Automation and Comparative Advantage*

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February 18, 2023

Abstract

I study how automation affects comparative advantage. In the past centuries, the initial stages of economic development featured comparative advantage in low-skill-intensive industries because of low-skill-labor abundance, as predicted by the Heckscher-Ohlin Theorem. I show, however, that this relationship has weakened—or even reversed—in the 21st century. This decoupling occurs because automation provides developed countries with endogenous comparative advantage in low-skill-intensive and automatable industries. My counterfactual analysis shows that recent developing countries would have specialized in low-skill intensive industries, as East Asian countries did, without automation in developed countries.

Keywords: Automation, Demographics, Economic growth, International trade patterns,
JEL Classification: E24, F14, F16, J10, J23, J31, L60, R12, R23

Preliminary. Please Do Not Circulate.

*I am deeply indebted to my advisors Daron Acemoglu and Arnaud Costinot for their invaluable guidance and support. I also thank Pol Antràs, Kosuke Aoki, David Atkin, David Autor, Martin Beraja, Dave Donaldson, Chris Edmond, Masao Fukui, Ippei Fujiwara, Anders Humlum, Kiminori Matsuyama, Marc Melitz, Daniel O'Connor, Karthik Sastry, and Iván Werning for their helpful comments. I also thank seminar participants at Canon Global Institute, Econometric Society Asian Meeting, Harvard, Keio, and MIT. All remaining errors are my own.

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1 Introduction

How do factor endowments affect trade patterns? Standard factor proportion theories, such as Heckscher-Ohlin, predict that countries specialize in industries, which intensively use their abundant factor. For instance, a low-skill-labor-abundant country specializes in low-skill-labor-intensive industries. This is because the unit cost of goods intensively using unskilled labor is lower. This comparative advantage has been thought of as one of the sources of industrialization and export-led economic growth in many developed countries, including East Asian countries.

The starting point of this paper is to signify that the previous, standard argument often takes factor intensity across industries as given, which may not be the case in reality. For example, labor-scarce countries adopt and develop automation technology more (Acemoglu and Restrepo, 2022). This can make previously labor-intensive industries more capital-intensive in developed countries. This change in factor intensity of the automated industries can counteract the Rybczynski and Heckscher-Ohlin effects and may even make labor-scarce countries specialize in initially labor-intensive industries if the productivity gain from automation is sufficiently high.

First, I offer new empirical evidence that low-skill-labor-abundant countries used to specialize in production-labor-intensive industries, but this pattern has recently weakened or even reversed. Motivated by a standard two-factor, multi-sector Armington trade model, I regress bilateral trade flows across 4-digit industries on the interaction between the origin country's factor abundance and sectoral factor intensity, controlling origin-destination fixed effects and destination-industry fixed effects. The baseline empirical result shows that skill endowment across countries becomes less and less important to explain trade flows in industries that differ in skill intensity. This empirical pattern is robust across specifications, variables construction, data sources, samples of countries, or levels of industry aggregations. More importantly, this pattern only appears in industries with high robot adoption. I also show that countries that increase the comparative advantage in low-skill labor-intensive industries increase robot adoption in the same time periods.

Second, to explain these empirical patterns, I propose a theoretical framework to study how automation can change comparative advantage. I embed the task framework developed by Acemoglu and Autor (2011) into the standard multi-sector, multi-factor Armington trade model. I show that automation affects trade patterns by changing the factor intensity in each sector. In particular, automation makes industries that initially rely on low-skill labor less low-skill intensive so that the comparative *disadvantage* for low-skill scarce countries weakens. Using a two-country numerical illustration, I show two things. First, automation can weaken or reverse the comparative advantage of labor-scarce countries in labor-intensive industries. Second, automation can explain premature de-industrialization in developing countries.

Finally, I build a quantitative model to show how much automation can explain the empirical regularities of comparative advantage over time. My model performs well to fit the changes in comparative advantage over time. A counterfactual analysis, where I fix automation technology at the level in 1990, shows that comparative advantage would have not changed if it were no improvement in automation technology.

Related Literature

This paper contributes to four strands of the literature. First, this paper expands the rich theoretical literature on the role of factor endowment differences in comparative advantage and trade patterns, such as the Ricardo-Viner model and Heckscher-Ohlin model (Rybczynski, 1955; Morrow and Trefler, 2017, 2020). To the best of my knowledge, this is the first paper to examine the implication of changes in factor endowments on trade patterns with factor-replacing technology. Only factor-replacing technology, not factor-augmented technology, can weaken or reverse the usual implications for comparative advantage originating from factor endowment.

Second, this paper provides a dynamic aspect to the literature which empirically examines how factor endowments matter for trade. Previous research in this literature, including Wood (1994), Davis and Weinstein (2001), Romalis (2004), Sayan (2005), Nunn (2007), Levchenko (2007), Cai and Stoyanov (2016) and Gu and Stoyanov (2019), do not focus on how comparative change evolves over time. My paper shows that skill endowments are becoming less important as a source of comparative advantage over time.[1]

Third, this paper contributes to the literature on the interaction between trade and technology, such as Epifani and Gancia (2008), Loebbing (2022), Matsuyama (2019), and Autor et al. (2020). Most of these previous papers study skill-biased technical changes and not labor-replacing technical change (i.e., automation), except for Loebbing (2022), which provides a general theoretical framework to consider the relationship between directed technical change and wage inequality. I expand this literature by embedding the technical change into multi-country, multi-sector, and multi-factor settings to study the implication of technical change for changes in comparative advantage.

Fourth, 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 and can explain premature deindustrialization.[2]

Outline The rest of the paper is organized as follows. Section 2 presents a baseline framework for the relationship between factor endowment and comparative advantage and motivates the empirical specification used. Section 3 provides empirical analysis to show how patterns of comparative change have changed over time. Section 4 provides a theoretical framework to consider the relationship between automation and comparative advantage. Section 6 provides quantitative analysis. Section 7 concludes.

[1] Cai and Stoyanov (2016) and Gu and Stoyanov (2019) argue that demographics and skill endowments are important for comparative advantage. While they use data from 1962 to 2000, my paper focuses on years after 2000, when automation technology has become more ubiquitous (Autor, 2015). My results that skills were important until the 1990s are consistent with these findings.

[2] There is a small, but growing, literature on premature deindustrialization, including Rodrik (2016), Fujiwara and Matsuyama (2020), and Sposi et al. (2021) My paper provides a new potential source of premature deindustrialization in developing countries, that is, automation diminishes comparative advantage in manufacturing industries for developing countries.

2 Baseline Model for Factor Endowment and Comparative Advantage

2.1 Settings

First, I lay out a standard Armington trade model with multi-factor to show which regressions are informative to study comparative advantage. Consider a multi-sector, two-factor Armington model. Denote country: $i, j \in \mathcal{N}$, industry (sector): $s \in \mathcal{S}$. Denote total factor endowments of high-skill and low-skill workers in each country H_i and L_i respectively.

Preference Consider a representative household in country j with Cobb-Douglas utility across industries as follows:

$$U_j = \prod_{s \in \mathcal{S}} (q_{js})^{\mu_{js}}$$

where U_j is utility in country j, q_{js} is consumption of goods in sector s consumed in country j, and μ_{js} is the expenditure share. A representative household maximizes this subject to the budget constraint,

$$X_{js} = \mu_{js} E_j,$$

where X_{js} is a nominal consumption of goods in sector s in country j and E_j is total nominal expenditure in country j.

A representative household is with the CES utility within the sector across origin countries i as follows:

$$q_{js} = \left(\sum_{s \in \mathcal{S}} (q_{ijs})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \quad P_{j,s} = \left(\sum_{i \in \mathcal{N}} (c_{is} \tau_{ijs})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \quad X_{ij,s} = \frac{(c_{is} \tau_{ijs})^{1-\sigma}}{P_{js}^{1-\sigma}} X_{js}$$

where q_{ijs} is consumption of goods in sector s, produced in country i, consumed in country j. σ is the elasticity of substitution across goods with different producing countries, τ_{ijs} is an iceberg trade cost, and c_{is} is a unit cost in country i, sector s.

