# 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 only evident in countries and sectors with high automation, with the presence of offshoring not being a significant driver of the decline. Using a quantitative trade model incorporating both automation and offshoring, I confirm that observed changes in automation can account for the evolution of comparative advantage while observed changes in offshoring cannot. Through the lens of the same model, I draw implications for the relationship between technology and inequality: automation increases skill premia in high-automation, developed countries and increases welfare globally, while offshoring has smaller, more evenly distributed welfare gains.



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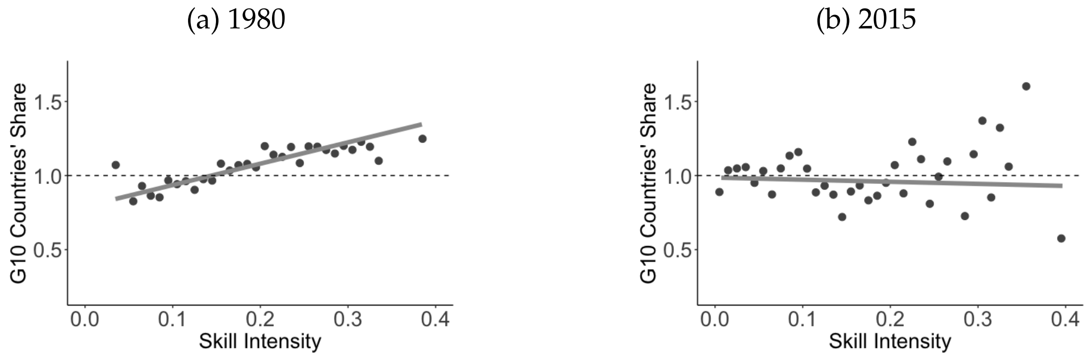
# 1 Introduction

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 shows this new fact in a parsimonious way. I plot the revealed comparative advantage of the G10 countries against the skill intensity of different products, where the revealed comparative advantage is defined as the G10's export share out of world export in each sector divided by their export share in all sectors, and the skill intensity is defined as the share of non-production worker's payroll share in valued added in the US data. Since G10 countries are skill-abundant, one may expect these countries to have relatively lower costs and, in turn, relatively higher exports in skill-intensive sectors. Panel 1a shows that this indeed is the case in 1980. By 2015, however, the comparative advantage of G10 countries in skill-intensive sectors has entirely disappeared. In Section 2, using a more systematic specification, I show that while this empirical relationship was present (Romalis, 2004; Morrow, 2010; Chor, 2010) but disappeared by the 2000s. In addition, in Section 3, I show that the relationship only disappeared in countries and sectors exposed to high automation.

In the second half of the paper, I quantify the mechanisms and draw macroeconomic implications. In Section 4, I develop a multi-sector, multi-factor 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. In Section 5, using structural accounting exercises, I find that automation is the most plausible explanation for the evolution of comparative advantage in the last few decades. Through the lens of the same model, automation increases skill premia only in developed countries with high automation and increases in welfare in all countries. In contrast, offshoring leads to smaller, more equally distributed increases in skill premia and welfare in all countries.

Figure 1: Revealed Comparative Advantage of G10 Countries in Skill-Intensive Sectors




Notes: The figures show binned scatterplots of G10's share of global exports in each sector divided by its share of aggregate global exports across 397 four-digit sectors with different skill intensities. Skill intensity is defined as the share of non-production workers' payroll in value-added in the US. 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 characteristics, skill abundance, and sector's characteristics, skill intensity. I control the exporter-importer and importer-sector fixed effects. This specification follows the literature to reveal comparative advantage using bilateral trade flow data, relying on a multi-sector Eaton-Kortum model, such as Chor (2010), Costinot et al. (2012), and Levchenko and Zhang (2016). The fixed effects control the trade pattern determinants specific to exporter-importer pairs, such as distances or trade agreements, as well as those specific to importer-sector pairs, such as tariffs or expenditure shares. My main variable of interest is the interaction of an exporter's skill abundance and a sector's skill intensity. If the coefficient of this interaction is positive, skill-abundant countries have a comparative advantage in skill-intensive 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.

**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 because they substitute low-skill workers with machines or foreign intermediates, thus potentially reducing the role of domestic low-skill workers in production (Grossman and Rossi-Hansberg, 2008; Acemoglu and Restrepo, 2022b). They may also blur the mapping from skill abundance to relative costs 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 the skill-abundance-driven comparative advantage. Using data on robot adoption, intermediate imports, and factor payment shares, I construct measures of automation share, the share of factor payment to machines, and offshoring shares, the share of foreign intermediates in total intermediates, by country, sector, and year. I then examine the heterogeneity in changes in comparative advantage across countries and sectors. My specifications allow the importance of skill abundance in comparative advantage to vary with the automation or offshoring shares.

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.[1] 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 qualitatively consistent with the story that automation, rather than offshoring, causes the decline in the importance of skill abundance in comparative advantage. In Section 4, I develop a model to clarify and quantify the effect of automation and offshoring on the evolution of comparative advantage. In particular, I develop 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).

[1] 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 10 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 25 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 production processes. Intuitively, this task displacement makes low-skill-scarce countries like 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 use machines or foreign intermediates instead of relying on 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 three counterfactual scenarios, using the exact hat algebra (Dekle et al., 2008).[2] Using the automation and offshoring shares constructed in Section 3, I consider the following three counterfactual scenarios: (a) only automation shares change from 1995 to 2008, (b) only offshoring shares change from 1995 to 2008, and (c) only automation and offshoring share 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 both automation and offshoring shocks, can explain around 90% of the declines in the importance of skill abundance for comparative advantage observed in the data as found in Section 2. Furthermore, I find 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 and exploring how automation, offshoring, and the resulting change in comparative advantage would impact macroeconomic variables, such as manufacturing shares, skill premia, and welfare across countries. To do so, I simulate the model under the same counterfac-

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

tual scenarios, with and without automation and offshoring shocks, keeping other parameters and exogenous variables constant.

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 further highlight that the impact of automation on skill premia and welfare depends on the degree of changes in comparative advantage. When the trade elasticity is low and changes in comparative advantage are limited, skill premia rise in all countries because low-automation, skill-scarce countries do not specialize much in low-skill-intensive sectors. Additionally, the welfare effects become smaller across all countries. This implies 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; 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.[3] 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 automation is the most plausible explanation for this decline in the importance of a country's skill abundance.

[3]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).

Second, this paper contributes to the large literature on the interaction between globalization, technology, and inequality, including Wood (1994), Berman et al. (1998), Krugman (2000), Leamer (2000), and Matsuyama (2007).[4] 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).[5] While I demonstrate the implications of changes in trade and technology for 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 degrees of changes in comparative advantage.

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.

# 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).

[4] Earlier studies focus on the impact of trade on the rate of technological growth, such as Krugman (1979) and Grossman and Helpman (1991).

[5] There are also several papers 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).

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 $\alpha_s^H$ is the share of high-skill workers' payroll in value-added, which I call the sector's skill intensity.[6]

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

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

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, $\alpha_s^H$. 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

[6] 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).

$H_i/L_i$, instead of skill premia, $w_i^H/w_i^L$ and assume the negative relationship,

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

where $\gamma < 0$ and $\nu_i$ is an error term. This negative relationship means that skill-abundant countries have lower relative wages of skilled labor–skill premia. [7]

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, $\alpha_s^H$.[8] 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 $\alpha_s^H$) 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 $\alpha_s^H$. 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 sectors with higher $\alpha_s^H$, 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

[7] 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.

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

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.[9] 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.[10]

**Skill Intensities** Skill intensities across sectors come from the NBER-CES Manufacturing Industry Database (Becker et al., 2021).[11] 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 Periods: Every 5 years 1980-2015** 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

[9] 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.

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

[11] 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.

fluctuations and to focus on long-run trends, I take a 3-year moving average around each year.

**Sample Countries: 52 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.

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

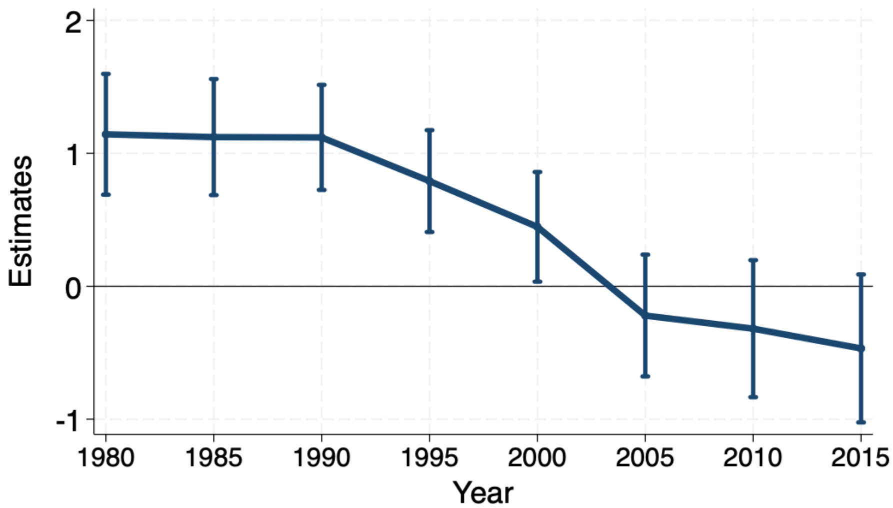
## 2.3 Main Results: Declining Importance of Skill Abundance

**Baseline Result** Figure 2 shows the estimates of $\beta_t$ 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 $\beta_t$ decrease over time and become insignificant by 2000. This suggests that a country's skill abundance, at least as measured 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

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




*Note*: The figures show the estimates of coefficients $\beta_t$ 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.

