# Evolution of Comparative Advantage: Why Skill Abundance No Longer Matters *

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Job Market Paper

October 14, 2024

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**Abstract**

This paper documents new facts about the evolution of comparative advantage and explores the causes and implications of this evolution. The key new finding is that the country's skill abundance once implied a comparative advantage in skill-intensive sectors, but this relationship weakened in the 1990s and disappeared by the 2000s. I show that larger declines in the importance of skill abundance occur in countries and sectors with higher levels of automation, with no significant—or even opposite—variation observed with offshoring. Based on a multi-sector quantitative trade model incorporating both automation and offshoring, I find that automation, rather than offshoring, is the primary driver behind the change in comparative advantage and that, without automation, skill abundance would have remained important in comparative advantage after 2000. As a result, automation benefits all countries, with a disproportionate increase in wages of high-skilled labor in developed countries. In contrast, offshoring benefits all countries, albeit to a lesser extent, and the benefits are more equally distributed.

*I am deeply indebted to my advisers Daron Acemoglu, David Atkin, and Arnaud Costinot for their invaluable guidance and support. I also thank Pol Antràs, Kosuke Aoki, David Autor, Martin Beraja, Saroj Bhattarai, Johannes Boehm, Robert Dekle, Dave Donaldson, Chris Edmond, Masao Fukui, Ippei Fujiwara (discussant), Hirokazu Ishise, Hiroyuki Kasahara, Nobuhiro Kiyotaki, Isabela Manelici, Kiminori Matsuyama, Marc Melitz, Daniel O'Connor, Tommaso Porzio, Karthik Sastry, Kazuatsu Shimizu, Yoichi Sugita, Yuta Takahashi, Fabian Trottner, Jose Vasquez, Conor Walsh (discussant), Iván Werning, and Christian Wolf for their comments and suggestions. I thank Xiang Ding for providing me with the data in Ding (2022).

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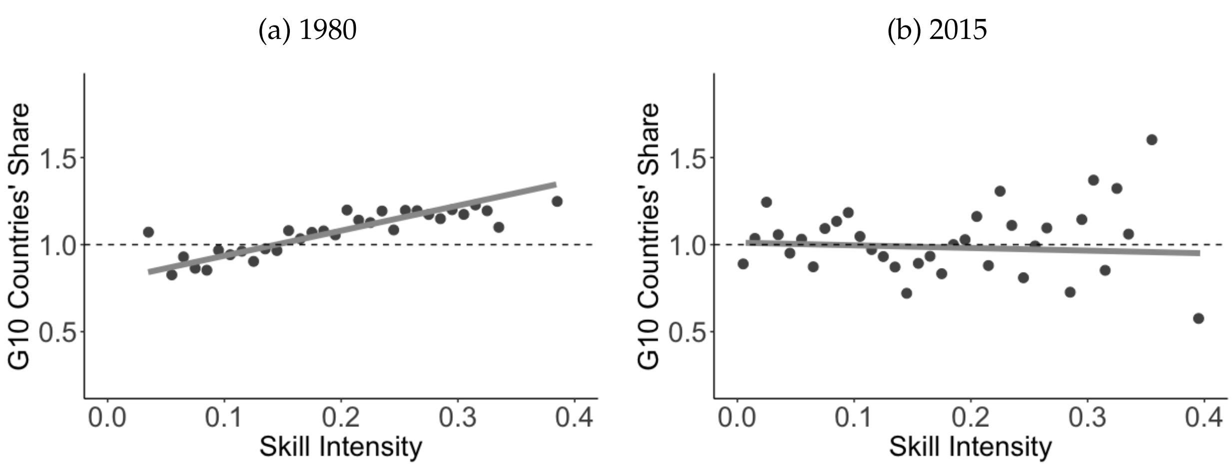
# Introduction

A country's skill abundance has been viewed as a source of comparative advantage in skill-intensive sectors in international trade (Rybczynski, 1955; Leamer, 1984; Romalis, 2004; Morrow, 2010; Chor, 2010). Low-skill-abundant countries specialize in low-skill-intensive sectors because their relative unit costs in these sectors are lower. For example, the US specializes in computer sectors, which are skill-intensive, while Bangladesh specializes in textile sectors, which are low-skill-intensive.

In this paper, I document new facts about the evolution of comparative advantage and explore the causes and implications of this evolution. The starting point of my paper is a simple descriptive analysis of international trade patterns. Figure 1 presents binned scatter plots of revealed comparative advantage, defined as a country's share of global exports in a sector divided by its share of total global exports, for G10 countries across 397 four-digit sectors with varying skill intensities. Panel 1a shows that in 1980, G10 countries, which were more skill-abundant than the rest of the world, had higher shares of exports in skill-intensive sectors. This finding is consistent with previous studies, which found that a country's skill abundance was a source of comparative advantage in skill-intensive sectors. However, Panel 1b shows that by 2015, the positive association between the G10's export share and sectoral skill intensity was no longer present.

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




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.

**New Facts on Evolution of Comparative Advantage.** Building on the facts shown in Figure 1, the first half of the paper empirically investigates the evolution of comparative advantage since 1980. Section 1 offers new empirical evidence of the evolution of comparative advantage, particularly the importance of countries' skill abundance in comparative advantage, in a more systematic manner than Figure 1.

For every five years from 1980 until 2015, I regress bilateral trade flows at the exporter-importer-sector level on the interaction between the exporter's skill abundance and the sector's skill intensity, controlling exporter-importer fixed effects and importer-sector fixed effects. This specification follows the standard in the literature based on a multi-sector Eaton-Kortum model (Eaton and Kortum, 2002) to recover comparative advantage at the exporter-sector level from bilateral trade flow data (Chor, 2010; Costinot et al., 2012). Using that specification, I examine whether skill-abundant countries export more in skill-intensive sectors at each point in time, with the fixed effects controlling the determinants of trade patterns specific to exporter-importer pairs, such as distances or trade agreements, and those specific to importer-sector pairs, such as tariffs or expenditure shares.

The first finding is that skill-abundant countries used to specialize in skill-intensive sectors until the 1990s. This is consistent with the findings of previous papers, such as Leamer (1984), Davis and Weinstein (2001), Romalis (2004), Morrow (2010), and Chor (2010).

The second, new finding is that the relationship between the exporter's skill abundance and the sector's skill intensity weakened over time and eventually disappeared after 2000. This result indicates that skill abundance has become less important in explaining trade flows across sectors with varying skill intensities and no longer plays a significant role after 2000. This empirical finding is robust across different specifications, variable constructions, and data sources.

**Heterogeneous Patterns by Automation and Offshoring.** Then, what can be a potential source of this change in comparative advantage? In Section 2, I explore two potential hypotheses—automation and offshoring—by examining the heterogeneity in the changes in comparative advantage across countries and sectors. Using data on robot adoption, intermediate imports, and factor payment shares, I construct measures of automation and offshoring by country, sector, and year. I adopt specifications, which allow the importance of skill abundance for comparative advantage in skill-intensive sectors to depend on the degrees of automation or offshoring by country, sector, and year.

For automation, the decline in the importance of skill abundance is more pronounced in countries and sectors with higher levels of automation, such as electronics or automobile sectors in Germany, South Korea, and Japan. Furthermore, in countries and sectors where automation levels are below the global median, such as textile or food production sectors in developing countries, skill abundance remains as important for comparative advantage in 2015 as it was in the 1990s. In contrast, for offshoring, there is little heterogeneity and, if any, the impacts are opposite.

**Theoretical Framework.** The heterogeneity across countries and sectors found in Section 2 is suggestive of the causes behind the decline in the importance of skill abundance in comparative advantage. However, the heterogeneity only reveals the relative declines in the importance of skill abundance in countries or sectors with different degrees of automation or offshoring.

To understand the quantitative importance of the mechanisms, incorporating general equilibrium effects, in Section 3, I develop a multi-sector Eaton-Kortum model with a task framework of automation and offshoring. Compared to a standard multi-sector Eaton-Kortum model, the key difference is the unit production cost function, which incorporates automation and offshoring.

Theoretically, automation and offshoring can reduce the importance of domestic skill abundance in the unit cost function by replacing low-skill labor with machines or foreign intermediates. These task displacements mitigate the comparative *disadvantage* of low-skill-scarce countries in low-skill-intensive sectors. For example, countries such as Germany and Japan automate or offshore production processes in the automobile sector, allowing them to use machines or foreign intermediates instead of relying on their scarce production workers. This change in production technology enables Germany and Japan to gain a comparative advantage in the automobile sector, making it harder for countries like Vietnam or Malaysia to have a comparative advantage based on their abundant production workers.

**Quantitative Relevance.** Using the model developed in Section 3, Section 4 quantifies the mechanisms and the implications of the evolution of comparative advantage. To do so, I calibrate the model to the economy in 1995 and solve it using the exact hat algebra Dekle et al. (2008) to avoid explicitly calibrating the exporter-sector level productivity and the exporter-importer-sector level trade costs. I consider the following three counterfactual scenarios: (a) only automation shocks from 1995 to 2008, (b) only offshoring shocks from 1995 to 2008, and (c) only automation and offshoring shocks from 1995 to 2008. The shocks I feed are the automation and offshoring shares by country, sector, and year, which I directly constructed from the data as in Section 2. This means that I do exactly match the factor payment shares by country, sector, and years and that I do not target any moments of changes in trade patterns directly. I fix other parameters, such as trade costs or final goods sectoral expenditure shares, at their levels in 1995.