Production Goods in country i in sector s, Y_{is} are produced by the following production technology

$$Y_{is} = L_{is}^{\alpha_s^L} H_{is}^{1-\alpha_s^L}$$

where L_{is} and H_{is} are low- and high-skilled workers employed at country i in sector s, and α_s^L is a production-labor factor share in sector s.

Factor Market Clearing I do not allow factors to move across countries so that the factor market clearing conditions are

$$\sum_{s \in \mathcal{S}} L_{is} = L_i \quad \sum_{s \in \mathcal{S}} H_{is} = H_i$$

National Income Identity Denote w_i^L and w_i^H wages of low- and high-skilled workers. Then the national income identity implies

$$Y_i = w_i^L L_i + w_i^H H_i$$

Equilibrium An equilibrium is a set of factor price and allocations where households and firms maximize utility and profits respectively given the factor market clearing conditions.

2.2 "Reduced-form" Regression

Here, I show which regressions to run to understand the comparative advantage. The unit cost is characterized as follows.

$$c_{is} = \left[(\alpha_s^L)^{-\alpha_s^L} (1-\alpha_s^L)^{\alpha_s^L - 1} \right] (w_i^L)^{\alpha_s^L} (w_i^H)^{1-\alpha_s^L}$$

Assuming that the trade cost take the form of $\tau_{ijs} = \tau_{ij} \times \tau_{js}$, we can write bilateral trade flow as

$$\ln X_{ijs} = (\sigma - 1) \left[\alpha_s^L \ln \left(\frac{w_i^H}{w_i^L} \right) \right] + \delta_{ij} + \delta_{js}$$

where δ_{ij} and δ_{js} are collections of exporter-importer and importer-sector specific terms, respectively. As $\sigma > 1$, other things equal, L-abundant (high $\frac{w_i^H}{w_i^L}$) countries export more in L-intensive (high α_s^L) sectors.

To empirically examine this relationship, it would be ideal to have relative wages in the regression. However, relative wages are hard to observe in a consistent manner for many countries. Thus, I assume $\ln \left(\frac{L_i}{H_i} \right)$ negatively correlates with $\ln \left(\frac{w_i^L}{w_i^H} \right)$ and use it for a proxy, following the literature.[3]

In each period t, I estimate the following equation:

$$\ln X_{ijs,t} = \beta_t \left[\alpha_{s,t}^L \times \ln \left(\frac{L_{i,t}}{H_{i,t}} \right) \right] + \eta_{ij,t} + \eta_{js,t} + u_{ijs,t} \tag{1}$$

where $\eta_{ij,t}$ and $\eta_{j,s,t}$ are pair- and destination-sector fixed effects, which accounts for unobservables, including pair-level trade cost and country-level comparative advantage.

Based on the discussion above, we expect $\beta_t > 0$. Intuitively, countries endowed with more low-skilled labor (high $\frac{L_{it}}{H_{it}}$ and low $\frac{w_{it}^L}{w_{it}^H}$) have a comparative advantage in a sector with higher intensity of low-skilled labor (high $\alpha_{s,t}^L$).

3 Empirical Analysis: Changing Comparative Advantage

3.1 Data

Below, I summarize how I construct data sets for the analysis, separately for bilateral trade flows X_{ijst}, factor intensity $\alpha_{s,t}^L$, and factor endowments L_{it}/H_{it}.

3.1.1 Bilateral Trade Flow Data from UN Comtrade

The first variable is $X_{ijs,t}$ is bilateral trade flow from i to j in sector s in year t. The data source is the UN Comtrade data. I focus on manufacturing industries because service trade data is not

[3]See Davis and Weinstein (2001), Romalis (2004), Chor (2010) and others.

available for long time horizons. I use 4-digit industrial categories as a baseline, but the results are robust if I use 3 or 2-digits instead. I summarize the steps to construct data below.

First, I take the data from UN Comtrade data.[4] I take annual values of traded goods from 1979 to 2016 across industries categorized in SITC Rev. 2, 4-digit. I convert all trade flows into real 2015 US dollars using the US CPI from OECD (2010).

Second, using a cleaner provided by Feenstra and Romalis (2014), I convert data at SITC Rev.2, 4-digit level across countries 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, accounts for re-exports of Chinese goods through Hong Kong, and put Taiwan back as an importer and an exporter.[5]

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

Finally, I convert these SITC Rev.2, 4-digit industrial categories into HS 1996/2002 6-digit using the crosswalk provided by the United Nation[6] and then into sicdd 4-digit using the crosswalk by Autor et al. (2013).[7]

3.1.2 Factor Intensity across Industries from NBER-CES Manufacturing Industry Database

The second variable is the production labor share across industries, $\alpha^L_{s,t}$, which is defined as the share of wage payment for production workers out of total wage payment in each sector s. We use the US data following the literature (Chor (2010)). I use data from the NBER-CES Manufacturing Industry Database (Becker et al., 2021) for SIC 4-digit code and convert the into sic87dd code using the crosswalk by Autor et al. (2013). This leads to factor intensity across 397 4-digit manufacturing industries for each year. As an example, Figure 1 shows histogram of the production labor share across these 397 industries in the US in 1990, and there are wide variations across these sic87dd 4-digit industries. For these 397 4-digit industries' production labor share, the mean is 0.61 with the median of 0.64 and the standard deviation of 0.13. While I use these sic87dd 4-digit industries as a baseline categorization, the results are robust if I instead use 3-digit industries.

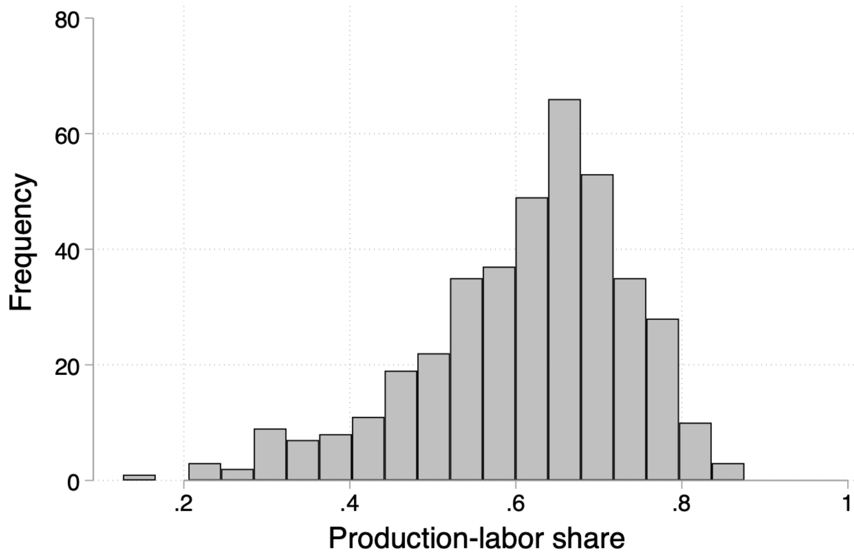
[4] Bulk downloads are available in their United Nation's web page here.

[5] Their cleaner is available here.

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

[7] The crosswalk is available in David Dorn's web page here. sic87dd is a industry classification, which Autor et al. (2013) slightly modifies SIC 4-digit code in 1987 to make the classification time-consistent. See Autor et al. (2013) for details.