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 $\alpha_s^H$ despite deriving a specification that calls for the skill intensity is $\alpha_s^H$. 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).[12] They aggregate bilateral trade flows

[12]For Nunn (2007) and Levchenko (2007), the importance of skill abundance is not their main subject of

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.[13] 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.

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

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

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.

[13] 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.

ratio using data of the real capital stock and employment Penn World Table (PWT) data (Feenstra et al., 2015).[14] 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 $\beta_t$ 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.

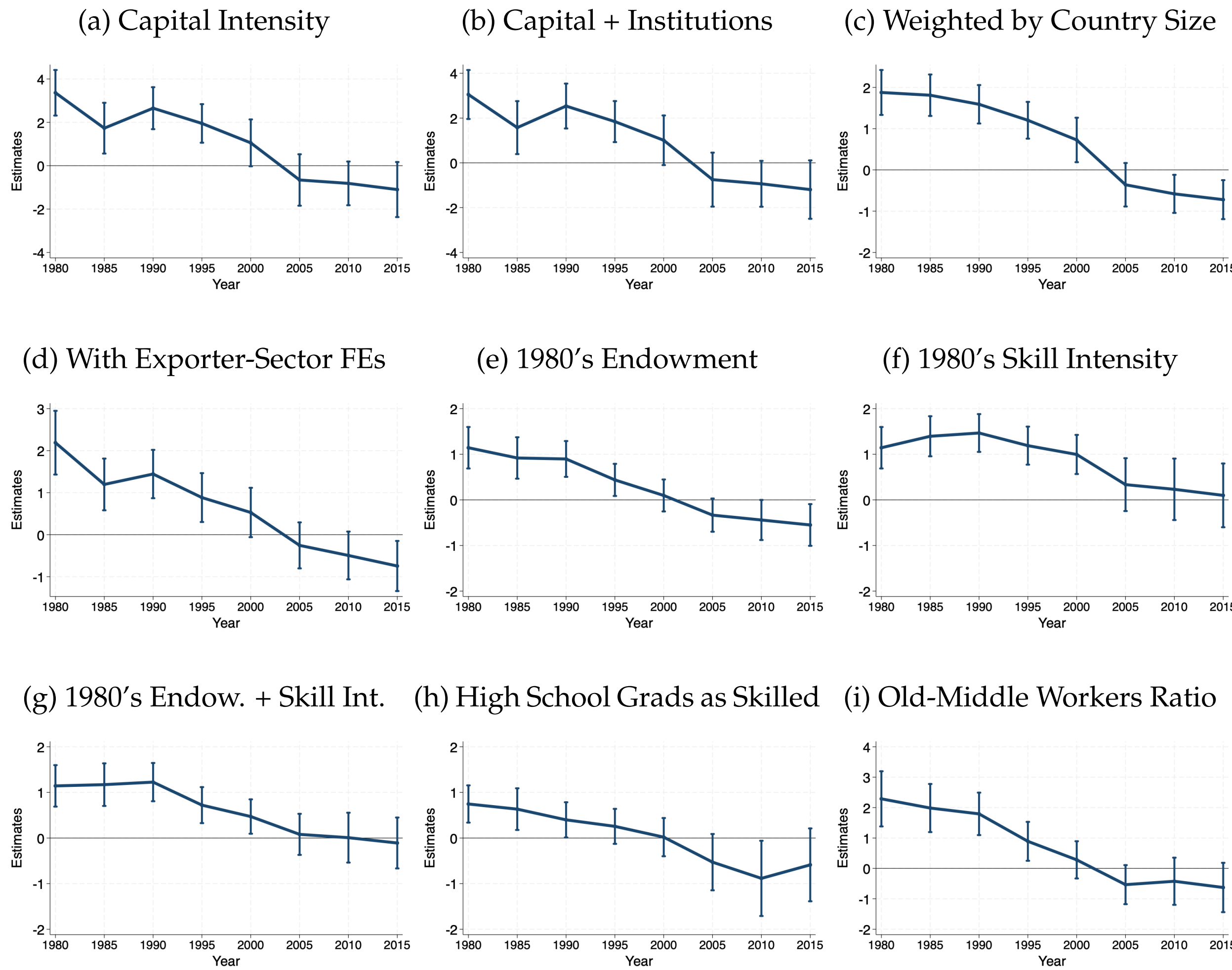
**Unobserved Heterogeneity at Exporter-Sector Level** Figure 3d pools the samples for all the years and includes fixed effects at the exporter-sector level. This specification controls for unobserved heterogeneity at the exporter-sector level and focuses on the variations over time. The pattern is still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

**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 $\beta_t$ hold with these alternative measures.

[14] 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.

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




Notes: The figures show the estimates of coefficients $\beta_t$ 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).

# 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 explore the potential hypotheses behind this trend. In particular, I focus on two factors: automation and offshoring. I construct measures of automation and offshoring by countries, sectors, and years. I then examine the heterogeneity in changes in $\beta_t$, depending on the degrees of automation and sectors.

While I present a formal analysis in Section 4, I briefly explain why automation and offshoring can change the roles of skill endowments in trade patterns. Automation replaces production workers who complete routine tasks with machines. This task displacement allows firms to rely on machines instead of routine occupation workers, and domestic labor endowment can become less relevant 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 endowments will become less relevant for trade.

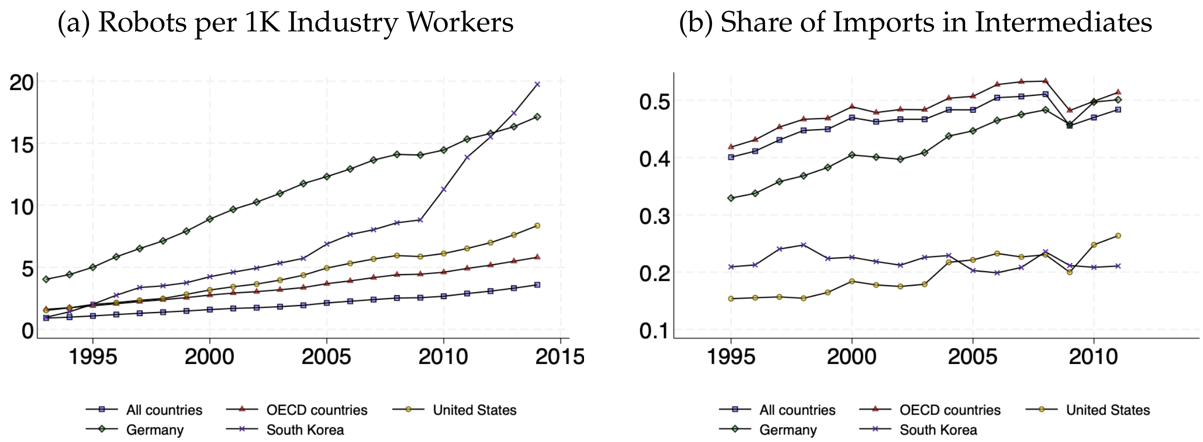
## 3.1 Trends in Automation and Offshoring

Before going into the analyses, I give a quick overview of the trends in automation and offshoring during the period. As Figure 4 shows, automation and offshoring have been rising since 1990. Figure 4a shows the robots per thousand industry workers from Acemoglu and Restrepo (2022a). The number of robots per thousand workers increased from 0.63 in 1993 to 3.47 in 2014 on average across all countries in my sample, but the increase was more pronounced among labor-scarce countries, such as Germany or South Korea. Figure 4b shows the share of imports in total intermediate uses from the World Input-Output Database (Timmer et al., 2015). The share of imports in intermediates, which I call offshoring share hereafter, increased from 40% in 1995 to 50% in 2011 on average across all countries, but the levels and the changes of offshoring shares are heterogeneous across countries. South Korea's offshoring share is stable at around 20% while Germany's offshoring share increased from 33% in 1995 to 50% in 2011. The US offshoring share also increased by 11% points, but the levels were still low at 26% in 2011.