I quantify the roles of automation and offshoring in the evolution of comparative advantage. To do so, I simulate the model under the three counterfactual scenarios and run the same regression as in Section 1 using the data generated by the model. I find that the model with automation and offshoring shocks captures the declines in the importance found in Section 1 well. Moreover, I find that automation, rather than offshoring, is the primary driver behind the decline in the importance of skill abundance in comparative advantage. Specifically, without the advancements in automation since 1995, skill abundance would have remained important in 2008.

**Macro Implications.** Having quantified the roles of automation and offshoring in the evolution of comparative advantage, I demonstrate their macroeconomic implications beyond changes in export patterns. To do so, I simulate the model under the counterfactual scenarios and examine the macroeconomic implications, such as manufacturing shares, skill premia, and welfare across countries.

First, I show that automation shifts tasks from low-skilled labor worldwide to high-skilled labor in high-income countries. This shift relocates 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. The welfare effects are positive for all countries but larger for high-automation countries, such as Germany and Japan.

I also highlight that the impact of automation on skill premia and welfare depends on changes in comparative advantage. When trade elasticity is low, leading to limited sectoral reallocation, 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 due to reduced specialization. This implies that it is important to incorporate changes in comparative advantage and sectoral reallocation when analyzing the effects of automation on skill premia.

Second, I show that offshoring moves tasks from low-skilled labor in skill-abundant countries to low-skilled labor in skill-scarce countries. The effects of offshoring on the manufacturing shares, skill premia, and welfare are smaller and more equal across countries than those of automation. This is because offshoring occurs more equally across countries.

**Literature.** This paper contributes to six strands of the literature. First, this paper contributes to the rich literature that empirically investigates the sources of comparative advantage (Leamer, 1984; Bowen et al., 1987; Trefler, 1993, 1995; Davis and Weinstein, 2001; Romalis, 2004; Nunn, 2007; Levchenko, 2007; Costinot, 2009; Morrow, 2010; Chor, 2010; Costinot et al., 2012). Previous papers stressed the importance of the Ricardian or Heckscher-Ohlin sources of comparative advantage, and most of them do not study how comparative change evolves over time. My paper offers a new fact that skill abundance becomes less important over time and no longer matters for comparative advantage in skill-intensive sectors, following the literature's state-of-art specifications as in Chor (2010) and Costinot et al. (2012).

At the cross-sectional level, several papers have found that skill abundance is the source of comparative advantage between the late 1980s and the late 1990s. Chor (2010) and Morrow (2010) find that skill abundance is important for comparative advantage in skill-intensive sectors in the late 1980s or the early 1990s, and Romalis (2004) shows it for the 1990s.[1] My results are consistent with their findings in these periods and, on top of it, provide the evolution of the relationship between the country's skill abundance and the sector's skill intensity over time.

A few empirical papers study changes in comparative advantage over time. Among others, Hanson et al. (2015) and Levchenko and Zhang (2016) found the mean reversion or convergence of comparative advantage over time. While mean reversion can potentially explain the decreasing importance of skill abundance in comparative advantage for all the sectors, I show that the pattern is heterogeneous across sectors with different exposures to automation and offshoring. Thus, unless mean reversion is systematically correlated with automation and offshoring, it cannot explain my empirical facts entirely.[2]

Second, this paper contributes to the empirical literature that studies the impacts of automation technology on trade patterns, such as Wang (2021), Krenz et al. (2021), and Artuc et al. (2023). Wang (2021) shows that robot adoption by US firms increases imports using the US census data. Krenz et al. (2021) show that robot adoption at the country level leads to the reshoring of manufacturing. Artuc et al. (2023) show that robot adoption in developed countries at the country-sector level leads to both the increase in imports from and exports to less developed countries. The results of my paper echo the findings of

[1] While the importance of skill abundance is not their main subject of interest, several papers report that skill abundance is one of the sources of comparative advantage along with the variables of their interests, including Nunn (2007) for the early 1990s, Levchenko (2007) for the 1990s, and Bombardini et al. (2012) for the 1990s.

[2] Another related literature is theoretical literature that studies endogenous comparative advantage, including Redding (1999).

these papers and, moreover, I show that automation has impacts on comparative advantage, not just total volumes of trade.

Third, this paper contributes to the literature that studies the determinants of skill premium. One strand of the literature, such as Autor et al. (2013), Burstein et al. (2013), Parro (2013), Cravino and Sotelo (2019) focuses on the role of international trade. Another strand of the literature, such as Katz and Murphy (1992), Autor et al. (2003), Acemoglu and Autor (2011), and Acemoglu and Restrepo (2022b), focuses on the role of skill-biased or automation technology. As in Burstein and Vogel (2017) and Burstein et al. (2019), I incorporate trade to study the effect of technology (automation and offshoring) on skill premium. Compared to Burstein and Vogel (2017) and Burstein et al. (2019), I examine the heterogeneous changes in automation shares across countries and sectors.[3]

Fourth, this paper contributes to the literature on the interaction between trade and technology, such as Epifani and Gancia (2008), Loebbing (2022), Matsuyama (2019), Autor et al. (2020), and Furusawa et al. (2022). Most of these previous papers study skill-biased technical changes and not automation, except for Loebbing (2022) and Furusawa et al. (2022).[4] Loebbing (2022) provides a general theoretical framework to consider the relationship between directed technical change and wage inequality. Compared to Loebbing (2022), my paper focuses on the implication of technical change for comparative advantage and trade. My paper also provides empirical and quantitative analysis. Furusawa et al. (2022) develop a quantitative model to draw implications of automation and trade on labor markets. However, their counterfactual analysis uses increases in capital technology in all tasks, which is essentially capital-augmented technology and not automation technology in the sense of the task model. Moreover, compared to Furusawa et al. (2022), I focus on comparative advantage and sectoral specialization and provide empirical and theoretical analyses.

Fifth, this paper adds to the literature on the role of international trade in structural change. Following Matsuyama (2009), there are several papers that study patterns of structural change in open economy models (Uy et al., 2013; Święcki, 2017; Matsuyama, 2019). These papers study the *standard* patterns of structural change, that is, a steady decline in agriculture and a rise in manufacturing, following a decline in manufacturing and a rise in services. My paper shows that labor-replacing technology in developed countries can weaken this pattern.

Finally, this paper contributes to the literature on task framework. In the context of

[3]Section 5.5 in Burstein and Vogel (2017) studies the "Global Skill-Biased Technical Change", which is common across countries and sectors,

[4]Artuc et al. (2023) also build a stylized two-region quantitative trade model with task framework but has only one type of labor.

automation, previous papers, such as Acemoglu and Autor (2011) and Acemoglu and Restrepo (2022b), focus on closed economy settings. In the context of offshoring, Grossman and Rossi-Hansberg (2008) provide a model to explain the effects of offshoring on factor prices. I embed task framework in a standard trade model to jointly study automation and offshoring, and the previous papers are special cases of the framework in this paper.

**Outline** The rest of the paper is organized as follows. Section 1 provides empirical analysis to show how patterns of comparative change have changed over time. Section 2 examines the heterogeneous changes in the pattern of comparative advantage across countries and sectors. Section 3 develops a theoretical framework to study the effects of automation and offshoring on comparative advantage. Section 4 provides quantitative importance of automation and offshoring in trade patterns and structural change across countries. Section 5 concludes.

# 1 Facts: Skill Abundance and Comparative Advantage

In this section, I examine how the relationship between skill abundance across countries and skill intensity across sectors determines comparative advantages and how the relationship changes over time.

## 1.1 Refresher: Multi-sector Eaton Kortum Model

To motivate the regression that reveals comparative advantage of countries across sectors with different skill intensities, I provide a quick review of a multi-sector Eaton Kortum (Eaton and Kortum, 2002) model, following Chor (2010) and Costinot et al. (2012).

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

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

where $c_{i,s}$ is the unit production cost in country $i$ in sector $s$, $\tau_{i,j,s}$ is the bilateral trade cost, $X_{j,s}$ is the total expenditure of country $j$ in sector $s$, and $\theta > 0$ is the trade elasticity. 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 $s$. Under this assumption, Costinot et al. (2012) show that bilateral trade flows $X_{i,j,s}$ are decreasing in unit production cost at the origin-sector level $c_{i,s}$ after partialing out origin-destination and destination-sector fixed effects, $\eta_{i,j}$ and $\eta_{j,s}$.

Now, let's assume that the unit production cost $c_{i,s}$ 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. Then, combining this with equation (1), the bilateral trade flows can be written as follows:

$$\ln \tag{2}$$

## 1.2 Empirical Strategy

My estimation equation takes the form

$$X_{i,j,s,t} = \exp\left[\beta_t \left(\alpha_{s,t}^H \times \ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right) + \eta_{i,j,t} + \eta_{j,s,t}\right] + \varepsilon_{i,j,s,t}, \tag{3}$$

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. I use the Poisson Pseudo Maximum Likelihood (PPML) method following Silva and Tenreyro (2006).

In my context, the coefficient of interest is $\beta_t$, which is the coefficient on the interaction of sector-level factor intensity $\alpha_{s,t}^H$ and origin-level factor endowments $\ln\left(\frac{H_{i,t}}{L_{i,t}}\right)$, and we expect $\beta_t > 0$. While I rationalize this specification as a special case of the full model presented in Section 3, here is the intuition of how the interaction term matters for trade patterns and why we expect that $\beta_t > 0$. Compare two countries, the US and India, for example. Which country is more efficient in producing high-skill-intensive goods, such as computers, than low-skill-intensive goods, such as clothes? We naturally expect that the US has a comparative advantage in more skill-intensive goods, in this case, computers. This is because producing computers requires designers or engineers with Ph.D. degrees and thus the computer sector has higher skill intensity $\alpha_{s,t}^H$. This relationship between the country's skill abundance and the sectors' skill intensity means the US, with higher $\frac{H_{i,t}}{L_{i,t}}$, has lower unit production costs and larger exports in sectors with higher $\alpha_{s,t}^H$, which implies that $\beta_t > 0$.