Figure 1: Production Labor Share, $\alpha^L_{s,1980}$ across 397 industries in the US in 1990



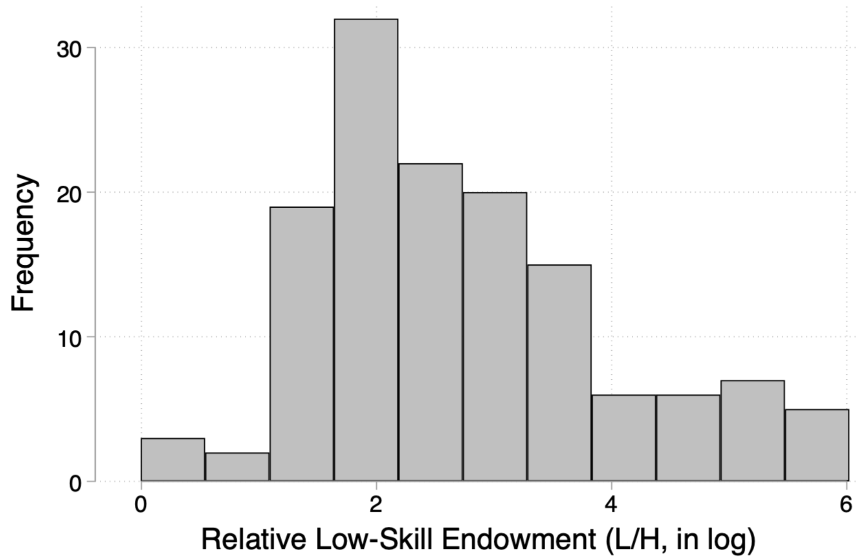
Note: The figure shows the histogram for the factor share of production labor across 397 sic87dd 4-digit manufacturing industries in the US in 1990. Data is from NBER-CES Manufacturing Industry Database.

3.1.3 Factor Endowment across Countries from Barro-Lee Educational Attainment Dataset

The third variable is skill endowment across countries, $\ln\left(\frac{H_i}{L_i}\right)$. I use the ratio of people aged 25-64 with tertiary (college) education from the Barro-Lee Educational Attainment Dataset (Barro and Lee, 2013).[8] Figure 2 shows the histogram of the relative low-skill endowment, $\ln(L_{it}/H_{it})$, across 58 countries in 1990. For these 58 countries, the mean is 2.75 with the median of 2.54 and the standard deviation of 1.27. The results are robust if I use the ratio for people aged 15-64 or the ratio with a high-school education.

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

Figure 2: Relative Low-skill Endowment, $\ln(L_{it}/H_{it})$ across 58 countries in 1990



Note: The figure shows the histogram for the relative low-skill endowment, $\ln(L_{it}/H_{it})$, across 58 countries in 1990. Data is from the Barro-Lee Data.

3.2 Final Samples

Periods: Every 5 years 1980-2015 Since factor endowments data are available only every five years from 1980 to 2015, I use data in every 5 years, which leads to 8 time periods in total. For the trade flow data, to eliminate fluctuations and to focus on long-run trends. I take 3-year moving average and keep data only every 5 years from 1980 to 2015.

Countries: 58 countries First, I restrict samples of countries to those which have import and export data covering all the periods from 1980 to 2015. Second, to ensure that results are not driven by the smallest countries, I also restrict samples to those which have ever had imports and exports more than 100 millions USD (in 2015 value) at least once in 1980 to 2015 as in Atkin et al. (2021). These restrictions lead to 58 countries, and these 58 countries account for more than 97% of world exports in 1980.

Industries: 397 industries I use all of the 397 industries (in sic 4 digit) available in NBER-CES Manufacturing Industry Database (Becker et al., 2021).

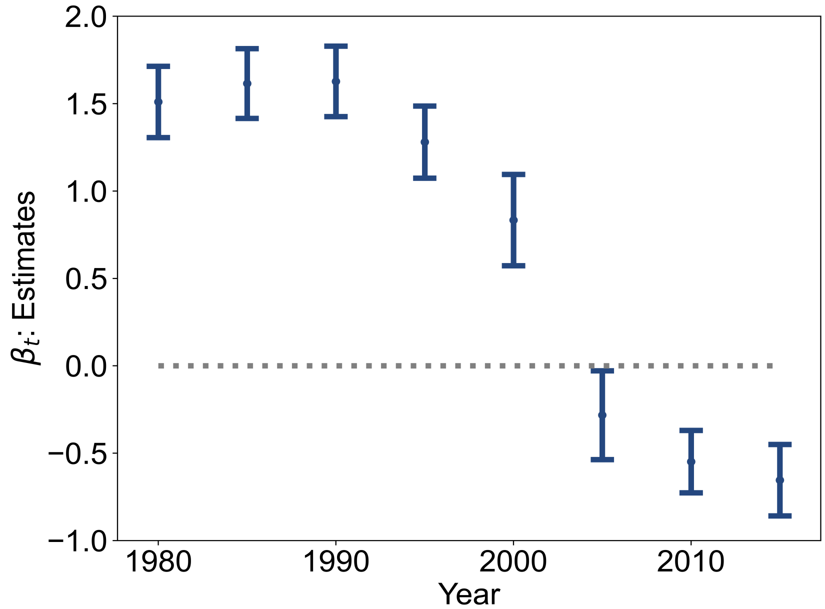
3.3 Regression Results

I estimate equation (1) using Poisson pseudo-maximum likelihood regressions (PPML, Correia et al. (2020)) for each 5 year window (1980, 1985,...,2015) and plot β_t for each year. I use countries' total export each year as weights.

Figure 3 shows the baseline result over time in a one figure, and Table 1 shows the corresponding point estimates and standard errors. The figure shows the estimates of β_t and its 95%

confidence interval based on heteroskedasticity-robust standard errors. In the 1980s and 1990s, the estimates are around 1.5 to 1.7. However, after 1995, the estimates declined and became even negative after 2005. Figure A.1 presents robustness checks. Regardless of the specifications, skill endowments become less important over time.

Figure 3: Comparative Advantage over Time



Note: The figures show the estimates of coefficients β_t in equation (1) in each point time separately. Bars indicate 95% confidence intervals based on heteroskedasticity-robust standard errors.

Table 1: Changes in Comparative Advantage

Year	1980	1985	1990	1995	2000	2005	2010	2015
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_t	1.74	1.73	1.57	1.18	0.78	-0.31	-0.52	-0.61
	(0.11)	(0.10)	(0.10)	(0.10)	(0.13)	(0.12)	(0.08)	(0.09)
Obs.	1,093,210	1,147,832	1,211,854	1,271,194	1,257,409	1,247,811	1,241,522	1,240,437

Notes: The figures show the estimates of coefficients β_t in equation (1) in each point time separately. Standard errors are heteroskedasticity-robust standard errors. All columns use the country's total export as weights.

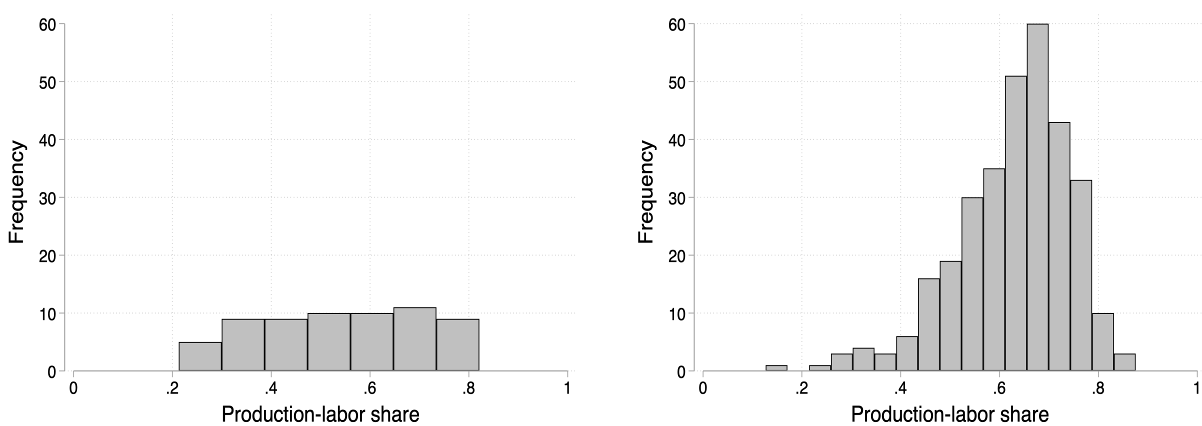
3.4 Sub-sample Analysis: High- or Low-Robot Industries

The results in Figure 3 is surprising and at odds with the standard factor endowment theories. However, there are many hypothesis behind the change in patterns of the relationship between factor endowment. To motivate that the rise of robots can be the cause, I re-estimate equation (1) by sub-samples. Specifically, I compare the estimates of β_t, the importance of skill endowments, for high- and low-robot industries.