## 3.2 Specifications for Heterogeneity

In this section, I allow the importance of skill abundance, $\beta_t$ in equation (5), to depend on the degrees of automation and offshoring, $\beta_{i,s,t}$, for each country $i$ and sector $s$ as in the

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 2013 (Timmer et al., 2015).

following specification.

$$X_{i,j,s,t} = \exp\left[\beta_{i,s,t} \cdot \left(\alpha^H_{s,t} \times \ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right) + \eta_{i,j,t} + \eta_{j,s,t}\right] + \varepsilon_{i,j,s,t}, \tag{7}$$

To explore the heterogeneity, I adopt two specifications for the key parameter to estimate, $\beta_{i,s,t}$, that varies across countries and sectors.[15]

**Trend by Groups using Time-Invariant Dummy Variables** The first specification defines high- and low-automation and high- and low-offshoring groups for countries and sectors and runs regressions where the coefficient $\beta_{i,s,t}$ depends on the dummy variables. In particular, we model $\beta_{i,s,t}$ in equation (7) as

$$\beta_{i,s,t} = \underbrace{\beta^0_t}_{\text{Base Group}} + \underbrace{\sum_{g \in G} \beta^g_t \cdot \mathbb{1}\left((i,s) \in g\right)}_{\text{Heterogeneous Trends}}, \tag{8}$$

[15]Note that the analyses in this section only capture cross-sectional differences of the exposure to automation or offshoring and importantly, do not consider the general equilibrium effects, including the effects coming from changes in skill premia.

where $g$ is a group of countries and sectors by the degree of automation and offshoring. Since we fix which group each country-sector pair belongs to over time, this specification reveals the differential trends by groups of the degrees of automation and offshoring.

I consider four dummies for groups, high-automation country, high-automation sector, high-offshoring country, and high-offshoring sector. For automation, I define a country as a high-automation country if the number of robot stocks in 2014 from the IFR data is above the median. I define each 4-digit sector as a high-automation sector if it falls into one of the following 2-digit broad sectors: Electronic & Other Electric Equipment sector, Transportation Equipment sector, and Plastic Chemical sectors as high-automation sectors.[16] For offshoring, I define a country and a sector as a high-offshoring country or a high-offshoring sector if the increases in the offshoring shares from 1982 to 2017 are above the median. I compute the offshoring shares as the share of import in total intermediate uses, using the US BEA Input-Output Table and World Input-Output Database (WIOD) (Timmer et al., 2015), following Feenstra and Hanson (1996). In particular, I construct offshoring share by country, sector, and year as

$$\text{Offshoring Share}_{i,s,t} = \frac{\text{Imported Intermediates}_{i,t}}{\text{Total Intermediates}_{i,t}} \times \frac{\text{Imported Intermediates}_{US,s,t}}{\text{Total Intermediates}_{US,t}},$$

where Imported $\text{Intermediates}_{i,t}$ is the value of imported intermediates of country $i$ in year $t$ from the WIOD, Total $\text{Intermediates}_{i,t}$ is the value of total intermediate uses of country $i$ in year $t$ from the WIOD, Imported $\text{Intermediates}_{US,s,t}$ is the value of imported intermediates in the US in 4-digit sector $s$ in year $t$ from the US BEA Input-Output Table, and Total $\text{Intermediates}_{US,t}$ is the value of total intermediate uses in the US in year $t$ from the US BEA Input-Output Table.

**Trends and Levels using Time-Variant Continuous Variables** The second specification constructs continuous measures of automation and offshoring across countries, sectors, and years. In particular, we model $\beta_{i,s,t}$ in equation (7) as

$$\beta_{i,s,t} = \beta^0 + \beta^1 \cdot t + \beta^{\text{Auto}}\text{Automation Share}_{i,s,t} + \beta^{\text{Ofs}}\text{Offshoring Share}_{i,s,t}. \tag{9}$$

Automation $\text{Share}_{i,s,t}$ 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

[16] I follow this strategy because the robot data is only available at the level of 2-digit broad sectors, and these three 2-digit broad sectors have a share of 79% of the total number of robots in all sectors in 2014.

capital to the sum of the payments for automation capital and low-skilled labor.

$$\text{Automation Share}_{i,s,t} \equiv \frac{p^M_{i,s,t} M_{i,s,t}}{p^M_{i,s,t} M_{i,s,t} + w^L_{i,t} L_{i,s,t}}, \tag{10}$$

where $p^M_{i,s,t} M_{i,s,t}$ is factor payment for automation capital and $w^L_{i,t} L_{i,s,t}$ is the total payroll for low-skilled workers. This is the standard definition to measure the degree of automation in the task framework literature (Acemoglu and Restrepo, 2022b). 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 (2-digit) level from the WIOD data, (2) time-invariant equipment-to-capital ratio at the sector (4-digit) level from the NBER CES data in the US, and (3) time-variant robot adoption data at the country-sector (2-digit) level from the IFR data. In particular, I construct $p^M_{i,s,t} M_{i,s,t}$ as

$$p^M_{i,s,t} M_{i,s,t} = \underbrace{p^K_{i,s,t0} K_{i,s,t0}}_{\text{Country} \times \text{2-digit Sector}} \cdot \underbrace{\frac{p^M_{US,s,t0} M_{US,s,t0}}{p^K_{US,s,t0} K_{US,s,t0}}}_{\text{4-digit Sector}} \cdot \underbrace{\frac{p^R_{i,s,t} R_{i,s,t}}{p^R_{i,s,t0} R_{i,s,t0}}}_{\text{Country} \times \text{2-digit Sector} \times \text{Year}}$$

Offshoring Share$_{i,s,t}$ is the share of import in total intermediate uses as in the first specification.

Compared to the first specification, this specification includes the levels of the degrees of automation and offshoring that vary over time. This feature allows the importance of skill abundance to depend not on the relative but the absolute levels of automation and offshoring.

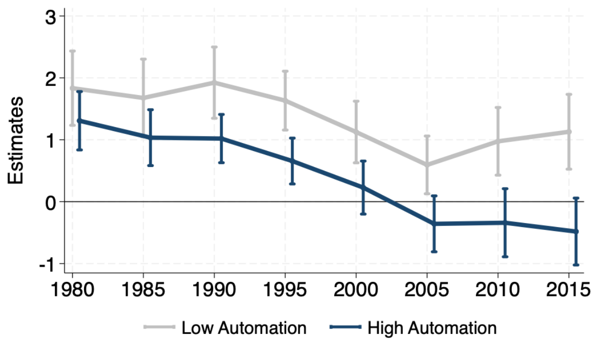
## 3.3 Results

### 3.3.1 Trends by Groups using Time-Invariant Dummy Variables

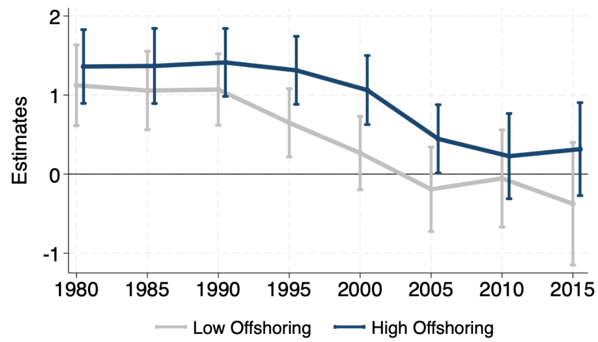
I first start results with the first specification using time-invariant dummy variables. Figure 5a shows the result for automation. I estimate (8) for automation, and the gray line shows the time path of $\widehat{\beta^0_t}$, the coefficient for the low-automation group. The navy line shows the time path of $\widehat{\beta^0_t} + \sum_{g \in G_{\text{Auto}}} \widehat{\beta^g_t}$ where $G_{\text{Auto}}$ is a set of groups, high-automation countries and high-automation sectors. I compute the confidence intervals using the delta method. The result in Figure 5a shows that the importance of skill abundance decreased more in countries or sectors exposed to more automation as shown in the navy line. More importantly, the gray line does not go down over time, which means that skill abundance

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. The left panel shows the estimates from (8) for low-automation and high-automation groups. The gray line shows the time path of $\widehat{\beta_t^0}$, the coefficient for the low-automation group. The navy line shows the time path of $\widehat{\beta_t^0} + \sum_{g \in G_{\text{Auto}}} \widehat{\beta_t^g}$ where $G_{\text{Auto}}$ is a set of groups, high-automation countries and high-automation sectors. The right panel shows the estimates from (8) for low-offshoring and high-offshoring groups. The gray line shows the time path of $\widehat{\beta_t^0}$, the coefficient for the low-offshoring group. The navy line shows the time path of $\widehat{\beta_t^0} + \sum_{g \in G_{\text{Ofs}}} \widehat{\beta_t^g}$ where $G_{\text{Ofs}}$ is a set of groups, high-offshoring countries and high-offshoring sectors. In both panels, the 95% confidence intervals are computed using the delta method.

is still as important as in the 1980s for the countries and sectors with below-median exposure to automation.

Figure 5b shows that the importance of skill abundance decreased both in high- and low-offshoring groups and exhibits no significant heterogeneity across countries or sectors exposed to offshoring in different degrees.