## 1.3 Data

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

### 1.3.1 Data Sources

**Bilateral Trade Flow** The first main dataset is the bilateral trade flow data from the UN Comtrade data. 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. 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.

**Factor Intensity** The second main data is the factor intensity across sectors from the NBER-CES Manufacturing Industry Database (Becker et al., 2021).[5] The data contains sector-level data on output, employment, and input costs. I compute factor payment shares of non-production workers out of total wage payments. This leads to skill intensity across 397 4-digit manufacturing sectors for each year.

**Factor Endowment** The third main data is factor endowment across countries from the Barro-Lee Educational Attainment Dataset (Barro and Lee, 2013), which is commonly used in the previous studies, including Hall and Jones (1999) and Romalis (2004). I construct a relative skill endowment, the ratio of college-educated people aged 25-64 relative to non-college-educated people aged 25-64.[6]

### 1.3.2 Final Samples

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

[5] 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.

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

**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 49 countries accounted for more than 98% of world exports in 1990.

**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).

## 1.4 Main Results: Declining Importance of Skills in Trade

### 1.4.1 Baseline Result

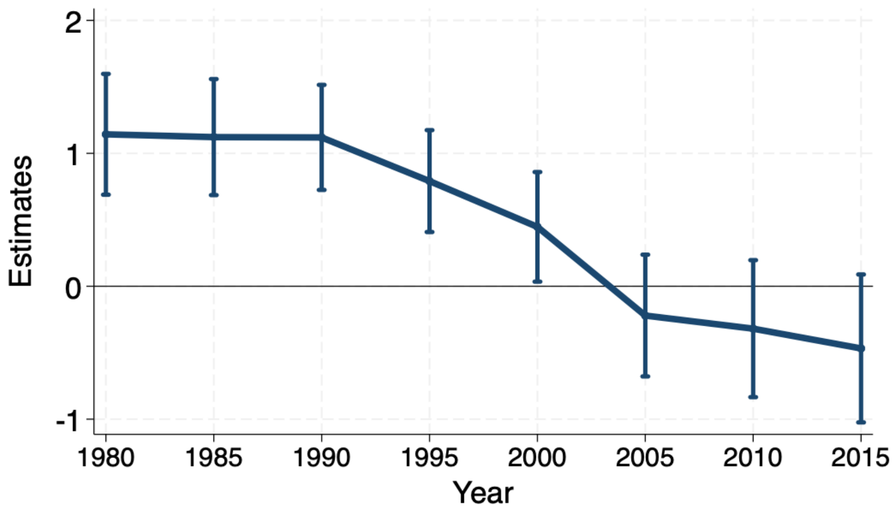
Figure 2 shows the estimates of $\beta_t$ and its 95% confidence intervals based on heteroskedasticity robust standard errors clustered at the origin-sector level. The first finding is that the estimates had been positive until 1995. This means that the country-level skill endowments were the source of comparative advantage in skill-intensive sectors and that developing countries specialize in low-skill-intensive sectors. This result is consistent with the previous papers, which found that more skill-abundant countries specialize in skill-intensive sectors, including Chor (2010) using data of the 1980s, Romalis (2004), Levchenko (2007), and Nunn (2007) using data of the 1990s.

The second, and new, finding is that the estimates decreased over time and became insignificant by 1995. This suggests that skill abundance across countries has become less important for comparative advantage in skill-intensive sectors and is not as important as it used to be in 1980 to explain trade patterns.

### 1.4.2 Robustness in Other Paper's Specifications

While this paper is the first to show the evolution of comparative advantage over time by running the regression in (3) over time, several papers have used similar specifications at the cross-section level. One of the closest papers is Chor (2010), which microfounds its specification based on an extension of the Eaton and Kortum (2002) model and studies the sources of comparative advantage using data around 1980. Chor (2010) found that skill endowments were a source of comparative advantage in 1980. There are two small differences between my specification and the one in Chor (2010). First, Chor (2010) did not partial out the origin-destination fixed effects and instead included several

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




*Note*: The figures show the estimates of coefficients $\beta_t$ in equation (3) in each point time separately. The bars indicate 95% confidence intervals based on heteroskedasticity-robust standard errors, clustered at the origin-sector level.

origin-destination $(i, j)$ level variables, such as physical distance, common languages, or trade agreements, in the regression. My specification of Equation (3) nonparametrically controls these origin-destination $(i, j)$ level variables by the fixed effects, $\eta_{i,j,t}$, and focuses only on the variation at origin-sector $(i, s)$ level. Second, Chor (2010) used the ratio of non-production workers in sector $\ln(H_s/L_s)$ instead of skill intensity $\alpha_s^H$ while Chor (2010) itself mentioned that the skill intensity $\alpha_s^H$ is the right, theory-consistent measure. Nevertheless, the result is robust. Figure C.2 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 adopted related specifications include Davis and Weinstein (2001), Romalis (2004), Nunn (2007), or Levchenko (2007). They aggregate bilateral trade flows to total exports at the origin-sector level and regress on different potential sources of comparative advantage. They also found that skill-abundant countries or regions have relatively larger exports in skill-intensive sectors at each point of time. Conceptually, their specifications and the specification in (3) are similar in that both focus on the variation at the origin-sector $(i, s)$ level. Importantly, however, the specification (3) 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. Nevertheless, the result is robust. Figure C.3 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.

### 1.4.3 Some Potential Explanations

Before exploring the potential hypotheses behind the decreases in $\beta_t$, I show that the finding is robust across different specifications and is inconsistent with some of the explanations. Figure 3 shows the results for various alternative specifications. All the panels show the same, decreasing trends over time.

**Other Factor Endowments** Figure 3a adds another term to consider capital intensity and capital endowment across countries as follows.

$$X_{i,j,s,t} = \exp\left[\beta_t \cdot \left(\alpha^H_{s,t} \times \ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right) + \beta^K_t \left(\alpha^K_{s,t} \times \ln\left(\frac{K_{i,t}}{L_{i,t}}\right)\right) + \eta_{i,j,t} + \eta_{j,s,t}\right] + \varepsilon_{i,j,s,t}, \quad (4)$$

Now, I use a value-added share of production labor for the skill intensity, $\alpha^H_{s,t}$, and a value-added share of capital for the capital intensity, $\alpha^K_{s,t}$. The data is from the NBER-CES Manufacturing Industry Database (Becker et al., 2021). To compute the capital to low-skilled labor ratio across countries, $K_{i,t}/L_{i,t}$, I use the real capital stock and employment Penn World Table (PWT) data from Feenstra et al. (2015) and combine it with the data from the Barro-Lee Dataset.[7] 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 skill becomes less important over the years and that the estimate has become insignificant after 2000.

**Weights** One concern is that some of the small countries drive the results and do not describe trade patterns in the world. Figure 3c weighs each observation by the total volumes of exports in each year at the country level. Nonetheless, the result has not changed.

**Unobserved Heterogeneity at Aggregated Sectoral Level** Figure 3d controls the fixed effects at the level of origin countries and 2-digit sectors. This specification controls unobserved heterogeneity at the level of origin countries and 2-digit sectors and focuses on the variations of skill intensity within 2-digit sectors. The pattern is still unaffected.

[7] 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.

**Fixing Factor Endowment and/or Intensity Data as of 1980** One may think that decreasing $\widehat{\beta}_t$ can be just a result of increases in 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. To address this concern, I fix the running variable, using data as of 1980, for all the sample years. Figure 3e uses factor endowments across countries in 1980 for the entire sample period. Figure 3f uses factor intensity across sectors in 1980 for the entire sample period. Figure 3g uses factor endowments across countries and factor intensity across sectors in 1980 for the entire sample period. Using 1980's skill intensity in Figure 3f and 3g widens the confidence intervals, but the patterns are still the same.

**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 uses the old-to-middle workers ratio for skilled to non-skilled labor ratio from Acemoglu and Restrepo (2022a). The time-series patterns hold with these alternative measures.

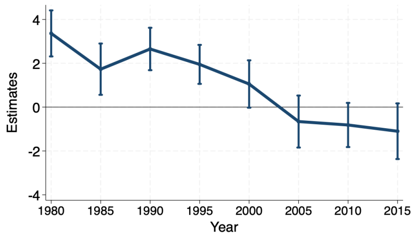
# 2 Potential Hypotheses: Heterogeneous Evolution by Automation and Offshoring

The result in Figure 2 suggests that skill endowments 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.

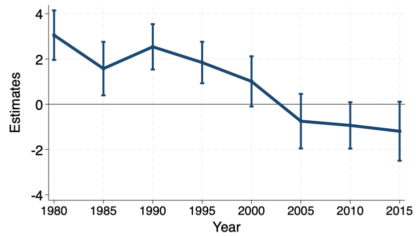
While I present a formal analysis in Section 3, I briefly explain why automation and offshoring can change the roles of skill endowments in trade patterns. Automation replaces production workers who complete routine tasks with machines. This task displacement allows firms to rely on machines instead 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.