I choose the automotive and electronic industries as high-robot industries. They are 2 out of 13 aggregated sectors defined by the International Federation of Robots (IFR), which have distinctively high robot penetration, defined as the total number of robot installments over 1995-2015 across the world, normalized by the number of production workers in the US.[9] Within these two aggregated industrial categories, the automotive and the electronic industries include 63 (out of 397 manufacturing) sic87dd 4-digit industries. While the number of 4-digit industries is small in the high-robot group, the group accounts for about 40% of exports in the world in 1990.

Figure 4 shows the histograms of the production labor share for each group. The cross-industry variations I am going to exploit are these factor shares at sic 4-digit 397 industries *within* each group. While the production labor share has more variations within high-robot industries, low-robot industries also have variations.

Figure 4: Production Labor Share, α_k^L within High- and Low-robot Industries in the US in 1990



(a) Within High-Robot Industries

(b) Within Low-Robot Industries

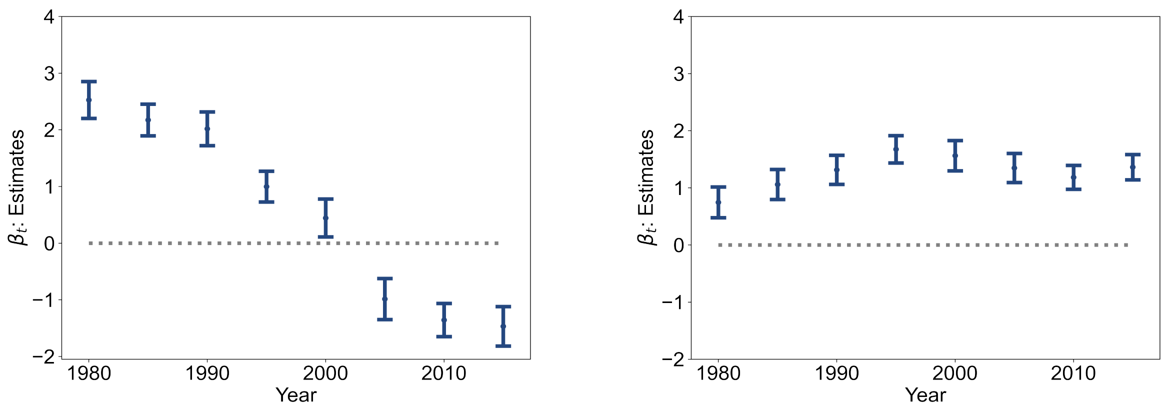
Note: This figure shows the density of production labor share for two sectoral groups: high-robot and low-robot industries. I define automobile and electronic industries as high-robot industries based on the total number of robot installments over 1995-2015 across the world, normalized by the number of production workers in the US across industries. The left panel is for high-robot industries while the right panel is for low-robot industries. Data are from Becker et al. (2021).

Figure 5 shows the results for regressions by sub-sample. Figure 5a is for high-robot industries and Figure 5b is for low-robot industries high-robot industries. It is clear that skill endowments become less important only within high-robot industries (Figure 5a), and they are still as important as they were in previous periods within low-robot industries (Figure 5b). This figure suggests that the declining pattern in Figure 3 is not just a general empirical regularity that skill endowments

[9] Automotive and electronic industries have 550 and 211 robots in the world per 1,000 workers in the US respectively while the third most robot-adopting industry, the plastic/chemical industry, adopts 105, fourth, the metal products, industry adopts 79 robots in the world per 1,000 workers in the US. Including the plastic/chemical industry in the high-robot category does not change the results of this subsample-analysis.

become less important for comparative advantage.[10] Rather, it suggests that robot adoption can be a cause behind the declining importance of skill endowments in comparative advantage.

Figure 5: Estimates of Importance of Skill Intensity; β_t by Industrial Robot Penetration



(a) Within High-Robot Industries

(b) Within Low-Robot Industries

Note: The two figures show the estimates of coefficients β_t in equation (1). I run regressions in each point time separately. I use sic87dd 4-digits industries in electronic and automobile industries for high-robot industries for Figure 5a. I use the rest sic87dd 4-digits industries for 5b. Bars indicate 95% confidence intervals based on heteroskedasticity-robust standard errors.

3.5 More Data-Driven Approach

3.5.1 Changes in Comparative Advantage

To strengthen the empirical results presented in this section, I provide results from an alternative approach, which is more data-driven. Consider the following equation:

$$\ln X_{i,j,s,t} = \sum_c \delta^L_{c,t} \left[\mathbb{1}_{i=c} \times \alpha^L_{s,t} \right] + \eta_{i,j,t} + \eta_{j,s,t} + u_{i,j,s,t} \tag{2}$$

where, as before, X_{ijs} is a bilateral trade flow from country i to j in sector s, and $\alpha^L_{s,t}$ is production labor share in sector s at time t. ν_{ijt} and η_{jst} are origin-destination and destination-sector fixed effects in each time t, and u_{ijst} is an error term.

The differences from the previous specification are $\mathbb{1}_{i=c}$ and $\delta^L_{c,t}$. $\mathbb{1}_{i=c}$ is an indicator function, which takes one if country i is country c and $\delta^L_{c,t}$ is a country-time specific parameter to be estimated, which is country's comparative advantage in low-skill-labor-intensive industries, controlling origin-destination and destination-sector fixed effects.

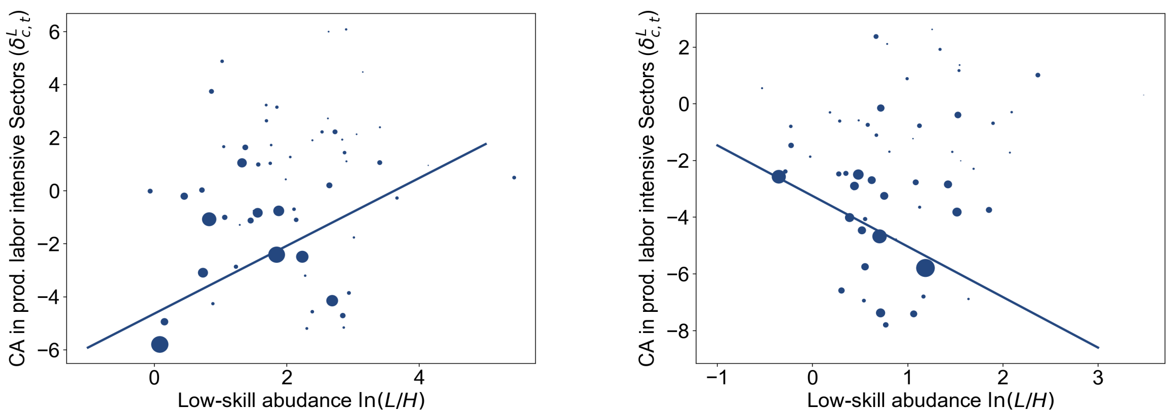
Using the same data for X_{ijst} and α^L_{st} as in the previous regression, I estimate the equation using PPML. As before, I use countries' total export each year as weights. Since δ^L_{ct} is a high-dimensional object, I estimate the equation by penalized PPML using a plug-in lasso following

[10] For instance, this comes neither from a decreasing elasticity of substitution σ over time nor from weakening relationships between relative factor price and relative factor endowment at country level.

