{i,r}^{XD})'(Y_{i,r})' \\
&+ \sum_j \sum_r \pi_{ij,r}^X \widehat{\pi_{ij,r}^X} \alpha_{j,sr}^X (1-\alpha_r^H)(\Gamma_{j,r}^{XF})'(Y_{j,r})'
\end{aligned}
$$

Trade Shares

$$
\widehat{\pi_{j,i,r}^F} = \frac{(\widehat{c_{j,r}} \widehat{\tau_{j,i,r}^F})^{1-\sigma}}{\sum_l \pi_{l,i,r}^F (\widehat{c_{l,r}} \widehat{\tau_{l,i,r}^F})^{1-\sigma}}, \quad \widehat{\pi_{j,i,r}^M} = \frac{(\widehat{c_{j,r}} \widehat{\tau_{j,i,r}^M})^{1-\sigma}}{\sum_l \pi_{l,i,r}^M (\widehat{c_{l,r}} \widehat{\tau_{l,i,r}^M})^{1-\sigma}}, \quad \widehat{\pi_{j,i,r}^{XF}} = \frac{(\widehat{c_{j,r}} \widehat{\tau_{j,i,r}^X})^{1-\sigma}}{\sum_{l \neq j} \pi_{l,i,r}^{XF} (\widehat{c_{l,r}} \widehat{\tau_{l,i,r}^X})^{1-\sigma}}
$$

Unit Cost

$$
\begin{aligned}
\widehat{c_{i,s}} &= (\widehat{w_i^H})^{\alpha_s^H} \cdot (\widehat{w_{i,s}^T})^{1-\alpha_s^H}, \\
\widehat{w_{i,s}^T} &= \prod_{f=\{M,L,XD,XF\}} \cdot \left(\frac{\widehat{w_i^f}}{\widehat{A^f \Gamma_{i,s}^f}} \right)^{\Gamma_{i,s}^f} \times (\Pi_{i,s}^M)^{(\Gamma_{i,s}^M)' - \Gamma_{i,s}^M} \cdot (\Pi_{i,s}^{XF})^{(\Gamma_{i,s}^{XF})' - \Gamma_{i,s}^{XF}}
\end{aligned}
$$

where $\Pi_{i,s}^{M}$ and $\Pi_{i,s}^{XF}$ are cost saving from automation and offshoring, which are exogenous variables.

Machine Price

$$\widehat{w_{i,s}^{M}} = \prod_{r} \left(\frac{\widehat{w_{i,rs}^{M}}}{\alpha_{i,rs}^{M}} \right)^{\alpha_{i,rs}^{M}}, \quad \widehat{w_{i,rs}^{M}} = \left(\sum_{j} (\widehat{c_{j,r}} \widehat{\tau_{ji,r}^{M}})^{-\theta} \right)^{-1/\theta}$$

Intermediate Price

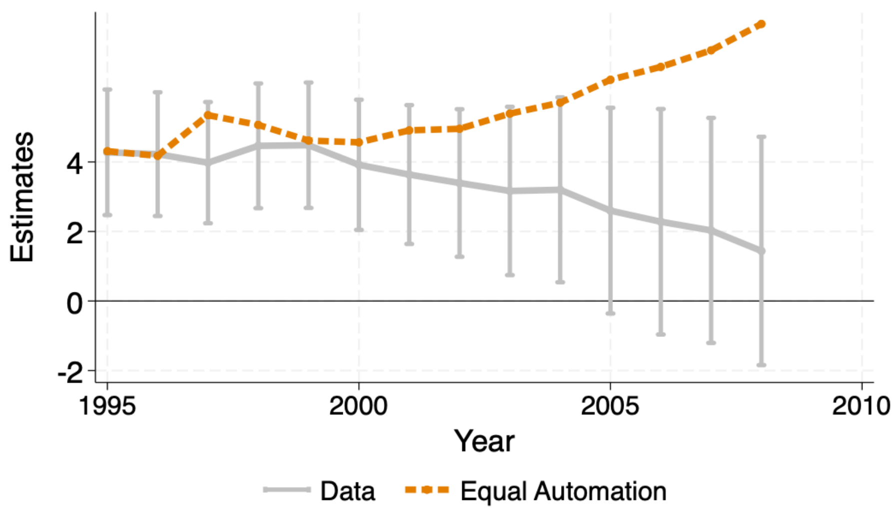
$$\widehat{w_{i,s}^{XD}} = \prod_{r} \left(\frac{\widehat{c_{i,r}}}{\alpha_{i,rs}^{X}} \right)^{\alpha_{i,rs}^{X}}, \quad \widehat{w_{i,s}^{XF}} = \prod_{r} \left(\frac{\widehat{w_{i,rs}^{XF}}}{\alpha_{i,rs}^{X}} \right)^{\alpha_{i,rs}^{X}}, \quad \widehat{w_{i,rs}^{XF}} = \left(\sum_{j \neq i} (\widehat{c_{j,r}} \widehat{\tau_{ji,r}^{X}})^{-\theta} \right)^{-1/\theta}.$$

G Additional Quantitative Results

G.1 Changes in Comparative Advantage with Equal Automation

Figure G.9 shows the results when all the countries are exposed to the same magnitudes of automation shocks, $\widehat{\Gamma^M_{i,s}}$. I find that skill-abundant countries still have comparative advantage in skill-intensive sectors in 2008 under the counterfactual trade pattern. This implies that heterogeneous automation shocks across countries are the key to change the patterns of comparative advantage.