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

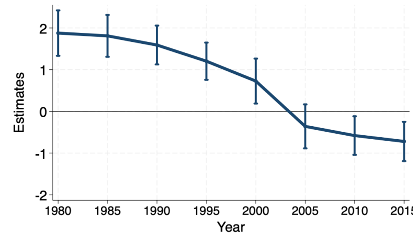
(a) Capital Intensity



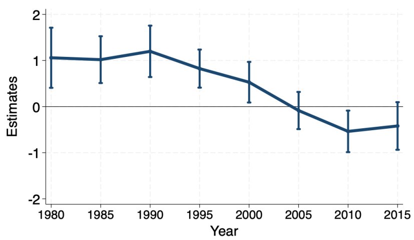

(b) Capital + Institutions



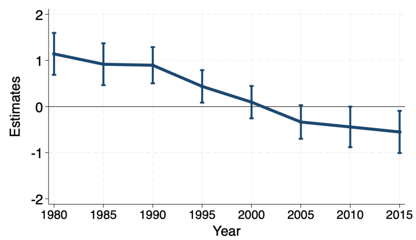

(c) Weighted by Country Size



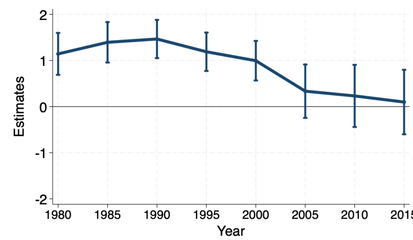

(d) Origin-2 digit Sector FEs



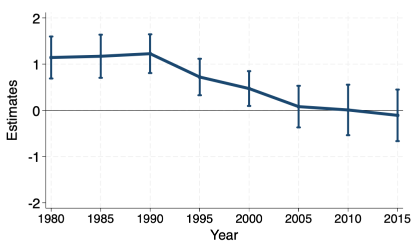

(e) 1980's Endowment



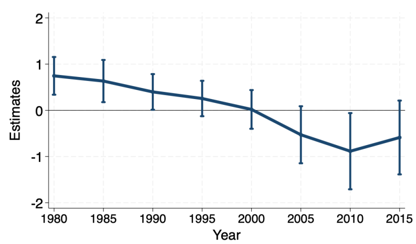

(f) 1980's Skill Intensity



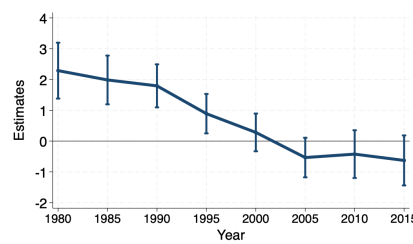

(g) 1980's Endow. + Skill Int.




(h) High School Grads as Skilled



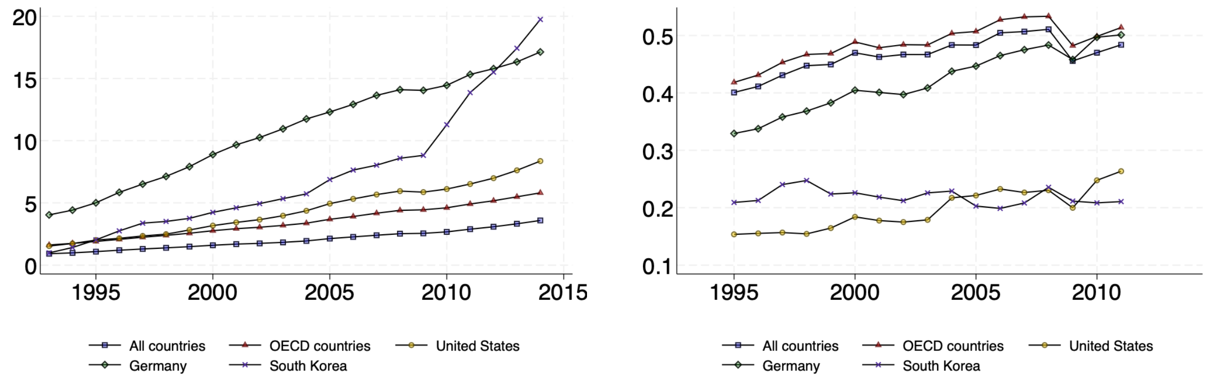

(i) Old-Middle Workers Ratio




Notes: The figures show the estimates of coefficients $\beta_t$ in equation (3) 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 controls fixed effects at the level of a pair of the origin country and the 2-digit sector. Figure 3e replaces skill endowments in each year with those in 1980. Figure 3f replaces skill intensities in each year with those in 1980. Figure 3g replaces both endowments and intensities in each year with those in 1980. Figure 3h replaces skill endowments based on college graduation with those based on high school graduates. Figure 3i replaces skill endowments with the old-to-middle worker's ratio in Acemoglu and Restrepo (2022a).

Figure 4: Automation and Offshoring

(a) Robots per 1K Industry Workers (b) Share of Imports in Intermediates




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).

## 2.1 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.

## 2.2 Specifications for Heterogeneity

In this section, I allow the importance of skill abundance, $\beta_t$ in equation (3), to depend on the degrees of automation and offshoring, $\beta_{i,s,t}$, for each country $i$ and sector $s$ as in the following specification.

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

To explore the heterogeneity, I adopt two specifications for the key parameter to estimate, $\beta_{i,s,t}$, that varies across countries and sectors.[8]

**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 (5) as

$$\beta_{i,s,t} = \underbrace{\beta^0_t}_{\text{Base Group}} + \underbrace{\sum_{g \in G} \beta^g_t \cdot \mathbb{1}\left((i,s) \in g\right)}_{\text{Heterogeneous Trends}}, \tag{6}$$

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.[9] 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

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

[8] 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.

[9] 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.

where Imported Intermediates$_{i,t}$ is the value of imported intermediates of country $i$ in year $t$ from the WIOD, Total Intermediates$_{i,t}$ is the value of total intermediate uses of country $i$ in year $t$ from the WIOD, Imported 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 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 (5) as

$$\beta_{i,s,t} = \beta^0 + \beta^1 \cdot t + \beta^{\text{Auto}}\text{Automation Share}_{i,s,t} + \beta^{\text{Ofs}}\text{Offshoring Share}_{i,s,t}. \tag{7}$$

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

$$\text{Automation Share}_{i,s,t} \equiv \frac{p^M_{i,s,t}M_{i,s,t}}{p^M_{i,s,t}M_{i,s,t} + w^L_{i,t}L_{i,s,t}}, \tag{8}$$

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.

## 2.3 Results

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

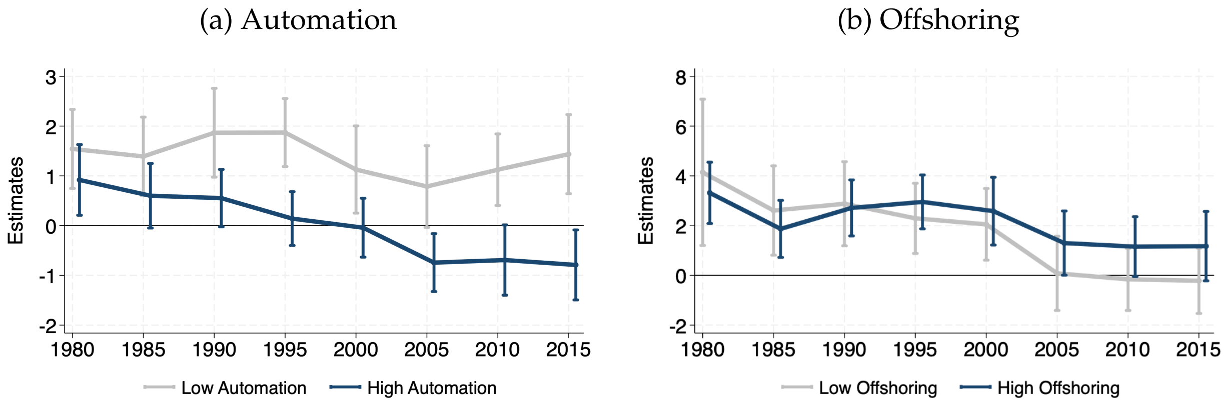
I first start results with the first specification using time-invariant dummy variables. Figure 5a shows the result for automation. I estimate (6) for automation, and the gray line shows the time path of $\widehat{\beta_t^0}$, the coefficient for the low-automation group. The navy line shows the time 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. 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 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.

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

The second specification is to use the time-variant continuous variables as in Equation 7. 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 the 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.

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




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 (6) 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 (6) 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.

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 the 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.

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 (7). 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 as the running variable, "Skill Term". 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.

# 3 Model of Automation, Offshoring, Comparative Advantage

In this section, I develop a quantitative trade model with automation and offshoring to quantify the mechanisms and to draw implications for more macro outcomes, such as industrialization and welfare. The model builds on a multi-country, multi-sector, multi-factor Eaton-Kortum model. In particular, I embed the task framework of Acemoglu and Restrepo (2018) and Acemoglu and Restrepo (2022a) into a quantitative trade model with input-output linkages of Caliendo and Parro (2015).

## 3.1 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.

### 3.1.1 Preference

The demand side is a version of standard multi-sector Eaton-Kortum trade models as in Costinot et al. (2012).

Assume that trade frictions take the form of the standard iceberg trade cost, $\tau^F_{ij,s} \geq 1$ for final goods $s$ exported from country $i$ to $j$, bilateral exports from country $i$ to $j$ in sector $s$, $X_{ijs}$ can be expressed as

$$X_{ij,s} = \pi^F_{ij,s}\mu_{j,s}\left(w^L_j L_j + w^H_j H_j\right)$$

where trade share of final goods, $\pi^F_{ij,s}$ is given by

$$\pi^F_{ij,s} = \frac{(c_{i,s}\tau^F_{ij,s})^{1-\sigma}}{\sum_l (c_{l,s}\tau^F_{lj,s})^{1-\sigma}}, \tag{9}$$

$\mu_{j,s}$ is the expenditure share of country $j$ in sector $s$, $w^L_j L_j + w^H_j H_j$ is the aggregate income of country $j$, and $\sigma$ is the trade elasticity.