Belloni et al. (2016). The model chooses 44 countries out of 58 countries in 1980, and I include these countries throughout the period until 2015.

In Figure 6, I plot the "estimated" comparative advantage in low-skill-intensive industries against low-skill abundance across countries (again from Barro and Lee (2013)) in 1980 and 2015. The left panel shows a positive relationship in 1980, which means that low-skill-labor-abundant countries had a comparative advantage in production-labor-intensive industries. This result is consistent with the result from the main regression in Figure 3. The right panel shows a negative, albeit insignificant, relationship. This is also consistent with my baseline result that the relationship has been weakened or reversed recently.

Figure 6: Comparative Advantage and Low-skill Abundance



(a) 1980

(b) 2015

Note: These figures show the relationship between estimated comparative advantage, $\delta^L_{c,t}$ and relative low-skill labor endowment in log (from Barro and Lee (2013)) across countries in 1980 and 2015. Each dot is a country and the line is a linear fit of linear regression weighted by the country's total export.

3.5.2 Automation and Changes in Comparative Advantage

Equipped with the estimated comparative advantage in L-intensive sectors for each country, $\hat{\delta}^L_{c,t}$, I then study whether the *changes* in comparative advantage relate to automation. Consider the following equation:

$$\Delta\hat{\delta}^L_{c,t,t'} = \zeta\Delta\ln \text{Robot}_{c,t,t'} + \Gamma' X_{c,t} + \eta_c + \eta_t + \varepsilon_{c,t} \tag{3}$$

where $\Delta\hat{\delta}^L_{c,t,t'} \equiv \hat{\delta}^L_{c,t'} - \hat{\delta}^L_{c,t}$ is a change in comparative advantage in low-skill-labor intensive industries in country c from year t to t', $\Delta\ln\text{Robot}_{c,t,t'}$ is the total numbers of robots adopted in country c from year t to t' (from the IFR data). $X_{c,t,t'}$ is country-specific observables at year t. η_c and η_t are country- and year-fixed effects, respectively. $\varepsilon_{c,t}$ is an error term.

Table 2 shows the result. Columns (1) and (2) use long-difference specifications from 1995 to 2015. Column (2) includes the initial level of comparative advantage. Both columns show that robot adoption associates with increases in comparative advantage. Columns (3) and (4) use 10-year stacked difference specifications for periods 1995-2005 and 2005-2015. Both columns include period-fixed effects. Column (3) includes the initial comparative advantage, and Column (4) includes the country-fixed effect, which is a more demanding specification. Both columns suggest that robot adoption associates with increases in comparative advantage in low-skill-intensive industries.

Table 2: Automation and Changes in Comparative Advantage

	(1)	(2)	(3)	(4)
log Robot Adoption	0.51	0.45	0.14	0.17
	(0.15)	(0.14)	(0.03)	(0.03)
Initial CA		-0.26	-0.11	
		(0.11)	(0.05)	
Observations	44	44	88	88
Period fixed effects			Yes	Yes
Country fixed effects				Yes

Notes: This table shows the relationship between changes in comparative advantage in low-skill-intensive industries and robot adoption between 1995 and 2015. The changes in comparative advantage are from the estimation in this paper. The robot adoption data is from the IFR data. Columns (1) and (2) use long-difference specifications from 1995 to 2015. Column (2) includes the initial level of comparative advantage. Columns (3) and (4) use 10-year stacked difference specifications for periods 1995-2005 and 2005-2015. Both columns include period-fixed effects. Column (3) includes the initial comparative advantage, and Column (4) includes the country-fixed effect. All columns use the country's total export as weights.

4 New Model: Automation and Comparative Advantage

The empirical results in the previous section show that the pattern of comparative change based on skill intensity has changed over time. The results also suggest that automation can be responsible for the change. In this section, I develop a theoretical framework to study how automation can change comparative advantage. To do so, I extend the baseline framework in Section 2 by embedding the task framework as Acemoglu and Restrepo (2022).

4.1 Setting

Preference Consider a representative household in country j with CES utility across industries as follows:

$$U_j = \left[\sum_{s \in \mathcal{S}} \gamma_j^{\frac{1}{\phi}} (q_{js})^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}$$

where U_j is utility in country j, q_{js} is consumption of goods in sector s consumed in country j, γ_{js} is the share parameter, and $\phi > 0$, $\phi \neq 1$ is the elasticity of substitution across industries.[11] This implies that the expenditure share of country j in sector s, which I denote μ_{js} is

$$\mu_{js} \equiv \frac{X_{js}}{E_j} = \frac{\gamma_{js} (P_{js})^{1-\phi}}{\sum_{s'} \gamma_{js'} (P_{js'})^{1-\phi}}$$

[11]In a special case when $\phi = 1$, the preferences are assumed to be the Cobb-Douglas form across industries. I adopt that assumption in some of the analyses below but keep it general here.

Within each sector across goods produced in different countries, a representative household is with the CES utility within the sector across origin countries i as before:

$$q_{js} = \left(\sum_{s \in \mathcal{S}} (q_{ijs})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

$$P_{j,s} = \left(\sum_{i \in \mathcal{N}} (c_{is}\tau_{ijs})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \quad X_{ij,s} = \frac{(c_{is}\tau_{ijs})^{1-\sigma}}{P_{js}^{1-\sigma}} X_{js}$$

Production In each country-industry (i, s), a final product is produced in a competitive market. The production function is

$$Y_{i,s} = A_{i,s} (Y_{i,s}^{Q})^{\alpha_{i,s}^{P}} (H_{i,s})^{1-\alpha_{i,s}^{P}}$$

where $A_{i,s}$ is TFP in country i, sector s, α_{is}^{P} is the factor share of production task (the sum of capital share and production workers factor share), and $Y_{i,s}^{Q}$ is the intermediates produced by combining tasks. Task are combined as the CES structure as follows:

$$Y_{i,s}^{Q} = \left(\int_0^1 \left(y_{i,s}^{Q}(z) \right)^{\frac{\varepsilon-1}{\varepsilon}} dz \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

where ε is the elasticity of substitution across tasks.

As in the standard task model, task $y_{i,s}^{Q}(z)$ can be produced either by low-skill labor or machines if the task is not too complex ($z \in [0, \theta_{is}]$) and can only be produced by low-skill labor otherwise.

$$y_{i,s}^{Q}(z) = \begin{cases} L_{i,s}(z) + K_{i,s}(z) & \text{if } z \in [0, \theta_{is}] \\ L_{i,s}(z) & \text{if } z \in (\theta_{is}, 1] \end{cases}$$

I assume that machines, K_{is} are supplied at an exogenously fixed rental price r.

Exogenous Development of Automation Technology θ_{is} is the automation technology threshold, which is different across countries and industries. I assume θ_{is} is exogenously set.

National Income Identity National income identity holds as follows:

$$Y_i = w_i^L L_i + w_i^H H_i + rK_i$$

Equilibrium Conditions Then the equilibrium conditions are reduced to the following systems of equations

$$w_i^L L_i = \sum_s \sum_j \alpha_{is}^{P} s_{is}^{L} \pi_{ijs} \mu_{js} \left(w_j^L L_j + w_j^H H_j + rK_j \right)$$

$$w_i^H H_i = \sum_s \sum_j (1 - \alpha_{is}^{P}) \pi_{ijs} \mu_{js} \left(w_j^L L_j + w_j^H H_j + rK_j \right)$$

$$rK_i = \sum_s \sum_j \alpha_{is}^{P} (1 - s_{is}^{L}) \pi_{ijs} \mu_{js} \left(w_j^L L_j + w_j^H H_j + rK_j \right)$$

where trade share π_{ijs}, labor share within production task s^L_{is}, and unit cost c_{is} are defined as follows:

$$\pi_{ijs} = \frac{(c_{is}\tau_{ijs})^{1-\sigma}}{\sum_l (c_{ls}\tau_{ljs})^{1-\sigma}}$$

$$s^L_{is} \equiv \frac{(1-\theta_{i,s})(w^L_i)^{1-\varepsilon}}{(1-\theta_{i,s})(w^L_i)^{1-\varepsilon}+\theta_{i,s}r^{1-\varepsilon}}$$

$$c_{is} = \frac{\lambda_s}{A_{is}}\left((1-\theta_{i,s})(w^L_i)^{1-\varepsilon}+\theta_{i,s}r^{1-\varepsilon}\right)^{\frac{\alpha^P_s}{1-\varepsilon}}(w^H_i)^{1-\alpha^P_s}$$

where $\lambda_s \equiv (\alpha^P_s)^{-\alpha^P_s}(1-\alpha^P_s)^{\alpha^P_s-1}$.