**Discussion** These heterogeneous results suggest that explanations common across countries and sectors may not explain the observed decline in $\widehat{\beta}_t$ entirely. For example, Hanson et al. (2015) and Levchenko and Zhang (2016) show the mean reversion or convergence in comparative advantage over time. While they can potentially explain the decreasing importance of a country's skill abundance in comparative advantage in skill-intensive sectors for all countries and sectors, I show that the pattern is heterogeneous across countries and sectors with different exposures to automation. More importantly, 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 and offshoring, it cannot explain my empirical facts entirely.

Therefore, my results are complementary to and not inconsistent with the findings in Hanson et al. (2015) and Levchenko and Zhang (2016).

### 3.3.2 Trends and Levels using Time-Variant Continuous Variables

The second specification is to use the time-variant continuous variables as in Equation 9. The use of the WIOD data makes the sample smaller, and the final sample is 26 countries, 393 4-digit sectors, and three periods, 1995, 2000, and 2005. Table 1 shows the results. All columns include the interaction between the exporter's skill abundance and the sector's skill intensity as the running variable, "Skill Term", $\alpha_{s,t}^{H} \times \ln(H_{i,t}/L_{i,t})$. All columns also control the interaction between the "Skill Term" and linear time trend. Column (1) shows that the coefficient on the "Skill Term" is 1.17, implying that a country's skill abundance was an important source of comparative advantage in skill-intensive sectors in 1995, the beginning sample period. The coefficient of the interaction between the "Skill Term" and the linear trend is -1.18, implying that the importance is decreasing over time. Since there are three periods, 1995, 2000, and 2005, this means that the skill abundance used to be important in comparative advantage in skill-intensive sectors in 1995 and no longer matter in 2000. Column (2) adds the interaction between the "Skill Term" and automation shares. The coefficient is -3.18, meaning that higher automation makes the skill abundance less important. Column (3) adds the interaction between the "Skill Term" and offshoring shares. The coefficient is 0.47 with a standard error 0.43, implying that there is no large heterogeneity across countries and sectors with different offshoring shares. Column (4) adds both automation shares and offshoring shares to incorporate the correlation between automation and offshoring shares. The coefficient on the interaction between the "Skill Term" and automation shares is -3.05, which is close to the one in Column (2). This means that the heterogeneity in the importance of skill abundance based on different levels of automation is robust after controlling offshoring shares.

These results are robust if I drop the linear time trend or if I add the interaction between the sector's capital intensity and the country's capital abundance as in (6). Table D.1 and D.2 in Appendix D, respectively.

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

| | Dep. Var. Log Trade Flow | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Skill Term | 1.17 | 2.36 | 1.00 | 2.23 |
| | (0.53) | (0.62) | (0.58) | (0.69) |
| x Automation Share | | -3.18 | | -3.05 |
| | | (1.04) | | (1.05) |
| x Offshoring Share | | | 0.47 | 0.24 |
| | | | (0.43) | (0.41) |
| x Linear Trend | -1.18 | -1.06 | -1.18 | -1.07 |
| | (0.17) | (0.16) | (0.17) | (0.16) |
| Observations | 1,528,800 | 1,528,800 | 1,523,612 | 1,523,612 |
| Origin-Dest-Year FE | ✓ | ✓ | ✓ | ✓ |
| Dest-Sector-Year FE | ✓ | ✓ | ✓ | ✓ |

Notes: The table shows the results for the importance of skill abundance in comparative advantage, based on the specification for $\beta_t$ in equation (9). The dependent variable is the bilateral trade flow. All columns include the interaction between the exporter's skill abundance and the sector's skill intensity, "Skill Term", as the running variable. All columns also control the interaction between "Skill Term" and linear time trend. Columns (2) and (4) include the interaction between "Skill Term" and the automation share. Columns (3) and (4) include the interaction between "Skill Term" and the offshoring share. All the columns include origin-exporter-year fixed effects and importer-sector fixed effects. The standard errors are in parentheses and clustered at the exporter-sector level.

# 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

$$Y_{i,s} = z_{i,s}(\omega) \cdot (H_{i,s}(\omega))^{\alpha_s^H} \cdot (T_{i,s}(\omega))^{1-\alpha_s^H}, \tag{11}$$

where $z_{i,s}(\omega)$ is the productivity for the $\omega$th variety of country $i$ and sector $s$, $\alpha_s^H$ is the factor share of high-skilled labor. [17]

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

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

$$\begin{aligned} T_{i,s}(\omega, x) = {} & A^M \psi_{i,s}^M(x) M_{i,s}(\omega, x) + A^L \psi_{i,s}^L(x) L_{i,s}(\omega, x) \\ & + A^{XD} \psi_{i,s}^{XD}(x) XD_{i,s}(\omega, x) + A^{XF} \psi_{i,s}^{XF}(x) XF_{i,s}(\omega, x), \end{aligned} \tag{12}$$

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.[18]

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:

$$c_{i,s} = \Lambda_s \cdot (w^{H}_{i})^{\alpha^{H}_{s}} \cdot \left[ \left( \frac{w^{M}_{i,s}}{\Gamma^{M}_{i,s}} \right)^{\Gamma^{M}_{i,s}} \cdot \left( \frac{w^{L}_{i}}{\Gamma^{L}_{i,s}} \right)^{\Gamma^{L}_{i,s}} \cdot \left( \frac{w^{XD}_{i,s}}{\Gamma^{XD}_{i,s}} \right)^{\Gamma^{XD}_{i,s}} \cdot \left( \frac{w^{XF}_{i,s}}{\Gamma^{XF}_{i,s}} \right)^{\Gamma^{XF}_{i,s}} \right]^{1-\alpha^{H}_{s}} \tag{13}$$

where $\Lambda_s$ 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,

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

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

[18] 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:

$$w^u_{i,s} = \prod_r \left(\frac{w^u_{i,rs}}{\alpha^u_{i,rs}}\right)^{\alpha^u_{i,rs}}, \tag{14}$$

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 $\omega$ is

$$p^u_{i,s}(\omega) = \min_{i\in\mathcal{I}^u_i}[c^u_{i,k}(\omega)] \tag{15}$$

where $\mathcal{I}^u_i = \mathcal{I}$ for $u = F, M$, $\mathcal{I}^u_i = \mathcal{I}/i$ for $u = XF$, $c^u_{i,k}(\omega) = (\tau^u_{i,j,k} \cdot c_{i,k})/z_{i,k} > 0$, 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 $\omega$ 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:

$$\pi^F_{ij,s} = \frac{(c_{i,s}\tau^F_{ij,s})^{-\theta}}{\sum_l (c_{l,s}\tau^F_{lj,s})^{-\theta}}. \tag{16}$$

**Souring of Machines and Foreign Intermediates** Similarly, machines and intermediates are sourced from different varieties $\omega$ within each country-sector.[19] Then, in country $j$, total expenditure on variety $\omega$ 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:

$$\pi^u_{ji,r} = \frac{(c_{j,r}\tau^u_{ji,r})^{-\theta}}{\sum_{l \in \mathcal{I}^u_i} (c_{l,r}\tau^u_{li,r})^{-\theta}}, \tag{17}$$

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

$$w^u_{i,rs} = \left( \sum_{j \in \mathcal{I}^u_i} (c_{j,r}\tau^u_{ji,r})^{-\theta} \right)^{-1/\theta}. \tag{18}$$

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

$$\sum_{j \in \mathcal{I}} \sum_{s \in \mathcal{S}} \pi^F_{i,j,s} \mu_{j,s} \zeta_j = \zeta_i \tag{19}$$

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.

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

**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

$$\begin{aligned}
Y_{i,s} = & \underbrace{\sum_j \pi^F_{ij,s}\mu_{j,s}(w^L_j L_j + w^H_j H_j)}_{\text{Final Consumption in } j} + \underbrace{\sum_j \sum_r \pi^M_{ij,r}\alpha^M_{j,sr}(1-\alpha^H_r)\Gamma^M_{j,r}Y_{j,r}}_{\text{Machine Service in } j-r} \\
& + \underbrace{\sum_r \alpha^X_{i,sr}(1-\alpha^H_r)\Gamma^{XD}_{i,r}Y_{i,r}}_{\text{Domestic Intermediates in } i-r} + \underbrace{\sum_j \sum_r \pi^X_{ij,r}\alpha^X_{j,sr}(1-\alpha^H_r)\Gamma^{XF}_{j,r}Y_{j,r}}_{\text{Foreign Intermediates in } j(\neq i)-r} \qquad (20)
\end{aligned}$$

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

$$\begin{aligned}
w^L_i L_i &= \sum_s (1-\alpha^H_s)\Gamma^L_{i,s}Y_{i,s} \\
w^H_i H_i &= \sum_s \alpha^H_s Y_{i,s} \qquad (21)
\end{aligned}$$

**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 (13), (14), and (18),

(ii) Given unit costs in each country and sector, trade shares for final goods, machines, and intermediates are determined by (16) and (17),

(iii) Trade is balanced as in (19),

(iv) Goods and labor markets clear by (20) and (21).