#### 3.1.2 Production Technology

Compared to the standard multi-sector, multi-factor Eaton-Kortum model, the key difference is the unit production cost $c_{i,s}$, which comes from the production technology I explain here. Specifically, the production side follows the task framework developed in Acemoglu and Restrepo (2018). 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.[10] The gross production function is

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

where $\alpha_s^H$ is the factor share of high-skilled labor. Goods produced can be used as final goods, intermediate goods, or capital. [11]

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

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

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

$$T_{i,s}(z) = A^M \psi_{i,s}^M(z) M_{i,s}(z) + A^L \psi_{i,s}^L(z) L_{i,s}(z) + A^{XD} \psi_{i,s}^{XD}(z) XD_{i,s}(z) + A^{XF} \psi_{i,s}^{XF}(z) XF_{i,s}(z), \tag{10}$$

where $M_{i,s}(z), L_{i,s}(z), XD_{i,s}(z), XF_{i,s}(z)$ 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. $\psi_{i,s}^M(z)$, $\psi_{i,s}^L(z)$, $\psi_{i,s}^{XD}(z)$. and $\psi_{i,s}^{XF}(z)$ 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.

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

$$\int_0^1 L_{i,s}(z)dz = L_{i,s}, \quad \int_0^1 M_{i,s}(z)dz = M_{i,s}, \quad \int_0^1 XD_{i,s}(z)dz = XD_{i,s}, \quad \int_0^1 XF_{i,s}(z)dz = XF_{i,s}.$$

[10] Here, the machine includes equipment and excludes structures, such as buildings.

[11] 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.

### 3.1.3 Supply of Machines and Intermediates

Final outputs can be used either as final consumption, machines, or intermediates. Here, I explain how machines and intermediates from different coun

**Machines** Firms can either use domestic or foreign machines. The machine used in the country $i$ and sector $s$ is the combination of the machines sourced from different sectors.

$$M_{i,s} = \prod_r M_{i,rs}^{\alpha_{i,rs}^M},$$

where $M_{i,rs}$ is the machine sourced from sector $r$, and $\alpha_{i,rs}^M$ is the input-output coefficient for machines, which sums up to one as $\sum_r \alpha_{i,rs}^M = 1$.

The machine sourced from sector $r$ can be sourced from domestic or foreign suppliers with the elasticity of substitution $\sigma$.

$$M_{i,rs} = \left( \sum_j (M_{ji,rs})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

**Domestic Intermediates** Firms combine intermediates from different sectors with the input-output coefficient for intermediates $\alpha_{i,rs}^X$, which sums up to one as $\sum_r \alpha_{i,rs}^X = 1$. $\alpha_{i,rs}^X$ is the cost share of intermediates from sector $r$ when producing goods $s$ in country $i$.

Then, the domestic intermediates used in country $i$ and sector $s$ are given by

$$XD_{i,s} = \prod_r XD_{i,rs}^{\alpha_{i,rs}^X}.$$

**Foreign Intermediates** Firms can also have access to foreign intermediates. I follow Caliendo and Parro (2015), and within each sector, $r$ across origin countries, the elasticity of substitution is $\sigma$.[12]

Then, foreign intermediates $XF_{i,s}$ are given by

$$XF_{i,s} = \prod_r (XF_{i,rs})^{\alpha_{i,rs}^X}, \quad XF_{i,rs} = \left( \sum_{j \neq i} (XF_{ji,rs})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

[12] The common elasticity with the one for the final goods is just for simplicity.

**Prices and Trade Shares of Machines and Intermediates** These supply structures lead to prices and trade shares of machines and intermediates. First, machine price $w^M_{i,s}$ is

$$w^M_{i,s} = \prod_r \left( \frac{w^M_{i,rs}}{\alpha^M_{i,rs}} \right)^{\alpha^M_{i,rs}}, \tag{11}$$

where the price of machines in country $i$ and sector $s$ sourced from sector $r$ is given by

$$w^M_{i,rs} = \left( \sum_j (c_{j,r} \tau^M_{ji,r})^{1-\sigma} \right)^{1/(1-\sigma)},$$

and the share of machines used in country $i$ sourced from country $j$ is

$$\pi^M_{ji,r} = \frac{(c_{j,r} \tau^M_{ji,r})^{1-\sigma}}{\sum_l (c_{l,r} \tau^M_{li,r})^{1-\sigma}}. \tag{12}$$

Second, the price of domestic intermediates is given by the Cobb-Douglas aggregate of unit costs across sourcing sectors $r$ as follows

$$w^{XD}_{i,s} = \prod_r \left( \frac{c_{i,r}}{\alpha^X_{i,rs}} \right)^{\alpha^X_{i,rs}}. \tag{13}$$

Finally, the price of foreign intermediates is given by

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

where

$$w^{XF}_{i,rs} = \left( \sum_{j \neq i} (c_{j,r} \tau^X_{ji,r})^{1-\sigma} \right)^{1/(1-\sigma)},$$

and the share of foreign intermediates used in country $i$ in sector $r$ from country $j$ is given by

$$\pi^{XF}_{ji,r} = \frac{(c_{j,r} \tau^X_{ji,r})^{1-\sigma}}{\sum_{l \neq i} (c_{l,r} \tau^X_{li,r})^{1-\sigma}}. \tag{15}$$

#### 3.1.4 Market Clearing Conditions

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

$$
\begin{aligned}
Y_{i,s} = & \underbrace{\sum_j \pi^F_{ij,s}\mu_{j,s}(w^L_j L_j + w^H_j H_j)}_{\text{Final Consumption in } j} + \underbrace{\sum_j \sum_r \pi^M_{ij,r}\alpha^M_{j,sr}(1-\alpha^H_r)\Gamma^M_{j,r}Y_{j,r}}_{\text{Machine Service in } j-r} \\
& + \underbrace{\sum_r \alpha^X_{i,sr}(1-\alpha^H_r)\Gamma^{XD}_{i,r}Y_{i,r}}_{\text{Domestic Intermediates in } i-r} + \underbrace{\sum_j \sum_r \pi^X_{ij,r}\alpha^X_{j,sr}(1-\alpha^H_r)\Gamma^{XF}_{j,r}Y_{j,r}}_{\text{Foreign Intermediates in } j(\neq i)-r}
\end{aligned} \tag{16}
$$

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

$$
\begin{aligned}
w^L_i L_i &= \sum_s (1-\alpha^H_s)\Gamma^L_{i,s}Y_{i,s} \\
w^H_i H_i &= \sum_s \alpha^H_s Y_{i,s}
\end{aligned} \tag{17}
$$

## 3.2 Equilibrium

**Definition 3.1.** A *decentralized equilibrium* is defined as consumption, investment, an allocation of tasks, and sourcing plans of intermediates in which

(i) A representative household in each country chooses consumption to maximize utility subject to budget constraint

(ii) Firms choose factor demand and allocation of tasks to maximize profits

(iii) Goods and factor markets clear

**Proposition 3.1.** The equilibrium exists and is unique.

The model is a variant of Eaton-Kortum model Eaton and Kortum (2002) with intermediates, so that the model is within the universal gravity framework of Allen et al. (2020).

### 3.2.1 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:

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

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

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.[13]

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

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

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

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

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, $\Gamma_{i,s}^{XD} = \Gamma_{i,s}^{XF} = 0$, 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, $\Gamma_{i,s}^M = \Gamma_{i,s}^{XD} = 0$, and the foreign intermediates are produced only using foreign labor.

**Unit Production Cost** Consequently, the unit production cost in country $i$ sector $s$ can be written as follows:

$$c_{i,s} = \Lambda_s \cdot (w_i^H)^{\alpha_s^H} \cdot \left[ \left( \frac{w_{i,s}^M}{\Gamma_{i,s}^M} \right)^{\Gamma_{i,s}^M} \cdot \left( \frac{w_i^L}{\Gamma_{i,s}^L} \right)^{\Gamma_{i,s}^L} \cdot \left( \frac{w_{i,s}^{XD}}{\Gamma_{i,s}^{XD}} \right)^{\Gamma_{i,s}^{XD}} \cdot \left( \frac{w_{i,s}^{XF}}{\Gamma_{i,s}^{XF}} \right)^{\Gamma_{i,s}^{XF}} \right]^{1-\alpha_s^H} \tag{18}$$

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

where $\Lambda_s$ is

$$\Lambda_s = (\alpha_s^H)^{-\alpha_s^H}(1-\alpha_s^H)^{\alpha_s^H - 1}.$$

#### 3.2.2 Characterization of Equilibrium

Having established the task shares and the unit production cost, I can now characterize the equilibrium as follows.

**Definition 3.2.** A *decentralized equilibrium* consists of a vector of wages $\{w_i^H, w_i^L\}$ that satisfies the following systems of equations.

(i) Given the vector of wages, prices of machines, prices of intermediates, and unit production costs are jointly pinned down by (11), (13), (14), and (18),

(ii) Given unit costs in each country and sector, trade shares for final goods, machines, and intermediates are determined by (9), (12), and (15),

(iii) Goods and labor markets clear by (16) and (17).