4.2 Some Theoretical Observations

While the full general equilibrium effects need to be analyzed numerically, I provide some useful comparative statics given factor prices.

The unit cost function is as follows:

$$c_{is} = \lambda_s\left((1-\theta_{i,s})(w^L_i)^{1-\varepsilon}+\theta_{i,s}r^{1-\varepsilon}\right)^{\frac{\alpha^P_s}{1-\varepsilon}}(w^H_i)^{1-\alpha^P_s}$$

First, one can observe that if $\theta_{is} = 0$, $c_{is} = \lambda_s(w^L_i)^{\alpha^P_s}(w^H_i)^{1-\alpha^P_s}$ holds so that this collapses to the baseline framework.

Second, automation (higher θ_{is}) decreases the log unit cost $\ln c_{is}$ more in production-intensive industries (higher α^P_s) for low-skill labor scarce countries (higher w^L_i). Mathematically,

$$\frac{\partial^3 \ln c_{is}}{\partial\alpha^P_s\partial w^L_i\partial\theta_{is}} = \frac{-(w^L_i)^{-\varepsilon}r^{1-\varepsilon}}{\left[(1-\theta_{is})(w^L_i)^{1-\varepsilon}+\theta_{is}r^{1-\varepsilon}\right]^2} < 0$$

This implies that automation weakens the comparative advantage. In the next section, I provide a numerical illustration based on a two-country model to graphically demonstrate this mechanism.

5 Two-country Numerical Illustration

In this section, I use a two-country (North and South) version of my model to illustrate two important essences of the model.

5.1 Comparative Advantage within Manufacturing industries

First, I show how automation can change comparative advantage within manufacturing industries. To ease the exposition, I assume $\phi = 1$ and directly take value-added share across industries γ_j and α^H_s from NBER-CES data. For other parameters, as a numerical illustration, I use the following values. I set $\sigma = 6$ (Costinot et al., 2012), $\tau_{ijs} = 1.1$ if $i \neq j$, $r = 0.1$, $\varepsilon = 0.49$ (Humlum, 2019), and $A_s = 1$ (No sectoral difference in TFP).

The only ex-ante difference across North and South is the factor endowment of skilled workers relative to unskilled workers. I set $\{(H/L)_N, (H/L)_S\} = \{0.34, 0.04\}$ from the average ratio of college-educated to others in 1990 data for OECD and non-OECD (from Barro and Lee (2013)).

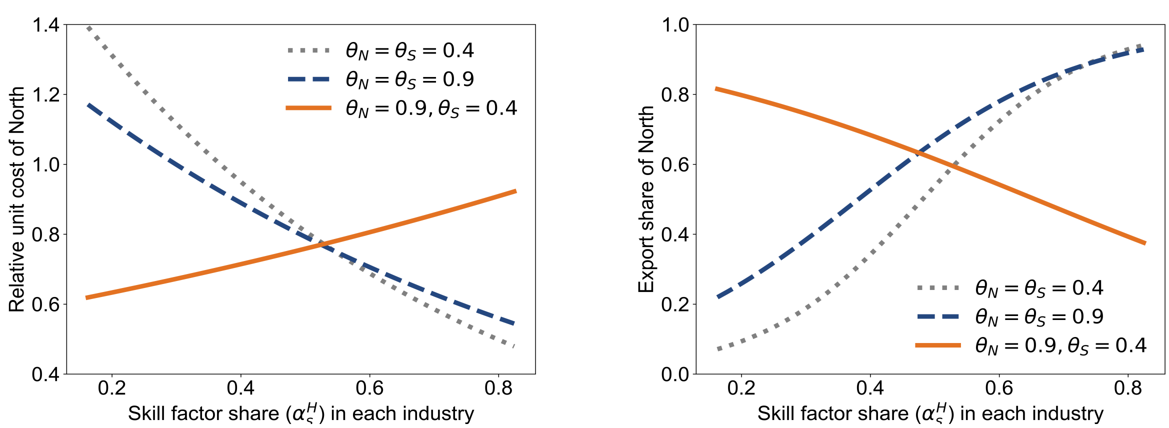
The experiment is to change $\theta_{i,s} = \theta_i$ for all industries s in the country i and see how these changes affect unit costs and export share across industries, which differ in skill intensity. The first baseline case is that both North and South have low-level automation technology ($\theta_N = \theta_S = 0.4$). The second case is that both North and South have a higher level of automation technology ($\theta_N = \theta_S = 0.9$). The final case is that only North has a higher level ($\theta_N = 0.9 > \theta_S = 0.4$).

Figure 7 shows the results. Panel (a) shows the relative unit cost of North to South across 397 sic87dd 4 digit industries with different skill factor share. Panel (b) shows the export share of the North across industries. In the baseline case ($\theta_N = \theta_S = 0.4$) shown as gray dotted lines, the relative unit cost of North is lower in skill-intensive industries (high α_s^H), and the export share is higher in these industries. This follows a standard Heckscher Ohlin argument that the skill-abundant North has comparative advantage in skill-intensive industries.

When automation technology advances in both countries ($\theta_N = \theta_S = 0.9$), both of the curves become more flattered as shown in the blue dashed lines. This means that a reduction of unit cost is higher for North in industries that rely more on unskilled workers (low α_s^H). As a result, North's export shares in low α_s^H industries increase. This corresponds to the decline in β_t shown in Section 3.

Moreover, when automation technology advances only in North ($\theta_N = 0.9 > \theta_S = 0.4$), the patterns can be reversed as shown in the orange solid lines.

Figure 7: Automation and Comparative Advantage: Two-country Illustration



(a) Relative Unit Cost

(b) Export Share

Note: The left panel shows the relative unit cost of North to South across industries with different factor-intensity. The right panel shows the export share of North across industries with different factor intensities. In each panel, the gray dotted line shows the result in the baseline case when $\theta_N = \theta_S = 0.4$. The blue dashed line shows the result in the case when $\theta_N = \theta_S = 0.9$. The orange solid line shows the result in the case when $\theta_N = 0.9$, $\theta_S = 0.4$. Factor intensities are defined at 397 sic87dd 4-digit industries, directly taken from the data in Becker et al. (2021) in 1990. Relative unit cost and export share are from the numerical analysis in this section.