## 4.2 Changes in Comparative Advantage

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

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

**Proposition 4.1.** **(Changes in Comparative Advantage due to 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 $s$ satisfied $\Gamma^M_{i,s} = \Gamma^M_i \cdot \Gamma^M_s$ for all $i, s$. Then, the trade flow follows*

$$\ln X_{i,j,s} = -\theta\left(1 - \overline{\alpha^H_R}\Gamma^M_{i,s}\right)\left[\alpha^H_s \times \ln\left(\frac{w^H_i}{w^L_i}\right)\right] - \theta\overline{\alpha^H_R}\Gamma^M_{i,s}\ln\left(\frac{w^H_i}{w^L_i}\right) + \eta_{i,j} + \eta_{j,s}, \tag{22}$$

*where $\overline{\alpha^H_R}$ is the skill intensity in machine-producing sector $s = R$.*

This equation (22) extends the expression (2), which is the trade flow equation without automation. The first additional component is $-\overline{\alpha^H_R}\Gamma^M_{i,s}$ in front of the interaction term. I call this the displacement term, which is increasing in $\Gamma^M_{i,s}$. When $\Gamma^M_{i,s}$, the task share of machine (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 the 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 $-\theta\overline{\alpha^H_R}\Gamma^M_{i,s}\ln\left(\frac{w^H_i}{w^L_i}\right)$ adjusts the comparative advantage of countries with lower skill premium in high automation sectors, regardless of the sector's skill intensity $\alpha^H_s$.

**Proposition 4.2.** **(Changes in $\widehat{\beta}$ due to Automation)** *Consider the following regression.*

$$\ln X_{i,j,s} = \beta_i\left[\alpha^H_s \times \ln\left(H_i/L_i\right)\right] + \delta \cdot \Gamma^M_{i,s}\ln\left(H_i/L_i\right) + \eta_{i,j} + \eta_{j,s} + \varepsilon_{i,j,s}$$

*Suppose that $\Gamma^M_{i,s} = \Gamma$ for all $i, s$. Then, increases in $\Gamma$ (automation) decreases $\widehat{\beta}_i$ (importance of skill abundance for comparative advantage in skill-intensive sectors), where*

$$\widehat{\beta}_i = \theta\left(1 - \overline{\alpha^H_R} \cdot \Gamma\right) \times \frac{\phi}{Var\left(\ln(H_i/L_i)\right)}, \quad \phi \equiv Cov\left(\ln(H_i/L_i), \ln(w^L_i/w^H_i)\right)$$

*if $\phi > 0$ and $\frac{d\phi}{d\Gamma} < 0$.*

The first assumption, $\phi > 0$, means that skill-abundant countries have lower skill premia. The second assumption, $d\phi/d\Gamma$, means that automation increases skill premia more in skill-abundant (developed) countries.[20]

Under these assumptions, this proposition characterizes the effect of automation on the importance of skill abundance for comparative advantage in skill-intensive sectors,

[20] These assumptions are verified in the quantitative section.

which I show the decline in Section 2. This specification is consistent with the specification for the heterogeneous effects in (9).

This proposition shows that automation can decrease $\widehat{\beta}_i$ via (i) the displacement effect in sectors with automation, which I study in Section 3 and (ii) the general equilibrium effect, that is, a decrease in $\phi$ regardless of the levels of automation in each sector, which is absent in Section 3. The quantitative results in Section 5 incorporate this general equilibrium effect and evaluate the full quantitative implications of automation and offshoring.

## 4.3 Changes in Skill Premium

Before going to the quantitative section, I show how automation and offshoring affect skill premia across countries.

**Proposition 4.3. (Changes in Skill Premium due to Automation and Offshoring)** Changes in skill premium can be decomposed into task displacement and sectoral reallocation terms as follows:

$$\widetilde{w_i^H} - \widetilde{w_i^L} = - \underbrace{\sum_s \zeta_{i,s}^L \cdot \widetilde{\Gamma_{i,s}^L}}_{\text{Task Displacement}} + \underbrace{\sum_s \left(\zeta_{i,s}^H - \zeta_{i,s}^L\right) \cdot \widetilde{Y_{i,s}}}_{\text{Sectoral Reallocation}}, \tag{23}$$

where $\widetilde{X} \equiv dX/X$ and $\zeta_{i,s}^H$ and $\zeta_{i,s}^L$ are sectoral share in payroll for each labor type 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, $\Gamma_{i,s}^L$. The first term captures the task displacement effect. Automation and offshoring in this model decrease the task share of low-skill labor $\Gamma_{i,s}^L$. This decreases the relative demand for low-skill labor in the economy. The second term captures the sectoral reallocation effect. Automation and offshoring can change the output in that country and sector. If automation or offshoring increases output in that sector, the relative demand for high-skill to low-skill labor increases if that sector relatively relies more on high-skill labor than low-skill labor, $\zeta_{i,s}^H > \zeta_{i,s}^L$. The second term highlights the importance of changes in comparative advantage when considering the effects of automation or offshoring on skill premium, which I come back to in the quantitative analysis.

# 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

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.[21]

I use the exact hat algebra following Dekle et al. (2008), which does not require me to calibrate productivity levels across countries and sectors or trade costs across exporters, importers, and sectors. The only parameter I need to calibrate is the trade elasticity, $\theta$, and I set it to be 5, which is standard (Anderson and Van Wincoop, 2004; Arkolakis et al., 2012).

For the benchmark year $t_0$, I directly feed trade shares, $\pi_{i,j,s,t_0}$, expenditure shares, $\mu_{i,s,t_0}$, factor shares, $\{\alpha^H_{s,t_0}, \Gamma^L_{i,s,t_0}, \Gamma^M_{i,s,t_0}, \Gamma^{XD}_{i,s,t_0}, \Gamma^{XF}_{i,s,t_0}\}$, factor endowments, $\{L_i, H_i\}$, 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).[22] The input-output coefficients for intermediates and machines, $\alpha^X_{i,rs}$ and $\alpha^M_{i,rs}$, are from Ding (2022).[23]

Since the WIOD with labor compensation by multiple labor types is only available between 1995 and 2008, I choose 1995 as the benchmark year, $t_0$.

[21] 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 of m&eq 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.

[22] 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.

[23] Ding (2022) 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.

## 5.2 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 E

## 5.3 Changes in Comparative Advantage

### 5.3.1 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 three scenarios, (1) only the path of automation share, $\Gamma^M_{i,s,t}$, changes over time, (2) only the path of offshoring share, $\Gamma^{XF}_{i,s,t}$, changes over time, and (3) only the paths of automation share and offshoring share change 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 $\beta_t$ 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 flows, which the model generates under different counterfactual scenarios.

### 5.3.2 Result

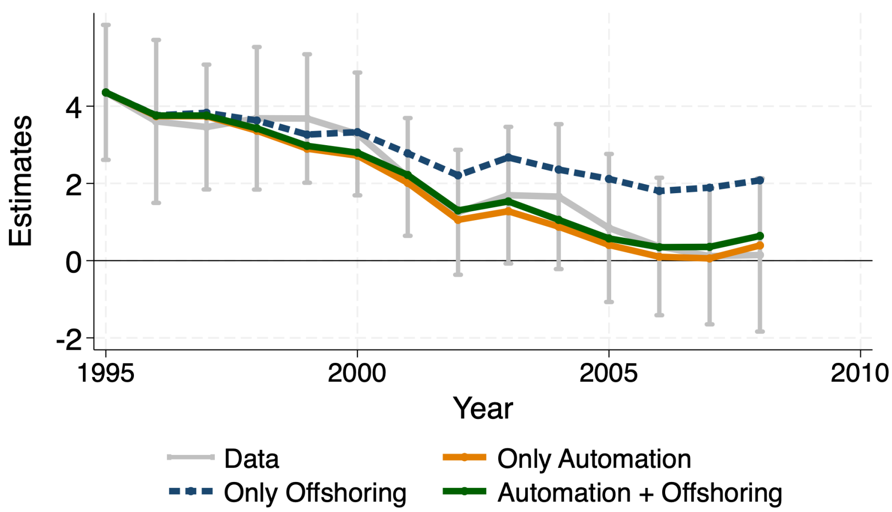
Figure 6 shows the results for the importance of skill abundance in comparative advantage in the different counterfactual scenarios. To start with, the gray line shows the estimates of $\widehat{\beta}$ in the WIOD as in the data. Consistent with the findings in Section 2 where I used more detailed data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

The navy line shows the estimates based on the generated data under the counterfactual case where only the offshoring share changes over time. While the estimate is decreasing over time, it cannot explain the change in the estimates based on the data (the gray line).