### 3.3 Changes in Skill Premia

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

**Proposition 3.2.** Changes in skill premium can be decomposed into task displacement and sectoral reallocation terms as follows:

$$\widehat{w_i^H} - \widehat{w_i^L} = - \underbrace{\sum_s \zeta_{i,s}^L \cdot \widehat{d\Gamma_{i,s}^L}}_{\text{Task Displacement}} + \underbrace{\sum_s \left(\zeta_{i,s}^H - \zeta_{i,s}^L\right) \cdot \widehat{Y_{i,s}}}_{\text{Sectoral Reallocation}}, \tag{19}$$

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

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

The first term captures the task displacement effect. Automation and offshoring in this model decreases 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, relative demand for high-skill to low-skill labor increases if that sector relatively rely more in high-skill labor than low-skill labor, $\zeta^H_{i,s} > \zeta^L_{i,s}$. 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 in the quantitative analysis.

# 4 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 (3) in Section 1 using the data generated under counterfactual scenarios. Finally, I explore the quantitative implications for skill premia, manufacturing shares, and welfare across countries.

## 4.1 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 1. I used 396 4-digit sic manufacturing sectors in Section 1 while I use 18 sectors, including service sectors here.[14]

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, and I set it to be 6, 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).[15] The input-output coefficients for intermediates and machines, $\alpha^X_{i,rs}$ and $\alpha^M_{i,rs}$, are from Ding

[14] 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.

[15] 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.

(2022).[16]

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

## 4.2 Changes in Comparative Advantage

### 4.2.1 Overview

In this subsection, I quantify the roles of automation and offshoring in the changes in comparative advantage, observed in Section 1. 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 (3) 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.

### 4.2.2 Result

Figure 6 shows the results for the importance of skill abundance in comparative advantage in the different counterfactual scenarios. To start with, the gray line shows the estimates of $\widehat{\beta}$ in the WIOD as in the data. Consistent with the findings in Section 1 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

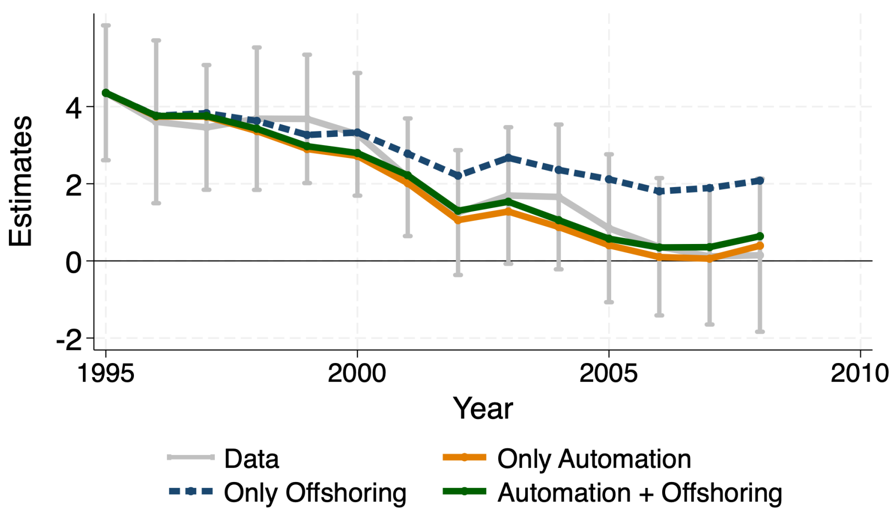
[16] Ding (2022) constructs a novel dataset on inter-sectoral capital service flow. I use the input-output coefficient for capital for the ones for machines in my paper.

I 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.

## 4.3 Macro Implications

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

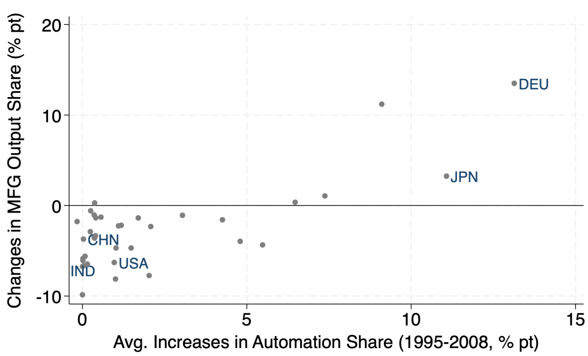
### 4.3.1 Manufacturing Output Shares within Each Country

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.

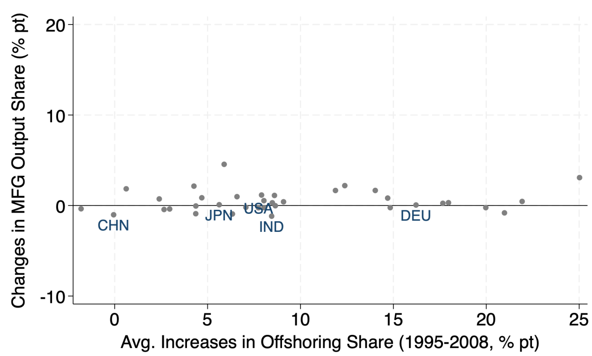
Figure 7b shows the result for offshoring. The horizontal axis now shows the country-level average increases in the offshoring share between 1995 and 2008. Compared to the results for automation, the effects of offshoring are small for most countries.

Figure 7: Changes in Manufacturing Output Share within Each Country

(a) Automation




(b) Offshoring




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

### 4.3.2 Skill Premium

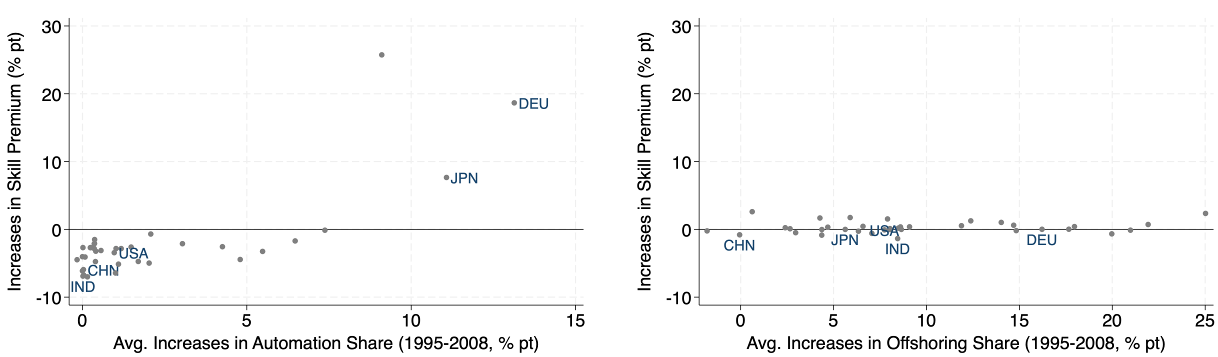
I then explore the implications of automation and offshoring for skill premia. Figure 8 shows the results. Figure 8a shows the changes in skill premia across countries when only automation shares changes since 1995. The horizontal axis shows the country-level average increases in the automation share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

Figure 8: Changes in Skill Premia

(a) Automation

(b) Offshoring

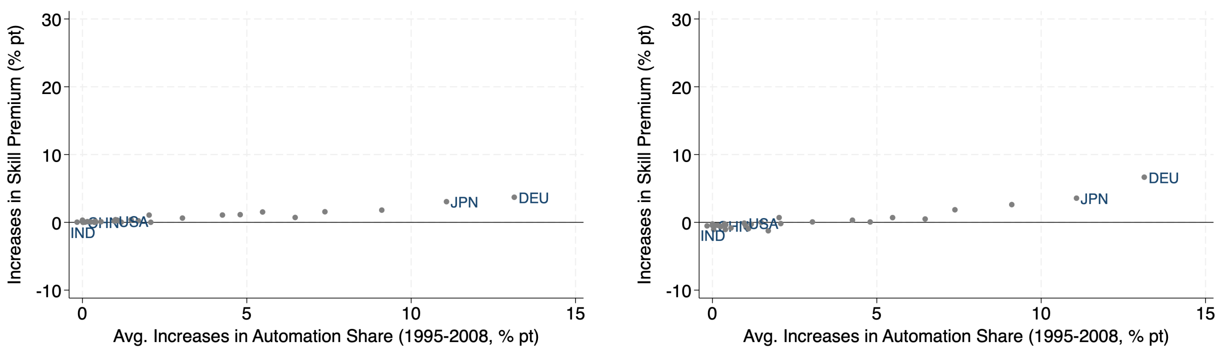



Notes: Both panels show the changes in skill premia across countries in response to automation (Figure 8a) and offshoring (Figure 8b) from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share (Figure 8a) or the offshoring share (Figure 8b) between 1995 and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

To investigate the roles of this sectoral reallocation, Figure 9a shows the effects of automation on skill premia when the trade share is fixed ($\sigma = 1$). 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 $\sigma = 1.5$ where the output is not fixed, but the trade elasticity is lower than the baseline $\sigma = 5.0$. 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.