5.2 Premature Deindustrialization

Second, I study how automation in North and international trade can affect structural change in South. As an illustration, I first pick $\phi = 0.5$, $g_A = 0.08$, $g_M = 0.04$, and $g_S = 0.02$. I set

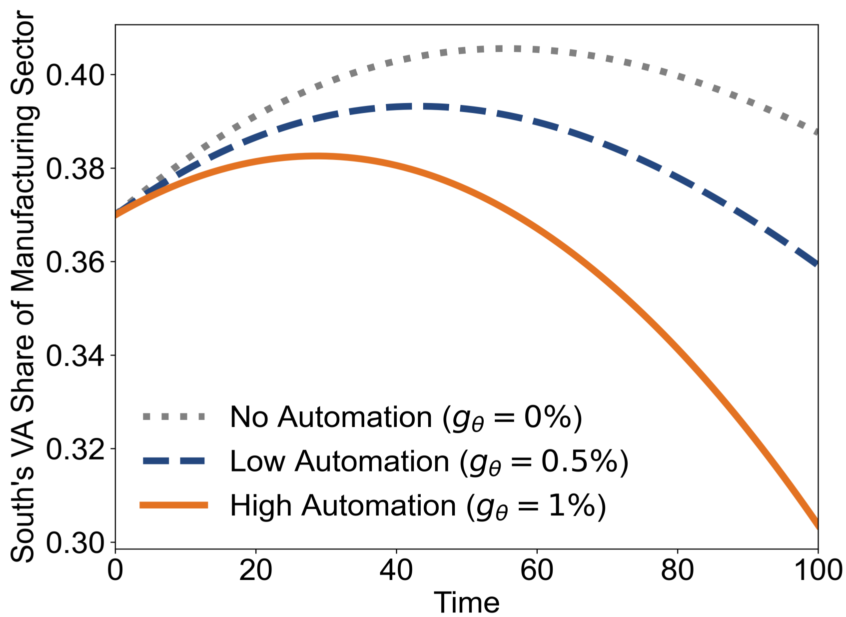
$A_s(0) = 0$ for $s = A, M, S$. This leads to a standard productivity-based structural change in a closed economy model.

The key experiment is to change the growth rate of θ. For simplicity, I assume only the manufacturing sector in North experiences growth in θ (if any) and set $\theta_{is}(t) = 0.05$ for $i = S$ or $(i,s) = \{(N,A),(N,S)\}$. I experiment with three different growth rates of $\theta_{N,M}(t)$. First, I set $\theta(0) = 0.05$ and fix it. Second, I assume low automation technology progress ($g_\theta = 0.005$). Finally, I assume high automation technology progress ($g_\theta = 0.01$).

I simulate the economy for 100 periods using the same values for other parameters in the previous subsection and see how South's value-added share of the manufacturing sector over time.

Figure 8 shows the result. Higher automation leads to a lower peak of manufacturing industries' share and a faster de-industrialization. This replicates the pattern, which Rodrik (2016) calls "premature deindustrialization".[12]

Figure 8: Automation and Premature Deindustrialization



Note: This figure shows the South's manufacturing valued-added share over time with different growth rates of automation technology. The gray dotted line shows the path with $g_\theta = 0$. The blue dashed line shows the path with $g_\theta = 0.005$. The solid orange line shows the path with $g_\theta = 0.01$.

[12]This result is highly complementary to Fujiwara and Matsuyama (2020), which shows that the technology gap across countries can be a hypothetical reason for premature deindustrialization in a closed economy model.

6 N-country Quantitative Analysis

In this section, I quantify the role of automation in comparative advantage. The current version of the draft focuses on comparative advantage within manufacturing industries and abstracts from drawing conclusions for structural change. including premature industrialization.

6.1 Calibration

Parameters Table 3 summarizes the parameters calibrated. Panel A shows the parameters externally calibrated. α_s^H, μ_s, and L_i, H_i are directly taken from the data as in the empirical section. I assume $\phi = 1$ and $A_s = 1$ to abstract from the productivity-based structural change. I set the machine price r to be 0.1. I pick $\sigma = 6$ from the literature, but the result is robust to different values as in the quantitative trade literature. I use $\varepsilon = 0.49$ from Humlum (2019).

The most considerable challenge in the calibration of quantitative trade models is how to choose trade cost. Since the factor shares change, I cannot use the exact hat algebra, where one does not have to know the level of trade cost to study the changes in equilibrium outcomes. Therefore, I have to fully specify τ_{ijs}. Here, I set τ_{ijs} following a residual approach by Head and Ries (2001). Suppose that intra-national trade is free, that is, $\tau_{ijs} = 1$. Also, suppose that international trade is symmetric within each industry $\tau_{ijs} = \tau_{jis}$. Then we have

$$(\tau_{ijs})^{1-\sigma} = \sqrt{\frac{X_{ijs}X_{jis}}{X_{iis}X_{jjs}}}$$

I estimate τ_{ijs} as above using the World Input-Output Table (Timmer et al., 2015) in 2000 and set them as time-invariant. Due to this estimation, I need to restrict samples of countries and industries in the World Input-Output Table. This leads to 38 countries and 18 manufacturing aggregated industries (roughly SIC 2-digit manufacturing industries).

Panel B shows the parameter internally calibrated, which is the key exogenous process to feed—automation technology $\theta_{is,t}$. I first set $\theta_{US,s,2000}$ to match the US production labor share across industries (from the NBER-CES manufacturing database). I then simply extrapolate this to automation technology in other countries and other periods, $\theta_{i,s,t}$, using the ratio of robot density (the number of robots per employment) from the IFR data. Since the IFR data starts in 1994, $\theta_{is,t}$ set to be the same within country-industry pairs between 1980 and 1990.

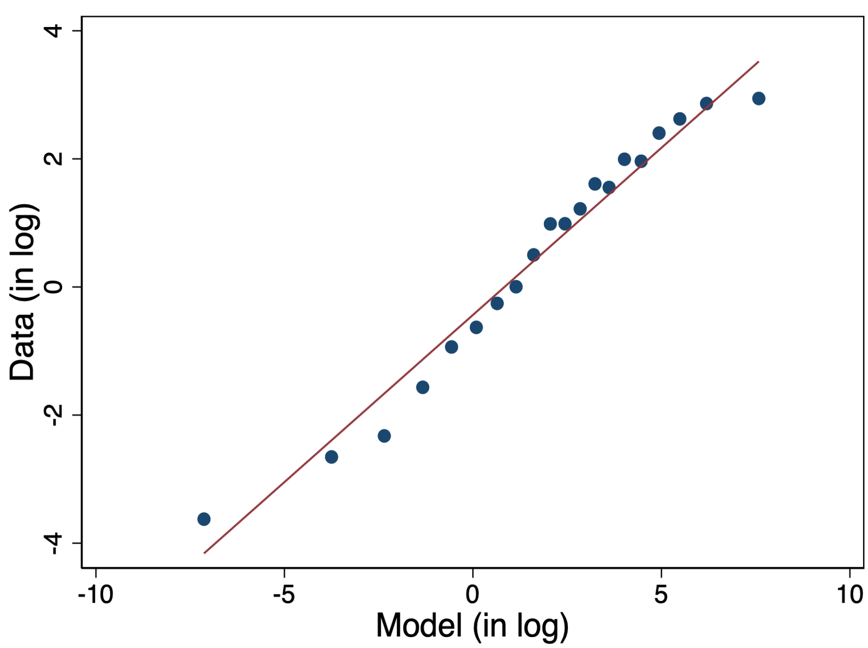
6.2 Model Fits

Trade Flows in 2000 The first moment to check is bilateral trade flows in 2000. Figure 9 is a binned scattered plot of $\ln X_{ijs}$ in data against that in the model. Overall, the model well captures the bilateral trade flows across country pairs and industries.

Table 3: Parameter Values

Parameters	Description	Value	Target/Source
Panel A: Externally calibrated			
α_{st}^{H}	Non-production factor share	Data	US Becker et al. (2021)
μ_{st}	Value-Added share	Data	World Input Output Table
L_{it}, H_{it}	Factor endowments	Data	Barro and Lee (2013)
ϕ	Sectoral EoS	1	Assumption
A_{st}	Sectoral TFP	1	Assumption
r	Machine price	0.1	Imposed
σ	Trade EoS	6	Costinot et al. (2012)
ε	EoS between tasks	0.49	Humlum (2019)
τ_{ijs}	Trade cost	-	Head and Ries (2001) approach
Panel B: Internally calibrated			
θ_{ist}	Automation	-	US Production Labor share and IFR

Figure 9: Model fit: Bilateral Trade Flows in 2000



Note: This figure plots bilateral trade flows across industries in data (from the World Input-Output Table) and the one generated by the model. The plot is a binned scattered plot.