Finally, the green line shows the estimates under the case where only automation and offshoring shares change. It almost matches the path of the case with only automation. This implies that offshoring does not have a strong, additional force to decrease the importance of skill abundance in comparative advantage on top of automation.

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 green line is the one when I only change automation share $\Gamma^{M}_{i,s,t}$ and offshoring share $\Gamma^{XF}_{i,s,t}$ (and corresponding changes in $\Gamma^{L}_{i,s,t}$) and fix everything else at the levels in 1995.

## 5.4 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.

### 5.4.1 Manufacturing Output Shares within Each Country

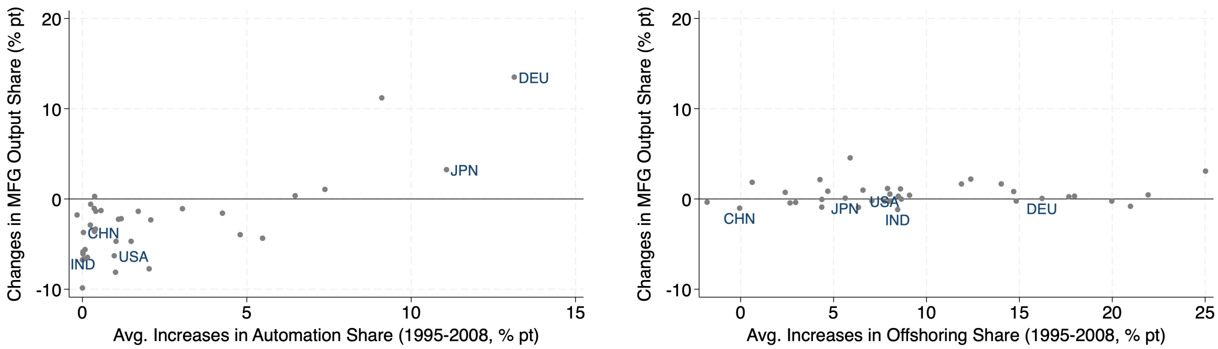
First, I study the effect of automation and offshoring on manufacturing output shares within each country. Figure 7a shows the result for automation. The horizontal axis shows the country-level average increases in the automation share between 1995 and 2008. The vertical axis shows the country-level 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% pt 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.

### 5.4.2 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 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

Figure 7: Changes in Manufacturing Output Share within Each Country




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.

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.

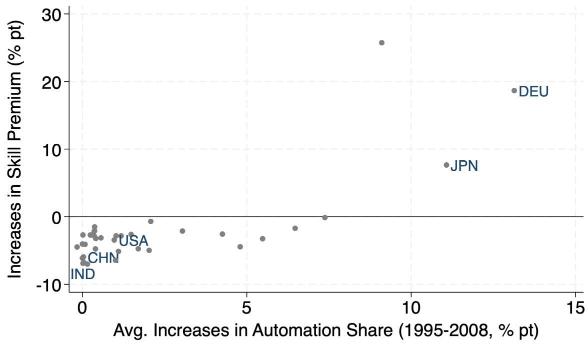
To investigate the roles of this sectoral reallocation, Figure 9a shows the effects of automation on skill premia when the trade share is fixed ($\theta = 0$). In this case, the output shares in each country and sector are fixed because the expenditure shares are fixed by the Cobb-Douglass assumption on the final goods expenditure shares. The result in 9a 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 9b shows the results when $\theta = 0.5$ where the output is not fixed, but the trade elasticity is lower than the baseline $\theta = 5.0$. Still, skill premia increase in all of the countries. This highlights that sectoral reallocation via trade has important implications for the effects of automation on skill premia.

### 5.4.3 Welfare

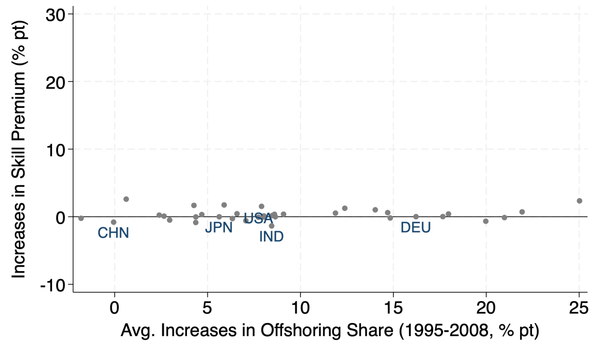
Finally, I examine the welfare effect of automation and offshoring across countries. Here, welfare change is the real consumption, which is equal to the real labor income, $(w_i^L L_i +$

Figure 8: Changes in Skill Premia

(a) Automation




(b) Offshoring



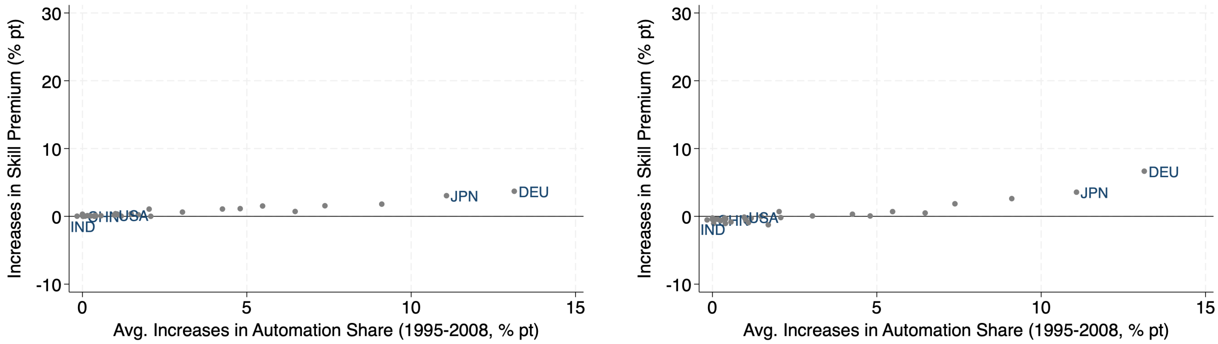

Notes: Both panels show the changes in skill premia across countries in response to automation (Figure 8a) and offshoring (Figure 8b) from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share (Figure 8a) or the offshoring share (Figure 8b) between 1995 and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

$w_i^H H_i)/P_i$ where $P_i$ is the consumer price index for country $i$. Figure 10a shows the changes in welfare when only the automation shares change. All countries 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 10b shows the results for offshoring. Again, all countries benefit from offshoring while there is not much heterogeneity in gains across countries.

Again, I examine how the effects depends on the trade elasticity. Figure 11 shows the results when the trade elasticity is 0.0 or 0.5. Compared to the results in Figure 10a, 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 $\theta = 5.0$. 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 9: Changes in Skill Premia due to Automation with Different Trade Elasticity

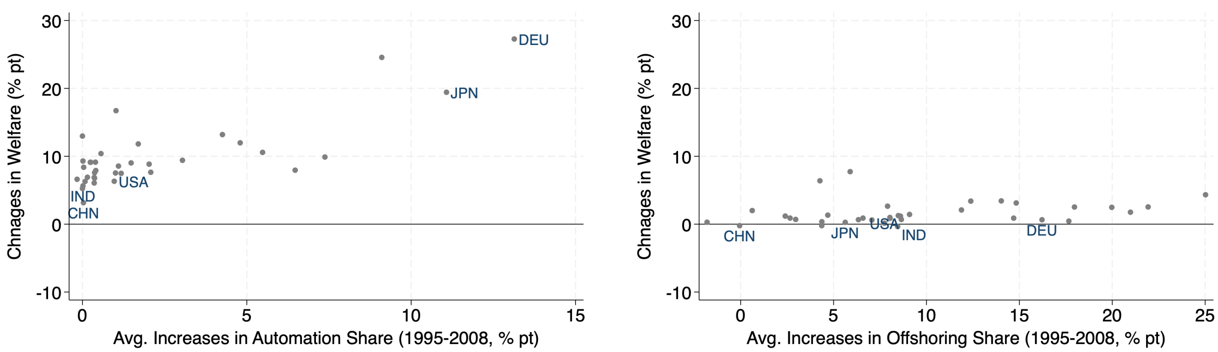
(a) Automation: $\theta = 0$ (b) Automation: $\theta = 0.5$




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 9a shows the results when the trade elasticity is zero ($\theta = 0.0$) so that the trade shares are fixed. Figure 9b shows the results when only automation shares change since 1995 when the trade elasticity is 0.5 ($\theta = 0.5$) so that the trade shares are lower than the baseline value ($\theta = 5.0$). Each dot represents a country.