Figure 9: Changes in Skill Premia due to Automation with Different Trade Elasticity

(a) Automation: $\sigma = 1$ (b) Automation: $\sigma = 1.5$



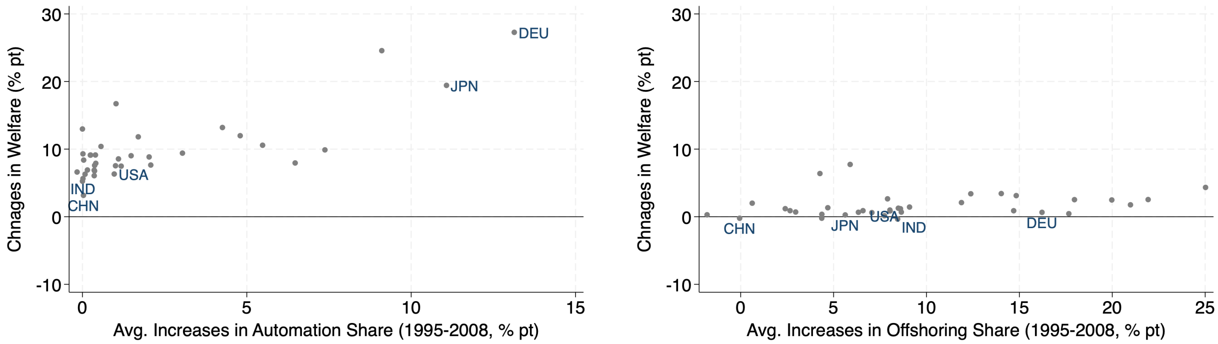

Notes: Both panels show the changes in skill premia across countries in response to automation from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share between 1995 and 2008. In both panels, the vertical axis shows the changes in skill premia across countries. Each dot represents a country. Figure 9a shows the results when the trade elasticity is one ($\sigma = 1.0$) so that the trade shares are fixed. Figure 9b shows the results when only automation shares change since 1995 when the trade elasticity is 1.5 ($\sigma = 1.5$) so that the trade shares are lower than the baseline value ($\sigma = 5$). Each dot represents a country.

### 4.3.3 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, $(w_i^L L_i + w_i^H H_i)/P_i$ 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.

Figure 10: Changes in Welfare

(a) Automation (b) Offshoring

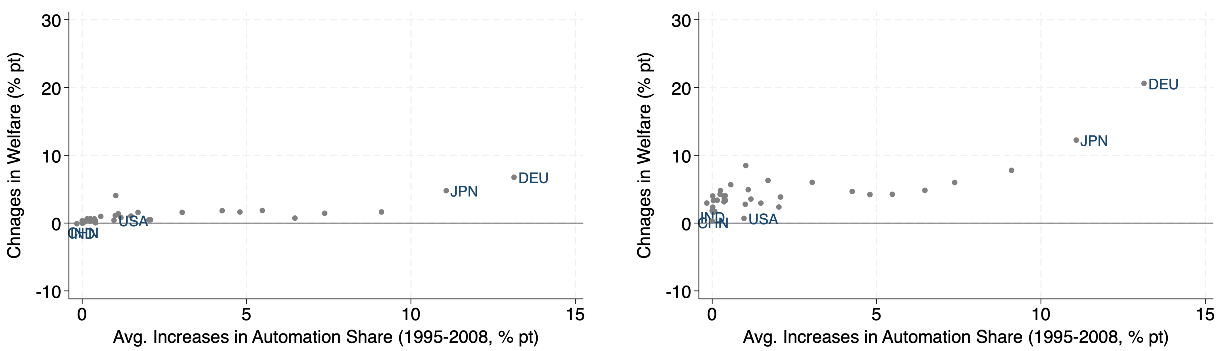



Notes: Both panels show the changes in welfare across countries in response to automation (Figure 10a) and offshoring (Figure 10b) from 1995 to 2008. The horizontal axis shows the country-level average increases in the automation share (Figure 10a) or the offshoring share (Figure 10b) between 1995 and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

Again, I examine how the effects depends on the trade elasticity. Figure 11 shows the results when the trade elasticity is 1.0 or 1.5. Compared to the results in Figure 10a, the welfare effects are smaller in these figures. For instance, when $\sigma = 1$, the welfare effects of automation for India, which is a low-automation country, is around 0% pt while it was 5% pt when $\sigma = 6.0$. 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 11: Welfare Effects of Automation with Different Trade Elasticity

(a) Automation: $\sigma = 1$ (b) Automation: $\sigma = 1.5$




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 one ($\sigma = 1.0$) so that the trade shares are fixed. Figure 11b shows the results when only automation shares change since 1995 when the trade elasticity is 1.5 ($\sigma = 1.5$) so that the trade shares are lower than the baseline value ($\sigma = 5$). Each dot represents a country.

# 5 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

## A.1 Bilateral Trade Flow Data

First, I take the bilateral trade flow data from the UN Comtrade data.[17] I take annual values of traded goods from 1964 to 2016 across 4-digit SITC product categories in SITC

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

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.[18]

Third, I combine countries, which 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).[19] [20]

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-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

[18]Their cleaner is available here.

[19]The crosswalk is available in the UNSD web page here.

[20]The crosswalk is available in 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.

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 Additional Tables

## B.1 Summary Statistics

Table B.1 shows the summary statistics of sector-level variables across 2-digit sector categories. Columns (1) and (2) show the employment share in 1980 and 2015 for each 2-digit sector. Columns (3) to (10) show the weighted averages of the variables originally at the 4-digit sector level, using employment in 1980 as the weights. Columns (3) and (4) show the skill intensity across sectors, which is, the payroll share of non-production workers, $\alpha^H_{s,t}$. The economy-wide average was 36% in 1980. Textile Mill (22%), Apparel (25%), Lumber & Wood Products (25%), and Leather Products (25%) sectors have low skill intensity while Instruments (Electronic, 54%), Printing & Publishing (49%), and Chemical Products (48%) sectors have higher skill intensity in 1980. Most of the sectors have experienced increases in skill intensity between 1980 and 2015, and the economy-wide average has become 41%.

Columns (5) and (6) show the share of employment exposed to robots and offshoring within each 2-digit sector. As explained, a 4-digit sector is defined as being exposed to robots if the 4-digit sector is a subset of IFR's 2-digit sectors, such as automobile and electronic sectors. A 4-digit sector is defined as exposed to offshoring if the 4-digit sector's offshoring score is above the median. Electronic, Transportation Equipment, and Instruments (Electronic instruments) sectors have high shares of employment exposed to robots. The share of employment exposed to offshoring is high for the Textile, Apparel, and Petroleum sectors.

Columns (7) and (8) show the routine occupation share in 1980 and 2015. Columns (9) and (10) show the offshoring share in 1980 and 2015.

Table B.1: Summary Statistics by sector

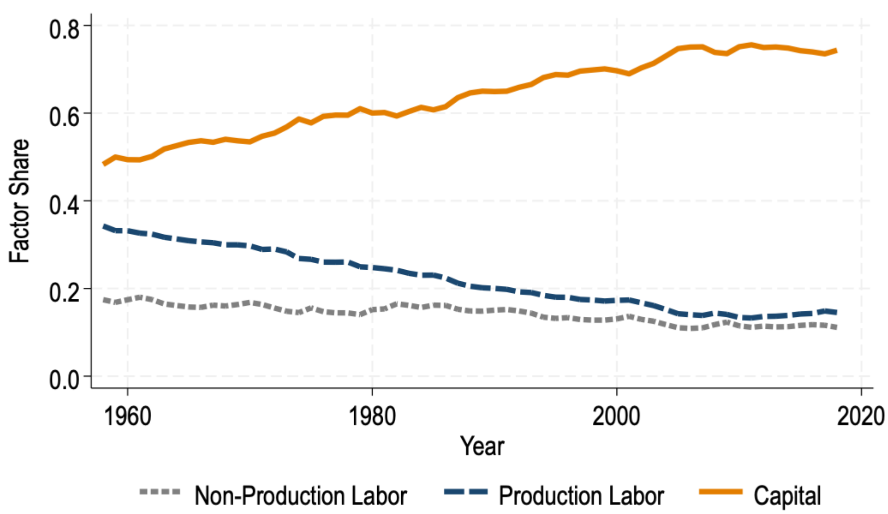
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| SIC 2-digit | Emp.Share | | Skill Int. | | Share | | Routine Share | | Offs. Share | |
| | 1980 | 2015 | 1980 | 2015 | Robot | Frag. | 1980 | 2015 | 1980 | 2015 |
| Food | 0.08 | 0.13 | 0.36 | 0.31 | 0.00 | 0.70 | 0.24 | 0.25 | 0.03 | 0.06 |
| Tobacco | 0.00 | 0.00 | 0.27 | 0.40 | 0.00 | 0.22 | 0.13 | 0.11 | 0.03 | 0.04 |
| Textile Mill | 0.04 | 0.01 | 0.22 | 0.33 | 0.00 | 0.97 | 0.35 | 0.61 | 0.06 | 0.21 |
| Apparel | 0.07 | 0.02 | 0.25 | 0.37 | 0.02 | 0.99 | 0.96 | 0.86 | 0.13 | 0.43 |
| Lumber & Wood | 0.04 | 0.04 | 0.25 | 0.30 | 0.00 | 0.52 | 0.09 | 0.05 | 0.07 | 0.07 |
| Furniture | 0.02 | 0.03 | 0.30 | 0.40 | 0.00 | 0.13 | 0.17 | 0.30 | 0.05 | 0.34 |
| Paper | 0.03 | 0.03 | 0.31 | 0.32 | 0.00 | 0.53 | 0.06 | 0.04 | 0.04 | 0.06 |
| Printing | 0.07 | 0.04 | 0.49 | 0.38 | 0.00 | 0.00 | 0.55 | 0.51 | 0.01 | 0.04 |
| Chemical | 0.05 | 0.07 | 0.48 | 0.51 | 0.00 | 0.58 | 0.22 | 0.14 | 0.04 | 0.18 |
| Petroleum | 0.01 | 0.01 | 0.40 | 0.43 | 0.00 | 0.77 | 0.19 | 0.14 | 0.06 | 0.01 |
| Rubber | 0.04 | 0.06 | 0.34 | 0.37 | 0.00 | 0.00 | 0.07 | 0.06 | 0.05 | 0.15 |
| Leather | 0.01 | 0.00 | 0.25 | 0.43 | 0.00 | 0.46 | 0.13 | 0.51 | 0.31 | 0.70 |
| Stone & Glass | 0.03 | 0.03 | 0.28 | 0.32 | 0.00 | 0.02 | 0.12 | 0.05 | 0.06 | 0.17 |
| Primary Metal | 0.06 | 0.04 | 0.27 | 0.30 | 0.00 | 0.71 | 0.16 | 0.17 | 0.11 | 0.18 |
| Fabricated Metal | 0.09 | 0.11 | 0.33 | 0.38 | 0.06 | 0.45 | 0.29 | 0.28 | 0.04 | 0.15 |
| Ind. Machine. | 0.12 | 0.12 | 0.42 | 0.46 | 0.15 | 0.30 | 0.42 | 0.42 | 0.08 | 0.24 |
| Electronic | 0.09 | 0.07 | 0.42 | 0.53 | 1.00 | 0.18 | 0.16 | 0.13 | 0.10 | 0.44 |
| Trans. Equip. | 0.09 | 0.11 | 0.37 | 0.38 | 0.41 | 0.37 | 0.30 | 0.17 | 0.10 | 0.23 |
| Instruments | 0.05 | 0.06 | 0.54 | 0.69 | 1.00 | 0.02 | 0.18 | 0.16 | 0.09 | 0.23 |
| Miscellaneous | 0.02 | 0.02 | 0.38 | 0.54 | 0.00 | 0.22 | 0.10 | 0.06 | 0.17 | 0.29 |
| Average | | | 0.36 | 0.41 | 0.20 | 0.41 | 0.30 | 0.23 | 0.08 | 0.19 |