Model fits: Comparative Advantage I first re-estimate Equation (1) using the exact data from the World Input-Output Table to be consistent with the model. Then, I solve the model under the parameter calibrated and estimate the same gravity equation (1) using the model-generated data.

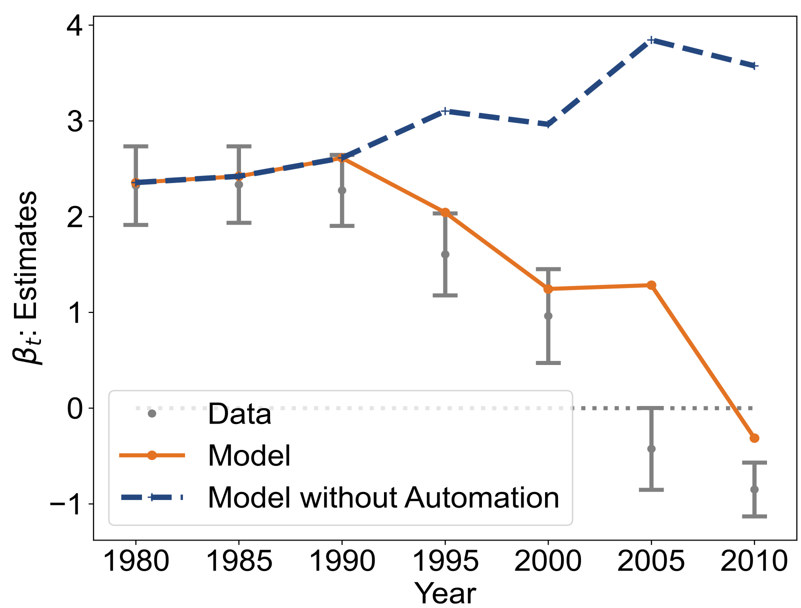
The orange solid line in Figure 10 shows the model fits, that is, the line compares the estimates of coefficients β_t in Equation (1) using the actual data and the model-generated data. While the only time-varying calibrated parameters θ_{ist} target only at the US labor share over time, the model explains the pattern found in Section 3 over time very well.

6.3 Counterfactual Experiment: Comparative Advantage without Automation

Using the model, I study how comparative advantage would have been without automation. In particular, I fix θ_{ist} to be the 1980-1990 level over time, re-simulate the model, and re-estimate the gravity equation. I use the same values for all the parameters but θ_{ist}.

Again, Figure 10 shows the result. The blue dashed line shows the estimates of β_t under the model without automation. It shows that without automation deepening after 1990, the pattern of comparative advantage would have been similar or even stronger according to the model.

Figure 10: Comparing Model against Data



Note: The figures show the estimates of coefficients β_t in Equation (1) using the actual data and the model-generated data at 18 aggregated industries. The orange solid line is based on the simulation with calibrated path of $\theta_{i,s,t}$, and the blue dashed line is based on the simulaton fixed path of $\theta_{i,s,t}$ to be the same level over time. I run regressions in each point time separately. Bars for the lines from the estimated based on the data indicate 95% confidence intervals based on heteroskedasticity-robust standard errors.

7 Conclusion

In this paper, I study how automation affects comparative advantage. I find that skill endowment has become less important for comparative advantage over time since 1980. I show that automation can be a source of this weakening relationship.

As comparative advantage in low-skill labor-intensive industries is one of the main drivers for industrialization and subsequent growth for developing countries, this changing nature of specialization is not just important by itself but also consequential for economic growth and welfare.

In particular, automation has been thought to be a source of inequality within countries as in Acemoglu and Restrepo (2020). In fact, automation can also be an important source of inequality *across* countries via the mechanisms I show in this paper because automation in developed countries reduces gains from trade of developing countries. In an ongoing extension, I am working on is to draw implications for growth and income differences within and across countries.[13]

Another extension is to endogenize automation technology. A theoretical prediction is that production-labor-scarce countries specialize in production-labor-intensive industries *because* they are production-labor-scarce and automate more.

[13]There are several recent papers that study the relationships between technology and skill premium in multi-country settings such as Burstein and Vogel (2017) and Burstein et al. (2019), Morrow and Trefler (2020).

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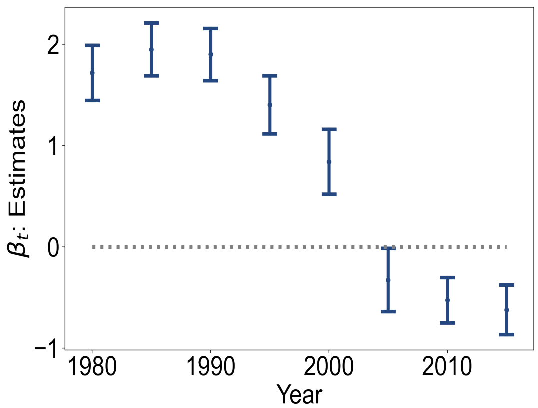
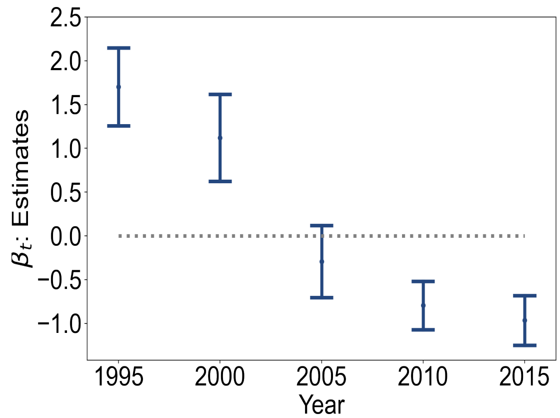
A Additional Figures

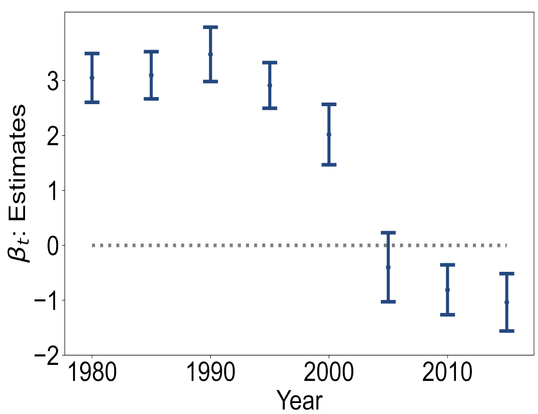
Figure A.1: Estimates of Importance of Skill Intensity; β



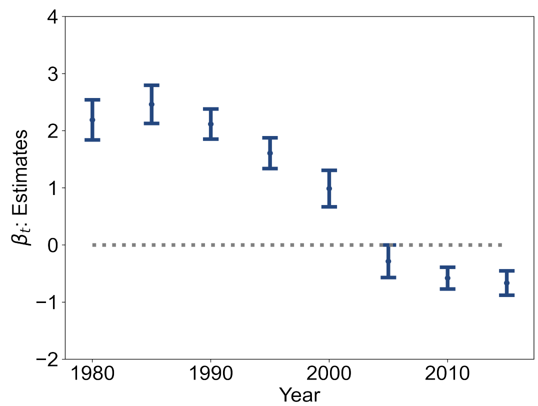
(a) More Aggregated Categories (75, US Census)



(b) More Aggregated Categories (13, IFR)



(c) Controlling Capital Intensity



(d) High school as High-skill

Note: The four figures show the estimates of coefficients β_t in equation (1). I run regressions in each point time separately. Figure (a) is based on the same regression but using 75 aggregated industries defined in US census. Figure (b) is based on the same regression but using 13 aggregated industries defined in IFR. Figure (c) controls the interaction between capital intensity and capital endowments (in log, relative to labor). Figure (d) uses the ratio of high school graduates to others as the skill endowment instead of college to others. Bars indicate 95% confidence intervals based on heteroskedasticity-robust standard errors.