Figure G.9: Counterfactual: Importance of Skill Abundance in Comparative Advantage (Equal Automation)

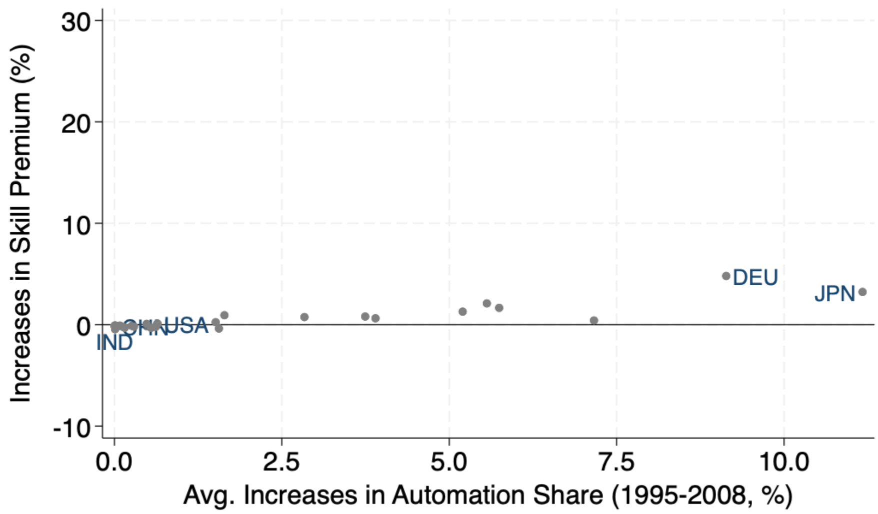


Notes: The figures show the importance of skill abundance in comparative advantage in the different counterfactual scenarios. The gray line is the path of the estimates $\widehat{\beta}$ using the WIOD with the 95% confidence interval cluster at the exporter-sector level. The orange line is the one when I only change automation share $\Gamma^M_{i,s,t}$ (and corresponding changes in $\Gamma^L_{i,s,t}$) as in the data and fix everything else at the levels in 1995.

G.2 Roles of Sectoral Reallocation

Skill Premia To investigate the roles of this sectoral reallocation, Figure G.10 shows the effects of automation on skill premia when the trade share is fixed ($\theta = 0$). In this case, the output shares in each country and sector are fixed because the expenditure shares are fixed by the Cobb-Douglass assumption on the final goods expenditure shares. The result in G.10 shows that skill premia increased in all of the countries, which is consistent with the standard arguments in closed economies (Katz and Murphy, 1992; Acemoglu and Restrepo, 2022b).

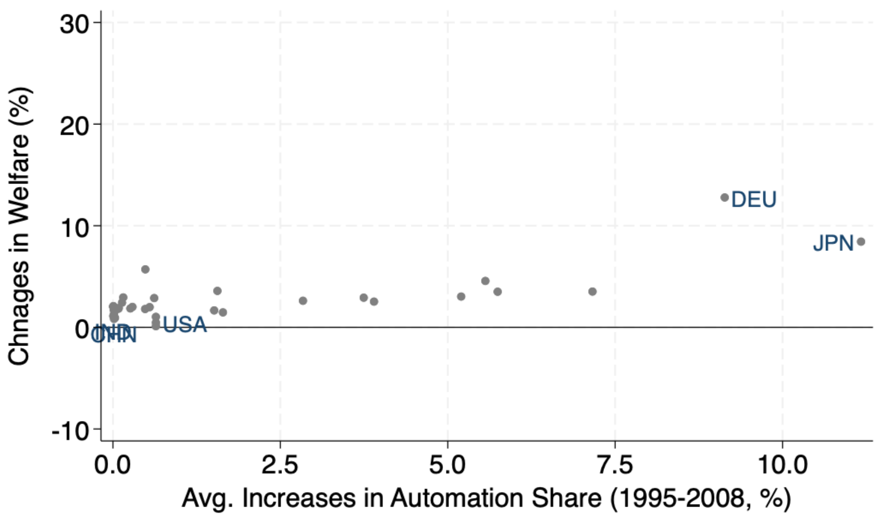
Figure G.10: Changes in Skill Premia due to Automation with Different Trade Elasticity



Notes: Both panels show the changes in skill premia across countries in response to automation from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share between 1995 and 2008. In both panels, the vertical axis shows the changes in skill premia across countries. Each dot represents a country. Figure G.10 shows the results when the trade elasticity is zero ($\theta = 0.0$) so that the trade shares are fixed. Each dot represents a country.

Welfare I examine how the effects depends on the trade elasticity. Figure G.11 shows the results when the trade elasticity is 0. Compared to the results in Figure 9a, the welfare effects are smaller in these figures. For instance, when $\theta = 0.0$, the welfare effects of automation for India, which is a low-automation country, is around 0% pt while it was 5% pt when $\theta = 4.0$. This implies that the positive spillover from automation in high-automation countries becomes muted. This highlights that incorporating trade is important when considering the effect of automation on welfare across countries.

Figure G.11: Welfare Effects of Automation with Different Trade Elasticity



Notes: Both panels show the changes in welfare across countries in response to automation from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share between 1995 and 2008. In both panels, the vertical axis shows the changes in welfare across countries. Figure G.11 shows the results when only automation shares change since 1995 when the trade elasticity is zero ($\theta = 0.0$) so that the trade shares are fixed. Each dot represents a country.