Notes: The table shows the summary statistics of sector-level variables across 2-digit sector categories. Columns (1) and (2) show the employment share in 1980 and 2015 for each 2-digit sector. Columns (3) to (10) show the weighted averages of the variables originally at the 4-digit sector level, using employment in 1980 as the weights. Columns (3) and (4) show the skill intensity across sectors, which is, the payroll share of non-production workers. Columns (5) and (6) show the share of employment in 1980 exposed to robots and offshoring within each 2-digit sector. A 4-digit sector is defined as being exposed to robots if the 4-digit sector is a subset of IFR's 2-digit sectors, including automobile and electronic sectors. A 4-digit sector is defined as exposed to offshoring if the 4-digit sector's offshoring score is above the median. Columns (7) and (8) show the routine occupation share in 1980 and 2015. Columns (9) and (10) show the offshoring share in 1980 and 2015.

# C Additional Figures for Section 1

Figure C.1 shows the factor share in the US manufacturing sectors. The orange solid line shows a capital share, the blue dashed line shows a production labor share, and the gray dotted line shows a non-production labor share. Since 1958, the capital share increased from 48% to 74% while the production labor share declined from 34% to 15%. The non-production labor share declined from 17% to 11%, the size of which is less than that of the production labor share.

Figure C.1: Factor Share in the US Manufacturing Sectors




*Note*: The figure shows the factor share in the US manufacturing sectors. Data is from the NBER-CES Manufacturing Industry Database.

Figure C.2: Estimates of Importance of Skills in Comparative Advantage: Specification of Chor (2010)

(a) Bivariate (b) Controlling Capital Term

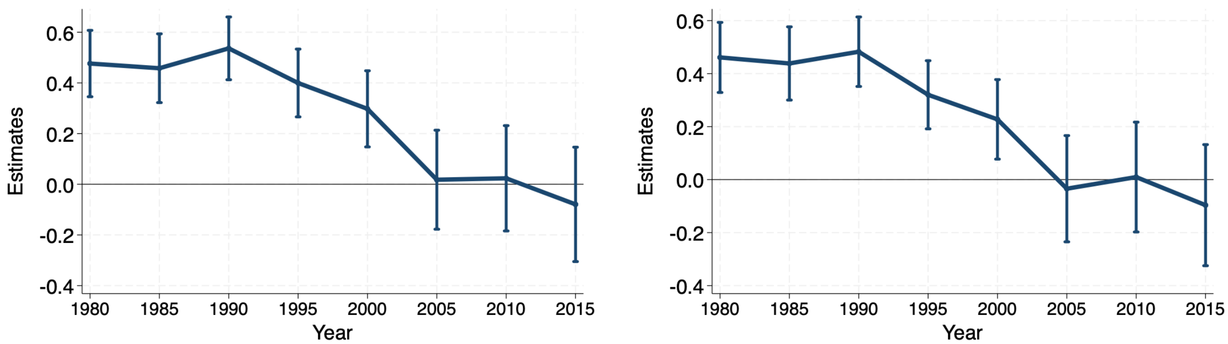
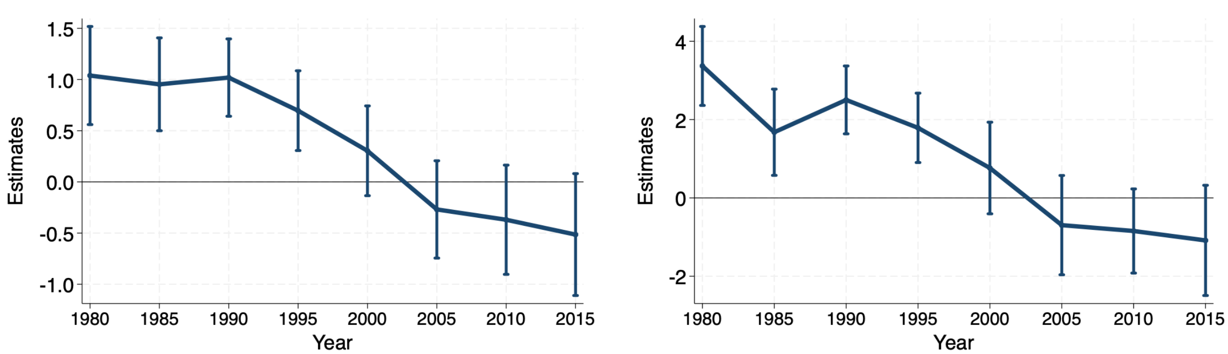



Figure C.3: Estimates of Importance of Skills in Comparative Advantage: Specification of Romalis (2004)

(a) Bivariate (b) Controlling Capital Term



# D Theory Appendix

In this section, I provide a simplistic theoretical framework, which rationalizes the regression in the main text.

Consider the following gravity evaluation

$$X_{i,j,s} = \left(c_{i,s}\tau_{i,j}\tau_{j,s}\right)^{1-\sigma} \cdot (P_{j,s})^{\sigma-1} X_{j,s},$$

where $X_{i,j,s}$ is a bilateral trade flow from country $i$ to $j$ in sector $s$, $c_{i,s}$ is a unit production cost, $\tau_{i,j}$ and $\tau_{j,s}$ are iceberg trade cost, specific at origin-destination and destination-sector level, $P_{j,s} \equiv \sum_l \left(c_{l,s}\tau_{l,j}\tau_{j,s}\right)^{1-\sigma}$ is the price of goods, and $X_{j,s}$ is the total import of goods $s$ in country $j$.

Taking log and collapsing origin-destination and destination-sector level variables into fixed effects, we have

$$\ln X_{i,j,s} = (1-\sigma) \cdot \ln c_{i,s} + \mu_{i,j} + \mu_{j,s}. \tag{20}$$

Also, consider a unit production cost at the origin-sector level as follows

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

where $\alpha_s^H$ is non-production labor share.

Taking log, we have

$$\ln c_{i,s} = \underbrace{\frac{d\ln(w^H/w^L)}{d\ln(H/L)}}_{\equiv \epsilon^w\text{: Rel. Wage Elas.}<0} \cdot \alpha_s^H \cdot \ln\left(\frac{H_i}{L_i}\right) + \ln w_i^L \tag{21}$$

Combining (20) and (21), we have

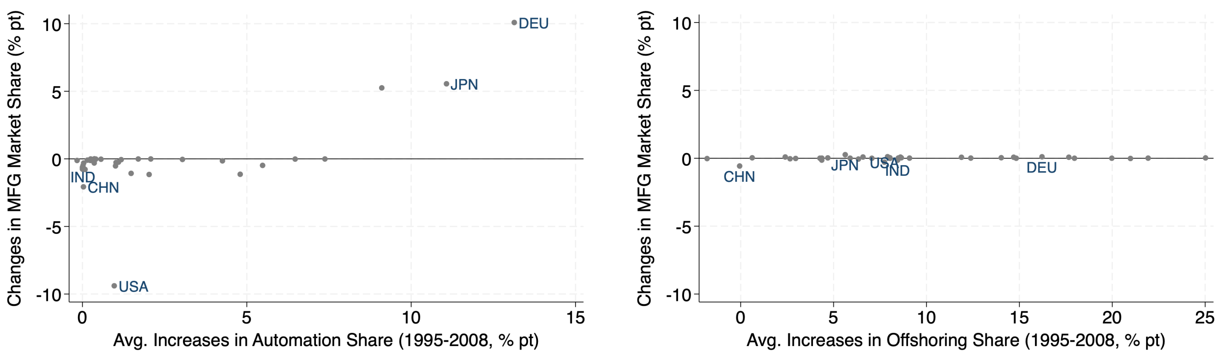
$$\ln X_{i,j,s} = (1-\sigma)\epsilon^w \left[\alpha_s^H \times \ln\left(\frac{H_i}{L_i}\right)\right] + \mu_{i,j} + \mu_{j,s} + \ln w_i^L$$

# E Additional Quantitative Results

### E.0.1 Manufacturing Market Share in the World

Figure E.4: Changes in Manufacturing Market Share in the World

(a) Automation (b) Offshoring




Notes: Figures E.4a and E.4b show the changes in manufacturing market shares in the world.