Figure 10: Changes in Welfare

(a) Automation (b) Offshoring

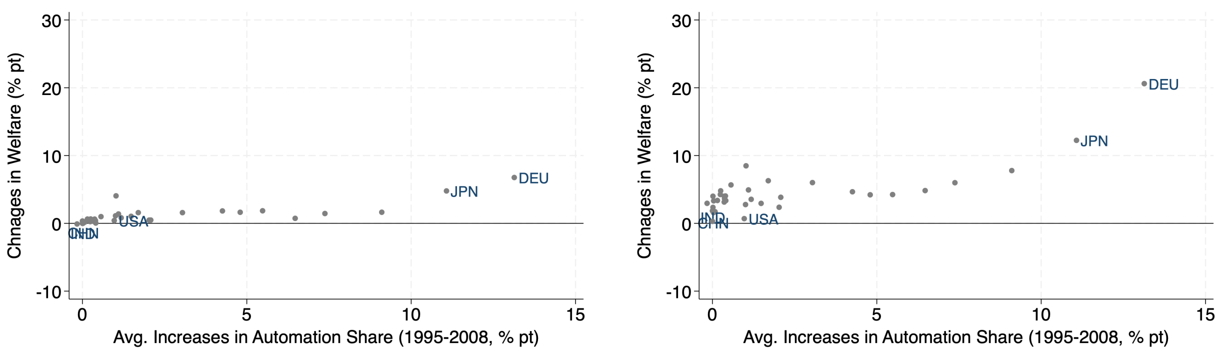



Notes: Both panels show the changes in welfare across countries in response to automation (Figure 10a) and offshoring (Figure 10b) from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share (Figure 10a) or the offshoring share (Figure 10b) between 1995 and 2008. In both panels, the vertical axis shows the changes in welfare across countries. Each dot represents a country.

Figure 11: Welfare Effects of Automation with Different Trade Elasticity

(a) Automation: $\theta = 0$

(b) Automation: $\theta = 0.5$




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 11a 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. Figure 11b shows the results when only automation shares change since 1995 when the trade elasticity is 0.5 ($\theta = 0.5$) so that the trade shares are lower than the baseline value ($\theta = 5.0$). Each dot represents a country.

# 6 Conclusion

In this paper, I document new facts about the evolution of comparative advantage and draw implications for macroeconomic variables. Empirically, I find that a country's skill abundance has become less important for comparative advantage in skill-intensive sectors over time. I show that automation is quantitatively more important in explaining these patterns than offshoring. Moreover, I show that automation in developed countries can lead to shifts in manufacturing production from developing to developed countries. Automation benefits rich countries more while offshoring benefits countries more equally.

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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.[24] 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.[25]

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).[26]

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-

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

[25] Their cleaner is available here.

[26] 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

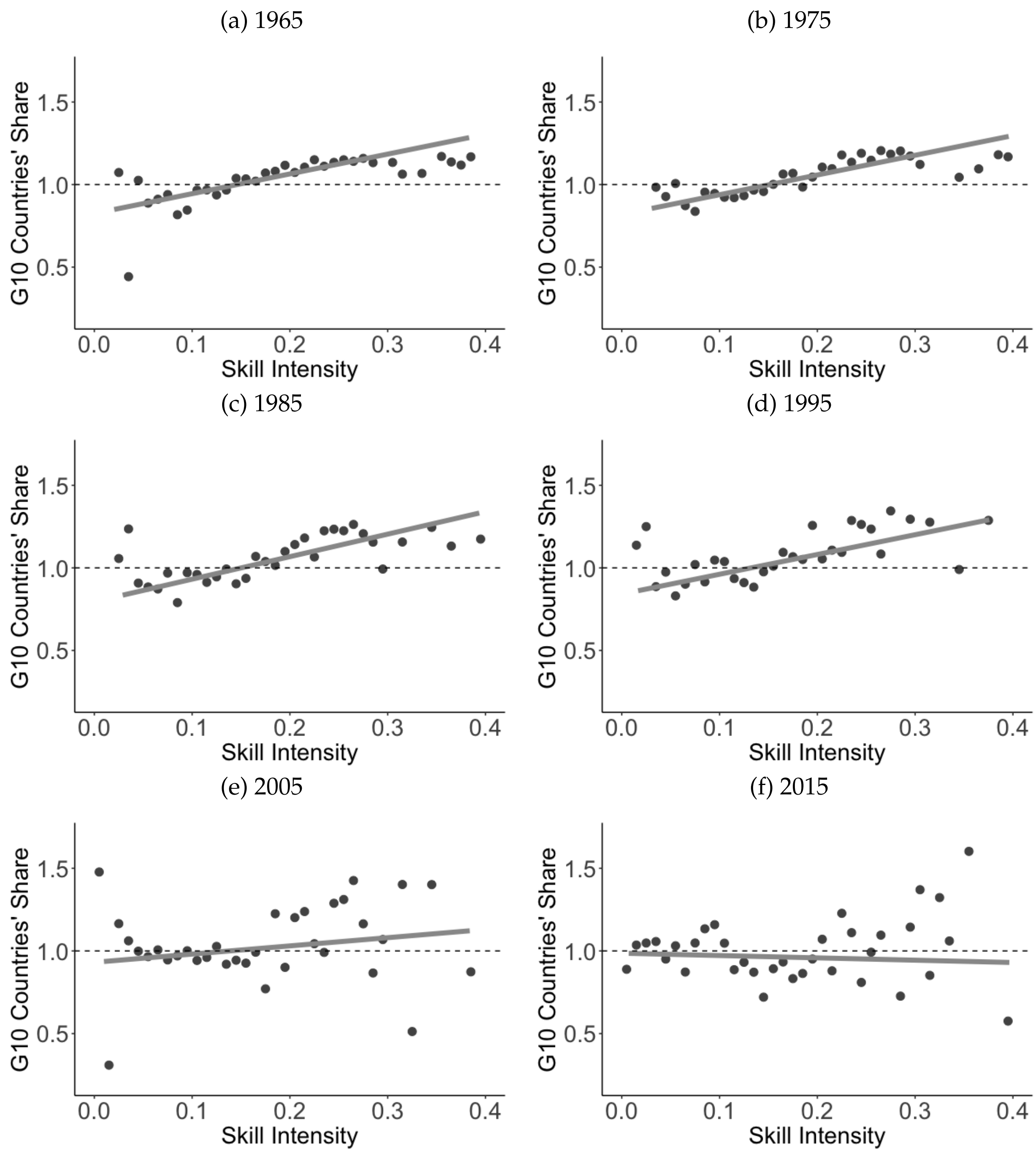
**Definition** G10 countries are Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, the United Kingdom, and the United States.

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).

## 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

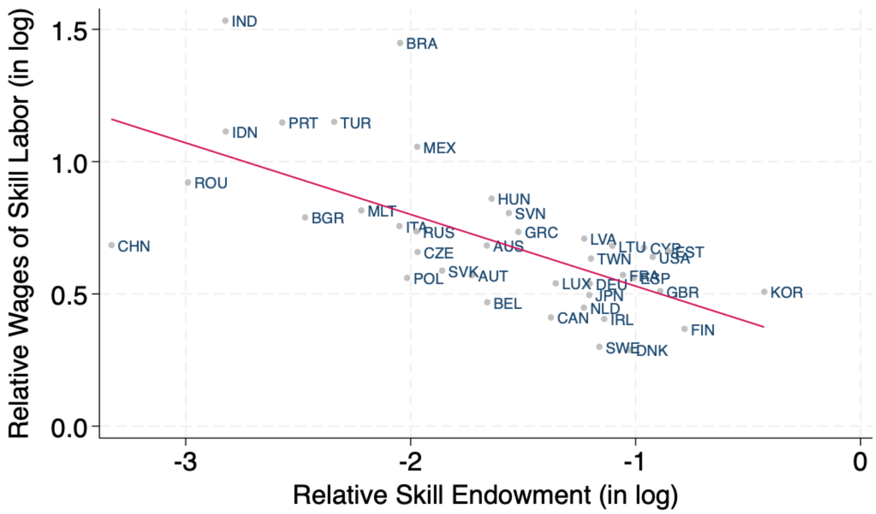



Notes: The figures show binned scatter-plots of revealed comparative advantage, a country's share of global exports in a sector divided by its share of aggregate global exports, for G10 countries across 397 four-digit sectors with different skill intensities, which I define as the share of non-production 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 2000. Each dot represents a country, and the red line is the fitted line. Data is from the World Input-Output Database (Timmer et al., 2015).

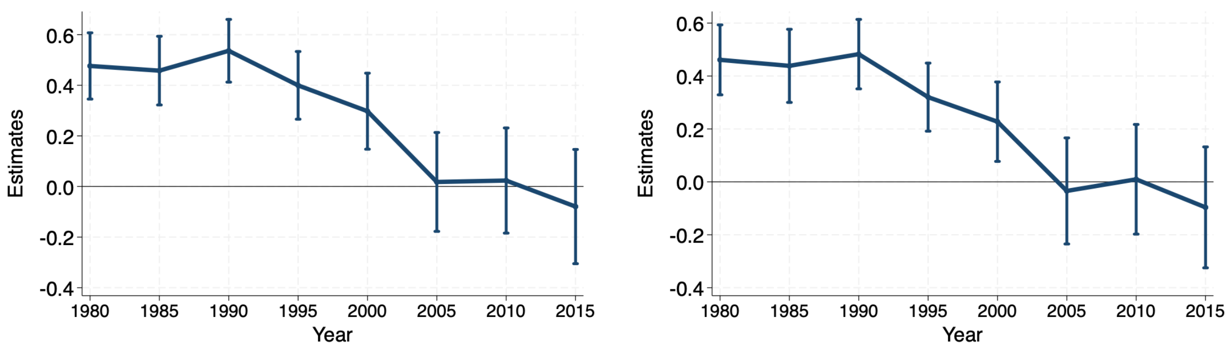
Figure C.2 shows the relative skill endowment and relative hourly wages of skilled labor across countries in 2000. Both are in the log unit. Each dot represents a country, and the red line is the fitted line. Data is from the July 2014 release of the WIOD Socio-Economic Accounts Basic data on output and employment in the World Input-Output Database (Timmer et al., 2015), and I aggregate medium and low-skilled as the low-skilled group. 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)

(a) Bivariate

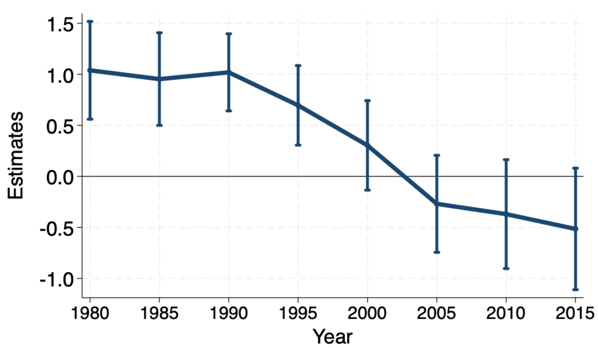
(b) Controlling Capital Term



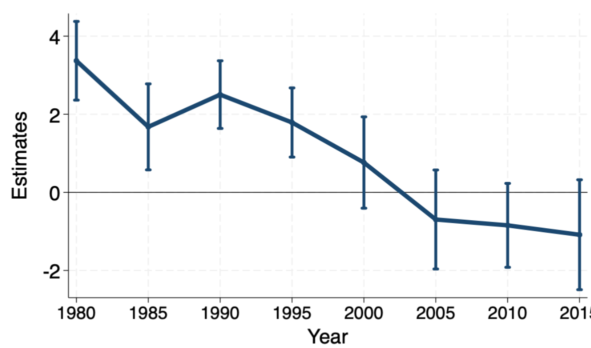

*Note*: The figures show the estimates of coefficients $\beta_t$ in equation (5) in each point time separately. The skill intensity measure is the log factor used in each sector in the US, $\ln(H_s/L_s)$, as in Chor (2010), instead of the skill intensity in the main specification. The bars indicate 95% 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)

(a) Bivariate




(b) Controlling Capital Term




*Note*: The figures show the estimates of coefficients $\beta_t$ 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. In particular, I provide two versions of robustness checks for Table 1.

Table D.1 shows the results without the linear trend. As before, the estimates of the coefficients on the interaction between the "Skill Term" and the automation share are negative and have similar magnitudes around -3. Moreover, since I do not include time trends, the quantitative importance of automation in the change in $\widehat{\beta_t}$ is easy to understand. Let's focus on Column (2). Suppose that a country-sector pair has zero automation. Then, $\widehat{\beta_0} = 1.08$ with the standard error of 0.60. Then, suppose that the automation share is 33%, which is about the top 25 percentile value in 2015. This leads to $\widehat{\beta_t} = 1.08 - 3.41 \times 0.33 \approx -0.05$, implying that the skill abundance is not important for the comparative advantage for country-sector pairs with the automation shares higher than the top 25 percentile value.

Table D.1: Importance of Skill Abundance in Comparative Advantage: Roles of Automation and Offshoring, Continuous Measures, Without the Linear Time Trend

| | Dep. Var. Log Trade Flow | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Skill Term | -0.37 | 1.08 | -0.54 | 0.94 |
| | (0.50) | (0.60) | (0.55) | (0.67) |
| x Automation Share | | -3.41 | | -3.27 |
| | | (1.03) | | (1.04) |
| x Offshoring Share | | | 0.49 | 0.25 |
| | | | (0.43) | (0.41) |
| Observations | 1,528,800 | 1,528,800 | 1,523,612 | 1,523,612 |
| Origin-Dest-Year FE | ✓ | ✓ | ✓ | ✓ |
| Dest-Sector-Year FE | ✓ | ✓ | ✓ | ✓ |

Notes: The table shows the results for the importance of skill abundance in comparative advantage, based on the specification for $\beta_t$ in equation (9). The dependent variable is the bilateral trade flow. All columns include the interaction between the exporter's skill abundance and the sector's skill intensity, "Skill Term", as the running variable. Columns (2) and (4) include the interaction between "Skill Term" and the automation share. Columns (3) and (4) include the interaction between "Skill Term" and the offshoring share. All the columns include origin-exporter-year fixed effects and importer-sector fixed effects. The standard errors are in parentheses and clustered at the exporter-sector level.

Table D.2 shows the results when I control the interaction between the exporter's capital abundance and the sector's capital intensity. Again, the magnitudes of the coefficient that represents the role of automation in the importance of skill abundance for comparative advantage are similar, which are around -3.0.

Table D.2: Importance of Skill Abundance in Comparative Advantage: Roles of Automation and Offshoring, Continuous Measures, With Capital Term

| | Dep. Var. Log Trade Flow | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Skill Term | 2.34 | 3.44 | 2.22 | 3.39 |
| | (0.58) | (0.66) | (0.63) | (0.73) |
| x Automation Share | | -3.00 | | -2.94 |
| | | (1.03) | | (1.04) |
| x Offshoring Share | | | 0.33 | 0.12 |
| | | | (0.42) | (0.41) |
| x Linear Trend | -1.11 | -1.00 | -1.11 | -1.01 |
| | (0.18) | (0.17) | (0.18) | (0.17) |
| Capital Term | 1.20 | 1.18 | 1.19 | 1.17 |
| | (0.26) | (0.25) | (0.26) | (0.25) |
| Observations | 1,528,800 | 1,528,800 | 1,523,612 | 1,523,612 |
| Origin-Dest-Year FE | ✓ | ✓ | ✓ | ✓ |
| Dest-Sector-Year FE | ✓ | ✓ | ✓ | ✓ |

Notes: The table shows the results for the importance of skill abundance in comparative advantage, based on the specification for $\beta_t$ in equation (9). The dependent variable is the bilateral trade flow. All columns include the interaction between the exporter's skill abundance and the sector's skill intensity, "Skill Term", and the interaction between the exporter's capital abundance and the sector's capital intensity, "Capital Term", as the running variables. Columns (2) and (4) include the interaction between "Skill Term" and the automation share. Columns (3) and (4) include the interaction between "Skill Term" and the offshoring share. All the columns include origin-exporter-year fixed effects and importer-sector fixed effects. The standard errors are in parentheses and clustered at the exporter-sector level.

# E 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

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

### 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

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

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

**Machine Price**

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

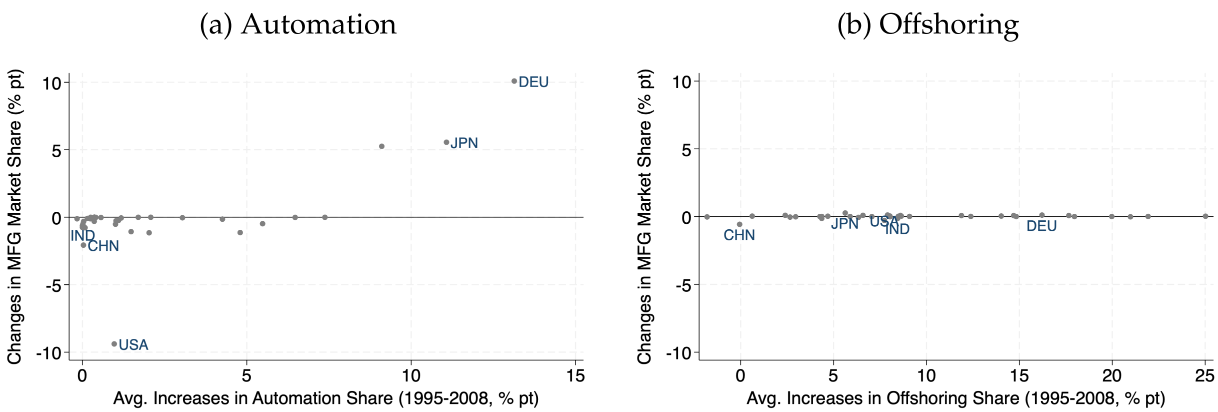
**Intermediate Price**

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

# F Additional Quantitative Results

## F.1 Manufacturing Market Share in the World

Figure F.5: Changes in Manufacturing Market Share in the World




Notes: Figures F.5a and F.5b show the changes in manufacturing market shares in the world.